The Decline in Rent Sharing

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WEB-ONLY APPENDIX

APPENDIX 1: PATENTS

The identification strategy in this paper exploits patents as an exogenous source of economic rents. Patents affect rents for two reasons. First, they provide temporary monopoly rights over an innovation, allowing the patenting firm to set prices above marginal cost. Second, a new innovation might boost firm's productivity and profits. Not every innovation, however, is equally valuable and relevant for the size of economic rents. In order to capture the economic relevance of patents, the literature has used various measures, including forward patent citation (Trajtenberg, 1990); patent renewal behaviour (Pakes, 1985; Bessen, 2008); patent ownership reassignment (Serrano, 2010); patent litigation (Harhoff et al., 2003); submission of patent applications to multiple countries (Putnam, 1996) or patent claims (Lanjouw and Schankerman, 2001).

These measures, however, are rather noisy proxies of economic value of a patent. In this paper we follow the seminal works by Kogan et al. (2017) and Kline et al. (2019), and measure the economic value of patents using abnormal changes in stock market prices of the company around the day of patent publication – the measure called 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 valuation after the patent is announced is informative about the economic value of the patent.

In the first part of this appendix, we describe our data on patents, how we link them with the top 300 sample of UK-domiciled firms, and show descriptive statistics. In the second, we outline how we estimate the ESMR value of patents and show descriptive statistics.

Patent Data

The information about patents comes from the European Patents Office's PATSTAT dataset. PATSTAT is a worldwide patent statistical database and contains detailed information about patent applications submitted to almost all developed and developing countries and going back in time to the beginning of the 20th century.

The unit of observation in PATSTAT is patent application, regardless of whether it was granted or not. Patent applications are organized into *families* – a collection of closely related applications refereeing to one invention. For instance, obtaining patent protection of a certain machine might require submission of several applications, each referring to a different element of the machine. In addition, the company might also submit the same application to patent offices in several countries. All these applications will be separate observations in PATSTAT but will belong to the same family. Because we are interested in inventions, our unit of analysis is a family. Henceforth, for the sake of simplicity, when speaking about a "patent" we mean a family of patent applications relating to the same invention.

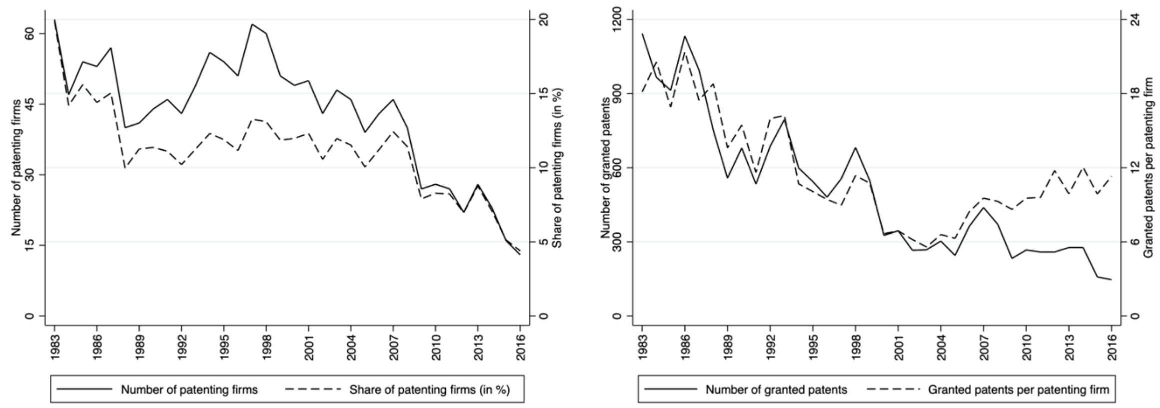
Several applications might constitute a patent (family), and some of those applications might be granted or not, they might be announced on different dates, they might be submitted by different innovators and in different countries. We consider a patent to be granted if at least one application is granted, we take the earliest application publication date as a date of the patent publication and we associate the patent with all inventors listed in the applications.

Our 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 and exclude different types, for instance, "design" or "plant" (e.g., flowers) patents.

PATSAT provides limited information about innovators, usually including only name, type (e.g., a company, an individual, a government institute) and address (but not always detailed). Unfortunately, in the case of firms, commonly used identifiers (such as SEDOL or ISIN) are not available. Our strategy to match innovators-patents from PATSTAT with our top 300 sample is twofold: 1) we use a cross-walk between PATSTAT patents and Bureau van Dijk's firm ID (BvD ID) generously provided to us by Ralf Martin and Dennis Verhoeven. The cross-walk provides a relatively good coverage of the top 300 firms, yet it is not sufficient to properly link the datasets with the companies active during the 1980s and the early 1990s, and which do not have BvD ID; 2) in these cases, we manually match the top 300 firms with PATSTAT using names. Since there is a lot of variation in how one name can be written in PATSTAT, we acknowledge that the match might be not perfect. However, as Figure A1 below show, the share of patenting companies is remarkably stable between 1983 and 2008 suggesting that the match is relatively successful.

