The Decline in Rent Sharing

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Abstract

The evolution of rent sharing is studied. Based upon a panel of the top 300 publicly quoted British companies over thirty-five years and using excess stock market returns to patenting activity as an instrument for economic rents, the paper reports evidence of a significant fall over time in the pass-through from rents to wages. It confirms that wages do respond to firm-level shocks to economic rents, but by significantly less after 2000 than they did during the 1980s and 1990s. The evidence of decline is a robust finding, corroborated with alternative instruments and industry-level analysis for the US and EU.

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I. Introduction

To varying degrees, the real wages of workers across a number of advanced economies have been stagnating and lagging productivity growth (Dustmann et al., 2009; Acemoglu and Autor, 2011; Stansbury and Summers, 2019; LSE Growth Commission, 2017). Against this backdrop, one key thrust in recent empirical research on wage determination has been to intensively study the role of firms.[1] One development has been the resurrection of a body of earlier work on rent sharing – a firm-level pass-through from economic rents to wages - (e.g., Nickell and Wadhwani, 1990; Blanchflower et al., 1996; Van Reenen, 1996; Hildreth and Oswald, 1997) where more recent studies have significantly advanced that research in several directions. This includes the use of rich linked employee-employer data (Bagger et al., 2014; Card et al., 2014; Card et al., 2018; Hirsch and Mueller, 2020), explicitly modelling matching processes (Card et al., 2018; Kline et al., 2019; Lamadon et al., 2022) and generating more plausible causal estimates (Kline et al., 2019; Garin and Silverio, 2022; Howell and Brown, 2022). On the theoretical side, some of the recent monopsony literature challenges the traditional view that rent sharing[2] describes the bargaining power of workers and argues that it arises as a result of firms facing upward-sloping labour supply curves (Manning, 2011; Card et al., 2018; Kline et al., 2019; Lamadon et al., 2022).

Despite such progress, little is known about long-run patterns of rent sharing and on changes in the extent of pass-through. One obvious reason is that the data requirements to study the long-run evolution of rent sharing are extremely demanding. For this paper a very significant data collection exercise was undertaken to assemble a major new dataset enabling the study of changes over time in rent sharing. Much more detail is given later in the paper, as

[1] The literature initially tended to focus on the macro- or sectoral-level determinants of income inequality, highlighting the influence of technology (Acemoglu, 2003a; Karabarbounis and Neiman, 2014), trade (Autor et al., 2014) and institutions (Acemoglu, 2003b).
[2] The term "rent sharing" originates from the wage bargaining literature, however it has been widely used to describe a relationship between wages and rents regardless of the underlying model. We follow this convention throughout the paper.

the process was complex, but it involved the construction of a comprehensive and consistent annual panel of the top 300 companies in the UK over 35 years from 1983 to 2016. This was not a straightforward exercise, especially regarding the challenges of data collection when going further back in time. Firm-level information was manually collected from annual reports and combined with various existing databases. The construction of the dataset ensures coverage of the entire economy and so limits sample selection bias. Overall, the (unbalanced) panel consists of 843 firms, which in the final year of analysis (2016) employ over 7 million workers worldwide and constitute around 95% of total UK stock market capitalization.

The empirical approach used to analyse these data draws on and extends beyond the older and newer rent-sharing literatures. A rent-sharing coefficient is estimated using a panel firm fixed-effect model that regresses log compensation per employee on measures of economic rents and external forces influencing wage determination (industry-level wages and time fixed effects). Potential endogeneity is addressed by instrumenting rents with the excess stock market return value of granted patents (in a similar vein to Van Reenen, 1996; Kogan et al., 2017; Kline et al., 2019). The instrument captures firm-level shocks to rents as reflected in the strong first stage of the estimation process. The results show a positive and statistically significant rent-sharing parameter and the exclusion restriction is validated in several ways. Estimated over the whole sample, the rent sharing elasticity when rents are measured as value added per worker is 0.15 – similar in magnitude to estimates from other rent-sharing studies (Card et al., 2018).

When the time series evolution of rent sharing is considered, a striking and robust finding emerges. The 0.15 average masks a significant decline in the long-run rent-sharing elasticity, which drops from 0.26 between 1983 and 1999 to 0.09 from 2000 to 2016. The finding of a significantly reduced rent sharing parameter holds in an alternative specification of the rent-sharing model in which employment changes are controlled for – which potentially limits the confounding effects of the adjustments in workforce composition and the influence of a monopsonistic channel[3] (Nickell and Wadhwani, 1990). We also find no evidence linking changes in the product market power of employers with the temporal decline in rent sharing.

Various specification checks and alternative sample definitions corroborate the decline – for example, using profits per employee as a measure of economic rents and lagged levels of variables as alternative instruments (Arellano and Bond, 1991). Importantly, whilst the *level* of rent sharing depends on the choice of measure and instrument, the direction of *change* in rent sharing does not. Moreover, a similar temporal decline in rent sharing emerges for a panel of UK manufacturing companies, which provides data on domestic operations only. In addition, industry-level data for the US and for nine EU countries again show the same pattern. Consistent with the firm-level analysis, there is a strongly falling correlation between log compensation per employee and value added per employee for almost all countries since the early 2000s (EU) and the 1980-90s (US).

This paper offers a first comprehensive attempt to examine the long-run evolution of rent sharing. According to the two dominant interpretations of rent sharing - that it reflects the bargaining power of workers or the monopsonistic power of firms – the presence of positive rent sharing signals the ability of workers and firms to capture economic rents. The decline in rent sharing that we document suggests therefore that at least one, and possibly both, of these elements has become less important over time. Our data do not allow us to identify which mechanism is driving the reduction but our findings speak to the burgeoning recent literature that tries to link rent sharing with monopsonistic competition (Manning, 2011; Card et al., 2018; Kline et al., 2019; Lamadon et al., 2022), changes in the bargaining power of workers[4]

[3] In this channel, rent sharing occurs because firms facing an upward-sloping labour supply curve must increase wages in order to increase employment. Therefore, in a firm hit by a demand shock, there is a common co-movement of rents, wages, and employment.

[4] Often linked to the decline of unions (e.g., Machin, 2000; Farber et al., 2021). As is visible in Figure A4, union membership in the OECD countries declined from 37% in 1980 to 16% in 2019; in the UK from 52% to 24%, and in the US from 22% to 9%.

(Elsby et al., 2013; Stansbury and Summers, 2020) or declines in risk sharing (Guiso et al., 2005; Howell and Brown, 2022).

The paper's findings also contribute to the recent literature on wage inequality in the US and the UK, which documents a diminishing contribution of firm-specific wage premia (after controlling for worker composition), to earnings dispersion, especially among large firms (Song et al., 2019; Schaefer and Singleton, 2020; Lamadon et al., 2022). The results shed light on the mechanisms behind this trend. The observed decline in rent sharing in a sample of large multinational companies might be a reason for the decline in their wage premia. As these companies are increasingly global, one might expect these trends to become worldwide phenomena. Yet, the effect of the decline in rent sharing on overall wage inequality depends on how workers are sorted into companies with different wage premia. A positive sorting (Song et al., 2019) implies that the decline in rent sharing lowers wage inequality, while a negative sorting (Hirsch and Mueller, 2020; Mertens, 2022) implies that inequality might increase.

The rest of the paper is organised as follows. Section II briefly discusses the related theoretical and empirical literature on the links between firm rents and wages. Section III provides details of the data construction and presents summary statistics on performance and compensation in the sample. The identification strategy and the firm-level results are presented in Section IV, and the industry-level results in Section V. Section VI concludes.

II. Rent Sharing

II.A. Theoretical Considerations

A positive correlation between wages and rents is not a feature of a standard perfect competition model. Wages are given and do not depend on firm characteristics. If a company experiences a positive productivity or demand shock, it will increase employment but keep wages fixed. In more realistic models, a portion of the rents ensuing from the shock are captured by workers in the form of higher wages. There are at least three ways this result can occur (Blanchflower et al., 1996).

The first approach incorporates a wage bargaining process between workers and firms over an economic rent, which results in a division of the rent into profits and a wage mark-up over the market level. This is consistent with the literature looking at Continental Europe (Belgium, Germany, Italy and Portugal), which finds that rent sharing is higher in more unionized firms/sectors and that it depends on institutional details of collective bargaining (Teulings and Hartog, 1998; Estevao and Tevlin, 2003; Cardoso and Portela, 2009; Rusinek and Rycx, 2013; Card et al., 2014; Hirsch and Mueller, 2020). On the other hand, one criticism of the wage bargaining approach points out the *smaller* estimates of rent sharing in unionised sectors for US and UK (Hildreth and Oswald, 1997; Manning, 2011), heterogeneity of rent sharing across workers within a firm (Card et al., 2018; Kline et al., 2019; Garin and Silverio, 2022) and no evidence for investment holdup (Card et al., 2014).

