The London School of Economics and Political Science

The Economics of Cultural Diversity: Lessons from British cities

Max Nathan

A thesis submitted to the Department of Geography and Environment of the London School of Economics for the degree of Doctor of Philosophy. September 2011

Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorization does not, to the best of my belief, infringe the rights of any third party.

MAX NATHAN

Abstract

This thesis examines the economic effects of cultural diversity; it focuses on recent experience in British cities, and on links between migrant and minority communities, diversity and innovation. Like many western societies Britain is becoming more culturally diverse, a largely urban process driven by net immigration and growing minority communities. Despite significant public interest we know little about the economic impacts. This PhD aims to fill these major gaps.

First, I explore connections between diversity, immigration and urban outcomes. I ask: does diversity help or hinder urban economic performance? Initial cross-sectional analysis finds positive associations between 'super-diversity' and urban wages. Using panel data and instruments to establish causality, I find that net immigration helps raise native productivity, especially for high-skilled workers, but may help exclude lower-skill natives from employment opportunities. De-industrialisation and casualization of entry-level occupations partly explain the employment results.

Next I investigate links between co-ethnic groups, cultural diversity and innovation. I explore effects of co-ethnic and diverse inventor groups on individual members' patenting rates, using patents microdata and a novel name classification system. Controlling for individuals' human capital, I find small positive effects of South Asian and Southern European co-ethnic membership. Overall group diversity also helps raise individual inventors' productivity. I find mixed evidence of effects on majority patenting.

I then explore the case of London in detail, using a unique survey of the capital's firms. I ask: does organisational diversity or migrant/ethnic ownership influence firms' product and process innovation? Results show small positive effects of diverse managements on ideas generation. Diverse firms are more likely than homogenous firms to sell into London's large, cosmopolitan home markets as well as into international markets. Migrant entrepreneurship helps explain the main result.

Together, these papers make important contributions to a small but growing literature on diversity, innovation and economic development.

Acknowledgements

Many thanks to Henry Overman and Ian Gordon for outstanding supervision, to Malo Hutson for hosting me at UC Berkeley, and to Lou and my family for love and support.

Thanks also to Philippe Bracke, Maria Carvalho, Tony Champion, Riccardo Crescenzi, Ted Egan, Giulia Faggio, Tommaso Frattini, Steve Gibbons, Ben Gidley, Harvey Goldstein, Christian Hilber, Jennifer Hunt, Simona Iammarino, Kath Jones, Bill Kerr, Mark Kleinman, Jed Kolko, Neil Lee, Carlo Menon, Max Neiman, Ceren Ozgen, Andrés Rodríguez-Pose, Rosa Sanchis-Guarner, Allen Scott, Will Somerville, Madeleine Sumption, Carlos Vargas-Silva, Vivek Wadhwa, Kim Walesh, Niels Westergaard and Peter Wood for advice, comments and ideas along the way.

I am grateful to Pablo Mateos at University College London's Centre for Advanced Spatial Analysis, Gianluca Tarasconi and Francesco Lissoni at Università Bocconi, Matthew Waite at the Greater London Authority, and the Office of National Statistics Virtual Microdata Lab – without whose data these papers could not have been written.

Previous versions of the papers were presented at the following conferences: Association of American Geographers (2010 and 2011); North American Regional Science Council-Urban Economics Association (2009); Regional Studies Association Early Careers group (2010); Regional Studies Association (2011); Spatial Economics Research Centre (2010) and University College London/NORFACE (2011). In addition it was discussed at invited seminars at SERC/LSE, COMPAS/Oxford University, the Institute of Urban and Regional Development/UC Berkeley and at the universities of Liverpool and Manchester. Thanks to participants and discussants for helpful feedback.

The Economic and Social Research Council (ESRC) and the Department of Communities and Local Government provided generous financial support. The views expressed in this thesis do not necessarily represent those of the Department or the ESRC. This work also contains statistical data from the Office of National Statistics (ONS), which is Crown copyright and reproduced with the permission of the controller of Her Majesty's Stationery Office and Queen's Printer for Scotland. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research datasets that may not exactly reproduce National Statistics aggregates.

All errors and omissions remain my own.

Conjoint work: joint authorship statement

The paper 'Does Cultural Diversity Help Innovation in Cities? Evidence from London Firms' was written with Neil Lee, then a fellow PhD student at LSE. An early version was published in a peer-reviewed journal using 2007 London Annual Business Survey (LABS) data, running a simple model testing cross-sectional links between workforce diversity and ideas generation (Lee and Nathan, 2010).

The new paper is a substantively improved version of the original analysis. I led the process of re-working and re-focusing. My contributions include:

- Expanding the sample to three years of data, from 2005 – 2007 inclusive. The new format exploits quasi-experimental conditions following A8 accession

- Rewriting the original Stata code for data cleaning, variable-building and regressions

- Developing improved independent, main and control variables

- Significantly expanding the original analysis to cover 1) firms' commercialisation of new ideas, 2) an exploration of the influence of diversity on the geography of firm sales 3) variations within knowledge intensive sectors

- Developing, coding and interpreting a series of causality checks to control for the potential influence of 1) individual migrant entrepreneurs and 2) firm-level endogeneity issues

- Leading the interpretation of the analysis, and the re-drafting of the paper.

Overall, my contribution amounts to 60% of the total work on the paper.

Contents

Overview

Introduction, critical discussion and conclusion

1. Introduction

This thesis explores the economic impacts of cultural diversity: it focuses on recent experience in British cities, and on links between migrant and minority communities, diversity and innovation. Like many Western societies Britain is becoming more culturally diverse, a largely urban process driven by net immigration and growing minority communities. These are issues of great importance for the public, business and policymakers. However, we know little about the real economic impacts of immigration and diversity, and little about which policy choices maximise welfare in these areas. The thesis aims to fill these important gaps; it comprises four papers, which form the subsequent chapters of the document.

This introductory chapter provides an overview and synthesis. I begin with a brief discussion of some basic concepts and the UK policy context. Next, I survey academic perspectives on cities and cultural diversity, before introducing economic frameworks in more detail. I identify three main research questions and outline the metastructure of my primary research. I provide brief summaries of each paper's methods, results and contribution, before concluding with some more general thoughts and lessons for policymakers.

2. Background and motivation

There is a vast and sprawling literature on cities and cultural diversity, covering (among others) historical, ethnographic, sociological, social capital, urbanist and post-colonial perspectives, as well as a large body of economic research. The economic literature has been dominated by two major debates. First, labour economists have developed a large literature on both the migration decision, and the effects of immigration on sending and receiving countries. In the case of receiving countries, analysis has largely focused on labour market impacts for natives, and on broader social and economic outcomes for migrants ('immigrant integration') (Dustmann et al., 2008, Kerr and Kerr, 2011). Second, in the development and economic growth fields a number of country-level studies have explored the impact of cultural, ethnic and linguistic divisions on long term economic, social and political outcomes (Ranis, 2009, Fernandez, 2010).

Four strands of current thinking on growth and economic development suggest the potential for a broader approach. First, endogenous growth theories highlight the importance of human capital in driving productivity and long term growth, and in sustaining spatial disparities (Romer, 1990). Second, research in economic geography highlights cities' productivity-enhancing functions, in particular via knowledge spillovers and economic diversity (Jacobs, 1969, Duranton and Puga, 2001). Third, theoretical and experimental studies suggest that the diversity of economic agents may accelerate the creation of knowledge, or improve the quality of ideas (Page, 2007, Berliant and Fujita, 2009). Fourth, these studies also suggest co-ethnicity and diversity channels may be amplified in urban areas through agglomeration effects, large migrant/minority communities and a cosmopolitan city population's taste for new and diverse goods and services.

In recent years a small number of empirical studies have started to combine these elements. For example, in spatial economics, Ottaviano and Peri (2005a, 2006) have explored the effects of cultural and linguistic diversity on urban economic performance. In economic sociology Saxenian (2006) has investigated the role of migrants and diasporic communities on regional economic development and high-technology sectors. Meanwhile, in economic geography Richard Florida has argued that a cities need to attract a tolerant, diversity-loving 'creative class' in order to maintain long term economic success (Florida, 2002).

This thesis contributes to this growing literature on the economic effects of immigration and diversity: in particular, it explores impacts on innovation and urban economic development.

2.1. Endogenous growth and the economic role of cities

The first building block of my research is the continued relevance of cities, and the role of endogenous growth and economic geography frameworks in explaining this. Over 50% of the world population now live in urban areas, and this share is predicted to keep rising. Despite predictions of the 'death of distance', large urban centres remain of great demographic, social and economic importance. As McCann argues, "the global economy appears to be simultaneously characterised by global flattening and local steepening" (2008) (p361). Other see it as 'spiky' (Florida, 2005) or an 'archipelago economy' of linked urban centres (Veltz, 2000).

Geographers have developed a variety of frameworks for understanding cities and urban systems. Peet (1998) provides a brief history, from the cultural and regional geography of the 1920s and 1930s, through to the 'quantitative revolution' of the 1950s and 60s and the emergence of radical and environmental perspectives in the 1970s. There has been a proliferation of approaches in the past few decades: realist perspectives, postmodernist frameworks and a re-emergence of quantitative approaches in the 'New Economic Geography'.

Some of these frameworks provide important foundations for the thesis. From an urbanist perspective Jane Jacobs proposes we view neighbourhoods and cities as 'problems in organised complexity' (Jacobs, 1961). Unpicking urban systems requires a focus on the economic, social and cultural processes shaping areas from the outside, as well as close observation of local actors and specificities. Critical realist Doreen Massey similarly argues that local economies are the product of national / global processes, but that local conditions produce variety and uniqueness (Massey, 1984). Michael Storper's 'transformationalist' approach develops this line further, arguing that capitalism is structured by societal specifics and thus 'the local helps make the global' (Storper, 1997).

Storper is also clear that to understand the continued relevance of cities under globalisation, geographers need to use the tools of other disciplines. His 'heterodox paradigm' combines elements of economics, sociology, management science and geography to explain regional development as a relational process, with regions as the nexus of formal economic interactions and informal 'untraded interdependencies' (Storper, 1997). Within regions, cities are 'socio-economies' that play critical roles in the organisation of high-value economic activity.

These geographical frameworks repeatedly intersect with those of urban economics (hence UE) and the 'New Economic Geography' (hence NEG). These latter are particularly helpful in explaining the location patterns of economic activity. While classical models of economic growth predict the long run convergence of countries and regions, in practice spatial disparities between and within countries turn out to be persistent.

Endogenous growth theories help to explain these trends by highlighting the importance of human capital and knowledge in advancing the technological frontier. Subsequent productivity gains help drive countries' long term economic growth and development (Lucas, 1988, Romer, 1990). National and regional differences in knowledge creation and diffusion thus help explain spatial disparities – both across and within countries. In these frameworks, human capital spillovers are the key channel for both the diffusion of existing ideas and the development of new ones.

Drawing on these ideas, both UE and NEG have developed a number of insights that help explain the behaviour of urban systems and spatial economies, and thus explain spatial differences. In these accounts of long term growth, cities play a number of important and well-established roles. Both perspectives partly develop out of Marshall's ideas on agglomeration economies: thick labour markets, input-sharing and knowledge spillovers that help raise firms' productivity in urban environments (Marshall, 1918). Jane Jacobs (1969) extends these ideas by highlighting the importance knowledge spillovers across sectors. Cities' long term economic resilience is thus partly a product of economic diversity, which facilitates innovation.

UE and NEG approaches share many insights, but also contain important differences of emphasis (Combes et al., 2005, Glaeser, 2008). Urban economics frameworks begin with the spatial location models of Alonso (1964), Mills (1967) and Henderson (1974). These models focus on the balance of agglomeration economies and diseconomies in a system of cities (Combes et al., 2005). Productivity gains driven by agglomeration effects help raise nominal wages and (often) employment rates; conversely, urban crowding in growing cities raises costs and eats into real wages. In spatial equilibrium, labour, housing and amenities markets clear, real wages equalise and workers and firms are indifferent between locations.

New Economic Geography begins with firms' location decisions under globalisation, assuming monopolistic competition and both internal and external scale economies (Krugman, 1991). As transport costs decline, internal increasing returns mean that firms will want to consolidate activity in single large plants and to specialise production. Agglomeration economies, notably upstream-downstream linkages and local knowledge spillovers will lead to clustering (Krugman and Venables, 1995). Conversely, congestion, pollution and competition may lead firms to exit. Overall, the balance of 'centrifugal' and 'centripetal' forces determines the location of economic activity (Fujita et al., 1999). The clustering process is characterised by feedback loops, so that existing agglomerations often have first mover advantage (Krugman and Obsfeldt, 2003); however, technological change and sectoral differences also tend to produce 'production jumps' from higher to lower cost regions (Venables, 2006). These jumps occur within sectors as well as between them: Venables gives the example of a financial services firm with offshored call centres, IT services outsourced to local partners, an international network of retail branches and a London-based headquarters. These complex production chains require careful co-ordination, and can imply high search, transaction and management costs (McCann, 2008, Saxenian and Sabel, 2008). Most recently, the 'globalisation of innovation' has seen the international re-organisation of increasingly high-value, 'knowledge-intensive' activities (Mudambi, 2008).

Both perspectives help explain important stylised facts for UK cities. Recent structural shifts in national economies – in particular, an increased share of employment in services and 'knowledge-intensive' activity – have helped to accelerate the sorting of employers and skilled workers across urban areas (Overman and Rice, 2008). Urban environments play increasingly important roles in local knowledge spillovers and ideas flow, by supporting face to face interactions and other 'learning' economies. At the same time, there are important differences in the 'demand for cities' between and within sectors, and across the lifecycle (Champion and Fisher, 2004, Graham, 2007, Melo et al., 2009).

2.2 Cultural diversity

The second building block of my research is the notion of 'cultural diversity', in particular as it relates to the city: as Amin (2002) makes clear, cities are the primary sites of cultural diversity. While multicultural societies and cities are usually seen as new phenomena, their roots often go back for centuries (Sandu, 2004). Britain and many other European societies share a long history of demographic change. Migrations typically resulted in new minority communities assimilating, to different degrees, into the cultural mainstream (Sassen, 2004). In his history of London, for example, Peter Ackroyd writes that "by the tenth century [the city] was populated by Cmyric Brythons and Belgae, by remnants of the Gaulish legions, by East Saxons and Mercians, by Danes, Norwegians and Swedes, by Franks and Jutes and Angles, all mingled and mingling together to form a distinct tribe of 'Londoners'" (Ackroyd, 2000).

Cultural diversity is not straightforward to define. As the popular discussion around the summer 2011 riots in London and other English cities makes clear, disentangling culture and ethnicity from class, education and other socio-economic factors is both important and difficult to do. Quantitative approaches have much to offer in principle, helping to illuminate over-arching trends, patterns and relationships; but they are hard to implement. Diversity metrics typically borrow from demographics or industrial economics, deploying Fractionalisation and other indices. However, accurate measurement of diversity requires a robust measure of cultural or ethnic identity. This is challenging, as identity is a multifaceted concept with objective, subjective and dynamic elements (Mateos, 2007, Aspinall, 2009).

Quantitative measures of identity thus tend to be partial: they focus on identity's visible, objective components, assuming away self-ascription and endogeneity issues (Ottaviano et al., 2007). For quantitative researchers, therefore, identifying identity involves a least-worst proxy, such as country of birth, language or religion – or official ethnic typologies, such as those built by the UK Office of National Statistics (hence ONS) (Office of National Statistics, 2003). Aspinall (2009) argues that all such identity proxies offer a trade-off between 'granularity' and 'utility', between high levels of detail and wider tractability.

I discuss definition and measurement issues in greater detail in the next chapter. Over the course of the thesis I make use of three identity proxies: country of birth, ONS ethnic groups, and the ONOMAP cultural-ethnic-linguistic (hence CEL) name classification system. These are used to construct measures of immigrant and ethnic groups, and to populate measures of cultural diversity at firm, group and area level. Each proxy offers a different balance of granularity and utility. More detail on the classifications is given in Appendix A, and the ONOMAP system is explained in Appendix B. I use a Fractionalisation Index as my main diversity metric, following others in the literature; the Index is helpful in that it captures both the number of identity groups in a population or area, and their relative sizes. I discuss the Index further in the first paper.

2.3 UK context

The economic impacts of immigration and diversity have particular salience for the UK and for British cities. Britain and many other Western societies are becoming more culturally diverse, a process driven by both net immigration and the growth of new and established minority communities (Champion, 2006, Putnam, 2007). In 2007 immigration accounted for 52% of overall UK population growth, with natural change explaining the remaining 48%. Natural change is taking a rising share of overall change, and since 2007 has overtaken migration as a driver of population growth. Natural change includes a rising share of live births to mothers born outside the UK; this is currently running at over one in four (Office of National Statistics, 2011).

In turn, this reflects both higher levels of recent migration and higher birth rates in some minority groups (Performance and Innovation Unit, 2003). Between 2001 and 2009, non-White British groups in England and Wales have grown from 6.6m to 9.1m and now comprise one in six of the population (Office of National Statistics, 2011). Projections for the UK suggest that minority ethnic populations are likely to comprise 21% of the population by 2050, from 7.7% in 2001 (Wohland et al., 2010).

These trends make the UK's current and recent experience an important area for study. Not surprisingly, there are also very high levels of public and policy interest in these issues in the UK. Of course, worries about diversity are not new. In the year 883 King Alfred banished the Danes from London, restricting them to land east of the river Lea (Keith, 2005); Vertovec (2007) chronicles complaints across medieval Britain that "foreigners were practising their own customs".

However, over the past decade and a half diversity and immigration have become particularly high-profile agendas. Race and immigration are now commonly chosen 'most important issues' in public opinion surveys (Blinder, 2011). While attitudes to immigration and diversity vary significantly by class and education, overall large majorities of British people oppose mass immigration: the Government's most recent Citizenship Survey, taken in 2009-10, found that 78% of respondents favoured reducing immigration, 56% by "a lot" (Blinder, 2011). By contrast, UK business voices have been strongly supportive of open immigration policy, to help firms fill skills gaps and hire from global talent pools (McSmith and Russell, 2007, London First, 2008, BBC, 2010), and the business community has taken a similarly supportive stance on workforce diversity.

Reflecting these complexities, national immigration policy has undergone several major re-organisations since 2001 (Somerville, 2007). Immigration was a major issue in the 2010 UK election. While the previous Labour administration sought to encourage skilled migrants via a points-based entry system, the current Coalition government has capped net migration, with significant restrictions on entry for those outside the EU. Significantly, it has retained the Migration Advisory Committee (hence MAC), which provides intelligence on sectors and occupations facing skills shortages.

There is a continued debate on the wider impacts of growing diversity on the economy, society and public services (see for example (Goodhart, 2004, Putnam, 2007, Caldwell, 2009, Simpson and Finney, 2009, Fanshawe and Sriskandarajah, 2010, Goodhart, 2010). Since 9/11, 1980s models of multiculturalism have come under increased criticism, and both Labour and the coalition government have developed policies emphasising integration and community cohesion. Reflecting this, broader public and policy debates have tended to focus on issues of religious/racial tension and social cohesion, and on British towns and cities – such as Burnley and Oldham – that have seen ethnic / racial disturbances in recent years. The wider economic dimensions of diversity have tended to be underplayed (Wolf, 2008).

These issues have a distinctive urban footprint. Migrants and minority communities are unevenly distributed across the UK, with the highest numbers in cities. Since 2004, a number of rural areas and small towns have experienced very rapid growth in migrant populations (Bassere et al., 2007, Green, 2007a); however, bigger British cities still contain the largest migrant volumes and population shares. In 2002-3, over half of all net migration was to London, and over half of the rest was to the other conurbations and large cities (Champion, 2006). The urban share of both migrant groups and visible minorities has been increasing over the past decade and a half.

These are important times to be studying such issues. The economics of immigration and diversity is of great concern to national government, with policymakers needing to balance public opinion, local community dynamics and business interests. Many city leaders also need to manage larger, more diverse populations to maximise economic and social benefit. And as we shall see below, there remain important evidence gaps on the economic impacts of immigration and cultural diversity in the UK.

3. Cultural diversity and cities: perspectives

The literature on diversity and urban places is large and itself diverse. It includes historical analysis, such as the history of 'creative cities' (Hall, 1998) or the role of migrants in developing the 19th century Atlantic Economy (Crafts and Venables, 2001); ethnic group studies, covering the prospects and progress of (for example) Jewish, Italian and Caribbean communities in the US and UK (Sante, 1998, Sandu, 2004); the post-colonial literature, exploring diasporas, the development of cultural identity and the changing nature of 'home' (Gilroy, 1993, Urry, 2000); urban sociology, exploring related ideas of the cosmopolitan, transnational or 'mongrel' city (Smith, 2001, Sandercock, 2003, Keith, 2005); health (Fernandez, 2010); a number of studies looking at political participation, social capital and community cohesion (Alesina and La Ferrara, 2004, Putnam, 2007) as well as a related literature on segregation and immigrant integration (Landry and Wood, 2008, Simpson and Finney, 2009); development studies examining the role of ethnic fractionalisation in social development (Collier and Hoeffler, 1998); and a wide-ranging economic literature covering management and organisational performance, labour markets and human capital, entrepreneurship, innovation, productivity and the cost of living. These are discussed further in the next section.

As noted above, within the economic strand there are two traditional preoccupations. First, there is an extensive literature on the migration decision, and on immigration's impact on sending and receiving countries. In the latter case the focus is on migration-related labour supply shocks (for reviews see Dustmann et al (2008) or Kerr and Kerr (2011)). Researchers have focused on both the effects of immigrants on natives – at local and national scales – and on the social / economic outcomes of immigrants. Most recently within the UK, Anne Green and colleagues have conducted a number of important studies exploring the labour market effects of, and outcomes for migrants from Central and Eastern European countries that have recently joined the European Union (Green et al., 2007a, Green et al., 2007b, Green, 2007b, Green, 2008, 2009). Despite the largely urban footprint of immigration to the UK, few studies have looked at the urban level (see below).

Second, in the development studies and economic growth fields a number of country-level studies have looked at the role of 'ethno-linguistic fractionalisation' in affecting long-term economic development. Ranis (2009) reviews this literature, suggesting that the low population density of some countries in sub-Saharan Africa makes it even harder to generate trust relationships across ethno-linguistic groups – conversely, smaller, more highly populated Asian countries have been better able to foster the necessary social capital. Specifically, fractionalisation reduces trust and increases transactions costs (Collier and Hoeffler, 1998). Some recent studies have also made use of genetic distance data (Spolaore and Wacziarg, 2009) and global values surveys (Gorodnichenko and Roland, 2011) to proxy cultural commonality and difference, and its effect on countries' economic performance. A number of researchers, in particular Ottaviano and Peri (2005a, 2006, 2007), have extended these analyses to cities in the US and EU.

4. The economics of cultural diversity: frameworks

This thesis develops a broad-based view on the economic effects of cultural diversity, drawing on the economic literature and more widely. Specifically, I explore two crosscutting topics: first, links between immigration, urban population mix and the economic performance of cities; second, connections between migrant communities, diversity and innovative activity at individual, group and firm level. Basic theoretical frameworks are set out below: the relevant chapters provide more detail, and cover relevant empirics.

4.1 Immigration, diversity and urban economies

How might net immigration and growing cultural diversity affect urban economic performance? In recent years a number of influential authors have suggested that there are significant economic gains from migration and diversity, especially in cities (Florida, 2002, Legrain, 2006, Landry and Wood, 2008, Leadbeater, 2008).

In the geography field, much of the thinking in this area has been driven by Richard Florida's 'Creative Class' framework (Florida, 2002). Florida argues that in the US, UK and other Western countries, economic, demographic and social shifts have seen the emergence of a skilled, liberally minded 'Creative Class' of workers. Members of the Creative Class have a preference for diverse, cosmopolitan urban neighbourhoods. Employers – and thus, jobs – follow the Creative Class to specific cities. Urban employment rates and investment rise, as do firms' innovation and productivity (although urban inequality may also increase). These 'Creative Class' perspectives have become pervasive among policymakers, but have been criticised for their lack of empirical foundation (Glaeser, 2005, Nathan, 2007). There is certainly a need to subject these ideas to further testing.

Economic and economic geography frameworks suggest a wider set of perspectives. In a spatial economy, net immigration increases the size of the labour force. Immigration also changes population and workforce composition, increasing diversity. This may be direct through the arrival of new people and/or departure of existing workers, and indirect via impacts on birth rates. The overall effects on urban economic outcomes are ambiguous. Under neoclassical assumptions, the main effects are through the labour market. In small open economies – like cities – average wages are temporarily bid down, but then readjust via capital flows and expansion of labour-intensive sectors. If wages are sticky, employment may fall in the short term. Initially, immigrants typically 'cluster' in entry-level occupations, so that low-skill UK-born workers (so-called 'natives') may experience short term wage losses and high-skill natives short-term gains (Dustmann et al., 2008).

Once externalities are allowed, the picture changes significantly. Immigration – and the diversity migrants bring – may lead to production complementarities for firms and workers (Ottaviano and Peri, 2005a, Ottaviano and Peri, 2006, Bellini et al., 2008, Südekum et al., 2009, Longhi, 2011). For example, these may operate through more diverse workforces and diasporic communities (Saxenian, 2006, Page, 2007, Kerr and Lincoln, 2010). These channels will raise average labour productivity, not least by improving levels of innovation (see below). Larger urban populations also induce home market effects, raising demand for non-tradables. The combination of these channels may influence agglomeration economies, leading to further inward migration. However, greater competition for space in growing cities may raise the local cost of living (Saiz, 2003, Ottaviano and Peri, 2006). Over time, shifts in urban industrial structure and labour market institutions further influence economic outcomes. More cosmopolitan urban populations may also raise demand for new/hybridised goods and services, triggering Jacobian knowledge spillovers across sectors (Mazzolari and Neumark, 2009).

Conversely, employers in labour-intensive sectors may respond to long-term migrant inflows by permanently adjusting production functions to take advantage of cheap labour. Low value-added firms may then become reliant on migrant workers, locking out lower-skilled UK born workers from employment opportunities (Stenning et al., 2006). If these firms raise labour intensity and lower capital investment, migration may contribute to 'low skills equilibrium' in some urban areas (Finegold and Soskice, 1988).

My first and second papers review this theory and relevant empirics in more detail. They suggest a number of evidence gaps remain, particularly in a UK context. First, there are still few studies that explore economic impacts of immigration beyond labour markets. Second, we know relatively little about the specific effects of urban *diversity*, over and above migrant populations. Third, the transmission mechanisms linking population shifts to urban economic outcomes are under-developed. The papers in this thesis are able to address all of these issues, and add to our knowledge of the UK experience.

4.2 Innovation, immigration and diversity

I develop these ideas further by focusing on a specific set of transmission mechanisms: the links between migrant and minority communities, diversity and innovation. I define innovation as 'the successful exploitation of new ideas'; a combination of invention, adoption and diffusion (Fagerberg, 2005, Department of Innovation Universities and Skills, 2008).

Conventional theories of innovation have relatively little to say to about immigration, ethnicity or the composition of inventor communities. Schumpeter (1962) focuses on the 'entrepreneurial function' inside and outside firms, and the role of individuals in identifying and commercialising new ideas, in the face of social inertia or resistance. National 'innovation systems' approaches explore relationships between firms and public institutions such as government agencies and universities (Freeman, 1987).

Spatial approaches focus on clustering of innovative activity due to agglomeration-related externalities, particularly local knowledge spillovers (Jacobs, 1969, Jaffe et al., 1993, Audretsch and Feldman, 1996). More recently, a number of authors have explored the 'globalisation of innovation', as businesses in high-cost countries relocate research and development activity into lower-cost locations (Mowery, 2001, Archibugi and Iammarino, 2002, Cantwell, 2005, Yeung, 2009).

However, endogenous growth theories provide the basis for a number of newer studies linking demography to innovation, by highlighting the importance of human capital stocks and knowledge spillovers to levels of innovation. In practice, access to knowledge is likely to be uneven across locations, business sectors and social groups (Agrawal et al., 2008). Migrants, co-ethnic groups and group diversity may all affect knowledge creation, access and flow. Recent work suggests four ways in which this could occur.

First, migrant status may induce positive selection of highly skilled or entrepreneurial individuals (Borjas, 1987). For example, both firms and wider research communities may benefit from the presence of migrant 'stars' (Stephan and Levin, 2001). Conversely, exclusion from mainstream economic institutions may force members of minority communities to develop new businesses, products and services (Kloosterman and Rath, 2001). The empirical challenge here is to distinguish migrant/minority status from other human capital endowments and wider structural conditions.

Second, social networks such as diasporic groups can accelerate ideas generation and (in particular) transmission (Docquier and Rapoport, 2011). Social networks offer their members higher social capital and levels of trust, lowering transaction costs and risk. In turn, networks seem to positively affect innovative activity (Rodríguez-Pose and Storper, 2006, Kaiser et al., 2011). As innovation systems globalise, co-ethnic networks such as diasporas may be an important channel for knowledge spillovers and ideas flow – improving awareness of new technologies and passing on tacit knowledge (Kapur and McHale, 2005, Saxenian and Sabel, 2008, Kerr, 2009). Firms employing diaspora members may thus benefit from these improved ideas flows, as well as a wider set of potential joint venture partners (Foley and Kerr, 2011). Conversely, other social networks – such as family or kinship networks, or professional associations – might turn out to be more important in determining knowledge spillovers (Agrawal et al., 2008). Discrimination against minority groups from other communities will limit knowledge spillovers.

Third, diversity may improve ideas generation, if a diverse set of economic agents has access to a larger set of ideas, perspectives and skills. Both Berliant and Fujita (2009) and Hong and Page (2001, 2004) model systems of group-level knowledge creation, showing that heterogeneity can accelerate ideas generation through individual-level production complementarities. But, group-level cultural diversity may have a negative effect if it leads to lower trust and poor communication between individuals. Spillovers (and co-operation) will be limited, leading to fewer, lower-quality solutions (Alesina and La Ferrara, 2004). Fujita and Weber (2003) argue that positive diversity effects will be most likely observed in 'knowledge-intensive' activities and industries.

Finally, we might observe bigger co-ethnicity and diversity effects on innovative activity in cities because of composition effects: innovative activity, migrant and minority communities tend to be clustered in urban areas. Cities may also have positive or negative 'amplifying' effects. For example, if cultural diversity contributes to economic diversity, it may help foster knowledge spillovers across sectors at urban level (Jacobs, 1969). Conversely, members of minority communities may be physically isolated in particular urban neighbourhoods, limiting the opportunity for knowledge spillovers and interaction with other groups (Zenou, 2011).

This is another emerging research field in which there are a number of knowledge gaps: my third and fourth papers discuss theory and empirics in more detail. There are few studies exploring any one of the channels set out above, or comparing their relative impacts. A small number of studies explore the urban footprint of population-innovation effects, but data is often limited and results partial. Most importantly for my own research, there is virtually no empirical coverage of these issues in a British or wider European context. The papers in this thesis add to a small but growing global literature on immigration, diversity and innovation.

5. Questions and approach

My main research questions are:

1) What are the effects, if any, of ethnic / cultural diversity on the economic performance of UK cities?

2) What transmission mechanisms link diversity to economic outcomes?

3) What does this imply for policymakers?

My basic approach is built on economic geography concepts and frameworks. I am also making use of a wider range of research literatures and evidence bases, including: spatial/urban economics; labour economics; economic sociology; migration studies, diversity literature and cultural studies. The research draws predominantly on quantitative methods, particularly econometric analysis.

In order to identify migrant, ethnicity and diversity effects on innovation, I need to distinguish these from other individual, firm, industry, area and national trends and processes. I therefore pay careful attention to causality when designing research methods and identification strategies.

The thesis involves three phases of primary research, presented in papers. Phase 1 (linkages) tests potential connections between diversity and urban-level economic outcomes. Using Labour Force Survey and Land Registry microdata plus material from UK Electoral Registers, I construct cross-sections and panels of UK urban areas. Phase 2 (channels) explores how 'diversity effects' might be conferred. I focus on innovation channels, using patents microdata and the novel ONOMAP name classification system to explore effects of co-ethnic communities and diversity on inventor productivity. Phase 3 (experiences) examines the case of London in detail, exploring effects of cultural diversity and migrant entrepreneurs using a survey of firms in the capital. The papers are some of the first contributions to a growing European literature on diversity, innovation and urban economic performance.

6. The economics of 'super-diversity'

My first paper explores patterns of cultural diversity in British cities and their links to urban economic outcomes, focusing on the years 2001-2006 and the emergence of 'super-diversity' in some urban areas.

6.1 Context and contribution

The UK and many other Western societies have a long, sometimes hidden history of cultural diversity and multiculturalism (Sandu, 2004, Sassen, 2004). Over the past few decades, these societies have become dramatically more diverse, a process driven both by shifts in international migration and by natural change (Putnam, 2007). Vertovec (2006, 2007) argues that the resulting spread of new communities, languages, religious practices and people flows across the UK represents a shift from traditional patterns towards a new ‘super-diversity’, particularly in urban areas. As discussed in Section 4, there is now some suggestive evidence that cultural diversity may be an economic asset at the urban level (Ottaviano and Peri, 2005a, Page, 2007). However, there has been little empirical research on the economics of super-diversity, especially in the UK.

The paper makes two main contributions to this growing literature. First, it assembles new data on patterns of cultural diversity in UK cities. Specifically, I use two ‘traditional’ metrics based on country of birth and official ethnic groups, plus new measurements derived using ONOMAP, a new and fine-grained system of cultural-ethnic-linguistic (CEL) name classification. This produces a very rich set of descriptive statistics covering recent experience in UK cities (see Appendix A for resulting typologies, and Appendix B for more on ONOMAP). Second, the paper tests linkages between cultural diversity measures, urban wages and employment rates, using cross-sectional analysis.

6.2 Data and estimation strategy

My three diversity measures draw on different sources. Labour Force Survey (hence LFS) microdata are used to construct metrics based on country of birth and official Office of National Statistics ethnic groups. The UK Electoral Register provides raw input for ONOMAP, which is provided as a pooled cross-section for 2001-6 on 67 ‘cultural - ethnic- linguistic’ groups.

Both datasets are supplied with local authority district-level identifiers. These are aggregated to 2001 Travel to Work Areas (hence TTWAs) using postcode weighting; following Gibbons et al (2011) I restrict the sample to ‘primary urban’ TTWAs to minimise the risk of sampling error (see Appendix C). I estimate a simple model linking diversity to average wages and employment rates. I include controls covering demographic, social and economic characteristics, drawn from the LFS.

6.3 Results

Diversity is a complex concept, and the descriptive analysis confirms that different metrics capture different aspects of demographic change. Country of birth and ethnic group-based measures show the growth of new migrant and minority communities in the years since 2001. ONOMAP-based analysis highlights the long history of the multicultural city in the UK, as well as the complex regional, religious and linguistic patterns of urban population mix. All three measures shed light on the emergence of ‘super-diversity’, in contrast with the established late 20th century urban demographics.

Regression analysis suggests some positive links between super-diversity and both wages and employment at the urban level. However, the size and sign of the relationship crucially depends on the diversity measure used. Specifically, country of birth and ethnic group-based measures show strong positive links to urban wages, as do some CEL-based measures. Links to urban employment rates are more mixed, with only one CEL measure showing a positive relationship (the other shows a negative link).

These results are drawn from a small cross-section. As such, my findings have to be taken as suggestive, and coefficients as upper bounds. However, they are in line with a growing body of international evidence suggesting some economic benefits of cultural diversity, particularly in urban areas.

7. The long term impacts of migration in British cities

My second paper examines the long term economic impacts of migration on British cities, using a new 16-year panel. Since the early 1990s the UK has experienced 'the single biggest wave of immigration in British history' (Goodhart, 2010). Net migration has been highly urbanised: has it affected the wages, employment rates and prices faced by UK-born workers?

7.1 Context and contribution

There is a large existing literature on the local economic impacts of migration, predominantly focused on labour market effects. As outlined above, most studies find little impact on average UK-born ('native') labour market outcomes (see Dustmann et al (2008) for a recent review). However, few authors examine broader effects of migration on the spatial economy, as more diverse communities emerge. This paper helps fill the gaps, adapting the pioneering US work of Ottaviano and Peri (Ottaviano and Peri, 2005a, Ottaviano and Peri, 2006) for a British context.

Wider urban impacts of migration may be productivity-enhancing, if migrants facilitate knowledge spillovers or reduce trade costs (Saxenian, 2006, Berliant and Fujita, 2009). Net migration may then lead to higher native productivity, wages and employment rates: crowding raises the local cost of living. Alternatively, parts of the local economy may become 'migrant-dependent' (Stenning et al., 2006). Net migration damages native employment if lower-skilled natives cannot move into better jobs. If this sustains a low-skills equilibrium (Finegold and Soskice, 1988), wages and prices also fall over time.

7.2 Data and estimation strategy

The analysis follows the spatial correlations approach (Altonji and Card, 1991) but has several novel features. These allow me to improve on existing UK studies (Frattini, 2008, Lee, 2010, Longhi, 2011) with a longer sample period, better-defined spatial units, and richer data. Specifically, I assemble a new 16-year panel of urban economies between 1994 and 2008, using postcode weighting to aggregate microdata from the UK Labour Force Survey, Land Registry and other sources. I use 2001 Travel to Work Areas to approximate local labour markets, focusing on 79 'primary urban' areas (see Appendix C). To measure the size and diversity of migrant populations, I use both migrant population shares and an inverse Herfindahl Index of country of birth groups.

I estimate a parsimonious two-period model with time dummies and area fixed effects, linking net migration to changes in UK-born average wages, employment rates and house prices. I am able to explore detailed interactions between different skill groups of migrants and natives. The model also allows me to infer the effects of migrant-related changes in urban labour productivity, since over time, productivity changes are reflected in shifting nominal wage rates (Combes et al., 2005). Finally, I run several robustness checks – including tests for native outflows and for positive migrant selection (Borjas, 1994). The latter test uses a shift-share instrument based on historic migrant settlement patterns.

7.3 Results

The results suggest important impacts of net migration on urban economies, within and beyond the labour market. Specifically, the diversity migrants bring helps drive up high-skill native productivity and wages, implying both production complementarities and relative scarcity effects. Conversely, increasingly migrant-intensive labour markets appear to 'lock out' some intermediate and low-skilled British-born workers from employment opportunities, particularly since 2000. 'Migrants taking British jobs' is an oversimplification, however: on-going impacts of long-term industrial decline and the increasing casualisation of entry-level jobs partly explain the employment findings. For the UK, the dynamic effects of immigration also appear to be significantly different from the US, reflecting Britain's distinctive urban system, migrant populations and labour market institutions.

8. Ethnic inventors and innovation in the UK

The next phase of my research focuses on transmission channels, in particular links between demographic change and innovation. My third paper looks at 'ethnic inventors', building on growing academic and policy interest in links between immigration and innovation (Legrain, 2006, Page, 2007, Leadbeater, 2008, Kerr and Kerr, 2011). Interest in ethnic inventor communities is largely based on the experience of high-tech US regions like Silicon Valley (Saxenian, 2006). Little is known about how ethnic inventors might shape innovative activity in the UK. The paper explores recent British experience, using a new panel of patents microdata.

8.1 Context and contribution

As suggested in Section 4, demographic shifts might affect innovation in four broad ways. First, migration or minority status may induce positive selection of skilled or entrepreneurial individuals, although this needs to be distinguished from other human capital endowments (Borjas, 1987, Stephan and Levin, 2001, Hunt and Gauthier-Loiselle, 2008). Second, co-ethnic diasporic groups can accelerate ideas generation and transmission, although discrimination may constrain knowledge spillovers (Kloosterman and Rath, 2001, Docquier and Rapoport, 2011). Third, cultural diversity may improve ideas generation, if the benefits of a larger set of ideas, perspectives outweigh trust or communication difficulties (Alesina and La Ferrara, 2004, Berliant and Fujita, 2009). Finally, urban areas may have positive influences via 'demand push' from cosmopolitan populations, or negative influences if immigrant communities are spatially segregated (Gordon et al., 2007).

This paper looks at the role of ethnic inventors in innovation in the UK, using a new 12-year panel of patents microdata. Using the novel ONOMAP name classification system to build on pioneering US work by Agrawal et al (2008) and Kerr (2008a) I am able to explore all four 'population-innovation' channels (Appendices A and B give more detail on ONOMAP). As far as I am aware, it is the first paper of its kind in the UK or Europe.

8.2 Data and estimation strategy

I construct a panel of inventor activity 1993-2004, using European Patent Office microdata cleaned by the KITES team at Bocconi University. I then apply the ONOMAP name-scoring system to inventor surname-forename combinations. Together, these enable me to identify individual migrant inventors and co-ethnic groups, and to build measures of inventor group diversity.

I estimate a simplified knowledge production function linking counts of inventor patenting activity – 'inventor productivity' – to individual, group and Travel to Work Area-level area characteristics. Controls are taken from Labour Force Survey microdata, aggregated using postcode weights. Using techniques popularised by Blundell et al (1995), I exploit historic patent information to fit inventor-level fixed effects. I also run a series of robustness checks, testing for dynamic feedback effects within the panel, the influence of area-level demographic characteristics on inventor composition, the role of historic patent stocks, and distributional impacts of ethnic inventors on 'majority' groups.

8.3 Results

I fit the model as a negative binomial and in OLS, with similar results. Ethnic inventor status has no effect on inventor productivity once human capital is controlled for. However, membership of some co-ethnic groups has a positive effect – specifically South Asian and Southern European communities. I also find small but robust positive effects of inventor group diversity on individual patenting counts. Distributional impacts are less clear – I find some individual-level evidence that majority inventors are crowded out, but not at area level.

In contrast to theory, I do not find that urban location or density has a significant effect on individual patenting counts once other area-level factors are taken into account. The results survive a range of robustness tests, although alternative measures of area-level human capital weaken diversity effects.

Overall, ethnic inventors are a net positive for patenting in the UK, although the British experience is significantly different from the US. This is likely to reflect distinctive patterns of US and UK migrant settlement – in particular skill-biased migration of engineers and scientists to the US – as well as culturally distinctive US attitudes to entrepreneurship. This is an emerging field of research, and further studies could explore alternative measures of innovative activity, more precise identification of migrant / ethnic inventors, sectoral and area differences, distributional impacts and other ethnicity/diversity transmission channels.

9. Does cultural diversity help firms to innovate?

The third phase of research looks in detail at the experience of London. My fourth paper, written with Neil Lee, examines cultural diversity and innovation in 7,600 London businesses. The UK capital is one of the world's most diverse – in terms of country of birth, language and ethnicity (Burdett and Sudjic, 2011). London's diversity is seen as a social asset. This paper asks: does it help London firms to innovate?

9.1 Context and contribution

In theory, diversity's effect on innovation is ambiguous. Diverse organisations may have higher communication costs and lower trust (Alesina and La Ferrara, 2004); however, diverse teams may be better at generating new ideas or problem solving (Page, 2007, Berliant and Fujita, 2009). Through diasporic networks, firms can access additional markets, assisting process innovation and the commercialisation of new ideas (Saxenian and Sabel, 2008, Docquier and Rapoport, 2011). But diverse firms may also face discrimination in the marketplace, especially in taking new products / processes to market.

Empirical evidence suggests that individual migrant entrepreneurs play critical roles within and around firms, developing new ideas and linking companies in different countries (Kapur and McHale, 2005, Saxenian, 2006, Wadhwa et al., 2007). Diverse cities may amplify these processes (Berliant and Fujita, 2009). Minority populations concentrate in cities (Champion, 2006); large, diverse urban markets encourage the emergence of new products (Mazzolari and Neumark, 2009).

We make several contributions to this growing field. We believe this is the first study to use a large sample of real-world firms in an urban context, and allows examination of multiple diversity-innovation channels. And as far as we know, our results are original for the UK.

9.2 Data and estimation strategy

We use data from the London Annual Business Survey (LABS), constructing a repeat cross-section of over 7,600 firms from 2005-2007. Exploiting LABS' unique structure, we develop multiple measures for both innovation and its commercialisation, and a series of diversity variables covering the birth country and ethnicity mix of business owners/partners. We also identify migrant-run and 'UK-run' firms.

We deploy a simplified knowledge production function linking firms' innovative activity to ownership characteristics, estimating the model as a conditional logit with a range of controls, sector and year dummies. We extend the model to look at links between firms' owner/partner composition and market orientation, and examine the extent of migrant entrepreneurship using a subset of company founders. We also examine innovative activity across 'knowledge-intensive' and less knowledge-intensive firms in the city, which allows us to explore patterns of high-value and 'ordinary' innovations.

We adopt various checks to try and identify causality. We use the natural experiment of A8 accession in 2004 to minimise city-level demand-pull factors. To control for firm-level positive selection, we fit a shift-share instrument based on historic migrant settlement patterns within London neighbourhoods.

9.3 Results

Our results suggest small but robust positive effects of diverse top teams and migrant-run firms on the development of new products and processes. In contrast to the wider literature, we find diversity-innovation effects across London's industrial structure – particularly in less knowledge-intensive sectors. This suggests the 'diversity bonus' is particularly important for 'ordinary' innovations. London's large and diverse home markets, diasporic communities and international connectivity play important roles, as do entrepreneurial migrant business owners.

Overall, the results support claims that London's cultural diversity helps support innovative activity, strengthening the capital's long-term economic position. Our findings for the UK capital contrast with findings from the author's earlier papers, which suggest rather weaker effects of diversity on urban level productivity. Intuitively, our results might be replicated in other UK conurbations where urban scale effects are similar. Parallel research would be fruitful.

10. Conclusions

Britain and other Western societies are becoming more culturally diverse, with immigration, shifting patterns of settlement and natural change all important drivers. The UK's cultural diversity is largely urbanised, reflecting both historical patterns and the economic pull of large cities. My research explores the economics of cultural diversity – in particular, links to innovative activity and to urban economic performance. Despite high levels of interest, there is surprisingly little research on these issues, especially in a British context, and many of the papers are UK 'firsts'.

The first phase of research explores connections between diversity, immigration and urban economic performance. While cross-sectional analysis finds positive associations, panel data analysis reveals a more complex story. I find that net immigration helps raise native productivity, especially for high-skilled workers, but may help exclude lower-skill natives from employment opportunities. De-industrialisation and casualisation of entry-level occupations partly explain the employment results. Phase two investigates how 'diversity effects' might be conferred, in particular links to innovation. Analysis of patents microdata suggests that in some cases, co-ethnic group membership raises inventor productivity, as does the overall diversity of inventor groups. Exploring impacts on majority patenting, I find some evidence of individual-level 'crowd-out' but no effects of displacement at area level. I explore diversity-innovation links further in phase three, a case study of London firms. I find positive effects of diverse managements on ideas generation. Diverse firms are also more likely than homogenous firms to sell into London's large, cosmopolitan home markets – and into international markets. Migrant entrepreneurship helps explain our main result. London's megacity status is also likely to influence the findings, and parallel research is required in other large UK cities.

The research has been conducted against the backdrop of intense public and policy conversations. Over the past decade and a half, race and immigration have consistently scored among the issues of greatest concern to the UK public. On immigration, policymakers have had to reconcile a largely anti-immigration public and strong pro-immigration business voices. On diversity, the 1980s model of multiculturalism has faced widespread criticism post-9/11 and policy has shifted, placing greater emphasis on 'integration' and maintaining community cohesion. Policymakers in both areas would benefit from a better understanding of the *economic* effects of larger, more diverse communities and cities.

Overall, my findings contrast with popular narratives that net immigration and diversity are straightforwardly 'good' or 'bad' for the UK. They show positive effects on productivity, wages and innovation, although these tend to be small. Significantly, EU and non-EU groups both appear to influence levels of innovative activity. Distributional analysis is more complex, with high skill workers and firms the winners, and some evidence that low-skill native workers can lose out. The UK's 'diversity experience' is distinctive, reflecting historical factors and policy choices.

The results suggest that the right policy mix can help British cities and citizens achieve greater economic benefit from bigger and more diverse communities. An 'economics of diversity' strategy would consist of two main elements. The first element would exploit the connections between high-skill immigration, diversity, innovation and productivity. Policymakers need an unambiguous policy of encouraging high-skill migrants from around the world. This would imply a move away from the current migration cap, and allowing universities to compete more easily for international students. At the same time, policymakers should take active steps to help build diasporic communities in the UK, for example by facilitating return migration and remittance flows, and promoting greater trade flows with producers in key 'home' countries.

The second element of the strategy would mitigate negative effects, in particular the labour market lock-out that seems to be affecting some lower-skilled UK-born workers. This would require a re-regulation of entry-level occupations in 'migrant-intensive' sectors such as food processing, with stronger enforcement of minimum wage and working conditions legislation and a restriction of some of the activities of temporary recruitment agencies. This strategy also requires that we raise the skills and employability of low-skill Britons, through more effective welfare to work and in-work support programmes. In some areas, these supply-side interventions could be combined with economic development policies to raise the quality of employer business models; by encouraging firms to move into higher-value production, these might help lift areas out of low-skills equilibrium. Together, these interventions could help the UK make the most of its growing diversity.

Papers

The Economics of Superdiversity: Findings from British Cities, 2001-2006

1. Introduction

This paper explores the patterns of cultural diversity in British cities and their links to urban economic outcomes, focusing on the years 2001-2006 and the emergence of so-called 'super-diversity' in some urban areas. It looks at the distribution of diversity[1] across urban areas in the UK, using new and innovative measures based on cultural-ethnic-linguistic (CEL) name classification, as well as conventional measures based on birth country and the UK's official ethnic groups. CEL data also allows me to show results from cross-sectional analysis of these diversity measures on urban wages and employment.[2]

The UK and many other Western societies have a long, sometimes hidden history of cultural diversity and multiculturalism (Sandu, 2004, Sassen, 2004). Over the past few decades, these societies have become dramatically more diverse, a process driven both by shifts in international migration and by natural change (Putnam, 2007). Vertovec (2006, 2007) argues that the resulting spread of new communities, languages, religious practices and people flows across the UK represents a shift from traditional patterns towards a new 'super-diversity'.

The effects of bigger, more mixed societies are now of major public and policy interest (Florida, 2002, Goodhart, 2004, Wolf, 2008, Aspinall, 2009, Caldwell, 2009, Simpson and Finney, 2009, Fanshawe and Sriskandarajah, 2010). However, public debate has tended to focus on the short-term impacts of migrants on labour markets, public services and community cohesion (House of Lords Economic Affairs Committee, 2008, Card et al., 2009, Somerville and Sumption, 2009). There has been little research on the broader economic impacts of super-diversity.

In order to understand the economic effects of cultural diversity in the UK, it is important to look at cities and urban economies. There is a simple reason for this: put crudely, cities are 'where the diversity is'. Despite more dispersed patterns of migration in recent years, in spatial terms cultural diversity remains an urban phenomenon (Champion, 2006).

There is good evidence that economic diversity in cities helps support long-term economic growth (Glaeser et al., 1992, Duranton and Puga, 2001). Furthermore, there is now some suggestive evidence that *cultural* diversity may also be an economic asset at

[1] For the purposes of this paper I use 'cultural diversity', 'ethnic diversity' and 'diversity' as interchangeable terms. Section 3 discusses these concepts in more detail.
[2] CEL data is only available on a pooled basis at area level. The next chapter focuses on immigration and develops a full panel dataset and IV checks.

the urban level. For example, diversity may lead to production complementarities if diverse workforces make better decisions, or if firms have access to diasporic networks that reduce transactions costs (Page, 2007, Berliant and Fujita, 2009, Docquier and Rapoport, 2011). However, diverse firms may also suffer trust or communication problems, and the effect of co-ethnic diasporas may be limited through discrimination or exclusion (Alesina and La Ferrara, 2004, Zenou, 2011). Given the spatial distribution of diversity, these channels are likely to be stronger in urban areas. Urban-level features may also support positive effects of diversity: a more diverse urban population may drive the development of new goods and services (Leadbeater, 2008), and a diverse urban environment may help attract a 'creative class' of skilled, liberally-minded employees (Florida, 2002). However, minority communities may be physically isolated in urban areas, with limited participation in the mainstream economy.

Immigration is one of the main drivers of demographic shifts in cities. While the diversity that immigration brings may support some of these positive channels, the clustering of migrants in some entry-level occupations may lead firms to become 'migrant-dependent', potentially locking out UK-born workers from job opportunities (Stenning et al., 2006, Green, 2007b).

There is now some international evidence supporting these ideas, mainly from the US (see section 4 of this paper and the overview chapter). However, there is much less European or UK evidence of the existence and magnitude of 'diversity effects' on urban economies. It is important to fill these gaps, given the high levels of public and policy interest in the economic impacts of both net immigration – and the larger, more diverse societies and cities that result.

The paper makes two main contributions to the field. First, it develops rich new descriptive data on recent patterns of cultural diversity in UK cities, using three different identity measures. Specifically, I use the ONOMAP system of cultural-ethnic-linguistic (CEL) name classification, alongside more conventional metrics based on country of birth and Office of National Statistics ethnic groups. I then use Fractionalisation Indices to measure urban diversity, generating a largely intuitive picture of urban mix.

Second, the paper tests linkages between these measures and urban wages and employment rates, using a simple growth model and cross-sectional analysis. The results suggest the diversity measures are complements, capturing distinct aspects of 'super-diversity' – and that there are a number of channels from demographic change to urban economic outcomes, not all of them positive. Country of birth and ethnic group-based measures show significant positive links to urban wages, as do some CEL-based measures. Links to urban employment rates are more mixed, with predominantly non-significant or negative coefficients.

The paper is structured as follows. Section two discusses key trends and policy context. Section three looks at the concept of 'cultural diversity' in more detail, and introduces the CEL methodology. Section four reviews theory and evidence on the economics of cultural diversity, particularly in relation to urban areas. The rest of the paper describes the primary research. Section five outlines the approach, datasets and sample. Section six gives the results of the descriptive analysis, and section seven the regression results. Section eight concludes.

2. The multicultural city in history

Multicultural society and 'the multicultural city' are usually seen as new phenomena. In fact, their roots often go back for centuries (Sandu, 2004). Britain and many other European societies share a long history of people movement and demographic change. Migrations typically resulted in new minority communities assimilating, to different degrees, into the cultural mainstream: 'even when [new groups] kept their differences, they were members of the community: part of the complex, highly heterogeneous 'we' of any developed society' (Sassen, 2004). Vertovec (2007) chronicles complaints across Medieval Britain that 'foreigners were practising their own customs'. By 1867 the *Times* was arguing that 'there is hardly such a thing as a pure Englishman on this island … our national denomination, to be strictly correct, would be a composite of a dozen national titles' (Sandu, 2004).

This 'complex we' is usually highly urbanised: cities are the primary sites of cultural diversity (Amin, 2002). Again, many urban communities in the UK have surprisingly deep roots. In his history of the city, Peter Ackroyd writes that 'by the tenth century [London] was populated by Cmyric Brythons and Belgae, by remnants of the Gaulish legions, by East Saxons and Mercians, by Danes, Norwegians and Swedes, by Franks and Jutes and Angles, all mingled and mingling together to form a distinct tribe of 'Londoners'' (Ackroyd, 2000).

Even apparently recent phenomena such as 'Chinatowns' often turn out to be venerable. For example, Chinese communities in London, Liverpool and Manchester were well established by the end of the 19^{th} century. Liverpool's Chinatown grew up in the

1860s on the back of a regular steamer service to Chinese ports: by the 1930s, there were around 20,000 ethnic Chinese living in the city.

This is not only true of Britain, of course. Since the 1970s, Indo- and Chinese-American entrepreneurs have played an important role in the growth of Silicon Valley. But the Bay Area has had large communities from both countries since the 19th century: Indian migrants started arriving from the 1850s onwards, many becoming prominent figures in the Santa Clara valley during its first, agricultural phase (Randolph and Erich, 2009).

The main changes over the past few decades are the scale and speed of population movement. As the world's population grows, so does the scale of global mobility (Landry and Wood, 2008). The US, historically a 'country of immigrants' (and the descendents of slaves) has also experienced large upturns in net migration from South American countries, South and South East Asia (Putnam, 2007).

The UK has experienced particularly striking changes. Vertovec (2006, 2007) argues that since the early 1990s, there has been a transformative 'diversification of diversity' leading to the emergence of 'super-diversity'. Vertovec's terminology captures a number of linked changes. At the most basic level, the UK has moved from a net exporter of people to a net importer. At the same time, the range of country of birth groups in Britain has substantially expanded (Kyambi, 2005). For England and Wales between 2001 and 2009, non 'White British' groups have grown from 6.6m to 9.1m and now comprise one in six of the population (Office of National Statistics, 2011).

