Knowledge workers, cultural diversity and innovation: evidence from London

Neil Lee and Max Nathan*

Department of Geography and Environment,
London School of Economics,
Houghton St., London, WC2A 2AE, UK
E-mail: n.d.lee@lse.ac.uk
E-mail: m.a.nathan@lse.ac.uk
*Corresponding author

Abstract: London is one of the world's major cities and one of its most culturally diverse. A number of studies link diverse workforces and populations to levels of urban innovation, especially in global cities. While widely explored as a social phenomenon, there has been little work on the importance of London's diversity for the city's businesses. This paper uses the 2007 London Annual Business Survey to investigate, exploiting the survey's unique coverage of both workforce composition and innovation outcomes. From a cross-section of over 2300 firms, we find significant positive relationships between workforce and ownership diversity, and product and process innovation. These provide some support for claims that London's cultural diversity is a source of economic strength.

Keywords: cultural diversity; migration; ethnicity; cities; firms; innovation; knowledge economy; economics; urban policy; economic development; knowledge workers; knowledge-based development; London.

Reference to this paper should be made as follows: Lee, N. and Nathan, M. (xxxx) 'Knowledge workers, cultural diversity and innovation: evidence from London', *Int. J. Knowledge Based Development*, Vol. X, No. Y, pp.000–000.

Biographical notes: Neil Lee is a Doctoral candidate in the Department of Geography and Environment at the London School of Economics. His thesis focuses on the impact of innovation on urban inequality in the EU and the USA. He is also a Senior Researcher at The Work Foundation where his work focuses on the implications of economic change for urban policy and a Doctoral Scholar at the TC Lab at Columbia University, New York City.

Max Nathan is based at the London School of Economics, where he is doing PhD research on the economics of cultural diversity in UK cities. He is also a Visiting Scholar at the Institute of Urban and Regional Development, UC Berkeley and a Senior Policy Adviser at the UK Government's Department of Communities and Local Government (CLG). He is an Associate Fellow of the Institute of Public Policy Research and an Associate at the Centre for Cities, an independent urban research unit that he helped establish in 2005. He contributes to this paper in a personal capacity. Its views are not those of CLG and are not a statement of UK Government policy.

1 Introduction

London is one of the world's major cities – and one of its most diverse. The UK capital dominates the British economy, contributing nearly a quarter of national GVA. It also contains the biggest stocks of migrant and minority communities, with over 300 languages spoken by the capital's schoolchildren (Gordon et al., 2009, 2007). The city operates as a global entrepot and its workforce reflects this. In 2006, an estimated 38% of the working-age population were born abroad, with around 31% from ethnic minority groups (Spence, 2008). London's government, business community and commentators all consider this diversity one of the city's strengths (GLA, 2008; London First, 2008; Smallbone et al., 2006).

This paper explores these claims, focusing on one of the main ways in which diversity is held to benefit London's firms: its impact on innovation. There are several channels from diversity to innovation. Within firms, diverse teams may be more effective than homogenous teams in problem-solving (Page, 2007). 'Cognitive diversity' – a range of backgrounds, experiences and approaches – may be particularly relevant in knowledge-intensive environments, such as business services (Fujita and Weber, 2003). Firms in more diverse cities may also have access to a bigger range of upstream and downstream markets, through a combination of diasporic links and urban infrastructure. Diversity may assist international knowledge spillovers, with 'ethnic entrepreneurs' playing a key role (Kerr, 2008; Saxenian, 2006).

Diverse firms may be more attractive places to work: Richard Florida (2002) argues that a 'creative class' of skilled workers has a strong preference for social diversity. If these workers drive innovation, diverse firms may be more innovative. Florida's argument implies that diverse cities are likely to be the biggest beneficiaries of national shifts towards a creativity-driven economy. Other mechanisms may also link diversity and innovation at the urban level: for example, the populations of culturally diverse cities are likely to demand a greater variety of non-traded goods and services (Mazzolari and Neumark, 2009). This presents further opportunities for innovation within and across sectors, shifting the composition of the local economy (Jacobs, 1970).

Many of these processes are likely to be in play in London. It a city with significant presence in both knowledge-based and consumer-orientated sectors, as well as a highly skilled workforce and excellent international connectivity. This paper uses data from the 2007 London Annual Business Survey to investigate the performance of culturally diverse firms on innovation in the capital. The paper exploits the Survey's unique structure to explore links between workforce and ownership characteristics and a range of innovation outcomes, for a cross-section of over 2,300 firms.

The results suggest that London's diversity has a positive impact on innovation in London firms. Workforce diversity is strongly associated with improvements in process innovation, especially in knowledge-intensive firms. Migrant and minority ethnic business-owners are important in hybridising new products and services and improving ways of working. Given the importance of innovation to knowledge-based development, this suggests that diversity has an important role to play. However, because these findings are based on a cross-sectional sample, we cannot be fully confident about causality. But we feel they provide some support for claims that London's cultural diversity is an economic asset.

The paper makes several contributions to the growing literature on the economics of diversity. First, it links economic geography to firm-level data: geographers' work in this area tends to focus on the regional or city-regional level.[1] Second, unlike lab-based studies, we use a large sample of firms operating in a highly competitive business environment. Third, we examine different aspects of both diversity and innovation. Finally, we provide valuable evidence on the UK experience: to date, most research on the economics of diversity has come from the USA. As far as we are aware, this is the first primary research on urban diversity and innovation in a British context.

The paper is structured as follows. The next section sets out motivation and background. Section 3 reviews the existing evidence base. Section 4 outlines data, descriptives and estimation strategy. Section 5 summarises our results. Section 6 concludes.

2 Background and motivation

2.1 Defining 'diversity'

This paper investigates whether culturally diverse firms in London are more innovative and what forms of diversity are associated with what form of innovation. 'Cultural diversity' is not a natural construct, however. The 'diversity' of a group, city or society is complex and hard to quantify adequately: it remains 'one of the most contested and unstable research concepts of social science' (Mateos et al., 2009).

Cultural or ethnic diversity[2] is multifaceted, with subjective elements and with categories that alter over time (ONS, 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' (ONS 2003). And both culture and ethnicity are 'context-driven social and psychological concepts' whose meanings shift as societies evolve (Aspinall, 2009).

For these reasons, attempts to quantify cultural diversity almost always lose something in the process. We focus on two specific aspects of diversity, country of birth and ethnic group that are widely used in the literature as proxies for diversity generally. Country of birth has the advantage of being objective, but is one-dimensional and does not capture established minority communities. Ethnic grouping attempts 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 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 is not a problem for objective country of birth-based data, but might bias measures based on ethnic groups. In practice, though, it is unlikely that (for example) commercial success might lead business owners of South Asian origin to identify as 'White'. 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 in 2004, the UK experienced two migration 'spikes'. Many new migrant communities have developed (Kyambi, 2005). The capital's current cultural diversity is largely driven by migrants from visible minorities, alongside groups captured in the 'other' category.[3] Table 1 shows the pairwise correlation between migrant and minority working-age population shares in greater London is over 95%. 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.

Table 1 Correlation matrix of diversity measures, Greater London, 1995–2005

	% migrants	*% ethnic minorities*
% migrants	1.0000	
% ethnic minorities	0.9561	1.0000

Source: LFS

2.2 Policy context

Links between diversity, cities and business success are questions of both academic and policy interest. The UK's productivity gap with competitor countries – particularly the USA – is an area of major policy concern. Innovation and entrepreneurship are two of the current Government's five 'drivers of productivity'; innovation is seen as a major driver of long-term economic growth (Department of Innovation, Universities and Skills, 2008). The current government is also clear that growing diversity brings economic benefits (Home Office/Department of Work and Pensions, 2007). But there is also worry about the long-term effects of a more diverse society (House of Lords Select Committee on Economic Affairs, 2008). While many business voices have embraced workforce diversity, workplace discrimination is also a live issue (Goulding, 2009).

Urban areas are important to all of these agendas. Cities and their hinterlands are widely seen as economic assets, conferring productivity payoffs and helping to support innovative activity (Overman and Rice, 2008; Glaeser, 2008). UK Government strategy now recognises the role of 'place' to innovation (Department of Innovation, Universities and Skills, 2008). British cities also contain the vast majority of the UK's migrant and minority populations (Champion, 2006); cities are 'where the diversity is' (Nathan, 2008).