The left panel of Figure A1 below presents the number of patenting firms in the top 300 sample since 1983 until 2016. At the beginning of our sample, around 50-60 firms were granted at least one patent every year. This declined to 40 at the end of the 1980s, but the patenting activity rebounded and reached back to the previous level in 1997 and 1998. After that we observer almost continuous decline in the number of patenting firms, and in 2016 only 12 firms in the top 300 sample were granted some patents. This pattern can be simply driven by the changes in the size of the top 300 sample – as seen in Figure 1 and discussed in Section III.A, the number of firms in the sample has an inverse U-shaped evolution. The same figure, however, shows that the share of patenting companies was 15% between 1984 and 1987, then fell to 12% and stabilized at this level for 20 years until 2007, after which it further declined to 8% between 2008 and 2014 and to nearly 4% in 2016. It must be stressed that if there is a significant number of missing links between patents and firms in our sample, it should be more problematic for the earlier periods, where we had to rely on manual matches. It is thus reassuring to observe the relatively high share of patenting firms at the beginning of our sample window, and the relatively stable evolution from 1988 until 2008.

Figure A1: Patenting Firms and Granted Patents



Notes: The left panel presents the evolution of the total number of patenting firms and the share of patenting firms in the top 300 sample. The right panel presents the evolution of the total number of granted patents and the average number of granted patents per patenting firm. Data is for companies in the top 300 sample.

The evolution of the number of patenting firms is informative about the extensive margin of patenting activities. The firms in our sample are big and it is not uncommon that they are granted multiple patents per year. The documented decline on the extensive margin, might be thus alleviated by the increase at the intensive margin. The right panel of Figure A1 presents the total number of granted patents in the top 300 sample and the average number of granted patents per patenting firm. The two graphs consistently point out to a substantial decline in patenting activity among large UK-domiciled companies. The total number of patents fell from more than 1000 in the 1980s to less than 200 in 2016 – a five-fold decline.

The average number of patents granted to patenting firms halved, from around 20 in the 1980s to around 10 in 2016.

The decline in the number of patenting firms and the number of patents does not imply that the large UK-domiciled companies are less innovative. Some patents might yield a substantial economic gain to their inventors, some might be worthless. The documented decline after 2000 might be because the companies are less likely to patent inventions with low economic value, in which case the companies might still earn a sizeable rent from innovation.

Economic Value of Patents – Excess Stock Market Return

We follow Kogan et al. (2017) and Kline et al. (2019) and estimate the economic value of patents using abnormal changes in stock market prices of the company around the day of patent publication – the measure called Excess Stock Market Return (ESMR). The estimation of ESMR requires two types of data: 1) information about date of patent publication; 2) daily stock prices and market capitalization. The patent publication dates come from the PATSTAT dataset, and the daily stock market data from Compustat and Worldscope. We link the two sources with the Top 300 sample (as described in the previous section).

Our estimation of ESMR follows precisely methodology described in the seminal paper of Kogan et al. (2017). In this section, we provide a simplified description. In the first step, we calculate the three-working day idiosyncratic return for each firm-day in our sample, that is, for each firm-day we calculate difference between the firm's price change and the corresponding return on the market (average price change weighted by market capitalization). The idiosyncratic return calculated on the day when a patent was issued is affected by the effect of the patent on the firm's valuation, and by other unrelated shocks. Therefore, in the next step, we separate the component of the firm's stock market return related to the patent announcement (signal) from other shocks (noise). In particular, we run a regression of the log squared return on a patent issue-day dummy, day of week and firm-by-year fixed effects, in order to estimate signal-to-noise ratio. Under several assumptions,[1] we can use signal-to-noise ratio and the firm- and year-specific variance of the idiosyncratic return to uncover the component of the firm's stock market return unrelated to the patent (noise).

The economic value of a patent, expressed as a fraction of the firm's market capitalization, can be estimated from the three-working day idiosyncratic return around the

[1] That is, the signal-to-noise ratio is constant, which means that the components of the firm's stock market return related to the patent announcement (signal) and other shocks (noise) are allowed to vary across firms and time, but in constant proportion to each other.

date of patent announcement, the estimate of signal-to-noise ratio, and the component of the firm's stock market return unrelated to the patent (noise) (see Kogan et al. 2017, Section II.D). We multiply the measure by the firm's market capitalization, which yields a value of patents expressed in pounds: ξ_{fjt} – where f stands for firm, j for patent and t for year.[2] In rare cases, companies were granted patents on adjacent days, which creates a problem of double-counting the value of patents when using the three-working day idiosyncratic return. We therefore treat adjacent patent announcement as one event.