As new communities form, the number of languages spoken and religions practised has also grown. In 2003, the first year data was collected, 10.4% of primary schoolchildren and 8.8% of secondary schoolchildren had a first language other than English. By 2009, these had risen to 15.2% and 11.1% respectively (Department for Children Schools and Families, 2009).

International migration is a key driver of growing cultural diversity in the UK, but not the only one. By mid-2007, net births had overtaken immigration as a source of population growth (Office of National Statistics, 2008b). This includes a rising share of births to mothers born outside the UK, reflecting higher than average birth rates in some migrant / minority groups. It also reflects the tendency of new migrants to put down roots in host countries, even when economic conditions turn down (Department of Communities and

Local Government, 2009b). By 2051, the UK's black and minority ethnic communities may have grown to 21% of the population, up from 8% in 2001 (Wohland et al., 2010).

The UK's cultural diversity is a largely urban phenomenon. England's migrant and minority ethnic populations are largely concentrated in and around London, the conurbations and other cities. In 2001 the capital contained 48.2% of England's non-white population (Champion, 2006). Schoolchildren in London speak at least 300 different languages at home (Baker and Eversley, 2000). As new communities settle, they tend to de-concentrate across urban space, moving from inner urban areas into suburban neighbourhoods (Simpson and Finney, 2009). Vertovec emphasises that changes in spatial patterning also inform super-diversity – while urban cores represent the largest stocks and inflows of minority communities, many suburban and rural areas have seen rapid relative change (Vertovec, 2007). At the same time better, cheaper technology and transport facilitate transnational lifestyles and strengthens diasporas.

2.1 Policy context

Worries about diversity and migration are nothing new. Fearing unrest, in the year 883 King Alfred banished the Danes from London, restricting them to land east of the river Lea (Keith, 2005). Elizabeth I issued a proclamation in 1610 ordering the expulsion of 'negars and Blackamoores' from the capital (Sandu, 2004). Sassen points out that all the major European countries have centuries-long histories of anti-immigrant sentiment (Sassen, 2004). In the America of the late 19th and early 20th century, urban communities like New York, Chicago, San Francisco and New Orleans were often riven with inter-ethnic conflict as established groups – self-described 'Americans' – battled with newer arrivals (Sante, 1998).

Cultural and ethnic conflicts are often hard to disentangle from other fears about class, poverty and access to resources, as the 2001 disturbances in many northern English towns illustrate (Cantle, 2001). Similar discussions have taken place in the wake of the summer 2011 riots in London and other English cities. There remain widespread public and policy concerns about the social and economic effects of larger, more diverse communities in the UK (Goodhart, 2004, Caldwell, 2009, Goodhart, 2010). Around 80% of Britons say that the UK has good relations between different types of people (Landry and Wood, 2008). Nevertheless, since 2003, 'race and immigration' has been one of the top three issues in MORI's monthly omnibus surveys of public opinion (Somerville, 2007), and in public opinion surveys, large majorities consistently say they would like immigration reduced (Blinder, 2011).

The emergence of Muslim communities in many European cities has provoked particularly strong reactions. Cultural conservatives such as Caldwell (2009) raise the prospect of a future 'Eurabia' dominated by Islamic culture and laws; progressives argue that as new communities become established, religion and cultural customs typically evolve or are left aside (Kuper, 2009). In the UK there are periodic concerns about 'white flight' from urban areas – in 2005 Trevor Phillips, then head of the Equality and Human Rights Commission, suggested that Britain was 'sleepwalking into segregation', although evidence suggests little spatial segregation in British cities (Simpson and Finney, 2009).

Reflecting these debates, British policy frameworks have evolved in the past 40 years – from a broadly multiculturalist approach towards a greater focus on integration of minority groups and maintaining community cohesion (Landry and Wood, 2008, Department of Communities and Local Government, 2008, Department of Communities and Local Government, 2009a). Under the last government immigration policy became increasingly orientated towards meeting economic goals, attracting skilled workers and restricting the supply of others (Somerville, 2007). By contrast, the current Coalition has implemented much greater restrictions on migrants, with an overall cap on net immigration introduced from 2011.

3. Understanding cultural diversity: measures and bases

This paper seeks to answer two questions. First, how culturally diverse are British cities? Second, what are the links between urban cultural diversity and economic performance? To answer these satisfactorily, I need to settle a third, prior question: how best to conceptualise quantify, 'cultural diversity'? This section reviews the literature and issues, and introduces the three main diversity metrics used in this and other papers.

Defining cultural diversity is extremely challenging. Fundamentally, we are trying to classify human distinctiveness, something that tends to resist being pinned down (Landry and Wood, 2008). There are two basic steps in attempting to define cultural diversity. The first is to establish a working definition of 'cultural identity'; the second is to use this to classify the diversity of identities.

3.1 Understanding cultural identity

Culture and ethnicity are 'context-driven social and psychological concepts', and so are fundamentally difficult to identify and estimate (Aspinall, 2009). For researchers interested in identity, this presents three problems. First, cultural identity is multi-dimensional and multi-level: components of identity are commonly assumed to comprise kinship, religion, language, shared territory, nationality and appearance (Bulmer, 1996). As Casey and Dustmann (2009) point out, 'because 'identity' is not a uniquely defined concept, its correct measurement in empirical analysis is unclear'.

Second, identity has important elements of self-definition – it is our 'sense of self'. There is general agreement that 'membership of a … [cultural] group is something that is subjectively meaningful to the person concerned' (Office of National Statistics, 2003). However, many people (such as the children of immigrants) may not feel they belong uniquely to a single group. Casey and Dustmann (2009) find strong evidence of parental influence on identity in a study of German migrants; they also find that while fathers tend to 'transmit' German identity to children, mothers transmit 'home' identity, particularly to daughters. This suggests limits to the self-definition of identity, and that identities may evolve beyond childhood.

Third, both individuals' sense of identity *and* categories of ethnic and cultural classification tend to change over time. The UK has shifted from crude groupings such as 'coloureds' in the 1960s towards increasingly sophisticated categories today (Keith, 2005). The literature distinguishes 'primordial' views of ethnicity, which view identity as an exogenous given, and 'constructivist' theories -which stress the role of economic development and nation-building processes in shaping and re-shaping identity (see Green (2011) for an overview).

Over time, identities may be shaped by exogenous geographical conditions and man-made factors such as colonisation (Michalopoulos, 2008), or coalition-building to secure public goods (Ahlerup and Olsson, 2007). Using cross-country data, Green (2011) finds that in developing countries urbanisation is a significant influence on identity formation, while in countries with mature urban systems such as the UK, international migration plays a more important role. Studies of migrant communities suggest certain aspects of identity become more or less salient as groups assimilate. Manning and Roy (2007)find that age, years of residence and years of education have a positive association with the strength of British identity. Evolving aspects of identity within communities help shape that community's view of itself. Discussing the evolution of cultural identity within French Muslim communities, sociologist Olivier Roy uses the concept of *'formatage'* – a dynamic process in which aspects of 'traditional' cultural or religious behaviour, typically those of first generation migrants, are reshaped by subsequent generations to reflect new socio-cultural milieux (Roy, in Kuper (2009)).

3.2 Classifications of cultural identity

These properties of identity suggest that all attempts to classify and measure it will be imperfect. At the extreme, if we believe that individual identity is essentially self-ascribed, or entirely fluid, it becomes very difficult to ascribe behaviour to identity – especially aspects of identity that are malleable, such as nationality or religion (Casey and Dustmann, 2009). Most researchers therefore look for relatively stable, objective proxies for cultural identity (Mateos et al., 2009).

Researchers are getting to grips with many of the conceptual challenges (Aspinall 2009). However, existing datasets tend to be relatively crude, particularly those relying on a single 'tick-box' approach (Fanshawe and Sriskandarajah, 2010).

There are two major practical criteria for identity proxies (Aspinall, 2009). The first is the need for high 'granularity', to distinguish different groups at a high level of detail. The second is the 'validity / utility tradeoff': we need to balance granularity with the need to link smaller groups into larger ones. These are not simply theoretical concerns: multi-dimensional, multi-level classifications seem to help explain economic and social outcomes. A recent major study found that at cross-country level, high-level ethno-linguistic cleavages are good predictors of civil conflict and redistributive tendencies; finer-grained, sub-national distinctions matter more for economic growth and the provision of public goods (Desmet et al., 2009).

I deploy three metrics for quantifying cultural diversity, which are discussed in outline here. Further details are given in Appendices A (classifications) and B (the ONOMAP / CEL system).

My first two proxies for cultural identity are country of birth and ethnicity. Both have pros and cons – both inherent, and for use in the UK context. Country of birth is objective, and data is available at high levels of detail (information is provided for over 100 countries in the UK Labour Force Survey). As a measure of immigration, country of birth is obviously more than adequate. However, birth country is only one aspect of cultural identity. While it offers high granularity, country of birth provides limited validity as a diversity proxy: notably, in the 2001 Census only half the ethnic minority population was born outside the UK (Mateos et al., 2007).

The UK Office of National Statistics (ONS) also provides typologies of 'official' ethnic groups, which are used in the Census and a number of other public datasets. In the

2001 and 2011 Census the ONS has worked with a typology of 15 ‘major’ ethnic groups such as ‘White British’, ‘Indian’, ‘Pakistani’ and ‘Black Caribbean’. These groups have the advantage of aggregating a number of dimensions of cultural identity, and have been designed for ease of use. However, they have been criticised for both poor granularity – hiding substantial variation between groups – and limited validity, bearing little relation to actual cultural norms or socio-economic outcomes (Mateos et al., 2009). By focusing on ‘visible minorities’, the ONS classifications also provide limited information on the recent growth of ‘white other’ communities in the UK, in particular arrivals from central and Eastern Europe (Green, 2007b).

Cultural-ethnic-linguistic (CEL) name classification is an alternative approach, designed to capture multiple aspects of identity including religion, geography, language and kinship using name information (see Mateos (2007) for a review of recent research). I use the ONOMAP system, which classifies individuals according to most likely cultural-ethnic characteristics identified from forenames, surnames and forename-surname combinations. ONOMAP is developed from very large names database extracted from UK Electoral Registers and other sources, covering 500,000 forenames and a million surnames across 28 countries (see Appendix B for more details).

ONOMAP has the advantage of providing objective information at several levels of detail and across several dimensions of identity. For example, it can usefully disaggregate complex groups, such as the British ‘Muslim community’, into distinct geographical, ethnic and linguistic sets. It is also able to deal with Anglicisation of names, and names with multiple origins, giving it additional granularity and validity. However, it has three limitations. First, by observing only objective elements of identity it provides information on *most likely* identity. Second, it does not easily distinguish ‘British’ names from those in other English-language countries. Third, it does not distinguish migrants from those in existing minority communities.

3.3. From cultural identity to cultural diversity

Having identified three – relatively – stable identity proxies, I am now able to generate measures of diversity. In a review of the literature, Ottaviano et al (2007) identify various salient dimensions of diversity: richness / number of groups; evenness / distribution of groups, and distance between groups. In practice, most metrics can only capture one or two of these dimensions.

For instance, isolation indices and dissimilarity indices – which measure, respectively, the extent to which members of a given group are only exposed to members of that same group, and the exposure of one group to members of another – are good measures of distance and evenness. By construction, however, they are unhelpful if we want to examine a number of different groups (rather than two).

Researchers interested specifically in diversity have often used the Fractionalisation Index, which I also adopt here. Fractionalisation Indices are derived from the Herfindahl Index of industrial concentration, and are widely used in the literature (Easterley and Levine, 1997, Alesina and La Ferrara, 2004, Ottaviano and Peri, 2005a). For area *a* in year *t*, the value of the Index is given by:

$$FRAC_{at} = 1 - \Sigma_g [SHARE_{gat}]^2 \qquad (1)$$

Where SHARE is group *g*'s share of the total area population, and *g* indexes (1 ... *n*) groups. The Index measures the probability that two individuals in an area come from different birth country/ethnic/CEL groups: it takes the value 0 when everyone is in the same country of birth group and 1 when each individual is in a different group.

The Index is suitable for measuring diversity in that it reflects both the number of different groups in an area and their relative sizes. In this way, it captures both richness and evenness of groups. However, this latter property can also lead to some unexpected results. The evenness property implies that Fractionalisation Index scores increasing in both number of groups and evenness of group sizes. This means that, for example, a city with a lot of small identity groups and a city with a few large, evenly sized groups get similar scores on the Index. I obtain precisely this result in Section 6, where the CEL-based Index generates similar scores for London and for large Scottish cities.

4. The economics of cultural diversity: reviewing the evidence

The introductory chapter sets out some basic theoretical frameworks on immigration, diversity, innovation and urban economic performance. This section considers specific issues in more detail, and summarises relevant empirical results.

4.1 Cultural diversity and cities: approaches

The literature on diversity and urban places is large and itself diverse, covering historical analysis (Hall, 1998, Crafts and Venables, 2001), ethnic group studies (Sante, 1998, Sandu, 2004), the post-colonial literature (Gilroy, 1993, Urry, 2000), urban sociology (Smith, 2001, Sandercock, 2003, Keith, 2005); health (Fernandez, 2010), political participation, social capital and community cohesion (Alesina and La Ferrara, 2004, Putnam, 2007).

The economic literature is wide-ranging, covering topics including diversity and organisational performance (Ozgen et al., 2010, Parrotta et al., 2011), entrepreneurship (Honig et al., 2010), labour markets (Borjas, 1994, Card, 2005); innovation (Saxenian, 2006, Hunt and Gauthier-Loiselle, 2010, Kerr and Lincoln, 2010), productivity (Ottaviano and Peri, 2006), the cost of living (Saiz, 2003) and long term economic development (Easterley and Levine, 1997, Spolaore and Wacziarg, 2009, Gorodnichenko and Roland, 2011). Within the economic strand there are two major preoccupations. First, there is an extensive literature on migration decisions and migration-related labour supply shocks (see Kerr and Kerr (2011)and Dustmann et al (2008) for recent reviews). Second, in the development studies field a number of country-level studies have looked at the role of 'ethno-linguistic fractionalisation' in affecting long term economic development, particularly in some African countries (Ranis, 2009).

In order to understand the economics of cultural diversity at urban level, it is important to look beyond both of these debates. To do this I develop a simple theoretical framework, using perspectives from growth theory and new economic geography. I then populate the framework with evidence from the UK and elsewhere.

4.2 Cities and economic development

Classical models of economic growth predict the long run convergence of countries and regions. By contrast, endogenous growth theories highlight the importance of human capital and knowledge in advancing the technological frontier. Subsequent productivity gains drive long term growth rates (Romer, 1990). National and regional differences in knowledge creation and diffusion thus help explain spatial disparities.

In these accounts of long term growth, cities play a number of important and well-established roles. Agglomeration economies help raise firms' and workers' productivity. Duranton and Puga (2003) summarise these as 'matching', 'sharing' and 'learning' effects.

In particular, cities facilitate knowledge spillovers and ideas flow, by supporting face to face interactions and other 'learning' economies. Jacobs (1969) suggests cities offer dynamic productivity gains to firms by enabling innovation. Recent structural shifts in national economies – in particular, an increased share of employment in services and 'knowledge-intensive' activity – have helped sort employers and skilled workers across urban areas (Overman and Rice, 2008). Productivity gains driven by agglomeration help raise nominal wages and (often) employment rates; conversely, urban crowding in growing cities raises costs and eats into real wages (Combes et al., 2005).

4.3 Cultural diversity and urban economies: frameworks

These theories also suggest various roles for cultural diversity in urban economic development. Net immigration to a city changes both the size and composition of the population and the workforce. Under neoclassical assumptions, the main effects are through the labour market. In small open economies – like cities – average wages are temporarily bid down, but then readjust via capital flows and expansion of labour-intensive sectors. Initially, immigrants typically 'cluster' in entry-level occupations, so that low-skill UK-born workers (so-called 'natives') may experience short term wage losses and high-skill natives short term gains (Dustmann et al., 2008).

Allowing for diversity-related externalities sets up a number of other impact channels: most notably, production complementarities for firms and workers (Ottaviano and Peri, 2005a, Ottaviano and Peri, 2006, Bellini et al., 2008, Südekum et al., 2009, Longhi, 2011). First, diversity may influence knowledge *creation* at the group (team, firm) level, via the benefits of a wider set of perspectives for problem-solving and ideas generation (Page, 2007, Berliant and Fujita, 2009).[3] On the other hand, more diverse groups or communities may suffer from communication problems or a lack of trust (Alesina and La Ferrara, 2004). Second, the composition of economic agents may influence knowledge *flows*: diverse groups may have better access to new ideas and markets via access to co-ethnic diasporas - which reduce information and communication costs (Rodríguez-Pose and Storper, 2006). Third, *migrants themselves* act as mobile carriers of knowledge. Migration decisions reflect both expected returns and the taste for risk-taking. Ethnic entrepreneurs may also act as 'reputational intermediaries', forging partnerships and helping markets access (Kapur and McHale, 2005, Saxenian and Sabel, 2008). But

[3] Page's Diversity Prediction Theorem suggests that given a group of predictive models, the greater the diversity of modellers, the smaller the chances of error. This also implies that in some circumstances, the diversity of the problem-solving group is more important than individual talent. Cultural diversity (analogous to Page's 'identity diversity') is related to cognitive diversity, since different backgrounds and experiences are likely to generate different views and ideas. Various empirical studies confirm this.

migrants and minority groups may face discrimination from majority groups, restricting the role of diasporas and ethnic entrepreneurs.

These diversity-growth channels may be more important for some types of economic activity than others. Intuitively, we would expect greater benefits in 'knowledge-intensive' environments – such as R&D, creative industries, academia and strategic management / consulting (Fujita and Weber, 2003). At urban level these channels will directly influence average labour productivity. Urban areas may also have indirect amplifying effects. These may be positive, via the composition effects of larger, more diverse populations and the presence of agglomeration economies. Conversely, members of minority communities may be physically isolated in particular neighbourhoods, limiting opportunities for knowledge spillovers and interaction with other groups (Zenou, 2011).

If the overall effect of these channels is net positive it may influence agglomeration economies, leading to further in-migration. However, greater competition for space in growing cities may raise the local cost of living (Saiz, 2003, Ottaviano and Peri, 2006). Over time, shifts in urban industrial structure and labour market institutions further influence economic outcomes. More cosmopolitan urban populations may also raise demand for new / hybridised goods and services, triggering Jacobian knowledge spillovers across sectors (Mazzolari and Neumark, 2009). Conversely, employers in labour-intensive sectors may respond to long term migrant inflows by permanently adjusting production functions to take advantage of cheap labour. If low value-added firms may then become reliant on migrant workers, locking out lower-skilled UK born workers from employment opportunities (Stenning et al., 2006).

4.4 Cultural diversity and urban economies: evidence base

In theory, the effects of cultural diversity on urban economic performance are ambiguous. What empirical evidence exists is similarly mixed. US city-level evidence suggests that long term, increases in cultural diversity are linked to both productivity and price gains in American cities, so that real welfare effects are close to neutral (Saiz, 2003, Ottaviano and Peri, 2006, Sparber, 2007). Bellini and colleagues (2008) find similar effects in a sample of European regions. UK panel studies of urban areas suggest similar productivity-driven wage gains, alongside employment losses for lower-skilled workers (see next paper).

There are also a number of studies on wider diversity effects in cities. There is some evidence the co-location of migrant inventors is linked to higher levels of urban innovation (Peri, 2007, Hunt and Gauthier-Loiselle, 2008, Ozgen et al., 2010). Several studies also find that migrant networks also facilitate international links and reduce trade costs (Peri and Requena, 2009). Saxenian (2006) provides detailed evidence on the roles of migrant and ethnic diasporas in the Silicon Valley area. Similarly, Kerr's analysis of international patent citations suggests that ethnic research communities in the US, who tend to be heavily urbanised, play a critical role in generating and exporting new ideas (Kerr, 2009, Kerr and Lincoln, 2010). At the other end of the economy, immigration is positively associated with an increased range of restaurants in California (Mazzolari and Neumark, 2009). However, overall levels of 'ethnic entrepreneurship' seem to vary greatly by group, country and community class structures (Nakhaie et al., 2009).

Alesina and La Ferrara (2004) review a number of studies on diversity and urban social outcomes, finding some links between ethnic fragmentation, lower trust in others and lower provision of public goods. More recently, Putnam (2007) finds some evidence that US neighbourhood-level bonding social capital falls when diversity increases, but suggests that the long term economic and social benefits of diverse communities outweigh short-term losses. Card (2007) argues along similar lines, suggesting that the diversity immigrants bring to US cities is net positive in welfare terms.

4.5 Diversity and a Creative Class?

An alternative view is suggested by Richard Florida (Florida, 2002). In this model, urban economies are increasingly dominated by a 'Creative Class' of skilled workers with strong preferences for cultural diversity. Open and tolerant cities attract the Creative Class, improving their human capital mix and attracting new investment. This implies that diverse cities might have stronger economic performance primarily because of the Creative Class, with cultural diversity contributing nothing directly. In practice, the Creative Class performs poorly in both US (Glaeser, 2005) and UK contexts (Nathan, 2007). Significantly, there is little UK evidence that a single 'Creative Class' exists – skilled workers have a range of location preferences covering city centres, suburbs and rural locations.

5. Data and sample

There is little British evidence on the issues just discussed. I build a sample of UK urban areas to explore. The structure of the main data sources result in a pooled cross-section of 79 UK urban areas for the years 2001-6.

5.1 Data sources

I draw on two main data sources, the UK Electoral Registry and the Labour Force Survey (LFS). Electoral data provides the main input for ONOMAP and was kindly provided by Pablo Mateos at CASA, UCL. Electoral Register information is provided as a continuous cross-section; at the time of writing the most recent data was for the years 2001-6. This determines the basic shape of the urban areas sample.

Raw data for ONOMAP is drawn from names in Electoral Registers, with additional data provided by Experian's 'Consumer Dynamics' database.[4] The version of ONOMAP I am using has been designed for analysis at the urban level, and provides information for 65 CEL 'subgroups', aggregating smaller CEL communities into larger units.

The Labour Force Survey provides detailed information on country of birth and ONS ethnic groups, and so is used to construct the other diversity measures. While not as large as the Census, the LFS has the advantages of quarterly surveys and access to individual-level information for the whole sample[5]. I am interested in links between diversity, wages and employment: I therefore restrict observations to the LFS working age population (16-64 for men, 16-59 for women). I drop observations from Northern Ireland, which is not covered by CEL data. The LFS also provides information for demographic, economic and social controls for the regression analysis (see section seven).

The relatively small size of the LFS raises the risk of measurement error when used below regional level (Dustmann et al., 2005). I am interested in the sub-regional level – specifically the local spatial economy – so need to minimise sources of error. ONOMAP data is provided at local authority level, and LFS microdata is provided with local authority-level identifiers. I aggregate the microdata to local authority level, and use a postcode share weighting system to aggregate both sets of data to Travel to Work Area Level (2001 TTWAs, the most recent iteration).[6] TTWAs have the additional benefits of being designed

[4] Since 2001 UK residents have been able to opt out of the publicly available version of the Register. The raw data highlights deregisters, but does not identify which are genuine opt-outs and which are simply moves from one constituency to another. As a result, a number of records in the raw data may be duplicates. The ONOMAP team have performed extensive de-duplication, minimising this risk.

[5] From the ONS Virtual Microdata Lab (VML). The quarterly LFS samples around 60,000 households. Each quarter consists of five overlapping 'waves', with an 80% overlap within that quarter. As per ONS recommendations, to ensure a sample of unique individuals I keep only observations from waves 1 and 5 in each quarter. I then pool the remaining data to produce calendar years. This approach gives me c.120,000 individual-level observations per year.

[6] I aggregate individual-level LFS data to local authority-level averages and combine with Electoral Register data. I then aggregate everything to TTWA level averages using postcode shares, as follows. Local Authority District (LAD) boundaries are not congruent with TTWA boundaries, so straightforward aggregation is not possible. Using the November 2008 National Postcode Sector Database (NSPD), I calculate the number of postcodes in each 2001 TTWA and in each of its constituent LADs. I then calculate each LAD's 'postcode share' of the relevant TTWAs' total postcodes. For each TTWA, shares sum to one. Shares are then used to construct TTWA-level averages from the relevant LAD-level

to represent largely self-contained local labour markets, and are regarded as good proxies for a spatial economy (Robson et al., 2006). I further restrict the analysis to 'primary urban' TTWAs where the sample sizes are biggest, drawing on analysis by Gibbons et al (2011) (see Appendix C).

5.2 Diversity variables

My main measure of cultural diversity is the ONOMAP CEL classification, which covers 67 urban-level subgroups. From this, I construct Fractionalisation Indices of cultural diversity, as defined in Section 3.

For the ONOMAP data I make two Fractionalisation Indices. The first Index looks at the distribution of all 67 sub-groups, and covers the whole UK urban population. The second Index is based on the groups not classified as English, Celtic, Welsh or Scottish geographical origin, who comprise around 20% of the total urban population. This second Index puts greater weight on recent migrant and minority communities, and acts as a rough 'Super-diversity Index'. The intention here is not to make a judgement on the inherent 'Britishness' of names, but rather to use geography and geographical 'roots' as a proxy for recent patterns of population change.

I construct further Indices of diversity using birth country and ethnic group information. The birth country Index covers 101 countries, and the ethnic groups Index the 15 main ONS ethnic groups (see Appendix A). I also develop two alternative 'Super-diversity' Indices covering migrant and minority ethnic populations respectively.

6. Descriptive analysis

My data provides for very rich descriptive statistics, which are set out in Tables 1-8. Table 1 presents summary statistics. Tables 2– 4 break down the various diversity measures by area, focusing on the urban areas of greatest cultural diversity; Tables 5-8 look at the largest groups.

---

averages. Each TTWA cell contains an average of 517 individual-level LFS observations: sample sizes will be higher for the final cross-section, which uses urban areas only.

6.1 Stylised facts

Table 1 presents summary statistics for the 79 urban TTWAs – covering demographic characteristics, economic performance measures and information on population density, industrial and economic structure. The first panel covers economic performance variables: average hourly wages (measured in £ and pence) and employment rates (given as a percentage of the working age population). The mean wage for 2001-6 is just under £10 an hour and is lowest is Burnley (£8.09) and highest in London (£13.88). Employment rates average 75 percent, from 62.3% in Hartlepool to just over 82% in Swindon.

The second panel refers to diversity measures and throws up two striking points. First, as measured by CEL sub-groups, average levels of urban cultural diversity are considerably higher than using 'traditional' measures such as country of birth. Specifically, the mean of the CEL Fractionalisation Index is 0.416 with minimum 0.197, compared to other means of 0.28 (ONS ethnicity) and 0.143 (country of birth). The most diverse city on the CEL Index is Glasgow, and the least diverse Crawley (more on this below). Birth country and ethnicity-based Indexes are distributed as one would expect. In both cases London is the most diverse, Hartlepool the least diverse.

Second, the descriptives start to shed light on urban super-diversity – with majority name subgroups removed, the average value of the CEL Index is 0.826, with London scoring the maximum of 0.946 and Lanarkshire the minimum of 0.368. Indexes of migrant groups and minority ethnic groups also put London at the top, and (respectively) Hartlepool and Darlington at the bottom.

6.2 Urban cultural diversity by group

Tables 2 and 3 give information on the major CEL name subgroups. As expected, 'English', 'Celtic', 'Scottish' and 'Welsh' country-origin subgroups make up over 88% of names in UK urban areas (Table 2). Beyond this, ONOMAP data provides richer disaggregation than country of birth and much finer-grained information ONS ethnicity-based rankings. For example, ONOMAP is able to distinguish between Ashkenazi and Sephardic Jewish communities, and also illustrate the complexity of constructions like the 'British Muslim community', which turns out to incorporate disparate groups from Pakistan (around six per cent of minority subgroups), Kashmir (0.74%), Somalia (0.5%), the Balkans (0.37%), Iran (0.14%) and a range of smaller 'other Muslim' groups including Sudan, Malaysia and some Central Asian Republics.

Tables 4 and 5 provide some illustrative dynamics, using country of birth and ethnicity measures from 2001 – 2006. Table 4 shows that Germany, India, Pakistan and Ireland consistently form the largest migrant communities among the urban working-age population. The 2001 figures are likely to include many in the 'new migrant communities' that developed in urban Britain over the 1990s – notably those from Zimbabwe, Poland, South Africa and Hong Kong (Kyambi, 2005). Many of these continued to grow during the 2000s, particularly South Asian and North American groups. Table 4 also illustrates the rapid growth of some migrant communities from the Central / Eastern countries which acceded to the EU in 2004. Most notably, Polish migrants made up 1.27% of the migrant population in 2001, but this had risen to almost 5% by 2006.

Table 5 provides similar information by ONS ethnic group. The figures show that while 'White British' is by far the single largest official ethnic group, its overall share of ethnic groups fell over four percentage points during the sample period. The largest gains were for 'Other White' and 'Other' groups, whose population shares gained 1.98 and 0.61 percentage points between 2001 and 2006. Unfortunately the construction of ONS groupings prevents further examination of these 'other' groups, although given the previous analysis the majority are likely to be from countries in Central / Eastern Europe and across North America.

6.3 Urban cultural diversity by area

Tables 6-8 ranks urban areas' cultural diversity by Fractionalisation Index scores. Table 6 gives results for the CEL Index: the left hand columns give results for the full Index, the right hand columns scores for the super-diversity Index. Perhaps surprisingly, the full Index suggests that Scottish cities are more culturally diverse than London, with the biggest Welsh cities only fractionally behind the capital.

By construction, Fractionalisation Index scores increase with the number of groups and with groups of equal size. Scottish and Welsh cities will tend to have relatively few groups of fairly even size, with large, historic populations of 'Celtic' and 'English' CEL origin alongside majority 'Scottish' and 'Welsh' groups. By contrast, London has a very large number of distinct cultural communities, but with widely varying sizes (Kyambi, 2005). This is borne out in the right hand column, which shows ranking by areas once 'English', 'Scottish', 'Welsh' and 'Celtic' groups are removed. Without these name group populations, CEL-based rankings look closer to intuition, as well as more established diversity measures.

Tables 7 and 8 give scores for country of birth and ethnicity Indexes, both drawn from LFS data. Unlike ONOMAP data, the LFS is available year by year so I am able to examine change within the period. Table 7 examines 'migrant diversity'. With the exception of Guildford and Aldershot, the 15 most diverse urban areas have also all increased their migrant population share during the sample period.[7] The biggest climbers are Cambridge, Reading and Bracknell, Leeds, and Wycombe and Slough, with Luton and Watford some way behind.

Table 8 shows area diversity using ONS ethnic groups. The set of most diverse urban areas is broadly similar to measures using country of birth, although Wycombe does not feature in the top 15. The list of climbers is also broadly similar, although the largest increases in ethnic group diversity have been in Bolton, where the Fractionalisation Index rose by 0.142. Whether measured by birth country or ethnicity – although not by CEL groups – London is by some way the most diverse city in the UK.

Overall, these results suggest that how diversity is measured makes a major difference. All three diversity measures capture different aspects of urban demography, and the measures for which we have dynamic information show substantial change across both migrant and ethnic groups. Second, on an area level diversity metrics using CEL information can be substantively different from those using country of birth or ethnicity as the identity proxy. However, once CEL information is restricted to 'non-UK origin' names, the Index scores converge.

7. Regression analysis

Using the dataset, I test for linkages between cultural diversity and economic performance in UK cities. The descriptive analysis above suggests significant variation between urban areas, so an area-level analysis seems useful. It also suggests important differences between diversity metrics: I therefore use all three measurement bases. Given the small number of observations I set up a parsimonious model linking urban economic outcomes to diversity and a range of demographic, economic and spatial controls. I briefly discuss the estimation strategy then highlight the main findings.

[7] Aldershot contains a major army base. As the Army is predominantly White British, this may affect trends during the 2001-6 period.

7.1 Estimation strategy

My estimation strategy follows the spatial correlations approach widely used in the migration and diversity literature, e.g. Altonji and Card (1991), Card (2001), Dustmann et al (2005), Ottaviano and Peri (2006). This exploits local variations in levels of cultural diversity and economic outcomes of interest. For TTWA *i*, the model is given by:

$$Y_i \quad = bDIV_i + \boldsymbol{DEM}_i c + \boldsymbol{ECON}_i d + eSPAT_i + e \tag{2}$$

I fit a log-linear specification, which allows me to interpret coefficients of *b* as marginal effects. In this case, *Y* is either the log of average hourly wages or the log of average employment rates, in each case for the working-age population. Because CEL data does not allow me to distinguish wages or employment rates by CEL subgroups, I focus in this paper on outcomes for the whole urban population. (The next paper looks at immigration and isolates outcomes for natives and various native skill groups.) The variable of interest is *DIV*, which is either the Fractionalisation Index of CEL subgroups, the 'super-diversity Index', or an Index of country of birth groups or of ONS ethnic groups. (For comparison I also fit indices of migrant groups and minority ethnic groups alongside the Super-diversity Index.)

I fit a series of controls for variables likely to affect the main relationship, or for precision. ***DEM*** represents two demographic controls (share of workers 24 and under, share of female workers). Relationships between diversity, wages and employment may partly reflect age factors. Migrants (particularly recent migrants) are younger than the average Briton, but younger workers are also likely to earn less and less likely to be in work (Lucifora et al., 2005, Goujard et al., 2011). I also fit the share of female workers for precision: women's wages are likely to be lower than men's (although in many areas their employment rates will be higher) (Swaffield, 2011).

ECON is a set of economic structure controls (share of workers with degrees, share of workers in manufacturing sectors, share of jobless who are long term unemployed). These are fitted for precision. Human capital is positively linked to urban productivity, and thus levels of urban wages (Glaeser et al., 1992). By contrast, the presence of manufacturing industry may be negatively linked to wages, and worklessness is negatively associated with both wages and employment rates (Berthoud, 2003).

SPAT is given by logged population density, measured as total population over surface area. This is a simple device for capturing agglomeration economies, which again may lead both to higher wages and employment rates, and simultaneously to larger, more diverse urban populations. I therefore need to control for this potentially intervening factor.

I estimate by Ordinary Least Squares on the pooled cross-section of 79 observations (76 for CEL models), using robust standard errors. The descriptive analysis shows that London is the main outlier in terms of both cultural diversity and economic performance, so I run models with and without the capital. Data constraints force a number of compromises. As my dataset is cross-sectional, I am relying purely on spatial variation and am unable to fit year or area dummies.[8] More seriously, robust causality checks are unavailable: the sample structure means that I am unable to construct any of the usual instruments for my main variables of interest.[9] This is problematic given the potential for positive selection of workers into high-performing cities, (Altonji and Card, 1991, Borjas, 1994), which is reduced but not eliminated by my controls.

7.2 Results

Regression results are set out in full in Tables 9 – 14. Each table sets out estimates for wage or employment models, by each set of diversity measures (CEL, country of birth, ethnic groups). For each table the left hand panel gives wage results, the right hand panel employment results. In each case specification (1) gives the sample univariate correlation between *DIV* and the dependent variable of interest; specification (2) adds controls, and specification (3) fits the model without including London.

Tables 9 and 10 give the main results for diversity measured by CEL subgroups. Table 9 shows diversity as measured across all CEL groups. We see that the coefficient of diversity is insignificant on wages (with coefficients close to zero). Conversely, there is a small negative link to employment rates: the coefficient of *DIV* is -0.140, significant at 1%, This implies that a 10 percentage point difference in the Index – for example, raising diversity in Cardiff to that in Dundee – is linked to a 1.40% lower average urban employment rates. By contrast, the Super-diversity Index – excluding the 'English', 'Welsh', 'Scottish' and 'Celtic' origin subgroups – turns up strong positive associations with both wages and employment rates. Table 10 shows that the coefficients of *DIV* are 0.275 (wages) and 0.095 (employment), significant at 1% and 5% respectively. The wage result implies that shifting Southampton's diversity to that of London, a roughly five-point difference in the Super-diversity Index, is linked to 1.375% higher average hourly wages.

[8] However, the model passes diagnostic tests for fit, collinearity and spatial autocorrelation.
[9] For example, time lags, 'migrant gateway' or shift-share instruments. For further discussion on causality and instruments see Ottaviano and Peri (2006) or Card (2007).

Tables 11 and 12 repeat the analysis for Fractionalisation Indices of country of birth and ethnic group. Strikingly, both show positive associations of diversity with average wages, but no significant links with employment rates. For example, the coefficient of migrant *DIV* on wages is 0.643, significant at 1% (Table 11), while for ethnic *DIV* the corresponding result is 0.518, also significant at 1% (Table 12). However, respective coefficients of *DIV* on employment rates are 0.026 and 0.020. Tables 13 and 14 show results for alternative 'super-diversity indexes', based on migrant and minority populations respectively. Unlike the CEL-based Super-diversity Index, coefficients of *DIV* on wages and employment rates are always insignificant for the full sample.

Taken together, the results suggest measures of diversity and 'super-diversity' capture qualitatively different phenomena, and that different diversity metrics are complementary. The CEL Super-diversity Index is positively linked to urban wages and employment, results not replicated using other identity bases. By contrast, Indices of all birth country and ethnic groups show positive links to wages, but the Index of all CEL groups shows no significant association. The CEL Index also shows a negative connection to urban employment rates, while corresponding Indices show no significant link.

7.3 Robustness checks

I then run three simple robustness checks. First, London is a clear outlier in terms of wages and diversity, and given the small number of observations may skew the results. Removing London from the sample changes the numbers slightly in a few cases (Tables 9-14, column 3). For CEL and ethnicity models, results are broadly the same. For country of birth models, coefficients of *DIV* are generally larger when London is left out. There seems to be a 'migrant effect' on employment rates in London: excluding the capital raises the coefficient of *DIV* from 0.026 to 0.138 and is now significant at 5% (Table 11). Similarly, without London, the coefficient of the ethnic groups Index on wages increases from 0.123 to 0.164, and is now significant at 5% (Table 14).

Second, there are a number of other areas in the UK with historically low diversity and low economic performance, or which are historically high-performing areas. 'Diversity effects' in these cases may reflect some omitted variable or variables. I therefore fit dummies for outliers, leverage points and influential observations from the sample. Outliers are defined as maxima on wages, employment rates and diversity; leverage points are observations in the top five leverage points across at least one wage or employment model; similarly, influential observations are those with the high values of Cook's D across more than one wage or employment model. Results are given in Tables 15 and 16, columns 1-3, and show very little difference to the main results.

Finally, I test for the influence of long term economic change by fitting dummies for 20 'de-industrialising' cities, taken from Turok and Edge (1999).[10] All of these locations lost substantial employment during the 1980s and early 1990s, and many will have continued to do so into the 2000s, leading to a persistent 'jobs gap'. Many of these locations also saw substantial inflows of migrant workers during the 1960s and 1970s to work in now-defunct factories. The combination of these factors could explain some of the negative or insignificant employment results. Results are given in column 4 of Tables 15 and 16. Again, both wage and employment models are essentially unaffected.

Taken together, these tests suggest the main results are robust to the effects of outlying urban areas and to omitted variable bias.

8. Conclusions

The UK has become more culturally diverse over the last decade and a half. A wider range of diaspora groups, languages and religions, as well as a greater fluidity of identities, has contributed to a new sense of super-diversity. British cities are where most of this change is taking place: super-diversity is a largely urban phenomenon. Public and policy interest in these issues is high, but there is surprisingly little research on the economic and social impacts of super-diversity. In part, this is because measuring and quantifying 'cultural diversity' beyond broad trends is extremely challenging. This paper makes two contributions to filling these gaps. First, it develops a new dataset of UK cities for the years 2001-6, using a range of diversity measures providing very rich descriptive statistics. Second, it tests links between cultural diversity, wages and employment, using the full range of diversity measures.

The analysis throws up two main messages. First, the basis on which identity and diversity are measured makes an important difference to the resulting picture. Given the multifaceted nature of cultural identity this is not a surprise. As identity proxies, CEL, country of birth and ethnic groups appear to be complements, capturing distinct aspects of diversity and 'super-diversity' – whether this is the composition of cultural-ethnic groups

[10] These are Birmingham, Clydeside (Glasgow and Lanarkshire TTWAs), West Yorkshire (Leeds and Bradford), Merseyside (Liverpool and Wirral), London, Manchester, South Yorkshire (Sheffield and Rotherham), Bristol, Cardiff, Coventry, Doncaster, Edinburgh, Hull, Leicester, Nottingham, Plymouth, Stoke-on-Trent, Sunderland and Wigan.

across the UK, or differences between different urban areas. Fractionalisation Indices generally perform well as measures of diversity, although care needs to be taken when using bases such as CEL, which distinguish between different parts of the indigenous / established UK population.

Overall, the descriptive results support other evidence that cultural diversity is both highly urbanised, and likely to remain so. UK urban areas increased their 'diversity share' between 2001-6, and more recent evidence suggests this will continue (Wohland et al., 2010). Descriptives for Scottish and Welsh cities, in particular, help illustrate the long history of the multicultural city in the UK.

Second, the regression results suggest there are a number of potential channels from demographic composition to urban economic outcomes. As suggested by the theoretical framework, not all of these are positive. Specifically, country of birth and ethnic group-based measures show significant positive links to urban wages, as do some CEL-based measures. Links to urban employment rates are more mixed, with predominantly non-significant or negative coefficients. These results are drawn from a single, relatively small cross-section. I am unable to infer causality, and legitimate concerns could be raised about sample size. As such, my findings have to be taken as suggestive. However, they are in line with a growing body of international evidence suggesting some economic benefits of cultural diversity – and probably some costs – particularly in urban areas.

There are a number of fruitful areas for further research. For example, collecting UK panel data would allow more robust analysis and the potential for causality checks. The next paper delivers some work along these lines, focusing on net immigration and country of birth-based diversity measures. The results also suggest a number of potential microfoundations to urban diversity-wages and diversity-employment connections. These would need to be explored using individual and firm-level data: the third and fourth papers make contributions in these areas by looking at connections between migrant and minority groups, diversity and innovation.

LIST OF TABLES

Table 1. Summary statistics.

Variable	N	Mean	SD	Min	Max
Ave hourly wage	79	9.991	1.319	8.089	13.879
Ave employment rate	79	0.75	0.044	0.623	0.821
Fractionalisation Index CEL subgroups	76	0.416	0.131	0.197	0.744
Frac Index, CEL 'super-diversity'	76	0.826	0.1	0.368	0.946
Fractionalisation Index, birth country	79	0.143	0.078	0.033	0.56
Frac Index, migrant groups	79	0.898	0.077	0.448	0.974
Fractionalisation Index, ethnicity	79	0.28	0.085	0.177	0.657
Frac Index, minority ethnic groups	79	0.749	0.108	0.404	0.877
% aged 24 or less	79	0.165	0.014	0.132	0.198
% female	79	0.497	0.008	0.48	0.522
% with NVQ4 (degrees/HE qualification)	79	0.242	0.053	0.146	0.373
% with NVQ2 or 3 (A-levels / 5+GCSEs)	79	0.474	0.031	0.349	0.531
% with NVQ1 (other / no qualifications)	79	0.284	0.048	0.197	0.402
% in senior/pro/associate pro occs	79	0.394	0.057	0.261	0.532
% in admin/secretarial/skilled trades	79	0.245	0.016	0.208	0.292
% personal services/sales/routine occs	79	0.361	0.052	0.252	0.496
% employed in service sector	79	0.5	0.05	0.368	0.639
% employed in manufacturing	79	0.146	0.044	0.054	0.259
% employed in other sectors	79	0.354	0.029	0.281	0.482
% long term unemployed who are jobless	79	0.198	0.06	0.081	0.347
Population density ('000s)	79	1.245	0.808	0.294	5.660
Working age population ('000s)	79	119.668	72.034	48.132	422.820

Source: ONS / LFS, ONOMAP
Notes: CEL data is missing for three TTWAs: Colchester, Preston, Tunbridge Wells.

Table 2. 50 largest CEL name subgroups, urban Travel to Work Areas (TTWAs). 2001-6.

CEL subgroup	% of all groups	CEL subgroup	% of all groups
ENGLISH	66.77	SOMALIAN	0.15
CELTIC	11.33	JEWISH	0.13
SCOTTISH	5.31	OTHER AFRICAN	0.13
IRISH	3.27	HISPANIC	0.12
WELSH	2.67	OTHER EAST ASIAN AND PACIFIC	0.11
PAKISTANI	1.67	HINDI NOT INDIAN	0.06
OTHER MUSLIM	1.17	INTERNATIONAL	0.05
INDIAN HINDI	1.08	JEWISH AND ARMENIAN	0.05
SIKH	0.82	VIETNAMESE	0.05
ITALIAN	0.46	CZECH / SLOVAK	0.05
BANGLADESHI	0.46	OTHER BALKAN	0.04
POLISH	0.42	SWEDISH	0.04
NIGERIAN	0.39	DANISH	0.04
OTHER EUROPEAN	0.36	RUSSIAN	0.04
CHINESE	0.34	DUTCH	0.04
GREEK	0.29	BLACK SOUTHERN AFRICAN	0.03
PORTUGESE	0.26	OTHER NORDIC	0.03
SPANISH	0.23	IRANIAN	0.03
FRENCH	0.23	SIERRA LEONIAN	0.03
GERMAN	0.22	HUNGARIAN	0.02
PAKISTAN KASHMIR	0.21	FINNISH	0.02
SRI LANKAN	0.20	JAPANESE	0.02
OTHER SOUTH ASIAN	0.19	AFRIKAANS	0.02
GHANAIAN	0.17	ALBANIAN	0.02
TURKISH	0.17	OTHER BALTIC	0.02

Source: ONOMAP.
Notes: 2001-6 pooled. CEL subgroups aggregate smaller CEL categories. See Appendix A for more details.

Table 3. 50 largest CEL name subgroups (excluding ‘English’, ‘Scottish’, ‘Welsh’, ‘Celtic’ subgroups), urban TTWAs, 2001-6.

CEL subgroup	% of all groups	CEL subgroup	% of all groups
PAKISTANI	12.02	HINDI NOT INDIAN	0.42
OTHER MUSLIM	8.42	INTERNATIONAL	0.38
INDIAN HINDI	7.77	JEWISH AND ARMENIAN	0.36
SIKH	5.86	VIETNAMESE	0.34
ITALIAN	3.33	CZECH / SLOVAK	0.33
BANGLADESHI	3.31	BALKAN	0.31
POLISH	3.02	SWEDISH	0.30
NIGERIAN	2.82	DANISH	0.27
OTHER EUROPEAN	2.62	RUSSIAN	0.27
CHINESE	2.43	DUTCH	0.26
GREEK	2.08	BLACK SOUTHERN AFRICAN	0.22
PORTUGESE	1.86	OTHER NORDIC	0.22
SPANISH	1.65	IRANIAN	0.21
FRENCH	1.62	SIERRA LEONIAN	0.18
GERMAN	1.61	HUNGARIAN	0.15
PAKISTAN KASHMIR	1.53	FINNISH	0.15
SRI LANKAN	1.42	JAPANESE	0.14
OTHER SOUTH ASIAN	1.38	AFRIKAANS	0.13
GHANAIAN	1.23	ALBANIAN	0.13
TURKISH	1.20	OTHER BALTIC	0.13
SOMALIAN	1.06	SERBIAN	0.11
JEWISH	0.97	NORWEGIAN	0.11
OTHER AFRICAN	0.96	MUSLIM NORTH AFRICAN	0.08
HISPANIC	0.86	UKRANIAN	0.07
OTHER EAST ASIAN AND PACIFIC	0.76	LEBANESE	0.06

Table 4. 15 largest migrant groups, urban TTWAs, 2001-6 and within-period change.

Country of birth	% total migrants			
	2001-6	2001	2006	% change
Germany	9.15	10.81	7.13	-3.68
India	9.15	9.17	9.71	0.54
Pakistan	7.73	7.05	7.03	-0.02
Ireland	7.64	8.64	6	-2.64
South Africa	4.61	4.3	4.26	-0.04
Bangladesh	3.03	3.06	3.42	0.36
USA	2.87	3.22	4.26	1.04
Australia	2.46	2.17	1.79	-0.38
Hong Kong	2.21	2.54	1.79	-0.75
Zimbabwe	2.13	1.3	2.63	1.33
Canada	2.1	2.69	3.42	0.73
Poland	2.04	1.27	4.84	3.57
Kenya	2	2.67	1.79	-0.88
Singapore	1.71	1.95	1.53	-0.42
Italy	1.67	1.93	1.32	-0.61
Migrants as % total working age population	*7.6*	*6.8*	*8.9*	*2.1*

Source: ONS / LFS
Notes: sample is working-age population.

Table 5. Largest ethnic groups, urban TTWAs, 2001-6 and within-period change.

Group	**% of all groups**			
	2001-6	**2001**	**2006**	**% change**
White	79.68	92.82	88.73	-4.09
Other White	10.35	2.21	4.19	1.98
Indian	1.39	1.38	1.66	0.28
Pakistani	1.35	1.2	1.58	0.38
Other	0.6	0.33	0.94	0.61
Black Caribbean	0.49	0.57	0.57	0
White and Black Caribbean	0.44	0.21	0.22	0.01
Black African	0.41	0.32	0.6	0.28
Bangladeshi	0.36	0.22	0.29	0.07
Other Asian	0.34	0.23	0.47	0.24
Chinese	0.33	0.29	0.36	0.07
Other Mixed	0.16	0.02	0.14	0.12
White and Asian	0.13	0.13	0.15	0.02
Other Black	0.09	0.04	0.04	0
White and Black African	0.08	0.04	0.06	0.02

Source: ONS / LFS
Notes: Sample is working-age population Figures are based on ETHCEN15 variable.

Table 6. Urban areas with the 20 largest values of the CEL Fractionalisation Index, 2001-6.

2001-6	
TTWA name	**Frac Index, all CEL subgroups**
Glasgow	0.744
Lanarkshire	0.724
Dundee	0.701
Edinburgh	0.698
Aberdeen	0.689
London	0.688
Swansea Bay	0.638
Cardiff	0.600
Blackburn	0.591
Birmingham	0.564
Wycombe & Slough	0.552
Bradford	0.551
Luton & Watford	0.543
Wolverhampton	0.527
Newport & Cwmbran	0.524
Liverpool	0.523
Leicester	0.522
Manchester	0.515
Coventry	0.511
Rochdale & Oldham	0.503
All urban TTWAs	*0.416*

2001-6	
TTWA name	**Frac Index, CEL 'Super-diversity'**
London	0.946
Southampton	0.941
Oxford	0.936
Reading & Bracknell	0.924
Nottingham	0.921
Guildford & Aldershot	0.920
Milton Keynes & Aylesbury	0.920
Peterborough	0.919
Wycombe & Slough	0.915
Cambridge	0.914
Walsall & Cannock	0.914
Southend & Brentwood	0.913
Bournemouth	0.910
Brighton	0.908
Poole	0.903
Hastings	0.901
Ipswich	0.899
Luton & Watford	0.897
Bedford	0.895
Northampton & Wellingborough	0.893
All urban TTWAs	*0.826*

Source: ONOMAP
Notes: Super-diversity Index excludes 'English', 'Welsh', 'Scottish' and 'Celtic' CEL subgroups. See Appendices A and B for more detail on ONOMAP.

Table 7. Urban TTWAs with the 15 highest values of the country of birth Fractionalisation Index, 2001-6 and within-period change.

TTWA name	Frac Index			
	2001-6	2001	2006	% change
London	0.56	0.530	0.588	0.058
Wycombe & Slough	0.308	0.257	0.345	0.088
Bradford	0.295	0.279	0.289	0.010
Birmingham	0.272	0.276	0.309	0.033
Leicester	0.266	0.255	0.282	0.027
Luton & Watford	0.265	0.244	0.323	0.079
Reading & Bracknell	0.253	0.226	0.326	0.100
Bedford	0.241	0.226	0.276	0.050
Cambridge	0.236	0.215	0.322	0.107
Guildford & Aldershot	0.215	0.211	0.238	0.027
Brighton	0.213	0.250	0.215	-0.035
Oxford	0.207	0.186	0.252	0.066
Wolverhampton	0.198	0.180	0.228	0.048
Milton Keynes & Aylesbury	0.196	0.179	0.188	0.009
Leeds	0.195	0.156	0.249	0.093
All urban TTWAs	*0.143*	*0.13*	*0.167*	*0.037*

Source: ONS / LFS
Notes: sample is working-age population

Table 8. Urban areas with the 15 largest values of the ethnic groups Fractionalisation Index, 2001-6 and within-period change.

TTWA name	**Frac Index**			
	2001-6	**2001**	**2006**	**% change**
London	0.657	0.579	0.648	0.069
Birmingham	0.496	0.394	0.482	0.088
Bradford	0.49	0.379	0.404	0.025
Leicester	0.425	0.299	0.361	0.062
Bedford	0.404	0.261	0.359	0.098
Luton & Watford	0.402	0.291	0.393	0.102
Huddersfield	0.389	0.274	0.314	0.04
Bolton	0.361	0.211	0.353	0.142
Leeds	0.358	0.205	0.310	0.105
Glasgow	0.349		0.350	0.35
Coventry	0.347	0.181	0.299	0.118
Dudley & Sandwell	0.345	0.199	0.319	0.12
Manchester	0.34	0.188	0.267	0.079
Blackburn	0.333	0.202	0.126	-0.076
Burnley, Nelson & Colne	0.321	0.186	0.113	-0.073
Cambridge	0.321	0.186	0.312	0.126
All urban TTWAs	*0.28*	*0.133*	*0.203*	*0.07*

Source: ONS / LFS
Notes: sample is working-age population. Variable is drawn from LFS variable ETHCEN15.

Table 9. Results for wages, employment and cultural diversity (all CEL subgroups). UK urban areas 2001-6.

Dependent variable	Wages			Employment rates		
	(1)	(2)	(3)	(1)	(2)	(3)
Frac Index	0.107	-0.042	-0.076	-0.132***	-0.140***	-0.134***
	(0.123)	(0.072)	(0.069)	(0.048)	(0.033)	(0.033)
% 24 or less		-1.725**	-1.450**		-0.590*	-0.641*
		(0.695)	(0.684)		(0.348)	(0.343)
% Female		-0.775	-0.777		-1.294**	-1.294**
		(0.963)	(0.894)		(0.598)	(0.603)
% degrees		1.522***	1.515***		0.699***	0.701***
		(0.292)	(0.297)		(0.105)	(0.105)
% manufacturing		-0.373	-0.265		0.151	0.131
		(0.291)	(0.288)		(0.102)	(0.101)
ln(population density)		0.011	-0.001		-0.011*	-0.008
		(0.016)	(0.013)		(0.006)	(0.006)
% unemployed who are long term jobless		-0.093	-0.147		-0.280***	-0.270***
		(0.125)	(0.112)		(0.070)	(0.071)
Constant	2.247***	2.613***	2.657***	-0.235***	0.447	0.439
	(0.052)	(0.530)	(0.498)	(0.021)	(0.282)	(0.284)
Observations	76	76	75	76	76	75
F-statistics	0.755	22.296	21.761	7.634	41.721	39.872
R^2	0.107	0.703	0.707	0.080	0.784	0.785

Source: ONS / ONOMAP.
Notes: Heteroskedasticity and autocorrelation-robust standard errors in parentheses. * = significant at 10%, ** 5%, *** 1%.

Table 10. Results for wages, employment and cultural diversity (CEL 'Super-diversity Index'). UK urban areas 2001-6.

Dependent variable	**Wages**			**Employment rates**		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Frac Index	0.577***	0.275***	0.241***	0.301***	0.095**	0.108**
	(0.172)	(0.092)	(0.084)	(0.083)	(0.046)	(0.047)
% 24 or less		-1.849***	-1.733***		-1.115***	-1.162***
		(0.650)	(0.637)		(0.367)	(0.362)
% Female		0.099	-0.139		-1.490**	-1.393**
		(1.077)	(0.972)		(0.639)	(0.631)
% degrees		1.403***	1.366***		0.479***	0.494***
		(0.266)	(0.267)		(0.092)	(0.092)
% manufacturing		-0.354	-0.282		0.101	0.072
		(0.267)	(0.264)		(0.109)	(0.107)
ln(population density)		0.001	-0.008		-0.015**	-0.012
		(0.014)	(0.013)		(0.007)	(0.007)
% unemployed who are long term jobless		0.063	-0.010		-0.260***	-0.231***
		(0.136)	(0.120)		(0.076)	(0.075)
Constant	1.820***	2.021***	2.219***	-0.535***	0.585*	0.505
	(0.141)	(0.599)	(0.538)	(0.069)	(0.310)	(0.309)
Observations	76	76	75	76	76	75
F-statistics	11.230	22.611	21.469	13.134	58.367	54.596
R^2	0.225	0.735	0.731	0.258	0.747	0.758

Source: ONS / ONOMAP.
Notes: Heteroskedasticity and autocorrelation-robust standard errors in parentheses. * = significant at 10%, ** 5%, *** 1%.