The second approach is in a monopsonistic model with an upward sloping labour supply curve facing the firm. In this class of models, a positive correlation between wages and profits arises in response to a positive demand shock. When a favourable shock occurs, companies respond by moving up their supply curve, and profits rise together with employment and wages. An older literature, however, remarks that the monopsonistic model offers an unlikely explanation of the existence of rent sharing - with one empirical method of justifying this because the correlation between wages and rents is not influenced by the inclusion of employment growth into firm-level wage equations (Nickell and Wadhwani, 1990; Blanchflower et al., 1996; Van Reenen, 1996; Hildreth and Oswald, 1997). Some of the more recent literature, however, looks favourably on the plausibility and relevance of models of monopsony based on workers' heterogenous preferences towards workplace non-wage amenities (Manning, 2011; Card et al., 2018; Kline et al., 2019; Lamadon et al., 2022).

A third, less commonly discussed, way in which rent sharing emerges is an incentive pay model (Lazear, 1986; Brown, 1990; Howell and Brown, 2022) or imperfect risk-sharing model (Guiso et al., 2005; Cardoso and Portela, 2009), where workers and firms can share economic rents. For example, when effort is hard to monitor but output is observable it might be optimal to offer a piece-rate pay scheme or back-loaded compensation, directly linking wages with output. Because the level of output is only partially explained by a worker's effort, then there is a positive correlation between wages and productivity shocks.

Overall, each of the three approaches generate a formulation of the firm's wages as a function of the outside options and the firm's economic performance (e.g., measured by value added or profits per employee), and which underpin the wage equation used in the empirical part of this paper.

Our baseline estimates of rent sharing are for a sample of UK firms, but we also provide auxiliary analysis using industry data from the EU and the US. While the theories presented above can explain pass-through elasticities estimated for industries, there are a few important theoretical distinctions, which must be considered when looking at this level of aggregation. Importantly, industry-level shocks might affect wages not only through rent sharing, but also through classic market-level forces. Consequently, a pass-through elasticity between wages and rents estimated at the industry level might be larger than at firm level, as it captures the effect of changes in aggregate labour demand on wages, and because labour supply to an entire market is less elastic than to a firm (Lamadon et al., 2022).

II.B. Existing Empirical Evidence

There is by now a vast literature investigating the relationship between wages and economic rents. The focus in the earlier studies was typically on panels of US manufacturing industries (Katz and Summers, 1989; Blanchflower et al., 1996; Estavão and Tevlin, 2003). A series of influential firm-level studies emerged during the 1990s which analysed British companies (Nickell and Wadhwani, 1990; Nickell, Vainiomaki and Wadhwani, 1994; Van Reenen, 1996; Hildreth and Oswald, 1997; Hildreth, 1998) and Canadian collective bargaining agreements (Abowd and Lemieux, 1993). Nickell and Wadhwani (1990) use a panel of UK listed firms from 1975 to 1982 and estimate an elasticity in the range of 0.07-0.09. In an early attempt to account for the potential endogeneity problem between wages and firm performance, Van Reenen (1996) employs a measure of technology innovations (patents) as an instrument for quasi rents in a panel of large British manufacturing firms. He finds that instrumenting rents more than doubles the rent-sharing elasticity, from 0.11 to 0.29. More recently, there has been a revival of interest in rent sharing. Newer studies often exploit employee-employer matched data and document a relatively small elasticity of individual wages with respect to firm-level measures of rents (Margolis and Salvanes, 2001; Arai, 2003; Guiso et al., 2005; Cardoso and Portela, 2009; Guertzgen, 2009; Bagger et al., 2014; Card et al., 2014; Card et al. 2016; Carlsson et al., 2016).

The availability and, if available, the validity of instrumental variables estimates in this literature remain a contentious issue. The ideal experiment needs to isolate a firm-specific shock to company performance but finding a valid and strong instrument at the firm level has proven difficult.[5] Van Reenen (1996) uses firm-level innovation, but the instrument is weak in the first stage. Building upon and further developing this idea, Kline et al. (2019) use the economic value of innovations, estimated from the excess stock market value (ESMR) of patents. The recent works by Garin and Silverio (2022) and Howell and Brown (2022) also advance in this area by exploiting recession-induced trade shocks and R&D grants, respectively. The main empirical strategy in this paper follows Van Reenen (1996) and Kline et al. (2019) by instrumenting the firm's economic rents with the annual ESMR value of

[5] As a result, most studies instrument firm-level rents with industry-level rents. As Manning (2011) points out, if labour has an industry-specific component and there is a positive shock to industry profits, then this raises the demand for labour in a competitive model and should lead to higher wages. In such a case, it is not at all clear that industry-level rents serve as a valid instrument for firm-level rents.

granted patents (Kogan et al., 2017). In addition, further specification checks are undertaken using Arellano-Bond (1991) estimates based upon two-period (and before) lags as instruments. Although the *level* of rent sharing does depend on the choice of instrument, the main result of the *fall* in rent sharing does not.

Perhaps surprisingly, not many studies have investigated the evolution of rent sharing. The likely reason is the lack of a consistent firm-level panel that is long enough to capture changes, and that is comprehensive enough to cover all sectors, and that includes information on compensation and measures of economic rents.[6] A notable exception is a study by Bell and Van Reenen (2011), which uses the matched US manufacturing worker-industry data from the Current Population Survey (CPS) and National Bureau of Economic Research (NBER) Productivity Database. The authors report an elasticity of around 0.05 in the period between 1964 and 1985, which falls to zero between 1986 and 2005. Using the same US data, Stansbury and Summers (2020) document a dramatic fall of the rent sharing elasticity between 1984 and 2016. The authors interpret this as evidence for the fall of workers' bargaining power. Benmelech et al. (2022) also report a fall in the elasticity of wages with respect to labour productivity between 1977 and 2009 for US manufacturing companies.

III. Data

III.A. Firm-Level Data

Publicly listed companies in the UK have been required to report staff costs in their company accounts since 1983. However, existing datasets on listed companies (e.g., Worldscope) have very poor coverage of the 1980s and early 1990s. Other possible sources prior to the mid-1990s have shortcomings, like being short-lived since the mandatory reporting of employee compensation began (e.g., the Cambridge Department of Trade and Industry

[6] For instance, US company-level data from Standard and Poor's (S&P) Compustat goes back to the 1960s. However, only a small (and changing) subset of firms contains information on compensation, as disclosure of this information is not obligatory.

databank) or being limited to cover only the manufacturing sector (e.g., the business microdata in the Annual Respondents Database). Since existing data are not suitable for the research questions posed here, we constructed a comprehensive and consistent panel of British public companies by drawing from published annual reports and existing databases.

The top 300 companies by market capitalization listed on the London Stock Exchange (LSE) between 1983 and 2016 are studied. To obtain these data, several steps were taken. First, the universe of listed companies was obtained from the London Share Price Database (LSPD), which records information on all listings that have been traded on the London Stock Exchange since 1955. The universe of listings was restricted to only those domiciled in the UK and excluded investment trusts, unit trusts and real estate trusts, as well as secondary share issues. The population of companies is on average 27% smaller than the raw number of listings, but the two series have an almost identical evolution.

The top 300 companies each year by market capitalization were selected, excluding those appearing in the top 300 for no more than three years over the entire study period. Finally, having established the full list of companies, data were collected for all years (within 1983-2016) when a company was publicly listed, even when it was outside the top 300. The resulting panel consists of 13,512 observations for 843 companies, which together employ over 7 million workers worldwide (2016) and constitute around 95% of total UK stock market capitalization.[7] The construction of the dataset ensures coverage of the entire economy and limits sample selection bias. This is crucial for the long-run analysis, especially given the dramatic shift of employment from manufacturing to service sectors over the sample period. This panel is referred to as the 'top 300' sample in the remainder of the paper.

[7] The share of the top 300 employment in the UK total market economy employment rises from around 20% in 1983 to 30% in 2016. When compared to the UK total economy, it remains stable throughout the period at around 20-22%. This is an upper bound, as the employment in the top 300 firms refers to their global operation, that is, it includes employees from the UK and elsewhere.

Figure 1 presents the top 300 sample size and decomposes it into observations that are at the top in a given year and observations outside the top (but are at the top in another year). By construction, the number of observations peaks in the middle period (1994-1998) because that period captures three types of companies: companies at the top in that period, companies at the top in the beginning of the time window (which are still alive in 1994-1998) and companies at the top in the end of the window (which already existed in the 1990s). The edges of the window (e.g., 1983 or 2016) have fewer observations as they capture fewer of those companies which were at the top in other years. The fluctuation in the number of companies at the top (the dashed line) results from the rule that companies must be at the top for at least three years to enter the sample. In particular, the dot-com bubble of 1999-2001 created many high-valued but short-lived tech companies.

The LSPD contains limited information on a firm's characteristics and accounts. Financial data were collected either manually from annual reports or existing datasets. The main data provider is Thomson Reuters Worldscope, complemented with S&P Compustat, Exstat, Bureau van Dijk (BvD) ORBIS, BvD FAME and Cambridge DTI. Company-years were matched across the dataset using unique identifiers (SEDOL and ISIN) and company names. The existing datasets do not cover over 1,700 company-year observations in the sample, mostly concentrated in the early years, and these observations were manually collected from scans of published financial reports available at Mergent Archive and Companies House.