Our goal is to obtain an annualized measure of the value of all patents granted to a company. To this end we simply calculate a sum of the value of all granted patents:

$$\Theta_{ft} = \sum_{j \in P_{ft}} \xi_{fjt}$$

Where P_{ft} denotes the set of days for company f in year t when patents were issued. Because patenting companies which are larger tend to generate more patents, we relativize this measure by dividing the sum by the number of employees:

$$\theta_{ft} = \frac{\Theta_{ft}}{EMP_{ft}}$$

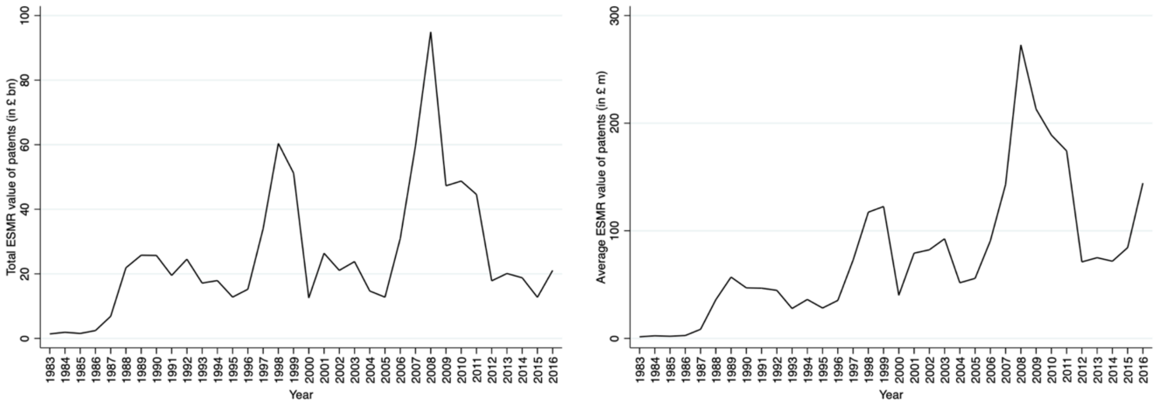
where EMP_{ft} is the employment size. θ_{ft} is our measure of the value of innovations generated by the company. This is also an instrument for value added and profits in our main rent-sharing model. Kogan et al. (2017) and Kline et al. (2019) winsorize the top values of θ_{ft}, in the main rent-sharing regressions (presented in Section IV) we have adopted a similar strategy and trimmed observations with the top 1% value of the annual ESMR value of granted patents per worker. We trim the instrument to be consistent with the approach to outliers used throughout the paper, but windorizing would not alter the results.

The left panel of Figure A2 plots the total ESMR value of patents issued to firms in the top 300 sample (i.e., the sum of Θ_{ft}, before the trimming). Table A1 provides descriptive statistics. In contrast to Figures A1 and A2, we do not find evidence for a decline in the total value of patents. Therefore, although the headcount of patenting firms and patents declined between 1983 and 2016, the total value of the granted patents did not. The total real value of granted patents was in fact lower in the first period 1983-1999 as it was between 2000 and

[2] When several patents of the same company are announced on the same day, we can only estimate the total value of those patents.

2016. This implies that the average ESMR value of patents increased, which is visible in the right panel of Figure A2. Table A1 reports that the median value of granted patents per firm rose from £16.4 million before 2000, to £30.6 million after 2000. Overall, these suggest that the main British companies today patent fewer less-valuable inventions compared with the 1980s. Also, because fewer companies are patenting today than in the past, the concentration of economic rents from patents likely increased. A similar increase in the dispersion of patenting activities is also reported for the US in Kogan et al. (2017).

Figure A2: The ESMR Value of Granted Patents



Notes: The graphs present the evolution of the total Excess Stock Market Return (ESMR) value of granted patents (left panel) and the average ESMR value of granted patents (right panel). Data is for companies in the top 300 sample.

Table A1: Descriptive Statistics of Patenting Activities

		Period		
		1983-2016	**1983-1999**	**2000-2016**
Number of granted patents		17,369	12,566	4,803
Median number of annual granted patents per firm	Unconditional	0	0	0
	Conditional	3	3	2
Total value of granted patents (2016£ million)		868,197.1	340,256.5	527,940.6
Median annual value of granted patents per firm (2016£ million)	Unconditional	0	0	0
	Conditional	20.3	16.4	30.6
Company-year with the most valued patents		Vodafone Group plc,2008	SmithKline Beecham plc,1999	Vodafone Group plc,2008

Notes: Patenting value is estimated by exploiting 3-day movements in stock prices following the days that patents are granted. Value is in 2015 price, adjusted by ONS CPI Index. 3-day return is measure after controlling for daily stock price market-level change and weighted by firm market value.

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APPENDIX 2: TRENDS IN RENT SHARING AND PRODUCT MARKET POWER

One consistent finding in the recent literature that is focused on the labour share has been the connection between the falling labour share and growing market concentration (Adrjan, 2018; Autor et al., 2020; Barkai, 2020; De Loecker and Eeckhout, 2020). This begs the question whether the observed decline in rent-sharing has been more pronounced among those firms with more market power. This section offers some evidence on this question.

To do so, the firm-level data are used with an aim to explore whether rent sharing depends on product market power and whether this has changed over time. Firm market and employment shares are the measures of market power that are considered. However, it is often unclear or difficult for global companies how to accurately define their market of reference. For supermarket chains that are primarily domestically focused (e.g., Tesco), one could argue that the UK retail sector is an appropriate reference market. However, for more global companies (e.g., British Petroleum or HSBC), one should arguably look at the worldwide market. In other words, taking the UK industry revenue or employment from EU-KLEMS could be a valid option for Tesco, but not for British Petroleum. A lack of information on the size of the global operation generates a need to take an alternative approach and define the company's reference market as the sample's industry total.