Table 11. Results for wages, employment and cultural diversity (country of birth measures). UK urban areas 2001-6.

Dependent variable	Wages			Employment rates		
	(1)	(2)	(3)	(1)	(2)	(3)
Frac Index, birth country groups	0.988*** (0.162)	0.643*** (0.089)	0.685*** (0.133)	0.184 (0.148)	0.026 (0.071)	0.138** (0.061)
% 24 or less		-2.448*** (0.559)	-2.510*** (0.602)		-1.029*** (0.387)	-1.195*** (0.364)
% Female		-0.612 (0.742)	-0.566 (0.761)		-1.820*** (0.682)	-1.695** (0.652)
% degrees		0.969*** (0.226)	0.948*** (0.229)		0.496*** (0.100)	0.441*** (0.092)
% manufacturing		-0.461** (0.221)	-0.481** (0.224)		0.122 (0.114)	0.067 (0.109)
ln(population density)		-0.016 (0.011)	-0.016 (0.011)		-0.011 (0.007)	-0.009 (0.007)
% unemployed who are long term jobless		-0.029 (0.101)	-0.012 (0.111)		-0.306*** (0.077)	-0.259*** (0.076)
Constant	2.153*** (0.020)	2.864*** (0.386)	2.846*** (0.394)	-0.315*** (0.021)	0.780** (0.311)	0.732** (0.301)
Observations	79	79	78	79	79	78
F-statistics	37.171	43.423	32.475	1.546	34.223	31.607
R^2	0.384	0.812	0.793	0.058	0.715	0.734

Source: ONS / LFS

Notes: Heteroskedasticity and autocorrelation-robust standard errors in parentheses. * = significant at 10%, ** 5%, *** 1%.

Table 12. Results for wages, employment and cultural diversity (ONS ethnic group measures). UK urban areas, 2001-2006.

Dependent variable	**Wages**			**Employment rates**		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Frac Index, ethnic groups	0.582***	0.518***	0.478***	0.022	0.020	0.078
	(0.181)	(0.090)	(0.107)	(0.093)	(0.055)	(0.050)
% 24 or less		-2.632***	-2.539***		-1.035***	-1.173***
		(0.608)	(0.642)		(0.384)	(0.363)
% Female		-1.074	-1.099		-1.839***	-1.802***
		(0.814)	(0.798)		(0.688)	(0.675)
% degrees		1.072***	1.086***		0.501***	0.480***
		(0.227)	(0.230)		(0.095)	(0.092)
% manufacturing		-0.606***	-0.566**		0.116	0.058
		(0.216)	(0.225)		(0.120)	(0.117)
ln(population density)		-0.018	-0.019*		-0.011	-0.009
		(0.011)	(0.011)		(0.007)	(0.007)
% unemployed who are long term		-0.079	-0.099		-0.308***	-0.279***
jobless		(0.108)	(0.111)		(0.076)	(0.076)
Constant	2.131***	3.084***	3.094***	-0.295***	0.789**	0.774**
	(0.047)	(0.422)	(0.413)	(0.027)	(0.319)	(0.315)
Observations	79	79	78	79	79	78
F-statistics	10.292	33.936	27.434	0.058	35.011	33.924
R^2	0.159	0.794	0.775	0.001	0.715	0.728

Source: ONS / LFS

Notes: Heteroskedasticity and autocorrelation-robust standard errors in parentheses. * = significant at 10%, ** 5%, *** 1%.

Table 13. Results for alternative 'super-diversity' Index (migrant groups). UK urban areas, 2001-2006.

Dependent variable	Wages			Employment rates		
	(1)	(2)	(3)	(1)	(2)	(3)
Frac Index, migrant groups	0.794***	0.016	0.069	0.345***	0.128	0.127
	(0.245)	(0.114)	(0.118)	(0.064)	(0.106)	(0.108)
% 24 or less		-2.123***	-1.834***		-0.754*	-0.762*
		(0.631)	(0.613)		(0.399)	(0.411)
% Female		-1.081	-0.935		-1.481**	-1.485**
		(1.085)	(0.936)		(0.662)	(0.663)
% degrees		1.395***	1.344***		0.510***	0.512***
		(0.271)	(0.269)		(0.100)	(0.101)
% manufacturing		-0.386	-0.270		0.257**	0.254**
		(0.245)	(0.239)		(0.112)	(0.115)
ln(population density)		0.000*	0.000		-0.000	-0.000
		(0.000)	(0.000)		(0.000)	(0.000)
% unemployed who are long term jobless		-0.156	-0.191*		-0.305***	-0.304***
		(0.119)	(0.105)		(0.070)	(0.071)
Constant	1.580***	2.886***	2.746***	-0.590***	0.374	0.378
	(0.220)	(0.594)	(0.520)	(0.057)	(0.348)	(0.350)
Observations	79	79	78	79	79	78
F-statistics	10.507	22.654	20.723	29.568	29.841	29.666
R^2	0.239	0.711	0.701	0.210	0.702	0.701

Source: ONS / LFS.
Notes: Heteroskedasticity and autocorrelation-robust standard errors in parentheses. * = significant at 10%, ** 5%, *** 1%.

Table 14. Results for alternative 'super-diversity' Index (minority ethnic groups). UK urban areas, 2001-2006.

Dependent variable	**Wages**			**Employment rates**		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Frac Index, minority groups	0.794***	0.123	0.164**	0.220***	0.055	0.048
	(0.245)	(0.083)	(0.081)	(0.066)	(0.050)	(0.051)
% 24 or less		-2.119***	-1.835***		-0.986**	-1.032***
		(0.597)	(0.583)		(0.375)	(0.384)
% Female		-0.807	-0.687		-1.663**	-1.683**
		(1.036)	(0.910)		(0.665)	(0.675)
% degrees		1.337***	1.284***		0.490***	0.498***
		(0.261)	(0.261)		(0.095)	(0.097)
% manufacturing		-0.321	-0.219		0.147	0.131
		(0.236)	(0.229)		(0.106)	(0.107)
ln(population density)		0.000	-0.000		-0.000**	-0.000
		(0.000)	(0.000)		(0.000)	(0.000)
% unemployed who are long term jobless		-0.124	-0.156		-0.290***	-0.285***
		(0.117)	(0.106)		(0.070)	(0.072)
Constant	1.580***	2.681***	2.571***	-0.454***	0.592*	0.610*
	(0.220)	(0.558)	(0.493)	(0.049)	(0.318)	(0.325)
Observations	79	79	78	79	79	78
F-statistics	10.507	25.649	24.756	11.259	35.185	32.961
R^2	0.239	0.729	0.725	0.159	0.727	0.725

Source: ONS / LFS.

Notes: Heteroskedasticity and autocorrelation-robust standard errors in parentheses. * = significant at 10%, ** 5%, *** 1%.

Table 15. Wage models. Results for robustness checks.

Log hourly wages	Outliers	Leverage	Influence	Jobs gap
Frac Index, CEL groups	-0.042	-0.048	-0.063	-0.035
	(0.072)	(0.072)	(0.070)	(0.078)
Controls	Y	Y	Y	Y
Observations	76	76	76	76
F-statistic	22.296	18.256	19.704	20.070
R^2	0.703	0.706	0.734	0.709

Log hourly wages	Outliers	Leverage	Influence	Jobs gap
Frac Index, CEL super-diversity	0.275***	0.275***	0.252***	0.260***
	(0.092)	(0.086)	(0.082)	(0.095)
Controls	Y	Y	Y	Y
Observations	76	76	76	76
F-statistic	22.611	19.351	20.205	20.153
R^2	0.735	0.738	0.760	0.737

Log hourly wages	Outliers	Leverage	Influence	Jobs gap
Frac Index, country of birth groups	0.643***	0.649***	0.599***	0.640***
	(0.089)	(0.100)	(0.133)	(0.093)
Controls	Y	Y	Y	Y
Observations	79	79	79	79
F-statistic	43.423	38.808	31.809	37.674
R^2	0.812	0.812	0.818	0.812

Log hourly wages	Outliers	Leverage	Influence	Jobs gap
Frac Index, ethnic groups	0.518***	0.520***	0.475***	0.510***
	(0.090)	(0.092)	(0.107)	(0.090)
Controls	Y	Y	Y	Y
Observations	79	79	79	79
F-statistic	33.936	29.991	30.393	30.108
R^2	0.794	0.794	0.802	0.795

Source: ONS / LFS/ONOMAP.
Notes: Controls fitted = % working-age population 24 and under, % female, % with degrees, % with manufacturing jobs, % of unemployed who are long term workless, log (population density). 'Outliers' fits dummies for Hartlepool, Lanarkshire, and London. 'Leverage' fits dummies for Brighton, Exeter, Hastings, Lanarkshire, London and Southend. 'Influence' fits dummies for Chelmsford, Exeter, London and Southend. 'Jobs gap' fits dummies for 20 'deindustrialising cities' identified by Turok and Edge (1999). These are Birmingham, Clydeside (Glasgow and Lanarkshire TTWAs), West Yorkshire (Leeds and Bradford), Merseyside (Liverpool and Wirral), London, Manchester, South Yorkshire (Sheffield and Rotherham), Bristol, Cardiff, Coventry, Doncaster, Edinburgh, Hull, Leicester, Nottingham, Plymouth, Stoke-on-Trent, Sunderland and Wigan. Heteroskedasticity and autocorrelation-robust standard errors in parentheses. * = significant at 10%, ** 5%, *** 1%.

Table 16. Employment models. Results for robustness checks.

Log employment rates	Outliers	Leverage	Influence	Jobs gap
Frac Index, CEL subgroups	-0.140***	-0.151***	-0.138***	-0.141***
	(0.033)	(0.035)	(0.033)	(0.033)
Controls	Y	Y	Y	Y
Observations	76	76	76	76
F-statistic	41.721	34.451	36.639	36.576
R^2	0.784	0.789	0.792	0.784

Log employment rates	Outliers	Leverage	Influence	Jobs gap
Frac Index, CEL super-diversity	0.095**	0.097**	0.085*	0.098**
	(0.046)	(0.047)	(0.050)	(0.045)
Controls	Y	Y	Y	Y
Observations	76	76	76	76
F-statistic	58.367	49.771	51.984	50.363
R^2	0.747	0.748	0.753	0.747

Log employment rates	Outliers	Leverage	Influence	Jobs gap
Frac Index, country of birth groups	0.026	0.037	0.046	0.021
	(0.071)	(0.066)	(0.059)	(0.073)
Controls	Y	Y	Y	Y
Observations	79	79	79	79
F-statistic	34.223	29.570	31.611	33.061
R^2	0.715	0.716	0.726	0.716

Log employment rates	Outliers	Leverage	Influence	Jobs gap
Frac Index, ONS ethnic groups	0.020	0.025	0.027	0.016
	(0.055)	(0.052)	(0.049)	(0.057)
Controls	Y	Y	Y	Y
Observations	79	79	79	79
F-statistic	35.011	30.664	32.469	34.430
R^2	0.715	0.715	0.725	0.715

Source: ONS / LFS/ONOMAP.
Notes: Controls fitted = % working-age population 24 and under, % female, % with degrees, % with manufacturing jobs, % of unemployed who are long term workless, log (population density). Outliers are Hartlepool, Lanarkshire, and London. Leverage points are Brighton, Burnley, Hastings, and London. Influence points are Burnley, Hastings, Hartlepool, Lanarkshire, London, Swansea, and Wirral. 'Jobs gap' fits dummies for 20 'deindustrialising cities' identified by Turok and Edge (1999). These are Birmingham, Clydeside (Glasgow and Lanarkshire TTWAs), West Yorkshire (Leeds and Bradford), Merseyside (Liverpool and Wirral), London, Manchester, South Yorkshire (Sheffield and Rotherham), Bristol, Cardiff, Coventry, Doncaster, Edinburgh, Hull, Leicester, Nottingham, Plymouth, Stoke-on-Trent, Sunderland and Wigan. Heteroskedasticity and autocorrelation-robust standard errors in parentheses. * = significant at 10%, ** 5%, *** 1%.

The Long Term Impacts of Migration in British Cities: Diversity, Wages, Employment and Prices

1. Introduction

This paper looks at the long term economic impacts of migration on British cities. Like the previous chapter, my starting point is the growing ethnic and cultural diversity of the UK in recent decades. It is clear that net migration is one of the main drivers of change. The past decade and a half represents 'the single biggest wave of immigration in British history' (Goodhart, 2010). Many new migrant communities have developed since the late 1990s; A8 accession in 2004 has led to a very large increase in arrivals from the Central and Eastern European countries joining the EU.

The economic and social impacts of recent immigration have been hotly disputed. The rise in net migration largely took place under the 1997-2010 'New Labour' government. By contrast, the current Conservative-Liberal Democrat coalition is actively trying to reduce net migration back to the levels of the mid-1990s.

Recent migration inflows to the UK have been heavily urbanised. Although many rural communities have seen very rapid growth in numbers of migrant workers, British cities have always had the biggest stocks of migrant (and minority) populations. Put simply, cities are 'where the diversity is', and much of this is migrant-driven. Has the growing immigration of the past fifteen years – and the diversity that migrants bring – been good for urban economies?

There is a large existing literature on the economic impacts of migration in the UK and elsewhere (for recent summaries see Dustmann et al (2008) or Kerr and Kerr (2011)). We can divide these studies into three types. The first group – the bulk of the literature – focus on the effects of migrants in local or regional labour markets, and are built on neoclassical frameworks. These typically find little or no average impact of migrants on the wages or employment prospects of UK-born (so-called 'native') workers; some turn up welfare losses for less-skilled groups via relative scarcity effects.

Over time, however, migration is also likely to have impacts on the wider urban economy – as new, more diverse communities become established. A second group of studies, most notably those by Ottaviano and Peri (2005a, 2006), explore dynamic effects of migration in an spatial economy framework. These studies allow externalities from immigrants, and impacts at the urban level. For example, the dynamic effects of net migration may be productivity-enhancing for natives – say, if skilled migrants facilitate knowledge spillovers or reduce trade costs (Saxenian, 2006, Page, 2007). Skilled workers may also prefer diverse environments (Florida, 2002). Net migration then leads to higher native productivity, wages and employment rates – and raises the local cost of living, if diverse cities become congested.

A third perspective focuses on employers' response to migration shocks, especially if these shocks are repeated or continuous (Lewis, 2005, Green, 2007b). If migrants are imperfect substitutes for natives, parts of the local economy may become progressively 'migrant-dependent'. Specifically, employers in low-cost sectors such as food processing become reliant on cheap migrant labour (Stenning et al., 2006). Net migration will impact negatively on native employment, especially if lower-skilled British-born workers are unable to move into better jobs. If this helps sustain low-skills equilibrium (Finegold and Soskice, 1988), wages and prices may also fall over the long term as the area's economy continues to perform sub-optimally.

This complex set of mechanisms will largely determine the long-term effects of migration on urban economies. Some of this will be captured via changes in wages and employment, but the effects of net migration should also show up in productivity and local prices. For this reason, it is important to look at migration's effects beyond local labour markets. This paper is one of only a handful of UK studies addressing these wider processes (Frattini, 2008, Lee, 2010, Longhi, 2011, Sá, 2011). I am able to improve on those studies with a longer sample period, better-defined spatial units and finer-grained, richer data. It is also able to explore effects across different native and migrant skill groups.

Robust time-series data on migration and diversity is very hard to find for British cities, so to overcome these limitations the analysis has several novel features. I assemble a new 16-year panel of urban economies from aggregated microdata. By using 2001 Travel to Work Areas as spatial units, I am able to estimate actual impacts on local economies. I investigate links between migration and changes in UK-born wages, employment rates and local house prices, exploring in detail economic interactions between different skill groups of migrants and natives. The model also allows inference on migrant-related changes in urban labour productivity, exploiting the fact that over time, productivity changes tend to be reflected in wage rates (Combes et al., 2005).

The results are robust to various checks for endogeneity issues, including instrumental variables regression. They suggest significant long term impacts of net migration on urban economies, within and beyond the labour market. Specifically, the diversity migrants bring helps drive up high skill native productivity and wages, suggesting the presence of both production complementarities and relative scarcity effects.

Conversely, increasingly migrant-intensive labour markets appear to be 'locking out' some intermediate and low-skilled British-born workers from employment opportunities, suggesting an endogenous employer response to shifts in net migration. Results from shorter panels suggest much of this took place after 2000. 'Migrants taking British jobs' is an oversimplification, however: the on-going impacts of long term industrial decline and the increasing casualisation of entry-level jobs also help explain the employment findings. Overall, the results differ both from previous UK research, and from US studies. I speculate that the UK's urban structure, labour market transformations and immigrant populations help explain these differences.

The paper is structured as follows. The next Section explores the background and policy context, and sets out key definitions and terms. Section Three reviews the UK and international evidence. Sections Four and Five introduce the datasets and estimation strategy. Section Six presents the main findings. Sections Seven and Eight explore potential native outflows and present IV results. Section Nine concludes.

2. Background and motivation

My research question is: what are the long-term effects, if any, of migration on the economic performance of British cities? I use changes in urban migrant populations as a way of exploring broader questions about the local economic impacts of cultural diversity. Both 'migration' and 'diversity' need careful definition. My analysis concentrates on 'long term migrants' – those people born outside the UK and resident in the country for at least 12 months (Home Office and Department of Work and Pensions, 2007). Most public datasets, do not identify 'short term migrants' who may only stay for a few months.

As the previous chapter makes clear, cultural (or 'ethnic') diversity is a multifaceted concept, with subjective and endogenous elements (Office of National Statistics, 2003, Aspinall, 2009, Green 2011). Therefore most attempts to quantify diversity with objective measures are incomplete (Mateos et al., 2007). Nevertheless, in the absence of reliable multidimensional indicators, country of birth is widely used as a proxy for diversity because it is objective, and because rich data is available (Ottaviano et al., 2007). In this chapter I am specifically interested in the diversity that immigrants bring, and use Fractionalisation Indices to measure the spread and distribution of birth country groups. These are discussed further below.

There are several reasons to be interested in the economics of migration, particularly at urban level.[11] Long term migration flows into the UK are relatively small – between 1971 and 2006 the UK population grew by 8.2%, while the US population grew by 44.6%, with migration the main driver in both cases (Blanchflower, 2007). Compared with countries like Canada and Australia, where immigrants comprise over a quarter of the population, the UK is a low-immigration country – immigrants make up around 13% of the working age population (Wadsworth, 2010, Card, 2011).

Since the late 1990s, however, 'netflows' to the UK have accelerated substantially. From just under 50,000 people per year in 1997, net annual migration rose to around 140,000 in 1999, and rose again in 2004/5 to over 200,000. The latter date marks A8 accession, when a number of East European countries joined the EU (Graph 1).[12] Just before the downturn the net inflow of migrants to the UK was around 198,000 people per year. The share of migrants in the working-age population almost doubled over the past 15 years, from 7.6% in 1992 to 13.6% in 2004 (Wadsworth, 2010). The diversity of migrant communities in the UK has also expanded dramatically during this period (Kyambi, 2005, Vertovec, 2006).

As a result, there are now high levels of interest in the impacts of migration on the economy, society and public services. Since 2003, 'race and immigration' has been one of the top three issues in the MORI organisation's monthly omnibus surveys of public opinion. There have been five major re-organisations of immigration policy since 2001, four under the 1997-2010 'New Labour' Government (Somerville, 2007) . The current Conservative-Liberal Democrat coalition Government is now implementing a migration cap on non-EU migration, with the aim of reducing net migration 'to the tens of thousands' – a reduction of around 100,000 people per year (HM Government, 2010).

There is also a broader on-going conversation about the wider effects of a bigger, more diverse society (Goodhart, 2004, Legrain, 2006, Wolf, 2008, Simpson and Finney, 2009, Fanshawe and Sriskandarajah, 2010, Goodhart, 2010). This reflects the fact that growing cultural diversity in Britain and many other Western societies is also driven partly by migrant communities (Champion, 2006, Putnam, 2007). In 2007 UK net immigration accounted for 52 percent of overall population growth, with 'natural change' (net births) explaining the rest (Graph 1). But natural change includes a rising share of live births to mothers born outside Britain (Office of National Statistics, 2011). This reflects higher net

[11] The focus of this paper is on migration in cities, which I will also refer to as 'urban areas' or 'local economies'. In the analysis I will approximate cities using 2001 Travel to Work Areas (TTWAs).
[12] ONS Total International Migration (TIM) figures. These will include some British return migrants.

migration and differential birth rates in some minority groups (Performance and Innovation Unit, 2003).

Migrants are unevenly distributed across the UK. Since 2004, rural areas and small towns have experienced very rapid growth in migrant populations (Green, 2008). However, British cities still contain the largest migrant volumes and population shares. In 2002-3, over half of all net migration was to London, and over half of the rest was to other large cities (Table 1). The urban share of both migrant groups and visible minorities has been increasing over the past decade and a half. Put simply, cities are 'where the diversity is', and much of this is migrant-driven.

In England alone, the 56 biggest urban areas contain over half the UK population and over two thirds of all employment (Parkinson et al., 2006). So any migrant-related changes to the economic performance of British cities might also impact on national economic trends. According to some commentators these impacts could be substantial. In recent years a number of authors have suggested that there are significant economic gains from net immigration, and that cities help drive these gains (Florida, 2002, Legrain, 2006, Leadbeater, 2008). These arguments are reviewed in the next section of the paper.

3. Review of theory and evidence

Changes in net migration affect urban economies by altering the size and composition of the urban population and labour force. The introductory chapter, above, provides a theoretical overview: these frameworks and relevant empirics are discussed in more detail below. I distinguish between frameworks focused on the labour market, the wider spatial economy models, and on employer business models and strategies. I argue that all three perspectives are needed to establish the effects of migration on urban areas.

3.1 Labour market impacts

Conventional economic analysis of the local impacts of immigration uses neoclassical assumptions and focuses on labour markets (Borjas, 2011). Assume an urban economy receives a one-off immigration 'shock'. If migrants are perfect substitutes for UK-born workers ('natives'), the increase in labour supply leads average native wages to fall in the short term. If wages are sticky, native employment may fall too. In an open economy – like a city – a combination of capital inflows and output composition changes then bid wages back up to their starting point (Dustmann et al., 2003, Dustmann et al., 2005). Within this, there are some distributional effects: typically migrants cluster at the bottom of the labour market, so that the main effect is on low skilled natives via labour market competition. Higher-skill natives receive wage gains through relative scarcity effects (Card, 2005, Dustmann et al., 2007)

If migrants are not perfect substitutes with natives, they may cluster in 'hard to fill' jobs at the bottom of the labour market (Manacorda et al., 2006). This means competition with natives is minimal; we should see little change on native wages and employment, particularly if new migrants predominantly compete with existing migrant groups. (If employers react to repeated inflows by changing production functions and/or hiring patterns, impacts on natives may be more significant – see below.)

A large number of empirical studies in the UK and elsewhere bear out these predictions, finding little or no significant effects of migration on average native wages, employment or unemployment. Some studies suggest small welfare losses for lower-skilled natives and gains for higher-skilled groups (see Dustmann et al (2008) and Nathan (2008) for recent reviews). Importantly, studies suggest that although migrants have similar skills profiles to natives and can be found across the occupational spectrum, they do not behave as perfect substitutes, particularly in the first few years of residence in the UK (Dustmann et al., 2007, Green et al., 2007a, Green et al., 2007b).

3.2 Wider economy impacts

Rather than replicate these labour market studies, I propose a broader approach. Net migration is also likely to have effects on the wider urban economy, particularly over longer timeframes as a) cities experience continuous inflows of immigrants and b) migrant communities are established. First, migration may generate human capital externalities – specifically, immigrants may raise the productivity of UK-born workers by facilitating market access, knowledge creation and diffusion. Second, some sectors of the local economy may become 'migrant-dependent' – if employers react to migrant inflows by permanently altering their production functions, low-skilled natives may become 'locked out' from entry-level employment.

The first channel is likely to raise native productivity and wages, employment and prices. In the second case, outcomes are ambiguous. In both cases, welfare gains from migration are likely to accrue to higher-skilled British-born, with losses accruing to lower-skilled native workers.

3.3 Migration, productivity and the spatial economy

Ottaviano and Peri (2005a, 2005b, 2007) develop a broader framework for thinking through the impacts of immigration on urban areas. They model a system of open cities, in which net migration can enhance labour productivity through various spillover effects – as well as working through the labour market as in the models above. Migration-induced productivity shifts in a given city may then lead to further in-migration, congestion and impacts on real wages / living costs.

Spillovers largely derive from the diversity that migrants bring. Endogenous growth theory highlights the importance of knowledge and human capital to long run economic development (Romer, 1990). Migrants play potentially important roles in knowledge creation, both as mobile carriers of human capital and by influencing ideas generation and diffusion. A number of lab and workforce studies suggest that 'cognitive diversity' in teams – a range of experiences and perspectives – helps problem-solving and can foster innovation. Cultural diversity is an important component: workforce diversity may be hard to manage initially, but tends to improve team performance over time (Page, 2007). These effects tend to be greatest in 'knowledge-intensive' sectors, which are largely concentrated in and around cities.

Similarly, migrant diasporas may also improve forward and backward linkages for firms – both through access to new customer markets, and via increased possibilities for distributed / off-shored production (Saxenian, 2006). Again, these effects are likely to be urbanised, as cities both have the highest levels of physical connectivity and large, diverse consumer markets.

By raising the productivity of 'knowledge-intensive' businesses and workers, these processes are also likely to raise wages and employment rates for the higher-skilled staff these firms typically employ. If productivity-enhancing effects are large enough they also may contribute to overall urban growth (Ottaviano and Peri, 2006). As per spatial economy models, average wages and employment rates will rise, reflecting increased productivity. But as in-migration accelerates, pressures on space raise local living costs (Combes et al., 2005, Overman and Rice, 2008).

US empirical studies suggest that migration shifts are linked to both productivity and price gains in American cities, so that real welfare effects are close to neutral (Saiz, 2003, Ottaviano and Peri, 2006, Sparber, 2007). Concentrations of migrant inventors make a difference to levels of urban innovation (Saxenian, 2002, Niebuhr, 2006, Peri, 2007, Hunt and Gauthier-Loiselle, 2008, Ozgen et al., 2010). Migrant networks also facilitate international links and reduce trade costs (Saxenian, 2006, Peri and Requena, 2009).

Ottaviano and Peri-type open cities models should also apply to the European context, where cities operate as small open economies in a large system. However, compared to the US, the UK and other European countries typically have fewer cities and less spatial variation in economic and demographic outcomes. So far there is almost no comparable European analysis – although there are a handful of studies on EU regions (Bellini et al., 2008, Huber et al., 2011), German regional wages (Südekum et al., 2009), UK regional prices (Frattini, 2008), UK employment growth (Lee, 2010), UK wages (Longhi, 2011) and house prices in England and Wales (Sá, 2011).

Frattini finds some positive relationships between immigrant population shares and prices. Lee finds positive links between migrant diversity and employment growth in English cities, but is unable to establish a causal relationship. Similarly, Longhi finds positive links between ethnic diversity and wages, but results using instruments are non-significant. Controlling for causality, Sa finds negative effects of immigrants on house prices at local authority level, but no effect at regional level.

3.4 Migration, employer response and labour market institutional change

A third perspective on the urban impacts of migration focuses on changes to labour market institutions and to individual employers' business strategies. As discussed above, new migrants tend to cluster in entry-level occupations – so that against a backdrop of rising net migration, there is effectively a 'permanent' rise in migrants' share of the entry-level workforce. This triggers outcomes which are distinctive from those set out in the neoclassical models above.

Lewis (2005) notes that employers may react to repeated / continuous migration shocks by shifting to more labour-intensive production functions. In practice, this could take two forms. First, in urban areas with large numbers of entry-level positions, employers of low-wage labour may switch hiring patterns to take advantage of a constant flow of cheap, motivated workers (Stenning et al., 2006). Some sectors of the local economy – such as food processing, routine manufacturing or low-cost retail – may become progressively 'migrant-intensive' or 'migrant-dependent' (Green, 2008). Second, firms in other sectors may also adopt more labour-intensive production functions. They may then fill new posts using migrant labour, particularly if the new jobs are of poor quality and unattractive to native workers.

These dynamic feedback effects have consequences for native workers, especially those with intermediate or lower skills. If migrants increasingly provide the main source of entry level labour, UK-born low-skill workers may be able to move up the occupational hierarchy. The extent of this 'bumping up' critically depends on the quality of available education and on-going vocational training, and on whether employers increase their demand for skilled labour. If low-skilled natives are bumped up, migration will leave their employment rates unaffected but their wages will increase. If natives are unable to move into better jobs, however, the dynamic effect of migration will be to bid down low-skill natives' employment rates. They will be unwilling to fill low-paid, insecure positions; migrants will dominate employment flows. Labour market competition becomes 'lockout'. At urban level, average wages and employment rates may fall in places where low value-added sectors dominate. As the area's economic trajectory turns downward, prices fall too.

There is some suggestive UK evidence to support this. Since the mid-1970s, technological and institutional changes have contributed to wage inequality and job polarisation, with rising employment shares for high-skilled 'knowledge' jobs and the least-skilled manual occupations (Goos and Manning, 2007). This helps explain persistent spatial disparities in many urban areas, which have lost 'middling' jobs and seen the share of manual jobs increase. Some of these places have also seen large increases in net migration. In some parts of the country (such as the North East and Midlands) food processing and manufacturing firms are becoming dependent on the 'quick fix' of migrant labour (Fitzgerald, 2007, Green et al., 2007b, Green et al., 2007a, Dawley and Stenning, 2008, MacKenzie and Forde, 2009, Wills et al., 2010, Cook et al., 2011). Temporary employment agencies appear to play increasingly important roles in helping low-wage employers source staff (Coe et al., 2006). A8 Accession has accelerated these trends, bringing potentially millions of new workers into the EU's transnational labour market (Ciupijus, 2011).

There are also difficulties for low-skilled workers looking to move up the occupational ladder. Critics point to persistent problems in the UK adult skills system (Westwood and Jones, 2004). Most famously, Finegold and Soskice (1988) suggest some sectors of the UK economy are in 'low-skills equilibrium': employers operate low-cost, low-quality business models and show little interest in changing task skill composition, or building workers' human capital.

3.5 Diversity and the Creative Class

An alternative view is suggested by Richard Florida (Florida, 2002). In this model, urban economies are increasingly dominated by a 'Creative Class' of skilled workers with strong preferences for cultural diversity. Open and tolerant cities attract the Creative Class, improving their human capital mix and attracting new investment. This implies that diverse cities might have stronger economic performance primarily because of the Creative Class, with cultural diversity contributing nothing directly. In practice, the Creative Class performs poorly in both US (Glaeser, 2005) and UK contexts (Nathan, 2007). Significantly, there is little UK evidence that a single 'Creative Class' exists – skilled workers have a range of location preferences covering city centres, suburbs and rural locations.

4. Data and descriptives

In order to examine potential effects on urban economies of migration and the diversity migrants bring, I construct a new panel of UK urban areas, from 1994-2008 inclusive. Unlike the previous chapter, the panel data structure allows me to fit area and time fixed effects, as well as develop more sophisticated strategies to try and establish causation.

The main dataset in this analysis is the Labour Force Survey (LFS): this is the single best source of long term data on migration, demographic and economic data, but the relatively small survey size raises the risk of measurement error when used at local level (Dustmann et al., 2003). Specifically, I am using the LFS at sub-regional level, which requires trying to safeguard against biased estimates.

LFS microdata[13] are provided with spatial identifiers at Local Authority District level. I therefore aggregate local authority averages to Travel to Work Area level (2001 TTWAs), using a postcode share weighting system.[14] TTWAs have the additional benefits of being

[13] Microdata kindly provided by the Office of National Statistics Virtual Microdata Lab (VML). The quarterly LFS samples around 60,000 households. Each quarter consists of five overlapping 'waves', with an 80% overlap within that quarter. As per ONS recommendations, to ensure a sample of unique individuals I keep only observations from waves 1 and 5 in each quarter. I then pool the remaining data to produce calendar years. This approach gives me c.120000 individual-level observations per year, approximately 517 per TTWA. This will be considerably higher for both total and migrant sample in the final panel, which is restricted to urban areas only.

[14] As in the previous chapter, I aggregate individual-level LFS data to local authority-level averages, and then aggregate these to TTWA-level using postcode shares. Local Authority District (LAD) boundaries are not congruent with TTWA boundaries, so straightforward aggregation is not possible. Using the November 2008 National Postcode Sector Database (NSPD), I calculate the number of postcodes in each 2001 TTWA and in each of its constituent LADs. For each TTWA, I then calculate constituent LADs' 'postcode shares'. Shares sum to one, and are used as weights to construct TTWA-level averages. *Example:* suppose a TTWA consists of parts of three LADs. The TTWA has 100 postcodes, 60 of which are in

designed to represent self-contained local labour markets, act as good proxies for a spatial economy, and minimise the risk of spatial autocorrelation (Robson et al., 2006). To further strengthen the analysis I restrict the analysis to 79 'primary urban' TTWAs where the sample sizes are biggest, following the approach of Gibbons et al (2011) (see Appendix C for details). Together, these precautions give me a panel with 1185 observations between the years 1994 and 2008 inclusive. I use this full panel for the descriptive analysis.

The LFS provides information for wages, employment, migration and most controls. This is combined with Land Registry microdata (for house prices) and ONS mid-year population estimates (for controls and robustness checks). Because I am interested in productivity, wages and employment, I restrict observations to the LFS working age population (16-64 for men, 16-59 for women). For simplicity I drop observations from Northern Ireland. At the time of modelling Land Registry data was only available for 1995-2006 inclusive, so house price data panels cover 1995-2006. As a final safety measure I pool years together, averaging observations across three years.

4.1 Diversity measures

To measure the diversity that migrants bring to the UK, I construct a Fractionalisation Index of country of birth groups. Following Ottaviano and Peri (Ottaviano and Peri, 2006), this captures the cultural diversity migrants bring to urban economies. For group g in area a in year t, the Index is given by:

$$FRAC_{at} = 1 - \Sigma_g \, [SHARE_{gat}]^2 \qquad (1)$$

Where g is one of (1 … n) birth country groups and SHARE is g's share of the total area population. The Index thus measures the probability that two individuals in an area come from different country of birth groups. Similar measures are used widely in the development literature, as well as some US city and state-level studies (Easterley and Levine, 1997, Alesina and La Ferrara, 2004).

I estimate the Index using 79 individual country of birth groups, including UK-born, and construct separate Indices for high, intermediate and low skilled workers. The Index reflects both the number of different groups in an area and their relative sizes. Specifically, it takes the value 0 when everyone is in the same country of birth group and 1 when each individual is in a different group. For comparison with the bulk of labour market impact

LAD_a, 30 in LAD_b and 10 in LAD_c. The relevant LAD weights are 0.6, 0.3 and 0.1 respectively. The TTWA-level average of variable x is given by (x)TTWA = 0.6*(x)_a + 0.3*(x)_b + 0.1*(x)_c.

studies I also show some results using migrant population shares. I run further cross-checks using aggregated birth country groups.[15]

4.2 Descriptives

Summary statistics for TTWA-year cells are set out in Table 2. The first panel covers my main dependent variables: wages, employment and prices. Wages are measured as average hourly wages for the TTWA; employment rates as the percentage of the working-age population; house prices as TTWAs' average prices for any residential property. As mentioned above, I use wage information to infer changes in labour productivity, following Combes et al (2005). Wages and employment rates are broadly similar between British-born and migrant workers, although migrants have slightly higher average wages and lower employment rates (thus higher unemployment rates).

As expected, London accounts for the maximum values of overall and resident wages, as well as house prices; employment rates are highest in Guildford. Resident wages and employment rates are lowest in Hartlepool and Liverpool respectively, while Mansfield has the cheapest housing. For migrants, wages and employment rates are highest in Worcester and Norwich respectively; respective minima are in Calderdale and Hartlepool. London has the highest value of the Fractionalisation Index and the largest migrant population share; Hartlepool has the lowest on both counts.

The second panel of descriptives covers area-level demographic, economic and social characteristics used as controls. I create three skill groups based on qualifications obtained, using the UK National Vocational Qualification (NVQ) system as a benchmark. 'High skill' workers have qualifications at NVQ4 level or above (a university degree or other Higher Education qualification); 'intermediate skill' workers obtain NVQ3 or 2 (equivalent to A-levels or at least five GCSE's at grades A*-C, respectively); 'low skill' workers obtain NVQ1, equivalent to other/no qualifications.[16] High skill workers comprise just over a fifth of the sample, intermediate skill workers over two-fifths and low-skill workers a third.

Table 3 breaks down these skill groups by migrant and native populations across the panel. Natives are slightly more likely than average to have intermediate skills: by contrast, migrants are slightly more likely to be high skilled, and substantially more likely than natives to be low skilled. For occupational groups, migrants are rather more likely

[15] Specifically, I run further regressions using 1) migrant population shares from 'Northern' and 'Southern' countries, where 'North' is defined as EU25, North America, Japan and Australasia, and 2) a simple Fractionalisation Index using 18 country of birth groups. For 1) results were largely insignificant on native wages and employment. For 2) results were very similar to the full Fractionalisation Index.

[16] A-level exams are taken at age 18, GCSE's at 16.

than average to be in high-level occupations (such as professional roles), reflecting the higher share of urban migrants with high skills. Migrants are less likely to be in intermediate roles (such as skilled trades, administration or secretarial jobs) but in entry-level jobs (personal and protective services, sales, and routine occupations) migrant workers and natives have similar employment shares.

Table 4 compares labour market performance for native and migrant skill groups. Average migrant wages are slightly higher than those for natives (first panel), but this is largely driven by wages for low-skilled migrants. The second panel looks at employment rates. In all three skill group categories, natives are more likely to be employed than migrants. Unemployment rates largely reflect this – although low-skilled migrants are less likely to be out of work than their low-skill native counterparts.

Table 5 looks at how migrant characteristics and outcomes have shifted over the panel period. It turns out that the headline figures just discussed hide some significant shifts between the 1990s and 2000s. Most notably, while the skill composition of migrants has not changed substantially, migrants had substantially bunched into entry-level occupations by 2006/8. This national trend hides some very large local shifts: for example, the share of migrants in entry-level occupations increased by 33% in Hartlepool, 48% in Burnley, 64% in Doncaster and 116% in Hull. Similarly, while wages and employment rates differ little by skill group, migrants in high-level occupations now earn above average; those in entry-level roles somewhat below. These shifts reflect important changes in labour market institutions, especially in 'migrant-intensive sectors', and are discussed further in Sections 7 and 9.

Table 6 shows the changing composition of the UK's migrant communities. The most striking fact here is that a third of the top 20 origin countries in 1994 do not even feature in the top 20 15 years later. The biggest-growing migrant community is Polish people in the UK (9.8% of migrants in 2008). Other important sending countries include Zimbabwe (2.76% of immigrants in 2008), China (2.49%), the former USSR (2.21%) and the Czech Republic / Slovakia (1.97%). Of the countries remaining major sources of immigrants, only Pakistan, South Africa and Bangladesh have seen a growing share of arrivals.

Finally, we turn to the spatial aspects of these demographic changes (Table 7). Between 1994 and 2008, average migrant working-age population shares increased from six to just over 10 per cent (similarly, the average value of the Fractionalisation Index rose by around 10 percentage points, from just under 0.1 to just under 0.2). London maintains the largest migrant stocks throughout the period, and records a 9.4% point rise in migrant population. Reading (9%), Luton and Watford (9.1%), Milton Keynes (10.1%) and Cambridge (12.3%) also record large increases.

The descriptives confirm the growing cultural diversity of urban areas, and highlight the role of immigration in this. The composition of the migrant population has shifted as new communities have emerged. Cities like London combine high wages, employment rates and large diverse populations; at the other end of the distribution are areas like Hartlepool with low wages, low employment rates and relatively small migrant numbers. Taken as a whole, migrants themselves are slightly more likely to be higher or lower skilled than natives, but are less likely to be employment. Migrants also exhibit clustering into less well-paid entry-level jobs by the mid-2000s.

5. Estimation strategy

I now explore how these features of the UK's immigrant population affect urban economic outcomes. I construct a simple model, linking urban economic outcomes to diversity and a range of demographic, economic and spatial controls. My estimation strategy is an example of the spatial correlations approach widely used in the migration and diversity literature (e.g. (Altonji and Card, 1991, Card, 2005, Dustmann et al., 2005, Ottaviano and Peri, 2006). The basic model is given by:

$$Y_{it} = bDIV_{it} + \mathbf{DEM}_{it}c + \mathbf{ECON}_{it}d + eSPAT_{it} + \mu_t + \partial_i + e \quad (2)$$

Where Y is variously the log of average hourly wages for UK-born residents ('resident wages'), log average employment rate for UK-born ('resident employment') and the log of average house prices ('prices'). In further regressions wages and employment rates are also broken down for high, intermediate and low-skilled natives. As in the previous chapter, the log-linear specification means that coefficients of *DIV* can be interpreted as marginal effects.[17]

Productivity gains in urban areas are typically reflected in higher long term wages (Combes et al., 2005). So this specification allows me to interpret wage changes as shifts in labour productivity.

[17] Log-linear specifications could cause problems if values of dependent variables were ever zero. However, there are no zero cells in the panel.

Because the UK lacks robust cost of living data at sub-regional level, and even regional-level data is very hard to obtain (Frattini, 2008), I use the local house prices as a proxy for the local cost of living. This has some important limitations. First, including mortgage costs, housing-related expenditure is the single largest item of UK consumer spending, covering 22 percent of spend (Office of National Statistics, 2008a). However, three quarters of spending is not covered. Second, most migrants tend to rent rather than buy, so that some of the direct impacts of migrants on local housing markets will probably not show up in sales figures (Gordon et al., 2007).

DIV is my variable of interest, and is given by the Fractionalisation Index of birth country groups. For comparison, I also present results where *DIV* is the population shares of migrant workers. Further regressions estimate the effects of migrant skill groups on native skill groups, and these use Fractionalisation Indices and population shares for high, intermediate and low-skilled migrants as appropriate.

I fit a number of control variables, following the approach of the previous chapter. ***DEM*** represents two demographic controls. Migrants are younger than average, and younger workers tend to earn less, so I fit the area share of workers age 24 and under to control for potentially spurious correlations between diversity, wages and employment (Dustmann et al., 2005, Goujard et al., 2011). I fit the share of female workers for precision: women still earn less than men, although in many areas female employment rates are higher than male (Swaffield, 2011).

ECON is a set of economic structure controls (share of workers with degrees, share of workers in manufacturing sectors, share of jobless who are long term unemployed). Human capital is positively linked to urban productivity, and thus wage levels; urban areas with high nominal wages also tend to have higher house prices (Glaeser, 2008). The descriptives also suggest that migrants are slightly more likely to be high-skilled than natives. I therefore need to control for compositional effects which may drive diversity-productivity and diversity-prices relationships.

Given the steady decline of manufacturing employment in the UK, manufacturing activity may be negatively linked to wages and employment; worklessness is negatively associated with both wages and employment rates (Berthoud, 2003). The descriptive analysis shows that migrants are more likely than natives to be unemployed. I therefore fit the share of manufacturing jobs for precision, and use the worklessness control to capture potentially spurious links between migrant presence, wages and employment rates.

SPAT is given by logged population density, measured as total population over surface area. This is a simple device for capturing agglomeration economies, which again may lead both to higher wages, prices and employment rates, and simultaneously to larger, more diverse urban populations. μ_t and ∂_i denote time dummies and area fixed effects, respectively.

The panel comprises 158 TTWA observations for 1994/6 and 2006/8, using moving averages to minimise measurement error. I estimate the model as a two-period model with area fixed effects and year dummies, which is equivalent to estimating in differences. As a cross-check I replicate the main regressions in differences, finding very similar results.

There are a number of validity challenges here, in particular the issue of majority outflows and migrant selection (Borjas, 1994). I deal with the former in robustness tests, and the latter through a shift-share instrument based on Ottaviano and Peri (2006). See Sections Seven and Eight for further details.

6. Main results

The results from the main regressions are set out in Tables 8 through 10. In each table, specifications (1) to (4) give results for the Fractionalisation Index. Of these, (1) shows *DIV* only, (2) adds controls and year dummies, (3) adds fixed effects and (4) removes London from the sample. Specifications (5) – (8) repeat for migrant population shares.

6.1 Results from whole sample

Table 8 shows positive associations between migrant diversity and native productivity / wages. As measured by the Fractionalisation Index, *DIV* is 0.317, significant at 5% (column 3). This implies that a 10 point rise in the Index, the average change over the panel period, is associated with a [(0.1*0.317)*100] = 3.17% rise in UK-born workers' productivity / wages. Migrant population shares also show a positive link to native wages. Column 7 indicates the coefficient of *DIV* is 0.476, significant at 5% (column 3). A one percentage-point rise in migrant population share is associated with a [(0.01 x 0.476]*100] = 0.476% rise in resident productivity / wages: a five percentage-point rise, roughly the average change in migrant population shares from 1994-2008, is linked to a 2.38% rise.

In contrast, Table 9 shows a negative association between migrants and UK-born average employment rates. For the Fractionalisation Index, the coefficient of *DIV* is -0.13, significant at 5% (column 3). This implies that a 10 point rise in the Index is associated with a [(0.1*0.213)*100] = 2.13% fall in resident employment rates. I also find a negative link between migrant population share and native employment in urban areas. Column 7 shows the coefficient of *DIV* on native employment is somewhat larger than previously, at -0.377. As with the Fractionalisation Index the result is significant at 5%.

Table 10 gives results for the house price models. Once area fixed effects are added (column 3) I find no significant relationship between *DIV* and the local cost of living, as measured by average house prices. For migrant population shares results are very similar, and no significant link is established. In large part, this is likely to be driven by limitations in the dependent variable (see Section 5).

6.2 Results by skill group

LFS data allows me to disaggregate the sample by migrant and native skill groups. I use this information in two ways. First, I look at the impact of overall diversity on different native groups, by regressing *DIV* on the wages/productivity and employment rates of high skill, intermediate skill and low skill natives. Results are given in Table 11.

Labour market frameworks predict that migrants tend to benefit high-skill natives and put pressure on lower-skill natives via relative scarcity effects. The first panel of Table 10 shows that as expected, migrant diversity is positive for the wages/productivity of higher skilled workers and slightly negative for low skilled workers. However, *DIV* is not significant in any specification.[18] Results for employment models are given in the second panel, and here coefficients of *DIV* are negative for all worker groups. The association is only significant for intermediate and low skilled natives, where the coefficients of *DIV* are -0.272 and -0.514, significant at 5% and 1% respectively.[19] For high skill natives, effects are insignificant and close to zero, as would be expected.

Second, I regress high, intermediate and low-skilled migration on the economic outcomes of respective native skill groups. Specifically, I regress diversity of the three migrant skill groups on the wages/productivity and employment rates of *all* native skill groups. This specification should allow me to disentangle relative scarcity effects from production complementarities. Relative scarcity effects should be manifest in positive effects of low-skill migrants on wages and employment of high-skill natives, but negative effects of low and intermediate skill migrants on outcomes for similar natives. By contrast,

[18] This is partly explained by collinearity between the dependent variable and the human capital control, especially for high skill natives' wages. When the latter is removed, *DIV* is weakly significant (at 10%) on productivity / wages. Employment results are unaffected.
[19] I experiment with migrant population shares, finding similar results.

production complementarities should be characterised by positive wage effects of low (intermediate, high) skill migrants on low (intermediate, high) skill natives.

Results are given in Table 12. Productivity / wage results are in the first panel. There is some weak support for production complementarities, with positive links between diversity and native productivity / wages for high skill and low skill cells. For example, the coefficient of low-skill diversity on low skill native productivity / wages is 0.177, significant at 5%, compared with 0.317 for the whole sample.

There is also some support for relative scarcity effects. Specifically, low skill diversity is associated with increased wages for both intermediate and higher skill natives (both significant at 5%), and there is a negative – albeit insignificant – association of intermediate skill diversity and intermediate native wages. The coefficient of intermediate skilled diversity on low-skill native wages is rather larger, at -1.267 (significant at 5%).

The second panel looks at employment outcomes for natives. Here, there is very little evidence of production complementarities, with coefficients of high skill diversity on high skill native employment insignificant and, at 0.076, close to zero. Conversely, there is more evidence of relative scarcity effects: the presence of intermediate and low skill migrants both have negative links to employment rates in their respective native skill groups. The coefficient of low skill diversity on low-skill native employment rates is -0.178, significant at 10%.

6.3 Robustness checks

To test the robustness of these main results I run some basic checks. First, the descriptive analysis suggests London is a clear outlier on both diversity and dependent variables. My main results may therefore be skewed by the capital's presence. Removing London from the sample makes some difference to the results, although less than one might expect (see columns 4 and 8 of Tables 8-10). For example, column 4 of Table 7 shows that removing the capital slightly raises the coefficient of *DIV* on native productivity / wage rates, from 0.317 to 0.334. In Table 8, taking out London slightly lowers the effect of *DIV* on employment rates, from -0.213 to -0.210. For productivity / wage models significance remains unchanged, but removing London from employment models reduces significance to 10%.

Second, I re-run the wage / productivity models by for native occupational groups. Given the clustering of migrants into high-end and entry-level occupations highlighted in the descriptive analysis, we might expect to see some effects on native wage outcomes, as detected in other UK research by Nickell and Saleheen (2009). While none of the results is significant at this stage (Table 13), there are some changes once instruments are introduced (see section 8).

Third, I repeat the main regressions without the principal outliers, leverage points and influential observations.[20] As in the previous chapter, the descriptives suggest a number of areas with historically strong, or poor economic performance. Overall diversity-performance relationships may be affected by omitted variables in these areas. Outliers are defined as maxima of resident wages, resident employment and the Fractionalisation Index; leverage and influence points are the five cells with the highest leverage scores and values of Cook's D, and are specified separately for wage/productivity and employment models. Results are given in Table 14. Wage models are essentially unaffected by these additional controls, with coefficients of *DIV* of similar sign, magnitude and significance. However, employment models are sensitive to the presence of leverage and influence points. Controlling for leverage reduces the coefficient of *DIV* from -0.213 to just -0.139. Similarly, controlling for influence points reduces *b* to -0.154. In both cases the result is no longer significant.

In employment models some of these outlying points are former industrial cities. I explore these issues further with a fourth set of checks for the influence of long term industrial change on the employment results. In past decades, many migrants arrived in the UK to take manufacturing jobs in areas such as Burnley and Bradford, which subsequently underwent substantial deindustrialisation during the 1980s and 1990s. The employment results may therefore be driven by a spurious correlation between large migrant populations and low employment rates.

As in the previous chapter, to test the effects of industrial decline I examine economic activity and employment rates for the 20 de-industrialising urban areas identified by Turok and Edge (1999). It turns out that the areas losing the most employment during the 1980s and early 1990s also tend to have the weakest labour market performance during the panel period. I re-run the employment regressions without these TTWAs.[21] Results are given in the last column of Table 14. Again, productivity / wage models are

[20] Because outliers etc are TTWA cells and the model fits area fixed effects, it is not possible to run models on a pooled sample with relevant dummies.
[21] The 20 urban areas identified by Turok and Edge are Birmingham, Clydeside (Glasgow and Lanarkshire TTWAs), West Yorkshire (Leeds and Bradford), Merseyside (Liverpool and Wirral), London, Manchester, South Yorkshire (Sheffield and Rotherham), Bristol, Cardiff, Coventry, Doncaster, Edinburgh, Hull, Leicester, Nottingham, Plymouth, Stoke-on-Trent, Sunderland and Wigan.

unaffected: but coefficients of *DIV* on native employment are now smaller and marginally significant.

Finally, I check model specification by re-estimating in first differences. Results for the main productivity/wages and employment models are given in Table 15. The size and sign of the diversity variables is very similar: however, model fit statistics are considerably worse, providing support for the original two period fixed effects specification.

Overall, the results so far suggest two broad themes. First, I find positive links between diversity and native productivity and wages, especially for higher skilled natives. Skill group regressions provide some support for underlying production complementarities, although relative scarcity effects are also present. As suggested by the literature, area-level averages may hide much stronger channels in specific sectors. Second, I find negative associations between migrant populations, migrant diversity and native employment rates – particularly for intermediate and low skilled native groups. The results are sensitive to a few influential observations, and the effects of de-industrialisation partly explain the findings. However, immigration impacts cannot be ruled out.

These results are simply the correlations of diversity and urban economic performance. The next two sections attempt to establish causality more precisely.

7. Native outflows

The UK-born population in a given area may respond to immigrants arriving by leaving that area – because they are displaced in the labour market, because of more expensive housing, or because they dislike diversity. If this occurs any economic impacts of the migration shock may not be picked up by a spatial correlations approach, and coefficients of *DIV* will be biased towards zero (Borjas, 1994, Borjas, 2006).

Recent reviews of the international literature suggest there is still no consensus on the extent of native outflows (Card, 2007, Dustmann et al., 2008). In theory, there are reasons to think UK native outflows should be small. Despite declining internal mobility in in the United States (Molloy et al., 2011), levels of internal migration in the UK are relatively low compared to the US, and low-income groups are particularly unlikely to move. Gordon and colleagues (2007) suggest that as migrants are willing to live at high housing densities, net immigration will have little effect on the local cost of living and thus is unlikely to price out natives.

Empirical evidence is mixed. Hatton and Tani (2005) suggest outflows are quite large at regional level, especially in the Greater South East. By contrast, Lemos and Portes (2008) find no effect of migrants' arrival on UK native 'netflows'. Most recently Sa (2011) finds evidence of native inflows and outflows, with the latter outweighing the former. Both these latter studies use local authority data. Arguably, neither regional nor local authority scales are appropriate scales for approximating local housing markets.

More broadly, there is a continued and unsettled debate on 'white flight' in the UK. In 2005 Trevor Phillips – then head of the Equalities and Human Rights Commission – warned that Britain was 'sleepwalking into segregation', with white families exiting many urban areas.[22] But Simpson and Finney (2009) provide evidence to show very little spatial segregation in British communities .[23]

The choice of native outflows test is important. Peri and Sparber (2011) conduct microsimulation tests on outflow models, finding some specifications contain inherent biases – and so report outflows even when none exist. The best-performing tests are those developed by Card (2001, 2005, 2007). Assuming migrants tend to compete with lower-skilled natives, Card regresses the share of all low-skilled workers on the share of low-skilled migrants. I adopt Card's 2007 specification, adding controls, area fixed effects and year dummies allowed by the panel data structure. The model is given by:

$$LOWSKILL_{it} = a + bLOWSKILLMIG_{it} + \mathbf{CONTROLSc_{it}} + \mu_t + \partial_i + e_{it} \qquad (3)$$

If migrants completely displace natives, *b* should be 0 or close to it. Conversely, if there is no displacement *b* should approach the value 1.

Results are shown in Table 16. The first panel gives results by skill group. The naïve OLS results suggest native outflows are quite large (column 1): however, this model has little explanatory power. Once fixed effects and controls are introduced (columns 2 and 3), the relationship is insignificant and coefficients of *b* are close to zero. The second panel gives results by occupational groups. Without controls values of *b* are quite similar to the skill group models: however, adding controls and area dummies does not remove the effect, which remains at 0.115, significant at 1%. While these results are correlations rather than causal effects, so need cautious interpretation. The approaching-zero coefficients suggest that native outflows are not present when the workforce is cut by skill

[22] http://news.bbc.co.uk/1/hi/uk/4270010.stm accessed 3 September 2009.
[23] Although there is some evidence that increasing parental choice in education has led to some largely white or non-white schools (ibid).

group, but there is suggestive evidence of crowding out in entry-level occupations. This is in line with some of the broader evidence discussed in Section 9.