When looking at more than thirty years of data, changes in the formal organization of companies are the norm rather than the exception. Most of the companies in the sample encountered some form of reorganization, merger or acquisition (M&A). This often leads to a discontinuous change in wages and measures of economic rents, which might introduce noise into the estimates. Whenever a company takes over another one and a new legal entity is created, the time series of the two companies are separated out and given a specific id/fixed effect for the new entity (if publicly listed). In many cases, however, the takeovers are relatively minor and do not result in substantial legal changes (except for the purchased company, which disappears). These cases were manually identified, and a dummy variable control for them was incorporated into regressions.

The data in the 'top 300' sample refers to the global operations of UK-domiciled companies. To see whether the main results hold for domestic operations, a panel of UK manufacturing (production sector) companies was set up using data from the Annual Respondents Database (ARD) for 1979 - 2008. Although the companies might operate in many countries, the ARD focuses exclusively on the UK operation. The data include all companies larger than 250 employees[8] and an annual sample of smaller ones. However, numerous companies with employment around the cut-off occasionally dropped in and out of the main sample. For this reason, only firms with employment larger than 300 and for which data availability was for at least four years were considered. After these adjustments, the sample consists of 28,533 firm-year observations for 3,143 firms.

The main measure of rents entered into the wage equations is value added per employee, but additional results are also provided for profits per employee. Since both measures are volatile and outliers might drive the results, the approach used in Card et al. (2014) was followed and for every year, observations with value added and profits per employee outside the 1^{st}-99^{th} percentile range were trimmed.[9]

The models outlined in Section II suggest that the wage-setting process is a function of 'outsider' forces. These are accounted for by including the average industry wage and year fixed effects. The data on the average industry wage comes from the UK files of EU-KLEMS. In addition, for the panel of manufacturing companies from ARD, we add information on

[8] To be more precise, all firms larger than 250 are included since the survey year of 1998. Between 1995 and 1997 all firms larger than 200 employees, and between 1980 and 1994 all firms larger than 100 employees.
[9] Observations with negative value added are dropped.

regional-level unemployment rates, which were matched from the Labour Force Survey (1979-1991) and NOMIS/LFS (1992-2008). The data on regional-level average hourly wages come from the New Earnings Survey Panel Database (NESPD).

III.B. Patent Data

The identification strategy in this paper exploits granted patents as exogenous firm-level shocks to economic rents. The information about patents comes from the European Patents Office's PATSTAT - a worldwide patent statistical database. It contains detailed information about patent applications submitted to almost all developed and developing countries, going back in time to the beginning of the 20th century.

The unit of analysis is a *family* – a collection of closely related grant applications referring to one invention. Henceforth, for the sake of simplicity, when speaking about a "patent", this means a family of patent applications relating to the same invention. A patent is considered to be granted to a firm if at least one application is granted, taking the earliest application publication date as a date of the patent publication, and associating the patent with all inventors listed in the applications. The initial sample consists of all granted patents, on which at least one inventor is UK-based, but the patents do not have to be submitted to the UK patent office. We focus only on standard "utility" patents.

Information about patents is matched to the baseline top 300 sample of firms using two methods: i) the crosswalk between PATSTAT patents and Bureau van Dijk's firm ID; ii) manually matching the datasets by company name. The details on the PATSTAT data, the matching procedure, and the basic descriptive statistics are presented in Appendix 1.

III.C. Industry Level Data

The analysis of industries for nine EU countries (Austria, Denmark, Finland, France, Germany, Italy, Netherlands, UK, and Spain) draws from the EU-KLEMS data. For the US, the data source is the NBER-CES Manufacturing Industry Database. Both sources provide information on productivity, employment, and compensation. EU-KLEMS covers the entire economy for 28 1-digit (2-digit for manufacturing) sectors, and the data are available since the 1990s until 2015 (coverage differs by country). NBER-CES Manufacturing Industry Database is limited only to the manufacturing sector but provides data for 459 industries from 1963 to 2011.

IIID. Descriptive Statistics

Table A3 reports the top five companies based on market capitalization, employment, and revenue for 1983, 2000 and 2016 for the top 300 UK firms. In the early 1980s, the UK economy was dominated by the manufacturing sector, with companies such as British Petroleum, General Electric Company and British American Tobacco making it to the top in all categories. Seventeen years later, there is a rise in the banking and finance (HSBC, Aviva, and Prudential), telecommunication (Vodafone) and retail (Tesco and Sainsbury) sectors. Within the manufacturing sector, pharmaceutical firms (GlaxoSmithKline and AstraZeneca) replaced the more traditional electronic and machinery producers at the top. Today, the British 'superstar' companies operate in finance, banking, and business services, such as G4S and Compass Group - providers of outsourced services. Interestingly, British Petroleum and British American Tobacco are found at the top in 1983 and 2016, which testifies to the continued importance of the oil and tobacco industries.

Table 1 reports the average firm size in the top 300 sample (with trimmed profits). At the beginning of the 1980s, the average company in the sample employed over 15,000 workers and grew until the end of the decade. After a drop to around 13,000 employees in 1994, firm size has experienced undisrupted growth until 2016. Today the average company in the sample has more than 22,000 employees. However, the standard deviation is over twice as large as the mean, indicating a sizeable variation in firm size – the smallest company in the sample has 5 employees, whereas the largest employs more than half a million.

Table 1 and Figure 2 document the evolution of mean real revenue, compensation and profit per employee expressed in thousands of £2016 (weighted by employment). Average revenue and compensation per head grew steadily from 1983 until the Great Recession, after which they started falling and, in 2015, they dropped to the levels reported in the early 2000s. The year 2016 witnessed a recovery of revenue and wages. Although the reported numbers refer to global operations, the sample average annual compensation in 2016 is £34,400, close to the UK average for full-time workers. The average profit per employee is more volatile. The positive trend between 1983 and 2011 was interrupted by the recession of 1991-92, the dot-com bubble of 1999-2001 and the Great Recession. Profits peaked in the years before and after the latter, but since 2011 they have been steadily falling.

IV. Trends in Firm-Level Rent Sharing

IV.A. Identification

Section II.A concluded with a formulation of the firm-level wage as a function of economic rents per employee and outside forces. In the next subsection, this wage equation is taken as the basis for formulating and implementing the empirical strategy, together with introducing a set of modifications to account for potential endogeneity bias. First, looking at granted patents as exogenous firm-level shocks to economic rents. Second, firm fixed-effects are included, so as to absorb time-invariant company characteristics affecting firm performance and wages.

Patents might affect economic rents through two channels. First, they provide temporary monopoly rights over an innovation, allowing the patenting firm to set prices above marginal cost. Second, an innovation might boost the firm's economic performance. Some patents, however, might be more valuable from an economic point of view than others. The analysis uses the approach in the seminal works by Kogan et al. (2017) and Kline et al. (2019) to measure the economic value of patents using abnormal changes in stock market prices of the company around the day of patent publication – a measure termed excess stock market return (ESMR). The intuition is that a granted patent increases the value of the company by the expected value of the patent, and that the market internalizes it. Therefore, a change in the company's valuation after the patent announcement is informative about the economic value of the patent. Appendix 1 provides details on the construction of the ESMR value of granted patents.

The idea to instrument economic rents with patents was also used in Van Reenen (1996) and Kline et al. (2019). Van Reenen (1996) uses the number of major innovations as an instrument for quasi-rents in the sample of UK manufacturing companies. Like Van Reenen, the focus here is also on large British companies, but instead of using a patent headcount analogous to his innovation headcount, the economic value of patents using the ESMR is adopted. This approach provides a much stronger first stage than the simple headcount of patents.

Kline et al. (2019) focus on private and public firms that filed a patent application for the first time and only once during a year. In their identification strategy, the authors estimate the ESMR value for granted patents and use these estimates to extrapolate the value of non-granted patents. Next, they interact the ESMR value of patents with a dummy indicating whether an application was granted or not - leading to a difference-in-differences-style regression. The empirical strategy of Kline et al. (2019) is closer to a randomized experiment than the approach adopted here. But the use of a sample of large public companies which have patented a lot and are usually granted more than one patent per year means it is not possible to also adopt the identification strategy from Kline et al. (2019). However, below we provide arguments for the validity of our instrument in the current setting.

We use the ESMR value of granted patents as an instrument for economic rents in a rent-sharing model. As shown in Table 2, the ESMR value of granted patents has a significant and positive relationship with our measures of economics rents – value added per employee (Columns 1-3) and profits per employee (Columns 4-6). The values of the Kleibergen-Paap F test are high in each specification and similar to those reported in Kline et al. (2019) (Table 8 of their paper). The Cragg-Donald Wald F test for the entire sample is above the Stock-Yogo critical value for 10% maximal TSLS bias. Overall, these results testify to the strong first stage. Nevertheless, our baseline results are the same when using weak-identification-robust confidence intervals.

Three pieces of evidence suggesting that the exclusion restrictions are satisfied are offered. First, it is possible to explore whether there is evidence for reverse causation that economic rents determine the value of patents. If this is the case, the contemporary realisations of the ESMR value of granted patents should be correlated with the past realisation of economic rents. Contrary to this, as presented in Appendix Table A4, there appears to be no systematic relationship between the instrument at time *t* and value added per employee at time *t-1* and *t-2*, after controlling the average industry wage, firm, and year fixed effects.

