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DISCUSSION PAPER

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Patents, Firm Rents, and Worker Compensation: Causal Evidence from Quasi-Random Patent Allocation

Patents, Firm Rents, and Worker Compensation: Causal Evidence from Quasi-Random Patent Allocation*

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Abstract

This paper provides new causal evidence on how patent allowances affect firms and their employees based on quasi-random assignment of patent applications to examiners. Exploiting employer–employee records with newly linked German firm data and web-scraped patent documents, we show that patent-induced shocks reduce firm exit, improve productivity, and increase wages, with rent-sharing elasticities between 0.10 and 0.21. Wage gains are broadly observed across occupational tasks, with substantial heterogeneity: managers benefit disproportionately in publicly traded firms, whereas broader wage increases accrue to workers in non-traded firms. Our findings highlight the role of institutional features and firm organization in shaping how rents are shared.

Keywords: Innovation, Firm Performance, Worker Compensation, Rent Sharing.

JEL classification: O31, O34, J31, D22

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1 Introduction

Innovative activity is a key driver of long-term economic growth and improvements in societal welfare. However, the benefits of technological advances are often unevenly distributed (Gordon 2016; Johnson and Acemoglu 2023). These developments have intensified the public debate about the appropriate role of government in shaping the distribution of economic gains (Furman and Seamans 2019). Firms that pioneer superior products or production technologies are central to this process, as successful innovation can generate substantial rents. Yet it remains unclear to what extent, and under which institutional circumstances, economic rents are shared with the workforce, and which types of workers benefit or lose.

Our study contributes to the literature examining how firm-level shocks transmit to workers through wages and employment outcomes. We provide new causal evidence on wage pass-through among innovative firms in Germany by studying shocks generated through patent allowance decisions. Specifically, we define a patent allowance shock as the change in firm outcomes induced by a patent application being granted rather than rejected. We document the disruptive nature of patent allowance on firms and workers by exploiting quasi-random assignment of patent applications to examiners in a judge-IV setting. By combining employer–employee records with newly linked firm-level data and web-scraped patent documents, we present three main findings. First, patent allowance shocks reduce the probability of market exit and increase firm productivity. Second, leveraging rich worker-level biographies, we show that patent shocks raise wages, with baseline rent-sharing elasticities around 0.1, implying that a 10% increase in labor productivity raises wages by roughly 1%. Third, we document wage gains across occupational tasks and highlight the role of firm organization in shaping how rents are shared.

Our analysis relies on a new and unique dataset linking firms, establishments, and workers over the years between 2000 and 2021 (for a description of the linkage, see Diegmann, Gottschalk, Hälbig, Schmucker, Wolter, and Zimmermann 2026).[1] We exploit patent applications at the European Patent Office (EPO) from PATSTAT linked to the universe of firms in Germany. A major advantage of the data is that PATSTAT covers not only granted patents but also rejected patent applications. This allows us to compare successful and unsuccessful innovations. The firm data are provided by *Creditreform* and organized by the ZEW – Leibniz Centre for European Economic Research in Mannheim. This data contains comprehensive information at the firm-level such as employment, sales, credit scores, firm entry and exit dates to construct firm performance measures. Social security data provided by the Institute for Employment Research (IAB) allow us to measure worker compensation and the stability of employment. The data further contain detailed information at the worker-level, including demographic characteristics and occupational information, which allow us to differentiate potential gains from innovations by studying wage developments and employment prospects for different groups of the workforce.