As a secondary test I also develop a very simple internal migration model, regressing the log population share of British-born workers on the logs of wages, house prices, employment rates and the share of long term unemployed, plus migrant population share. Results are shown in Table 17. While there is a negative association between migrant stock and the population share of British-born, other factors appear to play a larger role. Again, this suggests that native outflows play little part in my main results.

8. Migrant selection and instruments

A more serious issue is migrant selection. If migrants are attracted to the cities with the highest economic performance, the best-performing place may also be the most diverse even if there is no causal relationship. This will bias coefficients of *DIV* upwards. Equally, if migrants are located in cities that suffer exogenous, negative economic shocks, *DIV* will be biased downwards if the shock is not controlled for.

I use an instrumental variables (IV) strategy to deal with this issue. A number of potential instruments have been developed in the literature. Time lags are the simplest approach (see e.g. Dustmann et al (2005)) but are hard to interpret in a spatial economy framework. Accessibility measures have also been used, based on the fact that migrants tend to settle in and around major entry points such as ports and land borders (Ottaviano and Peri, 2006, Bellini et al., 2008). Unfortunately, the geography of the UK makes it difficult to apply these instruments successfully: there are no land borders, and many key entry points are regional airports close to several urban cores, making it hard to link migrant flows to specific local communities.[24] Compared to many other countries the UK has made relatively few policy changes that have significantly changed migrant flows (Ortega and Peri, 2009). The most suitable policy shock is the natural experiment created by A8 accession in 2004 (Lemos and Portes, 2008). However, accession effects arguably kick in too close to the end of the panel to be useful in this case.

I therefore construct a shift-share instrument of the kind popularised by Card (2005, 2007). The intuition is that migrant populations tend to be attracted to existing migrant communities. In its simplest form, the instrument uses an area's historical migrant

[24] Lemos and Portes (2008) experiment with an instrument based on regional airports, numbers of flights and distance from airport to home countries. This performs poorly for the reasons above, and probably because their period of study (2004-2006) also saw considerable dispersal of migrants around the UK.

population to assign the area a share of the current national migrant population. By construction, the instrument builds local migrant populations on the basis of historical and non-local information only. It should thus remove the effect of local demand shocks that might otherwise affect net migration to a city.

The specific instrument used here is based on Ottaviano and Peri (2006). Let SH_{gat} denote the share of the total population accounted for country of birth group g, in area a, year t. Then SH_{gt} is the corresponding national share of group g, summed across cities. tb denotes a base year. Then the predicted population share of g is given by:

$$pSHARE_{gat} = SH_{gatb} + [SH_{gatb} * (SH_{gt} - SH_{gtb}) / SH_{gatb}] \quad (4)$$

The predicted migrant population share is given by summing $pSHARE_{gat}$ across all non-UK birth country groups. The predicted Fractionalisation Index is then given by:

$$pFRAC_{gt} = 1 - \sum_g (pSHARE_{gat})^2 \quad (5)$$

I set 1991 as the base year, which allows me to use 1991 Census population data.

There are two other potential challenges for shift-share instruments. First, patterns of historic migrant settlement may be influenced by historical factors that also shape current economic outcomes. This would suggest choosing a base year deep in the past to ensure exogeneity. However, an overly distant base year may have little relevance to current migration patterns. I experiment with base years 1981 and 1991, with the latter performing best in first stage tests. The second problem is that local demand shocks within the panel might have an impact on national migrant stocks (for example, a construction boom in London during the late 1990s). This weakness is harder to deal with, although in theory one could do so by generating predicted national migrant stocks – using a country-level model of international migration flows, for instance. Ortega and Peri (2009) offer one such model: further research could apply it at the sub-national level.

8.1 Results from IV regressions

Results from IV regressions are given in Table 18. First stage results show that the instrument is a good predictor of *DIV* with an F-statistic of between 21 and 39 and partial R^2 between 0.28 and 0.33. The instrument also passes Kleibergen-Paap tests for under-identification and weak identification, and the Stock-Yogo test at the highest critical value.

Second-stage results are given in Table 19. The top panel shows that the positive effect of *DIV* on resident wages disappears in the IV results (column 1). In the middle panel, the negative association between *DIV* and resident employment remains and is significant at 1%. Coefficients of *DIV* are now rather larger (-0.692 for the Fractionalisation Index). The right-hand panel shows that, as in the main regressions, *DIV* is not significant on average house prices. As in the main results, I experiment with simple robustness checks. For all three dependent variables, removing London, outliers, leverage and influence points and de-industrialising cities makes little difference to the results.

Table 20 looks at outcomes for different native skill groups (data limitations prevent a full replication of the skill group cells analysis). The top panel covers productivity/wages, and shows coefficients of *DIV* are positive for high and intermediate skill workers (columns 1 and 2) and negative for low skilled natives (column 3). For the former, *DIV* is 0.653, significant at 10%. The middle panel repeats this analysis for native occupation groups. Results here suggest a weak negative effect of migrant diversity on the wages of natives in entry-level occupations. The bottom panel gives employment results. Here, coefficients of *DIV* are negative for all three groups. For high-skill natives the result is marginal, but stronger for intermediate skilled workers (-0.926, significant at 1%) and low skilled workers (-0.772, significant at 10%). As before, experimenting with the various robustness checks does not change the overall pattern of these findings.

Overall, these results confirm some elements of the main findings. The dynamic impacts of migration are not uniform. Any positive impacts on productivity/wages are driven by gains for skilled workers, particularly in London. Conversely, negative employment effects seem to be driven by losses for intermediate or lower-skilled native groups. The occupational group results provide some evidence of downwards wage pressure for natives in entry-level occupations. As such, the IV results provide support for the existence of production complementarities and dynamic labour market change.

9) Conclusions

This paper has considered the economic effects of migration on a panel of UK cities between 1994 and 2008. Over this period the UK, and urban areas in particular, have become significantly more culturally diverse, with migration a main driver of change. Migration may have distinctive economic impacts in cities, as opposed to the UK as a whole. Investigating this is difficult for the UK. Unlike the bulk of British studies I have been able to look at causal effects beyond the labour market, over two decades, and across 'real' local economies. The trade-off is that the data is pushed very hard, but the estimation strategy takes care to minimise measurement error.

The results imply there are significant dynamic effects of net migration on UK urban areas, over and above the labour market change considered in conventional analyses. First, there is some evidence that migration helps drive up native productivity and wages, particularly for high-skill UK-born workers and particularly for those in London. Second, more migrant-intensive economies may have a lockout effect on some lower-skilled natives, although others may be 'bumped up' the occupational hierarchy. Third, net migration appears to have no effect on average house prices at the urban level. All of these results are robust to various checks, including instrumental variables regression,.

The paper proposes two main mechanisms by which net migration might change urban economic outcomes over the long term: production complementarities, particularly among skilled workers, and structural changes to entry level employment, concentrated on lower skilled workers. The empirical results suggest that both of these mechanisms are operating in UK urban areas. Productivity and wage gains largely accrue to skilled workers, although lower-skilled natives also gain; while employment pressure is largely felt by intermediate and low-skilled workers.[25]

An alternative explanation is that all this simply reflects relative scarcity effects in the labour market. Results from skill group cells suggest that both are at least part of the answer. To test whether the results 'collapse to the labour market', I experiment with breaking the panel into shorter periods, covering 1994-1999 and 2000-2008. I find no statistically significant changes to average productivity/wages, or to particular worker types. In turn, this suggests that these results from the main panel are the result of longer term shifts in urban economies and firms, rather than simple labour market effects. Conversely, I also find significant negative associations of migration and resident employment rates in the period 2000-2008. This suggests the very large increase in net migration during the 2000s partly drives the main employment results.

Overall, these findings are less clear-cut than parallel studies in the US (Ottaviano and Peri, 2005a, 2006), Germany (Südekum et al., 2009) and the wider EU (Bellini et al., 2008). And as might be expected, both my results differ from previous UK research on immigration and local labour markets, and from studies linking diversity to employment

[25] A striking feature of the employment results is that the effects of migration appear to be strongest for intermediate skill British-born workers rather than for low skill natives. This is probably explained by the urban focus, which does not capture the large numbers of migrants in rural areas, working in agricultural or food processing sectors.

(Lee, 2010) and wages (Longhi, 2011). The UK's urban structure, labour market transformations and immigrant populations help explain these differences. For example, the UK has fewer cities and smaller immigrant populations than the US; a number of UK cities have been affected by de-indutrialisation, while these trends affect a much smaller share of the US urban system.

In a UK context, the results help explain some of the current public conversation about migration and diversity. Net migration is good for high skilled workers, employers and Government, which receives migrants' taxes but typically spends less on healthcare or education (Reed et al., 2005). On the face of it, outcomes seem to be less positive for 'blue-collar Britain', as sceptical commentators such as Goodhart have suggested. However, the reality is likely to be more complex. First, across the UK new migrants compete against previous migrant cohorts as well as natives (Manacorda et al., 2006). I run separate robustness checks to confirm this, comparing the main results with outcomes for all workers, including existing migrants. Second, the employment results need to be put in the broader context of industrial decline and the restructuring of entry-level work in many urban labour markets.

In particular, changes to labour market institutions are likely to condition the effects of migration: it is simplistic to ascribe the results to 'migrants taking jobs'. Several commentators have highlighted the growing share of part time and temporary positions in sectors such as retail, leisure, agribusiness and routine manufacturing, the increasing use of sub-contracting, and the growing dependence of many employers in these sectors on migrant employment (Fitzgerald, 2007, Green et al., 2007b, Green et al., 2007a, Dawley and Stenning, 2008, MacKenzie and Forde, 2009, Wills et al., 2010, Cook et al., 2011). One recent estimate suggests 40% of the 1.5m A8 migrants since 2004 work in agency-dominated sectors such as manufacturing and process work, office employment or retail / hospitality.[26] Wills and colleagues (2010) suggest that in some sectors of the London economy, such as cleaning, immigrants may account for 2/3 of all employees. Many 'migrant-intensive' employers – particularly those in retail, agribusiness and routine manufacturing – operate low-quality, low-cost production models (Green, 2007b, Dawley and Stenning, 2008). They also depend heavily on temporary employment agencies – which play an important role in organising migrant employment, and in some cases take over firms' overall Human Resources function (Green, 2008, Fitzgerald, 2007, Equality and Human Rights Commission, 2010).

[26] Kath Jones and Kevin Ward (Manchester University) point out that 2008 WERS data suggests that since 2004, 39% of migrants are employed in 'administration, business and management', food processing, manufacturing, hospitality or 'temporary work'.

MacKenzie and Forde (2009) provide an illuminating case study of a glass packaging firm, based in Barnsley and employing around 90% migrant workers in a workforce of 200-300. Interviews with managers show the firm's increasing focus on migrant workers – seen as 'good workers' with a strong work ethic – in preference to the local labour force. MacKenzie and Forde suggest this is an integral element of the firm's "low road approach to competitive advantage" (p155), which they characterise as minimising labour costs, non-unionisation and 'minimal compliance' with regulatory interventions. However, as migrant workers "become more embedded in the local community and labour market, their aspirations develop beyond the willingness to accept long hours of work for low pay" (p156). They leave for new jobs, necessitating further rounds of migrant recruitment.

Taken together, these changes have helped produce strata of insecure, poorly-paid 'lousy jobs' (Goos and Manning, 2007), with employers increasingly dependent on networks of imported migrant labour to fill them. Migrant workers are often exploited or ill-treated (Equality and Human Rights Commission, 2010). UK-born workers may lack access to employment networks, or they may be unwilling to take low quality jobs (Samuels, 2008). At urban level, the migrant-employer-agency nexus may be supporting low-skills equilibrium in some places – particularly lower-growth areas, many of which now have large numbers of migrant workers in entry-level occupations. In turn, this suggests that policy responses need to encompass a number of elements – improving the employability of low-skilled native workers, re-regulating entry-level employment and 'bad' employers, and promoting economic development in de-industrialising areas. Conversely, evidence that higher-skill migration helps improve native productivity suggests that national immigration policy should actively encourage the arrival and settlement of high human capital migrant workers. On this basis, overall caps on immigration are undesirable to the extent that they conflict with these aims.

Further research could take several directions. Sectoral, firm or individual-level analysis is needed to explore transmission mechanisms in more depth. Specifically, explorations of production complementarities, such as links from diversity to innovation could be valuable. Case study work could also explore different cities' experiences in detail, particularly London. The next two papers tackle these issues in turn. More broadly, access to robust local cost of living data would allow a proper investigation into migration and local prices in the UK. Finally, it would be worth developing richer diversity measures to explore different facets of Britain's increasingly cosmopolitan urban life.

LIST OF TABLES

Table 1. Net international migration across England, 2002-3.

Area	Net migration	% England total
London	77,276	53.0
North / West Mets	23,822	16.4
South / East large cities	13,605	9.3
South / East small cities	10,760	7.4
North / West large cities	7,064	4.8
South / East large towns	5,902	4.1
North / West small cities	3.977	0.0
South / East small towns / rural	3,825	2.6
North / West large towns	1,768	1.2
North / West small towns / rural	-2,281	1.6
England	*145,688*	*100*

Source: Champion (2006), Office of National Statistics Total International Migration data. Note: percentages may not sum to 100 due to rounding. Area typology is based on Primary Urban Area geographies. ‘Mets’ = Birmingham, Leeds, Liverpool, Manchester, Newcastle upon Tyne, Sheffield. ‘Large cities’ = cities not in metropolitan counties, with at least 275,000 residents. ‘Small cities’ = 175,000-27500 residents. ‘Large towns’ = 50,000-175,000 residents. ‘Small towns and rural areas’ = less than 50,000 residents.

Table 2. Summary statistics.

Variable	N	Mean	SD	Min	Max
Ave house price (£ '000s)	147	60.120	13.439	40.697	102.784
Ave hourly wage	158	9.28	2.57	5.50	16.06
Ave hourly wage, UK-born	158	9.30	2.61	5.50	16.74
Ave hourly wage, migrants	158	9.58	3.15	4.75	29.48
Ave employment rate	158	0.734	0.048	0.587	0.822
Ave employment rate, UK-born	158	0.74	0.048	0.586	0.824
Ave employment rate, migrants	158	0.677	0.094	0.399	0.848
Ave unemployment rate	158	0.052	0.017	0.024	0.11
Ave unemployment rate, UK-born	158	0.052	0.017	0.023	0.111
Ave unemployment rate, migrants	158	0.056	0.026	0.001	0.154
% long term unemployed share	158	0.301	0.105	0.103	0.548
% long term unemployed share, UK-born	158	0.302	0.102	0.099	0.551
% long term unemployed share, migrants	158	0.282	0.196	0	0.846
% non-UK born	158	0.078	0.047	0.01	0.366
Frac. Index, all birth countries	158	0.146	0.082	0.02	0.595
Frac. Index, migrant populations	158	0.999	0.001	0.99	1
% ethnic minority	158	0.057	0.055	0.002	0.305
% aged 24 or less	158	0.172	0.016	0.131	0.218
% aged 29 or less	158	0.506	0.009	0.484	0.53
% female	158	0.494	0.009	0.47	0.516
% male	158	0.228	0.063	0.106	0.409
% with high skills	158	0.459	0.036	0.332	0.532
% with intermediate skills	158	0.313	0.073	0.179	0.504
% with low skills	158	0.172	0.016	0.131	0.218
% in high-level occupations	158	0.383	0.065	0.243	0.559
% in intermediate occupations	158	0.256	0.033	0.174	0.337
% in entry-level occupations	158	0.361	0.046	0.239	0.489
% employed in service sector	158	0.484	0.062	0.34	0.646
% employed in manufacturing	158	0.16	0.057	0.044	0.316
% employed in other sectors	158	0.344	0.033	0.281	0.493
Population density ('000s)	158	798.92	276.49	5824.01	1245.07
Working age population ('000s)	158	119.07	72.38	44.91	448.13

Source: ONS / LFS / Land Registry.

Notes: Due to ONS disclosure rules some observations are suppressed. ONS population data is available from 1994-2007 inclusive. Land Registry house price data is for England and Wales, from 1994-2006 inclusive. High skills = NVQ4 (degrees / HE qualification), intermediate skills = NVQ2 or 3 (A-levels / good GCSEs), low skills = NVQ1 (other / no qualifications). High-level occupations = professional / senior / associate professional. Intermediate occupations = admin and secretarial, / skilled trades. Entry-level occupations = personal and protective services / sales / routine / other.

Table 3. Human capital and occupational characteristics for the full sample, migrants and natives, 1994/6-2006/8.

	Everyone	Natives	Migrants
% with high skills	0.228	0.228	0.259
% with intermediate skills	0.459	0.478	0.264
% with low skills	0.313	0.294	0.477
% in high-level occupations	0.383	0.382	0.434
% in intermediate occupations	0.256	0.261	0.183
% in entry-level occupations	0.361	0.357	0.383

Source: ONS / LFS.
Notes: Sample = 158 TTWA-level averages. High skills = NVQ4 (degrees / HE qualification), intermediate skills = NVQ2 or 3 (A-levels / good GCSEs), low skills = NVQ1 (other / no qualifications). High-level occupations = professional / senior / associate professional. Intermediate occupations = admin and secretarial, / skilled trades. Entry-level occupations = personal and protective services / sales / routine / other.

Table 4. Labour market performance for migrants, natives and the full sample, 1994/6-2006/8.

Outcome	Group	Everyone	Natives	Migrants
Hourly wages	All	9.28	9.30	9.58
	High skill	13.10	13.14	12.89
	Intermediate skill	8.20	8.20	8.04
	Low skill	6.68	6.59	7.39
	High level occs	12.97	12.94	13.44
	Intermediate occs	7.70	7.71	7.65
	Entry level occs	6.19	6.23	5.89
Employment rate	All	0.734	0.74	0.677
	High skill	0.86	0.864	0.822
	Intermediate skill	0.756	0.759	0.691
	Low skill	0.615	0.616	0.605
ILO unemployment rate	All	0.052	0.052	0.056
	High skill	0.031	0.03	0.042
	Intermediate skill	0.051	0.051	0.062
	Low skill	0.068	0.07	0.06

Source: ONS / LFS.
Notes: Sample = 158 TTWA-level averages. High skills = NVQ4 (degrees / HE qualification), intermediate skills = NVQ2 or 3 (A-levels / good GCSEs), low skills = NVQ1 (other / no qualifications). High-level occupations = professional / senior / associate professional. Intermediate occupations = admin and secretarial, / skilled trades. Entry-level occupations = personal and protective services / sales / routine / other.

Table 5. Labour market shifts for natives and migrants, 1994/6-2006/8.

Variable	Natives		Migrants	
	1994/6	2006/8	1994/6	2006/8
% with high skills	0.187	0.269	0.229	0.290
% with intermediate skills	0.445	0.473	0.294	0.234
% with low skills	0.367	0.258	0.477	0.476
% high-level occupations	0.346	0.419	0.445	0.423
% intermediate occupations	0.283	0.229	0.199	0.167
% entry-level occupations	0.371	0.352	0.356	0.410
Wages, high skills	10.58	15.62	10.13	15.65
Wages, intermediate skills	6.39	10.00	6.24	9.84
Wages, low skills	5.14	8.21	6.14	8.65
Wages, high-level occupations	10.03	15.90	10.27	16.60
Wages, intermediate occs	5.88	9.52	5.78	9.55
Wages, entry-level occs	5.07	7.32	5.02	6.76
Employment rate, high skills	0.852	0.868	0.823	0.820
Employment rate, intermediate skills	0.751	0.762	0.689	0.693
Employment rate, low skills	0.622	0.608	0.565	0.645

Source: ONS / LFS.
Notes: Sample = 158 TTWA-level averages. High skills = NVQ4 (degrees / HE qualification), intermediate skills = NVQ2 or 3 (A-levels / good GCSEs), low skills = NVQ1 (other / no qualifications). High-level occupations = professional / senior / associate professional. Intermediate occupations = admin and secretarial, / skilled trades. Entry-level occupations = personal and protective services / sales / routine / other.

Table 6. The 20 largest migrant groups in UK urban areas, 1994-2008 and changes.

Country of birth	% total migrants		
	1994/6	2006/8	Change
Ireland	13.02	4.72	-8.3
India	12.84	10.44	-2.4
Pakistan	10.37	10.58	0.21
Germany	7.38	5.70	-1.68
USA	3.20	2.20	-1
Kenya	3.08	2.10	-0.98
Italy	2.52	1.75	-0.77
Jamaica	2.42	1.22	-1.2
Bangladesh	2.32	2.76	0.44
Canada	2.21	1.12	-1.09
Hong Kong	2.02	1.85	-0.17
South Africa	1.98	3.98	2
Australia	1.95	1.87	-0.08
France	1.86	1.85	-0.01
Malaysia	1.69	1.01	-0.68
Other West Indies	1.48	0.56	-0.92
Uganda	1.45	0.76	-0.69
Singapore	1.34	0.97	-0.37
Cyprus	1.31	0.86	-0.45
Malta and Gozo	1.30	0.65	-0.65
% urban migrants	*6.0*	*10.4*	*4.4*

Note: Sample is UK working-age population in urban areas. To ensure comparability over time, country of birth data is drawn from the LFS variable CRYO c.1992. This means that some countries which have emerged since are not included (e.g. former Yugoslavia) and there is limited detail on others (e.g. Middle East outside Israel and Iran). * = not Iran or Israel. Includes e.g. Iraq, Jordan, and Lebanon.

Table 7. Travel to Work Areas (TTWAs) with the 25 largest migrant working-age populations, 1994-2008 and changes.

TTWA name	**% non-UK born**		
	1994/6	**2006/8**	**Change**
London	27.4	36.8	9.4
Bradford	12.7	17.5	4.8
Birmingham	12.7	18.8	6.1
Wycombe & Slough	12.3	20.2	7.9
Bolton	10.9	12	1.1
Leicester	10.8	19	8.2
Coventry	10.4	16.2	5.8
Luton & Watford	10	19.1	9.1
Peterborough	10	15.1	5.1
Rochdale & Oldham	9.5	13.6	4.1
Manchester	9.4	12.9	3.5
Brighton	9.2	14	4.8
Guildford & Aldershot	9.2	13.5	4.3
Reading & Bracknell	9	18	9
Bedford	8.7	19.7	11
Crawley	8.1	12.9	4.8
Huddersfield	8.1	10.8	2.7
Wolverhampton	7.9	13.8	5.9
Oxford	7.8	13.9	6.1
Stevenage	7.7	12	4.3
Milton Keynes & Aylesbury	7.7	17.8	10.1
Blackburn	7.5	14	6.5
Cambridge	7.4	19.7	12.3
Leeds	7	12.4	5.4
Worthing	6.9	8.8	1.9
Dudley & Sandwell	6.9	10.2	3.3
All urban TTWAs	*6*	*10.4*	*4.4*

Source: ONS/LFS.

Table 8. Native wage results, 1994/6-2006/8.

ln(average hourly wages, UK born)	DIV = Frac Index				DIV = migrant population share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DIV	0.979***	0.605***	0.317**	0.334**	1.649***	1.008***	0.476*	0.545**
	(0.122)	(0.073)	(0.146)	(0.147)	(0.213)	(0.129)	(0.241)	(0.246)
% 24 or under		-2.220***	-0.626	-0.629		-2.220***	-0.634	-0.638
		(0.384)	(0.419)	(0.419)		(0.385)	(0.421)	(0.422)
% female		0.416	1.644**	1.677***		0.349	1.611**	1.667***
		(0.586)	(0.630)	(0.625)		(0.585)	(0.634)	(0.628)
% degrees		0.963***	0.891***	0.898***		0.986***	0.898***	0.903***
		(0.193)	(0.230)	(0.231)		(0.192)	(0.231)	(0.231)
% manufacturing employment		-0.451***	-0.050	-0.035		-0.439***	-0.044	-0.025
		(0.144)	(0.213)	(0.216)		(0.144)	(0.213)	(0.215)
ln(population density)		0.010	0.149	0.155		0.010	0.150	0.155
		(0.011)	(0.157)	(0.158)		(0.011)	(0.157)	(0.158)
% unemployed who are long term jobless		-0.095	-0.003	-0.005		-0.106	-0.001	-0.006
		(0.097)	(0.109)	(0.109)		(0.096)	(0.109)	(0.110)
Constant	2.265***	2.252***	0.457	0.395	2.283***	2.286***	0.480	0.408
	(0.021)	(0.257)	(1.148)	(1.150)	(0.020)	(0.258)	(1.151)	(1.150)
Area fixed effects	N	N	Y	Y	N	N	Y	Y
Observations	158	158	158	156	158	158	158	156
F-statistic	2292.525	622.047	1333.541	1297.962	2252.748	615.290	1307.949	1288.839
R^2	0.889	0.956	0.989	0.989	0.887	0.955	0.989	0.989

Source: ONS / LFS.
Notes: All specifications include time dummies. Heteroskedasticity and autocorrelation-robust standard errors in parentheses. Columns (1) – (4) use Fractionalisation Index of birth countries, columns (5) – (8) use migrant population shares * = significant at 10%, ** = 5%, *** = 1%.

Table 9. Native employment rate results, 1994/6-2006/8.

ln(ave employment rate, UK-born)	DIV = Frac index				DIV = migrant population share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DIV	0.266*	0.207***	-0.213**	-0.210*	0.415*	0.322**	-0.377**	-0.386**
	(0.140)	(0.070)	(0.105)	(0.108)	(0.248)	(0.128)	(0.164)	(0.179)
% 24 or under		-0.938***	-0.182	-0.182		-0.939***	-0.179	-0.178
		(0.241)	(0.277)	(0.277)		(0.242)	(0.275)	(0.274)
% female		-1.166**	-0.649*	-0.643*		-1.205**	-0.647*	-0.653*
		(0.513)	(0.337)	(0.339)		(0.524)	(0.334)	(0.338)
% degrees		0.345***	0.376***	0.377***		0.364***	0.380***	0.379***
		(0.099)	(0.117)	(0.117)		(0.102)	(0.117)	(0.116)
% manufacturing employment		0.200**	0.083	0.086		0.205**	0.084	0.081
		(0.085)	(0.137)	(0.140)		(0.085)	(0.137)	(0.140)
ln(population density)		-0.020***	-0.271***	-0.270***		-0.019***	-0.266***	-0.266***
		(0.007)	(0.083)	(0.083)		(0.007)	(0.083)	(0.083)
% unemployed who are long term jobless		-0.355***	-0.220***	-0.221***		-0.358***	-0.219***	-0.218***
		(0.069)	(0.058)	(0.058)		(0.070)	(0.058)	(0.058)
Constant	-0.330***	0.509**	1.837***	1.819***	-0.322***	0.524**	1.796***	1.798***
	(0.025)	(0.231)	(0.589)	(0.591)	(0.024)	(0.235)	(0.588)	(0.589)
Area fixed effects	N	N	Y	Y	N	N	Y	Y
Observations	158	158	158	156	158	158	158	156
F-statistic	40.126	35.720	28.162	27.532	40.350	34.660	28.282	27.772
R^2	0.188	0.677	0.718	0.718	0.173	0.671	0.720	0.720

Source: ONS / LFS.
Notes: All specifications include time dummies. Heteroskedasticity and autocorrelation-robust standard errors in parentheses. Columns (1) – (4) use Fractionalisation Index of birth countries, columns (5) – (8) use migrant population shares * = significant at 10%, ** = 5%, *** = 1%.

Table 10. Average house price results, 1994/6-2006/8.

	DIV = Frac index				DIV = migrant population share			
ln(ave house prices)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
DIV	1.667***	0.828***	-0.281	-0.080	2.799***	1.371***	-0.650	-0.154
	(0.305)	(0.177)	(0.450)	(0.442)	(0.549)	(0.306)	(0.779)	(0.769)
% 24 or under		-4.157***	-1.468	-1.660		-4.104***	-1.421	-1.656
		(1.321)	(1.643)	(1.630)		(1.324)	(1.657)	(1.632)
% female		-3.465**	-1.352	-1.336		-3.514**	-1.366	-1.339
		(1.656)	(1.617)	(1.592)		(1.652)	(1.618)	(1.590)
% degrees		2.172***	1.036**	1.000*		2.226***	1.062**	1.002*
		(0.413)	(0.513)	(0.520)		(0.408)	(0.512)	(0.520)
% manufacturing employment		-1.221***	0.603	0.670		-1.209***	0.614	0.669
		(0.395)	(0.641)	(0.643)		(0.396)	(0.646)	(0.647)
ln(population density)		-0.012	1.747***	1.800***		-0.011	1.773***	1.802***
		(0.028)	(0.339)	(0.332)		(0.028)	(0.337)	(0.332)
% unemployed who are long term jobless		-0.249	-0.310**	-0.300**		-0.269	-0.312**	-0.301**
		(0.246)	(0.145)	(0.143)		(0.247)	(0.145)	(0.144)
Constant	11.749***	14.044***	1.126	0.796	11.777***	14.058***	0.953	0.786
	(0.053)	(0.704)	(2.311)	(2.259)	(0.052)	(0.701)	(2.301)	(2.259)
Area fixed effects	N	N	Y	Y	N	N	Y	Y
Observations	147	147	147	145	147	147	147	145
F-statistic	1792.911	502.649	1002.025	1060.740	1759.328	490.471	1037.504	1061.668
R^2	0.851	0.944	0.988	0.988	0.849	0.943	0.988	0.988

Source: ONS / LFS / Land Registry.

Notes: House price data for England and Wales only, 1995-2006. All specifications include time dummies. Columns (1) – (4) use Fractionalisation Index of birth countries, columns (5) – (8) use migrant population shares. Heteroskedasticity and autocorrelation-robust standard errors in parentheses. * = significant at 10%, ** = 5%, *** = 1%.

Table 11. Results for diversity and native wages/employment, by skill groups. DIV = Fractionalisation Index, birth countries.

ln(average hourly wages, UK born)	High skills		Intermediate skills		Low skills	
	(1)	(2)	(3)	(4)	(5)	(6)
Frac Index	0.301	0.273	0.289	0.303	-0.161	0.022
	(0.221)	(0.223)	(0.218)	(0.222)	(0.275)	(0.210)
Controls	Y	Y	Y	Y	Y	Y
Area fixed effects	Y	Y	Y	Y	Y	Y
Observations	158	156	158	156	158	156
F-statistic	397.130	387.141	552.294	540.850	431.511	501.349
R^2	0.971	0.970	0.976	0.976	0.973	0.978

ln(ave employment rate, UK-born)	High skills		Intermediate skills		Low skills	
	(1)	(2)	(3)	(4)	(5)	(6)
Frac Index	-0.077	-0.068	-0.272**	-0.237**	-0.514**	-0.500**
	(0.100)	(0.104)	(0.104)	(0.104)	(0.227)	(0.232)
Controls	Y	Y	Y	Y	Y	Y
Area fixed effects	Y	Y	Y	Y	Y	Y
Observations	158	156	158	156	158	156
F-statistic	10.538	10.398	7.902	8.018	11.410	11.132
R^2	0.475	0.476	0.411	0.419	0.455	0.451

Source: ONS/LFS. Notes: All specifications include time dummies and controls (% 24 or under, % female, % manufacturing employment, ln(population density), share of unemployed who are long term jobless). Columns (2), (4) and (6) estimate the model without London. Heteroskedasticity and autocorrelation-robust standard errors in parentheses. * = significant at 10%, ** = 5%, *** = 1%.

Table 12. Results for wages/employment, native and migrant skill group cells. *DIV* = Fractionalisation Index.

ln(native wage), by skill group	**Native skill group**		
	High	**Int.**	**Low**
Frac Index, high skill workers	0.081 (0.229)	0.064 (0.214)	-0.190 (0.223)
Frac Index of int. skill workers	-0.236 (0.372)	-0.383 (0.396)	-1.267** (0.563)
Frac Index of low skill workers	0.177** (0.088)	0.230** (0.103)	0.284** (0.108)
Controls	Y	Y	Y
Observations	158	158	158
F-statistic	351.178	462.936	386.912
R^2	0.971	0.977	0.977

ln(native empl), by skill group	**Native skill group**		
	High	**Int.**	**Low**
Frac Index, high skill workers	-0.076 (0.062)	-0.025 (0.091)	-0.275 (0.202)
Frac Index of int. skill workers	0.011 (0.171)	-0.255 (0.206)	0.291 (0.389)
Frac Index of low skill workers	-0.021 (0.045)	-0.096* (0.049)	-0.178* (0.091)
Controls	Y	Y	Y
Observations	158	158	158
F-statistic	8.447	6.856	9.211
R^2	0.481	0.427	0.463

Source: ONS/LFS. Notes: All specifications include time dummies and controls (% 24 or under, % female, % manufacturing employment, ln(population density), share of unemployed who are long term jobless). Heteroskedasticity and autocorrelation-robust standard errors in parentheses. * = significant at 10%, ** = 5%, *** = 1%.

Table 13. Results for native wages / productivity, by occupational groups.

Log native hourly wages	High-level occs	Intermediate occs	Entry-level occs
Frac Index, country of birth groups	0.162 (0.191)	0.280 (0.285)	0.270 (0.253)
Controls	Y	Y	Y
Observations	158	158	158
F-statistic	632.915	455.818	295.778
R^2	0.981	0.974	0.956

Source: ONS / LFS.
Notes: Controls fitted = % working-age population 24 and under, % female, % with degrees, % with manufacturing jobs, % of unemployed who are long term workless, log (population density). Heteroskedasticity and autocorrelation-robust standard errors in parentheses.
* = significant at 10%, ** 5%, *** 1%.

Table 14. Robustness checks: results for outliers, leverage and influence tests.

Log native hourly wages	Outliers	Leverage	Influence	Jobs gap
Frac Index, country of birth groups	0.284* (0.145)	0.355** (0.160)	0.394** (0.158)	0.338** (0.158)
Controls	Y	Y	Y	Y
Observations	152	148	148	112
F-statistic	1368.631	1167.793	1220.037	1001.908
R^2	0.990	0.988	0.989	0.990

Log native employment rate	Outliers	Leverage	Influence	Jobs gap
Frac Index, country of birth groups	-0.234** (0.105)	-0.139 (0.106)	-0.154 (0.108)	-0.217* (0.112)
Controls	Y	Y	Y	Y
Observations	152	148	148	112
F-statistic	24.741	26.718	25.036	16.598
R^2	0.706	0.745	0.714	0.613

Source: ONS / LFS.
Notes: Controls fitted = % working-age population 24 and under, % female, % with degrees, % with manufacturing jobs, % of unemployed who are long term workless, log (population density). 'Outliers' fits dummies for Hartlepool, Liverpool, and London. 'Leverage' fits dummies for Burnley, Cambridge, Edinburgh, London, and Wirral. 'Influence' fits dummies for Cambridge, Chelmsford, Edinburgh, Hastings, and Southend. For employment models 'influence' fits dummies for Burnley, Cambridge, Hartlepool, London, and Swansea. For both models 'Jobs gap' fits dummies for 20 'deindustrialising cities' identified by Turok and Edge (1999). These are Birmingham, Clydeside (Glasgow and Lanarkshire TTWAs), West Yorkshire (Leeds and Bradford), Merseyside (Liverpool and Wirral), London, Manchester, South Yorkshire (Sheffield and Rotherham), Bristol, Cardiff, Coventry, Doncaster, Edinburgh, Hull, Leicester, Nottingham, Plymouth, Stoke-on-Trent, Sunderland and Wigan. Heteroskedasticity and autocorrelation-robust standard errors in parentheses. * = significant at 10%, ** 5%, *** 1%.

Table 15. Robustness checks: results for first differences specification.

Δ log native wages	All	High skill	Int. skill	Low skill
Δ Fractionalisation Index	0.331**	0.317	0.305	-0.143
	(0.149)	(0.232)	(0.217)	(0.279)
Controls	Y	Y	Y	Y
Observations	158	158	158	158
F-statistic	8.017	1.585	1.312	1.673
R^2	0.300	0.100	0.061	0.102

Δ log native employment	All	High skill	Int. skill	Low skill
Δ Fractionalisation Index	-0.209**	-0.081	-0.261**	-0.509**
	(0.104)	(0.098)	(0.109)	(0.220)
Controls	Y	Y	Y	Y
Observations	158	158	158	158
F-statistic	6.883	2.986	5.315	3.296
R^2	0.372	0.196	0.267	0.164

Source: ONS / LFS.
Notes: Controls fitted = % working-age population 24 and under, % female, % with degrees, % with manufacturing jobs, % of unemployed who are long term workless, log (population density).
Heteroskedasticity and autocorrelation-robust standard errors in parentheses.
* = significant at 10%, ** 5%, *** 1%.

Table 16. Results for native outflow tests, based on Card (2005).

% all low skilled workers	**(1)**	**(2)**	**(3)**
% low skilled migrants	0.255*** (0.051)	0.050 (0.052)	-0.004 (0.043)
Area fixed effects, year dummies	N	Y	Y
Controls	N	N	Y
Observations	158	158	158
F-statistic	25.1296	503.0060	216.323
R^2	0.1194	0.9249	0.954

% all workers in entry-level occs	**(1)**	**(2)**	**(3)**
% migrants in entry-level occupations	0.252*** (0.040)	0.190*** (0.034)	0.115*** (0.029)
Area fixed effects, year dummies	N	Y	Y
Controls	N	N	Y
Observations	158	158	158
F-statistic	39.606	34.006	24.343
R^2	0.239	0.501	0.699

Source: ONS/LFS.
Notes: heteroskedasticity and autocorrelation-robust standard errors in parentheses. Controls fitted in (3) are % 24 and under, % female, % manufacturing employment, ln(population density), share of unemployed who are long term jobless.
* = significant at 10%, ** = 5%, *** = 1%.

Table 17. Alternative test for native outflows: simple internal migration model, 1994-2006. Dependent variable = ln(% UK-born population).

ln(% UK-born)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
ln(% migrants)	-0.0807***	-0.0771***	-0.0749***	-0.0833***	-0.0805***	-0.0767***
	(0.011)	(0.009)	(0.008)	(0.012)	(0.011)	(0.008)
ln(house prices)	-0.0043	-0.0218	-0.0220**	0.0039	-0.0103	-0.0193*
	(0.008)	(0.015)	(0.010)	(0.006)	(0.010)	(0.011)
ln(wages)	-0.0568**	-0.0766**	-0.0099			
	(0.026)	(0.034)	(0.025)			
ln(employment rate)	0.2280**	0.2896**	0.2201***			
	(0.096)	(0.119)	(0.044)			
% unemployed who are long term jobless	-0.0174 (0.013)	-0.0065 (0.009)	-0.0065 (0.006)			
ln(native wages)				-0.0711**	-0.0881**	-0.0239
				(0.035)	(0.042)	(0.029)
ln(native empl. rate)				0.2272**	0.2721**	0.2181***
				(0.098)	(0.116)	(0.044)
% native unemployed long term jobless				-0.0160 (0.013)	-0.0083 (0.010)	-0.0054 (0.005)
Constant	-0.0839	0.2211	0.0528	-0.1554**	0.0908	0.0478
	(0.094)	(0.241)	(0.120)	(0.065)	(0.193)	(0.121)
Year dummies		Y	Y		Y	Y
Area fixed effects			Y			Y
Observations	147	147	147	147	147	147
R^2	0.8197	0.8318	0.7672	0.8163	0.8251	0.7678

Source: ONS / LFS / Land Registry. Notes: heteroskedasticity and autocorrelation-robust standard errors in parentheses. * = significant at 10%, ** = 5%, *** = 1%.

Table 18. Results for IV regressions: first stage.

Fractionalisation Index, country of birth groups	(1)	(2)
Predicted Frac Index, country of birth groups	-3.637***	-5.570***
	(0.785)	(0.888)
Controls	Y	Y
Observations	158	146
F-statistic	73.258	29.765
R2	0.879	0.800
Partial R^2 for instrument	0.281	0.330
Excluded instruments test F-statistic	21.49	39.39
P-value for excluded instruments test	0.000	0.000
Kleibergen-Paap under-identification test	13.975	10.068
P-value for under-identification test	0.0002	0.0015
Kleibergen-Paap weak identification test	21.489	39.93
Stock-Yogo 10% critical value, weak ID test	*16.38*	*16.38*

Source: ONS/LFS.
Notes: heteroskedasticity and autocorrelation-robust standard errors in parentheses. Column (1) fits productivity/wage and employment models, column (2) fits house price models. Controls fitted are % 24 and under, % female, % manufacturing employment, ln(population density), share of unemployed who are long term jobless. * = significant at 10%, ** = 5%, *** = 1%.

Table 19. Results for IV regressions: second stage.

Dependent variable	Wages		Employment		Prices	
	(1)	(2)	(1)	(2)	(1)	(2)
Fractionalisation Index	0.129	0.215	-0.692***	-0.779***	-1.045	-0.231
	(0.308)	(0.369)	(0.173)	(0.206)	(0.803)	(0.755)
Area fixed effects	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	158	156	158	156	146	144
F-statistic	1311.988	1306.960	21.442	20.025	1208.685	1180.526
R^2	0.989	0.989	0.648	0.621	0.987	0.988

Source: ONS / LFS.
Notes: All specifications include time dummies and controls (% 24 or under, % female, % manufacturing employment, ln(population density), share of unemployed who are long term jobless). Column (2) fits the sample without London. Heteroskedasticity and autocorrelation-robust standard errors in parentheses. * = significant at 10%, ** = 5%, *** = 1%.

Table 20. Results for IV regressions: skill and occupational group analysis.

Log native wages	High skill	Intermediate	Low skill
Fractionalisation Index	0.653* (0.372)	0.142 (0.332)	-1.480 (0.970)
Area fixed effects	Y	Y	Y
Controls	Y	Y	Y
Observations	158	158	158
F-statistic	442.151	557.171	317.728
R^2	0.970	0.976	0.965

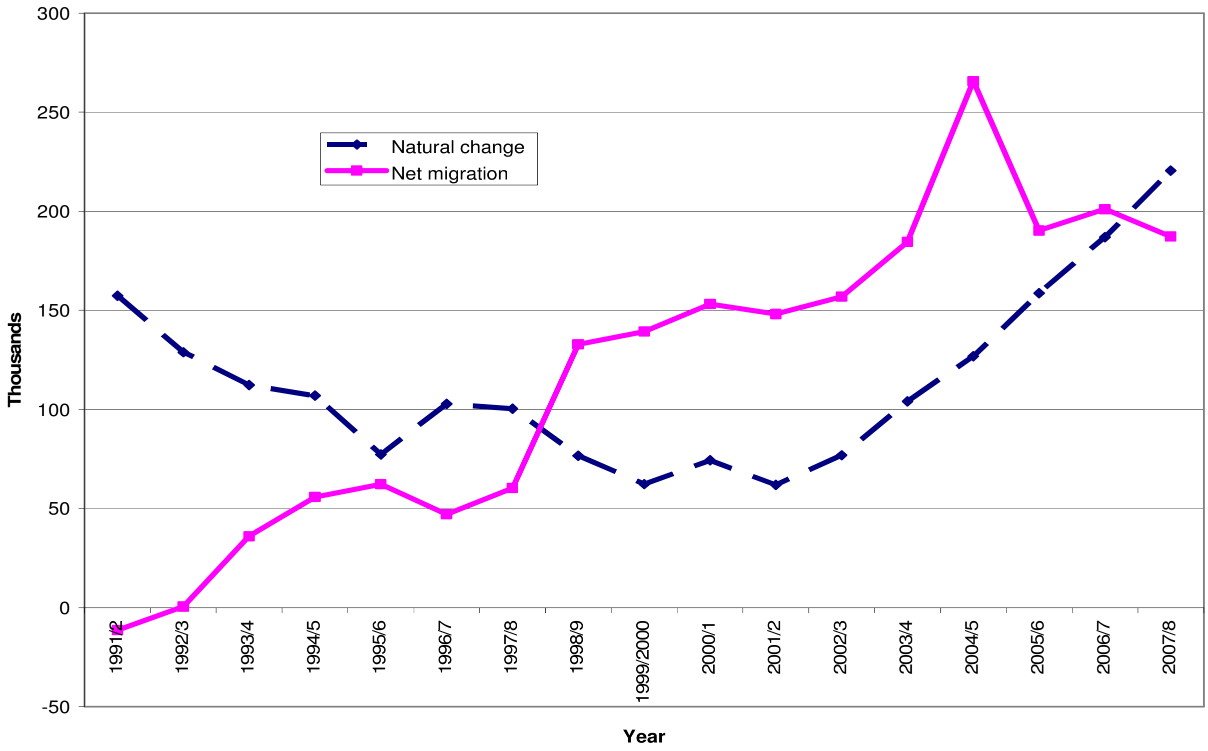
Log native wages	High end occs	Intermediate occs	Entry level occs
Fractionalisation Index	0.047 (0.324)	0.508 (0.374)	-1.196* (0.628)
Area fixed effects	Y	Y	Y
Controls	Y	Y	Y
Observations	158	158	158
F-statistic	730.597	458.759	201.853
R^2	0.981	0.974	0.942

Log native employment	High skill	Intermediate skill	Low skill
Fractionalisation Index	-0.241* (0.143)	-0.926*** (0.205)	-0.772*** (0.296)
Area fixed effects	Y	Y	Y
Controls	Y	Y	Y
Observations	158	158	158
F-statistic	11.002	6.469	10.641
R^2	0.457	0.167	0.445

Source: ONS / LFS.
Notes: All specifications include time dummies and controls (% 24 or under, % female, % manufacturing employment, ln(population density), share of unemployed who are long term jobless). Heteroskedasticity and autocorrelation-robust standard errors in parentheses. * = significant at 10%, ** = 5%, *** = 1%.

FIGURES

Graph 1. Drivers of population growth in the UK, mid-1991-mid-2008.



Source: ONS / Total International Migration data.

Ethnic Inventors, Diversity and Innovation in the UK: Evidence from Patents Microdata

1. Introduction

The previous two chapters looked at links between immigration, diversity and urban economic performance. This chapter shifts the emphasis to look at *how* minority communities and cultural diversity might affect economic outcomes. I focus on innovation for two reasons. First, innovation is a major driver of productivity, and the previous chapter found links between diversity and productivity, especially for higher skilled workers. Second, in recent years there has been growing academic, policy and public interest in the role of 'ethnic inventors' in innovative activity, both in the UK and elsewhere (Legrain, 2006, Leadbeater, 2008, Kerr and Kerr, 2011).

These discussions and debates have largely drawn on recent experience in the United States. Since the 1980s minority communities, particularly those of South / East Asian origin, have played increasingly important roles in ideas generation in the science and technology sectors (Stephan and Levin, 2001, Chellaraj et al., 2005). US ethnic inventors – who are often migrants – are spatially concentrated at city-region level (Kerr, 2008a). High-tech US clusters like Silicon Valley have benefited from 'ethnic entrepreneurs' who both help connect South Bay firms to global markets, and are responsible for 52% of the Bay Area's startups (Saxenian, 2006, Wadhwa et al., 2007, Foley and Kerr, 2011). There are positive links between the presence of migrants and US regional patenting (Peri, 2007, Hunt and Gauthier-Loiselle, 2008). Diasporic communities appear to play important roles in the diffusion of knowledge both across US cities, and between US regions and 'home' countries (Kerr, 2008b, Kerr, 2009).

By contrast, surprisingly little is known about the role of 'ethnic inventors' on innovation in the UK. As documented in the past two chapters, over the past two decades Britain has become substantially more ethnically diverse. The number of people from non-white ethnic groups grew by 53% between 1991 and 2001. For England and Wales between 2001 and 2009, non-'White British' groups have grown from 6.6m to 9.1m and now stands at one in six of the population (Office of National Statistics, 2011). Immigration has been a main driver, with a number of 'new migrant communities' forming since the early 1990s (Kyambi, 2005). This paper asks: has UK innovation benefited from these population shifts as it has in the US?

Changing demography could affect innovation in at least four complementary ways. First, migrants or individuals from minority communities may be positively selected on the basis of skills or entrepreneurial behaviour, although this needs to be distinguished from other human capital endowments (Borjas, 1987). Second, by lowering transaction costs, co-ethnic groups can accelerate within-group ideas generation and transmission, although discrimination may constrain knowledge spillovers (Agrawal et al., 2008, Docquier and Rapoport, 2011). Third, cultural diversity may improve ideas generation across all groups, if the benefits of a larger set of ideas, perspectives outweigh trust or communication difficulties between those groups (Alesina and La Ferrara, 2004, Page, 2007, Berliant and Fujita, 2009). Finally, these channels may be more pronounced in urban areas because of the spatial clustering of minority communities, agglomeration economies, or both. In addition, cosmopolitan urban populations may raise demand for new goods and services, especially in non-tradable sectors (Gordon et al., 2007, Mazzolari and Neumark, 2009).

This paper looks at the role of ethnic inventors in innovation in the UK, using a new 12-year panel of patents microdata. Kerr (2008a) and Agrawal et al (2008) have pioneered names analysis as a way of identifying ethnic inventors from patent data. I build on these studies, using the novel ONOMAP name classification system to explore all four 'population-innovation' channels. I estimate a knowledge production function linking inventors' patenting activity to individual, group and area-level characteristics. Using techniques popularised by Blundell et al (1995), I exploit historic patent information to control for individuals' human capital and other otherwise unobserved characteristics.

Once human capital is controlled for, I find that simply being an ethnic inventor has no significant effect on an individual's patenting rates. Conversely I find that members of specific co-ethnic groups – Indian, South Asian and Southern European inventors – do tend to patent more, even when other factors are controlled for. I also find small positive effects of inventor group diversity on individual patenting activity.

Effects on majority inventors are less clear: increasing ethnic diversity has some negative links to individual majority inventors' patenting activity, but I find no crowding out at area level. Urban location and density have small effects on individual patenting after other individual and area-level factors are included. The results survive extensive robustness checks, although alternative measures of area-level human capital weaken diversity effects. Overall, the UK's 'ethnic inventor' communities and their effects are substantially different from those in the US: this has implications for current immigration and skills policy.

The paper adds to a small but growing empirical literature on immigration, ethnicity and innovation. It also contributes to the emerging field of inventor microdata analysis (OECD, 2009). It is one of very few studies exploring multiple ethnicity-innovation channels, at individual, group and area level. As far as I am aware, this is the first research of its kind in Europe.

The paper is structured as follows. Section 2 set out research questions and key terms. Section 3 reviews relevant theoretical frameworks and empirics. Sections 4 and 5 introduce the main data sources and provide descriptive statistics. Section 6 outlines the model and estimation strategy. Sections 7 – 9 give results, extensions and robustness checks. Section 10 concludes.

2. Research questions

My research questions are:

- Do ethnic inventors or co-ethnic groups influence patenting rates in the UK?
- Does the cultural diversity of inventor groups influence patenting rates?
- Do urban environments affect ethnicity- or diversity-innovation effects?

'Innovation', 'ethnicity' and 'diversity' are fuzzy concepts that need to be carefully defined. The innovation process is commonly divided into three phases: invention, adoption and diffusion (Fagerberg, 2005): a standard UK definition of innovation is thus 'the successful exploitation of new ideas' (Department of Innovation Universities and Skills, 2008). My chosen measure of innovation, patenting, is primarily an indicator of invention (OECD, 2009). Specifically, I look at shifts in individual patenting rates, or 'inventor productivity'.

Patent data has several advantages: it has a positive relationship with other indicators of overall innovation 'performance' such as productivity and market share; it provides detailed information on geography and patent owners, both inventors and applicant firms; and is available for long time periods at relatively low cost. Not all inventions are patented, however, and patents have variable coverage across industries (with a well-known bias towards manufacturing) (OECD, 2009). Patenting also responds to policy shocks – for example, US Supreme Court decisions in the 1980s and 1990s (particularly *Re Alappat* in 1994) led to spikes in software and information technology patenting activity (Li and Pai, 2010).

I am able to deal with most of these challenges through careful identification strategies (see section 4). Unlike the majority of patent data studies, I am able to work at individual inventor level – using the KITES-PATSTAT patents dataset developed at Bocconi University (more of which below).

'Ethnicity' is as hard to pin down. Ethnic identity is a multifaceted concept with objective, subjective and dynamic elements (Aspinall, 2009). Quantitative measures of identity tend to be partial: they focus on identity's visible, objective components, assuming away self-ascription and endogeneity issues (Ottaviano et al., 2007). Given these limitations, quantitative researchers working with ethnic identity will always need to use a 'least-worst' proxy. I deploy two such measures, using the ONOMAP system to analyse inventor name information and read off likely ethnicity characteristics (see Section 4 for details). The first proxy is the ethnic group classifications prepared by the UK Office of National Statistics (ONS). The ONS measures attempt to combine different aspects of ethnic identity, but operate at a high level of generality and tend to focus on 'visible minorities' such as Black and Asian communities (Mateos et al., 2007).

I use 'geographical origin' as a second proxy measure. Geographical origin can offer very fine-grained information, but is one-dimensional as a measure of identity. In this case, because name data conflates migrants and their descendents, origin effectively operates as a measure of geographical 'roots'.[27] As such, it offers an alternative way of identifying likely ethnicity and co-ethnic group membership.

To measure the diversity of these ethnic groups, I use a Fractionalisation Index as commonly used in the development literature. See Section 4 for details.

3. Theoretical frameworks and evidence

As noted in the introductory chapter, conventional theories of innovation have relatively little to say to about ethnicity or the composition of inventor communities. Schumpeter (1962) focuses on the 'entrepreneurial function' inside and outside firms, and the role of individuals in identifying and commercialising new ideas, in the face of social inertia or resistance. National 'innovation systems' approaches explore relationships between firms and public institutions such as government agencies and universities (Freeman, 1987). More recently, spatial approaches focus on clustering of innovative activity due to agglomeration-related externalities, particularly local knowledge spillovers (Jaffe et al., 1993, Audretsch and Feldman, 1996).

[27] Although not national identity: the vast majority of those born in the UK think of themselves as British (Manning and Roy 2007). More broadly, ethnicity, nationality, sexuality and class are all elements in a broader sense of self (Fanshawe and Sriskandarajah 2010).

Endogenous growth theories provide the basis for a number of newer studies linking demography to innovation. Endogenous growth models suggest that shifts in the technology frontier help determine economic development. They also highlight the importance of human capital stocks and knowledge spillovers to levels of innovation (Romer, 1990). In practice, access to knowledge is likely to be uneven across locations, sectors and social groups (Agrawal et al., 2008).

Recent work suggests four ways in which demographic factors could positively influence ideas generation and transmission. Building on the material in the introduction, theoretical frameworks and empirics are discussed for each in turn.

3.1 Individual selection

Migrants are mobile carriers of ideas – so high-skilled migrants, in particular, may positively contribute to overall innovation rates (Kerr and Lincoln, 2010). More broadly, from an economic perspective, migration decisions reflect expected returns: potential migrants balance out economic gains from migration and costs of moving abroad (Borjas, 1987). The income maximisation approach implies that migrants are 'pre-selected' – and are more likely to be entrepreneurial, seeking out new ideas (Wadhwa et al., 2007).

Both these factors suggest migrant status may positively predict patenting rates, over and above other human capital attributes. Discrimination has ambiguous effects. It may lead to 'lock-out' from conventional labour market opportunities (Gordon, 2001). Conversely, it may operate as a spur to innovation if excluded minorities are forced to develop new economic opportunities (Rath and Kloosterman, 2000). The challenge is to distinguish ethnicity from wider human capital endowments and relevant industry / area characteristics.

US experience suggests some positive selection effects in science and high-tech sectors of the economy, particularly for migrant workers. US employers in these sectors report heavy dependence on skilled migrants (Wadhwa et al., 2007, Kerr and Lincoln, 2010). Indo- and Chinese-American communities make disproportionate contributions to US science and engineering, in terms of workforce membership as well as Nobel Prize counts, elections to scientific academies and patent citations (Stephan and Levin, 2001).

Anderson and Platzer (2007) report that immigrants have founded 40% of venture capital-backed technology companies currently trading in the US, including Google, eBay, Yahoo and Sun Microsystems. Wadhwa et al (2007) find the national immigrant contribution to patenting rose from 7.3% in 1998 to 24.6% in 2006. Using time series data, Chellaraj et al (2005) report that foreign graduate students and skilled immigrants have a significant positive impact on patent applications and grants. However, in a recent US study on immigrant patenting, Hunt and Gauthier-Loiselle (2008) suggest that once education and industry characteristics are controlled for, effects of individual migrant status disappear.

There is much less evidence from the UK. In the next chapter, I report some evidence that migrant entrepreneurs in London are more likely to innovate than average company founders. Basu (2002, 2004) suggests considerable variation in levels of entrepreneurship across minority communities, with class, education and family status important mediating influences.