A second concern is that the value of granted patents might be correlated with the unobservable outside factors affecting wages. This might be the case when, for instance, there is a strong within-industry correlation of the value of granted patents, such that companies in certain industries are likely to obtain similarly valued patents in the same year. In this case, patents might affect wages through the market-level demand for labour, rather than rent sharing. This possibility is explored by regressing the leave-out average wage in the 2-digit industry[10] and our instrument. Reassuringly, while there is a significant "reduced form" effect of the instrument on the firm wages, Appendix Table A5 shows that there is no evidence for a significant effect of the instrument on the leave-out average.

[10] That is, for each observation, the industry average wage is calculated after excluding that observation.

The third concern is that a company might react to the granted patents by changing the composition of workers, and more skilled workers are hired, increasing the average wage in the company. Kline et al. (2019) show that this is not the case using the matched employee-employer data from the US. It is not possible to undertake this kind of exercise here because we do not have data on individual workers. Nevertheless, suggestive evidence shows that employment changes are unlikely to drive the results. Adding to the baseline rent-sharing model (discussed in Section IV.E) controls for the changes in the level of employment – a proxy for the adjustment in workforce composition – does not affect the key findings (Table A6).

IV.B. Empirical Specification

The baseline rent-sharing elasticity is estimated using a first-difference IV model, with the first and second stage of the following form:

$$\log \frac{VA}{n}_{ijt} = \alpha' + \beta'_1 \theta_{ijt} + \gamma' \log \overline{w}_{jt} + \mu'_t + \mu'_i + \epsilon'_{ijt} \quad (1.1)$$

$$\log w_{ijt} = \alpha + \beta \log \frac{VA}{n}_{ijt} + \gamma \log \overline{w}_{jt} + \mu_t + \mu_i + \epsilon_{ijt} \quad (1.2)$$

where the outcome variable $\log w_{ijt}$ is log compensation per employee for company i, in industry j at time t. The variable of interest $\log VA/n_{ijt}$ is log value added per employee, and μ_i captures all time-invariant firm effects. Outside forces are specified using the 1-digit industry (2-digit for manufacturing) log average wage $\log \overline{w}_{jt}$ and year fixed effects μ_t, which account for all nationwide time effects. In the first stage equation, log value added per employee is instrumented with the ESMR value of granted patents – denoted by θ_{ijt}. In addition, every regression includes a dummy for significant episodes of mergers and acquisitions.

A dynamic version of the model, which includes lagged measures of economic rents and lagged wages, is also presented. The latter accounts for the existence of long-term employment contracts that can generate a certain amount of inertia in wage determination. The model is first-differenced which, by construction, leads to a correlation between the lagged dependent variable and the error term (Nickell, 1981). This mechanical problem is dealt with by instrumenting the lagged dependent variable in the first-differenced model with their lagged levels (Arellano and Bond, 1991), instrumenting current and lagged value added with current and lagged θ_{ijt}. The second stage equation takes the following form:

$$\log w_{ijt} = \alpha \log w_{ijt-1} + \sum_{l=0}^{1} \beta_l \log \frac{VA}{n}_{ijt-l} + \sum_{l=0}^{1} \gamma_l \log \overline{w}_{jt-l} + \mu_t + \mu_i + \epsilon_{ijt} \qquad (2)$$

In this model, the short-run (SR) elasticity is captured by the coefficient β_0, that is, the effect of contemporaneous value added on wages. The long-run (LR) elasticity, for the specification with one lag of value added, is given by $(\beta_0 + \beta_1)/(1-\alpha)$, since in the long run $\log \frac{VA}{n}_{ijt} = \log \frac{VA}{n}_{ijt-1}$ and $w_{ijt} = w_{ijt-1}$.

As robustness checks, two additional modifications are made to the above models. First, profit before tax per employee is used as an alternative measure of economic rents. Since profits can take negative values, profits per employee are entered in levels but the reported coefficients are transformed into elasticities. Second, instead of using patents as an instrument for rents, the dynamic panel data instrumentation using the current and lagged value added (or profit) in the first-differenced model with their lagged levels is adopted (Arellano and Bond, 1991). In this case, specifications with up to three lagged values of value added (or profit) and the outside forces are included (e.g., as in Blanchflower et al., 1996). Results from these robustness checks are in line with the findings from the baseline model.

IV.C. Total-sample estimates

The starting point of our empirical analysis is to estimate a single rent sharing elasticity for the entire period. Table 3, Columns 1 to 3, presents baseline estimates for the whole period 1983-

2016. Column 1 reports an OLS estimation of the model specified in Equation (1.2). The rent-sharing elasticity is 0.132 and significant, implying that, on average, a ten per cent increase in value added per employee is associated with a 1.3% increase in the average wage. Column 2 presents the baseline specification, which deals with the potential endogeneity bias by instrumenting value added with the ESMR value of granted patents. The elasticity increases to 0.150 but is more noisily estimated (p-value 12%). Finally, the dynamic specification described in Equation (2) is presented in Column 3, the short-run (SR) elasticity increases to 0.167 and becomes highly significant. The long-run (LR) elasticity 0.144 is closer to the non-dynamic specification and significant at the 10% level.

The elasticities of wages with respect to profits are presented in Table 5. The OLS estimate (Column 1) is small - on average, a ten per cent increase in profits is associated with a 0.06% increase in wages. Instrumenting profits with patents (Column 2) increases the elasticity to 0.024, but the estimate is noisy. On the other hand, the dynamic specification yields much lower estimates, with the LR elasticities of 0.004. As pointed out by Card et al. (2018), rent-sharing elasticities estimated using profits should be multiplied by the average ratio between value-added and profits (roughly equal to four in our sample) in order to compare them to estimates based on value-added or revenue. After this adjustment, the estimate of rent sharing in the baseline non-dynamic specification (Column 2) is 0.096 – 30% lower than the analogous estimate for value added (Table 3, Column 2).

In the next robustness check, lagged levels of value added and profits are used as an alternative set of instruments. Table A7, Columns 1 to 2 present the estimates for the model with value added, Columns 7 to 8 with profits. The results are close to the baseline estimates for the entire period reported in Tables 3 and 5. Finally, in Table A8, Columns 1 and 4, the results do not alter if a richer dynamic specification is considered, with three lags of independent variables included.

The baseline results therefore indicate the presence of positive and significant rent sharing among these UK companies. How do these estimates compare to the existing empirical studies? The baseline value added estimates of rent sharing for the entire period are around 0.15, which is similar to the UK firm-level estimates from Nickell and Wadhwani (1990) (0.07-0.09), Hildreth and Oswald (1997) and Hildreth (1998) (0.17), but below the estimates from Van Reenen (1996) (0.29). They are also higher than the estimates typically found using worker-level data, for instance, from Portugal by Card et al. (2018) (0.04-0.05) or from Italy by Card et al. (2014) (0.06-0.08).

IV.D. Temporal patterns

The analysis is extended beyond the older and newer rent sharing literatures by studying the evolution of rent sharing over time. Columns 4 to 9 of Table 3 (Table 5) reports results for value added per worker (profit per worker) as a measure of economic rents and look separately at the two sub-periods: 1983-1999 and 2000-2016. Figure 3 presents the estimates graphically. According to these estimates, there has been a marked fall in rent sharing since 1983. In the period 1983-1999, the elasticity was 0.264 (Column 5), which is very close to the elasticity reported in Van Reenen (1996). In terms of profits, the elasticity was around 0.071 (Table 5, Column 5), comparable to the existing estimates from that period (Nickell and Wadhwani, 1990; Hildreth, 1998). However, in the subsequent period 2000-2016, the elasticity was approximately three times smaller for value added and seven times smaller for profits.[11] How economically significant a fall is this? In the period before 2000, a standard deviation of value added per employee was 130% of the average. The baseline elasticity implies that a one standard deviation increase in value added per employee leads to a 34% (130% times 0.264) wage increase due to rent sharing. After 2000, a standard deviation is 186% of the average,

[11] Is the observed fall in rent sharing merely a result of attenuation bias? Table 1 reports an increasing number of small companies with potentially more volatile series. As an additional robustness check, we estimate the rent-sharing coefficients only for the sample of companies larger than 50 employees. The results are practically unchanged (results are available upon request).

implying that the rent-sharing effect of one standard deviation increase in value added per employee on wages was 16%.[12]

The decline in rent sharing is also reflected in the first stage estimates when value added per workers is used as a measure of economic rents (Table 2). Higher rent sharing implies that, for a given patent-induced increase in value added, the ESMR value of patents should increase less.[13] Consequently, in the period with high rent sharing (1983-1999), we observe a relatively *larger* coefficient[14] in the first stage regression - a one standard deviation increase in the ESMR per workers leads, on average, to 2.5% increase in value added per employee. In the period when rent sharing is lower (2000-2016), the first-stage coefficient is smaller - a one standard deviation increase in the ESMR per workers leads, on average, to 2% increase in value added per employee. On the other hand, we should not expect a similar change in the first stage regression, when profits per worker are used as a measure of economic rents.[15] Indeed, in both periods, a one standard deviation increase in the ESMR per workers leads, on average, to around 10% increase in profits per employee.