London exemplifies all of this. The UK capital is one of the original 'global cities' (Sassen, 1991). Alongside New York, London remains one of the main centres of the global financial system (Gordon et al., 2009; Masters 2009). The capital dominates the British economy: in 2006–2007, it contained around 13% of the UK population but contributed nearly 20% of national GVA (Gordon et al., 2007). London is also highly diverse, with over 300 languages spoken by schoolchildren (Gordon et al., 2007). In 2002–2003, London accounted for around two thirds of English net migration; in 2001 the capital had over 48% of England's non-white population (Champion, 2006). 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/Department of Work and Pensions, 2007, GLA, 2008; London First, 2008). In particular, London's diversity is seen as driving forward ideas generation and the emergence of new products and services (Leadbeater, 2008).

3 Cultural diversity, innovation and cities: a review of the evidence

This section summarises the recent literature on cities, cultural diversity and innovation. We follow the common definition of innovation as ‘the successful exploitation of new ideas’ (Department of Innovation, Universities and Skills, 2008). Economic geography has seen increasing interest in links between aspects of diversity and aspects of urban economic performance. Several studies find that innovative activity is spatially concentrated and that economic diversity is a driver of urban innovation (Jacobs 1970; Jaffe and Trajtenberg 1999; Duranton and Puga, 2001).

There is also some suggestive evidence that firms in culturally diverse cities also display higher levels of innovation. Peri (2007), looking at the USA, finds that 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. Hunt (2008) finds 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 spill-overs.

We pick out five main ways in which urban cultural diversity may promote higher levels of innovation at the firm level, then explore how these might operate in a city like London.

3.1 Diverse teams

There is some evidence from the business literature and experimental economics that a culturally diverse team may outperform a homogenous team at problem solving or ideas-generation. Hong and Page (2001, 2004) show that when there are a large number of problem solvers, the best problem solvers will often come up with similar solutions. So a diverse range of problem solvers may be preferable to a homogenous group, even if the latter group has higher objective ability. Berliant and Fujita (2007) suggest these dynamics are particularly important in research-based or ‘knowledge intensive’ activities. Three mechanisms underpin the benefits of ‘cognitive diversity’: the ‘wisdom of crowds’, complementary skills and exploiting a wider pool of talent. Cultural diversity is also likely to be a good proxy for cognitive diversity (Page, 2007).

Theory suggests two negative effects of cultural diversity in the workplace. First, in the short term diversity may trigger higher communication costs. Second, diverse groups may be less likely to trust each other (Alesina and La Ferrara, 2004).

Page (2007) reviews the evidence, concluding that there is a small but significant ‘diversity advantage’ in problem solving situations – short term costs are outweighed by longer term benefits. Firms based around team work and focused on ‘knowledge-intensive’ activity are most likely to be benefit. Studies also suggest a strong overlap between cognitive and cultural diversity. Cities, with large labour pools and an increasing share of high-skilled activity, are likely to amplify these effects.

3.2 The preferences of skilled workers

Richard Florida suggests that a ‘creative class’ of liberal, tolerant and highly skilled workers has become the driving force of Western economies. This group is attracted to diverse firms and environments. Since the creative class disproportionately contributes to ideas generation, diverse businesses and cities will tend to have higher levels of innovative activity (Florida, 2002). This work has been widely criticised for both its theory and its empirics and appears to lose much of its predictive power in a UK context (Glaeser, 2005; Nathan 2005). However, it is plausible that creative class dynamics might be operating in a large urban core like London (see Section 3.6).

3.3 Diasporas, knowledge flows and market access

Diversity could broaden firms' knowledge sources, increase options for organising production or widen the set of downstream markets. All of these processes are likely to foster innovation. Diasporas play a number of underpinning roles. First, they may reduce the direct costs of sourcing information, if members have existing contacts in the origin country. Second, they may foster higher levels of trust. Third, international ethnic networks may reduce the cost of communication, as migrants are more likely to speak the language of those in their origin country and will be more astute at tacit communication (Rodríguez-Pose and Storper, 2006).

Saxenian (2006) provides detailed evidence on the roles of migrant and ethnic diasporas in the Silicon Valley area. Large communities of South and South East Asian origin have helped maintain the Valley's long term economic position – through high levels of new business formation, opening up new forms of distributed production and creating new market opportunities for American firms. Similarly, Kerr's analysis of international patent citations suggests that ethnic research communities, who tend to be heavily urbanised, play a critical role in generating and exporting new ideas (Kerr, 2008).

3.4 Diverse populations and hybridisation

Diverse urban environments are likely to provide further spurs to firm-level innovation. Populations in culturally diverse cities are likely to demand a greater variety of non-traded goods and services. This will be driven both by the presence of new communities and by shifting preferences in the majority population. The more cosmopolitan the milieu is, the greater the potential for hybridisation of ideas, products and services are – particularly in non-traded sectors. This presents further opportunities for innovation across sectors, shifting the composition of the local economy (Jacobs, 1969).

A few studies have investigated these effects. Immigration is positively associated with an increased range of restaurants in California (Mazzolari and Neumark, 2009). And UK case studies have highlighted the role of migrant communities in the emergence of new sub-sectors of retail and leisure (Kitching et al., 2009; Jones et al., 2004; Henry et al., 2002).

3.5 'Ethnic entrepreneurs'

So-called 'ethnic entrepreneurs' may play a critical role in these processes – organising professional networks and helping diaspora formation, spotting new product opportunities and starting up new businesses (Gordon et al., 2007; Landry and Wood, 2007). This could be positive selection: migrants may be more talented and ambitious than the average worker, reflecting the get up and go required to make a new life in another country. Negative selection is also plausible: ethnic entrepreneurs may be locked out of more conventional employment opportunities, particularly if prejudice is a factor (Gordon et al., 2007).

There is mixed evidence on levels of ethnic entrepreneurship and its impacts. Some migrant and minority communities make disproportionate contributions to knowledge creation – most notably in US science and high-tech sectors (Stephan and Levin, 2001). Some US studies also suggest that skilled migrants and diasporic networks play an important role in start-ups and firm-firm linkages, notably in Silicon Valley (Saxenian, 2006). But levels of self-employment seem to vary greatly by migrant group, host country and community class structures (Gordon et al., 2007; Nakhaie et al., 2009).

3.6 Cultural diversity and innovation in London

London is a both powerful urban economic system and a diverse, cosmopolitan city. If there are links between cultural diversity and firm-level innovation, they are likely to be found here (Smallbone et al., 2006). The city has a significant presence in knowledge-based sectors such as finance, business services and the creative industries. It also has a large consumer-facing retail and leisure economy. London has excellent international connectivity and a large HE sector that acts as a magnet for skilled and highly motivated people from all over the world. And Londoners appear to highly value the city's diversity: a recent survey suggested that 85% of London residents value the capital's cultural mix (GLA, 2006). These features will help us identify diversity-innovation effects; the trade-off is that they may limit the wider applicability of our findings.

4 Model, data and descriptives

4.1 Main dataset

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

For this paper we construct a cross-section of firms from the 2007 survey. LABS is quota-sampled to obtain robust sample sizes for particular groups of the population. The raw data is for individual sites, rather than for the enterprise itself. We restrict the sample to firms for which we have information about workforce and ownership diversity. This gives us 2,371 observations.

4.2 Diversity measures

We construct four diversity measures, exploiting LABS' coverage of workforce and ownership characteristics, country of birth and ethnicity. Three of our diversity measures are simple shares for the 'stock of diversity' in a given firm. Specifically:

- *Cobran – the number of partners or owners who were born outside the UK*. This is a continuous variable coded 0-1 where zero indicates no partners or owners were born outside the UK, 0.5 where half are and one where all were.[4]
- *Ethown – for whether half the owners are not white British.* This is derived from question Q16a, 'Whether at least half the owners are White British'. This is recoded so that a 'yes' becomes zero and a value of 'no' is one.
- *Ethstaff – the percentage of non-white staff.* This is taken from the Q19_1 'The percentage of staff who belong to ethnic group: white' which is reversed and scaled between zero and one. A value of 1 indicates that 100% of staff are non-white.