Therefore, firm-level market share is the firm's revenue or employment share in the sample's industry total. A composite sample for the industry total is constructed to ensure that sample size changes do not drive the results. By construction, the sample size varies, implying a larger industry total for years with more observations. Without correction, this would then underestimate market shares in the middle of the sample window and overestimate at the ends. To adjust for this, the approach in Nickell (1996) is adopted by imputing the number of 'outside the top' observations for all years using the sample composition from 1996-1999 (when the sample size peaks). Second, owing to the exclusion of companies that were within the top 300 for fewer than three years, the ends of the sample (1983-84 and 2015-16) have less 'at the top' observations. These are imputed using the sample composition from 1985 and 2014 correspondingly.

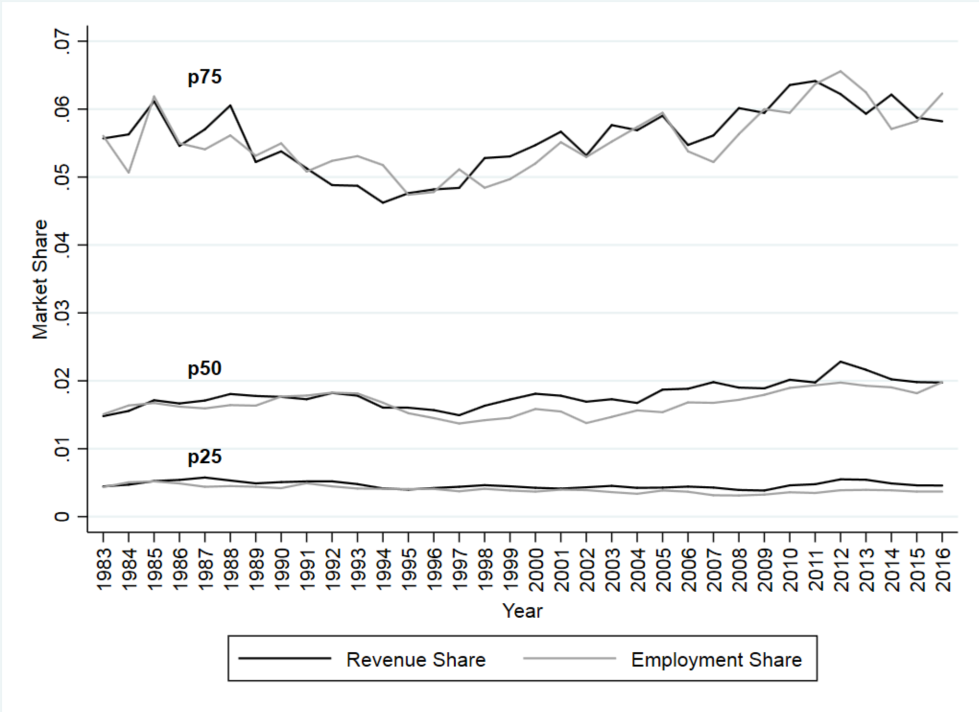
The revenue-based market share of company i from industry j at time t is:

$$MS_{ijt} = \frac{R_{ijt}}{R_{jt}}$$

where the denominator R_{jt} is the sum of revenue for 1-digit (2-digit for manufacturing) industry j at time t, calculated for the adjusted composite sample. The employment-based market share ES_{ijt} can be computed analogously.

Figure A3 illustrates the growth of the median and the upper quartile of the market share measures since 1983. Market share exhibits a U-shaped evolution through time, which is especially visible for the 75$^{\text{th}}$ percentile, which dips in the early 1990s and then peaks after the Great Recession. For example, the median company in 1983 earned and employed around 1.5% of its industry total revenue and employment. Thirty-three years later, the median share had grown to 2%.

Figure A3: Market and Employment Share



Notes: The graph presents the evolution of the 75th (p75), median (p50) and 25th (p25) percentiles of market share. The black lines marks estimates based on revenue. The grey line marks estimates based on employment. Data is for companies in the top 300 sample.

The same empirical strategy as for the earlier firm-level analysis is adopted, but, in addition, now exploring the interaction between rent sharing and market share. In particular, in the first and second stage regressions, the instruments (patents) and value added are interacted with the measures of market share in the following way:

$$\log \frac{VA}{n}_{ijt} = \alpha' + \beta'_1\theta_{ijt} + \beta'_3\theta_{ijt} \times MS_{ijt} + \vartheta' MS_{ijt} + \gamma' \log \overline{w}_{jt} + \mu'_t + \mu'_i + \epsilon'_{ijt} \quad (6.1)$$

$$\log w_{ijt} = \alpha + \beta_1 \log \frac{VA}{n}_{ijt} + \beta_2 \log \frac{VA}{n}_{ijt} \times MS_{ijt} + \vartheta MS_{ijt} + \gamma \log \overline{w}_{jt} + \mu_t + \mu_i + \epsilon_{ijt} \quad (6.2)$$

where MS_{ijt} can be either the revenue share (RS_{ijt}) or the employment share (ES_{ijt}). The rest of the notation is as in Section IV. The model is estimated separately for the two sub-periods: 1983-1999 and 2000-2016.