Next, the fall in rent sharing is considered further as Table 4 reports the baseline value added estimates for three sub-periods: 1983-1994, 1995-2005, and 2006-2016. The rationale for such division is to look separately at the periods before and after the significant decline of unions (the early 90s) and after the recent economic crisis (2008-2009). The rent-sharing elasticity in the first period was very large, significant, and positive at 0.589. Between 1995 and 2005, the elasticity fell to 0.195 and remained statistically significant. The falling trend continues after 2006 when the elasticities is 0.114, but statistically indistinguishable from zero.

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[12] In the case of profits, before (after) 2000 a standard deviation of profits per employee is 235% (318%) of the average. The rent-sharing effect of one standard deviation increase in profits per employee on wages is thus around 16% (3%).
[13] This is because a portion of the increase in value added is captured by the workers. The ESMR internalizes this, as it captures the economic value of patents for shareholders.
[14] When rent sharing is high, for a given increase in ESMR, value added must increase even more. Conversely, with no rent sharing, an increase in ESMR will be reflected in a similar increase in value added.
[15] This is because high rent sharing reduces both the ESMR value of patents and profits per employee.

Finally, the lagged levels of value added are used as an alternative instrument. Columns 3 to 6 of Table A7 report the estimates for the two sub-periods. The elasticity in the first period (1983-2000) is smaller (0.147) than in the baseline model (Table 3, Column 5). In the following period (2000-2016), the rent sharing elasticity is smaller (0.097) than in the first period, similar to the baseline estimates for the second period (Table 3, Column 8). We also document a decline in rent sharing in the case of profits (Columns 9-12), but the estimates in the two periods are smaller than those in the baseline models. Similar findings are reported when a richer dynamic specification is considered (Table A8). Overall, although using alternative instruments changes the estimated levels, Tables A7 – A8 show that it does not change the main result of the decline in rent sharing.

IV.E. Further Analysis

The evidence considered so far shows that rents influence wages in the top 300 sample of UK-domiciled companies, but less so now than in the past. One possibility is that the documented level and changes in rent sharing reflect unobserved changes in worker composition. For instance, hiring high-skilled workers might boost firm performance and raise the average wage. As argued in Section IV.A, patents isolate an exogenous variance in economic rents, therefore changes in the composition of workers - unrelated to the patenting activities - should not drive the results. However, a company might react to the granted patents by changing the composition of workers and more skilled workers are hired, increasing the average wage in the company. Kline et al. (2019) show that this is not the case using the matched employee-employer data from the US. It is not possible to undertake this kind of exercise here because we do not have data on individual workers. Nevertheless, we might roughly control for the adjustment in workforce composition by adding to the baseline rent-sharing model (described in Equations 1.1 and 1.2) controls for the changes in the level of employment.

However, as explained in Section II.A, controlling for employment might also switch off the monopsony source of rent sharing (Nickell and Wadhwani, 1990; Blanchflower et al., 1996; Van Reenen, 1996; Hildreth and Oswald, 1997). Because of the upward-sloping firm-specific labour supply curve, a monopsonist who wants to increase employment must also increase wages. This inextricable connection between rent sharing and employment change in the monopolistic model, implies that a regression of changes in wages on changes in value added per employee, conditional on keeping employment fixed, should produce no pass-through between value added and wages. The other models of rent sharing, on the other hand, have no similar implications.

Table A6 presents the results from the baseline model with added control for employment. Consistent with the expectations, controlling for employment reduces the estimated rent-sharing elasticities. However, the effect is modest, and we cannot reject that the rent-sharing coefficients are the same as when we do not control for employment. When considering the entire sample, the baseline estimates are reduced by 45% from 0.15 (Table 3, Column 2) to 0.083 (Table A6, Column 2). However, the reduction in the elasticity is much smaller in the first period (26%, from 0.264 to 0.194), than in the second period (58%, from 0.088 to 0.037). Some of the estimates are a little imprecise to enable reaching a strong conclusion, and this robustness exercise ends up providing only suggestive evidence that changes in workforce composition and monopsonistic competition do not seem to be an important explanation for the decline in rent sharing after 2000.

One important finding in the recent literature that is focused on the labour share has been the connection between the falling labour share and growing product market concentration (Adrjan, 2018; Hall, 2018; Autor et al., 2020; Barkai, 2020; De Loecker et al., 2020).[16] This begs the question whether the observed decline in rent-sharing has been more pronounced among those firms with more product market power. As detailed in Appendix 2, we use two firm-level measures of market share (based on employment and revenue) as a proxy for product market power and explore the extent to which companies with higher market power share more or less of their profits. First, consistent with recent work that shows market power is rising over time, the median market share has increased among UK companies since 1983 (Figure A3). Second, companies with higher market share, on average, share less of their rents than companies with low share. However, the magnitude of the effect is very small (Table A2). Third, the small and negative association between market share and rent sharing is only present in the period 1983-1999, but not in 2000-2016. In other words, we find no evidence linking changes in the market power of employers, proxied by market share, with the temporal decline in rent sharing. In addition, rent sharing has become more uniform across firms over time.

IV.F. Manufacturing Companies

Modern companies are increasingly global, with boundaries crossing not only countries but also continents. Consequently, it is important to interpret the above results in their appropriate context as offering evidence for UK-*domiciled* companies, since many firms in the sample have operations extending beyond the border. While this analysis is still informative about rent sharing in the British economy, it can be complemented with a similar analysis of domestic operations from the panel of UK manufacturing companies, described in Section III.A above.

Since it is not possible to link information about patents to this panel,[17] the identification strategy reverts to the dynamic panel data approach using the lagged levels of

[16] Hall (2018) looks at the issue in a different way, computing shifts in market power from industry price/marginal cost mark-ups (in similar ways to his earlier classic study of market power), concluding similarly to De Loecker et al. (2020) that mark-ups have risen through time in the US, but not at quite the same rate as their study (where costs are measured only using accounting information on costs of goods sold).

[17] The panel of UK manufacturing companies is the Annual Respondents Database (ARD), which is accessible only from a secure lab of the Office for National Statistics. The firms are anonymized; therefore, we are not able to use public firm IDs or names to link the firm data with the data on patenting activities from PATSTAT.

economic rents as instruments for the contemporaneous first differences (Arellano and Bond, 1991). Otherwise, the same methodology as previously is adopted, with the exception that the regional unemployment rate (U_{rt}) and regional average wages are added to the rent-sharing model to better account for the outsider effects. In particular, the model now becomes:

$$\log w_{irt} = \alpha \log w_{irt-1} + \sum_{l=0}^{1} \beta_l \log \frac{VA}{n}_{ijt-l} + \sum_{l=0}^{1} \gamma_l \log U_{rt-l} \sum_{l=0}^{1} \delta_l \log \overline{w}_{rt-l} + \mu_t + \mu_i + \varepsilon_{irt} \quad (3)$$

ewhere i indexes firms, r stands for region and t indicates time. The remainder of the notation is the same as before.

Columns 1 and 2 of Table 6 present the estimates for the whole period 1983-2008. Up to one lag of each independent variable are included. The elasticities of pay with respect to value added are estimated between 0.261 and 0.302[18] with the dynamic specifications located at the upper end of the range. The estimates are around 50% higher than those reported for the top 300 sample using the Arellano-Bond instruments (see Tables A7-A8). One possibility is that the elasticity is higher when both economic rents and wages originate from the same (domestic) market operation. Alternatively, it could be that the level of rent sharing is higher in the manufacturing sector.

Turning to the evolution of rent sharing, Columns 3 to 5 of Table 6 look separately at the three sub-periods: 1983-1989, 1990-1999 and 2000-2008. As with the top 300 data, there is a substantial fall in rent sharing since 1983. In the first period, the magnitude of the rent-sharing elasticity is almost 0.384. In the following periods, however, the coefficient gradually falls.[19] For example, between 1990 and 1999 it was 0.213, and 0.175 after 2000.[20]

[18] Table A9 presents results for profits. The estimated rent-sharing elasticity is between 0.015-0.022.

[19] The results for profits in Table A9 show an even more dramatic fall in the rent-sharing elasticity: in the first period, the magnitude was 0.070, between 1990 and 1999 it fell to 0.022, and finally reached zero after 2000.

[20] The effect in terms of an increase in one standard deviation is 27% for the period 1983-1989, 18% for the period 1990-1999 and 17% for 2000-2008.

Overall, the results presented in this Section show a remarkable similarity, indicating that the dramatic fall in rent sharing was a characteristic of the whole economy and was not unique to global UK-domiciled public companies or the domestic manufacturing sector. The next section shows that the fall in rent sharing through time is, in fact, also visible for EU and US industries.

V. Trends in Industry-Level Rent Sharing

V.A. Evidence from EU Industries

The firm-level data show that the rent-sharing coefficient has been falling for the global operations of UK-domiciled companies from all sectors, and for the domestic operation of UK-based manufacturing companies. In this section, industry-level data, which allow the study of domestic operations across all sectors for the UK and other advanced economies, are analysed.