The fourth measure is a fractionalisation index, capturing both the number of workforce groups in a firm and their relative sizes. This measures the probability that any two workers taken at random will be from different groups (Alesina and La Ferrara, 2004; Ottaviano and Peri, 2006). For a firm *c* with *j* groups, the index takes the form:

$$FRAC(DIV_c) = 1 - \sum_j (L_{jc})^2 \qquad (j = 1,\ldots..,n) \tag{1}$$

This gives us the fourth diversity measure:

- *Frac – A fractionalisation index* for the five ethnic groups in the Survey, derived from Q19_1. These are: 'White'; 'Black'; 'Asian'; 'mixed race' and 'Chinese/other'.

The index takes the value zero when a firm's workforce all belongs to a single group and a maximum of one when they all belong to different groups. For *n* groups, the index takes the value 1 – 1/*n* when the groups are of equal size.[5]

Table 2 Summary statistics for diversity variables

Variable	*Interpretation*	*Obs*	*Mean*	*Std. dev*	*Min*	*Max*
Cobran	Higher = greater proportion of owners born abroad	2371	*0.29186*	*0.4175895*	0	1
Ethown	Higher = greater proportion of owners are non-white	2371	*0.1737663*	*0.3789884*	0	1
Ethstaff	% of staff who are non-white	2371	*0.2738591*	*0.3388715*	0	1
Frac	Fractionalisation index of ethnic diversity of staff	2371	*0.203589*	*0.230294*	0	0.8

Source: LABS

Tables 2 and 3 provide summary statistics and a correlation matrix for the diversity measures. The results suggest the average London firm is unlikely to be migrant or minority-owned, but almost a third of employees in London firms are from ethnic minorities. There is a strong link between measures of ethnic minority ownership and workforce, but otherwise ownership and staff composition measures seem to be capturing different aspects of organisational character.

Table 3 Correlations between diversity variables

	Cobran	*Ethown*	*Ethstaff*	*Frac*
Cobran	1.0000			
Ethown	0.5039	1.0000		
	(0.0000)			
Ethstaff	0.4117	0.6797	1.0000	
	(0.0000)	(0.0000)		
Frac	0.0997	0.1119	0.4856	1.0000
	(0.0000)	(0.0000)	(0.0000)	

Note: significance in parenthesis

Source: LABS

4.3 Innovation measures

London is unusual in that while, it is seen as an innovative city, it performs poorly on many traditional measures of innovation such as patenting (Wilson, 2007). We develop four broader innovation measures, exploring new products, modifications to existing product ranges, new equipment and new working methods. Our four dependent variables are:

- *Innovation 1/new product* – this takes the value 1 if the firm has introduced any major new products or services in the past 12 months (from Q61_1).
- *Innovation 2/major modification* – takes the value 1 if the firm introduced any major modifications to existing products (from Q61_2).
- *Innovation 3/new equipment* – takes the value 1 if the firm has introduced major new equipment in the past 12 months (from Q61_3).
- *Innovation 4/working methods* – measures whether or not the firm has brought in any major changes to working practices during the year (from Q61_4).

The first and second are measures of product innovation, the last two are measures of process innovation. Table 4 summarises the sample across these four variables.

Table 4 Levels of innovation

	Innovation 1: new product	*Innovation 2: major modification*	*Innovation 3: new equipment*	*Innovation 4: working methods*
All firms	28%	24%	21%	24%
Knowledge based	28%	27%	20%	26%
Non-knowledge based	27%	21%	21%	22%

As a basic robustness check, we also split the sample into 1,176 ‘knowledge-intensive’ and 1,195 ‘non-knowledge-intensive’ firms, using The Work Foundation’s definition of knowledge economy sectors and occupations (Brinkley, 2008).[6] We might expect knowledge-intensive firms to be driving overall levels of innovation. In fact, the descriptives suggest that knowledge-sector firms are slightly more likely than 'non-knowledge' sector companies to modify products or introduce new working practices, but slightly less likely to invest in new equipment or to introduce new completely new products.

4.4 Estimation strategy

We regress the probability of innovative activity occurring on a diversity measure plus firm-level controls. For a firm *c* the model takes the form:

$$Pr\,(\,INNOVATE\,)_c = a + bDIV_c + \boldsymbol{CONTROLS}_c d + e_c \qquad (2)$$

Where *INNOVATE* is one of our four measures of innovative activity, *DIV* is one of our diversity variables and ***CONTROLS*** is a set of control variables (summarised in Table 5). We estimate the model in a series of binary logistic regressions in Stata using logit.

Our controls reflect the general discussion of firm-level innovation in the previous section. Levels and types of innovation are likely to vary by sector. We account for sectoral composition through 156 dummy variables, representing sectors at three-digit SIC code level. Firms' age and size may also affect innovation. Large or established firms can generate large amounts of patent activity; but small, often new firms may introduce disruptive innovations (Griffith et al., 2006; Kelley and Helper, 1999). The age and size of the firm is tested through the natural log of the firm's size (employees per site) and age (2007 minus the year the firm was established).

Table 5 Control variables

Area	*Variable*	*Description*	*Likely impact on innovation*
Sector		Dummy variable for each of 156 sectors, at the three-digit SIC level	+/–
Characteristics	Lnage	Natural log of the age of the firm	+/–
	Lnsize	Natural log of the size of the firm	+
	HQ	Whether the unit sampled is the headquarter of the firm	+
	PLC	Whether the firm is a public limited company	+
	Foreign	Whether the firm has foreign ownership	+/–
Activities	Collab	Whether the firm has embarked on any collaborative ventures	+
	RD	Whether the firm has embarked on any R&D that year	+
	Export	Whether a firm exports or not	+
Skills	Skillneed	variable for the extent to which finding highly skilled staff is a problem	+

Other controls cover whether the site in question is a headquarters, whether the firm is a public limited company or whether the firm has foreign ownership. Each of these is a dummy variable taking the value 1 if (respectively) the site is an HQ, the firm is a PLC or the firm is foreign-owned. We expect PLCs to perform better as they have to provide shareholder value. This variable will also account for those firms which are run as lifestyle businesses. Foreign owned firms should perform better as they have access to a wider range of knowledge sources (Simmie and Sennett, 2001).

To complete the model we add three further controls: levels of collaborative activity, R&D spending and presence of skilled staff. All three are likely to have a strong positive influence. There is an established literature on 'open innovation' and collaboration between firms and other actors (Von Hippel, 2005); similarly, the role of R&D spending in promoting innovation is clear (Romer, 1990). As with other controls, these are dummy variables for which the value one is yes.

Unfortunately LABS has no variable for the proportion of employees with higher education, Most of the variation should be accounted for by the 156 sectoral dummies, but we also include a variable for the extent to which finding highly skilled staff is a problem. This is a Likert scale where one indicates no problem and five indicates a big problem. A positive sign on this coefficient suggests a strong need for skilled workers, indicating higher chances of innovative activity (Tether et al., 2005). However, the relatively indirect nature of this variable – as opposed to measuring a firm's share of graduates– suggests that it may have a correspondingly weak link to innovation.

5 Results

The main results of the analysis are set out in Tables 6–13. Tables 6, 8, 10 and 12 present results for the whole sample, for each dependent variable. Tables 7, 9, 11 and 13 break down the sample into knowledge-based and non-knowledge-based firms. For the full sample, specification (1) presents the controls, while specifications (2) through (5) test each diversity measure. Other tables focus on results including DIV.

5.1 Model performance

We run the model through a series of diagnostics for specification, goodness of fit, collinearity and influential observations.[7] The model passes tests for specification error, both Pearson and Hosmer and Lemeshow tests of fit suggest the model is generally well specified, and multicollinearity is not an issue (with mean VIF around one).[8] In most cases pseudo-R^2 varies between 0.117 and 0.15, in line with other studies using similar data – for example, Gordon and McCann (2005) report a pseudo-R^2 of 0.159. Analysis of residual plots reveals that two observations are notable outliers, although when these are removed the results change only slightly. The diagnostic tests reveal no other problems.

5.2 Results for product innovation

Table 6 looks at the association between our diversity measures and the introduction of new products. Across the regressions, most controls perform broadly as expected. As suggested by other studies, collaboration, R&D spending and firm size all have a significant positive association with innovation. Those firms with a greater need for skilled staff appear more likely to innovate, implying the expected positive association between human capital and innovation. PLC structure also appears to have a positive significant association. Other controls have little significant effect.