Table A2 reports the estimated interaction terms between profits and the measures of market share - revenue-based and employer-based. In the whole sample (Columns 1 and 4), companies with high market share have, on average, lower rent sharing than companies with low share, but this effect is noisy. The negative association between market share and rent sharing is stronger and more significant in the first period 1983-1999. However, the magnitude of the effect is small, companies in the 25th percentile of the revenue (employment) share distribution have a rent-sharing elasticity higher, on average, by around 10% (23%), compared to companies in the 75th percentile. On the other hand, there is no significant effect of the market share of firms on rent sharing after 2000, showing that rent sharing has become more uniform across firms over time.

Overall, we find no evidence linking changes in the market power, as proxied by market share, of employers with the temporal decline in rent sharing These results are at best indicative of the role of market power since the measures of market power are imperfect, but they suggest an important area for further research.

Table A2: Baseline Results for Value Added, Interacted with Product Market Power

	Dependent variable: Wages					
	1983-2016	1983-1999	2000-2016	1983-2016	1983-1999	2000-2016
	(1)	(2)	(3)	(4)	(5)	(6)
Value Added	0.136	0.336***	0.080	0.130	0.306***	0.071
	(0.094)	(0.118)	(0.112)	(0.088)	(0.105)	(0.108)
Value Added x Market Share	-0.173	-0.632***	-0.067			
	(0.157)	(0.154)	(0.183)			
Value Added x Emp. Share				-0.328	-1.270***	-0.115
				(0.275)	(0.376)	(0.319)
Market Share	1.862	6.693***	0.723			
	(1.656)	(1.643)	(1.948)			
Employment |Share				3.237	13.352***	0.743
				(2.932)	(3.991)	(3.443)
Industry Wages	-0.001	-0.031	0.015	0.000	-0.039	0.016
	(0.011)	(0.035)	(0.013)	(0.011)	(0.041)	(0.013)
Firm-Years	10,976	5,671	5,305	10,997	5,692	5,305
Firms	775	595	540	776	596	540
Instruments	Patents	Patents	Patents	Patents	Patents	Patents

Notes: The table present the IV second-stage results from first-differenced firm-level regression of log wages on log value added per worker, its interaction with market share (Columns 1-3) or employment share (Columns 4-6), log average industry wage and year fixed effects (not reported). The instrument is the ESMR value of patents and its interaction with either market share or employment share. Data are for companies in the top 300 sample with trimmed value added and profits per employee (top/bottom 1%). Standard errors clustered at firm level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

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APPENDIX 4: FIGURES

Table A3: Rankings of Companies in the Top 300 Sample

	1983		2000		2016	
	Market Capitalization (in mln GBP)		Market Capitalization (in mln GBP)		Market Capitalization (in mln GBP)	
1	British Petroleum	7421	Vodafone Group	158124	HSBC Holdings	130498
2	General Electric Company	4888	British Petroleum	121844	British Petroleum	99236
3	Imperial Chemical Industries	3880	GlaxoSmithKline	118910	British American Tobacco	86162
4	Marks and Spencer Group	2830	HSBC Holdings	91284	GlaxoSmithKline	76695
5	British American Tobacco	2631	AstraZeneca	59619	AstraZeneca	56137
	Employment		Employment		Employment	
1	British American Tobacco	187173	Unilever	295000	G4S	592897
2	General Electric Company	170865	Anglo American	249000	Compass Group	527180
3	Grand Metropolitan	136297	Sainsbury	185200	Tesco	464520
4	British Petroleum	131600	HSBC Holdings	161624	HSBC Holdings	235175
5	Unilever	127000	Tesco	152210	Sainsbury	181900
	Revenue (in mln GBP)		Revenue (in mln GBP)		Revenue (in mln GBP)	
1	British Petroleum	32381	British Petroleum	97900	British Petroleum	136100
2	Imperial Chemical Industries	8256	Aviva	40244	Legal and General Group	77969
3	British American Tobacco	7904	HSBC Holdings	33182	Prudential	71842
4	Barclays	7888	Unilever	28977	HSBC Holdings	60495
5	National Westminster Bank	6605	Prudential	28078	Tesco	55917

Notes: The table shows the top 5 observations in terms of market capitalization, employment, and revenues for years 1983, 2000 and 2016. The data are for companies in the top 300 sample. See Section IIIA for more details on the data sources and the sample construction.