The starting point is an analysis of the EU-KLEMS industry-level data, which provides information on wages and rents for 28 industries across EU countries since the 1990s until 2015[21] (O'Mahony and Timmer, 2009). The UK and eight countries for which the data goes back to the early 1990s (Austria, Denmark, Germany, Italy, Finland, France, Netherlands, and Spain) are studied. The evolution of rent sharing for all the pooled countries and industries comprising a panel of 25 years (*T*) of data for 28 industries (*N*) is considered. These data are "small *N,* large *T*" and, therefore, not feasible for Arellano-Bond estimation and, in general, for dynamic panel models (Roodman, 2009). Therefore, long-run changes in wages are regressed on long-run changes in rents measured by value added per worker:

$$\log \overline{w}_{jct} - \log \overline{w}_{jct-l} = \beta \left(\log \frac{\overline{VA}}{n}_{jct} - \log \frac{\overline{VA}}{n}_{jct-l} \right) + \mu_j + \mu_c + \epsilon_{jct} \qquad (4)$$

where $l = 14$ if $t = 2005$ and $l = 10$ if $t = 2015$.

[21] We do not include the 1970s and 1980s, as the provided numbers are estimates.

The outcome variable w_{jct} is log compensation per employee in industry j from country c at time t. The variable of interest $\log \frac{VA}{n}_{jct}$ is log value added per employee. In Table A10 we also look at profits per employee (π/n_{jct}) as an alternative measure of economic rents. Country (μ_c) and industry fixed effects (μ_j) are included. The time breakdown is the fourteen-year change 1991-2005 and the ten-year change between 2005 and 2015. In order to reduce measurement error, wages and value added for each year are smoothed and replaced with the three-year moving average $\overline{w}_{jct}$ and $\frac{\overline{VA}}{n}_{jct}$.

Table 7 presents the estimates of the rent-sharing coefficient for pooled industries and countries (the coefficient β). Each row displays results for separate periods and measures of economic rents. For instance, the first row shows the effect of the change between 1991 and 2005 in log value added per employee on the change in the same period in log wages. In the first period, the correlation between value added and wages, 0.207-0.357 is consistently positive and significant. In the second period, the estimates are much smaller, in the range of 0.067-0.075. Interestingly, the inclusion of industry fixed effects matters relatively little for the estimates, suggesting that the fall of rent sharing cannot be explained by a shift from high to low rent-sharing sectors. On the other hand, the inclusion of country fixed effects lowers the estimates in the first period, suggesting some roles of country-specific (institutional) factors.[22]

V.B. Evidence from US Manufacturing

The evolution of rent sharing in the US is studied using the NBER-CES Manufacturing Industry data from 1963 to 2011. Although the data covers only the production sector, it allows us to use 459 4-digit industries and avoid the "small *N*, large *T*" problem. The rent-sharing

[22] Similar conclusions are drawn when looking at profits per employee (Table A10). The estimates in the first period are between 0.001-0.002, but in the second period, they are zero.

elasticity is produced in a similar fashion as it was in the firm-level analysis by using a non-dynamic industry fixed-effect models of the following form:

$$\log w_{jt} = \alpha + \beta \log \frac{VA}{n}_{jt} + \gamma \log \overline{w}_{jt} + \mu_t + \mu_j + \epsilon_{jt} \qquad (5)$$

where the outcome variable w_{jt} is log compensation per employee for manufacturing industry j at time t. The variable of interest $\log \frac{VA}{n}_{jt}$ is log value added per employee, but we also show estimates when the rent-sharing elasticity is produced using profit before tax per employee (π/n_{jt-l}) in Table A11.[23] μ_j captures time-invariant industry effects. Outsider forces are controlled for via inclusion the log 2-digit industry average wage $\overline{w}_{jt-l}$[24] and year fixed effects. Since we have no information on the industry level value of patents in the US, the model is first-differenced and the current value added or profits are instrumented with their lagged levels (Arellano and Bond, 1991).

Table 8 report the estimates for the whole period 1963-2011 for specifications with value added. There is a positive and significant rent-sharing parameter with a magnitude 0.109 for value added. The results for profits in Table A11 show the elasticity of 0.008, which is almost ten times smaller than those reported in Blanchflower et al. (1996) for the shorter period between 1964 and 1985. Can this difference be attributed to a fall in rent sharing after 1985? To check for this possibility, Columns 2 to 4 of Table 8 and Table A11 split the sample into three periods: 1963-1979, 1980-1996 and 1997-2011. The rent-sharing elasticity for value added over the first period is 0.164 (Column 2 of Table 8) and for profits is 0.052 (Column 2 of Table A11), which is close to the estimates from Blanchflower et al. (1996). However, there are already declines in the 1980s and early 1990s (Column 3) to 0.063 for value added, and

[23] The level of profits per employee is used in a log-levels specification, however the reported coefficients are transformed into elasticities.

[24] Regressing a variable on its group's mean (i.e., 2-digit average industry wage) mechanically leads to a coefficient of one for the mean and zero for other variables. To avoid this problem, we use the 2-digit average industry wages from the IPUMS-CPS March files (Flood, King, Ruggles and Warren, 2017).

0.016 for profits. For the rent sharing calculated using value added, the magnitude increases slightly in the most recent period 1997-2011, but remains much lower than in the 1960s and 1970s. However, we document near-zero estimates in the case of profits, implying an almost complete lack of rent sharing in the US manufacturing sector. These findings are consistent with Bell and Van Reenen (2011), who use the same data and find no evidence for rent sharing in 1986-2005.

The results from the EU-KLEMS and NBER-CES samples, along with the firm-level evidence, consistently show a negative trend in rent sharing. The fall among the US manufacturing industries happened earlier, in the 1980-90s, than in Europe which experienced a dramatic fall after the turn of the millennium. As mentioned in Section IIA, the interpretation of industry-level pass-through from rents to wages is different from firm-level ones. With this respect, it is thus not surprising to find a difference in the estimated rent-sharing elasticities from firm- and industry- level data. Nevertheless, it is reassuring that both show the decline in rent sharing.

VI. Conclusions

A growing body of research on the role of firms in wage determination has significantly developed our understanding of the long standing research question on the importance of firm performance for workers' wages. One dimension of this has been evidence homing in on the extent to which workers benefit from the company's success. Most of the existing literature exploits rich data that are available for only short periods of time and so are unable to address the temporal pattern of rent sharing. This paper addresses that gap by constructing a comprehensive and consistent annual panel of the top 300 companies in the UK over 35 years from 1983 to 2016. This allows us to credibly document changes in the extent of rent-sharing over recent decades.

The paper presents causal estimates of rent sharing by instrumenting rents with the excess stock market return value of granted patents. This builds on a recent literature, but again extends it to allow variation over time. The key result is that rent sharing amongst UK companies has declined over the last forty years. Whilst wages still depend on company value-added and profits, the magnitude has dropped substantially. A set of robustness tests on this baseline shows that whilst the *level* of rent sharing depends on the choice of measure and instrument, the direction of *change* in rent sharing does not. Furthermore, the finding is corroborated with an array of different firm and industry data sources covering the UK, US and Europe.

More needs to be done to understand better implications of lower rent sharing for a wide ranging literature that focusses on one or more of the following: rising firm mark-ups, increased product and labour market concentration, the falling labour share, and the rising inequalities. To this end, one promising avenue of future research is investigating in more detail the sources of the decline in rent sharing and changes in modern corporations' wage-setting arrangements.