Of the diversity variables, only the variable for the country of birth of the owners is significantly associated with new product innovation. The coefficient of *cobran* is 0.255; the interpretation is that adding another foreign owner to the firm multiplies the odds of introducing a new product by (exp (0.255) * 0.25) %, or 3.26 percentage points (to two decimal places). Of the other three variables, none are significant.

Table 6 Firms producing new products and services, full sample

Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
	prodin1	*prodin1*	*prodin1*	*prodin1*	*prodin1*
Lnage	–0.0949*	–0.0868*	–0.0886*	–0.0875*	–0.0911*
	(0.0493)	(0.0495)	(0.0494)	(0.0497)	(0.0495)
Lnsize	0.172***	0.181***	0.179***	0.165***	0.147***
	(0.0471)	(0.0471)	(0.0472)	(0.0473)	(0.0506)
HQ	0.292*	0.296*	0.297*	0.299*	0.293*
	(0.166)	(0.166)	(0.166)	(0.165)	(0.166)
Collab	0.588***	0.596***	0.593***	0.586***	0.578***
	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)
RD	0.772***	0.774***	0.774***	0.772***	0.769***
	(0.121)	(0.121)	(0.121)	(0.121)	(0.121)
Export	0.161	0.162	0.171	0.174	0.169
	(0.138)	(0.138)	(0.138)	(0.139)	(0.138)
Foreign	–0.0337	–0.162	–0.0312	–0.0379	–0.0500
	(0.249)	(0.260)	(0.249)	(0.249)	(0.249)
Plc	0.962***	0.969***	0.960***	0.951***	0.949***
	(0.304)	(0.302)	(0.302)	(0.305)	(0.306)
Skillneed	0.0783**	0.0738*	0.0767**	0.0781**	0.0793**
	(0.0378)	(0.0378)	(0.0378)	(0.0378)	(0.0378)
Cobran		0.255*			
		(0.132)			
Ethown			0.212		
			(0.140)		
Ethstaff				0.226	
				(0.162)	
Frac					0.318
					(0.250)
Constant	–1.221***	–1.348***	–1.298***	–1.292***	–1.223***
	(0.351)	(0.363)	(0.359)	(0.361)	(0.354)
Observations	2371	2371	2371	2371	2371
Pseudo R-squared	0.137	0.138	0.138	0.138	0.138
DF	80	81	81	81	81
Log likelihood	–1206	–1204	–1205	–1205	–1205

Notes: robust standard errors in parentheses, significance levels *10%, **5%, ***1%

Source: LABS

Table 7 Firms producing new products and diversity, split sample

Variables	*Knowledge-intensive firms*				*Non-knowledge-intensive firms*			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
	prodin1	*prodin1*	*prodin1*	*prodin1*	*prodin1*	*prodin1*	*prodin1*	*prodin1*
Lnage	–0.174**	–0.168**	–0.169**	–0.174**	–0.0210	–0.0285	–0.0284	–0.0291
	(0.0771)	(0.0774)	(0.0775)	(0.0772)	(0.0651)	(0.0649)	(0.0651)	(0.0649)
Lnsize	0.120*	0.120*	0.0926	0.0714	0.261***	0.256***	0.252***	0.245***
	(0.0620)	(0.0620)	(0.0627)	(0.0689)	(0.0744)	(0.0747)	(0.0745)	(0.0781)
HQ	0.398*	0.388*	0.401*	0.388*	0.232	0.237	0.235	0.232
	(0.214)	(0.214)	(0.213)	(0.213)	(0.269)	(0.270)	(0.269)	(0.270)
Collab	0.563***	0.555***	0.544***	0.537***	0.595***	0.597***	0.595***	0.590***
	(0.163)	(0.163)	(0.163)	(0.163)	(0.184)	(0.185)	(0.185)	(0.185)
RD	0.731***	0.743***	0.741***	0.726***	0.829***	0.828***	0.827***	0.827***
	(0.159)	(0.159)	(0.159)	(0.158)	(0.186)	(0.186)	(0.186)	(0.186)
Export	0.206	0.227	0.247	0.226	0.192	0.191	0.188	0.186
	(0.177)	(0.178)	(0.179)	(0.177)	(0.223)	(0.224)	(0.224)	(0.223)
Foreign	–0.888**	–0.727*	–0.705*	–0.696*	0.330	0.428	0.422	0.415
	(0.407)	(0.388)	(0.386)	(0.386)	(0.333)	(0.324)	(0.323)	(0.325)
Plc	1.069**	1.024**	1.048**	1.096**	0.807*	0.804*	0.799*	0.791*
	(0.445)	(0.443)	(0.440)	(0.450)	(0.421)	(0.425)	(0.427)	(0.428)
Skillneed	0.158***	0.161***	0.161***	0.164***	–0.00324	–8.60e-05	0.000591	0.00109
	(0.0534)	(0.0531)	(0.0533)	(0.0533)	(0.0545)	(0.0545)	(0.0544)	(0.0544)
Cobran	0.324				0.232			
	(0.198)				(0.179)			
Ethown		0.424**				0.0595		
		(0.201)				(0.196)		
Ethstaff			0.439*				0.0513	
			(0.240)				(0.222)	
Frac				0.466				0.107
				(0.370)				(0.344)
Constant	–1.753*	–1.268	–1.740*	–1.688*	–1.448***	–1.351***	–1.346***	–1.329***
	(1.007)	(2.248)	(1.010)	(1.008)	(0.404)	(0.395)	(0.395)	(0.388)
Observations	1176	1176	1176	1176	1195	1195	1195	1195
Pseudo R-squared	0.144	0.145	0.145	0.143	0.143	0.142	0.142	0.142
DF	48	48	48	48	42	42	42	42
Log likelihood	–598.1	–597.3	–597.8	–598.6	–598.4	–599.2	–599.2	–599.2

Notes: robust standard errors in parentheses, significance levels *10%, **5%, ***1%

Source: LABS

In Table 7, we repeat these results for knowledge-based firms (columns 1–4). There is a stronger response to the diversity variables in these firms. The country of birth of the owners is no longer significant. However, the ethnicity of the owners (*ethown*) is significant at the 5% level (0.426) and the ethnicity of the staff (*ethstaff)* is significant at the 10% level (0.505). This suggests that compared to firms with a white owner, the odds of introducing new products or services are 1.53 times higher in knowledge-intensive businesses with a minority owner. A 1% increase in the share of minority staff multiplies the odds of introducing new products by exp (0.505), or 1.65 percentage points, although this is only marginally significant.

Columns 5–8 show the same results for non knowledge-based firms. In this case, none of these variables are significant. In this case it appears that the relationship between diversity and the introduction of new products applies only to knowledge-based firms.

Table 8 Firms introducing major modifications to products and services, full sample

Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
	prodin2	*prodin2*	*prodin2*	*prodin2*	*prodin2*
Lnage	–0.0197	–0.0139	–0.0125	–0.0155	–0.0158
	(0.0513)	(0.0515)	(0.0514)	(0.0517)	(0.0516)
Lnsize	0.158***	0.164***	0.167***	0.154***	0.133***
	(0.0474)	(0.0474)	(0.0475)	(0.0476)	(0.0513)
HQ	–0.0947	–0.0924	–0.0922	–0.0900	–0.0937
	(0.178)	(0.178)	(0.179)	(0.178)	(0.178)
Collab	0.590***	0.595***	0.594***	0.588***	0.579***
	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)
RD	0.829***	0.829***	0.831***	0.828***	0.826***
	(0.123)	(0.123)	(0.123)	(0.123)	(0.123)
Export	0.0844	0.0860	0.0977	0.0928	0.0924
	(0.142)	(0.142)	(0.142)	(0.142)	(0.142)
Foreign	0.577**	0.483*	0.580**	0.574**	0.561**
	(0.250)	(0.259)	(0.252)	(0.251)	(0.251)
Plc	0.167	0.178	0.166	0.163	0.158
	(0.328)	(0.326)	(0.327)	(0.326)	(0.326)
Skillneed	0.103***	0.0992***	0.101***	0.102***	0.103***
	(0.0377)	(0.0378)	(0.0377)	(0.0377)	(0.0377)
Cobran		0.188			
		(0.133)			
Ethown			0.254*		
			(0.137)		
Ethstaff				0.133	
				(0.164)	
Frac					0.313
					(0.259)
Constant	–2.775***	–2.874***	–2.870***	–2.816***	–2.775***
	(0.481)	(0.494)	(0.494)	(0.490)	(0.481)
Observations	2371	2371	2371	2371	2371
Pseudo R-squared	0.118	0.118	0.119	0.118	0.118
DF	80	81	81	81	81
Log likelihood	–1163	–1162	–1161	–1163	–1162

Notes: robust standard errors in parentheses, significance levels *10%, **5%, ***1%

Source: LABS

Table 8 gives results for the second measure of product innovation: whether firms have made major modifications to existing products in the past 12 months. Only one variable for diversity of ownership is significant here: e*thown*, which is positive at the 10% level. The control variables also perform slightly differently to those for the major product innovation measure: there is no relationship between firm age and modification of existing products.