3.2 Social networks and diaspora effects

A second set of theories suggests that cultural 'sameness' or 'proximity' helps knowledge spillovers (Agrawal et al., 2008). Co-ethnic social networks – such as diasporas or transnational communities – provide network externalities that accelerate ideas transmission (Docquier and Rapoport, 2011).

Social networks offer their members higher social capital and levels of trust, lowering transaction costs and risk. In turn, networks seem to positively affect innovative activity (Rodríguez-Pose and Storper, 2006, Kaiser et al., 2011). Co-ethnic networks such as diasporas may be an important channel for knowledge spillovers and ideas flow – improving awareness of new technologies and passing on tacit knowledge, both within and across countries (Kerr, 2008b, Kerr, 2009).

Of course, other social networks – such as family or kinship networks, or professional associations – might be equally or more important. And co-ethnic effects on individual patenting are ambiguous. Matching and learning economies may be present within the group ('enclave' activity) and between different groups ('middleman minority' activities) (Bonacich, 1973). But externalities will be constrained by group size, majority attitudes and links between groups. First, within a minority group, individual members are less likely to match ideas than those in the majority group since there will be a smaller set of possible matches. Second, if members of majority group(s) discriminate against minority groups, or if minority groups lack social connections to majority actors, this will limit matches across groups and 'middleman minority' activity (Zenou, 2011).

In a closed economy, effects of co-ethnic groups are determined by group size and the level of interaction between groups. Under globalisation, co-ethnic communities may be more influential. Increasing numbers of businesses in high-cost countries are looking to relocate research and development (R&D) activity into lower-cost countries (Mowery, 2001, Archibugi and Iammarino, 2002, Cantwell, 2005, Yeung, 2009). Diasporic communities with members present in high-cost 'host' countries may help firms move into lower-cost 'home' countries, identifying collaborators or accelerating joint ventures (Kapur and McHale, 2005, Saxenian and Sabel, 2008). This raises both the size of the innovating co-ethnic community and the rate of information flow between its members, in both 'home' and 'host' locations.

A number of case studies suggest that diasporas are important influences on knowledge flows (Bresnahan and Gambardella, 2004, Saxenian, 2006, Docquier and Rapoport, 2011). In a 2002 survey, Saxenian finds that 82% of Chinese and Indian immigrant scientists and engineers exchange technological information with colleagues in 'home' countries. Jaffe and Tratjenberg (1999) find that countries with a common language have larger R&D spillovers and international patent citation rates. Kerr (2008b) , studying co-ethnic inventors, finds that own-ethnicity citations are 50% higher than citations to other ethnicities, controlling for industry: co-ethnic communities in 'host' countries positively influence industrial performance in 'home' countries. Patenting growth in US cities is also faster for technologies that depend heavily on communities of immigrant inventors (Kerr, 2009). By contrast, Agrawal et al (2008, 2011) compare co-ethnic and co-location effects on patent citations, finding that physical location is up to four times more important.

US ethnic inventor communities are relatively recent phenomena largely shaped by migration flows since the 1960s (Saxenian, 2006). The UK's immigration story is very different: migrant and minority communities are the result of both colonial history (Australasia, some African and South-East Asian groups) and geographical proximity (many European countries). British-based diasporas may not, therefore, share the characteristics of US-style transnational communities.

The existing UK evidence base is mixed. I am unaware of any European studies that explicitly link co-ethnicity to patenting. Fairlie et al (2009) find some support for co-ethnicity effects on British-Indian business performance, although innovation is not considered. Qualitative work by Nakhaie et al (2009) confirms that co-ethnicity effects both vary significantly across groups, and are shaped by wider socio-economic contexts.

3.3 Diversity effects

'Cultural distance' between economic agents may also influence innovation rates. Specifically, individual inventors in a group may benefit from group-level diversity if this brings a richer mix of ideas and perspectives. Berliant and Fujita (2009) model a system of firm-level knowledge creation, showing that worker heterogeneity can accelerate ideas generation through individual-level production complementarities. Hong and Page (2001, 2004) similarly model scenarios in which 'cognitively diverse' teams exploit a larger pool of ideas and skills, suggesting that cultural mix is a good proxy for cognitive diversity.

On the other hand, group-level cultural diversity may have a negative effect if it leads to lower trust and poor communication between individuals – for example, because of language barriers, misunderstandings, discriminatory attitudes or both. Spillovers (and co-operation) will be limited, leading to fewer, lower-quality solutions (Alesina and La Ferrara, 2004). Fujita and Weber (2003) argue that positive diversity effects will be most likely observed in research-based or 'knowledge-intensive' activities – such as those leading to patenting. Parrotta et al (2011) suggest that while diversity of knowledge is likely to be positive for innovation, especially in research-intensive tasks, cultural diversity's effects are much harder to predict.

The overall empirical evidence here is positive, though not uniformly so. At organisation level, several recent studies link workforce diversity and innovation in knowledge-intensive environments. Parrotta et al (2011) find positive effects of workforce cognitive and cultural diversity on Danish firms' patenting rates. My study of London firms in the next chapter finds that both management and workforce diversity help raise product and process innovation.

However Ozgen et al (2011) find weaker links between cultural diversity and product/process innovation in 'white collar' Dutch firms. Maré et al (2011) find no systematic links between workforce characteristics and innovation among businesses in New Zealand.

More broadly, reviews of organisational and management literature find a small but significant workplace 'diversity advantage' on measures of business performance. Negative communication and trust effects are present in the short term but progressively decline (Landry and Wood, 2008).

3.4 Urban effects

We might observe bigger co-ethnicity and diversity effects on innovative activity in cities because of population mix, agglomeration economies or both. Innovative activity, migrant and minority communities tend to be spatially clustered in urban areas. Kerr (2008a) finds that US ethnic inventors are spatially concentrated, largely in the biggest urban agglomerations.

Urban areas may also have positive or negative 'amplifying' effects. For example, if cultural diversity contributes to economic diversity, it may help foster knowledge spillovers across sectors at urban level (Jacobs, 1969). Jacobs also argues that cities accelerate innovation by fostering the recycling and recombination of existing products and ideas into new forms. The more cosmopolitan the urban population, the greater the potential for hybridisation (Hall, 1998, Gordon et al., 2007). Conversely, members of minority communities may be physically isolated in particular urban neighbourhoods. Spatial segregation may limit the opportunity for knowledge spillovers and interaction with other groups (Zenou, 2011).

A number of US and European studies suggest a link between area level diversity and innovative activity, although none look at the UK case. Peri (2007) finds that US states' share of foreign-born PhDs is positively associated with levels of patenting. Hunt and Gauthier-Loiselle (2008) find that immigrant population shares raise state-level patenting, and that these effects are greater than individual-level effects – suggesting urban, group and individual-level dynamics are all in play. Kerr and Lincoln (2010) use shifts in US visa quotas to identify effects of immigrant scientists on patenting in US cities, suggesting positive effects of skilled migrants on both 'ethnic' and overall innovative activity at urban level.

Ozgen et al (2010), studying EU NUTS2 regions, find positive connections between migration, immigrant diversity and regional patenting. Niebuhr (2006) finds a positive link between the diversity of German regions and regional innovation, especially for highly skilled employees.

4. Data and identification strategy

I have three main data sources for the analysis. Patents information comes from the European Patent Office (EPO), which is made available through the OECD PATSTAT database.[28] Raw patent data cannot typically be used at inventor level, because of common/misspelled names, or changes of address: I use a cleaned form of the data provided by the KITES team at Bocconi University, which allows robust identification of individual UK-resident inventors (Lissoni et al., 2006).[29] Ethnicity information is then derived from inventor names using the ONOMAP name classification system (see below and Appendix B). Finally, I combine this individual-level information with area-level controls, assembled from UK Labour Force Survey held in the Office of National Statistics Virtual Microdata Lab. My data assembly strategy builds on pioneering US studies of inventor activity by Kerr (2008a, 2008b, 2009, 2010), but makes important adaptations to the UK case. This is because of a number of methodological challenges linked to both the patents and diversity data, which are dealt with briefly below.

4.1 Working with patents data

The raw patents data covers the period 1977-2010, dated by priority year.[30] The dataset contains geocoded information on 141,267 unique British-resident inventors and 131,738 patents with at least one British-resident inventor.[31] During this time the UK experienced generally low levels of immigration (from the late 1970s to the mid-90s), followed by an upshift from the late 1990s onwards (Wadsworth, 2010).

I make a number of changes to the patents data to make it fit for purpose. First, there is typically a lag between applying for a patent and its being granted. This means that in a panel of patents, missing values typically appear in final periods. Following Hall et al (2001), I truncate the dataset by three years to end in 2004.

Second, innovation and invention are processes, not events. Inventors typically work on an invention for some time before filing a patent. This means that year-on-year variations in patenting will not be driven simply by year-on-year variation in the things that drive innovation. In principle, the simplest way of dealing with this issue is to lag independent and control variables. However, it is not obvious *a priori* which length of lag should be fitted and there is also the problem that current drivers may still *partly* explain current patenting levels, even if other factors act with a lag.

[28] In full: EPO Worldwide Patent Statistical Database.
[29] Microdata from the PATSTAT-KITES database (http://db.kites.unibocconi.it/). For details of the algorithmic cleaning of the raw data, see Lissoni et al (2006).
[30] 'Priority dates' represent the first date the patent application was filed anywhere in the world. The OECD recommends using priority years as the closest to the actual time of invention (OECD 2009).
[31] The full dataset has 160,929 unique UK-resident inventors: 19,492 observations lack postcode information. In total 201,016 inventors are attached to these patents, indicating significant co-patenting.

I therefore follow the alternative approach of Menon (2009) and group patent observations together, using mean citation lags to specify the appropriate interval. If patent B cites patent A, the 'citation lag' between the two is the time period between the filing of A and the filing of B: the lag offers a rough way to capture the relevant external conditions affecting patenting. The mean citation lag for EPO patents is four years (Harhoff et al 2006, in OECD, 2009), so I group patents into four-year periods or 'yeargroups'. I organise independent variables and controls along the same lines (except for areas' historic patent stocks, where lags are straightforward to apply).

Third, the main analysis uses unweighted patent counts to measure 'inventor productivity', that is, the number of times an inventor engages in patenting activity in a given time period. Some of the extensions and robustness checks are done at area level. In this case I use weighted patent counts to avoid double-counting innovative activity: raw counts are divided by the number of inventors involved (OECD, 2009). For clarity, henceforth all patent counts are unweighted unless stated otherwise.

Finally, I use a combination of technology field dummies and area-level industrial structure controls to control for structural biases in patenting activity across different industrial sectors. These are described further in section 6.

4.2 Identifying ethnic inventors

Kerr (2008a) and Agrawal et al (2008) both use name-based analysis to identify ethnic inventors from individual patent records. Agrawal and colleagues manually code Indian-ethnicity inventors; Kerr uses the MELISSA commercial names database. I build on these approaches by using the ONOMAP name classification system to generate ethnicity information for individual inventors.

ONOMAP was originally designed for mining patient data for the UK National Health Service, and classifies individuals according to most likely cultural, ethnic and linguistic (CEL) characteristics identified from forenames, surnames and forename-surname combinations.

ONOMAP is built from a very large names database drawn from UK Electoral Registers plus a number of other contemporary and historical sources, covering 500,000 forenames and a million surnames across 28 countries. These are then algorithmically grouped together, combining information on geographical area, religion, language and language family. Separate classifications of surnames, forenames and surname-forename combinations are produced (see Appendix B).

ONOMAP has the advantage of providing objective information at several levels of detail and across several dimensions of identity. It is also able to deal with Anglicisation of names, and names with multiple origins, giving it additional granularity and validity. Like Kerr's similar work on US patents data (Kerr, 2008a), ONOMAP is unable to observe immigrants, and only observing objective characteristics of identity – the most conservative interpretation is that it provides information on *most likely* ethnicity. However, unlike the MELISSA commercial database used by Kerr, which only identifies high-level ethnicities, ONOMAP allows me to examine inventor characteristics from several angles and at several levels of detail. ONOMAP also matches 99% of inventor names (compared with Kerr's 92-98% success rates).

For the descriptive analysis I exploit the full range of CEL information, as well as ONS ethnic groups and geographical origin. For the regressions, I use ONS ethnic groups and geographical origin only. This is because CEL-coded information is not available for area-level controls, which would leave me unable to explore the influence of area-level demographic characteristics on inventor characteristics.

ONS ethnic group information is based on the nine categories developed for the 1991 Census. These are relatively dated and lose some important detail – for example, the second largest inventor group after 'white' is 'other' – so are likely to be subject to some measurement error.[32] Geographical origin information provides finer-grained information on twelve zones across Europe, Africa, Asia and the Americas.[33] Because name information does not distinguish migrants from their descendants, I use likely geographical origin as a measure of geographical 'roots' – an important, albeit partial, aspect of ethnicity. I use this as my preferred measure of ethnicity, as geographical origin is objective and provides a greater level of detail.

Combining geography and name information in this way is not problem-free. ONOMAP does not distinguish geography if countries share a common language, so that North American and Australasian-origin inventors are largely identified as British-origin inventors (or unclassified). This may understate the true extent of inventor diversity. In practice, resulting measurement error is likely to be small. First, these groups' spatial

[32] The full set of ONS 1991 groups is White, Black Caribbean, Black African, Indian, Pakistani, Bangladeshi, Chinese and Other.
[33] The full set of twelve geographical origin zones is Africa, Americas, British Isles, Central Asia, Central Europe, East Asia, Eastern Europe, Middle East, Northern Europe, South Asia, Southern Europe and Rest of the World.

distribution is not very different from minority communities as a whole. Second, they represent a relatively small share of the UK's minority population (see Appendix B).

To measure diversity of ethnic groups, I use a Fractionalisation Index. For a set of identity groups *g* in area *a* in year *t*, the Index is given by:

$$FRAC_{at} = 1 - \sum_g [SHARE_{gat}]^2 \qquad (1)$$

Where *g* is one of *n* groups, and SHARE is *g*'s share of the relevant population (here, all active inventors in a given area). The Index measures the probability that two individuals in an area come from different geographical origin or ethnic groups. Similar measures are used widely in the development literature, as well as some city and state-level studies (Easterley and Levine, 1997, Alesina and La Ferrara, 2004, Ottaviano and Peri, 2005a, Ottaviano and Peri, 2006).

5. Data assembly and descriptive analysis

I assemble a panel of UK-resident inventors' patenting activity between 1993 and 2004 inclusive, dividing the time period into three four-year 'yeargroups' as explained in the previous section. Each inventor-yeargroup cell records how many times an inventor patents in that time period. After cleaning, the basic panel covers 125,502 inventors across three four-year yeargroups, giving 376,506 observations. Cell counts vary from zero to 36, with a mean of 0.318.[34]

I use postcode information to locate inventors in UK Travel to Work Areas (TTWAs), which are good approximations of local economies (and superior to administrative units such as local authority districts).[35] Matching is done by postcode sector, which minimises the number of observations lost through incomplete or mistyped postcode information.[36] I then fit an urban / rural typology of TTWAs developed in Gibbons et al (2011), allowing me to explore the potential effects of urban environments (see Appendix C for details and maps).

[34] Just over 39% of inventors invent pre-1993, but do not invent during 1993-2004.
[35] TTWAs are designed to cover largely self-contained labour markets: 75% of those living in a given TTWA also work in the TTWA, and vice versa. TTWAs are thus a good approximation for local spatial economies and for city regions (Robson et al 2006).
[36] Matching on full postcodes drops around 12% of observations. Matching on postcode sector drops 5.77% of observations. I exclude information on inventors resident in Northern Ireland. A small number of postcode sectors cross TTWA boundaries, so matching is not perfect.

Working with inventors (rather than patents or applicants) presents three linked areas where measurement error may arise. The first issue is robustly identifying individuals. I minimise this risk by using appropriately cleaned data. The second issue is about inventor activity. Inventors are only visible when patenting, and we do not know for certain what they are doing the rest of the time. The most conservative solution is to blank all cells where the inventor is not active. However, as most inventors – in the UK and elsewhere – patent only once, this would radically reduce sample size (and would miss instances where inventors were constrained from patenting for some reason). For the main analysis I thus zero all cells when no inventor activity is recorded. Using a sub-sample of inventors, I run robustness checks comparing both 'zeroed' and 'blanked' approaches. I find sample construction has no effect on the results (see Section 8).

The third issue is about inventor location. We cannot be sure where inventors are when they are not actively patenting; and we need to identify those inventors who have moved location. I explore this issue by identifying likely movers. Following Agrawal et al (2006), I define movers as inventors with the same forename and surname, who patent in the same technology fields, in different TTWAs, at different points in time. As Agrawal and colleagues point out, this strategy minimises the risk of false positive errors – identifying inventors who are movers who are not – but does not deal with false negatives (identifying movers as non-movers). Measurement error from the latter is random, so will reduce the precision of, but not bias, my main results. The conservative estimates that result, suggest around 14% of the sample are likely movers. This suggests firstly that the vast majority of inventors do not move during the sample period; and therefore it is reasonable to count non-movers as present in the same TTWA in which they first patent.

5.1 Descriptive statistics

Some basic descriptives are set out in Tables 1-8, along with some wider population data from the Labour Force Survey.

Table 1 breaks down inventors by CEL subgroup, showing the 30 largest groups. Because CEL classifications are not available in the LFS, I do not present comparison data for the wider population here (although see my first paper for some simple area-level analysis). We can see that while English, Welsh, Scottish and Celtic[37] inventors make up the bulk of the sample, other inventor groups divide fairly evenly into geographically proximate communities (e.g. Irish, plus a series of European groups), groups reflecting the

[37] 'Celtic' denotes names common to Scottish, Welsh and Irish CEL types.

UK's colonial history in South and East Asia (e.g. Indian Hindi, Sikh, Pakistani, Hong Kong Chinese) plus some largely recent migrant communities (e.g. Polish, Vietnamese).

Tables 2 and 3 recut the sample by probable geographical origin zones and by 1991 ONS ethnic groups. Geographical origin zones (Table 2) allow me to preserve some of the detail from the full CEL classification, including several areas of Europe as well as South and East Asia. As highlighted in the previous section, ONS ethnic groups (Table 3) are much less flexible, focusing on visible majorities and minorities, relegating the rest of the inventors to 'other'.

Tables 4 – 6 cut the sample geographically. Table 4 presents the 40 Travel to Work Areas (TTWAs) with the largest shares of ethnic inventors by geographical origin, and for comparison provides migrant shares in the wider TTWA working-age population. High-ranking TTWAs are predominantly urban, although a number of rural areas also feature, predominantly university towns (St Andrews, Lancaster, Canterbury) or areas adjoining TTWAs with universities (Bude and Holsworthy) and/or manufacturing clusters (Holyhead, Pembroke and Tenby, Louth and Horncastle).[38] Comparing ethnic inventors with migrants in the overall population, we can see that areas in the top half of the table mostly have bigger shares of ethnic inventors than in the wider working-age population – London is one notable example. Table 5 presents the same data as location quotients, confirming that ethnic inventors are more spatially clustered than the wider migrant population.

Table 6 compares Fractionalisation Index scores for active inventors and wider working age populations. The cultural diversity of inventors is greater than that of the wider population in most TTWAs (London, Bradford, Birmingham, Brighton, Leicester and Reading are the six exceptions in the top 40). Again, there are a number of rural areas in the table. As some rural areas have fairly few inventors, a small sample may lead to high values of the Fractionalisation Index.

Finally, Table 7 gives weighted counts for the 40 TTWAs with the highest patenting activity: to minimise double counting, I weight each patent by the number of inventors involved. The results follow the familiar geography of UK innovative activity. A number of these high-patenting areas also have large ethnic inventor shares and diverse inventor groups (for example London, Southampton, Crawley, Oxford and Cambridge). However,

[38] Many inventors will work in professional / technical occupations, which are characterised by longer-than-average commuting distances. Building commuting zones on the basis of these workers' commuting patterns substantially reduces the total number of zones (Robson et al 2006), suggesting that commuting across conventional TTWAs is not uncommon.

another group of high-patenting TTWAs have rather more homogenous inventor and general populations (for example, Bristol, Manchester, Reading and Ipswich).

A number of broad lessons emerge from the descriptives. First, the UK's population of ethnic inventors appears substantially different from that of the US. American ethnic inventor communities are dominated by South and East Asian groups (Kerr, 2008a). By contrast, the UK has a number of European groups, with South Asian and East Asian inventors drawn in large part from former colonies. Second, as in the US ethnic inventors are spatially concentrated, and more clustered than minority populations in general. Third, not all high-patenting locations have large ethnic inventor shares or diverse inventor communities.

6. Regression analysis: estimation strategy

I now explore whether these inventor, group and area-level characteristics influence individual inventor productivity. The descriptives highlight the distinctive composition of UK ethnic inventors, as well as their spatial concentration. I use a knowledge production function (KPF) approach to model the links between inventors' characteristics, group and area-level factors, and individual knowledge creation. KPF models were originally developed to explore national innovation systems (Griliches, 1979) before being extended to incorporate spatial processes and specificities (Cooke et al., 1997).

In this case, the KPF is a useful way to incorporate channels operating at individual, group/community and territorial level. I am interested in whether these factors influence inventors' ideas generation activity, specifically, the rate at which new knowledge is created. For an inventor, a new item of knowledge is measured by an unweighted patent, or 'patent activity': I consider demographic factors as one of many 'inputs' and patenting as the main 'output' of interest. I therefore estimate a modified knowledge production function, linking counts of patenting activity to individual, group and area characteristics. The higher an individual's patenting activity in a given time period, the higher is her 'inventor productivity'.

I use aggregated LFS client file microdata to construct a range controls. As LFS microdata is only provided with local administrative district-level identifiers, I aggregate to

TTWA level using a postcode weighting system developed in earlier analysis.[39] Summary statistics for the 12-year panel are given in Table 8.

For inventor *i* in area *j* and yeargroup *t,* I estimate:

$$PCOUNT_{ijt} = aINV_i + bDIV_{jt} + \mathbf{CONTROLS_{jt}}\boldsymbol{c} + P_i + U_j + YG_t + e_i \quad (2)$$

Where PCOUNT is a simple count of the number of times an inventor engages in patenting during a given four-year period. My first variable of interest is INV, a dummy variable taking the value one if the inventor is a likely ethnic inventor. (I later extend the model replacing INV with a set of dummies for various co-ethnic groups.) My second key variable is DIV, the diversity of active inventors in a given TTWA and time period. DIV is given by the Fractionalisation Index in Section 4.

CONTROLS represents a vector of largely TTWA-level controls covering key spatial, economic, and demographic characteristics affecting relationships between INV and innovation, DIV and innovation or both. Unless otherwise stated, all controls are for the same 1993 – 2004 period as the patent data.

For example, innovative activity and patenting are both spatially concentrated, reflecting benefits from agglomeration that may persist over time (Simmie et al., 2008). Co-ethnicity or diversity effects on patenting might then simply reflect agglomeration and path-dependence. I fit a dummy for primary urban areas, U, and fit log of population density to explore agglomeration effects more broadly. I also fit the model with measures of 1981-84 area weighted patent stocks to control for historic asset effects, and experiment using different lags of the historic patent stocks control.

Inventor demographic characteristics may be entirely explained by area demographic characteristics: for example, places with more diverse populations may produce more diverse inventor groups. Failing to account for this leads to bias on DIV. I control for this by using area-level fractionalisation indices (and cross-check using migrant population shares).

---

[39] I aggregate individual-level data to local authority-level averages, and then aggregate these to TTWA-level using postcode shares. Local Authority District (LAD) boundaries are not congruent with TTWA boundaries, so straightforward aggregation is not possible. Using the November 2008 National Postcode Sector Database (NSPD), I calculate the number of postcodes in each 2001 TTWA and in each of its constituent LADs. For each TTWA, I then calculate constituent LADs' 'postcode shares'. Shares sum to one, and are used as weights to construct TTWA-level averages. *Example:* suppose a TTWA consists of parts of three LADs. The TTWA has 100 postcodes, 60 of which are in LAD_a, 30 in LAD_b and 10 in LAD_c. The relevant LAD weights are 0.6, 0.3 and 0.1 respectively. The TTWA-level average of variable *x* is given by $(x)TTWA = 0.6*(x)\_a + 0.3*(x)\_b + 0.1*(x)\_c$.

Human capital stocks are closely correlated with innovative activity (Romer, 1990) and as discussed in Section 3, may account for apparent ethnicity effects on patenting. Given the role of 'ethnic scientists' in the US and elsewhere, area-level human capital controls include the share of degree-holders with Science, Technology, Engineering and Mathematics (STEM) qualifications in the local working-age population. (The share of degree-holders with PhDs in any subject is used as an alternative control, as it is less precise in terms of subject.) Patent data provides very little individual-level information on human capital, but I am also able to fit P, an individual-level human capital control, explained below.

I fit various further controls for precision. Patenting is known to be higher in 'knowledge-intensive' high-tech and manufacturing sectors, so I include measures of the share of workers employed in 'knowledge-intensive' manufacturing, following The Work Foundation's definition of 'knowledge-intensive' firms (Brinkley, 2008).[40] Patenting activity is also vulnerable to sector-specific shocks, and the spike in software patenting since the mid-1990s is well-covered in the literature (Li and Pai, 2010). To account for this I fit a dummy for the IPC technology field 'electrical engineering and electronics'.[41] Patenting is likely to be lower in areas with a lot of entry-level jobs or areas of joblessness, so I include the share of workers in entry-level occupations and the share of long term unemployed as further controls.

6.1 Controlling for individual-level heterogeneity

Area-level controls for human capital may not fully account for differences between individual inventors, most obviously human capital endowments. In theory, the panel data structure should allow this to be controlled through individual fixed effects (Hausman et al., 1984). However, fixed effects panel estimators for nonlinear models require observations to have a non-zero value in at least one time period (Cameron and Trivedi, 2009). As I am as interested in whether or not inventors patent as the number of times they patent, such an approach is not ideal.[42]

[40] This follows standard OECD definitions but adjusts for the UK context. The final list of 3-digit SIC sectors includes medium and high-tech manufacturing (pharmaceuticals, aerospace, computers and office machinery, electronic communications, software, other chemicals, non-electrical machinery, motors and transport equipment).
[41] I also experiment with a more precise information technology dummy (OST30_4), with similar results.
[42] Random effects estimators are a potential alternative strategy, but Hausman tests (chi-squared = 19979.75, pr = 0.000) suggest these are not justifiable.

Blundell et al (1995) develop a now widely-used[43] alternative, exploiting historic information to control for permanent unobserved differences between agents (such as human capital). They argue that firms' capacity to innovate is largely explained by the build-up of knowledge in the firm at the point in which it enters the sample. With long enough time series data, pre-sample activity 'approximates an individual fixed effect'.

For individual inventors, historic patenting activity is likely to work in a similar way. The patent data provides information on inventor activity from 1977, 16 years before the start of the regressions panel in 1993: around 23% of inventors in the sample period also invent before 1993, covering 40% of cells. I replicate this 'entry stock' estimator, using the pre-sample mean of inventors' patent counts as a control for individual human capital endowments. Because the control is constructed as a continuous variable, it is never collinear to the ethnicity dummy, allowing me to fit both individual-level parameters together.

I exclude inventors with no pre-sampling history – they may have been inactive or not in the labour force – and run the model on a reduced sample of 89,309 observations. The new sample removes younger inventors and recent migrants. As such it may understate true inventor diversity (or indirectly affect results if younger people are more open to diverse environments). Critically, however, the restriction allows me to distinguish ethnicity, diversity and human capital effects. I experiment with the full sample to check robustness, finding key variables and overall model fit are poor.[44]

6.2 Model specification

Count data is usually modelled using Poisson or negative binomial estimators. My panel exhibits excess zeroes (78%) and over-dispersion (the variance of PCOUNT is over 2.5 times the mean). This means the basic assumptions of the Poisson model are not met, leading to likely inefficient estimates (Greene, 1994). As such, a negative binomial or zero-inflated model may be preferred. Diagnostic tests suggest the negative binomial is the better fit, and has the added benefit of running a Poisson model as a base case.[45] Against this, Angrist and Pischke (2009) argue that once raw coefficients are converted into

[43] A Google Scholar search turns up 351 citations, for example Baptista and Swann (1998), Katila and Ahuja (2002), Beaudry and Breschi (2003), Dushinitsky and Knox (2005), O'Shea et al (2005), Aghion and Howitt (2006).

[44] Fundamentally, I argue the reduced sample preferable to running a bigger sample of inventors for whom historic patenting information is ambiguous. Firm-level studies, in contrast, typically have information on exactly when agents enter/exit the market.

[45] Log-likelihood tests and AIC scores. I also experiment with zero-inflated models (ZIP and ZINB). Both perform well on diagnostic tests, although interpretation is extremely complex. Results from Poisson regressions are available on request.

marginal effects, non-linear modelling offers little over standard linear regression. I therefore fit the model with both negative binomial and OLS estimators.

7. Regression analysis: results

Results from the main regressions are given in Tables 9 (negative binomial) and 10 (OLS). In each table, column 1 shows a bivariate regression for the main variables of interest only, column 2 adds controls and column 3 adds the fixed effect. For ease of interpretation and comparison with OLS models, negative binomial results are presented as marginal effects at the mean. Negative binomial models show a significant log alpha term, confirming over-dispersion. Controls are generally of the expected size and sign.

7.1 All inventors

Ethnic status and inventor group composition have no significant effect on individual inventor productivity (column 1). The coefficient of INV is close to zero and DIV is negative insignificant. When controls are added (column 2), both INV and DIV become positive. Coefficients get bigger, and in the OLS results DIV is now significant at 5%.

As explained above, I am able to control for individual inventors' human capital endowments, allowing identification of the various ethnicity channels. As expected, once the human capital controls are included (column 3) overall model fit improves and the results change substantially. INV remains insignificant but its coefficient more than doubles, for both sets of models. For negative binomial models, the marginal effect of DIV is now 0.087, significant at 5%.

Specifically, a 10-point increase in the inventor Fractionalisation Index – increasing active inventor diversity in Bristol to that in Oxford, for example – is linked to an average marginal effect of 10*(0.087) = 0.87 extra patents per inventor. For OLS models, diversity effects are slightly larger. DIV is 0.099, significant at 10%: a 10-point rise in inventor group diversity is associated with a 0.99 unit increase in expected patenting, or an extra patent per inventor. Interestingly, coefficients of *area population* diversity are negative (significant at 10% for negative binomials, not for OLS).

To put this into perspective, effects of diversity on patent counts are smaller and/or weaker than human capital, whether the latter is measured at the area level or at individual level. This fits with the existing empirical evidence that diversity effects on innovation are generally fairly small, where they exist (see Section 3). For negative binomial models, for example, the marginal effect of STEM degrees is 0.304, significant at 5%. This suggests that a 10-point increase in the area's share of science graduates is linked to 3 extra patents per inventor. This is as expected given that patenting is concentrated in science and technology sectors. The marginal effect of the individual endowments control is 0.101, significant at 1%: past patenting activity is strongly linked to current patenting rates.

Results for ONS ethnic groups function as a basic cross-check (Table 11). These broadly confirm the main findings. For negative binomial models, INV remains close to zero throughout; with controls and individual endowments in the model, the marginal effect of ethnic DIV is 0.125, significant at 5%. For OLS models, coefficient sizes and magnitudes are similar but none of the results is significant.

Table 12 shows results from three initial robustness checks. First, I fit the TTWA share of degree holders with PhDs in any subject as an alternative area-level human capital control (column 2). PhDs are a prerequisite in many research positions, and as specialists, PhD-holders may be more likely to patent. I find that an area's share of PHDs strongly positively associated with inventor productivity, and dominates DIV in both model specifications. One interpretation of this result is that places that are attractive to PHDs also attract a diverse group of inventors, due to some other factor – such as a 'tolerant' milieu as suggested by Florida (2002).

An alternative explanation is that high-patenting PHDs are themselves ethnic inventors, as suggested by US studies on star scientists (Stephan and Levin, 2001, Chellaraj et al., 2005). In this case, diversity is the fundamental driver and the PhD variable is a so-called 'bad control' (Angrist and Pischke, 2009). As discussed in section 3, one then needs to disentangle the ethnic and human capital components of stars' performance. I am unable to observe whether or not inventors have PHDs, so am unable to make these checks. Further research is needed here, perhaps with a subset of inventors in academic institutions where PHDs are more or less essential. In the remainder of this chapter I continue to focus on diversity because this is my main interest. But the results when including the PHD variable urge caution in interpreting these results as purely causal (of course, this is not the only identification challenge, as discussed further below).

Second, I fit the model with a lagged dependent variable to control for effects of past patenting within the sample (column 3). Diversity effects persist: coefficients are now rather smaller but also more precise, with DIV significant at 1% (negative binomial) and 5% (OLS). Third, I fit the model without London – a city with high levels of cultural diversity and relatively low levels of patenting per head of population (Wilson, 2007).[46] Results, in column 4, show that diversity effects persist in the negative binomial specification (significant at 5%), but are insignificant in OLS.

Overall, the main results suggest no significant effect of ethnic inventor status on inventor productivity relative to other inventors, once individuals' human capital and area conditions are accounted for. However, the composition of the inventor group matters: more diverse inventor communities have a small positive effect on individual inventor productivity. The rest of this section examines other channels –urban location and co-ethnicity – in more detail.

7.2 Urban areas and urban inventors

The evidence review (Section 3) suggests that urban areas may 'amplify' ethnicity-innovation processes via population composition effects, agglomeration effects or a combination of the two. However, the main results (Tables 9 and 10) find a weakly negative relationship between urban TTWAs and inventor productivity. In the negative binomial, for example, the marginal effect the urban TTWA dummy is -0.021, significant at 10%; in the OLS results the coefficient is not significant and is close to zero. By contrast the agglomeration control, log population density, is positive at 0.0005 in the negative binomial specification, 0.008 in OLS, although neither is significant.

In order to identify the separate effects of urban location and urban density, I fit the two separately and then interact them. The pairwise correlation between the urban TTWA dummy and log population density is 0.565, suggesting some differences in urban characteristics. Results are given in Table 13. Column 2 includes urban TTWA dummies only, column 3 log population density only, column 4 an interaction effect. We can see that fitted separately, each is negative on inventor productivity (although marginally significant at best). Fitted together, each is positive – with a negative interaction effect, suggesting some diseconomies of agglomeration on inventor productivity in the largest conurbations.

Columns 5-7 explore specific effects of diverse urban areas. Column 5 interacts the Fractionalisation Index with the urban TTWA dummy. The coefficient of DIV is now higher (0.136, significant at 5%) but the interaction term is negative insignificant at -0.066. Column 6 repeats the exercise with population density. DIV is now much larger (0.284), but is insignificant with large standard errors: the interaction term is also negative insignificant. Finally, column 7 includes both urban variables and interacts the

[46] Although London has relatively *high* patenting per inventor – see Table 8.

Fractionalisation Index with population density. DIV is now very large and significant, but noisy: the interaction term is negative and marginally significant.

Taken together, these results suggest that agglomeration is helpful for inventor productivity, although has some diseconomies in bigger urban areas. Diverse urban areas do not seem to amplify inventor productivity, however. Overall, I find a weak effect of urban areas on inventor productivity, which is perhaps surprising given the emphasis on geographical proximity in the innovation literature. The UK context helps explain the discrepancy. Raw patent counts are highest in relatively small cities, notably Oxford and Cambridge. Conurbations, particularly London, are dominated by service sector activities where patenting is less likely to occur. The next chapter explores the London experience in more detail, using survey data which captures a broader range of innovative activity.

7.3 Co-ethnicity / diaspora effects

The data also allows me to explore co-ethnic / diasporic group effects. Specifically, rather than estimating INV as a single 'ethnic inventor' dummy, I now include a series of dummies taking the value one if the inventor is a member of each geographical origin zone. I run the model for all minority co-ethnic groups, taking UK-origin as the reference category. Results for negative binomial models are given in Table 14: for simplicity I restrict my analysis to the five biggest geographical origin zones (South Asia, Central Europe, East Asia, Southern Europe and Eastern Europe). Results are interpreted as the marginal effect of being in one of these co-ethnic groups, relative to membership of the majority group of UK-origin inventors.

I find significant positive effects of South Asian- and Southern European–origin inventors on expected patenting rates, and negative significant effects of East Asian-origin inventors, relative to UK-origin inventors. Specifically, marginal effects are 0.025 for South Asian inventors, significant at 10%, -0.037 (1%) for East Asian inventors; and 0.053(10%) for Southern European inventors.

The South Asian result is intuitively plausible given the strong historic connections between the UK and South Asian countries (India, Pakistan, and Bangladesh) and the presence of large migrant and established minority communities here. It also accords with US research showing significant diaspora effects of Indo-American communities. The Southern European result is likely to reflect the relatively large shares of inventors in the UK with Spanish, Italian or Portuguese backgrounds (Table 1). The East Asian result is in stark contrast to US research showing strong diaspora effects for Chinese and Taiwanese communities (Saxenian, 2006, Dahlman, 2010). This may reflect the lack of strong diasporas in the UK outside Hong Kong-origin Chinese, and the different circumstances behind recent community formation in the US (economic migration of skilled workers) and the UK (handover of Hong Kong to China between 1984 and 1997).

Results may also be driven by the large geographical origin zones I am using to proxy diasporic communities. I experiment with ONS ethnicity measures of Indian and Chinese inventors to conduct a partial cross-check using more tightly-defined groups, confirming my main result.[47] Overall, then, these results suggest that co-ethnic group membership, as well as the diversity of the local inventor community, both have small positive effects on individual patenting rates.

8. Further robustness checks

I conduct checks on a series of potential endogeneity problems. These fall into two broad categories: robustly identifying diaspora and diversity channels, and dealing with path-dependence. Results are shown in Tables 15 and 16.

8.1 Identifying human capital, diversity and diaspora effects

I face two immediate identification challenges. First, the combination of area-level controls and individual endowments may not be fully capturing inventors' human capital. Assuming that human capital has a positive effect on patenting, the resulting omitted variable bias will overstate effects of DIV, pushing coefficients of DIV upwards.

To explore, I include an alternative individual-level control in the main model, again exploiting pre-sample information. Alongside overall output, intellectual range is another plausible indicator of overall human capital. My original endowments control measures knowledge accumulation by summing pre-sample patents. In addition, I identify 'generalists' as inventors patenting across at least two technology fields (for example, filing patents in both electronics and biotechnology). The new control is a dummy with value one if an inventor patents across technology fields in the pre-sample period.[48]

[47] Indian inventors make up just over three quarters of South Asian inventors (see Table 9), so I also break down the South Asian result in more detail. I find a positive non-significant link between Pakistani inventors and inventor productivity, but a very strong negative link with Bangladeshi inventors. Given their small representation in the sample, this may be largely explained by measurement error.
[48] The dummy will also be capturing the minority of inventors who patent more than once.

Results are given in Table 15. Columns 1-3 compare the original human capital control, the 'generalist' control and both together. INV remains insignificant throughout; marginal effects of DIV fall from 0.087 to 0.05, 10% significance with the generalist control (column 2). Fitting both controls together (column 3) slightly increases the size and strength of the DIV marginal effect (to 0.055, 5% significance) and improves model fit. Columns 4-5 rerun this model for co-ethnic groups: with both controls in play, the main co-ethnic group effects remain significant albeit smaller.

Second, inventor diversity effects might collapse to simple size effects. Fractionalisation Indices tend to be highly correlated with group population shares (in this case, the pairwise correlation between DIV and the share of non-UK origin inventors in the TTWA is 0.8039). To test this, I replace the Fractionalisation Index of inventors with the share of ethnic inventors in the local inventor population. Results, in Table 16, show that the coefficient on ethnic inventor share is similar to group diversity, but is not significant on individuals' expected patent rates either when fitted individually (column 2) or with DIV (column 3). Interacting the two raises the marginal effect of DIV, which stays significant at 5%, but with a large negative value for the interaction term (column 4). This suggests that the overall diversity of inventors, rather than an aggregation of ethnic inventors, drives the main results. Column 5 repeats the analysis for diasporic groups, with similar outcomes.

8.2 Historic patent stocks / path-dependence

As explained in section 6, innovative activity is spatially concentrated, and these concentrations tend to persist over time as inventors and firms select into innovative locations, as areas progressively build innovative 'capacity'. If the historic patent stocks term in the main model is mis-specified, agglomeration and path-dependence will not be adequately controlled for. To test for this I plug a range of pre-sample historic patent counts into the main model. Negative binomial results are given in Table 17. I find as that as the historic lag decreases, the coefficient and significance of historic patenting activity rises (from -0.000 for 1981-84 to 0.001 for 1993-96, significant at 5%). The marginal effect of inventor diversity get smaller and weaker as the historic lag shortens – from 0.087, significant at 5%, for 1981-84 stocks to 0.067 (10%) for 1989-92 stocks. This suggests that historic area-level characteristics help explain some of the inventor diversity effect – but do not eliminate it.

8.3 Sample construction

I construct my sample by zeroing all inventor-yeargroup cells when an inventor is not patenting. As discussed in Section 5, this is not the most conservative way of treating inventors when they are not active, and there is some risk it may introduce measurement error into the results. To check for this I compare results from two samples – one with zeroed observations and one with non-active periods set as missing observations.

My identification strategy depends on using inventors' historic patenting activity, so blanking out non-activity has the effect of restricting the sample to inventors who patent more than once. I thus compare estimates for the set of multiple inventors across two different samples, one with zeroed and one with missing observations for non-activity. Results are given in Table 18. We can see that estimates for the two sub-samples are identical; suggesting that sample construction has no effect on my main results.

Overall, the results from these cross-checks suggest that my main results are robust to the main endogeneity challenges: omitted variables, path-dependence and sample construction issues. However, further research is required to identify the relative contribution of majority and ethnic PHDs to patenting.

9. Impacts on majority groups

The analysis has established some positive connections between inventor group composition, the presence of diasporic groups and individual inventor productivity. However, this has ignored distributional effects – that is, specific impacts of ethnic inventors on majority inventors. Given that immigration is a major driver of cultural diversity, it is important to look at these distributional impacts.

A number of studies in the immigration literature look at 'native outflows', in which UK-born physically leave an area after migrants arrive (Borjas, 1994). 'Geographical crowd-out' of this kind is hard to assess here – as explained in section 5, although the number of mobile inventors seems low, movers cannot be definitively identified. I conduct exploratory logit regressions to identify individual and area-level factors which might influence mover status. Results suggest individual human capital (measured by the endowments control) has a substantial, significant positive link to mover status. By contrast, coefficients for areas' share of migrant inventors are much smaller and statistically insignificant.

‘Resource crowd-out’ is a potentially more serious issue. There are two ways in which this might happen. First, the presence of ethnic inventors might affect majority patenting rates at the individual level. A given majority inventor may benefit from ethnic inventors via the production complementarities outlined in section 3, or may ‘lose’ from disbenefits such as lower trust or communications difficulties. The balance of these two effects on the average majority inventor needs to be identified.

Second, even if there are human capital externalities at the group level, majority individuals may lose out from the presence of minority inventors (Borjas, 2011). In this case, ethnic inventors might crowd out majority inventors from relevant jobs and resources, such as space in R&D labs; or diaspora benefits might only be accessible to group members. This will affect the composition of overall patenting at area level. At the extreme, increases in area-level patent counts might be partly or wholly explained by a rising share of ‘ethnic’ patents – majority patenting shares could be static or even falling. Conversely, there might be multiplier effects from ethnic inventors to majority group inventors, raising everyone’s patent counts.

I test for both forms of resource crowd-out. At the individual level, I first re-run model (1) for majority inventors only. Results are given in the first panel of Table 18. The marginal effect of DIV on majority inventor productivity is 0.072, significant at 10%. This implies a positive multiplier effect of inventor diversity on majority groups – but it is smaller and weaker than on all inventors.

Next, I run model (1) for the whole sample but fit INV as a majority inventor dummy. Results are given in the second panel of Table 18. As with minority status, majority status has no significant effect on inventor productivity when other factors are controlled for (columns 1 and 2). However, interacting majority status with inventor diversity produces a positive significant effect of majority status, a larger and stronger effect of diversity – but a significant negative effect on majority inventors in diverse areas (column 3). Unlike the previous test, this suggests that while inventor diversity brings benefits, majority inventors in diverse inventor communities lose out.

To explore area-level effects, I draw on recent work by Card (2005), Kerr and Lincoln (2010) and Faggio and Overman (2011). I assemble a panel of TTWA-level weighted patent counts for 1993-2004. I define ‘ethnic’ patents as patents with at least one ethnic inventor; all other patents are ‘majority’ patents. Following Faggio and Overman (2011), I then regress the percentage change in total weighted patents during the period on the percentage change in ethnic patents. For TTWA *j* I estimate:

$$\Delta TPATENTS_j = a + b\Delta EPATENTS_j + \mathbf{CONTROLS}\boldsymbol{c}_{jtbase} + e_j \quad (3)$$

Where:

$$\Delta TPATENTS_j = TPATENTS_{j2004} - TPATENTS_{j1993} / TPATENTS_{j1993} \quad (4)$$

And $\Delta EPATENTS_j$ is assembled similarly. **CONTROLS** is a vector of area-level controls for the base period 1993.[49] The coefficient of interest is *b*. As explained by Card (2005), if estimates of *b* are less than one, increases in ethnic patenting lead to a smaller increase in overall patenting, implying some crowd-out of majority patenting by ethnic inventors. Estimates of *b* larger than one imply multiplier effects; if *b* is equal to one, there are no distributional impacts either way.

OLS results are given in Table 19. The simplest specifications of (4) suggest some crowd-out, with *b* estimated at 0.199 and 0.259, significant at 1%. However, *b* becomes insignificant once controls and standard errors clustered on TTWAs are introduced (column 4). An alternative specification using shifts in TTWAs' technology field shares delivers very similar results (column 5). This suggests there is little evidence of crowd-out.

Model (4) does not fully control for simultaneity or reverse causality. I experiment with lags of ethnic patents as an instrument, but none pass the required first-stage tests. Results should therefore be interpreted with caution.

10. Conclusions

In recent years there has been growing academic and policy interest in links between immigration, ethnic diversity and innovation. This paper looks at the role of ethnic inventors on innovative activity in the UK, using a new 12-year panel of patents microdata. I have been able to explore a number of potential 'ethnicity-innovation' channels – individual positive selection, externalities from diasporic groups and from the cultural diversity of inventor communities, as well as 'amplifying' effects of urban environments. The research is one of very few studies to explore these links, and as far as I am aware is the first of its kind outside the US.

[49] Log of population density, % STEM degree, % employed in knowledge-intensive manufacturing, % migrant working-age population, % entry-level occupations, % long term unemployed, urban dummy. Alternative specifications control for TTWA change in OST7 technology field shares 1993-2004.

The results suggest that individual minority status has no significant effect on inventor patenting rates once other factors are controlled for. Conversely some diasporic groups, and group cultural composition, have small positive effects on inventor productivity. Effects on 'majority' inventors are unclear: there are some indications of individual-level crowd-out, but not at area level. Although patenting activity is very spatially clustered in the UK, in contrast to the wider literature, I find little evidence that urban environments improve individuals' patenting activity once other individual and area-level controls are taken into account.

Overall, ethnic inventors are a net positive for patenting in the UK, although the British experience is significantly different from the US. This partly reflects distinctive patterns of US migrant settlement: most notably, the recent emergence of ethnic inventor communities from Cold War science research, which have attracted very large numbers of skilled workers into a small number of locations (Saxenian, 2006). By contrast, recent 'calls' for migrant workers in the UK since the mid-20th century have been largely focused on less skilled occupations, although policy is now becoming more skill-biased. Results may also reflect culturally distinctive US attitudes to entrepreneurship, as evidenced by sociological studies of Jewish and Afro-Caribbean migrant communities in New York and London (Gordon et al., 2007), and by the complex interplay between class, skills, resources and attitudes that influence real-world entrepreneurial behaviour (Basu, 2002).

There are three important caveats to these results. First, diversity and diaspora effects are relatively small – human capital and patent field / industry effects are more important determinants of inventors' productivity. This is intuitive, and echoes much of the existing literature (see above). Second, working with inventor data presents a number of potential measurement error challenges. Most seriously, my data only allows a fuzzy identification of ethnic inventors and diasporic groups. Using geographical origin as a proxy for co-ethnicity also presents conceptual challenges, although cross-checks support my results. Third, although the results survive a number of robustness checks, alternative measures of area-level human capital weaken effects of DIV. Further work is needed on the relative contribution of majority and ethnic PHDs to patenting. Conversely, data restrictions mean that my sample understates the true numbers of ethnic inventors. The real benefits of ethnic inventors may thus be larger.

The results may have implications for the current Coalition government's migration policies. Net immigration is one of the main factors behind the growth of ethnic inventor communities in the UK: a phenomenon which appears to raise rates of innovation through a combination of diversity and diaspora effects, with no hard evidence of negative distributional effects on native inventors. A migration cap that places restrictions on skilled immigration from outside Europe is likely to put some constraints on innovative activity, leading to welfare losses both to the UK and to UK-born workers. Similar welfare losses may arise from proposed restrictions on post-study routes to work for non-EU students.

The paper leaves a number of questions for future research. Further work could explore social networks, co-ethnicity and geographical location in more detail – via analysis of patent citations and international co-invention / co-patenting. Within the UK, data offering better identification of ethnic and migrant inventors, in particular recent immigrants, would provide a clearer picture of current developments. Alternatively, qualitative methods could shine further light on migrant and diaspora dynamics. Further work could also examine sectoral and area differences, as well as distributional impacts in more detail. The next chapter takes some of these ideas forward, exploring the experiences of London firms in a number of industries.

LIST OF TABLES

Table 1. UK-resident inventors: 30 biggest Cultural-Ethnic-Linguistic (CEL) subgroups, 1993-2004.

CEL subgroup	Freq.	%	Cumulative %
ENGLISH	86,118	69.17	69.17
CELTIC	10,653	8.56	77.73
SCOTTISH	6,557	5.27	82.99
IRISH	3,583	2.88	85.87
WELSH	2,523	2.03	87.9
INDIAN HINDI	1,255	1.01	88.91
GERMAN	1,205	0.97	89.87
ITALIAN	975	0.78	90.66
FRENCH	958	0.77	91.43
CHINESE	920	0.74	92.16
POLISH	886	0.71	92.88
OTHER MUSLIM	793	0.64	93.51
OTHER EUROPEAN	665	0.53	94.05
HONG KONGESE	588	0.47	94.52
GREEK	574	0.46	94.98
PAKISTANI	551	0.44	95.42
SIKH	500	0.4	95.82
SPANISH	438	0.35	96.18
VIETNAMESE	427	0.34	96.52
JEWISH	351	0.28	96.8
PORTUGUESE	326	0.26	97.06
JAPANESE	293	0.24	97.3
EAST ASIAN & PACIFIC	263	0.21	97.51
DANISH	216	0.17	97.68
OTHER SOUTH ASIAN	209	0.17	97.85
SRI LANKAN	209	0.17	98.02
DUTCH	207	0.17	98.19
TURKISH	198	0.16	98.34
SWEDISH	191	0.15	98.5
RUSSIAN	138	0.11	98.61

Source: ONOMAP/KITES-PATSTAT.

Notes:

1) 'OTHER MUSLIM' subgroup includes CEL name types 'BALKAN MUSLIM', 'MALAYSIAN MUSLIM', 'MUSLIM INDIAN', 'SUDANESE', 'WEST AFRICAN MUSLIM', 'OTHER MUSLIM' (SMALLER MIDDLE EASTERN COUNTRIES, N/AFRICAN COUNTRIES, CENTRAL ASIAN REPS)
2) 'JEWISH' includes CEL name types 'JEWISH / ASHKENAZI', 'SEPHARDIC JEWISH'
3) 'EAST ASIAN AND PACIFIC' includes CEL name types 'BURMESE', 'CAMBODIAN', 'FIJIAN', 'HAWAIIAN', 'LAOTIAN','MAORI', 'MAURITIAN', 'POLYNESIAN', 'SAMOAN', 'SINGAPOREAN', 'SOLOMON ISLANDER', 'SOUTH EAST ASIAN' , 'THAI', 'TIBETIAN', 'TONGAN', 'TUVALUAN', 'EAST ASIAN & PACIFIC OTHER'
4) 'OTHER SOUTH ASIAN' includes CEL name types 'ASIAN CARIBBEAN', 'BENGALI', 'BHUTANESE', 'GUYANESE ASIAN', 'KENYAN ASIAN', 'NEPALESE', 'PARSI', 'SEYCHELLOIS', 'SOUTH ASIAN', 'TAMIL'

Table 2. UK-resident inventors: geographical origin groups, 1993-2004.

Probable geog. area of origin, CEL	Freq.	%	Cumulative %
BRITISH ISLES	109,429	87.89	87.89
SOUTH ASIA	3,074	2.47	90.36
CENTRAL EUROPE	3,035	2.44	92.8
EAST ASIA	2,557	2.05	94.85
SOUTHERN EUROPE	2,394	1.92	96.78
EASTERN EUROPE	1,395	1.12	97.9
MIDDLE EAST	1,060	0.85	98.75
NORTHERN EUROPE	606	0.49	99.24
REST OF WORLD	568	0.46	99.70
AFRICA	324	0.26	99.96
CENTRAL ASIA	31	0.02	99.98
AMERICAS	29	0.02	100.00

Source: ONOMAP/KITES-PATSTAT.

Table 3. UK-resident inventors: biggest ONS ethnic groups, 1993-2004.

Probable ethnic group in 1991 Census categories, CEL	%	Cumulative %
WHITE	94.28	94.28
ANY OTHER ETHNIC GROUP	1.76	96.04
INDIAN	1.69	97.73
CHINESE	1.41	99.14
PAKISTANI	0.54	99.68
BLACK - AFRICAN	0.24	99.92
BANGLADESHI	0.08	100
BLACK - CARIBBEAN	0	100

Source: ONOMAP/KITES-PATSTAT.

Notes: Ethnic groups typology taken from 1991 Census to allow comparability pre and post-2001. Frequencies have been supressed to avoid disclosure.

Table 4. Shares of migrants and ethnic inventors in Travel to Work Area (TTWA) working-age populations, 1993-2004. Top 40 areas.

% ethnic inventors	% migrants /population	TTWA name	TTWA type
0.287	0.158	Crawley	Primary Urban
0.241	0.148	Southampton	Primary Urban
0.206	0.359	London	Primary Urban
0.171	0.173	Oxford	Primary Urban
0.169	0.169	Cambridge	Primary Urban
0.166	0.113	Dundee	Primary Urban
0.158	0.101	Oban	N Scotland rural
0.153	0.174	Guildford & Aldershot	Primary Urban
0.152	0.147	Swindon	Primary Urban
0.147	0.113	St Andrews & Cupar	N Scotland rural
0.147	0.143	Edinburgh	Primary Urban
0.143	0.141	Colchester	Primary Urban
0.143	0.092	Pembroke & Tenby	Welsh rural
0.141	0.104	Carlisle	N England rural
0.138	0.114	Bude & Holsworthy	SW England rural
0.136	0.127	Aberdeen	Primary Urban
0.133	0.106	Holyhead	Welsh rural
0.129	0.174	Brighton	Primary Urban
0.126	0.122	Lancaster & Morecambe	N England rural
0.124	0.170	Bedford	Primary Urban
0.122	0.107	Livingston & Bathgate	N Scotland rural
0.121	0.136	Cardiff	Primary Urban
0.120	0.128	Glasgow	Primary Urban
0.120	0.098	Inverness & Dingwall	N Scotland rural
0.119	0.101	Lanarkshire	Primary Urban
0.119	0.114	Newcastle & Durham	Primary Urban
0.116	0.210	Birmingham	Primary Urban
0.115	0.092	Haverfordwest & Fishguard	Welsh rural
0.114	0.119	York	Primary Urban
0.114	0.200	Leicester	Primary Urban
0.114	0.184	Reading & Bracknell	Primary Urban
0.113	0.215	Wycombe & Slough	Primary Urban
0.111	0.109	Wirral & Ellesmere Port	Primary Urban
0.109	0.157	Leeds	Primary Urban
0.109	0.143	Newbury	SW England rural
0.108	0.111	Louth & Horncastle	Rest England rural
0.107	0.108	Liverpool	Primary Urban
0.106	0.139	Canterbury	Rest England rural
0.106	0.129	Margate, Ramsgate & Sandwich	Rest England rural
0.106	0.144	Harlow & Bishop's Stortford	Rest England rural

Source: ONOMAP/KITES-PATSTAT/ONS.
Note: TTWAs use 2001 boundaries. ‘Primary urban’ TTWAs contain an urban core with at least 125,000 people. TTWAs with fewer than 10 inventors suppressed.