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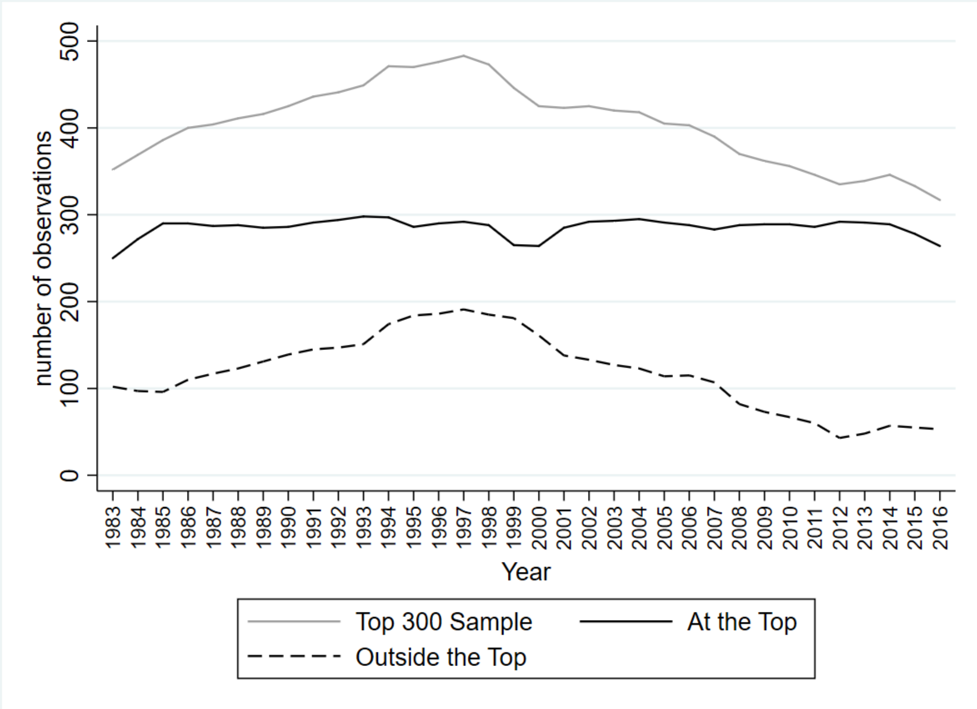
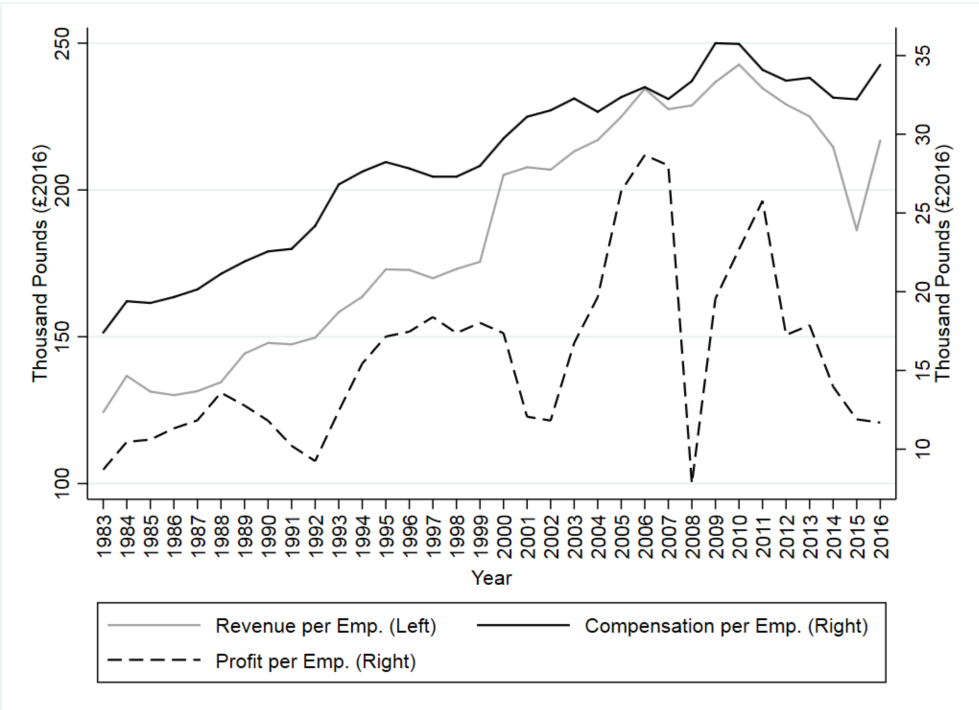
Figure 1: Composition of the Top 300 Sample



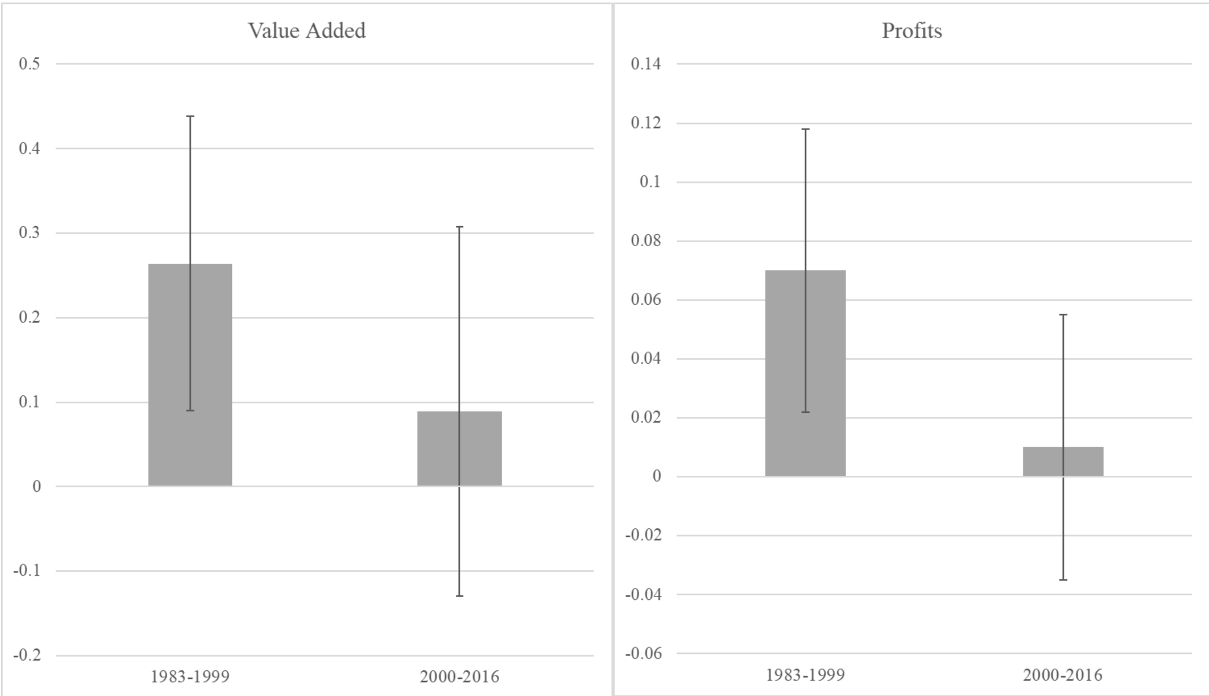
Notes: The grey line denotes the total number of companies in the top 300 sample. The black solid line marks the number of companies, which were within the top 300 in a given year. The black dashed line shows the number of companies, which were not within the top 300 in a given year but were in the top for some other year between 1983 and 2016. See Section III.A for more details on the data sources and the sample construction.

Figure 2: Real Revenue, Compensation and Profit per Employee in the Top 300 Sample



Notes: The graph presents the employment-weighted mean of total revenue, compensation, and profit before taxation per employee, deflated by the CPI. The data are for companies in the top 300 sample. See Section III.A for more details on the sample construction.

Figure 3: The Baseline Rent-Sharing Elasticities in the Top 300 Sample



Notes: The bars present the baseline estimates of the rent-sharing elasticities from the IV second-stage results from first-differenced firm-level regression of log wages on log value added per worker (left panel) or profits per employee (right panel), log average industry wage and year fixed effects. The instrument is the ESMR value of patents. Data are for companies in the top 300 sample with trimmed value added and profits per employee (top/bottom 1%), and trimmed the ESMR value of granted patents (top 1%). The lines represent 90% confidence intervals.

Table 1: Descriptive Statistics

	Year	N	Median	SD	Min	Max
Employment	**1983**	302	5329	26951	27	187173
	2000	398	4702	27755	22	249000
	2016	288	5686	60258	5	592897
Compensation per Employee (in th. £2016)	**1983**	291	18.4	7.3	7.3	46.1
	2000	398	34	24.5	8.5	193.3
	2016	290	43.8	42.5	4	354.5
Revenue per Employee (in th. £2016)	**1983**	299	100.2	167.3	31.6	1357.6
	2000	398	162.2	504.1	12.1	4525.1
	2016	292	190	557.6	0.0	6544.5
Profit per Employee (in th. £2016)	**1983**	302	7.4	35.9	0.3	298.5
	2000	398	11.8	121.5	-160.9	1092.2
	2016	288	14.9	144.4	-810.8	977.3
Value Added per Employee (in th. £2016)	**1983**	290	27.1	49.4	10.4	563.1
	2000	397	46.3	125.6	-94.9	1246.9
	2016	288	58.2	162.9	-646.7	1419.2

Notes: Compensation, revenue, profit before taxation, and value added per employee are deflated by the CPI and expressed in thousand £2016. The data are for companies in the top 300 sample with trimmed variables (top/bottom 1%). See Section III.A for more details on the data sources and the sample construction.

Table 2: First Stage Results

Depended Variable:	Value Added			Profits		
	1983-2016	1983-1999	2000-2016	1983-2016	1983-1999	2000-2016
	(1)	(2)	(3)	(4)	(5)	(6)
ESMR Value of Patents	3.194***	7.018**	2.535***	16.976***	29.026***	13.554***
	(0.833)	(2.783)	(0.904)	(4.949)	(9.324)	(4.805)
Industry Wage	0.032	-0.124*	0.060**	0.433***	-0.349	0.489***
	(0.023)	(0.068)	(0.024)	(0.167)	(0.274)	(0.163)
Firm-Years	10,750	5,579	5,171	11,309	5,731	5,578
Firms	686	560	486	708	571	508
Kleibergen-Paap rk Wald F	14.6	6.3	7.8	11.7	9.6	7.9
Cragg-Donald Wald F	17.7	15.2	7.7	9.0	10.5	3.8

Notes: The first-stage results from the IV first-differenced firm-level regression of log value added per employee (Columns 1-3) and profits per employee (Columns 4-6), on the Excess Stock Market Return (ESMR) value of granted patents, the log average industry wages and year fixed effects (not reported). Data are for companies in the top 300 sample with trimmed value added and profits per employee (top/bottom 1%), and trimmed the ESMR value of granted patents (top 1%). Standard errors clustered at firm level are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 3: Baseline Results for Value Added