Table 9 Firms introducing major modifications and diversity, split sample

Variables	*Knowledge-intensive firms*				*Non-knowledge-intensive firms*			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
	prodin2	*prodin2*	*prodin2*	*prodin2*	*prodin2*	*prodin2*	*prodin2*	*prodin2*
Lnage	–0.00192	–0.00123	0.00204	0.00257	–0.0319	–0.0311	–0.0407	–0.0402
	(0.0751)	(0.0756)	(0.0752)	(0.0754)	(0.0725)	(0.0717)	(0.0723)	(0.0720)
Lnsize	0.0755	0.0746	0.0631	0.0357	0.301***	0.311***	0.291***	0.281***
	(0.0621)	(0.0623)	(0.0626)	(0.0672)	(0.0738)	(0.0742)	(0.0741)	(0.0802)
HQ	–0.115	–0.119	–0.110	–0.117	0.0479	0.0731	0.0511	0.0488
	(0.225)	(0.225)	(0.225)	(0.225)	(0.285)	(0.287)	(0.289)	(0.289)
Collab	0.717***	0.712***	0.707***	0.703***	0.386**	0.396**	0.388**	0.381**
	(0.160)	(0.160)	(0.160)	(0.160)	(0.195)	(0.195)	(0.195)	(0.193)
RD	0.684***	0.687***	0.690***	0.681***	1.017***	1.008***	1.017***	1.015***
	(0.158)	(0.158)	(0.158)	(0.159)	(0.190)	(0.190)	(0.191)	(0.191)
Export	0.141	0.145	0.163	0.159	0.0233	0.0479	0.0155	0.0135
	(0.176)	(0.177)	(0.178)	(0.177)	(0.245)	(0.247)	(0.246)	(0.247)
Foreign	0.388	0.452	0.451	0.455	0.562	0.696**	0.662*	0.651*
	(0.387)	(0.366)	(0.366)	(0.366)	(0.352)	(0.350)	(0.348)	(0.350)
Plc	–0.00828	–0.0233	–0.0194	0.00975	0.265	0.274	0.254	0.243
	(0.516)	(0.520)	(0.514)	(0.520)	(0.421)	(0.420)	(0.423)	(0.422)
Skillneed	0.163***	0.165***	0.164***	0.166***	0.0249	0.0253	0.0282	0.0287
	(0.0533)	(0.0532)	(0.0532)	(0.0533)	(0.0539)	(0.0538)	(0.0536)	(0.0536)
Cobran	0.118				0.259			
	(0.196)				(0.185)			
Ethown		0.118				0.407**		
		(0.201)				(0.188)		
Ethstaff			0.233				0.0310	
			(0.236)				(0.231)	
Frac				0.451				0.145
				(0.368)				(0.371)
Constant	–1.994*	–2.492	–1.998*	–1.974*	–2.971***	–2.984***	–2.833***	–2.822***
	(1.080)	(1.946)	(1.078)	(1.068)	(0.557)	(0.553)	(0.540)	(0.529)
Observations	1176	1176	1176	1176	1195	1195	1195	1195
Pseudo R-squared	0.112	0.112	0.112	0.113	0.128	0.130	0.126	0.126
DF	–609.6	–609.6	–609.3	–609.0	–547.1	–546.0	–548.0	–547.9
Log likelihood	48	48	48	48	42	42	42	42

Notes: robust standard errors in parentheses, significance levels *10%, **5%, ***1%

Source: LABS

Table 9 gives the results for knowledge based and non-knowledge based firms separately.

For knowledge-based firms, none of the variables for diversity are significantly related to innovation. For non knowledge-based firms only *ethown* is positively related to the likelihood of innovation, a relationship significant at the 5% level. The relationship between diversity and the modification of existing products appears driven by this result.

Table 10 Firms introducing new equipment, full sample

Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
	procin1	*procin1*	*procin1*	*procin1*	*procin1*
Lnage	0.0167	0.0236	0.0245	0.0296	0.0233
	(0.0513)	(0.0515)	(0.0516)	(0.0521)	(0.0519)
Lnsize	0.115**	0.123**	0.125**	0.103**	0.0684
	(0.0486)	(0.0490)	(0.0490)	(0.0489)	(0.0533)
HQ	0.299*	0.302*	0.303*	0.312*	0.302*
	(0.166)	(0.165)	(0.166)	(0.165)	(0.166)
Collab	0.282**	0.286**	0.285**	0.275**	0.260**
	(0.127)	(0.127)	(0.127)	(0.128)	(0.128)
RD	0.500***	0.499***	0.504***	0.502***	0.495***
	(0.128)	(0.128)	(0.128)	(0.128)	(0.128)
Export	–0.121	–0.123	–0.107	–0.0970	–0.104
	(0.152)	(0.152)	(0.152)	(0.152)	(0.152)
Foreign	0.200	0.0780	0.207	0.196	0.170
	(0.264)	(0.271)	(0.265)	(0.263)	(0.266)
Plc	0.662**	0.676**	0.661**	0.645**	0.640**
	(0.301)	(0.298)	(0.303)	(0.295)	(0.300)
Skillneed	0.115***	0.111***	0.112***	0.114***	0.117***
	(0.0392)	(0.0393)	(0.0392)	(0.0392)	(0.0392)
Cobran		0.247*			
		(0.136)			
Ethown			0.306**		
			(0.143)		
Ethstaff				0.431**	
				(0.168)	
Frac					0.593**
					(0.269)
Constant	–1.653***	–1.773***	–1.761***	–1.790***	–1.659***
	(0.359)	(0.367)	(0.366)	(0.371)	(0.365)
Observations	2371	2371	2371	2371	2371
Pseudo R-squared	0.0732	0.0746	0.0751	0.0759	0.0754
Log likelihood	–1129	–1128	–1127	–1126	–1127
DF	80	81	81	81	81

Notes: robust standard errors in parentheses, significance levels *10%, **5%, ***1%