Table 5. Ethnic inventor Location Quotients (LQs), 1993-2004. Top 40 areas.

LQ	TTWA name	TTWA type
2.372	Crawley	Primary Urban
1.989	Southampton	Primary Urban
1.703	London	Primary Urban
1.414	Oxford	Primary Urban
1.394	Cambridge	Primary Urban
1.375	Dundee	Primary Urban
1.304	Oban	N Scotland rural
1.266	Guildford & Aldershot	Primary Urban
1.252	Swindon	Primary Urban
1.216	St Andrews & Cupar	N Scotland rural
1.213	Edinburgh	Primary Urban
1.180	Pembroke & Tenby	Welsh rural
1.180	Colchester	Primary Urban
1.162	Carlisle	N England rural
1.139	Bude & Holsworthy	SW England rural
1.122	Aberdeen	Primary Urban
1.101	Holyhead	Welsh rural
1.062	Brighton	Primary Urban
1.044	Lancaster & Morecambe	N England rural
1.024	Bedford	Primary Urban
1.005	Livingston & Bathgate	N Scotland rural
1.000	Cardiff	Primary Urban
0.995	Glasgow	Primary Urban
0.988	Inverness & Dingwall	N Scotland rural
0.981	Lanarkshire	Primary Urban
0.980	Newcastle & Durham	Primary Urban
0.955	Birmingham	Primary Urban
0.953	Haverfordwest & Fishguard	Welsh rural
0.941	York	Primary Urban
0.940	Leicester	Primary Urban
0.938	Reading & Bracknell	Primary Urban
0.932	Wycombe & Slough	Primary Urban
0.917	Wirral & Ellesmere Port	Primary Urban
0.898	Leeds	Primary Urban
0.897	Newbury	SW England rural
0.893	Louth & Horncastle	Rest England rural
0.886	Liverpool	Primary Urban
0.876	Canterbury	Rest England rural
0.875	Margate, Ramsgate & Sandwich	Rest England rural
0.872	Harlow & Bishop's Stortford	Rest England rural

Source: ONOMAP/KITES-PATSTAT/ONS.
Note: TTWAs use 2001 boundaries. 'Primary urban' TTWAs contain an urban core with at least 125,000 people. TTWAs with fewer than 10 inventors suppressed.

Table 6. Fractionalisation Index (FRAC) scores for inventors and TTWA working-age populations, 1993-2004. Top 40 areas.

Inventor FRAC	Population FRAC	TTWA name	TTWA type
0.384	0.498	London	Primary Urban
0.354	0.188	Southampton	Primary Urban
0.310	0.206	Crawley	Primary Urban
0.308	0.225	Oxford	Primary Urban
0.305	0.133	Dundee	Primary Urban
0.293	0.139	Honiton & Axminster	SW England rural
0.288	0.122	Lancaster & Morecambe	N England rural
0.283	0.226	Cambridge	Primary Urban
0.282	0.184	Swindon	Primary Urban
0.279	0.099	Bangor, Caernarfon & Llangefni	Welsh rural
0.273	0.168	Colchester	Primary Urban
0.256	0.106	Carlisle	N England rural
0.255	0.126	St Andrews & Cupar	N Scotland rural
0.255	0.122	Bude & Holsworthy	SW England rural
0.250	0.234	Guildford & Aldershot	Primary Urban
0.244	0.179	Edinburgh	Primary Urban
0.241	0.275	Bradford	Primary Urban
0.239	0.143	Glasgow	Primary Urban
0.237	0.263	Birmingham	Primary Urban
0.234	0.148	Aberdeen	Primary Urban
0.226	0.104	Wirral & Ellesmere Port	Primary Urban
0.225	0.164	Cardiff	Primary Urban
0.224	0.104	Livingston & Bathgate	N Scotland rural
0.222	0.206	Bedford	Primary Urban
0.218	0.135	Lincoln	Rest England rural
0.217	0.121	Liverpool	Primary Urban
0.215	0.225	Brighton	Primary Urban
0.213	0.289	Wycombe & Slough	Primary Urban
0.210	0.126	Newcastle & Durham	Primary Urban
0.208	0.172	Bristol	Primary Urban
0.208	0.269	Leicester	Primary Urban
0.207	0.184	Eastbourne	Rest England rural
0.203	0.134	Monmouth & Cinderford	Rest England rural
0.202	0.190	Leeds	Primary Urban
0.201	0.244	Luton & Watford	Primary Urban
0.199	0.142	Norwich	Primary Urban
0.194	0.158	Rugby	Rest England rural
0.194	0.239	Reading & Bracknell	Primary Urban
0.193	0.169	Harlow & Bishop's Stortford	Rest England rural
0.192	0.114	Stafford	Rest England rural

Source: ONOMAP/KITES-PATSTAT/ONS.
Note: TTWAs use 2001 boundaries. ‘Primary urban’ TTWAs contain an urban core with at least 125,000 people. TTWAs with fewer than 10 inventors suppressed.

Table 7. TTWAs' weighted patent stocks, 1993-2004. Top 40 areas.

Weighted patent count	TTWA name	TTWA type
1697.14	London	Primary Urban
1155.59	Cambridge	Primary Urban
719.36	Oxford	Primary Urban
705.62	Harlow & Bishop's Stortford	Rest England rural
531.69	Manchester	Primary Urban
489.87	Guildford & Aldershot	Primary Urban
483.41	Southampton	Primary Urban
440.96	Bristol	Primary Urban
428.15	Reading & Bracknell	Primary Urban
416.01	Crawley	Primary Urban
379.21	Ipswich	Primary Urban
365.63	Swindon	Primary Urban
342.90	Wycombe & Slough	Primary Urban
341.67	Stevenage	Primary Urban
312.93	Newcastle & Durham	Primary Urban
309.40	Wirral & Ellesmere Port	Primary Urban
301.75	Leicester	Primary Urban
289.82	Birmingham	Primary Urban
260.66	Nottingham	Primary Urban
223.87	Leeds	Primary Urban
218.49	Edinburgh	Primary Urban
213.60	Worcester & Malvern	Primary Urban
183.83	Margate, Ramsgate & Sandwich	Rest England rural
181.10	Coventry	Primary Urban
169.36	Bedford	Primary Urban
167.98	Luton & Watford	Primary Urban
165.09	Cardiff	Primary Urban
163.87	Glasgow	Primary Urban
161.37	Warwick & Stratford-upon-Avon	Rest England rural
161.20	Warrington & Wigan	Primary Urban
152.70	Hull	Primary Urban
148.04	Derby	Primary Urban
147.14	Aberdeen	Primary Urban
138.16	Portsmouth	Primary Urban
136.70	Milton Keynes & Aylesbury	Primary Urban
130.99	Middlesbrough & Stockton	Primary Urban
121.67	Chelmsford & Braintree	Primary Urban
121.35	Chester & Flint	Welsh rural
118.13	Northampton & Wellingborough	Primary Urban
113.95	Maidstone & North Kent	Primary Urban

Source: KITES-PATSTAT/ONS.
Note: TTWAs use 2001 boundaries. 'Primary urban' TTWAs contain an urban core with at least 125,000 people. Patents are weighted by number of inventors, not area population.

Table 8. Summary statistics.

Variable	N	Mean	SD	Min	Max
Inventor patent count / 4-year period	89312	0.114	0.694	0	25
Inventors' ave. patent count, pre-1993	89312	0.405	0.351	0.286	11.143
Inventor likely techfield mover	89312	0.256	0.437	0	1
Inventor likely TTWA mover	89312	0.143	0.35	0	1
Inventor is UK geog. origin	89312	0.937	0.243	0	1
Inventor is foreign geog. origin	89312	0.063	0.243	0	1
Inventor African origin	89312	0.002	0.041	0	1
Inventor Americas origin	89312	0.000	0.013	0	1
Inventor Central Asia origin	89312	0.000	0.018	0	1
Inventor Central Europe origin	89312	0.012	0.107	0	1
Inventor rest of world origin	89312	0.003	0.058	0	1
Inventor East Asian origin	89312	0.007	0.084	0	1
Inventor East Europe origin	89312	0.007	0.086	0	1
Inventor Middle East origin	89312	0.006	0.075	0	1
Inventor Northern Europe origin	89312	0.003	0.052	0	1
Inventor South Asian origin	89312	0.015	0.123	0	1
Inventor South European origin	89312	0.007	0.086	0	1
Frac. Index, geog. origin groups	89312	0.209	0.118	0	0.612
Inventor is white ethnicity	89312	0.97	0.172	0	1
Inventor is minority ethnic	89312	0.03	0.172	0	1
Inventor Black Caribbean	89312	0	0.01	0	1
Inventor Black African	89312	0.002	0.04	0	1
Inventor Indian	89312	0.012	0.107	0	1
Inventor Pakistani	89312	0.003	0.052	0	1
Inventor Chinese	89312	0.004	0.064	0	1
Inventor other ethnic group	89312	0.01	0.099	0	1
Frac. Index, ethnic groups	89312	0.108	0.066	0	0.449
TTWA Frac Index, geog. groups	89309	0.225	0.142	0	0.528
TTWA Frac Index, ethnic groups	89309	0.169	0.141	0	0.459
% graduates	89309	0.238	0.051	0.106	0.362
% graduates with STEM degrees	89309	0.121	0.032	0.041	0.196
% graduates with PhDs	89309	0.007	0.005	0	0.029
% employed hi-tech manufacturing	89309	0.027	0.014	0	0.194
% employed medium-tech m'facturing	89309	0.046	0.023	0	0.135
% in entry level occupations	89309	0.338	0.049	0.25	0.667
% unemployed >=12 months	89309	0.016	0.012	0	0.08
log(population density)	89309	6.605	1.053	2.06	8.359
Electronics patent	89312	0.009	0.093	0	1
TTWA weighted patent count	89312	493.094	578.301	0	1888.03
TTWA weighted patents, 1981-84	88726	144.814	201.789	0.25	613.859

Source: KITES-PATSTAT/ONS/LFS
Note: Area-level controls not available for all TTWAs.

Table 9. Negative binomial results for inventor productivity: ethnicity measured by geographical origin zones, 1993-2004.

Individual patent counts	(1)	(2)	(3)
Ethnic inventor, geog.	-0.000	0.004	0.009
	(0.011)	(0.008)	(0.007)
Frac Index of inventors, geog. origin groups	-0.061	0.079	0.087**
	(0.101)	(0.050)	(0.042)
Frac Index, TTWA country of birth		-0.203*	-0.140*
		(0.110)	(0.085)
% STEM degrees, TTWA		0.372**	0.304**
		(0.176)	(0.147)
Log of TTWA population density		0.005	0.005
		(0.008)	(0.007)
Area weighted patents, 1981-84		-0.000	-0.000
		(0.000)	(0.000)
% hi-tech mf empl, OECD defn.		-0.159	-0.111
		(0.281)	(0.226)
% medium-tech mf, OECD defn.		0.048	0.051
		(0.172)	(0.134)
% entry-level occupations		0.042	0.113
		(0.123)	(0.106)
% unemployed >=12 months		-0.313	-0.000
		(0.441)	(0.354)
Electronics / OST7 type 1 patents		2.074***	1.697***
		(0.132)	(0.176)
Urban TTWA		-0.018*	-0.021*
		(0.015)	(0.015)
Individual human capital			0.101***
			(0.007)
ln(alpha)			
Constant	2.991***	2.683***	2.491***
	(0.052)	(0.063)	(0.069)
Observations	89312	88726	88726
Log-likelihood	-25328.463	-24379.554	-23859.107
Chi^2 fit statistic (Wald)	376.947	3520.345	2693.200

Source: KITES-PATSTAT/ONS/LFS

Notes: Notes: All models use time dummies. Heteroskedasticity and autocorrelation-robust standard errors clustered on TTWA. Except for ln(alpha) term, coefficients are marginal effects at the mean. * = significant at 10%, ** 5%, *** 1%.

Table 10. OLS results for inventor productivity: ethnicity measured by geographical origin zones, 1993-2004.

Individual patent counts	(1)	(2)	(3)
Ethnic inventor, geog.	-0.002	0.004	0.011
	(0.011)	(0.011)	(0.010)
Frac Index of inventors, geog. origin groups	-0.055	0.119**	0.099*
	(0.088)	(0.058)	(0.055)
Frac Index, TTWA country of birth		-0.137	-0.079
		(0.127)	(0.115)
% STEM degrees, TTWA		0.302	0.334
		(0.292)	(0.278)
Log of TTWA population density		0.006	0.008
		(0.010)	(0.009)
Area weighted patents, 1981-84		-0.000	-0.000
		(0.000)	(0.000)
% hi-tech mf empl, OECD defn.		-0.166	-0.245
		(0.385)	(0.367)
% medium-tech mf, OECD defn.		0.120	0.093
		(0.240)	(0.216)
% entry-level occupations		0.084	0.149
		(0.166)	(0.154)
% unemployed >=12 months		-1.211	-0.934
		(0.747)	(0.719)
Electronics / OST7 type 1 patents		2.356***	2.305***
		(0.139)	(0.135)
Urban TTWA		-0.024	-0.028
		(0.019)	(0.017)
Individual human capital			0.266***
			(0.036)
Constant	0.196***	0.122	-0.034
	(0.010)	(0.107)	(0.105)
Observations	89312	88726	88726
F-statistic	76.283	52.523	50.226
R^2	0.007	0.107	0.125

Source: KITES-PATSTAT/ONS/LFS

Notes: All models use time dummies. Heteroskedasticity and autocorrelation-robust standard errors clustered on TTWA. * = significant at 10%, ** 5%, *** 1%.

Table 11. Negative binomial and OLS results for inventor productivity: ethnicity measured by ONS ethnic groups, 1993-2004.

Negative binomial

Individual patent counts	**(1)**	**(2)**	**(3)**
Ethnic inventor, ONS minority ethnic group	-0.006	-0.000	0.000
	(0.016)	(0.014)	(0.012)
Frac Index of inventors, ONS ethnic groups	-0.165	0.101	0.125**
	(0.145)	(0.067)	(0.056)
Controls	N	Y	Y
Individual human capital	N	N	Y
Observations	89312	88726	88726
Log-likelihood	-25319.277	-24386.644	-23864.136
Chi^2 goodness of fit statistic (Wald)	414.921	2706.003	2426.458

OLS

Individual patent counts	**(1)**	**(2)**	**(3)**
Ethnic inventor, ONS minority ethnic group	-0.010	-0.002	0.003
	(0.015)	(0.014)	(0.013)
Frac Index of inventors, ONS ethnic groups	-0.155	0.123	0.097
	(0.131)	(0.082)	(0.077)
Controls	N	Y	Y
Individual human capital	N	N	Y
Observations	89312	88726	88726
F-statistic	75.337	54.477	58.197
R^2	0.007	0.107	0.125

Source: KITES-PATSTAT/ONS/LFS.
Notes: All models use time dummies. Controls fitted: log of population density, % STEM degrees, % employed in knowledge-intensive manufacturing, fractionalisation index of area birth country groups, % entry-level occupations, % long term unemployed, urban TTWA dummy. Heteroskedasticity and autocorrelation-robust standard errors clustered on TTWA. Negative binomial models show marginal effects at the mean. * = significant at 10%, ** 5%, *** 1%.

Table 12. Robustness checks. Negative binomial and OLS results.

Negative Binomial

Individual patent counts	**(1)**	**(2)**	**(3)**	**(4)**
Ethnic inventor, geographic origin	0.009	0.007	-0.000	-0.002
	(0.007)	(0.007)	(0.001)	(0.001)
Frac Index of inventors, geog. origin groups	0.087**	0.046	0.016***	0.016***
	(0.042)	(0.039)	(0.006)	(0.006)
% with PhDs in TTWA		2.649***		
		(0.504)		
#times inventor patents in previous YG within sample			0.053***	0.057***
			(0.002)	(0.002)
Controls	Y	Y	Y	Y
Individual human capital	Y	Y	Y	Y
Include London?	Y	Y	Y	N
Observations	88726	88726	88726	75571
Log-likelihood	-23859.107	-23821.523	-16507.273	-21524.746
Chi^2 fit statistic (Wald)	2693.200	2181.073	4008.364	2095.403

OLS

Individual patent counts	**(1)**	**(2)**	**(3)**	**(4)**
Ethnic inventor, geographic origin	0.011	0.009	-0.001	-0.003
	(0.010)	(0.010)	(0.005)	(0.006)
Frac Index of inventors, geog. origin groups	0.099*	0.050	0.072**	0.047
	(0.055)	(0.048)	(0.035)	(0.033)
% with PhDs in TTWA		3.567***		
		(0.689)		
#times inventor patents in previous YG within sample			0.638***	0.640***
			(0.021)	(0.023)
Controls	Y	Y	Y	Y
Individual human capital	Y	Y	Y	Y
Include London?	Y	Y	Y	N
Observations	88726	88726	88726	75571
F-statistic	50.226	36.783	223.531	53.932
R^2	0.125	0.125	0.451	0.130

Source: KITES-PATSTAT/ONS/LFS
Notes: All models use time dummies. Controls fitted: log of population density, % STEM degrees, % employed in knowledge-intensive manufacturing, fractionalisation index of area birth country groups, % entry-level occupations, % long term unemployed, urban TTWA dummy. Heteroskedasticity and autocorrelation-robust standard errors clustered on TTWA. Negative binomial models show marginal effects at the mean. * = significant at 10%, ** 5%, *** 1%.

Table 13. Further exploration of urban areas' role in inventor productivity, 1993-2004. Negative binomial results.

Individual patent counts	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Ethnic inventor, geographic origin	0.009	0.009	0.008	0.008	0.009	0.008	0.009
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Frac Index of inventors, geog. origin groups	0.087**	0.085**	0.066	0.080*	0.136**	0.284	0.494**
	(0.042)	(0.043)	(0.041)	(0.041)	(0.067)	(0.201)	(0.231)
urban TTWA	-0.021	-0.016		0.054	-0.007		-0.028*
	(0.015)	(0.010)		(0.043)	(0.010)		(0.015)
log of TTWA population density	0.005		-0.002	0.016		0.004	0.016**
	(0.007)		(0.005)	(0.012)		(0.005)	(0.008)
urban TTWA * ln(pop density)				-0.016			
				(0.014)			
Frac Index * urban TTWA					-0.066		
					(0.076)		
Frac Index * ln(pop density)						-0.037	-0.067*
						(0.033)	(0.037)
Controls	Y	Y	Y	Y	Y	Y	Y
Observations	88726	88726	88726	88726	88726	88726	88726
Log-likelihood	-23859.107	-23861.196	-23871.085	-23853.923	-23859.802	-23868.311	-23850.578
Chi^2 fit statistic (Wald)	2693.200	2594.921	3234.725	2754.837	2720.994	4245.201	3717.697

Source: KITES-PATSTAT/ONS/LFS
Notes: all models use time dummies and individual fixed effects. Robust standard errors clustered on TTWA. Controls fitted: log of population density, % STEM degrees, % employed in knowledge-intensive manufacturing, frac. index of birth country groups, % entry-level occupations, % long term unemployed, individual human capital control. Coefficients are marginal effects at the mean. * = significant at 10%, ** 5%, *** 1%.

Table 14. Negative binomial results for inventor productivity and co-ethnic groups: ethnicity measured by geographical origin zones, 1993-2004.

Inventor patent count	Marginal effect
Africa origin	-0.037*
	(0.022)
Americas origin	0.176
	(0.166)
Central Asia origin	0.045
	(0.055)
Central Europe origin	-0.003
	(0.014)
Diasporic origin	-0.019
	(0.014)
East Asia origin	-0.037***
	(0.007)
Eastern Europe origin	0.032
	(0.034)
Middle East origin	-0.008
	(0.025)
Northern Europe origin	0.001
	(0.045)
South Asia origin	0.025*
	(0.015)
Southern Europe origin	0.053*
	(0.040)
Frac Index of inventors, geog. origin groups	0.087**
	(0.042)
Controls	Y
Observations	88726
Log-likelihood	-23843.642
Chi-squared	4438.933

Source: KITES-PATSTAT/ONS/LFS
Notes: all models use time dummies. Robust standard errors clustered on TTWA. Controls fitted: log of population density, % STEM degrees, % employed in knowledge-intensive manufacturing, fractionalisation index of ONS ethnic groups, % entry-level occupations, % long term unemployed, urban TTWA dummy, individual human capital control. Coefficients are marginal effects at the mean. * = significant at 10%, ** 5%, *** 1%.

Table 15. Robustness checks using alternative human capital measures, negative binomial results.

Individual patent counts	(1)	(2)	(3)	(4)	(5)
Ethnic inventor, geog. origin	0.009 (0.007)	0.003 (0.004)	0.005 (0.004)		
Africa origin				-0.037* (0.022)	-0.020* (0.011)
Americas origin				0.176 (0.166)	0.028 (0.049)
Central Asia origin				0.045 (0.055)	0.016 (0.028)
Central Europe origin				-0.003 (0.014)	-0.001 (0.009)
Diasporic origin				-0.019 (0.014)	-0.008 (0.014)
East Asia origin				-0.037*** (0.007)	-0.016*** (0.006)
Eastern Europe origin				0.032 (0.034)	0.013 (0.022)
Middle East origin				-0.008 (0.025)	0.001 (0.016)
Northern Europe origin				0.001 (0.045)	0.014 (0.040)
South Asia origin				0.025* (0.015)	0.012* (0.009)
Southern Europe origin				0.053* (0.040)	0.024 (0.017)
Frac Index of inventors, geog. origin groups	0.087** (0.042)	0.050* (0.028)	0.055** (0.027)	0.087** (0.042)	0.055** (0.026)
Average patents pre-sample	0.101*** (0.007)		0.028*** (0.004)	0.100*** (0.007)	0.028*** (0.004)
Patents in >1 IPC7 field		0.217*** (0.010)	0.184*** (0.009)		0.183*** (0.009)
Controls	Y	Y	Y	Y	Y
Observations	88726	88726	88726	88726	88726
Log-likelihood	-23859.107	-22138.191	-21926.052	-23843.642	-21917.627
Chi-squared	2693.200	3670.001	5323.670	4438.933	6041.785

Source: KITES-PATSTAT/ONS/LFS

Notes: all models use time dummies. Robust standard errors clustered on TTWA. Controls fitted: log of population density, % STEM degrees, % employed in knowledge-intensive manufacturing, fractionalisation index of birth country / ONS ethnic groups, % entry-level occupations, % long term unemployed, urban dummy. Coefficients are marginal effects at the mean. * = significant at 10%, ** 5%, *** 1%.

Table 16. Robustness checks using diversity effects versus size effects, negative binomial results

Individual patent counts	(1)	(2)	(3)	(4)	(5)
Ethnic inventor, geog. origin	0.009 (0.007)	0.009 (0.007)	0.009 (0.007)	0.008 (0.007)	
Africa origin					-0.037* (0.022)
Americas origin					0.181 (0.163)
Central Asia origin					0.045 (0.055)
Central Europe origin					-0.003 (0.014)
Diasporic origin					-0.020 (0.014)
East Asia origin					-0.037*** (0.008)
Eastern Europe origin					0.032 (0.034)
Middle East origin					-0.008 (0.025)
Northern Europe origin					0.001 (0.044)
South Asia origin					0.024* (0.015)
Southern Europe origin					0.054* (0.041)
Frac Index of inventors, geog. origin groups	0.087** (0.042)		0.108*** (0.041)	0.191** (0.080)	0.189** (0.079)
% ethnic inventors, geog. origin as share of all inventors		0.068 (0.145)	-0.058 (0.138)	0.060 (0.121)	0.057 (0.121)
Frac index * % ethnic inventors				-0.676* (0.345)	-0.662** (0.336)
Controls	Y	Y	Y	Y	Y
Observations	88726	88726	88726	88726	88726
Log-likelihood	-23859.107	-23868.208	-23858.221	-23851.433	-23836.126
Chi-squared	2693.200	3064.329	2830.487	3853.584	5748.078

Source: KITES-PATSTAT/ONS/LFS

Notes: all models use time dummies. Robust standard errors clustered on TTWA. Controls fitted: log of population density, % STEM degrees, % employed in knowledge-intensive manufacturing, fractionalisation index of birth country / ONS ethnic groups, % entry-level occupations, % long term unemployed, urban dummy, individual human capital control. Coefficients are marginal effects at the mean. * = significant at 10%, ** 5%, *** 1%.

Table 17. Robustness checks using alternative historic patent stocks: influence on inventor productivity. Negative binomial results.

Individual patent counts	**(1)**	**(2)**	**(3)**
Ethnic inventor, geog.	0.009 (0.007)	0.008 (0.007)	0.008 (0.007)
Frac Index of inventors, geog. origin groups	0.087** (0.042)	0.083** (0.041)	0.067* (0.040)
Area historic weighted stock of patents, 1981-1984	-0.000 (0.000)		
Area historic weighted stock of patents, 1985-1988		-0.000 (0.000)	
Area historic weighted stock of patents, 1989-1992			0.000 (0.000)
Controls	Y	Y	Y
Individual human capital	Y	Y	Y
Observations	88726	89196	89268
Log-likelihood	-23859.107	-23994.163	-24030.991
Chi^2 fit statistic (Wald)	2693.200	2720.995	2865.519

Source: KITES-PATSTAT/ONS/LFS
Notes: All models use time dummies. Controls fitted: log of population density, % STEM degrees, % employed in knowledge-intensive manufacturing, fractionalisation index of area birth country groups, % entry-level occupations, % long term unemployed, urban TTWA dummy. Heteroskedasticity and autocorrelation-robust standard errors clustered on TTWA. Coefficients are marginal effects at the mean. * = significant at 10%, ** 5%, *** 1%.

Table 18. Sample construction test for multiple inventor sub-sample, 1993-2004. Negative binomial results.

Individual patent counts	All, zeroed	Multiple, zeroed		Multiple, blanked	
	(1)	(2)	(3)	(4)	(5)
Ethnic inventor, geographic origin	0.009	-0.095	-0.093	-0.095	-0.093
	(0.007)	(0.110)	(0.110)	(0.110)	(0.110)
Frac Index of inventors, geog. origin groups	0.087**	0.856	4.103**	0.856	4.103**
	(0.042)	(0.575)	(2.057)	(0.575)	(2.057)
Urban TTWA	-0.021	-0.170		-0.170	
	(0.015)	(0.134)		(0.134)	
Log of TTWA population density	0.005	0.025	0.056	0.025	0.056
	(0.007)	(0.058)	(0.072)	(0.058)	(0.072)
Frac Index * log population density			-0.579		-0.579
			(0.370)		(0.370)
Controls	Y	Y	Y	Y	Y
Observations	88726	4842	4842	4842	4842
Log-likelihood	-23859.107	-8526.503	-8527.051	-8526.503	-8527.051
Chi-squared	2693.200	173.503	185.897	173.503	185.897

Source: KITES-PATSTAT/ONS/LFS
Notes: All models use time dummies. Controls fitted: log of population density, % STEM degrees, % employed in knowledge-intensive manufacturing, fractionalisation index of area birth country groups, % entry-level occupations, % long term unemployed, urban TTWA dummy, individual human capital control. Heteroskedasticity and autocorrelation-robust standard errors clustered on TTWA. Coefficients are marginal effects at the mean. * = significant at 10%, ** 5%, *** 1%.

Table 19. Distributional effects of minority inventors on majority inventor productivity, 1993-2004. Individual level results

Native patent counts	(1)	(2)	(3)
Frac Index of inventors, geog. origin groups	-0.069 (0.097)	-0.057 (0.077)	0.072* (0.041)
Controls	N	N	Y
Individual fixed effects	N	Y	Y
Observations	83672	83672	83098
Log-likelihood	-23726.567	-23236.532	-22334.827
Chi^2 fit statistic (Wald)	343.508	628.231	2536.289

Individual patent counts	(1)	(2)	(3)
UK inventor	-0.010 (0.008)	-0.009 (0.007)	0.027*** (0.008)
Frac Index of inventors, geog. origin groups		0.087** (0.042)	0.253*** (0.077)
UK * Frac Index			-0.172*** (0.056)
Controls	Y	Y	Y
Observations	88726	88726	88726
Log-likelihood	-23870.231	-23859.107	-23852.425
Chi^2 fit statistic (Wald)	3421.238	2693.200	2866.909

Source: KITES-PATSTAT/ONS/LFS
Notes: All models use time dummies. Controls fitted: log of population density, % STEM degrees, % employed in knowledge-intensive manufacturing, fractionalisation index of area birth country groups, % entry-level occupations, % long term unemployed, urban TTWA dummy, individual human capital control. Heteroskedasticity and autocorrelation-robust standard errors clustered on TTWA. Coefficients are marginal effects at the mean. * = significant at 10%, ** 5%, *** 1%.

Table 20. Distributional effects of minority inventors on majority inventor productivity, 1993-2004. Area level results

% change in total weighted patents, 1993-2004	(1)	(2)	(3)	(4)	(5)
% change in weighted ethnic patents, 1993-2004	0.199*** (0.065)	0.259*** (0.066)	0.248*** (0.068)	0.248 (0.177)	0.259 (0.178)
Controls	N	Y	Y	Y	Y
OST7 technology field dummies	N	N	Y	Y	N
HAC standard errors	N	N	N	Y	Y
Observations	220	220	210	210	206
F-statistic	9.299	1.467	3.646	1.144	0.966
R^2	0.041	0.041	0.141	0.141	0.151

Source: KITES-PATSTAT/ONS/LFS

Notes: All models use time dummies. Controls fitted: log of population density, % STEM degrees, % employed in knowledge-intensive manufacturing, % migrant working-age population, % entry-level occupations, % long term unemployed, urban dummy. Technology field dummies cover OST7 fields 1 -6: electrical engineering and electronics; instruments; chemicals and materials; pharmaceuticals and biotechnology; industrial processes; mechanical engineering, machines and transport. Consumer goods and civil engineering patents are used as the reference category. * = significant at 10%, ** 5%, *** 1%.

Does Cultural Diversity help Firms to Innovate? Evidence from London

1. Introduction

This chapter continues to examine connections between migrants and minority communities, diversity and innovation. It focuses on the firm and on individual entrepreneurs; it also focuses on the experiences of a single city, London.

As we know innovation is an important driver of long-term national economic growth and an important goal of policy intervention (Schumpeter, 1962, Romer, 1990). Cities and urban economic diversity enable innovative activity (Jacobs, 1969). A growing body of evidence also suggests that *culturally* diverse cities may be more innovative, as they benefit from a wider range of international links, diverse decision-making and being able to attract more innovative people (Niebuhr, 2006, Peri, 2007, Hunt and Gauthier-Loiselle, 2008, Ozgen et al., 2010). The last chapter found limited evidence that urban diversity helps *patenting*; this chapter explores a much large set of invention and diffusion measures.

Diversity-innovation effects should largely operate at individual, group or firm level, but will be amplified in an urban context (Berliant and Fujita, 2009). Yet as far as we are aware, no research has so far considered the impact of cultural diversity on innovation within firms in a highly diverse city. This paper looks at urban cultural diversity and innovation in detail, using a unique sample of 7,600 businesses in London. The UK capital is one of the world's major cities and one of its most culturally diverse – in terms of country of birth, language and ethnicity. London is substantially more diverse than 20 years ago: its cosmopolitanism is seen as a social asset. Does it help London firms to innovate?

Existing theory and evidence suggest that diversity-innovation channels for firms may run both ways. Culturally diverse teams may be better at generating new thinking or problem solving, particularly in knowledge-intensive environments (Fujita and Weber, 2003, Page, 2007). Through diasporic networks, migrant or minority staff and business owners can access additional upstream and downstream markets, assisting process innovation and the commercialisation of new ideas (Saxenian, 2006). But diverse organisations may also face higher communication costs, lower trust and discrimination, all of which will hold back innovation (Alesina and La Ferrara, 2004).

More generally, 'ethnic entrepreneurs' are argued to play a number of critical roles in urban innovation. They are seen as more likely to develop new ideas (Stephan and Levin, 2001) and can act as 'reputational intermediaries' between firms in different countries (Kapur and McHale, 2005). Conversely, minority ethnic communities may be excluded from mainstream economic opportunities (Gordon et al., 2007).

At city level, urbanisation economies may aid access to international markets; conversely, large and diverse domestic markets provide more opportunities for product hybridisation (Mazzolari and Neumark, 2009). In both cases diverse firms may be best placed to take advantage of these processes.

We use London as a test case for exploring these issues. We use data from London Annual Business Survey (LABS), using repeat cross-sections from 2005 to 2007. We exploit the survey's unique structure to look at links between the ownership characteristics of firms in London, the extent to which they innovate, the importance of these innovations and firms' success in commercialising them. We make use of the natural experiment conditions created by A8 accession in 2004, a policy shock that led to a large increase in net migration to the UK, and London in particular.

Our results suggest small but robust positive effects of management diversity on the development of new products and processes. In contrast to the wider literature, we find diversity-innovation effects in both high-value knowledge-intensive sectors and in 'ordinary' innovations in less knowledge-intensive activity. London's large and diverse home markets, diasporic communities and international connectivity play important roles, as do entrepreneurial migrant business owners.

Our results pass a series of robustness tests, although the cross-sectional structure of the data means that firm-level reverse causation cannot fully be ruled out. Since this likely creates upward bias, our preference is to treat the main results as upper bounds. Overall, our findings suggest a small but significant 'diversity effect' and support claims that London's cultural diversity acts as an economic asset. As far as we know, these are new findings for the UK, and the first research exploring firm-level diversity-innovation effects in an urban context.

The paper is structured as follows. The next section sets out motivation and background for the research. Section 3 frames the ways in which urban cultural diversity may influence innovation. Sections 4 and 5 introduce data, descriptives and estimation strategy. Section 6 summarises our main results. Sections 7 and 8 set out extensions and robustness checks. Section 9 concludes and makes suggestions for further research.

2. Background and motivation

This paper asks the question: what effect, if any, does the cultural diversity of London's businesses have on their innovative activity? It looks at different aspects of diversity and innovation, focusing on the roles of management, owners and business partners in the capital.

2.1 Defining terms

Both 'cultural diversity' and 'innovation' are complex concepts and need careful definition. We follow the common definition of innovation as 'the successful exploitation of new ideas' (Department of Innovation Universities and Skills, 2008). Innovative activity is generally held to involve both ideas generation and the commercialisation of those ideas, both around new products and new processes (Fagerberg, 2005). Individual entrepreneurs and entrepreneurial individuals within larger organisations are essential to the innovation process (Schumpeter, 1962). As a determinant of technical change and thus total factor productivity, innovation helps shape overall national productivity: innovative firms' discoveries permeate across the economy as a whole (Faggian and McCann, 2009). Our data allow us to look at both the generation of new products and processes, and – to an extent – their commercialisation.

Cultural or ethnic diversity is harder to pin down.[50] It is a multifaceted concept, with subjective elements, and with categories that alter over time (Office of National Statistics, 2003). The key dimensions include kinship, religion, language, shared territory, nationality and appearance (Bulmer, 1996). Group membership 'is something that is subjectively meaningful to the person concerned'. And both culture and ethnicity are 'context-driven social and psychological concepts' whose meaning may shift as society evolves (Aspinall, 2009).

For these reasons, attempts to quantify cultural diversity generally lose something in the process. We focus on two specific measures, diversity of country of birth and mix of ethnic group, which are widely used in the literature as proxies for diversity generally. As a proxy for identity, country of birth has the advantage of being objective, but is one-dimensional and does not capture established minority communities. Ethnic groups attempt to combine different aspects of diversity, but operate at a very high level of generality (Mateos et al., 2007). Ethnicity classifications also focus on classifying 'visible

[50] For the purposes of this paper, we use 'cultural diversity', 'ethnic diversity' and 'diversity' interchangeably.

minorities' such as Black and Minority Ethnic (BME) groups, without looking at ethnicity more broadly.

There are two potential problems with using these diversity proxies. First, if we believe identity is entirely self-ascribed, it becomes very hard to link behaviour to our measures (Casey and Dustmann, 2009). This may affect measures based on ethnic groups, which are partly self-ascribed. However, it is difficult to think that (for example) commercial success might lead business owners of South Asian origin to identify as 'White British'. So we are relatively confident 'identity uncertainty' is not a major source of bias.

The second issue is that country of birth and ethnic group are distinct but overlapping: some migrants will be members of BME groups, and some recent minority communities may be largely non UK-born. In London the overlap is greater than in many other British cities. In the late 1990s and again from 2004, the UK experienced two large jumps in net migration. Many 'new migrant communities' have developed (Kyambi, 2005). This means that the capital's current cultural diversity is largely driven by migrants from visible minorities, alongside groups captured in the 'other' category.[51] For example, Labour Force Survey data shows pairwise correlation between migrant and minority working-age population shares in Greater London is over 95% (Gordon et al., 2007).

Bearing in mind the caveats above, we feel justified in using both country of birth and ethnic group as interchangeable proxies for London's cultural diversity. However, we highlight individual diversity channels likely to be specific to migrant or minority-ethnic groups and explore a number of migrant-specific processes.

2.2 Wider context

Links between diversity, cities and business success matter for policymakers, both in London and at national level. The UK's productivity gap with competitor countries – particularly the US – is an area of major policy concern. Innovation and entrepreneurship were two of the previous Government's 'five drivers of productivity' (Department of Innovation Universities and Skills, 2008); the current Coalition has maintained a focus on innovation-led growth (HM Treasury and BIS, 2011). There is also a political consensus that growing diversity brings economic benefits, although there is disagreement about longer-term effects (Home Office and Department of Work and Pensions, 2007, House of Lords Economic Affairs Committee, 2008).

[51] In 2008, the 10 largest country of birth groups in UK cities were (in order of population share): Poland, India, Pakistan, Germany, Eire, Rep. South Africa, Zimbabwe, Bangladesh, and USA (Nathan 2009).

Urban areas also play a number of important roles in the UK. They are the locus of most people and economic activity (Parkinson et al., 2006). Increasing returns in cities confer productivity payoffs and help support innovative activity (Glaeser, 2008), although the subsequent contribution of innovation to urban growth is less clear-cut (Christopherson and Clark, 2007). British cities also contain the vast majority of the UK's migrant and minority populations (see previous chapters).

London is our test case: it exemplifies the idea of the cosmopolitan world city. The UK capital is one of the original 'global cities' (Sassen, 1991). Alongside New York, London remains a hub of the global financial system (Gordon et al., 2009). The capital dominates the UK economy: in 2006-7 it contained around 13% of the UK population but contributed nearly 20% of national GVA (Gordon et al., 2007). London is also one of the most culturally diverse cities on the planet (Burdett and Sudjic, 2011). Over the past 15 years it has become substantially more cosmopolitan, both by receiving the majority of new UK migrants and via the emergence of settled new communities in the city. As Guardian journalist Leo Benedictus (2005) wrote in a recent survey:

> *London in 2005 is uncharted territory. Never have so many different kinds of people tried living together in the same place before. What some people see as the great experiment of multiculturalism will triumph or fail here.*

London's schoolchildren speak over 300 languages (Baker and Eversley, 2000). In 2006, London contained 40% of the UK migrant population (Greater London Authority, 2008b). At least 50 'new migrant' communities with over 10,000 members live here (Benedictus, 2005). The city's cultural diversity is widely seen as an economic strength, by national and city government as well as London's business community (Home Office and Department of Work and Pensions, 2007, Greater London Authority, 2008a, London First, 2008).

In particular, London's diversity is seen as driving forward ideas generation and the emergence of new products and services (Legrain, 2006, Leadbeater, 2008). London's service-dominated economy means that it performs poorly on traditional innovation metrics, such as research and development spending or patenting activity (Wilson, 2007). So there is considerable interest in aspects and drivers of innovative activity in the city.

3. Diversity, innovation and business performance

Recent years have seen increasing interest in the links between aspects of urban diversity and cities' economic performance. A number of studies find that innovative activity is spatially concentrated, suggesting that cities and regions have an important role to play in fostering innovation by firms (Jaffe et al., 1993, Zucker et al., 1998). Spatial clustering seems to reflect localised knowledge spillovers (Storper and Venables, 2004); sectoral composition (Griffith et al., 2006); the presence of both very large firms and small businesses (Kelley and Helper, 1999); and concentrations of skilled workers (Faggian and McCann, 2009).

Economic diversity is related to urban innovation. Increasing returns in cities are linked to economically diverse environments (Jacobs, 1969, Glaeser et al., 1992); embryonic firms can benefit from diverse 'nursery cities' (Duranton and Puga, 2001). There is also some suggestive evidence that *cultural* diversity plays a role in enabling innovation in urban areas. Peri (2007) finds that US states' share of foreign-born PhDs is positively associated with levels of patenting; Niebuhr (2006) finds a positive link between the diversity of German regions and regional innovation, with a stronger effect for the diversity of highly skilled employees. Most recently, Ozgen et al (2010) find the diversity of migrants helps drive patenting rates in European NUTS2 regions.

These studies throw up obvious questions about how diversity effects may operate at the *firm level* in urban areas. In theory, the effects of diversity in firms are ambiguous on innovation. The introductory chapter summarises the four main ways in which firm-level diversity may influence innovative activity, two positive and two negative. The material below provides a more detailed discussion, plus relevant empirical results.

3.1 Diversity and innovation: firm-level processes

First, diverse workforces may be more effective than homogenous workforces in problem solving or generating new ideas – and thus for product and process innovation. 'Cognitively diverse' teams leverage a wider pool of perspectives and skills.[52] Crucially, cultural diversity is a good proxy for cognitive diversity (Page, 2007). Hong and Page (2001, 2004) show that in experiments with large teams of problem-solvers, the best problem-solvers often come up with similar solutions. So a diverse group may outperform a homogenous group, even if the latter have higher ability. These dynamics may be

[52] Page (2007) suggests that given a group of predictive models, the greater the diversity of modellers, the smaller the chances of error. This also implies that in some circumstances, the diversity of the problem-solving group is more important than individual talent.

particularly important in research-based or knowledge-intensive activities (Fujita and Weber, 2003). This has been modelled formally by Berliant and Fujita (2009) who show how in a system of firm-level knowledge creation worker heterogeneity can accelerates ideas generation through individual-level production complementarities.

Second, diverse firms may have access to diasporic networks, which confer externalities. Co-ethnic networks may reduce information and communication costs as knowledge is exchanged through groups with greater mutual understanding and trust (Rodríguez-Pose and Storper, 2006). This means firms with diaspora connections may have better access to international upstream and downstream markets. Access to 'global pipelines' should help firms to innovate, via access to new ideas and improvements to supply chains or production functions (Bresnahan and Gambardella, 2004).

Third, and conversely, diverse teams may find it harder to communicate, and levels of trust may also be lower (Alesina and La Ferrara, 2004). As a result, organisations may find it harder to make decisions or allocate resources, and the quality of those decisions may be lower than in more homogenous organisations. This will negatively affect both ideas generation and commercialisation activity.

Fourth, migrant and minority-owned firms may face additional constraints in the marketplace. They may have greater difficulty in raising finance, for example, finding affordable space or developing client relationships. These reflect management and product quality, but may also be the result of lack of connections into mainstream economic institutions or discrimination (Gordon, 2001). Lockout will make commercialisation harder. It is also likely to be a problem for minority-ethnic owned businesses.

Cultural diversity is thus good for firm performance if its on-going benefits outweigh initial disadvantages (Lazear, 1998).[53] Empirical evidence comes from the management literature, case studies and organisation-level research. The management literature broadly suggests diversity in firms is a net benefit. In a study of 165 Swiss firms, Nielsen finds that nationality mix in top management teams is linked to higher rates of foreign market entry and to higher firm profitability (Nielsen, 2010, cited in Hart (2010)).

In turn, Hart analyses 24,000 'high-impact' US firms, finding suggestive evidence that team diversity is linked to employment (used here as a rough proxy for business

[53] Firms which are wholly run by members of a single migrant / minority community should benefit from the second channel, but may lose from the fourth. We test for this separately in section six.

success). Wider reviews of the evidence find that there is a small but significant workplace 'diversity advantage' (Page, 2007, Landry and Wood, 2008). Negative communication and trust effects are often present in organisations, but are outweighed by positive effects of diversity over time. So younger firms may find it harder to knit diverse teams together.

More broadly, there is international evidence that diasporas can engage in innovative activity. Saxenian (2006) and Saxenian and Sabel (2008) provide detailed evidence on the roles of migrant diasporas in Silicon Valley, which have strong links to production clusters in India, Taiwan and (increasingly) China. Similarly, Kapur and McHale (2005) and Kerr (2008b) detail the influence of diasporas in ICT clusters across Ireland, Israel and South East Asia. Foley and Kerr find evidence that access to diasporas helps US firms 'globalise' their activities, for example by forming new affiliates abroad (Foley and Kerr, 2011).

There are still very few empirical studies looking specifically at diversity and innovation at firm level. Ozgen et al (2011) find some positive links between migrant worker share, workforce diversity and innovation in knowledge-intensive Dutch firms. In Denmark, Parotta and colleagues (2011) find significant positive effects of cultural diversity on firms' propensity to innovate – but again, only in 'white collar' sectors employing predominantly skilled workers. But Maré et al (2011) find no systematic links between workforce characteristics and innovation among businesses in New Zealand.

3.2 City-level effects

There will also be city-level channels linking innovation and diversity, which may amplify the firm-level effects on both products and processes. For example, if cultural diversity contributes to economic diversity, it may help foster knowledge spillovers across sectors (Jacobs, 1969). Specifically, diverse urban populations may demand a greater variety of goods and services, particularly in non-traded sectors. This will be driven both by the presence of new communities, and in some cases by shifting preferences in the majority population (Gordon et al., 2007). The more cosmopolitan the environment, therefore, the greater the potential for hybridisation. In principle, there is no reason why any firm should not be able to take advantage of these opportunities. In practice, diverse firms may be better placed to spot and act on emerging opportunities.

A few studies have investigated these city-level effects. Hunt and Gauthier-Loiselle (2008) find that immigrant population shares raise levels of patenting at the state level, and that state-level effects are greater than individual-level effects – suggesting some interaction between diversity, urban co-location and knowledge spillovers. Immigration is positively associated with an increased range of restaurants in California (Mazzolari and Neumark, 2009). And UK case studies highlight the role of migrant communities in the emergence of new sub-sectors of retail and leisure (Smallbone et al., 2006).

3.3 'Ethnic entrepreneurs'

Schumpeter (1962) highlights the importance of 'the entrepreneurial function' in fostering innovation. Individual entrepreneurs push against social inertia, identifying and commercialising new ideas through new firm formation; 'collective entrepreneurship' in large organisations plays a similar function within the firm.

Research on diversity and innovation places similar emphasis on so-called migrant or 'ethnic entrepreneurs'. Migration decisions reflect both expected returns and the taste for risk-taking. So migrants may be highly entrepreneurial, and more likely to look for and develop new products (Wadhwa et al., 2007). Ethnic entrepreneurs can also act as 'reputational intermediaries', forging partnerships and helping new processes (Kapur and McHale, 2005, Saxenian and Sabel, 2008, Honig et al., 2010).

Empirical evidence on ethnic entrepreneurship is mixed. Some migrant and minority communities make disproportionate contributions to knowledge creation in US science and high-tech sectors (Stephan and Levin, 2001). Migrants account for a disproportionate number of start-ups in US regions like Silicon Valley and the Raleigh-Durham Triangle (Wadhwa et al., 2007). More prosaically, UK case studies have highlighted the role of migrant communities in retail and leisure hybridisation, as migrants create new products influenced by their backgrounds and tailored to the needs of particular groups (Henry et al., 2002, Jones et al., 2004, Ram and Jones, 2008, Kitching et al., 2009). But levels of self-employment seem to vary by migrant group, host country and class structure (Basu, 2002, Basu, 2004, Nakhaie et al., 2009).

The phenomenon of ethnic entrepreneurship suggests a research focus on business owners and partners. But it also makes it harder to identify the specific role of *cities*: we need to test for positive and negative selection bias, in case diversity-innovation effects are actually explained by the individual characteristics of the entrepreneurs.

3.4 The 'Creative Class' and diversity

An alternative explanation for these results comes from 'Creative Class' theory (Florida, 2002). Florida suggests that liberal, tolerant skilled workers are now the driving force of Western economies. This group is attracted to diverse firms and environments. The Creative Class is largely responsible for knowledge creation, so that culturally diverse firms will be more innovative – although diversity itself may have no direct effect. It is plausible that in a consciously cosmopolitan city like London, at least some of the workforce is deliberately seeking a diverse milieu. However, Creative Class approaches have been criticised for their theoretical foundations (Glaeser, 2005), and appear to lose predictive power in the UK (Nathan, 2007).

4. Data and descriptives

Our main dataset is the London Annual Business Survey (LABS), an annual survey of firms conducted across the London region ('Greater London') by the London Development Agency (LDA).[54] The questionnaire asks a range of questions covering firm formation, workforce and management characteristics, firm performance and constraints. Until very recently, the survey was the UK's only single firm-level source of information about organisational characteristics, business innovation and performance.

In a previous paper we conducted preliminary analysis of 2007 LABS data (Lee and Nathan, 2010). In this paper we improve the analysis in a number of ways. First, we pool together cross-sections from 2005-2007 inclusive. This allows us to significantly increase the sample size to 7,615 firms. Second, although the sample is a repeated cross-section, we are able to use time-consistent industry codes to construct year and industry fixed effects (at three-digit SIC level).[55] Both steps will improve the precision of our estimates.

Third, we explore the natural experiment conditions created by A8 accession in 2004. An obvious objection to our approach is that both firms' innovative activity and workforce composition might be affected by external factors not captured in firm-level data. This could be a shock to the London economy that simultaneously influences innovation

[54] The LDA was one of nine Regional Development Agencies (RDAs) in England established in 1998. The RDAs were abolished in early 2011; the LDA's functions have transferred to the Greater London Authority.
[55] We restrict the sample to SIC3 sectors represented in all three years. Sectors excluded include agriculture, forestry and hunting; fishing; mining and quarrying; and secondary manufacture related to these sectors, such as food processing.

and diversity; or the positive selection problem discussed in previous chapters, where London's historic economic performance results in a larger, more diverse workforce.

The 'policy shock' of A8 accession provides a way around these problems. Policy choices made by the UK government of the time led directly to a very large, exogenous rise in net immigration to London and other cities from a particular set of sending countries, which subsequently increased both the number of migrant /minority groups in London, and their relative sizes. It thus exogenously raised levels of diversity in the city – and hence firm-level diversity – for reasons independent of the level of innovative activity in those firms. It thus helps address the concern that causality runs from innovation *to* diversity rather than vice-versa.

Specifically, eight Central and East European countries (the 'A8') joined the European Union in 2004. All existing member states apart from the UK and Sweden placed heavy restrictions on potential A8 migrants (notoriously, studies commissioned at the time by the UK Home Office suggested entry numbers would be very small). However, the lack of entry barriers then prompted very large immigration flows from A8 countries to the UK. Overall, Britain experienced one of the largest increases in net migration since World War II, of which London received the lion's share (Economist, 2006). These inflows significantly increased London's diversity by growing both the number of overall migrant groups and their relative sizes. Inflows began falling during the second half of 2008 as national economic conditions declined (Office of National Statistics, 2008b).

For all these reasons, LABS data allows us to explore diversity-innovation mechanisms in previously unavailable detail. However, focusing on London may limit the external validity of our results: the city's economy and demography are significantly different to other parts of the UK. We discuss this further in the concluding section.

4.1 Diversity measures

The data structure allows us to construct multiple diversity measures from LABS' coverage of ownership characteristics, country of birth and ethnicity. Our principle measures are proxies for different aspects of diversity, specifically the mix (or otherwise) of owners / partners.

Our first dimension is country of birth. We begin by defining 'migrant-diverse' firms as companies with a mix of UK-born and foreign-born owners / partners. Second, we define 'migrant firms' as those with all foreign-born owners / partners: in over 92% of cases these come from a single ethnic group. Finally we define ‘UK firms’ as those with no migrant owners / partners. We fit dummies for all three types of firms, taking the value 1 if the firm falls into the relevant category.

Our second dimension is the Office of National Statistics ethnic groups typology. We build a dummy for ‘ethnic diverse’ firms derived from Q16a in LABS, ‘whether at least half the owners are White British’. We define the variable so it takes the value 1 if at least half the owners are not White British, i.e. from minority ethnic groups. Because we are unable to precisely identify whether ‘ethnic diverse’ firms are wholly minority-run, we use this as a cross-check for our preferred migrant-based measures.

4.2 Innovation and commercialisation measures

We develop a number of innovation measures covering both ideas generation and commercialisation activities, and product and process innovations. Our first set of dependent variables cover aspects of ideas generation and adoption. We term these ‘innovation’ variables. We construct four dummies taking the value one if the firm has a) introduced a major new product or service in the past 12 months; b) significantly modified its product range or services during the year; c) introduced major new equipment, or d) introduced major new ways of working during the year.

These variables cover important aspects of innovation – the introduction of new products and processes. However, they have two important limitations.[56] First, although they focus on ‘major’ changes they do not attempt to directly rank the quality or importance of innovations. We can indirectly put a value on innovative activity by observing the kind of firm that innovates. Specifically, we are able to identify ‘knowledge-intensive’ and ‘non-knowledge-intensive’ firms using OECD definitions refined by The Work Foundation. The former include pharmaceuticals, electronics, software, finance and business services; the latter include low-tech manufacturing, retail, and personal and protective services.[57] We also identify innovation by ‘knowledge-intensive business services’ or KIBS, which may better represent the knowledge economy in a service-based city like London (Wood,

[56] Just as with patents data, there are some caveats with innovation survey data. Smith (2005) highlights the danger of ‘response bias’ towards innovating firms, and the difficulty of constructing survey questions that can capture the very different innovation processes across manufacturing and service sector firms. LABS deals with the latter by applying very broad definitions of ‘innovation’ in questions asked. It may thus risk capturing some trivial innovations, especially around ‘new ways of working’. Results from this measure should be interpreted carefully.

[57] The Work Foundation follows the OECD definition of knowledge-intensive industries, but adjusts for the UK context (Brinkley 2008). The final list of 3-digit SIC sectors includes medium and high-tech manufacturing (pharmaceuticals, aerospace, computers and office machinery, electronic communications, software, other chemicals, non-electrical machinery, motors and transport equipment) plus a range of ‘knowledge services’ (post and telecoms, business services, finance and insurance, education, health, recreational and cultural activities).

2006).[58] We suggest that firms in knowledge-intensive or KIBS sectors are more likely to deliver ‘high-value’ innovations. By contrast, firms in less knowledge-intensive industries are generally more likely to conduct ‘ordinary’ innovation.

Second, the basic measures also take no account of whether implementation has been successful. We construct measures of commercialisation to account for this. A commonly used proxy for commercialisation is rapid revenue growth: innovation researchers define ‘high-growth’ or ‘gazelle’ companies as those achieving annual turnover growth of 20% or more (Council on Competitiveness 2005). LABS provides limited turnover information in bands, so we define high-growth firms as companies in the sample that have achieved annual revenue growth of 10% or more. Just over 36% of firms are ‘high-growth’ by this definition (see below). This is a weaker definition than is commonly used in the literature, and may reflect other factors feeding revenue growth (such as a change in tastes).

We then construct four dummy ‘commercialisation’ variables that take the value one if firms have innovated along each of the dimensions a) to d) above, *and* seen annual revenue growth of at least 10%. Given the complex nature of much innovative activity in London, not many companies will be able to commercialise ideas at such a rapid rate. We therefore conduct some robustness checks using alternative commercialisation measures.

4.3 Descriptives

Descriptive statistics are given in Table 1: we briefly discuss some key variables here and return to controls in the next section.

The first panel of Table 1 covers innovation variables. Depending on the variable selected, between 25-30% of firms in the sample engaged in some kind of product or process innovation (for example, 31.4% of firms introduced a major new product or service). Just over 36% of firms are ‘gazelles’, and as expected, fewer firms were able to successfully commercialise new ideas (less than half the number who innovated around products or processes). The first panel also shows, for a subset of firms, the share of company turnover from new products and processes during that year. As only a minority of respondents answered this question we reserve it for robustness checks.