	Dependent Variable: Wages								
	1983-2016			1983-1999			2000-2016		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Wages (t-1)	-	-	0.207**	-	-	0.330**	-	-	0.212
			(0.100)			(0.165)			(0.133)
Value Added	0.132***	0.150	0.167***	0.150***	0.264**	0.193***	0.119***	0.088	0.141**
	(0.012)	(0.098)	(0.053)	(0.017)	(0.109)	(0.062)	(0.016)	(0.134)	(0.068)
Value Added (t-1)	-	-	-0.053	-	-	-0.039	-	-	-0.102
			(0.060)			(0.081)			(0.072)
Industry Wages	-0.004	-0.005	-0.001	-0.055**	-0.041	-0.047	0.119***	0.088	0.023
	(0.010)	(0.010)	(0.015)	(0.027)	(0.029)	(0.031)	(0.016)	(0.134)	(0.020)
Industry Wages (t-1)	-	-	0.005	-	-	0.062**	-	-	-0.025
			(0.020)			(0.031)			(0.027)
LR Coefficient	0.132***	0.150	0.144*	0.150***	0.264**	0.231**	0.119***	0.088	0.049
	(0.012)	(0.098)	(0.075)	(0.017)	(0.109)	(0.100)	(0.016)	(0.134)	(0.102)
Firm-Years	10,750	10,750	9,921	5,579	5,579	4,968	5,171	5,171	4,953
Firms	686	686	685	560	560	536	486	486	483
Instruments	OLS	Patents	Patents	OLS	Patents	Patents	OLS	Patents	Patents

Notes: Columns 2-3, 5-6 and 8-9 present the IV second-stage results from first-differenced firm-level regression of log wages on lagged dependent variable (Columns 3, 6 and 9), log value added per worker and its lag (Columns 3, 6 and 9), log average industry wage and its lag (Columns 3, 6 and 9) and year fixed effects (not reported). The instrument is the ESMR value of patents. The Columns 1, 4 and 7 show OLS estimates of the first-differenced model. Data are for companies in the top 300 sample with trimmed value added and profits per employee (top/bottom 1%), and trimmed the ESMR value of granted patents (top 1%). Standard errors clustered at firm level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 4: Results for Value Added, Sub-periods

	Dependent Variable: Wages		
	1983-1994	1995-2005	2006-2016
	(1)	(2)	(3)
	First Stage Regression (Dependent Variable: Value Added)		
ESMR Value of Patents	3.826***	4.223***	2.866***
	(1.447)	(1.608)	(0.961)
Industry Wage	-0.113	0	0.049**
	(0.105)	(0.078)	(0.025)
	Second Stage Regression		
Value Added	0.589*	0.195*	0.114
	(0.352)	(0.105)	(0.124)
Industry Wages	-0.022	-0.012	0.004
	(0.067)	(0.026)	(0.013)
Firm-Years	3,615	4,022	3,113
Firms	461	561	385
First Stage Kleibergen-Paap Wald F	7	6.9	8.8
Instruments	Patents	Patents	Patents

Notes: The table presents the IV results from first-differenced firm-level regression of log wages on log value added per worker, log average industry wage and year fixed effects (not reported). Log value added per worker is instrument by the ESMR value of patents. Data are for companies in the top 300 sample with trimmed value added and profits per employee (top/bottom 1%), and trimmed the ESMR value of granted patents (top 1%). Standard errors clustered at firm level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 5: Results for Profits

	Dependent Variable: Wages								
	1983-2016			1983-1999			2000-2016		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Wages (t-1)	-	-	0.241***	-	-	0.377***	-	-	0.194**
			(0.081)			(0.138)			(0.089)
Profits	0.006***	0.024	0.005	0.013***	0.071**	0.026**	0.005***	0.010	0.005
	(0.001)	(0.021)	(0.007)	(0.003)	(0.030)	(0.012)	(0.002)	(0.027)	(0.009)
Profits (t-1)	-	-	-0.002	-	-	-0.000	-	-	-0.003
			(0.002)			(0.002)			(0.004)
Industry Wages	-0.002	-0.010	-0.002	-0.063**	-0.043	-0.063**	0.005***	0.010	0.024
	(0.011)	(0.014)	(0.017)	(0.029)	(0.034)	(0.028)	(0.002)	(0.027)	(0.021)
Industry Wages (t-1)	-	-	0.001	-	-	0.040	-	-	-0.027
			(0.022)			(0.032)			(0.027)
LR Coefficient	0.006***	0.024	0.004	0.013***	0.071**	0.042*	0.005***	0.010	0.002
	(0.001)	(0.021)	(0.008)	(0.003)	(0.030)	(0.022)	(0.002)	(0.027)	(0.009)
Firm-Years	11,309	11,309	10,619	5,731	5,731	5,165	5,578	5,578	5,454
Firms	708	708	708	571	571	552	508	508	508
Instruments	OLS	Patents	Patents	OLS	Patents	Patents	OLS	Patents	Patents

Notes: Columns 2-3, 5-6 and 8-9 present the IV second-stage results from first-differenced firm-level regression of log wages on lagged dependent variable (Columns 3, 6 and 9), profits per worker and its lag (Columns 3, 6 and 9), log average industry wage and its lag (Columns 3, 6 and 9) and year fixed effects (not reported). The instrument is the ESMR value of patents. The reported coefficients for profits are transformed into elasticities. The Columns 1, 4 and 7 show OLS estimates of the first-differences model. Data are for companies in the top 300 sample with trimmed value added and profits per employee (top/bottom 1%), and trimmed the ESMR value of granted patents (top 1%). Standard errors clustered at firm level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 6: UK Manufacturing Companies

	Dependent variable: Wages				
	1983-08	1983-08	1983-89	1990-99	2000-08
	(1)	(2)	(3)	(4)	(5)
Wage (t-1)	-	0.393***	-	-	-
		(0.023)			
Value Added	0.261***	0.226***	0.384***	0.213***	0.175***
	(0.024)	(0.019)	(0.048)	(0.037)	(0.032)
Value Added (t-1)	-	-0.043***	-	-	-
		(0.011)			
Reg. Wages	0.067	0.044	0.334***	0.036	-0.039
	(0.056)	(0.067)	(0.110)	(0.089)	(0.079)
Reg. Wages (t-1)	-	0.022	-	-	-
		(0.081)			
Reg. Unemp.	0.041***	0.003	0.058**	-0.034	-0.084**
	(0.015)	(0.019)	(0.025)	(0.026)	(0.039)
Reg. Unemp. (t-1)	-	0.022	-	-	-
		(0.017)			
LR Coefficient	0.261***	0.302***	0.384***	0.213***	0.175***
	(0.079)	(0.092)	(0.048)	(0.037)	(0.032)
Firm-Years	28,217	25,723	12,781	9,156	6,280
Firms	3,130	3,047	2,288	2,086	1,294
Instruments	Lag. Levels	Lag. Levels	Lag. Levels	Lag. Levels	Lag. Levels

Notes: The Arellano-Bond estimates from the first-differenced firm-level regression of log wages, on log value added per employee, log average regional wages, log regional unemployment rate and year fixed effects (not reported). Data are for UK manufacturing companies (ARD) with trimmed value added/profits per employee (top/bottom 1%). Value added is instrumented with their previous lags. Standard errors clustered at firm level. *** p<0.01, ** p<0.05, * p<0.10.

Table 7: EU Industries

	Dependent Variable: Wage Change			
	(1)	(2)	(3)	(4)
		1991-2005		
Value Added Change	0.357***	0.263***	0.340***	0.207***
	(0.080)	(0.057)	(0.076)	(0.039)
		2005-2015		
Value Added Change	0.071**	0.067**	0.086*	0.075*
	(0.028)	(0.026)	(0.045)	(0.040)
Observations	255	255	255	255
Country FE	No	Yes	No	Yes
Industry FE	No	No	Yes	Yes

Notes: The pooled OLS estimates from the industry-level regression of the 14-years (1991-2005) or 10-years (2005-2015) change in log compensation per employee on the analogous change in log value added per employee, country fixed effects (Columns 2, 4) and industry fixed effects (Columns 3, 4), run separately for each period. The changes are calculated for the 3-years averages. Data are from EU-KLEMS. Standard errors clustered at country level. *** p<0.01, ** p<0.05, * p<0.10.

Table 8: US Manufacturing Industries

	Dependent Variable: Wages			
	1963-2011	1963-1979	1980-1996	1997-2011
	(1)	(2)	(3)	(4)
Value Added	0.109***	0.164***	0.063***	0.085***
	(0.014)	(0.028)	(0.016)	(0.019)
Industry Wages	0.039***	0.097***	0.023*	0.023***
	(0.009)	(0.015)	(0.013)	(0.008)
Industry-Years	22,381	7,803	7,798	6,780
Industries	459	459	459	452
Instruments	Lag. Levels	Lag. Levels	Lag. Levels	Lag. Levels

Notes: The Arellano-Bond estimates from the first-differenced industry-level regression of log compensation per employee, on log value added per employee, log average industry wages and year fixed effects (not reports). Value added is instrumented with their previous lags. Data are from IPUMS-CPS March files and NBER-CES Manufacturing database. Standard errors clustered at industry level. *** p<0.01, ** p<0.05, * p<0.10.