Identifying rent sharing elasticities requires idiosyncratic firm-level variation in rents, since shocks shared across firms in the same labor market directly affect workers' outside options and bias pass-through estimates. Moreover, identification of the causal effect of patent allowance on

[1] The linkage of administrative units is performed by Doherr (2023) using probabilistic name-and-address matching.

firms and workers suffers from selection bias. Firms with a granted patent are typically larger and more productive with better financial conditions. Although the data allows us to compare firms with granted patent applications to firms that receive a rejection—as exploited by Kline, Petkova, Williams, and Zidar (2019)—we show that major initial firm characteristics such as firm growth prior to the application differ between assignees with granted and non-granted patents. This generates concerns in the parallel trends assumption. We, therefore, develop a framework for reduced-form identification by exploiting within patent examiner variation in assigning patent grant status following methodologies from the judge-IV literature (Dobbie, Goldin, and Yang 2018; Sampat and Williams 2019; Bhuller, Dahl, Løken, and Mogstad 2020; Farre-Mensa, Hegde, and Ljungqvist 2020).

The empirical approach relies on heterogeneous preferences of patent examiners and their quasi-random assignment to patent applications. To obtain information on patent examiners, we first web-scrap patent documents based on around 330,000 patent applications from Patentscope provided by the World Intellectual Property Organization (WIPO). Based on these documents, we extract the names of the examiners with information on the regional office. This allows us to understand the examination process of the application and estimate the leniency of examiners to grant a patent. We show that (i) the probability of receiving a granting status increases continuously along the examiner preference measure, (ii) these preferences are heterogeneous across examiners, and (iii) they are persistent across time. Importantly, we provide evidence consistent with the quasi-random assignment mechanism of patent applications to examiners. We show that quasi-random assignment happens within technology classes by providing data-driven evidence that examiners typically evaluate patents within their field of technological expertise. This setting corroborates the view that decisions are idiosyncratic shocks to the firm. In addition, it mimics the random nature of innovation that is typically the result of trial-and-error research by competing firms with a positive reward of research being highly uncertain.

Our estimates represent a local average treatment (LATE) effect among complier firms, i.e., a firm that would have received a different allowance decision had its patent been examined by a different examiner. Besides instrument relevance and quasi-random assignment, we provide evidence that the exclusion restriction holds. Specifically, we show that the instrument does not correlate with the experience of the examiner or the examination workload of the person in charge. More or less lenient examiners also do not interact more often with the applicants, and the duration of the application process does not differ between lenient and tough examiners. Under heterogeneous effects, the interpretation of our instrumental variable estimates relies on the validity of the exclusion restriction and the monotonicity assumption. In our context, the monotonicity condition implies that patents that were granted with strict examiners will also be granted with lenient examiners. We follow Bhuller, Dahl, Løken, and Mogstad (2020), Frandsen, Lefgren, and Leslie (2023), and Humlum, Munch, and Rasmussen (2025) and provide empirical evidence that monotonicity holds.

Pakes (1986) and Hall, Jaffe, and Trajtenberg (2001) have first provided descriptive evidence that most patents are of low value to the firm. Consistent with this documentation, we find that among all EPO patents, 53% receive no citation over the following three years after the initial filing date and 20% are cited only once by other assignees. For this reason, we follow Kline, Petkova, Williams, and Zidar (2019) and Farre-Mensa, Hegde, and Ljungqvist (2020) and restrict the sample to firms applying for patent allowance for the first time. With this sample, we test whether first-time allowance or rejection of the patent application has significant consequences on firm performance and worker compensation.

Using this novel data, we first establish that winning a patent as compared to receiving a rejection affects the extensive margin of firm operation by lowering the probability of exiting the market. We test alternative hypotheses such that observed firm exits may be the result of mergers and acquisitions (M&A) activity, but do not find supporting evidence. Additionally, exploiting bankruptcy indicators supports the finding of lower market exit rates and suggest that firm financing plays a crucial role. Second, we show that firm sales and productivity—measured by sales over employment—increase due to patent allowance. Surviving firms, however, do not grow in terms of employment. Third, we provide evidence that average wages for incumbent workers and new hires increase in response to successful patenting. Taking these results, we calculate rent sharing elasticities by relating revenue per worker and wage bill responses. On average, our results imply rent sharing elasticities of 0.1, with stronger elasticities of 0.21 six years after the patent submission. This increase over time is driven by the fact that wage responses take time. The presented elasticities are substantially lower compared to Van Reenen (1996) and Kline, Petkova, Williams, and Zidar (2019) who show rent sharing elasticities of approximately 0.5 in a similar context for U.S. patenting firms.