[58] We use the definition of KIBS from Wood (2006). The mix of 3 and 4-digit SIC sectors includes financial intermediation, insurance and pension funding, auxiliary financial activities, real estate, legal, accountancy, hardware / software consultancy, data processing / database activities, advertising, market research, business / management consulting, architecture and engineering, technical testing, research and development.

The second panel covers diversity variables, and reflect London's rich people mix. Over 39% of firms have at least one migrant owner / partner: 18% are 'migrant diverse', with a mix of UK-born and migrants, and 21.3% are 'migrant firms' with all migrant owners / partners. Looked at it another way, of the firms with at least one migrant owner / partner, 53% are migrant-run. Around 21% of firms are 'ethnic diverse', i.e. have at least half owners/partners from minority ethnic communities.

The third panel shows that are 3594 'knowledge-intensive' firms, around 48% of the sample. The smaller set of KIBS firms make up 19% of the sample. Table 2 expands on this, breaking down levels of innovation by firm type. In the first instance we divide firms into knowledge intensive and non-knowledge intensive groups, following the OECD definitions above. As expected, in almost all cases knowledge intensive firms are more likely than average (and non-knowledge intensive firms) to engage in innovative activity, and more likely to successfully commercialise their ideas. On this basis, innovation in London's firms is more likely to be 'important' than 'ordinary'.

We then disaggregate knowledge-intensive firms into the subset of KIBS firms. KIBS firms are also more likely than average to engage in product innovation (although not process innovation) and to commercialise innovations. Interestingly, KIBS firms are slightly less likely to innovate than the set of knowledge-intensive firms. However, they are slightly more likely to successfully commercialise their innovations.

5. Estimation strategy

The descriptive analysis shows that London's cosmopolitan population is matched by a diverse workforce, and indicates sectoral differences in innovative activity. Our data allows us to explore links between firms' characteristics, their innovative activity and the commercialisation of innovations.

We develop a simplified firm-level knowledge production function (KPF), linking the probability of innovative activity occurring to a diversity measure, firm-level controls, and sector, industry and year effects. Widely used to measure the innovative capacity of nations and regions (Griliches, 1979, Cooke et al., 1997) the KPF approach makes intuitive sense at firm level, where a range of business inputs (human and physical capital) are put to work generating new products and processes (innovations); these processes being influenced by other firm-level characteristics (age, size, sector and so on).

For firm *i* in year *t*, we estimate:

$$\Pr(Y_{it} = 1) = a\mathrm{DIV}_{it} + \mathbf{CONTROLS_{it}}\boldsymbol{b} + \mathrm{SECTOR}_i + \mathrm{YEAR}_t + e_i \quad (1)$$

Where Y is variously one of our measures of ideas generation or commercialisation, as described above; DIV is the variable of interest, and covers whether firms are migrant diverse, ethnic diverse or migrant-only. CONTROLS represents a set of control variables. SECTOR and YEAR are dummies for SIC3 sectors and years, respectively

Controls draw on the literature on firm-level innovation: descriptives are provided in the third panel of Table 1. Levels and types of workforce diversity and innovation are likely to vary by sector (Glaeser, 2005). Diversity-innovation 'effects' may therefore simply reflect sectoral specificities, particularly in the knowledge-intensive services which dominate high-value activity in the London economy. These issues are dealt with via sectoral fixed effects, and an additional dummy which takes the value one if a firm is part of the knowledge-intensive business services subsector (KIBS).

Apparent diversity-innovation relationships may also be generated through firm age and/or size. For example, large or established firms often generate large amounts of patent activity, but small, often new firms may introduce disruptive innovations (Griffith et al., 2006). By default of having larger workforces, bigger firms may also have more diverse teams; but younger firms may be more likely to have diverse or migrant/minority managers. Following initial diagnostics, we fit the log of age, and the log and log squared of firm size. We also fit a dummy for company type: firms that are Public Limited Companies (PLCs) may be more innovative since they need to satisfy shareholder value.

We complete the model with dummies for exports, collaborative activity and R&D spending, plus further controls for human capital and management ability. There is an established literature on 'open innovation' and collaboration (Von Hippel, 2005); the role of human capital and R&D in innovation is well established (Audretsch and Feldman, 1996). Each of these factors may influence firm-level diversity as well. Companies that export or collaborate internationally may actively seek to hire diverse workforces. Equally, firms engaging in R&D may be more diverse if, as some evidence suggests, particularly ethnic groups dominate categories of skilled research activity (Stephan and Levin, 2001).

Unfortunately LABS has no information on workforce human capital (such as the share of a firm's employees with higher educational qualifications).[59] However, the survey provides detailed information on management experience and qualifications (shares of firms' managers with previous experience, formal qualifications, on-the-job training or with completed in-work management courses). We fit all four as controls for management ability.[60] All should be positively correlated with innovative activity.

We estimate the model as a conditional logit. This estimator allows data to be grouped by sector, so better handles sector-specific, time-invariant effects. All specifications use HAC standard errors clustered on SIC3 sector.

5.1 Identification challenges

As noted earlier, using London-only data may limit external validity – an issue we return to at the end of the paper. There are also several internal validity challenges. First, an apparent diversity effect might turn out to be something else, such as human capital or sectoral characteristics. We deal with this through careful model specification (in these two instances, four distinct human capital controls and a complete set of three-digit sectoral dummies). Second, an external economic shock might cause levels of diversity and innovative activity to rise at the same time. The natural experiment conditions reduce the risk of simultaneity and positive selection at *city level*, a common problem in studying the local economic effects of migration and diversity (Borjas, 1994).[61]

Two further issues are harder to deal with. Although city-level positive selection is minimised by the choice of years, individual migrant and minority owners/partners may still be positively or negatively selected (see section 3). There also is potentially both-ways causation at firm level: current innovative activity influence workforce characteristics (if more successful firms attract or recruit a more diverse workforce). For the first of these we conduct separate robustness tests, using a subset of company founders. In the second case we use shift-share instruments to check causality. See section 8 for further details.

[59] We experiment with a crude proxy by interacting the number of employees in the firm with the relevant industry-level share of graduates, assuming that bigger firms of a given industry type will employ a larger number of skilled workers. F-tests suggest the control makes little difference to overall model performance, so we exclude it from the final specification.
[60] Controls pass Wald and LR tests of joint significance. We also experiment with an index of management ability using principal components analysis. The Index has a strong positive relationship with innovative activity; however, for easier interpretation we prefer to use separate controls.
[61] If migrants choose to live in cities with the best economic performance, measures of economic success (such as innovation) might be correlated with higher diversity, even though the latter may have no causal effect. By choosing a period where London's diversity was largely set by exogenous policy factors, we minimise this risk. However, we cannot fully eliminate the risk that deeper structural factors may simultaneously influence both diversity and economic performance (such as London's historic position as a large and cosmopolitan milieu).

6. Main results

The main results of the analysis are set out in Tables 3 – 10. Tables 3-8 inclusive present the main diversity findings, focusing on migrant diverse, ethnic diverse and migrant firms. Column (1) presents the results for diversity measures alone, column (2) adds controls. Tables 9 and 10 investigate quality of innovation, looking at knowledge intensive and non-knowledge intensive firms. For ease of interpretation coefficients are given in odds ratios, which are the exponentials of the raw coefficients. Odds ratios above one indicate a positive association with the dependent variable, odds ratios below one a negative link.

The model generally performs well.[62] Tests suggest the model is generally well-specified, and collinearity is not an issue (mean VIF is about 1). Controls are of the expected sign, magnitude and significance. As expected, collaborative activity, R&D spending and management ability all appear to play important roles in explaining innovative activity. In line with the discussion above, firms in KIBS sectors are more likely to engage in innovation. While firm size is usually positive significant, the square of firm size has a slight negative association – suggesting size effects on innovation fall away in the largest organisations.

6.1 Results for innovation and commercialisation

Tables 3 and 4 look at the association between firm diversity and the adoption of new products / processes. We fit dummies for migrant diverse and migrant firms together, with UK firms as the reference category. In all cases, and as suggested by the literature, firms' ownership diversity has a small, significant link to innovative activity. However, there are differences between product and process innovations.

Table 3 focuses on product innovation. For new goods and services, the odds ratio of migrant diversity is 1.528 (column 1), falling to 1.238 when controls are added (column 2). Both are significant at 1%. We interpret the latter result as suggesting that relative to firms with no migrant owners/partners, the odds of introducing a new product or service are about 1.24 times higher for diverse firms. Note that this specification also controls for the effect of having an all-migrant 'top team' of owners/partners, so identifies the diversity effect precisely. For modifications to the product / service line, there is a slightly smaller and weaker effect of diversity: with controls, the odds ratio is 1.192, significant at 5%. This

[62] The numbers of observations differs slightly according in each specification. This is because the clogit command normally drops observations that perfectly predict success or failure. These have coefficients of +/- infinity: dropping them has no effect on estimates of other coefficients, and increases the stability of the estimation process. Some observations are always dropped, so *n* is always less than 7,615. However, the number dropped never exceeds 4.8% of the total sample.

translates to relative odds 1.19 times higher for diverse firms, controlling for other firm characteristics. The effects of having all-migrant owners / partners are generally weaker: although for modified products or services, the odds ratio is 1.182, significant at 5%.

Table 4 looks at process innovation. Here, all-migrant top teams appear to play a more important role than in product innovation. For new equipment, migrant firms are around 1.19 times more likely to innovate holding other characteristics constant; for new ways of working the odds ratio for migrant firms is 1.164. By contrast, the odds ratio of migrant diverse firms is significant when fitted alone, but not with controls.

Tables 5 and 6 shift the focus to commercialisation of product and process innovations. We find positive associations between firm diversity and commercialisation activity. Compared to the earlier results, very few of the diversity variables have a significant link to the commercialisation of new ideas once controls are included. For both product and process innovation, none of the coefficients of DIV are significant, and in the case of migrant firms are generally close to zero. While the diversity of London firms is strongly linked to new products and processes, then, it plays less of a role in successfully taking these ideas to market.

6.2 Basic robustness checks

We run a number of basic checks at this stage. None challenge our overall findings so far. First, initial diagnostics suggest a small number of outlier firms: removing the outliers makes little difference to the results. We also experiment with interacting diversity measures on the most powerful controls, collaboration and R&D activity: none of the interactions is significant.

Second, we change the diversity variable: Table 7 presents results for ethnic diverse firms. These confirm the broad pattern of the previous results, suggesting that cultural diversity has a salient effect irrespective of the identity base selected. The first panel looks at innovation: ethnic diverse firms have a positive relationship with levels of innovative activity. Odds ratios of DIV are significant at 5% in all models except modified products and services. The second panel looks at commercialisation. By contrast with the main results, ethnic diversity has some significant links to the successful exploitation of new processes: for commercialising new ways of working, firms with at least half minority ethnic owners/partners are 1.29 times more likely to have introduced new ways of working – and raised annual revenue by at least 10%.

Third, because our main commercialisation measures are less than perfect, we cross-check our headlines on a sub-sample of firms who gave information on the share of turnover derived from innovative activity. We fit the main model in OLS with year and industry dummies. Results are given in Table 8, columns 1 and 4: they back up our main findings, suggesting a positive link between firm diversity and commercialisation. However, coefficients are not precisely estimated and none is significant.

6.3 Innovation and commercialisation in different company types

We now turn to innovative activities by different types of firms. We focus on differences between 'knowledge-intensive' firms (such as architecture and financial services) and less knowledge-intensive firms (such as retail or personal services). The descriptive analysis suggests that knowledge-intensive businesses are more likely to innovate than both the average firm and less 'knowledge-driven' firms (Table 2). We also suggest that the knowledge-intensive firms are – broadly – more likely to engage in high value-added innovations, and less knowledge-driven firms in 'ordinary' innovations.

Tables 9 and 10 look at innovative activity across our two firm types.[63] In each case, column one fits a dummy for knowledge-intensive firms; column 2 fits interactions with migrant diverse and migrant firms.

Table 9 looks at product innovation. For introducing major new products and services, there is no significant effect of all-migrant top teams on the average firm. But knowledge-intensive migrant firms are 1.31 times more likely than other migrant firms to introduce new products / services (column 2), and this effect is significant at 1%.

For the other innovation measures, we find significant diversity effects in less knowledge-intensive firms. For modifications to the product / service line, for example, we find positive significant effects of both diverse and migrant firms and no significant effect of knowledge-intensive firms. However, firms that are both knowledge intensive and have diverse owners / partners are significantly *less* likely to innovate (column 2). The positive diversity effect is driven by less knowledge-intensive businesses.

We find similar results for process innovation measures, which are given in Table 10. The results imply that diverse top teams in less knowledge-intensive firms are more

[63] Our knowledge-intensity typology is operationalised at SIC2 and SIC3 level, so models presented here run with industry fixed effects at SIC1 level. This does not substantively affect our main results.

likely to invest in major new equipment, and more likely to introduce new ways of working. Both effects are significant at 5%.

We repeat the analysis with commercialisation measures, but as in the main results find no significant effects of either diversity measure. We also cross check using ethnic diversity measures. The only significant results are for new products / services. Ethnic diversity is positively and significantly linked to innovation; while knowledge-intensive businesses as a whole show no significant link, knowledge-intensive *and* ethnically diverse firms are 1.425 times more likely to innovate (significant at 5%).

Finally, we take a closer look within the set of knowledge-intensive firms. Specifically, we pool the sample and re-run model (1), adding in dummies each of the six OECD categories of knowledge-intensive business (high-tech services, management services, financial services, other knowledge-intensive services, high-tech manufacturing and medium-tech manufacturing). We also fit interaction terms for diverse firms and migrant firms with each category of knowledge-intensive business. Coefficients for knowledge firms are interpreted relative to less knowledge-intensive firms, who comprise the rest of the sample.

Results are given in Tables 11 and 12. As suggested in the descriptive analysis, in most cases knowledge-intensive firms are more likely to innovate than less knowledge-intensive businesses. Coefficients of diversity variables are also generally positive significant, relative to UK-run firms. The interaction terms indicate a complex set of diversity-innovation interactions in the different types of knowledge-intensive businesses.

For example, migrant-run knowledge-intensive firms are generally more likely to introduce major new products / services than their UK-run counterparts; these effects are significant for high-tech services, management services and high-tech manufacturing (table 11). By contrast, in financial services there is a positive significant effect for diverse firms over UK-run firms, but migrant-run financial services firms are less likely to innovate. Almost all types of knowledge-intensive firm are more likely to introduce major new equipment than less knowledge-based businesses (Table 12). While diverse firms are also more likely to innovate, most diverse knowledge-intensive firms are *less* likely to invest in new equipment. There is no significant effect of migrant-run firms overall, but a much more mixed picture for migrant firms within the knowledge-intensive sector.

Overall, these results suggest that contra the wider literature, diversity and migrant firm effects in London operate across all types of firms, not just knowledge-intensive firms.

It also suggests differences between ownership composition effects both between knowledge-intensive firms and their less knowledge-intensive counterparts, but also within the set of knowledge-intensive businesses. If our simple division of innovation quality is correct, moreover, our results suggest that the ‘diversity bonus’ in London firms contributes at least as much to ‘ordinary’ innovations than to high value-added activity.

7. Market orientation

The previous section examined some of the channels through which diversity-innovation effects might operate – configurations of management teams and the importance of knowledge intensive activity. This section extends the analysis to look at firms’ market orientation. It is useful to know whether there is any significant difference between the markets served by diverse firms and those served by other firms in the sample. If diverse firms are particularly geared towards very local markets, this implies that London’s large and diverse consumer economy is part of the diversity effect. Conversely, if diverse firms are more internationally orientated, the combination of diaspora networks and London’s connectivity may be more important.

LABS provides information on market orientation at various levels.[64] We use this to break down a firm’s market share into three parts: the share of sales within London, share of sales within the rest of the UK and share of sales to the rest of the world. The fourth panel of Table 2 provides some brief descriptives. We can see that overall, firms in the sample are very much orientated towards markets in London, which account for nearly three quarters of sales. By contrast, markets outside the UK account for just over six per cent of sales.

To establish whether firms’ cultural diversity has any influence on markets served, we estimate a simple model:

$$Y_{it} = a + b\mathrm{DIV}_{it} + \mathbf{CONTROLS}_{it}c + \mathrm{SECTOR}_i + \mathrm{YEAR}_t + e_i \qquad (2)$$

Where Y is one of our sales share measures, DIV is one of our diversity measures and CONTROLS is our previous vector of controls (firm age, firm size and its square, dummies for exporting, PPLC status, collaboration and R&D spending, plus the four management ability measures, year and SIC3 dummies).

[64] Although not all firms answer these questions, so *n* is slightly smaller for these regressions.

We fit the model as seemingly unrelated regressions, which provide some efficiency gains from OLS.[65] Results are given in Table 13. The first panel looks at migrant diverse and migrant firms relative to UK firms (the reference category). As expected given the descriptives, we find a positive link between both types of firm and local sales, although neither is significant.

By contrast, we find strongly significant negative relationships with national market orientation, and strongly positive links to international sales. For the latter, the coefficient of diverse firms is 2.318, significant at 5%, and for migrant firms 2.410, significant at 1%. These translate respectively into 2.3 and 2.4 percentage point differences in sales shares. Firms with some or all migrant owners/partners are thus significantly more likely than UK-run firms to sell into international markets, and less likely to operate in the rest of Britain.

The second panel of the table gives results for ethnic diverse firms. These are strikingly different to results for the first panel. Ethnic diverse firms have local sales shares nearly 6.5 percentage points higher than more ethnically homogenous firms, a difference significant at 1%. There is no significant difference in international sales shares. But as with migrant diversity measures, ethnic diverse firms are also significantly less plugged into UK markets than more homogenous firms, with over 5.7 percentage points fewer sales (significant at 1%).

The results suggest the market orientation of diverse and migrant firms in London is markedly different from UK-run or ethnically homogenous companies. For ethnically diverse firms, the capital's large and cosmopolitan home markets are an important source of revenue. For firms with migrant owners and partners, international markets matter, suggesting that diasporic effects (and connectivity) are in play. For both types of firms, London's home markets and international accessibility play bigger roles in sales than markets in the rest of the UK.

8. Robustness checks

Our analysis may be affected by endogeneity problems at individual, firm and city level. As discussed above, city-level positive selection is minimised by our choice of sample years,

[65] Specifically, the Breusch-Pagan test of error independence always gives a test statistic of over 2800. The null hypothesis is that standard errors in the three equations are not correlated. We therefore reject the null. The size of the test statistic suggests that error correlation is substantial, and SUR provides corresponding efficiency gains. As a cross-check we also run the model in OLS, with broadly similar results but substantially higher standard errors.

which are bracketed by an exogenous diversity shock. Individual and firm-level challenges remain. We take each in turn.

8.1 Individual selection bias

We need to check how far individual-level factors explain estimates of apparent diversity effects. Migrant and minority ethnic owners / partners may be highly 'entrepreneurial', and more likely than the average worker to develop new ideas and/or start new firms. Conversely, 'ethnic entrepreneurs' may be forced into starting their own businesses through exclusion from other economic institutions (Gordon, 2001). Positive selection of entrepreneurial individuals may explain the links between diversity and innovation. If this entirely accounts for diversity-innovation effects, coefficients of DIV will be biased upwards. By contrast, negative selection may explain the lack of connection between diversity and measures of commercialisation. If migrant and minority owners/partners face discrimination in marketing new ideas, estimates of DIV are biased downwards.

We partly deal with this by including controls for management ability. However, 'talent' is not fully observed via courses and qualifications. We therefore develop further robustness checks, focusing on reasons for firm formation. LABS allows us to identify respondents directly involved in founding each firm, and their motivation for doing so. We can observe some migrant founders by identifying firms where both the respondent is a founder, and all owners/partners are non-UK born.[66] We identify the share of founders who set up firms for reasons roughly corresponding to 'entrepreneurial' behaviour (e.g. 'I wanted to start my own business'), and for reasons that may reflect exclusion (e.g. 'I found it hard to get work').[67] We then construct dummies for 'entrepreneurial founders', 'locked out founders' and 'other founders', by country of birth.[68]

The final panel of Table 2 gives descriptives. 54% of all respondents were involved in firm formation; migrant founders comprise 12.2% of the sample, and 22.6% of all founders. Compared to founders as a whole, a higher share of migrant founders appears

[66] We are unable to observe all migrant founders in this way (e.g. migrant founders of firms with a mixed management team are excluded). We are also unable to identify minority ethnic company founders.

[67] Specifically, we select the three most common 'entrepreneurial' and 'excluded' reasons for firm formation. For the former, these are 'I wanted to start my own business' (q14_2), 'I wanted a new challenge' (q14_5), 'I wanted to be my own boss' (q15_12). For the latter, these are 'I was made redundant' (q14_3), 'I found it hard to get work' (q14_10) and 'My old business collapsed' (q14_23). We exclude around 8% of respondents gave multiple answers covering more than one of these categories.

[68] This approach is the best use of available data, although it is open to challenge. Our measures of 'attitude' are imperfect and involve some subjective judgement. More seriously, survey answers are likely to exaggerate positive reasons for firm formation, while playing down negative reasons. So the results are likely to overstate positive selection and understate negative selection.

to have founded the firm for entrepreneurial reasons (30.4% vs. 27.6%), with a lower share locked out (8.1% vs. 9.9%).[69]

We then run two checks. First, we regress reasons for firm formation on migrant status, management ability and migrant-ability interaction terms. We estimate the model as a conditional logit with year and SIC3 dummies. Results are given in Table 14. Being a migrant raises the possibility of entrepreneurially-motivated firm formation; migrant status has no significant link to 'locked out' motivations, and has a marginally significant link to other motivations. This suggests some role for positive selection via migrant entrepreneurship.

Second, we test whether entrepreneurial or locked out migrant founders affects firm-level innovation. To do this, we simply substitute these variables for DIV in equation (1), with 'other founders' as the reference category. In contrast with the full panel, the only significant result is for commercialising major new products or services, where entrepreneurial migrant founders are 0.556 times less likely to successfully commercialise their innovation. However, this result is only marginally significant.

Overall, these results suggest that positive selection of individual migrants plays some role in firm formation. This is a useful finding in itself, as it still suggests that the positive selection of the migrants who come to London is economically beneficial. However, this kind of ethnic entrepreneurship is not strong enough to explain our findings. Rather, a combination of individual, firm-level and urban-level diversity-innovation effects seem to be operating in London.

8.2 Firm-level endogeneity issues

Our model in equation (1) may be affected by reverse and/or both-ways causation. If firm-level diversity facilitates innovation, innovative firms may also seek out or attract a more diverse workforce. In this instance, coefficients of DIV are likely to be biased upwards.[70] To assess the extent of this problem we use an instrumental variables approach. Suitable instruments are not easy to find: as our sample is a repeat cross-section we are unable to use lagged data, and matching firms in LABS with other firm-level microdata would be extremely complex.

[69] Pearson tests, not reported here, suggest significant correlations between being an entrepreneurial founder and being a migrant; there is also a significant link between lockout and migrant status.

[70] Downwards bias may arise if less innovative firms have fewer opportunities to recruit from the mainstream labour market and recruit individuals – such as those from ethnic minorities or migrant groups – who face discrimination in the wider labour market. Evidence from the literature suggests this is less likely than upwards bias, which we take as our main endogeneity problem at firm level.

We examine two main candidates for potential instruments. First, migrants tend to cluster in certain industries (Green, 2008) so that migrant-intensive sectoral characteristics might form the basis of an instrumentation strategy. We test a number of shift-share instruments based on historic sectoral characteristics – however, these fail first stage tests (largely because sectoral properties may also influence innovative activity).[71]

Second, migrants and minority ethnic groups tend to cluster in certain urban neighbourhoods, and this may influence the pool of workers from which a firm recruits: historic location patterns have been used elsewhere in the literature (e.g. Altonji and Card (1991), Card (2005), Ottaviano and Peri (2006)). We develop a very simple instrument, which we deploy for the 2007 cross-section. For migrant firms and ethnic diverse firms in a given borough, we substitute firm-level DIV with historic borough-level migrant and minority population shares.

For firm *i* in borough *j* and year *t*, the instrument takes the form:

$$\mathrm{pDIV}_{ijt} = \mathrm{DIV}_{jtb} \tag{3}$$

In this case, *t* is 2007 and *tb* is 2001, with historic diversity data drawn from the 100% sample provided by the 2001 UK Census. To instrument *migrant firms* we use the proportion of the borough population who were not born in the UK. To instrument *ethnic diverse firms* we use the proportion of the population of the borough in which the firm is located, who are not of white ethnicity in 2001.

For *migrant diverse firms* we need a slightly different approach, and use a fractionalisation index of 14 country of birth zones as our instrument. Specifically:

$$\mathrm{pDIV}_{ijt} = 1 - \Sigma_a\, [\mathrm{SHARE}_{ajtb}]^2 \tag{4}$$

Where *a* is one of our country of birth zones.[72] As before, we are using information from a firm's borough, *j*, to instrument the firm *i*.

[71] These are: (1) a shift-share instrument based on Ottaviano and Peri (2006) which generates predicted ethnic / migrant shares in particular sectors based on 2003 data and changes in London's population over the period 2003-2007, (2) an interaction term between borough level diversity in 2001 and diversity at the firm or sectoral level, and (3) by collapsing the data to sector / borough averages for 2007 and using the lagged values for sector / borough diversity in 2003.

[72] These are taken from 2001 Census categories and comprise Great Britain, Ireland, Isle of Man, rest of Western Europe, Eastern Europe, Africa, Middle East, Far East, South Asia, North America, South America, Oceania, rest of the world.

Following Cameron and Trivedi (2009) we estimate in 2SLS with robust standard errors to obtain consistent estimates. Table 15 gives first stage results for the instruments. Fitted together, the instruments for migrant and migrant diverse firms perform badly. Model R^2 is extremely low, as is the first-stage F-statistic in one case. More worryingly, both instruments fail weak instrument and under-identification tests. We therefore do not report second-stage results. The instrument for ethnic diverse firms does rather better. First stage R^2 is again very low, but F-statistics and other instrument tests are satisfactory.

Table 16 gives second-stage results for ethnic diverse firms.[73] Coefficients of DIV are always positive but most of the significant results from the main regressions are not replicated here. There are three exceptions: introducing new ways of working and commercialising new ways of working (significant at 5%) and commercialising new equipment (significant at 10%). In these three cases coefficients of DIV are also substantially bigger than in the main regressions.

These results only give us a partial view on firm-level endogeneity. What we have suggests that simultaneity and/or reverse causation is indeed present at the firm level, but the findings subject to heavy caveats regarding the validity of the instrument. In particular, we lose a great deal of precision by instrumenting dummies with continuous variables, and are only able to use the instrument on a single cross-section.[74] More seriously, while our instruments arguably meet the exclusion restrictions it is less clear they meet relevance conditions, as expressed by the low R^2 scores in the first and second stages. The cautious conclusion is that simultaneity is likely to be present, and given that this will bias DIV upwards, the main results are interpreted as upper bounds not point estimates.

9. Discussion

This paper investigates whether culturally diverse firms in London are more innovative, and so whether this cultural diversity is an economic asset to the city, in terms of its impact on innovation. The analysis focuses on the role of migrant and minority business owners / partners, using a survey of over 7,600 firms in 2005-7. This period coincided with a significant increase in London's diversity via A8 accession, providing an ideal opportunity

[73] Results are shown with SIC3 dummies partialled out, in order to achieve a robust variance-covariance matrix with some singleton dummies. We also fit the model without partialling, giving very similar coefficient estimates and rather bigger model R2 and F-statistics.
[74] We experiment with various workarounds. We also constructed a synthetic panel at sector/borough level, following the approach of Angrist (1991) and Deaton (1985). In practice finding a suitable grouping variable proved difficult, and the final panel was not stable enough to provide reliable results.

to examine potential diversity-innovation links. As far as we are aware, this is the first research to look at cultural diversity and innovation in firms in an urban context.

We find some evidence to suggest that diverse firms are more innovative. There are small but robust effects of management team diversity on the development and implementation of new products and processes, and of migrant-run firms on process innovation, relative to UK-run firms. However, there is little connection between diversity and the successful commercialisation of new ideas.

In contrast to other studies that suggest diversity effects are restricted to knowledge-intensive environments, we find diversity-innovation effects across London's industrial structure. In three out of four innovation measures, diversity effects were driven by less knowledge-intensive firms. In turn, this suggests that the 'diversity bonus' in London firms often manifests itself as much in 'ordinary' innovations than in high value-added activities.

Compared to more homogenous firms, diverse businesses are more orientated towards London's large and diverse home markets (for ethnic diverse firms) and markets in the rest of the world (migrant firms). The talents and skills of migrant entrepreneurs explain part of our findings, but London's diasporic communities, home markets and international connectivity also play important roles through different aspects of diversity.

There are some important caveats to our findings. First, we use relatively noisy measures of 'cultural diversity' that arguably understate the true richness of the capital's people mix. Future research using richer measures of diversity (particularly at individual level) would be welcome. Second, although we are able to control for several endogeneity issues, we are unable to fully deal with potential firm-level simultaneity in our results. Simultaneity is likely to bias DIV upwards, so caution suggests that results are interpreted as upper bounds rather than point estimates.

We explain the gap between the innovation and commercialisation results as follows. One explanation is simply that diverse firms produce new ideas that tend to fail in the marketplace. A more plausible answer is that the measure of commercialisation is too restrictive to capture the benefits of innovation. Many new ideas take time to successfully commercialise, particularly for knowledge-based firms where idea-market-revenue lags may run to several years. Given London's knowledge-focused industrial structure, this may explain some of the gap. Further research using alternative measures of commercialisation might deliver different results. Better data on London firms, ideally a true panel, would also help to resolve this question. A third explanation is that diverse firms face difficulties bringing their products to market. That suggests potential co-ordination failures around business support, access to finance and workforce development. The GLA and the London Skills Board could usefully investigate these issues further, through sectoral and/or case study based research.

Overall, the results can be seen as providing support for claims that London's cultural diversity helps support innovative activity, and thus helps strengthen the capital's long-term economic position. In other words, London's diversity is an economic asset, not just a social one.

For London firms, London's diversity seems unambiguously positive. For Londoners as a whole, the impacts are less clear. For example, assume firms have a limited budget for staff. If firms alter hiring decisions to increase the diversity of teams, those workers who would previously have been hired are 'losers' – even though the firm (and the wider economy) may gain from the resulting externalities (Borjas, 2011). The objection to this argument is that it implies losers cannot get equally or better-paid jobs elsewhere. If losers have low skills or very specialised skills, they may move directly to lower-value employment or unemployment. However, in a large urban economy their chances of finding other work are maximised.[75]

It is also less clear whether our results generalise to different cities. In theory, we might find similar results for firms in other large UK cities. But London's size, economic structure and demography are unique, and we should be careful in applying these findings. Intuitively, our findings are likely to be replicated in other big British cities – such as Liverpool, Manchester, Glasgow or Birmingham – but diversity-innovation effects may be smaller, or driven by other channels. Further research is needed on a comparative urban scale to establish the wider potential benefits of urban diversity.

[75] Borjas uses the example of US mathematicians displaced from academia by arrivals from the former Soviet Union. In practice, as Borjas suggests, many of these 'losers' have moved into far better-paid jobs in merchant banks and hedge funds.

LIST OF TABLES

Table 1. Summary statistics.

Variable	N	Mean	SD	Min	Max
Firm introduces major new products or services	7615	0.314	0.464	0	1
Major modifications to product / service range	7615	0.261	0.439	0	1
Major new equipment	7615	0.228	0.42	0	1
Major new working methods	7615	0.258	0.437	0	1
‘Gazelle', annual revenue grows >=10%	7615	0.364	0.481	0	1
Gazelle, major new products or services	7615	0.13	0.336	0	1
Gazelle, sig. modifies products or services	7615	0.109	0.312	0	1
Gazelle, major new equipment	7615	0.096	0.294	0	1
Gazelle, major new ways of working	7615	0.107	0.308	0	1
% turnover from 'innovations' in last 12 months	2552	20.515	21.705	0	100
Firm has zero migrant owners / partners	7615	0.598	0.49	0	1
Firm has all migrant owners/partners	7615	0.213	0.409	0	1
Firm has some migrant owners / partners	7615	0.18	0.384	0	1
Of which migrant-run firm	3058	0.53	0.499	0	1
Firm has at least half minority ethnic owners/partners	7615	0.214	0.41	0	1
Company age	7615	16.011	21.415	2	307
Number of employees	7615	22.49	63.82	1	1700
Firm collaborates with others	7615	0.299	0.458	0	1
Firm does R&D	7615	0.337	0.473	0	1
Firm exports	7615	0.213	0.409	0	1
Firm is PLC	7615	0.038	0.191	0	1
Knowledge-intensive firm (OECD definition)	7615	0.472	0.499	0	1
Less knowledge-intensive firm (OECD definition)	7615	0.528	0.499	0	1
Knowledge-intensive business services firm	7615	0.19	0.392	0	1
% managers with management qualification	7603	0.307	0.699	0	1
% who've completed management course	7577	0.394	0.812	0	1
% with informal/on-job management training	7591	0.573	0.834	0	1
% with prior management experience	7593	0.565	0.708	0	1
% sales in London	7164	74.437	33.193	0	100
% sales in rest of UK	7164	19.035	27.37	0	100
% sales in rest of world	7164	6.533	19.021	0	100
Respondent is a/the founder of the firm	6952	0.540	0.498	0	1
Respondent is migrant and a/the founder of firm	6952	0.122	0.328	0	1
Founder, 'entrepreneurial' reason for starting firm	3752	0.276	0.447	0	1
Founder, 'locked out' reason for starting firm	3752	0.099	0.299	0	1
Founder, other reasons for founding firm	3752	0.624	0.484	0	1
Migrant, 'entrepreneurial' reasons for starting firm	851	0.304	0.460	0	1
Migrant, 'locked out' reasons for starting firm	851	0.081	0.273	0	1
Migrant, other reasons for starting firm	851	0.615	0.487	0	1

Source: LABS.
Notes: Not all firms answered all questions. Missing observations on % turnover from innovations, management qualifications and experience, firm founders.

Table 2. Innovative activity by firm type, 2005-7.

Firm type	major new product / service	modified product / service	major new equipment	new way of working
All firms	0.304	0.257	0.257	0.257
Non-knowledge intensive	0.292	0.23	0.221	0.239
Knowledge intensive	0.317	0.288	0.228	0.266
KIBS	0.306	0.284	0.184	0.249
	commercialised new product / service	**commercialised modified product / service**	**commercialised new equipment**	**commercialised new way of working**
All firms	0.127	0.107	0.094	0.105
Non-knowledge intensive	0.107	0.085	0.089	0.089
Knowledge intensive	0.149	0.132	0.098	0.123
KIBS	0.159	0.135	0.09	0.121

Source: LABS.

Table 3. Results for firms introducing major new / modified products or services: effects of business diversity, 2005-7.

Dependent variable	New product/service		Modified product/service	
	(1)	(2)	(1)	(2)
Migrant diverse firm	1.528***	1.238***	1.434***	1.192**
	(0.113)	(0.084)	(0.131)	(0.097)
Migrant firm	1.050	1.134	1.123	1.182**
	(0.077)	(0.087)	(0.109)	(0.095)
ln(firm age)		0.842***		0.898***
		(0.033)		(0.031)
ln(number of employees)		1.441***		1.299***
		(0.128)		(0.110)
ln(employees^2)		0.961**		0.974*
		(0.015)		(0.015)
firm collaborates		1.835***		1.646***
		(0.133)		(0.104)
firm does R&D		2.625***		2.094***
		(0.174)		(0.135)
firm exports		1.074		1.018
		(0.083)		(0.080)
firm is plc		1.638**		1.216
		(0.329)		(0.150)
% qualified managers		0.998		1.219**
		(0.141)		(0.119)
% management course		1.133		1.425***
		(0.176)		(0.128)
% management training		1.020		1.232**
		(0.181)		(0.106)
% management experience		0.935		1.071
		(0.146)		(0.069)
KIBS		2.466***		2.335**
		(0.823)		(0.977)
Observations	7529	7476	7510	7457
Pseudo R^2	0.005	0.088	0.004	0.071
Log-Likelihood	-4234.763	-3854.844	-3969.129	-3678.762

Source: LABS.
Notes: Results are odds ratios. HAC standard errors in parentheses. All specifications include year and SIC3 dummies: some obs dropped because of perfect prediction groups. * = significant at 10%, ** 5%, *** 1%.

Table 4. Results for firms introducing major new equipment / new ways of working: effects of business diversity, 2005-7.

Dependent variable	New equipment		New way of working	
	(1)	(2)	(1)	(2)
Migrant diverse firm	1.341**	1.128	1.385***	1.158
	(0.170)	(0.117)	(0.158)	(0.110)
Migrant firm	1.129	1.188**	1.101	1.164**
	(0.113)	(0.101)	(0.096)	(0.089)
ln(firm age)		0.988		0.908***
		(0.031)		(0.031)
ln(number of employees)		1.474***		1.480***
		(0.121)		(0.090)
ln(employees^2)		0.959***		0.958***
		(0.014)		(0.010)
firm collaborates		1.343***		1.422***
		(0.108)		(0.098)
firm does R&D		1.778***		1.927***
		(0.108)		(0.119)
firm exports		0.831**		0.870**
		(0.069)		(0.059)
firm is plc		1.197		1.060
		(0.230)		(0.167)
% qualified managers		1.277***		1.080
		(0.101)		(0.082)
% management course		1.197*		1.367***
		(0.119)		(0.116)
% management training		1.063		1.363***
		(0.086)		(0.078)
% management experience		0.903		1.057
		(0.063)		(0.093)
KIBS		2.372		0.797
		(2.200)		(0.325)
Observations	7486	7435	7494	7441
Pseudo R^2	0.002	0.041	0.003	0.059
Log-Likelihood	-3729.408	-3565.636	-4029.675	-3777.228

Source: LABS.
Notes: Results are odds ratios. HAC standard errors in parentheses. All specifications include year and SIC3 dummies: some obs dropped because of perfect prediction groups. * = significant at 10%, ** 5%, *** 1%.

Table 5. Results for firms commercialising major new / modified products or services: effects of business diversity, 2005-7.

Dependent variable	New product / service		Modified product/service	
	(1)	(2)	(1)	(2)
Migrant diverse firm	1.354*** (0.141)	1.122 (0.121)	1.286** (0.136)	1.111 (0.132)
Migrant firm	1.028 (0.119)	1.023 (0.119)	1.075 (0.140)	1.081 (0.130)
ln(firm age)		0.632*** (0.040)		0.645*** (0.035)
ln(number of employees)		1.385*** (0.118)		1.418*** (0.126)
ln(employees^2)		0.964** (0.016)		0.959** (0.017)
firm collaborates		1.796*** (0.169)		1.710*** (0.164)
firm does R&D		1.967*** (0.162)		1.918*** (0.186)
firm exports		1.113 (0.094)		1.043 (0.109)
firm is plc		1.033 (0.161)		0.890 (0.181)
% qualified managers		1.095 (0.114)		1.120 (0.132)
% management course		1.190** (0.103)		1.336*** (0.147)
% management training		1.108 (0.124)		1.147 (0.129)
% management experience		1.053 (0.088)		1.005 (0.106)
KIBS		0.835 (0.344)		0.713 (0.256)
Observations	7434	7370	7354	7301
Pseudo R^2	0.027	0.097	0.032	0.099
Log-Likelihood	-2555.120	-2346.350	-2238.543	-2068.579

Source: LABS.

Notes: Results are odds ratios. HAC standard errors in parentheses. All specifications include year and SIC3 dummies: some obs dropped because of perfect prediction groups. * = significant at 10%, ** 5%, *** 1%.

Table 7. Results for firms commercialising new equipment/ways of working: effects of business diversity, 2005-7.

Dependent variable	New equipment		New ways of working	
	(1)	(2)	(1)	(2)
Migrant diverse firm	1.358***	1.163	1.217**	1.042
	(0.156)	(0.124)	(0.116)	(0.097)
Migrant firm	1.149	1.185	1.087	1.080
	(0.157)	(0.148)	(0.138)	(0.121)
ln(firm age)		0.718***		0.660***
		(0.041)		(0.035)
ln(number of employees)		1.701***		1.602***
		(0.233)		(0.245)
ln(employees^2)		0.932***		0.946*
		(0.024)		(0.028)
firm collaborates		1.645***		1.502***
		(0.197)		(0.122)
firm does R&D		1.675***		1.762***
		(0.137)		(0.158)
firm exports		0.897		1.036
		(0.099)		(0.117)
firm is plc		0.849		0.722*
		(0.188)		(0.130)
% qualified managers		1.120		1.153
		(0.119)		(0.126)
% management course		1.137		1.151
		(0.132)		(0.143)
% management training		1.149		1.265***
		(0.109)		(0.103)
% management experience		0.840		0.983
		(0.093)		(0.108)
KIBS		3.082		0.697*
		(2.620)		(0.138)
Observations	7302	7243	7355	7305
Pseudo R^2	0.027	0.075	0.030	0.087
Log-Likelihood	-2104.292	-1986.532	-2270.112	-2119.610

Source: LABS.
Notes: Results are raw coefficients, not marginal effects. HAC standard errors in parentheses. All specifications include year and SIC3 dummies: some obs dropped because of perfect prediction groups. * = significant at 10%, ** 5%, *** 1%.

Table 7. Results for business innovation and commercialisation: effects of ethnic diverse firms, 2005-7.

Depvar = innovation	**New product / service**		**Modified product / service**		**New equipment**		**New way of working**	
	(1)	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
Ethnic diverse firm	1.089 (0.095)	1.211** (0.101)	1.032 (0.093)	1.077 (0.080)	1.131 (0.118)	1.187** (0.103)	1.144 (0.107)	1.218*** (0.091)
Controls	N	Y	N	Y	N	Y	N	Y
Observations	7529	7476	7510	7457	7486	7435	7494	7441
Pseudo R2	0.001	0.088	0.001	0.070	0.001	0.041	0.001	0.060
Log-Likelihood	-4253.437	-3855.603	-3981.824	-3682.347	-3735.615	-3565.890	-4037.946	-3776.440

Depvar =commercialisation	**New product / service**		**Modified product/service**		**New equipment**		**New way of working**	
	(1)	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
Ethnic diverse firm	1.098 (0.107)	1.124 (0.100)	1.039 (0.108)	1.023 (0.102)	1.111 (0.117)	1.141 (0.119)	1.264* (0.152)	1.288** (0.141)
Controls	N	Y	N	Y	N	Y	N	Y
Observations	7434	7370	7354	7301	7302	7243	7355	7305
Pseudo R2	0.025	0.097	0.031	0.099	0.025	0.074	0.030	0.088
Log-Likelihood	-2560.089	-2346.266	-2241.551	-2069.171	-2108.029	-1987.466	-2268.986	-2116.702

Source: LABS.
Notes: Results are odds ratios. HAC standard errors in parentheses. All specifications include year and SIC3 dummies. Controls fitted: log firm age, log firm size, log size squared, collaboration dummy, R&D dummy, exports dummy, PLC dummy, % qualified managers, % completed management course, % with informal management training, % with management experience, KIBS dummy. Some obs dropped because of perfect prediction groups. * = significant at 10%, ** 5%, *** 1%.

Table 8. Alternative commercialisation results: % turnover from product and/or process innovation 2005-7, OLS regressions.

Dependent variable	**% turnover from any kind of innovation**	
	(1)	**(2)**
Migrant diverse firm	0.576	
	(1.040)	
Migrant firm	1.305	
	(1.375)	
Ethnic diverse firm		1.495
		(1.119)
Controls	Y	Y
Observations	2539	2539
R^2	0.039	0.040

Source: LABS.
Notes: HAC standard errors in parentheses. All specifications include year and SIC3 dummies. Controls fitted: log firm age, log firm size, log size squared, collaboration dummy, R&D dummy, exports dummy, PLC dummy, % qualified managers, % completed management course, % with informal management training, % with management experience, KIBS dummy. Some obs dropped because of perfect prediction groups. * = significant at 10%, ** 5%, *** 1%.

Table 9. Results for product innovation by firm knowledge-intensity, 2005-7.

Dependent variable	New product / service		Modified product / service	
	(1)	**(2)**	**(1)**	**(2)**
Migrant diverse firm	1.240***	1.316***	1.250***	1.473***
	(0.083)	(0.073)	(0.080)	(0.103)
Migrant firm	1.153*	1.025	1.232***	1.221**
	(0.098)	(0.066)	(0.068)	(0.105)
Knowledge-intensive (KI) firm	1.168	1.127	0.984	1.034
	(0.114)	(0.127)	(0.067)	(0.070)
KI * migrant diverse		0.888		0.728***
		(0.082)		(0.067)
KI * migrant firm		1.313***		1.037
		(0.129)		(0.101)
Controls	Y	Y	Y	Y
Observations	7524	7524	7524	7524
Pseudo R2	0.088	0.088	0.074	0.075
Log-Likelihood	-4170.431	-4167.398	-3934.109	-3931.260

Source: LABS.
Notes: Coefficients are odds ratios, not raw coefficients. HAC standard errors in parentheses. All specifications include year and SIC1 dummies. Controls fitted: log firm age, log firm size, log size squared, collaboration dummy, R&D dummy, exports dummy, PLC dummy, % qualified managers, % completed management course, % with informal management training, % with management experience. * = significant at 10%, ** 5%, *** 1%.

Table 10. Results for process innovation by knowledge-intensity, 2005-7.

Dependent variable	Major new equipment		New way of working	
	(1)	(2)	(1)	(2)
Migrant diverse firm	1.083	1.348*	1.181**	1.363***
	(0.161)	(0.218)	(0.097)	(0.091)
Migrant firm	1.169**	1.152	1.190***	1.145*
	(0.075)	(0.105)	(0.062)	(0.088)
Knowledge-intensive (KI) firm	0.914	0.978	1.137	1.173*
	(0.076)	(0.102)	(0.096)	(0.100)
KI * migrant diverse		0.636**		0.751**
		(0.138)		(0.084)
KI * migrant firm		1.057		1.104
		(0.146)		(0.129)
Controls	Y	Y	Y	Y
Observations	7524	7524	7524	7524
Pseudo R2	0.038	0.039	0.059	0.059
Log-likelihood	-3838.197	-3832.756	-4012.463	-4009.598

Source: LABS.
Notes: Coefficients are odds ratios, not raw coefficients. HAC standard errors in parentheses. All specifications include year and SIC1 dummies. Controls fitted: log firm age, log firm size, log size squared, collaboration dummy, R&D dummy, exports dummy, PLC dummy, % qualified managers, % completed management course, % with informal management training, % with management experience. * = significant at 10%, ** 5%, *** 1%.

Table 11. Results for product innovation within the knowledge-intensive sector.

Dependent variable	New product/service		Modified product/service	
	(1)	(2)	(1)	(2)
Migrant diverse firm	1.204**	1.279***	1.256***	1.473***
	(0.096)	(0.089)	(0.089)	(0.102)
Migrant firm	1.111	1.011	1.218***	1.222**
	(0.077)	(0.059)	(0.066)	(0.104)
High-tech services * Diverse		0.876		0.687**
		(0.198)		(0.127)
High-tech services * Migrant		1.863***		1.041
		(0.334)		(0.166)
Management services * Diverse		0.886**		0.781***
		(0.053)		(0.053)
Management services * Migrant		1.261***		1.000
		(0.074)		(0.094)
Financial services * Diverse		1.212***		0.656***
		(0.066)		(0.058)
Financial services * Migrant		0.772***		0.817**
		(0.046)		(0.081)
Other services * Diverse		0.799		0.621***
		(0.224)		(0.071)
Other services * Migrant		1.176		0.938
		(0.237)		(0.119)
High-tech MF * Diverse		0.867**		2.217***
		(0.055)		(0.173)
High-tech MF * Migrant		1.482***		4.986***
		(0.120)		(0.518)
Medium-tech MF * Diverse		0.469		0.651***
		(0.451)		(0.087)
Medium-tech * Migrant		1.253		1.580***
		(0.379)		(0.183)
High-tech services firm	1.748***	1.536***	1.875***	1.951***
	(0.054)	(0.141)	(0.027)	(0.130)
Management services firm	0.612***	0.586***	0.858**	0.874**
	(0.033)	(0.023)	(0.056)	(0.047)
Financial services firm	0.952	0.946	0.727***	0.819***
	(0.038)	(0.033)	(0.013)	(0.032)
Other services firm	0.917***	0.924	1.139***	1.270***
	(0.024)	(0.085)	(0.033)	(0.072)
High-tech MF firm	1.858***	1.845***	0.665***	0.386***
	(0.140)	(0.131)	(0.040)	(0.021)
Medium-tech MF firm	1.430**	1.469	1.132	1.073
	(0.230)	(0.417)	(0.139)	(0.129)
Constant	0.135***	0.136***	0.093***	0.089***
	(0.021)	(0.023)	(0.018)	(0.017)
Controls	Y	Y	Y	Y
Observations	7524	7524	7524	7524
Pseudo R^2	0.112	0.114	0.088	0.090
Log-Likelihood	-4150.352	-4144.352	-3939.628	-3933.888

Source: LABS.
Notes: Coefficients are odds ratios, not raw coefficients. HAC standard errors in parentheses. Controls fitted as per Table 10. * = significant at 10%, ** 5%, *** 1%.

Table 12. Results for process innovation within the knowledge-intensive sector.

Dependent variable	New equipment		New way of working	
	(1)	(2)	(1)	(2)
Migrant diverse firm	1.098	1.358*	1.189**	1.370***
	(0.162)	(0.213)	(0.101)	(0.092)
Migrant firm	1.177**	1.162	1.191***	1.154*
	(0.077)	(0.107)	(0.062)	(0.089)
High-tech services * Diverse		0.687*		1.020
		(0.140)		(0.223)
High-tech services * Migrant		1.368		1.686***
		(0.547)		(0.141)
Management services * Diverse		0.652**		0.742***
		(0.113)		(0.053)
Management services * Migrant		1.089		0.969
		(0.113)		(0.109)
Financial services * Diverse		1.306		0.817***
		(0.244)		(0.061)
Financial services * Migrant		1.296**		1.126
		(0.134)		(0.095)
Other services * Diverse		0.461***		0.576**
		(0.122)		(0.129)
Other services * Migrant		0.827*		0.922
		(0.092)		(0.155)
High-tech MF * Diverse		0.376***		0.953
		(0.080)		(0.063)
High-tech MF * Migrant		0.553***		1.043
		(0.085)		(0.116)
Medium-tech MF * Diverse		0.597***		2.073**
		(0.104)		(0.594)
Medium-tech * Migrant		1.091		2.273**
		(0.177)		(0.932)
High-tech services firm	1.459***	1.430***	1.486***	1.324***
	(0.024)	(0.094)	(0.026)	(0.081)
Management services firm	1.754***	1.823***	1.158***	1.253***
	(0.031)	(0.058)	(0.041)	(0.066)
Financial services firm	0.822***	0.730***	1.145***	1.160***
	(0.021)	(0.037)	(0.028)	(0.053)
Other services firm	1.074***	1.278***	1.221***	1.382***
	(0.028)	(0.068)	(0.030)	(0.094)
High-tech MF firm	0.546***	0.756***	0.462***	0.444***
	(0.063)	(0.079)	(0.021)	(0.015)
Medium-tech MF firm	0.735	0.763	1.132*	0.886
	(0.240)	(0.269)	(0.085)	(0.081)
Constant	0.089***	0.087***	0.092***	0.091***
	(0.022)	(0.023)	(0.011)	(0.010)
Controls	Y	Y	Y	Y
Observations	7524	7524	7524	7524
Pseudo R^2	0.044	0.047	0.061	0.062
Log-Likelihood	-3862.953	-3853.315	-4037.755	-4030.885

Source: LABS.
Notes: Coefficients are odds ratios, not raw coefficients. HAC standard errors in parentheses. Controls fitted as per Table 10. * = significant at 10%, ** 5%, *** 1%.

Table 13. Results for market orientation and owner/partner diversity, 2005-7.

Dependent variable	% sales		
	local	**national**	**international**
Migrant diverse firm	1.348	-3.666***	2.318**
	(1.532)	(1.309)	(0.934)
Migrant firm	1.718	-4.128***	2.410***
	(1.290)	(1.102)	(0.786)
Controls	Y	Y	Y
Observations	3089	3089	3089
R^2	0.281	0.205	0.185
Joint sig test chi^2 statistic	24604.894	2546.327	1118.698
P-value of joint sig test	0.000	0.000	0.000
Breusch-Pagan error independence test	2830.291		

Dependent variable	% sales		
	local	**local**	**local**
Ethnic diverse firm	6.493***	-5.743***	-0.750
	(1.305)	(1.117)	(0.800)
Controls	Y	Y	Y
Observations	3089	3089	3089
R^2	0.286	0.207	0.182
Joint sig test chi^2 statistic	24799.371	2562.068	1102.669
P-value of joint sig test	0.000	0.000	0.000
Breusch-Pagan error independence test	2816.633		

Source: LABS.
Notes: Standard errors in parentheses. All specifications include year and SIC3 dummies. Controls fitted: log firm age, log firm size, log size squared, collaboration dummy, R&D dummy, exports dummy, PLC dummy, % qualified managers, % completed management course, % with informal management training, % with management experience, KIBS dummy. Some obs dropped because of perfect prediction groups. Breusch-Pagan test of error independence follows a chi-squared distribution. H0 = errors in equations are independent.
* = significant at 10%, ** 5%, *** 1%.

Table 14. Reasons for firm formation: testing the role of migrant founders on firm formation motives, 2005-7.

Reason for firm formation	Entrepreneurial	Locked out	Other reason
	(1)	(2)	(3)
Migrant, firm founder	1.363**	0.859	0.804*
	(0.193)	(0.188)	(0.096)
Controls	Y	Y	Y
Observations	3632	3475	3665
Pseudo R^2	0.004	0.008	0.004
Log-Likelihood	-1986.189	-1017.156	-2224.185

Source: LABS.
Notes: Coefficients are odds ratios. HAC standard errors in parentheses. All specifications include year and SIC3 dummies. Controls fitted: log firm age, log firm size, log size squared, collaboration dummy, R&D dummy, exports dummy, PLC dummy, % qualified managers, % completed management course, % with informal management training, % with management experience, KIBS dummy. Some obs dropped because of perfect prediction groups. * = significant at 10%, ** 5%, *** 1%.

Table 15. Instrumental variable results: first stage.

Dependent variable = instrument	(1)	(2)	(3)
Migrant diverse firm	1.200 (0.734)	-0.757 (0.752)	
Migrant firm	-1.520 (1.044)	1.658 (1.079)	
Ethnic diverse firm			0.353*** (0.066)
Controls	Y	Y	Y
Observations	1496	1496	1496
R^2	0.055	0.064	0.073
F-statistic	6.426	6.274	7.092
Partial R^2 for instrument	0.0034	0.0221	0.0199
Excluded instruments test F-statistic	2.8	16.26	28.51
P-value for excluded instruments test	0.0613	0.0000	0.0000
Kleibergen-Paap under-identification test	3.242		29.016
P-value for under-identification test	0.072		0.000
Kleibergen-Paap weak identification test	1.494		28.592
Stock-Yogo 10% critical value, weak ID test	7.03		16.38

Source: LABS / 2001 Census.
Notes. Sample is for 2007 only. HAC standard errors in parentheses. All specifications include year and SIC3 dummies. Controls fitted: log firm age, log firm size, log size squared, collaboration dummy, R&D dummy, exports dummy, PLC dummy, % qualified managers, % completed management course, % with informal management training, % with management experience, KIBS dummy. * = significant at 10%, ** 5%, *** 1%.

Table 16. Instrumental variable results: second stage.

Depvar = innovation	**New product, service**	**Modified product, service**	**New equipment**	**New way of working**
	(1)	**(2)**	**(3)**	**(4)**
Ethnic diverse firm	-0.098	0.010	0.257	0.465**
	(0.224)	(0.220)	(0.214)	(0.232)
Controls	Y	Y	Y	Y
Observations	1496	1496	1496	1496
R2	0.068	0.070	0.012	-0.056
F	8.941	7.813	4.151	6.420

Commercialisation	**New product, service**	**Modified product, service**	**New equipment**	**New way of working**
	(5)	**(6)**	**(7)**	**(8)**
Ethnic diverse firm	0.141	0.224	0.323*	0.426**
	(0.199)	(0.195)	(0.187)	(0.207)
Controls	Y	Y	Y	Y
Observations	1496	1496	1496	1496
R2	0.052	0.027	-0.046	-0.087
F	6.507	5.972	2.664	4.006

Source: LABS.
Notes: Sample is for 2007 only. Robust standard errors in parentheses. All specifications include year and partialled SIC3 dummies. Controls fitted: log firm age, log firm size, log size squared, collaboration dummy, R&D dummy, exports dummy, PLC dummy, % qualified managers, % completed management course, % with informal management training, % with management experience, KIBS dummy. * = significant at 10%, ** 5%, *** 1%.