Table A4: Reverse Causality

Dependent Variable:	ESMR Value of Patents					
	1983-1999		1983-1999		2000-2016	
	(1)	(2)	(3)	(4)	(5)	(6)
Value Added (t-1)	-0.00010		0.00006		-0.00014	
	(0.00023)		(0.00016)		(0.00031)	
Value Added (t-2)		0.00005		0.00013		0.00000
		(0.00022)		(0.00009)		(0.00033)
Industry Wage	0.00008	0.00009	0.00012	0.00016	0.00008	0.00008
	(0.00026)	(0.00027)	(0.00040)	(0.00049)	(0.00029)	(0.00031)
Firm-Years	9,921	9,133	4,968	4,399	4,953	4,734

Notes: The results from the OLS first-differenced firm-level regression of the Excess Stock Market Return (ESMR) value of granted patents on the lagged log value added per employee, the contemporaneous 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 A5: Industry Leave-out Average Wage

Dependent Variable:	Industry Leave-out Average Wages		
	1983-2016	1983-1999	2000-2016
	(1)	(2)	(3)
ESMR Value of Patents	0.00704	-0.07932	0.03998
	(0.18463)	(0.31401)	(0.20258)
Firm-Years	9,806	4,914	4,892

Notes: The results from the OLS first-differenced firm-level regression of the 2-digit industry leave-out average wages on the Excess Stock Market Return (ESMR) value of granted patents 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 A6: Baseline Results for Value Added, Conditional on Employment

	Dependent Variable: Wages								
	1983-2016			1983-1999			2000-2016		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Wages (t-1)	-	-	0.192*	-	-	0.328**	-	-	0.209
			(0.102)			(0.166)			(0.135)
Value Added	0.127***	0.110	0.157***	0.146***	0.214*	0.180***	0.112***	0.057	0.137**
	(0.012)	(0.109)	(0.051)	(0.016)	(0.117)	(0.063)	(0.015)	(0.148)	(0.063)
Value Added (t-1)	-	-	-0.052	-	-	-0.038	-	-	-0.103
			(0.062)			(0.081)			(0.077)
Industry Wages	-0.002	-0.002	0.001	-0.055**	-0.047	-0.05*	0.013	0.016	0.025
	(0.010)	(0.011)	(0.015)	(0.026)	(0.029)	(0.031)	(0.010)	(0.015)	(0.019)
Industry Wages (t-1)	-	-	0.003	-	-	0.056*	-	-	-0.024
			(0.019)			(0.030)			(0.027)
Employment	-0.004***	-0.004***	-0.004***	-0.003***	-0.003***	-0.004***	-0.004***	-0.005***	-0.005***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Employment (t-1)	-	-	0.002***	-	-	0.003***	-	-	0.002*
			(0.001)			(0.001)			(0.001)
LR Coefficient	0.127***	0.110	0.130*	0.146***	0.214*	0.176*	0.112***	0.057	0.043
	(0.012)	(0.109)	(0.085)	(0.016)	(0.117)	(0.106)	(0.015)	(0.148)	(0.120)
Firm-Years	10,750	10,750	9,921	5,579	5,579	4,968	5171	5171	4,953
Firms	686	686	685	560	560	536	486	486	483
Instruments	OLS	Patents	Patents	OLS	Patents	Patents	OLS	Patents	Patents

Notes: The table presents the IV second-stage results from first-differenced firm-level regression of log wages on lagged dependent variable, log value added per worker, log average industry wage, employment, 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-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 A7: Results for Value Added and Profits, Alternative Instruments

	Dependent variables: Wages											
	1983-2016		1983-1999		2000-2016		1983-2016		1983-1999		2000-2016	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Wages (t-1)		0.221***		0.349***		0.167*		0.240***		0.347***		0.202**
		(0.068)		(0.084)		(0.092)		(0.075)		(0.098)		(0.095)
Value Added	0.104***	0.128***	0.147**	0.153***	0.097**	0.107***						
	(0.033)	(0.027)	(0.061)	(0.035)	(0.039)	(0.035)						
Value Added (t-1)		-0.015		-0.026		-0.000						
		(0.024)		(0.030)		(0.029)						
Profits							0.009***	0.008***	0.016***	0.013***	0.009**	0.009**
							(0.003)	(0.003)	(0.005)	(0.003)	(0.004)	(0.004)
Profits (t-1)								0.000		0.001*		-0.000
								(0.001)		(0.000)		(0.001)
Industry Wages	-0.004	-0.002	-0.075**	-0.053**	0.011	0.025	-0.005	-0.005	-0.068**	-0.069**	0.012	0.024
	(0.010)	(0.015)	(0.029)	(0.027)	(0.010)	(0.017)	(0.011)	(0.016)	(0.030)	(0.029)	(0.012)	(0.019)
Industry Wages (t-1)		0.004		0.060**		-0.032		0.002		0.055*		-0.035
		(0.020)		(0.028)		(0.024)		(0.021)		(0.031)		(0.024)
LR Coefficient	0.104***	0.146***	0.147**	0.195***	0.097**	0.128***	0.009***	0.011***	0.016***	0.022***	0.009**	0.011**
	(0.033)	(0.041)	(0.061)	(0.075)	(0.039)	(0.044)	(0.003)	(0.004)	(0.005)	(0.006)	(0.004)	(0.004)
Firm-Years	10,750	9,921	5,579	4,968	5,171	4,953	10,750	10,094	5,579	5,028	5,171	5,066
Firms	686	685	560	536	486	483	686	686	560	542	486	486
Instruments	Lag. Levels	Lag. Levels	Lag. Levels	Lag. Levels	Lag. Levels	Lag. Levels	Lag. Levels	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 its lagged value (Columns 2, 4, 6, 8, 10, 12), log value added per employee (Columns 1-6) and its lagged value (Columns 2, 4, 6), profits per employee (Columns 7-12) and its lagged value (Columns 8, 10, 12), log average wages and its lagged value (Columns 2, 4, 6, 8, 10, 12), and year fixed effects (not reported). The lagged dependent variables, value added and profits are instrumented with their previous lags. Data are for companies in the top 300 sample with trimmed value added and profits per employee (top/bottom 1%). Standard errors clustered at firm level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A8: Results for Value Added and Profits, Alternative Instruments and Richer Dynamic Specification