We show that our results are heterogeneous across firm types and the type of inventions. Most importantly, we differentiate the sample by stock corporations and non-traded firms, which, we argue, serves as a proxy for distinguishing between lower and higher levels of employee participation in the decision-making process. Non-traded firms in Germany are typically private family-owned businesses with lower hierarchical layers, higher workforce attachment and commitment to job security, and a close relationship between owner-managers and employees (Simon 2009; Schlömer-Laufen, Kay, and Holz 2014; Audretsch, Lehmann, and Schenkenhofer 2018; Rammer and Spielkamp 2019; Kölling 2020; Gottschalk, Hauer, and Ahrens 2023). Public firms, in turn, typically add hierarchal layers that correlate with greater wage variation within firms (Bias, Lochner, Obernberger, and Sevilir 2026). Related with this, we show that managers employed in stock corporations experience substantial wage gains.[2] Part of this wage gain is driven by increased bonus payments that are only observed among managers in stock companies. In contrast, workers performing manual tasks, technicians, and administrative workers also experience significant positive wage effects when employed in non-traded firms (which represent the majority in Germany) with arguably stronger employer-employee relationships. These results suggest that institutional determinants are important drivers in distributing the gains from economic rents.

This paper contributes to three strands of literature. First, our paper contributes to the literature that studies how shocks to firm performance propagate to workers. Seminal studies have documented that firm performance and worker compensation are strongly related (Card,

[2]Managers' and executives' wages are determined by the Supervisory Board under the guidelines of the *German Corporate Governance Code*. The Supervisory Board defines specific performance criteria (financial and non-financial) that executives must meet.

Cardoso, Heining, and Kline 2018) and more productive firms pay wage premia for otherwise identically skilled workers (Abowd, Kramarz, and Margolis 1999; Card, Heining, and Kline 2013; Abowd, McKinney, and Zhao 2018; Sorkin 2018; Song, Price, Guvenen, Bloom, and Von Wachter 2019). Numerous studies have identified rent-sharing elasticities. Based on industry-level profit measures, Christofides and Oswald (1992), Blanchflower, Oswald, and Sanfey (1996), and Estevão and Tevlin (2003) report estimates ranging between 0.06 to 0.14. Studies at the firm level exploiting mean wages provide estimates of around 0.04 such as in Hildreth and Oswald (1997), Hildreth (1998) and Jäger, Schoefer, Young, and Zweimüller (2020). In contrast, Abowd and Lemieux (1993) and Barth, Bryson, Davis, and Freeman (2016) document elasticities of 0.20 and 0.16. A large number of studies estimate rent-sharing elasticities using firm-level data and individual-level wage information. Based on studies between 2000 and 2020, the average (inverse variance weighted) elasticity estimate amounts to 0.099.[3] More recently, Acemoglu, He, and le Maire (2022) and Garin and Silvério (2024) show wage pass-through elasticities between 0.14 and 0.19 exploiting firm-level variation in foreign demand among exporting firms. Mertens, Mueller, and Neuschaeffer (2026) provide elasticities of 0.2 by exploiting energy price shocks among German manufacturing firms. They show that workers do not benefit from energy price reductions but are harmed by price increases. Relative to the recent finding, our causal estimates of approximately 0.1 fall at the lower bound of the reported elasticities. We further highlight distributional aspects within the firm by providing evidence on wage gains by occupational tasks.