Source: LABS

Table 11 Firms introducing new equipment, split sample

Variables	*Knowledge-intensive firms*				*Non-knowledge-intensive firms*			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
	prodin1	*prodin1*	*prodin1*	*prodin1*	*prodin1*	*prodin1*	*prodin1*	*prodin1*
Lnage	0.156*	0.163*	0.178**	0.171**	–0.0704	–0.0742	–0.0751	–0.0796
	(0.0836)	(0.0845)	(0.0860)	(0.0856)	(0.0663)	(0.0659)	(0.0664)	(0.0661)
Lnsize	–0.0583	–0.0550	–0.0840	–0.131*	0.323***	0.330***	0.305***	0.283***
	(0.0659)	(0.0659)	(0.0660)	(0.0746)	(0.0730)	(0.0734)	(0.0725)	(0.0774)
HQ	0.569***	0.567***	0.588***	0.572***	0.0596	0.0835	0.0715	0.0621
	(0.218)	(0.218)	(0.217)	(0.218)	(0.269)	(0.270)	(0.268)	(0.269)
Collab	0.288*	0.287*	0.279	0.271	0.247	0.254	0.246	0.233
	(0.169)	(0.169)	(0.170)	(0.169)	(0.196)	(0.196)	(0.196)	(0.197)
RD	0.536***	0.546***	0.562***	0.533***	0.460**	0.456**	0.455**	0.457**
	(0.171)	(0.172)	(0.174)	(0.173)	(0.192)	(0.192)	(0.193)	(0.194)
Export	–0.0596	–0.0478	0.0109	–0.0169	–0.220	–0.193	–0.219	–0.223
	(0.205)	(0.206)	(0.208)	(0.207)	(0.245)	(0.246)	(0.245)	(0.245)
Foreign	0.465	0.493	0.494	0.500	–0.311	–0.121	–0.160	–0.184
	(0.422)	(0.413)	(0.405)	(0.411)	(0.366)	(0.359)	(0.356)	(0.358)
Plc	0.110	0.0776	0.0759	0.147	0.998**	1.001**	0.965**	0.945**
	(0.528)	(0.541)	(0.515)	(0.545)	(0.388)	(0.391)	(0.389)	(0.391)
Skillneed	0.137**	0.137**	0.134**	0.140**	0.0821	0.0828	0.0873	0.0893
	(0.0573)	(0.0569)	(0.0571)	(0.0569)	(0.0546)	(0.0545)	(0.0544)	(0.0544)
Cobran	0.0815				0.373**			
	(0.207)				(0.184)			
Ethown		0.239				0.402**		
		(0.223)				(0.189)		
Ethstaff			0.691***				0.266	
			(0.254)				(0.228)	
Frac				0.885**				0.350
				(0.409)				(0.368)
Constant	–1.595	–1.357	–1.673	–1.595	–1.877***	–1.835***	–1.770***	–1.687***
	(1.198)	(1.655)	(1.164)	(1.158)	(0.412)	(0.405)	(0.404)	(0.396)
Observations	1176	1176	1176	1176	1195	1195	1195	1195
Pseudo R-squared	0.0791	0.0800	0.0852	0.0833	0.0871	0.0873	0.0849	0.0846
DF	–544.2	–543.7	–540.6	–541.7	–572.6	–572.5	–574.0	–574.2
Log likelihood	48	48	48	48	42	42	42	42

Notes: robust standard errors in parentheses, significance levels *10%, **5%, ***1%

Source: LABS

5.3 *Results for process innovation*

Table 10 looks at the first measure of process innovation, whether firms have introduced any new equipment. Larger firms are more likely to innovate in this way, as are HQ's, firms which collaborate and those which undertake R&D. PLCs and firms which require skills are also more likely to innovate.

All four measures of diversity are linked to the introduction of new equipment. The country of birth of the owners is significant at 10%, the ethnicity of the owners, ethnicity of the staff and ethnic fractionalisation of the staff at 5%. Ethnicity of staff is significant at 1% with a coefficient of 0.429. Interestingly, the fractionalisation index of workforce diversity (*frac*) is also significant at 5%, with a larger coefficient of 0.593. This implies a 10% rise in the index would multiply the chances of new equipment being introduced by (exp(0.593) * 10)%, or 18.09 percentage points.

Table 12 Firms introducing new working practices, full sample

Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
	procin2	*procin2*	*procin2*	*procin2*	*procin2*
Lnage	–0.136***	–0.129**	–0.124**	–0.125**	–0.129**
	(0.0510)	(0.0513)	(0.0513)	(0.0515)	(0.0513)
Lnsize	0.218***	0.226***	0.234***	0.207***	0.172***
	(0.0492)	(0.0494)	(0.0497)	(0.0496)	(0.0530)
HQ	0.0844	0.0860	0.0894	0.0990	0.0854
	(0.168)	(0.168)	(0.169)	(0.168)	(0.168)
Collab	0.501***	0.507***	0.511***	0.497***	0.477***
	(0.123)	(0.123)	(0.124)	(0.124)	(0.124)
RD	0.747***	0.746***	0.752***	0.747***	0.743***
	(0.125)	(0.125)	(0.125)	(0.125)	(0.126)
Export	–0.0790	–0.0792	–0.0570	–0.0525	–0.0613
	(0.152)	(0.152)	(0.152)	(0.152)	(0.152)
Foreign	0.484**	0.364	0.490**	0.477*	0.455*
	(0.244)	(0.255)	(0.246)	(0.244)	(0.243)
Plc	0.281	0.293	0.270	0.262	0.258
	(0.328)	(0.327)	(0.328)	(0.323)	(0.322)
Skillneed	0.168***	0.164***	0.165***	0.168***	0.170***
	(0.0386)	(0.0387)	(0.0385)	(0.0386)	(0.0387)
Cobran		0.245*			
		(0.134)			
Ethown			0.421***		
			(0.138)		
Ethstaff				0.421**	
				(0.164)	
Frac					0.618**
					(0.254)
Observations	2371	2371	2371	2371	2371
Pseudo R-squared	0.106	0.107	0.110	0.109	0.108
Log likelihood	–1174	–1172	–1170	–1171	–1171
DF	80	81	81	81	81

Notes: robust standard errors in parentheses, significance levels *10%, **5%, ***1%

Source: LABS

Table 13 Firms introducing new working practices, split sample

Variables	*Knowledge-intensive firms*				*Non-knowledge-intensive firms*			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
	prodin2	*prodin2*	*prodin2*	*prodin2*	*prodin2*	*prodin2*	*prodin2*	*prodin2*
Lnage	–0.132*	–0.120	–0.127*	–0.131*	–0.141**	–0.140**	–0.135*	–0.142**
	(0.0751)	(0.0762)	(0.0759)	(0.0759)	(0.0717)	(0.0712)	(0.0718)	(0.0714)
Lnsize	0.125**	0.130**	0.0986	0.0777	0.371***	0.384***	0.359***	0.311***
	(0.0623)	(0.0626)	(0.0623)	(0.0679)	(0.0813)	(0.0818)	(0.0816)	(0.0858)
HQ	0.145	0.138	0.152	0.135	0.123	0.143	0.143	0.129
	(0.213)	(0.214)	(0.213)	(0.213)	(0.272)	(0.273)	(0.272)	(0.274)
Collab	0.304*	0.297*	0.283*	0.275*	0.712***	0.720***	0.706***	0.674***
	(0.161)	(0.162)	(0.161)	(0.161)	(0.188)	(0.189)	(0.190)	(0.191)
RD	0.837***	0.860***	0.850***	0.835***	0.653***	0.648***	0.641***	0.645***
	(0.165)	(0.166)	(0.165)	(0.165)	(0.194)	(0.193)	(0.195)	(0.195)
Export	0.106	0.134	0.149	0.125	–0.264	–0.239	–0.263	–0.274
	(0.192)	(0.193)	(0.194)	(0.192)	(0.260)	(0.260)	(0.261)	(0.261)
Foreign	–0.0490	0.0909	0.123	0.132	0.658*	0.759**	0.715**	0.672*
	(0.355)	(0.344)	(0.342)	(0.341)	(0.362)	(0.354)	(0.352)	(0.353)
Plc	0.262	0.187	0.234	0.283	0.182	0.185	0.153	0.104
	(0.513)	(0.524)	(0.509)	(0.515)	(0.414)	(0.413)	(0.408)	(0.408)
Skillneed	0.154***	0.158***	0.158***	0.162***	0.175***	0.174***	0.180***	0.183***
	(0.0536)	(0.0532)	(0.0535)	(0.0535)	(0.0560)	(0.0559)	(0.0560)	(0.0561)
Cobran	0.309*				0.177			
	(0.187)				(0.193)			
Ethown		0.515***				0.369*		
		(0.193)				(0.201)		
Ethstaff			0.433*				0.469**	
			(0.234)				(0.234)	
Frac				0.475				0.740**
				(0.367)				(0.360)
Constant	–1.784*	–1.884	–1.775*	–1.734*	–3.009***	–3.058***	–3.081***	–2.921***
	(0.965)	(2.234)	(0.965)	(0.963)	(0.485)	(0.495)	(0.498)	(0.477)
Observations	1176	1176	1176	1176	1195	1195	1195	1195
Pseudo R-squared	0.0936	0.0968	0.0941	0.0929	0.130	0.132	0.133	0.133
Log likelihood	–612.0	–609.8	–611.7	–612.5	–553.2	–552.0	–551.7	–551.5
DF	48	48	48	48	42	42	42	42

Notes: robust standard errors in parentheses, significance levels *10%, **5%, ***1%

Source: LABS

Table 11 gives results for knowledge-based and non-knowledge based firms. It appears the results are being driven by staff in knowledge-based firms, but diversity of management in non-knowledge based firms. For knowledge-based firms, both ethnicity of staff and fractionalisation are significant at the 1 and 5% levels respectively. For non-knowledge based firms, only *cobran* and *ethown* are significant, both at 5%. Different processes seem to be driving innovation in these two firm types.