	Dependent variable: Wages					
	1983-2016	1983-1999	2000-2016	1983-2016	1983-1999	2000-2016
	(1)	(2)	(3)	(4)	(5)	(6)
Wages (t-1)	0.384***	0.316***	0.429***	0.248***	0.195	0.274***
	(0.069)	(0.121)	(0.083)	(0.071)	(0.129)	(0.084)
Value Added	0.163***	0.149***	0.160***			
	(0.031)	(0.041)	(0.038)			
Value Added (t-1)	-0.042	-0.076**	-0.027			
	(0.032)	(0.035)	(0.039)			
Value Added (t-2)	-0.035**	0.019	-0.055***			
	(0.017)	(0.027)	(0.020)			
Value Added (t-3)	-0.005	0.005	-0.010			
	(0.008)	(0.011)	(0.012)			
Profits				0.008***	0.015***	0.008**
				(0.003)	(0.004)	(0.004)
Profits (t-1)				0.001	0.001*	-0.000
				(0.001)	(0.000)	(0.002)
Profits (t-2)				-0.000	0.000	0.000
				(0.001)	(0.001)	(0.001)
Profits (t-3)				0.000	0.001	-0.001
				(0.000)	(0.000)	(0.001)
Industry Wages	0.019	-0.030	0.037*	0.016	-0.035	0.037*
	(0.015)	(0.026)	(0.020)	(0.016)	(0.026)	(0.020)
Industry Wages (t-1)	-0.024	0.020	-0.050*	-0.024	0.017	-0.052*
	(0.021)	(0.028)	(0.029)	(0.020)	(0.030)	(0.027)
Industry Wages (t-2)	-0.018	-0.027	0.037	-0.004	-0.020	0.015
	(0.026)	(0.024)	(0.052)	(0.023)	(0.023)	(0.049)
Industry Wages (t-3)	0.026	0.060*	-0.003	0.008	0.046*	-0.026
	(0.028)	(0.035)	(0.048)	(0.025)	(0.027)	(0.049)
LR Coefficient	0.131**	0.142*	0.119	0.011**	0.021***	0.010*
	(0.057)	(0.086)	(0.077)	(0.004)	(0.004)	(0.005)
Firm-Years	8,383	3,867	4,516	8,829	4,028	4,801
Firms	665	482	465	683	495	484
Instruments	Lag. Levels	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 its lagged value, log value added per employee (Columns 1-3), profits per employee (Columns 4-6), log average wages, and year fixed effects (not reported). Three lags of all independent variables are included. The lagged dependent variables, value added, and profits are instrumented with their previous lags. Data are for companies in the top 300 sample with trimmed value added and profits per employee (top/bottom 1%). Standard errors clustered at firm level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A9: UK Manufacturing Companies - Profits

	Dependent Variable: Wages				
	1983-08	1983-08	1983-89	1990-99	2000-08
	(1)	(2)	(3)	(4)	(5)
Wage (t-1)	-	0.423***	-	-	-
		(0.024)			
Profits	0.015**	0.012**	0.070**	0.022*	0.007
	(0.006)	(0.005)	(0.028)	(0.012)	(0.010)
Profits (t-1)	-	0.001	-	-	-
		(0.003)			
Reg. Wages	0.180***	0.138*	0.574***	0.069	0.027
	(0.068)	(0.077)	(0.122)	(0.109)	(0.092)
Reg. Wages (t-1)	-	0.039	-	-	-
		(0.087)			
Reg. Unemp.	0.058***	0.011	0.080***	-0.030	-0.044
	(0.018)	(0.023)	(0.027)	(0.029)	(0.044)
Reg. Unemp. (t-1)	-	0.037*	-	-	-
		(0.020)			
LR Coefficient	0.015**	0.022***	0.070**	0.022*	0.007
	(0.006)	(0.008)	(0.028)	(0.012)	(0.010)
Firm-Years	28,533	26,116	12,893	9,252	6,388
Firms	3,143	3,066	2,296	2,100	1,303
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 profits 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%). Profits are instrumented with their previous lags. Standard errors clustered at firm level. *** p<0.01, ** p<0.05, * p<0.10.