We further contribute to the literature that studies innovation and firm performance specifically, with patent activity serving as a reliable gauge to measure successful innovation (Roberts 1999; Czarnitzki and Kraft 2004; Cho and Pucik 2005; Czarnitzki and Kraft 2010). Kogan, Papanikolaou, Seru, and Stoffman (2017) use grant information among U.S. patents assigned to publicly listed firms in an event study design to show positive stock market responses. Focusing on successful climate patent innovations, Hege, Pouget, and Zhang (2024) provide evidence for positive medium-run abnormal stock returns and lower capital costs. Farre-Mensa, Hegde, and Ljungqvist (2020) show that patent grants have strong impacts on the financing side of startups in the U.S. Winning a patent generates access to venture capital financing. Their results point to credit constraints that prevent firms from growing.[4] Kline, Petkova, Williams, and Zidar (2019) provide evidence for first-time applicants in the U.S. and show that ex ante valuable patents generate increases in firm productivity and employment. Lower value patents, in turn, do not affect firm performance. Compared to this literature, we show that patents generate a substantial survival advantage and lower the probability to be under financial stress measured by bankruptcy indicators—supporting the findings from the U.S. of better financing conditions. Unlike existing evidence, we do not find that firms grow in terms of employment. Firms, however, grow in terms of revenue when patents get granted, indicating a boost in labor productivity. These results suggest lower responsiveness of firms in the German environment in adjusting firm size following

[3] These include Arai and Heyman (2009), Gürtzgen (2009), Martins (2009), Du Caju, Rycx, and Tojerow (2011), Card, Devicienti, and Maida (2014), Bagger, Christensen, and Mortensen (2014), Carlsson, Messina, and Skans (2016), Card, Cardoso, and Kline (2016), Kline, Petkova, Williams, and Zidar (2019), Jäger, Schoefer, Young, and Zweimüller (2020).

[4] Related to this line of research, Desai, Gavrilova, Silva, and Soares (forthcoming) show the importance of trademarks for firm value and growth measured as firm-level employment, sales, and output.

positive productivity shocks; a literature that is emerging in recent years (Decker, Haltiwanger, Jarmin, and Miranda 2020; Biondi, Inferrera, Mertens, and Miranda 2025).

Lastly, we contribute to the literature on patenting activities and the future innovation of the company. Cumulative research is a dominant feature of modern innovation (Scotchmer 1991; Green and Scotchmer 1995). Galasso and Schankerman (2015) study the removal of patent rights on cumulative innovation. Their results suggest that patent invalidation significantly lowers cumulative innovation. This is consistent with Bessen and Maskin (2009) who show that sequential innovation is particularly sensitive to patent protection. In follow-up work by Galasso and Schankerman (2018) show that removing patent rights reduces future patenting activities and increases the likelihood of market exit with the effects being driven by small- and medium-sized firms. Sampat and Williams (2019), however, find no effect on follow-on innovation in human genomes innovation activity. Our results indicate that successful innovations not only stimulate subsequent inventive activity but also foster cumulative innovation.

The remainder of this paper is organized as follows. In Section 2, we describe the data and provide descriptive statistics of the firm, the worker, and patent sample. Section 3 provides institutional information on the patent examination process and patent allocation mechanism. The identification strategy and instrument diagnostics are shown in Sections 4 and 5, respectively. Section 6 reports our empirical results on firm performance. Section 7 show worker-level results. Section 8 concludes.

2 Data, Sample & Descriptive Statistics

2.1 Data

Firm-Level Data. The basis of our firm-level data is the *Mannheim Enterprise Panel* (MUP), which is generated and hosted by the ZEW – Leibniz Centre for European Economic Research. The data are provided by *Creditreform e.V.*, the largest credit rating agency in Germany. Besides the official Business Register of the Federal Statistical Office, the MUP is the most comprehensive micro database of companies in Germany with full coverage of all firms starting around 2000. Bersch, Gottschalk, Müller, and Niefert (2014) provide detailed information on data collection, processing, and variable definitions. For our analysis, we use wave 61 with the latest available year being 2021.

The dataset contains more than 8 million companies that are or were economically active in Germany with updated information on a semi-annual basis. Enterprise-specific information available in the dataset includes the number of employees, revenue, firm entry and exit dates, five-digit industry code, data on insolvency procedures, credit rating information, and shareholder information.