Table 12 uses the second measure of product innovation, whether a firm has introduced new working practices in the previous 12 months. When the full sample is included, all four diversity variables are significant. *Cobran* is positive but significant at only 10%. *Ethown* is higher and significant at the 1% level. Both the ethnicity of staff and the fractionalisation index of staff are positive and significant at the 5% level.

In Table 13, these results are shown for knowledge-based and non-knowledge based firms. For knowledge based firms, *cobran* is significant at 10%, *ethown* at 1% and *ethstaff* at 10%. For non-knowledge based firms, the country of birth of the owners is not significant. However, the variables for ethnicity of the owners is significant at 10%, for ethnicity of the staff and fractionalisation index of the staff are significant at 5%.

6 Conclusions

Table 14 summarises the results of the analysis. The first bar gives results for the whole sample, the other bars for knowledge- and less knowledge-intensive firms respectively.

Generally the results match up well – findings from the full sample are explained by findings from the split samples. The exception is the 10% significant coefficient of *cobran* on introduction of new products. This is marginally significant in any case, so should probably be discounted as sampling error.

Overall, the results seem to bear out claims that London's diversity is an economic asset – at least in terms of its impact on innovation. If correct, this relationship implies that diversity has an important role in knowledge based development. But cultural diversity is not the strongest variable in the mix: collaboration with other firms and investment in R&D explain much more of the variation in innovation outcomes. As other studies have found (e.g., Page, 2007), the 'diversity bonus' is significant but small.

Particular aspects of London's diversity seem to matter. Our firm-level approach delivers detailed information here. Table 14 shows that when ownership diversity is significant, 'visible minority' ethnic owners have a clearer role than migrant owners. Although some foreign-born owners will be from BME communities, the results suggest that it is BME status that is primarily driving their contribution.

However, not all innovative activity is affected in the same way. Again, our data delivers nuanced information about different aspects of innovation, and by firm type. Table 14 suggests that associations between DIV and innovative activity are much stronger for process innovation than for product innovation. Measures of product innovation are more strongly linked to ownership diversity: conversely, process innovation is most strongly connected to workforce composition in the full sample – although less strongly in knowledge-intensive firms, where management appear to be the main proponents of new ways of working. Strikingly, while a diverse knowledge workforce has the strongest links to introducing new equipment, workforce diversity in less knowledge-intensive firms explains our strong result for new working practices.

Table 14 Summary of analysis

Sample	*DV*	*Cobran: owners/partners born abroad*	*Ethown: ethnic diversity of owners/partners*	*Ethstaff: % of staff who are non-white*	*Frac: ethnic fractionalisation of staff*
All firms	Innovation 1: new product	+			
	Innovation 2: major modification		+		
	Innovation 3: new equipment		+	++	++
	Innovation 4: working methods	+	+++	++	++
Knowledge-based firms	Innovation 1: new product		++	+	
	Innovation 2: major modification				
	Innovation 3: new equipment			+++	+++
	Innovation 4: working methods	+	+++	+	
Non-knowledge based firms	Innovation 1: new product				
	Innovation 2: major modification		++		
	Innovation 3: new equipment	++	++		
	Innovation 4: working methods		+	++	++

Notes: code: + = positive; – = negative; + = 10% significance; ++ = 5%; +++ 1%

The existing literature on the economics of diversity suggests a number of mechanisms linking cultural mix to economic outcomes. Two of these seem particularly important to innovation in London firms. The first is that London's culturally diverse workforce appears to benefit both product and process innovation in all kinds of businesses. All types of firms derive benefits, not just knowledge-sector firms, as some other studies have suggested. These results refer only to the visible minority share of a firm's workforce, as we do not have separate information on migrants. However, results from other studies suggest the findings would be similar (for example, Hunt, 2008; Peri, 2007; Stephan and Levin, 2001).

The second factor is the role of 'ethnic entrepreneurs' in the London economy, particularly minority ethnic business-owners. Our results suggest their impact is particularly felt both in hybridisation of existing products and services and in introducing new ways of working, particularly in knowledge-intensive firms. We speculate that this may be driven by diasporic knowledge flows, by the evolving demands of London's cosmopolitan population, or a combination of the two.

There are a number of caveats to this analysis. The dataset we use is the richest available – but does not allow full comparison between migrant and minority ethnic workers, and ethnic groupings are relatively crude. We also do not know whether specific innovations by the firms in the sample led to business success: not all innovations pay off.

More importantly, the results are based on cross-sectional analysis and so we are unable to fully ascribe causality. High performing cities are likely to attract a larger and more culturally diverse workforce – whether or not that diversity shapes economic outcomes. Innovative firms may be more tolerant of diversity, regardless of its impact: case study work would be important in assessing the direction of this effect. Finally, we cannot account for the selection effects among diverse owners and workers, particularly for country of birth-based measures. Migrants are likely to be more skilled and entrepreneurial – so 'ethnic entrepreneur' owners and workers may drive our findings. If these people are innovative anywhere, however, we need to explain why London attracts such a large share of the UK's migrant population. Our innovation story would then put greater emphasis on socio-cultural features of London – notably its amenities and cosmopolitan milieu.

Overall, the results can be seen as providing some support for claims that London's cultural diversity helps support levels of innovation and strengthens the capital's competitive position and long-term economic performance. London's diversity is probably an economic asset, not just a social one.

The capital is unique in the UK urban system, which limits the external validity of our findings. Intuitively, our findings are likely to be replicated in other big British cities – such as Liverpool, Manchester, Glasgow or Birmingham – but the coefficients of diversity may be smaller, or driven by other channels.

Future research will develop our dataset into a full panel for richer analysis. Beyond this, it would be fruitful to conduct sector or firm-level case studies, particularly of knowledge-intensive businesses, to identify the influence of cultural diversity on real-world workflows.

Acknowledgements

The authors would like to thank Riccardo Crescenzi, Ian Gordon, Andrés Rodríguez-Pose, Henry Overman and Peter Wood for comments and support, Matthew Waite at the London Development Agency for the use of London Annual Business Survey data, and Emma Drever for suggesting this use of the data. All errors and omissions remain our own.

References

Alesina, A. and La Ferrara, E. (2004) 'Ethnic diversity and economic performance', NBER Working Paper No. 10313, NBER, Cambridge, MA.

Aspinall, P. (2009) 'The future of ethnicity classifications', *Journal of Ethnic and Migration Studies*, Vol. 35, No. 9, pp.1417–1435.

Berliant, M. and Fujita, M. (2007) 'Knowledge creation as a square dance on the Hilbert cube', MPRA Paper No. 2884.

Brinkley, I. (2008) *The Knowledge Economy: How knowledge is Reshaping the Economic Life of Nations*, The Work Foundation, London.

Bulmer, S. (1996) 'The ethnic group question in the 1991 census of population', in D. Coleman and J. Salt (Eds.): *Ethnicity in the 1991 Census of Population*, HMSO, London.

Casey, T. and Dustmann, C. (2009) 'Immigrants' identity, economic outcomes and the transmission of identity across generations. CReAM', Discussion Paper Series CDP 23/09, University College London, London.

Champion, T. (2006) 'State of the English cities: the changing urban scene: demographics and the big picture', Office of the Deputy Prime Minister, London.

Department of Innovation, Universities and Skills (2008) *Innovation Nation*, Department of Innovation, Universities and Skills, London.

Duranton, G. and Puga, D. (2001) 'Nursery cities: urban diversity, process innovation and the life cycle of products', *American Economic Review*, Vol. 91, No. 5, pp.1454–1477.

Florida, R. (2002) *The Rise of the Creative Class*, Basic Books, New York.

Fujita, M. and Weber, S. (2003) 'Strategic immigration policies and welfare in heterogenous countries', Institute of Economic Research Working Papers, Kyoto University, Kyoto.

Glaeser, E. (2005) 'Review of Richard Florida's 'the rise of the creative class'', *Regional Science and Urban Economics*, Vol. 35, No. 5, pp.593–596.

Glaeser, E. (2008) *Cities, Agglomeration and Spatial Equilibrium*, OUP, Oxford.

Gordon, I., Travers, T. et al. (2009) *London's Place in the UK Economy*, City of London, London.