Background

Appendix A. Classifications: country of birth, ethnicity, CEL

Country of birth categories (Labour Force Survey)

UK / GB	Algeria
Belgium	Angola
Denmark	Botswana
France	Ethiopia
Germany	Egypt
Greece	Gambia
Irish republic	Ghana
Italy (excl. Vatican City)	Kenya
Luxembourg	Libya
Netherlands	Malawi
Portugal	Mauritius
Spain	Morocco
Andorra	Nigeria
Austria	South Africa
Cyprus	Sierra Leone
Gibraltar	Seychelles
Finland	Somalia
Liechtenstein	Tanzania
Malta & Gozo	Tunisia
Norway	Uganda
Sweden	Zaire
Switzerland	Zambia
Turkey	Zimbabwe
Former Yugoslavia	Other Africa
Albania	Bangladesh
Bulgaria	India
Former Czechoslovakia	Pakistan
Hungary	Iran
Poland	Iraq
Romania	Israel
Former USSR etc.	Lebanon
Other Europe	Other Middle East
Barbados	Burma Myanmar
Belize	China
Canada	Hong Kong
Other Caribbean	Indonesia
Cuba	Japan
Guyana	Korea
Jamaica	Macau / Macao
Trinidad & Tobago	Malaysia
USA	Philippines
West Indies	Singapore
Other Central America	Sri Lanka
Mexico	Vietnam
Other South America	Other Asia
Argentina	Australia
Brazil	New Zealand
Chile	Caribbean Commonwealth
Columbia	Other New Commonwealth
Uruguay	Rest of the world
Venezuala	

Source: LFS.
Note: Categories are taken from the FLS variable CRYOX. At sea / in the air and stateless dropped in this analysis.

Office of National Statistics ethnicity categories (Labour Force Survey, Census)

ETHCEN15 categories
British
Other White
White and Black Caribbean
White and Black African
White and Asian
Other Mixed
Indian
Pakistani
Bangladeshi
Other Asian
Black Caribbean
Black African
Black Other
Chinese
Other

ETHNIC categories
White
Black Caribbean
Black African
Black Other
Indian
Pakistani
Bangladeshi
Chinese
Other

Source: ONS.
Note: Categories in the top panel are taken from the 2001 Census variable ETHCEN15. Categories in the bottom panel are taken from the 1991 Census variable ETHNIC.

ONOMAP Cultural-Ethnic-Linguistic (CEL) sub-groups

AFRIKAANS	LEBANESE
ALBANIAN	MALAYSIAN
AMERICAN	MUSLIM NORTH AFRICAN
ARMENIAN	MUSLIM STANS
BALKAN	NATIVE AMERICAN
BANGLADESHI	NIGERIAN
BLACK	OTHER AFRICAN
BLACK SOUTHERN AFRICAN	OTHER BALTIC
CELTIC	OTHER EAST ASIAN & PACIFIC
CHINESE	OTHER EUROPEAN
CONGOLESE	OTHER MUSLIM
CZECH & SLOVAK	OTHER NORDIC
DANISH	OTHER SOUTH ASIAN
DUTCH	NORWEGIAN
ENGLISH	PAKISTANI
ERITREAN	PAKISTANI KASHMIR
ETHIOPIAN	POLISH
FINNISH	PORTUGUESE
FRENCH	ROMANIAN
GERMAN	RUSSIAN
GHANAIAN	SCOTTISH
GREEK	SERBIAN
HINDI NOT INDIAN	SIERRA LEONIAN
HISPANIC	SIKH
HUNGARIAN	SOMALIAN
INDIAN HINDI	SPANISH
INTERNATIONAL	SRI LANKAN
IRANIAN	SWEDISH
IRISH	TURKISH
ITALIAN	UGANDAN
JAPANESE	UKRANIAN
JEWISH	VIETNAMESE
JEWISH AND ARMENIAN	WELSH
KOREAN	

Source: ONOMAP.

Notes: Categories refer to ONOMAP subgroups, which aggregate more detailed ‘types’. ‘Other …’ subgroups are composed as follows. 1) ‘OTHER MUSLIM’ subgroup includes CEL name types ‘BALKAN MUSLIM’, ‘MALAYSIAN MUSLIM’, ‘MUSLIM INDIAN’, ‘SUDANESE’, ‘WEST AFRICAN MUSLIM’, ‘OTHER MUSLIM’ (SMALLER MIDDLE EASTERN COUNTRIES, N/AFRICAN COUNTRIES, CENTRAL ASIAN REPS). 2) ‘OTHER SOUTH ASIAN’ includes CEL name types ‘ASIAN CARIBBEAN’, ‘BENGALI’, ‘BHUTANESE’, ‘GUYANESE ASIAN’, ‘KENYAN ASIAN’, ‘NEPALESE’, ‘PARSI’, ‘SEYCHELLOIS’, ‘SOUTH ASIAN’, ‘TAMIL’. 3) 'JEWISH' includes CEL name types ‘JEWISH / ASHKENAZI’, ‘SEPHARDIC JEWISH’ 4) ‘OTHER EAST ASIAN AND PACIFIC’ includes CEL name types ‘BURMESE’, ‘CAMBODIAN’, ‘FIJIAN’, ‘HAWAIIAN’, ‘LAOTIAN’,‘MAORI’, ‘MAURITIAN’, ‘POLYNESIAN’, ‘SAMOAN’, ‘SINGAPOREAN’, ‘SOLOMON ISLANDER’, ‘OTHER SOUTH EAST ASIAN’ , ‘THAI’, ‘TIBETIAN’, ‘TONGAN’, ‘TUVALUAN’, ‘OTHER EAST ASIAN & PACIFIC’. 5) ‘OTHER AFRICAN’ includes CEL name types ‘BENINESE’, ‘BOTSWANAN’, ‘BURUNDIAN’, ‘CAMEROONESE’, ‘GAMBIAN’, ‘GUINEAN’, ‘IVORIAN’, ‘KENYAN’, ‘LIBERIAN’, ‘MALAGASY’, ‘MALAWIAN’, ‘NAMIBIAN’, ‘RWANDAN’, ‘SENEGALESE’, ‘SWAZILANDER’, ‘TANZANIAN’, ‘ZAIREAN’, ‘ZAMBIAN’, ‘ZIMBABWEAN’, Other African not otherwise specified. 6) ‘OTHER BALKAN’ includes CEL name types ‘BOSNIAN AND HERZEGOVIAN’, ‘BULGARIAN’, ‘CROATIAN’, ‘MACEDONIAN’, ‘MONTENEGRIN’, ‘SLOVENIAN’, ‘BALKAN / OTHER’. 7) ‘OTHER BALTIC’ includes ‘ESTONIAN’, ‘LATVIAN’, ‘LITHUANIAN’, ‘BALTIC / OTHER’. 8) INTERNATIONAL includes otherwise unclassified names.

ONOMAP Geographical Origin Zones

Africa
Americas
British Isles
Central Asia
Central Europe
East Asia
Eastern Europe
Middle East
Northern Europe
South Asia
Southern Europe
Rest of the World

Source: ONOMAP.
Notes: Geographical origin zones are one of several elements used to construct full CEL typologies. They are used here as rough proxies for geographical ‘roots’.

Appendix B. ONOMAP Cultural-Ethnic-Linguistic classification

ONOMAP is an example of a Cultural-Ethnic-Linguistic (CEL) classification system. CEL classifications are designed to be objective and multidimensional typologies of ethnic / cultural identity (see Mateos (2007) for a review of recent CEL research). ONOMAP itself was originally designed for mining patient data for the UK National Health Service, and classifies individuals according to most likely cultural, ethnic and linguistic characteristics identified from forenames, surnames and forename-surname combinations.[76]

ONOMAP is built from a very large names database drawn from UK Electoral Registers plus a number of other contemporary and historical sources, covering 500,000 forenames and a million surnames across 28 countries (Mateos et al., 2007). These are then algorithmically grouped together, combining information on geographical area, religion, and language. Separate classifications of surnames, forenames and surname-forename combinations are produced. This gives 185 basic CEL categories (or 'types') which can be aggregated, broken down into constituent parts (such as likely geographical origin) and crosswalked onto other classifications (such as ONS ethnic groups).[77] For this thesis I use a typology of 67 CEL subgroups (for the 2001-6 urban areas analysis), and two constituent typologies for the analysis of ethnic inventors – 13 geographical origin zones and nine ONS ethnic groups.

ONOMAP exploits similarities and differences between name families – so that 'John Smith' is more likely to be ethnically British than French:

> *Each name … [is] assigned an Onomap type together with a probability score that summarises the likelihood of a particular name belonging to such a type. Such a probability score is derived from the share of the population with that (fore/sur)name that also has a (sur/fore)name belonging to the same Onomap type. When classifying a list of names, the Onomap software assesses both components of a person's name (forename and surname). In cases of conflict between … forename and surname it assigns the Onomap type with the highest probability score.* (Lahka et al (forthcoming), p3)

[76] For more details see http://www.onomap.org/FAQ.aspx.

[77] Names information is drawn from 1998 and 2004 GB Electoral Registers, Northern Ireland Electoral Register 2003, Irish Electoral Register 2003, plus electoral data from Australia (2002), NZ (2002), United States (1997) and Canada (1996). Experian MOSAIC geo-demographic data and the Experian Consumer Dynamics datafile are used to boost the sample. This produces 25360 surnames and 299797 first names. These are classified using a combination of triage, spatio-temporal analysis, geo-demographic analysis, text mining, 'name-to-ethnicity' techniques from population registers and researching international name frequencies. 'British names' are taken as those originating in the British Isles (including Ireland) or arriving there before 1700.

As with country of birth and ONS ethnic groups, ONOMAP has pros and cons as a proxy for ethnic / cultural identity. It offers its own version of Aspinall's 'granularity – utility' trade-off (Aspinall, 2009). Like all CEL approaches, ONOMAP has the advantage of being multidimensional and available at different levels of detail. Because ONOMAP uses surname *and* forename information, it is able to deal with many names with multiple cultural origins, and the alteration and/or adoption of names traditional to the UK.[78] All of these factors give it both high granularity and high utility.

However, ONOMAP has three important limitations. First, it has the drawback of only observing objective characteristics of identity – the most conservative interpretation is that it provides information on *most likely* cultural / ethnic identity. This is potentially an important limitation to utility, although robustness tests using Census birth-country and ethnicity information indicate that ONOMAP ascribes identity with a high degree of reliability (Mateos et al., 2007).

Second, ONOMAP does not distinguish countries with a common language, so that North American and Australasian-origin individuals are largely identified as British-origin (or unclassified). This is potentially a significant limitation on both granularity and utility. In practice, resulting measurement error is likely to be small. Although the largest concentrations of these groups are in London, their spatial distribution is not very different from minority communities as a whole. These groups also represent a relatively small share of the UK's minority population: for example, Labour Force Survey figures suggest that American, Canadian, Australian and New Zealand migrants comprised just 8.84% of migrants in 1994, falling to 7.98% in 2004.

Third, and most seriously, ONOMAP is unable to distinguish migrants from members of existing, established minority communities. In a few cases it could provide indirect identification – for example, when minority groups are very new and known to be composed of migrants. The rest of the time this is a major granularity limitation.

[78] The author's name is one of the more challenging to classify. According to Mateos (by email), 'Nathan is unclassified at the moment in Onomap, perhaps because there are conflicting frequencies in India, New Zealand and the UK. "Max" is classified as "Jewish", probably because it is common in this community in the UK compared to the national average. Therefore you would be classified as 'Jewish'." This is a good proxy for my actual British/English/secular Jewish sense of self.

Appendix C. Urban and rural Travel to Work Areas typology.

In order to identify urban areas in the UK, I use the ‘primary urban’ Travel to Work Areas (TTWAs) developed by Gibbons et al (2011). Travel to Work Areas are contiguous zones designed to approximate functional labour markets. Specifically, they require that 75% of the workers in a given zone also live in that zone, and that 75% of the residents in that zone also work in it (Bond and Coombes, 2007).

As a starting point Gibbons and colleagues take the most recent set of TTWAs, which were constructed by Newcastle University in 2007, based on 2001 Census data. Many TTWAs represent distinct cities and their hinterlands. From the 243 existing areas, Gibbons et al identify 79 ‘primary urban’ TTWAs. Primary urban TTWAs are those centred around, or intersecting urban footprints with populations of 100,000 or more (for example, London, Manchester or Plymouth).

A map of the 79 primary urban TTWAs is show in Figure 2 below.

Figure 2. 'Primary Urban' Travel to Work Areas.

Source: Gibbons et al (2011).

References

ACKROYD, P. 2000. *London: The Biography,* London, Vintage.

AGRAWAL, A., COCKBURN, I. & MCHALE, J. 2006. Gone but not forgotten: knowledge flows, labor mobility, and enduring social relationships. *Journal of Economic Geography,* 6**,** 571-591.

AGRAWAL, A., KAPUR, D. & MCHALE, J. 2008. How do spatial and social proximity influence knowledge flows? Evidence from patent data. *Journal of Urban Economics,* 64**,** 258-269.

AGRAWAL, A., KAPUR, D., MCHALE, J. & OETTL, A. 2011. Brain Drain or Brain Bank? The impact of skilled emigration on poor country innovation. *Journal of Urban Economics,* 69**,** 43-55.

AHLERUP, P. & OLSSON, O. 2007. The Roots of Ethnic Diversity. *WORKING PAPERS IN ECONOMICS No 281.* Gothenberg: School of Business Economics and Law, Gothenberg University.

ALESINA, A. & LA FERRARA, E. 2004. Ethnic Diversity and Economic Performance. *NBER Working Paper 10313.* Cambridge, MA: NBER.

ALONSO, W. 1964. *Location and Land Use,* Cambridge, MA, Harvard University Press.

ALTONJI, J. & CARD, D. 1991. The Effects of Immigration on the Labor Market Outcomes of Less-skilled Natives. *In:* ABOWD, J. & FREEMAN, R. (eds.) *Immigration, Trade and the Labor Market.* Chicago: University of Chicago Press.

AMIN, A. 2002. Ethnicity and the Multicultural City: Living with Diversity. *Environment and Planning,* 34**,** 959-980.

ANDERSON, S. & PLATZER, M. 2007. American Made: The Impact of Immigrant Entrepreneurs and Professionals Arlington: National Venture Capital Association.

ANGRIST, J. & PISCHKE, J.-S. 2009. *Mostly Harmless Econometrics,* Princeton, Princeton University Press.

ARCHIBUGI, D. & IAMMARINO, S. 2002. The globalization of technological innovation: definition and evidence. *Review of International Political Economy,* 9**,** 98–122.

ASPINALL, P. 2009. The Future of Ethnicity Classifications. *Journal of Ethnic and Migration Studies,* 35**,** 1417-1435.

AUDRETSCH, D. & FELDMAN, M. 1996. R&D Spillovers and the Geography of Innovation and Production. *American Economic Review,* 86**,** 630-640.

BAKER, P. & EVERSLEY, J. (eds.) 2000. *Multilingual Capital: The languages of London's Schoolchildren and the relevance to economic, social and educational policies,* London: Battlebridge.

BASSERE, V., DENSHAM, P., MILLAR, J. & SALT, J. 2007. Migrants from Central and Eastern Europe: New Geographies. *Population Trends,* 129**,** 7-19.

BASU, A. 2002. The Interaction between Culture and Entrepreneurship in London's Immigrant Businesses. *International Small Business Journal,* 20**,** 371-393

BASU, A. 2004. Entrepreneurial aspirations among family business owners: An analysis of ethnic business owners in the UK. *International Journal of Entrepreneurial Behaviour & Research,* 10**,** 12-33.

BBC. 2010. *Business cheers exclusions from migration cap* [Online]. London: BBC. Available: http://www.bbc.co.uk/news/business-11824383 [Accessed 23 August 2011].

BELLINI, E., OTTAVIANO, G., PINELLI, D. & PRAROLO, G. 2008. Cultural Diversity and Economic Performance: Evidence from European Regions. *HWWI Research Paper 3-14.* Hamburg: Hamburg Institute of International Economics.

BENEDICTUS, L. 2005. Every race, colour, nation and religion on earth. *The Guardian*, 21 January

BERLIANT, M. & FUJITA, M. 2009. The Dynamics of Knowledge Diversity and Economic Growth. *56th Annual North American Meeting, Regional Science Association International.* San Francisco.

BERTHOUD, R. 2003. Multiple disadvantage in employment A quantitative analysis York: Joseph Rowntree Foundation.

BLANCHFLOWER, D. 2007. Fear, Unemployment and Migration. *Esmee Fairbairn Memorial Lecture.* Lancaster University.

BLINDER, S. 2011. UK Public Opinion toward Immigration: Overall Attitudes and Level of Concern. *Migration Observatory Briefing.* Oxford: COMPAS.

BLUNDELL, R., GRIFFITH, R. & VAN REENEN, J. 1995. Dynamic Count Data Models of Technological Innovation. *The Economic Journal,* 105**,** 333-344.

BONACICH, E. 1973. A Theory of Middleman Minorities. *American Sociological Review,* 38**,** 583-594.

BOND, S. & COOMBES, M. 2007. 2001-based Travel-To-Work Areas Methodology. Office of National Statistics.

BORJAS, G. 1987. Self-Selection and the Earnings of Immigrants. *American Economic Review,* 77**,** 531-53.

BORJAS, G. 1994. The Economics of Immigration. *Journal of Economic Literature,* 32**,** 1667-1717.

BORJAS, G. 2011. The Benefits and Costs of High Skill Immigration. *Migration: Economic Change, Social Challenge* London UCL.

BORJAS, G. J. 2006. Native Internal Migration and the Labor Market Impact of Immigration. *Journal of Human Resources,* XLI**,** 221-258.

BRESNAHAN, T. & GAMBARDELLA, A. 2004. Old-Economy Inputs for new-Economy Outcomes: What have we learned? *In:* BRESNAHAN, T. & GAMBARDELLA, A. (eds.) *Building High-Tech Clusters.* Cambridge CUP

BRINKLEY, I. 2008. The Knowledge Economy: How knowledge is reshaping the economic life of nations. London: The Work Foundation.

BULMER, S. 1996. The ethnic group question in the 1991 Census of Population. *In:* COLEMAN, D. & SALT, J. (eds.) *Ethnicity in the 1991 Census of Population.* London: HMSO.

BURDETT, R. & SUDJIC, D. 2011. *Living in the Endless City,* London, Phaidon.

CALDWELL, C. 2009. *Reflections on the Revolution in Europe: Immigration, Islam and the West* London, Allen Lane.

CAMERON, A. C. & TRIVEDI, P. 2009. *Microeconometrics using Stata,* College Station, Stata Press.

CANTLE, T. 2001. Community Cohesion: A Report of the Independent Review Team. London: Home Office.

CANTWELL, J. 2005. MNCs, local clustering and science-technology relationships. *In:* SANTANGELO, G. (ed.) *Technological Change and Economic Catch-Up: The Role of Science and Multinationals.* Cheltenham: Edward Elgar.

CARD, D. 2001. Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration. *Journal of Labor Economics,* 19**,** 22-64.

CARD, D. 2005. Is the New Immigration Really So Bad? *The Economic Journal,* 115**,** 300-323.

CARD, D. 2007. How Immigration Affects US Cities. *CrEAM Discussion Paper 11/07.* London: UCL.

CARD, D. 2011. Understanding the Supply and Demand for Immigrants. *Migration: Economic Change, Social Challenge* London: UCL.

CARD, D., DUSTMANN, C. & PRESTON, I. 2009. Immigration, Wages, and Compositional Amenities *NBER Working Paper No. w15521.* Cambridge, Mass.: NBER.

CASEY, T. & DUSTMANN, C. 2009. Immigrants' Identity, Economic Outcomes and the Transmission of Identity Across Generations. *CReAM Discussion Paper Series CDP 23/09.* London: University College London.

CHAMPION, T. 2006. State of the English Cities: The Changing Urban Scene: Demographics and the Big Picture. London: Office of the Deputy Prime Minister.

CHAMPION, T. & FISHER, T. 2004. Migration, Residential Preferences and the Changing Environment of Cities. *In:* BODDY, M. & PARKINSON, M. (eds.) *City Matters.* Bristol: Policy Press.

CHELLARAJ, G., MASKUS, K. & MATTOO, A. 2005. The Contribution of Skilled Immigration and International Graduate Students to U.S. Innovation *World Bank Policy Research Working Paper 3588.* Washington DC: World Bank.

CHRISTOPHERSON, S. & CLARK, J. 2007. *Remaking regional economies: power, labour and firm strategies in the knowledge economy,* Abingdon, Routledge.

CIUPIJUS, Z. 2011. Mobile central eastern Europeans in Britain: successful European Union citizens and disadvantaged labour migrants? *Work, Employment & Society,* 25**,** 540-550.

COE, N., JOHNS, J. & WARD, K. 2006. Mapping the Globalisation of the Temporary Staffing Industry. *ESRC Globalisation of the Temporary Staffing Industry Working Paper 2.* Manchester: University of Manchester.

COLLIER, P. & HOEFFLER, A. 1998. On economic causes of civil war. *Oxford Economic Papers,* 50**,** 563-573.

COMBES, P.-P., DURANTON, G. & OVERMAN, H. 2005. Agglomeration and the Adjustment of the Spatial Economy. *Papers in Regional Science,* 84**,** 311-349.

COOK, J., DWYER, P. & WAITE, L. 2011. The experiences of accession 8 migrants in England: motivations, work and agency. *International Migration,* 49**,** 54-79.

COOKE, P., URANGE, M. & EXTEBARRIA, G. 1997. Regional Innovation Systems: Institutional and Organizational Dimensions. *Research Policy,* 26**,** 475-491.

CRAFTS, N. & VENABLES, A. Year. Globalisation in History: A Geographical Perspective. *In:* NBER Conference, 2001 London. LSE, 1-51.

DAHLMAN, C. 2010. Innovation Strategies of Three of the BRICS: Brazil, India and China- What Can We Learn From Three Different Approaches. *In:* FU, X. & SOETE, L. (eds.) *The Rise of Technological Power in the South.* Basingtoke: Palgrave MacMillan.

DAWLEY, S. & STENNING, A. 2008. Placing Migrant Workers in Peripheral Regions: A8 nationals and labour market intermediaries in the North East of England *AAG 2008 Annual Conference.* Boston, Mass.

DEPARTMENT FOR CHILDREN SCHOOLS AND FAMILIES. 2009. *Schools, Pupils and Their Characteristics* [Online]. London: DCSF. Available: http://www.dcsf.gov.uk/rsgateway/DB/SFR/s000843/index.shtml [Accessed 21 September 2009].

DEPARTMENT OF COMMUNITIES AND LOCAL GOVERNMENT 2008. Managing the Impacts of Migration: A Cross-Government Approach. London: Home Office and Department of Communities and Local Government.

DEPARTMENT OF COMMUNITIES AND LOCAL GOVERNMENT 2009a. Building Cohesive Communities: What frontline staff and community activists need to know. London: CLG.

DEPARTMENT OF COMMUNITIES AND LOCAL GOVERNMENT 2009b. Projections of Migration Inflows under Alternative Scenarios for the UK and World Economies. London: CLG.

DEPARTMENT OF INNOVATION UNIVERSITIES AND SKILLS 2008. Innovation Nation. London: Department of Innovation, Universities and Skills.

DESMET, K., ORTUÑO-ORTÍN, I. & WACZIARG, R. 2009. The Political Economy of Ethnolinguistic cleavages. *In:* 15360, N. W. P. (ed.). Cambridge, MA: NBER

DOCQUIER, F. & RAPOPORT, H. 2011. Globalisation, Brain Drain and Development. *IZA DP 5590.* Bonn: IZA.

DURANTON, G. & PUGA, D. 2001. Nursery Cities: Urban Diversity, Process Innovation and the Life Cycle of Products. *American Economic Review* 91**,** 1454-1477.

DURANTON, G. & PUGA, D. 2003. Micro-Foundations of Urban Agglomeration Economies. *NBER Working Paper 9931.* Cambridge, Mass.: NBER.

DUSTMANN, C., FABBRI, F. & PRESTON, I. 2005. The Impact of Immigration on the British Labour Market. *The Economic Journal,* 115**,** 324-341.

DUSTMANN, C., FABBRI, F., PRESTON, I. & WADSWORTH, J. 2003. The Local Labour Market Effects of Immigration on the UK. London: Home Office.

DUSTMANN, C., FRATTINI, T. & PRESTON, I. 2007. A Study of Migrant Workers and the National Minimum Wage, and Enforcement Issues That Arise. London: Low Pay Commission.

DUSTMANN, C., GLITZ, A. & FRATTINI, T. 2008. The labour market impact of immigration. *Oxford Review of Economic Policy,* 24**,** 477-494.

EASTERLEY, W. & LEVINE, R. 1997. Africa's Growth Tragedy: Policies and Ethnic Divisions. *Quarterly Journal of Economics,* 112**,** 1203-1250.

ECONOMIST, T. 2006. Second Thoughts: Migration from Eastern Europe. *The Economist*, 24 August.

EQUALITY AND HUMAN RIGHTS COMMISSION 2010. Inquiry into Recruitment and Employment in the Meat and Poultry Processing Sector. London: EHRC.

FAGERBERG, J. 2005. Innovation: A guide to the literature. *In:* FAGERBERG, J., MOWERY, D. & NELSON, R. (eds.) *The Oxford Handbook of Innovation.* Oxford: OUP.

FAGGIAN, A. & MCCANN, P. 2009. Human capital, graduate migration and innovation in British regions. *Cambridge Journal of Economics,* 33**,** 317-333.

FAGGIO, G. & OVERMAN, H. 2011. The effect of public sector employment on local labour markets. *Spatial Economics Research Centre Annual Conference.* London.

FAIRLIE, R., KRASHINSKY, H., ZISSIMOPOULOS, J. & KUMAR, K. 2009. Indian Entrepreneurial Success in the United States, Canada and the United Kingdom. *RAND Corporation Working Paper 727.* Santa Monica, CA: RAND Corporation.

FANSHAWE, S. & SRISKANDARAJAH, D. 2010. You Can't Put Me In a Box: Super-diversity and the end of identity politics in Britain. London: ippr.

FERNANDEZ, R. 2010. Does Culture Matter? *NBER Working Paper 16277.* Cambridge, Mass: NBER.

FINEGOLD, D. & SOSKICE, D. 1988. The Failure of Training in Britain: Analysis and Prescription. *Oxford Review of Economic Policy,* 4**,** 21-53.

FITZGERALD, I. 2007. Working in the UK: Polish Migrant Worker Routes into Employment in the North East and North West Construction and Food Processing Sectors. London: TUC.

FLORIDA, R. 2002. *The Rise of the Creative Class,* New York, Basic Books.

FLORIDA, R. 2005. The world is spiky. *The Atlantic Monthly,* 296**,** 48-51.

FOLEY, C. F. & KERR, W. R. 2011. Ethnic Innovation and U.S. Multinational Firm Activity. *National Bureau of Economic Research Working Paper Series,* No. 17336.

FRATTINI, T. 2008. Immigration and Prices in the UK. *mimeo.* London: UCL.

FREEMAN, C. 1987. *Technology Policy and Economic Policy: Lessons from Japan* London, Pinter.

FUJITA, M., KRUGMAN, P. & VENABLES, A. J. 1999. *The Spatial Economy: Cities, Regions, and International Trade,* Cambridge, MA, MIT Press.

FUJITA, M. & WEBER, S. 2003. Strategic Immigration Policies and Welfare in Heterogenous Countries. *Institute of Economic Research Working Papers.* Kyoto: Kyoto University.

GIBBONS, S., OVERMAN, H. & RESENDE, G. 2011. Real Earnings Disparities in Britain. *SERC Discussion Paper SERCDP0065.* London: LSE.

GILROY, P. 1993. *Black Atlantic: Modernity and Double Consciousness,* London, Verso.

GLAESER, E. 2005. Review of Richard Florida's 'The Rise of the Creative Class'. *Regional Science and Urban Economics,* 35**,** 593-596.

GLAESER, E. 2008. *Cities, Agglomeration and Spatial Equilibrium,* Oxford, OUP.

GLAESER, E., KALLAL, H., SCHEINKMANN, J. & SHLEIFER, A. 1992. Growth in Cities. *Journal of Political Economy,* 100**,** 1126.

GOODHART, D. 2004. Too Diverse? *Prospect,* 95.

GOODHART, D. 2010. A Crowded Island. *Prospect,* 168.

GOOS, M. & MANNING, A. 2007. Lousy and Lovely Jobs: The rising polarization of work in Britain. *Review of Economics and Statistics,* 89**,** 118-133.

GORDON, I. 2001. Unemployment and spatial labour markets: strong adjustment and persistent concentration. *In:* MARTIN, R. & MORRISON, P. (eds.) *Geographies of Labour Market Inequality.* London: Routledge.

GORDON, I., TRAVERS, T. & WHITEHEAD, C. 2009. London's Place in the UK Economy. London: City of London Corporation.

GORDON, I., WHITEHEAD, C. & TRAVERS, T. 2007. The Impact of Recent Immigration on the London Economy. London: City of London Corporation.

GORODNICHENKO, Y. & ROLAND, G. 2011. Which Dimensions of Culture Matter for Long-Run Growth? *American Economic Review,* 101**,** 492-98.

GOUJARD, A., PETRONGOLO, B. & VAN REENEN, J. 2011. The Labour Market for Young People. *In:* GREGG, P. & WADSWORTH, J. (eds.) *The Labour Market in Winter: The State of Working Britain.* Oxford: Oxford University Press.

GRAHAM, D. 2007. Identifying Urbanisation and Localisation Externalities in Manufacturing and Service industries. *Papers in Regional Science,* 88**,** 63-84.

GREATER LONDON AUTHORITY 2008a. Planning for a Better London. London: GLA.

GREATER LONDON AUTHORITY 2008b. A Profile of Londoners by Country of Birth. London: GLA.

GREEN, A. 2007a. Overview: Migration, Skills and Employment. *Migration, Skills and Employment.* London.

GREEN, A. 2008. Labour Market Intermediaries, Employment of Economic Migrants and Challenges for Regional Development. *AAG 2008 Annual Conference.* Boston, Mass.

GREEN, A., DE HOYOS, M., JONES, P. & OWEN, D. 2009. Rural development and labour supply challenges in the UK: the role of non-UK migrants. *Regional Studies,* 43**,** 1261 - 1273.

GREEN, A., JONES, P. & OWEN, D. 2007a. Migrant Workers in the East Midlands Labour Market. Warwick: Institute for Employment Research.

GREEN, A., OWEN, D. & JONES, P. 2007b. The Economic Impact of Migrant Workers in the West Midlands. Birmingham: Learning and Skills Council West Midlands Region.

GREEN, A. E. 2007b. Local action on labour market integration of new arrivals: Issues and dilemmas for policy. *Local Economy,* 22**,** 349-361.

GREEN , E. 2011. Endogenous Ethnicity. *monograph.* London: DESTIN, London School of Economics.

GREENE, W. H. 1994. Accounting for Excess Zeros and Sample Selection in Poisson and Negative Binomial Regression Models. *NYU Working Paper No. EC-94-10.* New York NYU.

GRIFFITH, R., HUERGO, E., MAIRESSE, J. & PETERS, B. 2006. Innovation and Productivity Across Four European Countries. *Oxford Review of Economic Policy,* 22**,** 483-498.

GRILICHES, Z. 1979. Issues in assessing the contribution of R&D to productivity growth. *Bell*

Journal of Economics, 10.

HALL, B., JAFFE, A. & TRAJTENBERG, M. 2001. The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools. Cambridge, Mass.: NBER.

HALL, P. 1998. *Cities in Civilisation: Culture, Innovation and Urban Order,* London, Weidenfeld and Nicholson.

HART, D. 2010. What Do Foreign-Born Founders Bring To Entrepreneurial Teams? An Exploration in the U.S. High-Tech Sector. *School of Public Policy Working Papers* Arlington, VA: George Mason University.

HATTON, T. & TANI, M. 2005. Immigration and Inter-Regional Mobility in the UK, 1982-2000. *The Economic Journal,* 115**,** 342-358.

HAUSMAN, J. A., HALL, B. H. & GRILICHES, Z. 1984. Econometric Models for Count Data with an Application to the Patents-R&D Relationship. *NBER Technical Working Paper No. 17.* Cambridge, MA: NBER.

HENDERSON, J. V. 1974. The sizes and types of cities. *American Economic Review,* 64**,** 640–656.

HENRY, N., MACEWAN, C. & POLLARD, J. S. 2002. Globalisation from below: Birmingham - postcolonial workshop of the world? *Area,* 34**,** 117-127.

HM GOVERNMENT 2010. The Coalition: our programme for government. London: Cabinet Office.

HM TREASURY & BIS 2011. The Plan for Growth. London: TSO.

HOME OFFICE & DEPARTMENT OF WORK AND PENSIONS 2007. The Economic and Fiscal Impact of Immigration. London: Home Office.

HONG, L. & PAGE, S. 2001. Problem Solving by Heterogeneous Agents. *Journal of Economic Theory,* 97**,** 123-163.

HONG, L. & PAGE, S. 2004. Groups of diverse problem solvers can outperform groups of high-ability problem solvers. *Proceedings of the National Academy of Sciences of the United States of America,* 101**,** 16385-16389.

HONIG, B., DRORI, I. & CARMICHAEL, B. (eds.) 2010. *Transnational and Immigrant Entrepreneurship in a Globalized World,* Toronto: University of Toronto Press.

HOUSE OF LORDS ECONOMIC AFFAIRS COMMITTEE 2008. The Economic Impact of Immigration. London: Stationery Office.

HUBER, P., LANDESMANN, M., ROBINSON, C. & STEHRER, R. 2011. Migration, Skills and Productivity. *Research Reports 365.* Vienna: Vienna Institute for International Economic Studies.

HUNT, J. & GAUTHIER-LOISELLE, M. 2008. How much Does Immigration Boost Innovation? *NBER Working Paper 14312.* Cambridge, Mass.: NBER.

HUNT, J. & GAUTHIER-LOISELLE, M. 2010. How Much Does Immigration Boost Innovation? *American Economic Journal: Macroeconomics,* 2**,** 31-56.

JACOBS, J. 1961. *The Life and Death of Great American Cities,* London, Pimlico.

JACOBS, J. 1969. *The Economy of Cities,* London, Vintage.

JAFFE, A. & TRAJTENBERG, M. 1999. International Knowledge Flows: Evidence from patent citations. *International Journal of Knowledge Organisation,* 8**,** 105-136.

JAFFE, A. B., TRAJTENBERG, M. & HENDERSON, R. 1993. Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *The Quarterly Journal of Economics,* 108**,** 577-598.

JONES, T., RAM, M. & ABBAS, T. 2004. Ethnic minority enterprise in an inner-city context: the case of the independent restaurant sector in Birmingham. *In:* BODDY, M. & PARKINSON, M. (eds.) *City Matters.* Bristol: Policy Press.

KAISER, U., KONGSTED, H. C. & RØNDE, T. 2011. Labor Mobility, Social Network Effects, and Innovative Activity. *In:* 5654, I. D. N. (ed.). Bonn: IZA.

KAPUR, D. & MCHALE, J. 2005. Sojourns and Software: Internationally mobile human capital and high tech industry development in India, Ireland and Israel. *In:* ARORA, A. & GAMBARDELLA, A. (eds.) *From Underdogs to Tigers: The Rise and Growth of the Software Industry in Brazil, China, India, Ireland and Israel.* Oxford: OUP.

KEITH, M. 2005. *After the Cosmopolitan? Multicultural cities and the future of racism,* Abingdon, Routledge

KELLEY, M. & HELPER, S. 1999. Firm size and capabilities, regional agglomeraiton and the adoption of new technology. *Economic Innovation and Technical Change,* 8**,** 79-103.

KERR, S. P. & KERR, W. 2011. Economic Impacts of Immigration: A Survey *NBER Working Paper 16736.* Cambridge, MA: NBER

KERR, W. 2008a. The Agglomeration of US Ethnic Inventors. *HBS Working Paper 09-003.* Boston, MA: Harvard Business School.

KERR, W. 2008b. Ethnic Scientific Communities and International Technology Diffusion. *Review of Economics and Statistics,* 90**,** 518-537.

KERR, W. 2009. Breakthrough Innovations and Migrating Clusters of Innovation. *NBER Working Paper 15443.* Cambridge, MA: NBER.

KERR, W. & LINCOLN, W. 2010. The Supply Side of Innovation: H-1b Visa Reforms and US Ethnic Invention *NBER Working Paper 15768.* Cambridge, Mass.: NBER

KITCHING, J., SMALLBONE, D. & ATHAYDE, R. 2009. Ethnic Diasporas and Business Competitiveness: Minority-Owned Enterprises in London. *Journal of Ethnic and Migration Studies,* 35**,** 689-705.

KLOOSTERMAN, R. & RATH, J. 2001. Immigrant entrepreneurs in advanced economies: mixed embeddedness further explored. *Journal of Ethnic and Migration Studies,* 27**,** 189-202.

KRUGMAN, P. 1991. *Geography and Trade,* Cambridge, MA, MIT Press.

KRUGMAN, P. & OBSFELDT, M. 2003. *International Economics: Theory and Policy,* Boston, Addison Weasley.

KRUGMAN, P. & VENABLES, A. 1995. Globalization and the inequality of nations. *Quarterly Journal of Economics,* 110**,** 857–880.

KUPER, S. 2009. The Myth Of Eurabia. *Financial Times*, 2 October.

KYAMBI, S. 2005. *Beyond Black and White: Mapping New Immigrant Communities,* London, ippr.

LAKHA, F., GORMAN, D. & MATEOS, P. forthcoming. Name analysis to classify populations by ethnicity in public health: Validation of Onomap in Scotland. *Public Health*.

LANDRY, C. & WOOD, P. 2008. *The Intercultural City: Planning for Diversity Advantage,* London, Earthscan.

LAZEAR, E. 1998. Diversity and Immigration *NBER Working Paper 6535.* Cambridge, Mass: NBER.

LEADBEATER, C. 2008. The Difference Dividend: Why Immigration is Vital to Innovation. *NESTA Provocation.* London: NESTA.

LEE, N. 2010. Ethnic Diversity and Employment Growth in English Cities. *Urban Studies*.

LEE, N. & NATHAN, M. 2010. Knowledge workers, cultural diversity and innovation: evidence from London firms. *International Journal of Knowledge-Based Development* 1, 53-78.

LEGRAIN, P. 2006. *Immigrants: Your Country Needs Them,* London, Little, Brown.

LEMOS, S. & PORTES, J. 2008. The Impact of migration from the new European Union Member States on Native workers. Leicester: University of Leicester.

LEWIS, E. 2005. Immigration, Skill Mix and the Choice of Technique. *Federal Reserve Bank of Philadelphia Working Paper #05-08.* Philadelphia: Federal Reserve Bank of Philadelphia.

LI, X. & PAI, Y. 2010. The Changing Geography of Innovation Activities: What do Patent Indicators Imply? *In:* FU, X. & SOETE, L. (eds.) *The Rise of Technological Power in the South.* Basingstoke: Palgrave MacMillan.

LISSONI, F., TARASCONI, G. & SANDITOV, B. 2006. The KEINS Database on Academic Inventors: Methodology and Contents. *CESPRI Working Paper 181.* Milan: Universita' Bocconi.

LONDON FIRST 2008. The World in One City.

LONGHI, S. 2011. Impact of Cultural Diversity on Wages and Job Satisfaction in England. *NORFACE MIGRATION Discussion Paper No. 2011-10.* NORFACE

LUCAS, R. 1988. On the Mechanics of Economic Growth. *Journal of Monetary Economics,* 22, 3-42.

LUCIFORA, C., MCKNIGHT, A. & SALVERDA, W. 2005. Low-wage employment in Europe: a review of the evidence. *Socio-Economic Review,* 3, 259-292.

MACKENZIE, R. & FORDE, C. 2009. The rhetoric of the `good worker' versus the realities of employers' use and the experiences of migrant workers. *Work, Employment & Society,* 23, 142-159.

MANACORDA, M., MANNING, A. & WADSWORTH, J. 2006. The Impact of Immigration on the Structure of Male Wages: Theory and Evidence from Britain. *IZA Discussion Paper 2352* [Online].

MANNING, A. & ROY, S. 2007. Culture Clash or Culture Club? The Identity and Attitudes of Immigrants in Britain. *CEP Discussion Paper 790.* London: Centre for Economic Performance, London School of Economics.

MARÉ, D. C., FABLING, R. & STILLMAN, S. 2011. Immigration and Innovation. *IZA Discussion Paper 5686.* Bonn: IZA.

MARSHALL, A. 1918. *Principles of Economics,* New York, Macmillan.

MASSEY, D. 1984. *Spatial Divisions of Labour: Social Structures and the Geography of Production,* New York, Metheun.

MATEOS, P. 2007. A review of name-based ethnicity classification methods and their potential in population studies. *Population, Space and Place* 13, 243-263.

MATEOS, P., SINGLETON, A. & LONGLEY, P. 2009. Uncertainty in the Analysis of Ethnicity Classifications: Issues of Extent and Aggregation of Ethnic Groups. *Journal of Ethnic and Migration Studies,* 35, 1437-1460.

MATEOS, P., WEBBER, R. & LONGLEY, P. 2007. The Cultural, Ethnic and Linguistic Classification of Populations and Neighbourhoods using Personal Names. *CASA Working Paper.* London: UCL.

MAZZOLARI, F. & NEUMARK, D. 2009. Beyond Wages: The effects of immigration on the scale and composition of output. *NBER Working Papers 14900.* Cambridge, MA: NBER.

MCCANN, P. 2008. Globalisation and Economic Geography: The World is Curved, not Flat. *Cambridge Journal of Regions, Economy and Science,* 1**,** 351-370.

MCSMITH, A. & RUSSELL, B. 2007. Migrants are essential for business growth, says CBI. *The Independent*, 3 January.

MELO, P., GRAHAM, D. & NOLAND, R. 2009. A meta-analysis of estimates of urban agglomeration economies. *Regional Science and Urban Economics,* 39**,** 332-342.

MENON, C. 2009. Stars and Comets: An Exploration of the Patent Universe. *SERC DP0037.* London: LSE.

MICHALOPOULOS, S. 2008. The Origins of Ethnolinguistic Diversity: Theory and Evidence. *Monograph.* Boston, Mass.: Tufts University.

MILLS, E. S. 1967. An Aggregative Model of Resource Allocation in a Metropolitan Area. *The American Economic Review,* 57**,** 197-210.

MOLLOY, R., SMITH, C. L. & WOZNIAK, A. 2011. Internal Migration in the United States. *Journal of Economic Perspectives,* 25**,** 173-96.

MOWERY, D. C. 2001. Technological Innovation in a Multipolar System: Analysis and Implications for U.S. Policy. *Technological Forecasting and Social Change,* 67**,** 143-157.

MUDAMBI, R. 2008. Location, control and innovation in knowledge-intensive industries. *Journal of Economic Geography,* 8**,** 699-725.

NAKHAIE, R., LIN, X. & GUEN, G. 2009. Social Capital and the Myth of Minority Self-Employment: Evidence from Canada. *Journal of Ethnic and Migration Studies,* 35**,** 625-644.

NATHAN, M. 2007. The Wrong Stuff? Creative Class Theory and Economic Performance in UK Cities. *Canadian Journal of Regional Science,* XXX**,** 433-450.

NATHAN, M. 2008. Your Place or Mine? The Local Economics of Migration. London: Institute for Public Policy Research.

NICKELL, S. & SALEHEEN, J. 2009. The impact of immigration on occupational wages: evidence from Britain. *SERC Discussion Paper DP0034.* London: LSE.

NIEBUHR, A. 2006. Migration and Innovation: Does Cultural Diversity Matter for Regional R&D Activity? *IAB Discussion Paper 14/2006.* Nuernberg: Institut fuer Arbeitsmarkt- und Berufsforschung.

OECD 2009. OECD Patent Statistics Manual. Paris: OECD.

OFFICE OF NATIONAL STATISTICS 2003. Ethnic Group Statistics: A guide for the collection and classification of ethnicity data. Newport: ONS.

OFFICE OF NATIONAL STATISTICS 2008a. Family Spending: A report on the 2007 Expenditure and Food Survey. Newport: ONS.

OFFICE OF NATIONAL STATISTICS 2008b. UK population approaches 61 million in 2007. *News Release, 21 August.* Newport: Office of National Statistics.

OFFICE OF NATIONAL STATISTICS 2011. Population Estimates by Ethnic Group 2002-2009. *ONS Statistical Bulletin.* London: ONS.

ORTEGA, F. & PERI, G. 2009. The Causes and Effects of International Migration: Evidence from OECD Countries 1980-2005. *NBER Working Paper 14833.* Cambridge, MA: NBER.

OTTAVIANO, G., BELLINI, E. & MAGLIETTA, A. 2007. Diversity and the Creative Capacity of Cities and Regions. *SUSDIV Paper 2.2007.* Bologna: FEEM.

OTTAVIANO, G. & PERI, G. 2005a. Cities and Cultures. *Journal of Urban Economics,* 58**,** 304-337.

OTTAVIANO, G. & PERI, G. 2005b. Rethinking the Gains from Immigration: Evidence from US Cities. *NBER Working Paper 11672.* Boston, Mass: NBER.

OTTAVIANO, G. & PERI, G. 2006. The Economic Value of Cultural Diversity: Evidence from US Cities. *Journal of Economic Geography,* 6**,** 9-44.

OTTAVIANO, G. & PERI, G. 2007. The Effects of Immigration on US Wages and Rents: A General Equilibrium Approach. *CrEAM Discussion Paper 13/07.* London: UCL.

OVERMAN, H. & RICE, P. 2008. Resurgent Cities and Regional Economic Performance. *SERC Policy Paper 1.* London: London School of Economics.

OZGEN, C., NIJKAMP, P. & POOT, J. 2010. Immigration and Innovation in European Regions. *Department of Spatial Economics working paper.* Amsterdam: VU University.

OZGEN, C., NIJKAMP, P. & POOT, J. 2011. The Impact of Foreign Workers on Innovation and Knowledge Spillovers: Analysis of Survey Data from the Netherlands. *Migration: Economic Change, Social Challenge.* London: UCL.

PAGE, S. 2007. *The Difference: How the Power of Diversity Creates Better Groups, Firms, Schools and Societies,* Princeton, Princeton University Press.

PARKINSON, M., CHAMPION, T., EVANS, R., SIMMIE, J., TUROK, I., CROOKSTON, M., PARK, A., BERUBE, A., COOMBES, M., DORLING, D., GLASS, N., HUTCHINS, M., KEARNS, A., MARTIN, R. & WOOD, P. 2006. *The State of English Cities Report,* London, Office of the Deputy Prime Minister.

PARROTTA, P., POZZOLI, D. & PYTLIKOVA, M. 2011. The Nexus Between Labor Diversity and Firm's Innovation [sic]. *NORFACE Discussion Paper 2011-5.*

PEET, R. 1998. *Modern Geographical Thought,* Oxford, Blackwell.

PERFORMANCE AND INNOVATION UNIT 2003. Ethnic Minorities in the Labour Market London: Cabinet Office Performance and Innovation Unit.

PERI, G. 2007. Higher Education, Innovation and Growth. *In:* BRUNELLO, G., GARIBALDI, P. & WASMER, E. (eds.) *Education and Training in Europe.* Oxford: Oxford University Press.

PERI, G. & REQUENA, F. 2009. The Trade Creation Effect of Migrants: Testing the Theory on the Remarkable Case of Spain. *CReAM Discussion Paper 15/09.* London: UCL.

PERI, G. & SPARBER, C. 2011. Assessing inherent model bias: An application to native displacement in response to immigration. *Journal of Urban Economics,* 69**,** 82-91.

PUTNAM, R. 2007. E Pluribus Unum: Diversity and Community in the Twenty-First Century. *Scandinavian Political Studies,* 30**,** 137-174.

RAM, M. & JONES, T. 2008. Ethnic minority businesses in the UK: an overview *MIGRAÇÕES,* 3**,** 61-71.

RANDOLPH, R. S. & ERICH, N. 2009 Global Reach: Emerging ties between the San Francisco Bay Area and India. San Francisco: Bay Area Council Economic Institute.

RANIS, G. 2009. Diversity of Communities and Economic Development: An Overview. *Economics Department Working Paper 69.* Yale: Economic Growth Center, Yale University.

RATH, J. & KLOOSTERMAN, R. 2000. Outsiders' Business: A Critical Review of Research on Immigrant Entrepreneurship. *International Migration Review,* 34**,** 657-681.

REED, H., COOLEY, L. & SRISKANDARAJAH, D. 2005. Paying Their Way: The Fiscal Contribution of Immigrants to the UK. London: IPPR.

ROBSON, B., BARR, R., LYMPEROPOULOU, K., REES, J. & COOMBES, M. 2006. A framework for City-Regions: Working Paper 1: Mapping City-Regions. London: Office of the Deputy Prime Minister.

RODRÍGUEZ-POSE, A. & STORPER, M. 2006. Better Rules or Stronger Communities? On the social foundations of institutional change and its economic effects. *Economic Geography,* 82**,** 1-25.

ROMER, P. 1990. Endogenous Technological Change. *Journal of Political Economy,* 98**,** 71-102.

SÁ, F. 2011. Immigration and House Prices in the UK. *IZA DP No. 5893.* Bonn: IZA.

SAIZ, A. 2003. Room in the Kitchen for the Melting Pot: Immigration and Rental Prices. *Review of Economics and Statistics,* 85**,** 502-521.

SAMUELS, T. 2008. *The £7-per-Hour Jobs Locals Don't Want* [Online]. BBC News Online. Available: http://news.bbc.co.uk/1/hi/magazine/7288430.stm [Accessed 18 April 2008].

SANDERCOCK, L. 2003. *Cosmopolis II: Mongrel cities in the 21st century,* London, Continuum

SANDU, S. 2004. *London Calling: How Black and Asian Writers Imagined a City,* London, Harper Perennial.

SANTE, L. 1998. *Low Life: Drinking, Drugging, Whoring, Murder, Corruption, Vice and Miscellaneous Mayhem in Old New York,* London, Granta Books.

SASSEN, S. 1991. *The Global City,* Princeton, Princeton University Press.

SASSEN, S. 2004. Europe and its Migrations: The Long View. *In:* BECHLER, R. (ed.) *Identities on the Move* London: British Council.

SAXENIAN, A.-L. 2002. Local and Global Networks of Immigrant Professionals in Siilicon Valley. San Francisco: Public Policy Institute of California.

SAXENIAN, A.-L. 2006. *The New Argonauts: Regional Advantage in a Global Economy,* Cambridge, MA, Harvard University Press.

SAXENIAN, A.-L. & SABEL, C. 2008. Venture Capital in the 'Periphery': The New Argonauts, Global Search and Local Institution-Building. *Economic Geography,* 84**,** 379-394.

SCHUMPETER, J. 1962. *The Theory of Economic Development,* Berlin, Springer.

SIMMIE, J., CARPENTER, J., CHADWICK, A. & MARTIN, R. 2008. *History Matters: Path dependence and innovation in British city-regions,* London, NESTA.

SIMPSON, L. & FINNEY, N. 2009. *Sleepwalking to Segregation? Challenging myths about race and migration,* Bristol, Policy Press.

SMALLBONE, D., ATHAYDE, R. & KITCHING, J. 2006. The Competitive Advantage of Diversity: An Introduction to the Project and Mid Term Research Findings. *Report to LDA.* London: London Development Agency.

SMITH, M. P. 2001. *Transnational Urbanism: Locating globalisation* Oxford, Blackwell.

SOMERVILLE, W. 2007. *Immigration under New Labour,* Bristol, Policy Press.

SOMERVILLE, W. & SUMPTION, M. 2009. Immigration and the Labor Market: Theory, Evidence, and Policy. Washington, DC: Migration Policy Institute

SPARBER, C. 2007. Racial Diversity and Macroeconomic Productivity Across US States and Cities. *monograph.* Hamilton, NY: Colegate University.

SPOLAORE, E. & WACZIARG, R. 2009. The Diffusion of Development. *Quarterly Journal of Economics,* 124**,** 469-529.

STENNING, A., CHAMPION, T., C, C., COOMBES, M., DAWLEY, S., DIXON, L., RAYBOULD, S. & RICHARDSON, R. 2006. Assessing the Local and Regional Impacts of International Migration. *New Horizons Report to DCLG.* Newcastle: CURDS.

STEPHAN, P. & LEVIN, S. 2001. Exceptional Contributions to US Science by the foreign-born and foreign-educated. *Population Research and Policy Review,* 20**,** 59-79.

STORPER, M. 1997. *The Regional World: Territorial Development in a Global Economy,* New York, Guilford.

STORPER, M. & VENABLES, A. 2004. Buzz: Face to Face Contact and the Urban Economy. *Journal of Economic Geography,* 4**,** 351-370.

SÜDEKUM, J., WOLF, K. & BLIEN, U. 2009. Cultural Diversity and Local Labour Markets. Monograph. Duisberg: University of Duisberg-Essen.

SWAFFIELD, J. 2011. Gender and the Labour Market. *In:* GREGG, P. & WADSWORTH, J. (eds.) *The Labour Market in Winter: The State of Working Britain.* Oxford: Oxford University Press.

TUROK, I. & EDGE, N. 1999. *The Jobs Gap in Britain's Cities,* York Joseph Rowntree Foundation.

URRY, J. 2000. *Sociology Beyond Societies: Mobilities for the Twenty-First Century,* London, Routledge.

VELTZ, P. 2000. European cities in the world economy. *In:* BAGNASCO, A. & LE GALÈS, P. (eds.) *Cities in Contemporary Europe.* Cambridge: Cambridge University Press.

VENABLES, A. 2006. Shifts in Economic Geography and Their Causes. *CEP Discussion Paper 767.* London: LSE.

VERTOVEC, S. 2006. The Emergence of Super-Diversity in Britain. *COMPAS Working Paper WP-06-25.* Oxford: Oxford University Centre on Migration, Policy and Society.

VERTOVEC, S. 2007. Super-diversity and its implications. *Ethnic and Racial Studies,* 30**,** 1024-1054.

VON HIPPEL, E. 2005. *Democratising Innovation,* Cambridge, MA, MIT Press.

WADHWA, V., SAXENIAN, A.-L., RISSING, B. & GEREFFI, G. 2007. America's New Immigrant Entrepreneurs. Durham, NC: Duke University / iSchool, UC Berkeley.

WADSWORTH, J. 2010. Immigration and the UK Labour Market: The Evidence from Economic Research. *CEP Election Analysis.* London: LSE.

WESTWOOD, A. & JONES, A. 2004. FEUK: Productivity, social inclusion and public sector reform London: The Work Foundation.

WILLS, J., DATTA, K., EVANS, Y., HERBERT, J., MAY, J. & MCILWAINE, C. 2010. *Global Cities at Work: New Migrant Divisions of Labour,* London, Pluto Press.

WILSON, R. 2007. Innovation in London. *Working Paper 19.* London: GLA Economics.

WOHLAND, P., REES, P., NORMAN P, BODEN P & JASINSKA M 2010. Ethnic Population Projections for the UK and Local Areas, 2001-2051. *Working Paper 10/2.* Leeds: School of Geography, University of Leeds.

WOLF, M. 2008. Four Falsehoods on UK Immigration. *Financial Times*, 3 April.

WOOD, P. 2006. Urban Development and Knowledge-Intensive Business Services: Too Many Unanswered Questions? *Growth and Change* 37**,** 335-361.

YEUNG, H. 2009. Regional Development and the Competitive Dynamics of Global Production Networks: An East Asian Perspective. *Regional Studies,* 43**,** 325-351.

ZENOU, Y. 2011. Spatial versus Social Mismatch: The Strength of Weak Ties. *IZA Discussion Papers 5507.* Bonn: Institute for the Study of Labor (IZA).

ZUCKER, L., DARBY, M. & ARMSTRONG, J. 1998. Geographically Localized Knowledge: Spillovers or Markets? . *Economic Inquiry,* 38**,** 65-86.