Patent-Level Data. Patents represent our measure of innovations.[5] The firm-level data is linked to patent data from PATSTAT via a record linkage procedure described in Doherr (2023). PATSTAT itself contains worldwide patents from main patent offices such as EPO and The United States Patent and Trademark Office (USPTO). The dataset provides bibliographical information on the patent, including the date of application, applicant ID, application country of origin, year of publication, the technology class, application grant decision, and citation information.

Our analysis contains all linked patents from German assignees submitted to the EPO available until 2019. Due to the fact that PATSTAT has time lags, we consider patent applications until 2016. Over the period between 1978 and 2016, we observe a total of 617,673 patents applied to the EPO, out of which around 90% of the assignees are firms, 7% are individuals, 2% are government non-profits organizations, and around 1% are from universities. Based on assignee firm names and address information, patents are merged with the MUP and this merge is provided to us by ZEW. With around 96%, the match rate is considered to be high. Over the years between 2000 to 2016, our main sample period, 24,689 unique firms account for 357,309 applications. An advantage of the data is that it contains information on both successful and unsuccessful patent applications. On average, 57% of all applications get granted.[6]

We enrich the patent information with information provided by the World Intellectual Property Organization (WIPO). The main purpose of this dataset is to obtain information on patent examiners and the examination process as the PATSTAT database does not provide any patent examiner information. This information will be exploited in our identification strategy. To obtain examiner information, we use patent documents available on Patentscope to extract relevant information from WIPO. Patentscope is a database that provides access to patent documents from participating national and regional offices. As of January 2024, Patentscope contained 4.8 million patent applications and 115.7 million patent documents. Based on the patent application ID, we web-scraped Patentscope to extract PDF documents with the respective names of the examiners. Out of 357,309 patent applications in the MUP sample, we successfully extract examiner information for 255,420 applications filed between 2000 and 2016, corresponding to an overall coverage rate of approximately 76% (with slightly lower coverage observed in 2004 and 2005 due to less available documents at WIPO). Details about web-scraping and the digitization process of the data are provided in Appendix C.

Additionally, we obtain the office information for the location where the application was submitted and the location where it is being evaluated.[7] We extract both locations because submitting

[5]While not all innovations are patented, patents present a strong signal of Research and Development (R&D) output and innovation activity. Using data from the Mannheim Innovation Panel (MIP), Appendix Figure A.1 shows that patenting firms account for the majority of total R&D expenditure (85%) and are considerably more likely to undertake both product and process innovations. Thus, a sample of patenting firm represents the most innovative firms in the German economy.

[6]The characteristics of firms that engage in patenting activities are distinct, and differ from other companies in the economy (Appendix Table A.1). They tend to be larger and older, with higher revenue and better credit ratings. Furthermore, the majority of firms with patent activities are in the manufacturing industry, retail trade, ICT, and technical service sectors.

[7]In many instances, the precise location is not specified in the documents; for these cases, we obtain the telephone number of the primary examiners. Similarly to the names, we eliminated special characters from the telephone numbers and use the first four digits of the calling code to determine locations, such as 4989 for Munich, 4930 for Berlin, and 3170 for The Hague.

the application at, for example, the Munich office does not guarantee that it would be examined at the same office. Table 1 shows the distribution of applications and examinations across the three offices with most patents being handled in Munich followed by The Hague and Berlin.

Table 1: Number of Applications by EPO Offices

Place	Application Office	Examination Office
Berlin	6,827	8,683
The Hague	77,144	87,092
Munich	163,490	152,049

Notes: The table presents office information of the patent application filed and examined. Office details of the examiners were extracted from the web-scraped PDF from Patentscope WIPO. Between 2000 and 2016, the data captures 247,824 applications.