Table A10: EU Industries - Profits

	Dependent Variable: Wage Change			
	(1)	(2)	(3)	(4)
		1991-2005		
Profits Change	0.002***	0.001***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
		2005-2015		
Profits Change	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
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 profits 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.

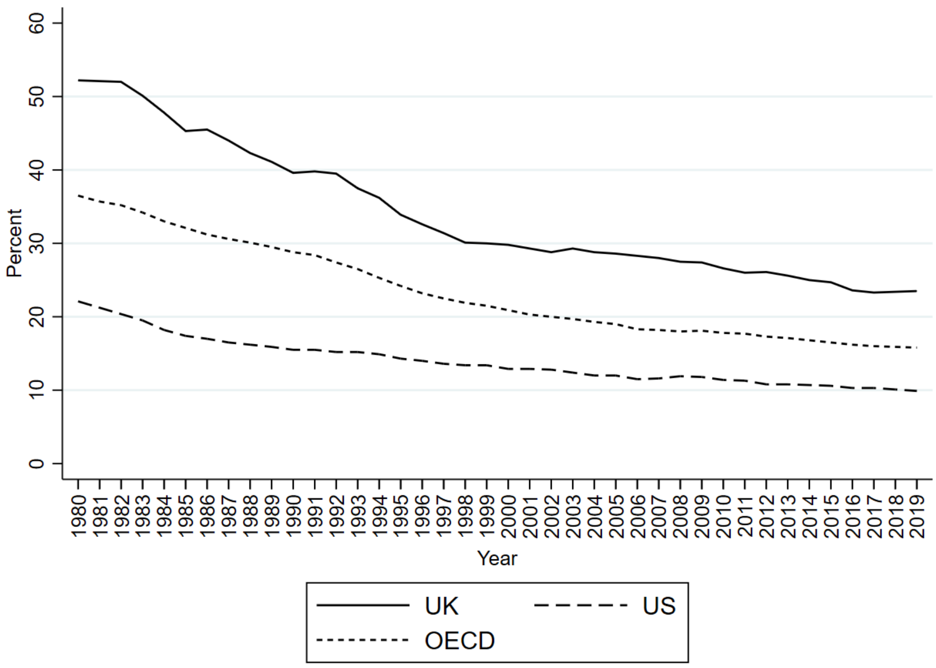
Table A11: US Manufacturing Industries - Profits

	Dependent Variable: Wages			
	1963-2011	1963-1979	1980-1996	1997-2011
	(1)	(2)	(3)	(4)
Profits	0.008***	0.052***	0.016***	-0.003
	(0.003)	(0.010)	(0.004)	(0.007)
Industry Wages	0.028***	0.084***	0.018	0.019**
	(0.006)	(0.015)	(0.012)	(0.010)
Industry-Years	21,922	7,803	7,791	6,328
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 profits per employee, log average industry wages and year fixed effects (not reports). Profits are 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.

APPENDIX 5: FIGURES

Figure A4: Union Membership



Notes: The graph presents the evolution of union membership rate in the UK (black line), the US (dashed lined) and the OECD countries (dotted line). Source: OECD.

APPENDIX 6: DATA SOURCES

Annual Respondents Database (ARD): Office for National Statistics, 1973-2008: Secure Data Service Access [computer file]. Colchester, Essex: UK Data Archive [distributor], March 2011. SN: 6644.

Compustat: Standard & Poor, 1980-2018. Access on-line through Warton Research Data Services https://wrds-web.wharton.upenn.edu/wrds/

EU-KLEMS: Jäger, K. (2016). EU KLEMS Growth and Productivity Accounts 2017 Release, Statistical Module1. December, *http://www.euklems.net/TCB/2016/Metholology_EU%20KLEMS_2016. pdf.*

FAME: Bureau van Dijk Electronic Publishing, 2007-2017. Access on-line through: https://fame.bvdinfo.com/

Labour Force Survey (LFS): Office for National Statistics, Labour Force Survey, 1979 – 1991: Colchester, Essex: UK Data Archive [distributor]. SN: 2360, 2265, 2839, 2029, 2875, 1756, 1888, 2722, 2143, 2721, 2720, 1758, 1757.

London Share Price Database (LSPD): London Business School, 1980-2018. Access on-line through Warton Research Data Services https://wrds-web.wharton.upenn.edu/wrds/

NBER-CES Manufacturing Industry Database: Randy Becker, Wayne Gray, Jordan Marvakov (2016). Access on-line: http://www.nber.org/nberces/

New Earnings Survey Panel Dataset (NESPD): Office for National Statistics. (2017). New Earnings Survey Panel Dataset, 1975-2016: Secure Access. [data collection]. 7th Edition. UK Data Service. SN: 6706, http://doi.org/10.5255/UKDA-SN-6706-7

NOMIS: Office for National Statistics. NOMIS Official Labour Market Statistics. Access on-line: https://www.nomisweb.co.uk/

ORBIS: Bureau van Dijk Electronic Publishing, 1980-2017. Access through the LSE Library.

PATSTAT: the European Patents Office, 1980-2017. Access through the LSE Library.

Worldscope: Thomson Reuters, 1980-2018. Access through Datastream