Gordon, I., Whitehead, C. et al. (2007) *The Impact of Recent Immigration on the London Economy*, London, City of London Corporation.

Gordon, I.R. and McCann, P. (2005) 'Innovation, agglomeration, and regional development', *Journal of Economic Geography*, Vol. 10, pp.523–543.

Goulding, N. (2009) 'Tackling prejudice at work', available at: http://www.hrzone.co.uk/topic/employment-law/tackling-prejudice-workplace', accessed on 24/11/2009.

Greater London Authority (GLA) (2006) *Press Release 026: Poll Shows Londoners Feel Safer and Support Cultural Diversity*, January 16.

Greater London Authority (GLA) (2008) *Planning for a Better London*, GLA, London.

Griffith, R., Huergo, E. et al. (2006) 'Innovation and productivity across four European countries', *Oxford Review of Economic Policy*, Vol. 22, No. 4, pp.483–498.

Henry, N., MacEwan, C. et al. (2002) 'Globalisation from below: Birmingham – postcolonial workshop of the world?', *Area*, Vol. 34, No. 2, pp.117–127.

Home Office and Department of Work and Pensions (2007) *The Economic and Fiscal Impact of Immigration*, Home Office, London.

Hong, L. and Page, S. (2001) 'Problem solving by heterogeous agents', *Journal of Economic Theory*, Vol. 97, pp.123–163.

Hong, L. and Page, S. (2004) 'Groups of diverse problem solvers can outperform groups of high-ability problem solvers', *Proceedings of the National Academy of Sciences*, Vol. 101, No. 46, pp.16385–16389.

House of Lords Select Committee on Economic Affairs (2008) *The Economic Impact of Immigration*, House of Lords, London.

Hunt, J. (2008) 'How much does immigration boost innovation?', *NBER Labor Studies Program Meeting 2008*, Boston, Mass.

Jacobs, J. (1970) *The Economy of Cities*, Vintage, London.

Jaffe, A. and Trajtenberg, M. (1999) 'International knowledge flows: evidence from patent citations', *International Journal of Knowledge Organisation*, Vol. 8, pp.105–136.

Jones, T., Ram, M. et al. (2004) 'Ethnic minority enterprise in an inner-city context: the case of the independent restaurant sector in Birmingham', M. Boddy and M. Parkinson (Eds,): *City Matters*, Policy Press, Bristol.

Kelley, M. and Helper, S. (1999) 'Firm size and capabilities, regional agglomeraiton and the adoption of new technology', *Economic Innovation and Technical Change*, Vol. 8, pp.79–103.

Kerr, W. (2008) 'Ethnic scientific communities and international technology diffusion', *Review of Economics and Statistics*, Vol. 90, No. 3, pp.518–537.

Kitching, J., Smallbone, D. et al. (2009) 'Ethnic diasporas and business competitiveness: minority-owned enterprises in London', *Journal of Ethnic and Migration Studies*, Vol. 35, No. 4, pp.689–705.

Kyambi, S. (2005) 'Beyond black and white: mapping new immigrant communities', ippr, London.

Landry, C. and Wood, P. (2007) *The Intercultural City*, Earthscan, London.

Leadbeater, C. (2008) *The Difference Dividend: Why Immigration is Vital to Innovation*, NESTA, London.

London First (2008) 'The world in one city', available at: http://www.london-first.co.uk/documents/Immigration_briefing_FINAL.pdf, accessed on 27/09/2009.

Masters, B. (2009) 'Asian cities catch up with London', *Financial Times*, Vol. 22, September, London.

Mateos, P., Singleton, A. et al. (2009) 'Uncertainty in the analysis of ethnicity classifications: issues of extent and aggregation of ethnic groups', *Journal of Ethnic and Migration Studies*, Vol. 35, No. 9, pp.1437–1460.

Mateos, P., Webber, R. et al. (2007) 'The cultural, ethnic and linguistic classification of populations and neighbourhoods using personal names', CASA Working paper, UCL, London.

Mazzolari, F. and Neumark, D. (2009) 'Beyond wages: the effects of immigration on the scale and composition of output', NBER Working papers, NBER, Cambridge, MA.

Nakhaie, R., Lin, X. et al. (2009) 'Social capital and the myth of minority self-employment: evidence from Canada', *Journal of Ethnic and Migration Studies*, Vol. 35, No. 4, pp.625–644.

Nathan, M. (2005) 'The wrong stuff? Creative class theory, diversity and city performance', Centre for Cities Discussion Paper No. 1, Centre for Cities, London.

Nathan, M. (2008) 'Your place or mine? The local economics of migration', Economics of Migration Discussion Paper No. 1, ippr, London.

Nathan, M. (2009) 'The long term impacts of migration on UK cities: diversity, wages, employment and prices', Paper presented at *56th Annual North American Meeting, Regional Science Association International*, San Francisco, November 18–21.

Niebuhr, A-K. (2006) 'Migration and innovation: does cultural diversity matter for regional R&D performance?', IAB Discussion Paper 14/2006, IAB, Nuernburg.

Office of National Statistics (ONS) (2003) *Ethnic Group Statistics: A Guide for the Collection and Classification of Ethnicity Data*, ONS, Newport.

Ottaviano, G. and Peri, G. (2006) 'The economic value of cultural diversity: evidence from US cities', *Journal of Economic Geography*, Vol. 6, pp.9–44.

Overman, H. and Rice, P. (2008) 'Resurgent cities and regional economic performance', SERC Policy papers, London School of Economics, London.

Page, S. (2007) *The Difference*, Princeton University Press, Princeton.

Peri, G. (2007) 'Higher education, innovation and growth', in G. Brunello, P. Garibaldi and E. Wasmer (Eds.): *Education and Training in Europe*, Oxford University Press, Oxford.

Rodríguez-Pose, A. and Storper, M. (2006) 'Better rules or stronger communities? On the social foundations of institutional change and its economic effects', *Economic Geography*, Vol. 82, No. 1, pp.1–25.

Romer, P. (1990) 'Endogenous technological change', *Journal of Political Economy*, Vol. 98, No. 5, pp.71–102.

Sassen, S. (1991) *The Global City*, Princeton University Press, Princeton.

Saxenian, A-L. (2006) 'The new argonauts: regional advantage in a global economy', Harvard University Press, Cambridge, MA.

Simmie, J. and Sennett, J. (2001) 'London: international trading metropolis', in J. Simmie (Ed.): *Innovative Cities*, pp.191–228, Spon, London.

Smallbone, D., Rosemary, A. et al. (2006) 'The competitive advantage of diversity: introduction to the project and mid-term findings', Report to the GLA, University of Kingston, Kingston.

Spence, L. (2008) 'ONS ethnic group population estimates: mid-2006', GD Briefing 2008-5.

Stephan, P. and Levin, S. (2001) 'Exceptional contributions to US science by the foreign-born and foreign-educated', *Population Research and Policy Review*, Vol. 20, pp.59–79.

Tether, B., Mina, A. et al. (2005) 'A literature review on skills and innovation', CRIC Report for DTI, University of Manchester ESRC Centre for Research on Innovation and Competition, Manchester.

Von Hippel, E. (2005) *Democratising Innovation*, MIT Press, Cambridge, MA.

Wilson, R. (2007) 'Innovation in London', Working Paper No. 19, GLA Economics, London.

Notes

1 For a recent summary, see Nathan (2008).

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

3 In 2008, the ten largest countries of birth groups in UK cities were (in order of population share): Poland, India, Pakistan, Germany, Eire, Rep. South Africa, Zimbabwe, Bangladesh, USA (Nathan, 2009).

4 1 = owners all born outside UK (coded 1); 2 = majority of owners born outside (coded 0.75); 3 = 50: 50 born outside UK (coded 0.5); 4 = majority of owners not born outside UK (0.25); 5 = none of the owners born outside (coded 0).

5 In this instance, the maximum value of the index for equally sized groups would be $1 - (1/5) = 0.8$.

6 The work foundation follows the OECD definition of knowledge-intensive industries, but makes some adjustments for the UK context. The final list of 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).

7 Full results are not reported here but are available on request.

8 The models contained in Table 7 demonstrate some potential specification problems. However, this problem is only marginal (10% significant). When the models are repeated separately for knowledge based and non-knowledge-based firms the problem disappears.