Linked Employer-Employee Data. We incorporate worker-level data in our analysis from the social security system in Germany, provided by the Institute for Employment Research (IAB). This data contains complete information on earnings and time worked in each employment spell. The data provides further information on workers' age, gender, occupation, industry, and receipt of unemployment insurance benefits. This worker-level data is linked to establishments in a linked employer-employee panel starting in 1975. We restrict the sample to regular workers who are employed subject to social security contributions, thereby excluding apprentices and marginal employees. To match the data with our annual firm panel, we retain all employment spells that contain June, 30th of the respective year and construct an annual worker panel. In case of parallel employment spells, we choose episodes with highest daily wages. We follow Dustmann, Ludsteck, and Schönberg (2009) and Card, Heining, and Kline (2013) and impute wages that lie above the social security contribution limit.

We make use of a recently established data merge between the MUP and social security data at IAB. The linkage and data cleaning procedure is described in method reports by Diegmann, Doherr, Hälbig, and Wolter (2025). During the years 2000 to 2020, around 81% of all observed establishments have been linked to the firm identifier in the MUP. At the employment level, match rates exceed 90% indicating that the matching process performs better for larger firms.

2.2 Constructing a Sample of First-Time Patenting Firms

The observed 357,309 patent applications come from around 24,689 firms indicating that, on average, a firm has 14 applications over the sample period. The distribution of the number of patent applications per firm has a long right tail as shown in Appendix Figure A.2. The top largest 10% of patenting firms account for 83% of all applications. Among these applications, there are typically granted and non-granted patents observed in the same year within the same applicant, complicating the analysis of a successful patent application on firm and worker outcomes.

For this reason, we construct a clean analysis sample in which we identify the *first* patent application event at the firm-level and follow these firms over time. To analyze firm performance and wage dynamics before and after the patent application event, we condition the sample on firms observed at least two years before the application with non-missing employment, revenue,

Table 2: Summary Statistics

	N (1)	Mean (2)	SD (3)	Minimum (4)	Maximum (5)
		A: Firm-level Data			
A1: Initial year of patent application					
Employment	3,453	138.33	449.60	1.00	10,530
Log revenue	3,453	16.27	1.66	0.21	25.16
Average real daily wages	3,453	117.55	30.03	4.42	265.71
Firm age	3,453	19.72	10.92	2.00	39.00
High credit rating	3,450	0.76	0.42	0.00	1.00
Low credit rating	3,450	0.03	0.18	0.00	1.00
Product innovation	3,453	0.55	0.50	0.00	1.00
Process innovation	3,453	0.16	0.36	0.00	1.00
Mixed innovation	3,453	0.37	0.48	0.00	1.00
Manufacturing	3,453	0.58	0.49	0.00	1.00
Retail trade	3,453	0.15	0.36	0.00	1.00
ICT	3,453	0.04	0.19	0.00	1.00
Technical service	3,453	0.12	0.33	0.00	1.00
A2: 6 years after patent application					
Firm exit	3,453	0.07	0.26	0.00	1.00
Employment	3,191	148.19	457.91	1.00	10,846
Revenue	2,703	16.53	1.60	10.21	23.27
Average real daily wages	3,153	129.17	36.05	35.61	381.25
Number of patents	3,453	1.68	8.27	0.00	375.00
Any patenting	3,453	0.40	0.49	0.00	1.00
Minority acquisition	3,453	0.11	0.31	0.00	1.00
Majority acquisition	3,453	0.27	0.45	0.00	1.00
Profit takeover agreement	3,453	0.06	0.23	0.00	1.00
Merger	3,453	0.05	0.22	0.00	1.00
		B: Individual-level Data			
B1: Initial year of patent application					
Female	383,929	0.31	0.46	0.00	1.00
Age	383,929	43.03	10.53	18.00	65.00
Nationality German	383,929	0.92	0.26	0.00	1.00
Daily wages	383,929	114.07	52.43	10.00	410.99
Bonus payments	383,929	0.02	0.14	0.00	1.00
No vocational training	383,929	0.10	0.30	0.00	1.00
Vocational training	383,929	0.76	0.43	0.00	1.00
University	383,929	0.14	0.35	0.00	1.00
Manual task	383,929	0.41	0.49	0.00	1.00
Skilled task	383,929	0.14	0.35	0.00	1.00
Technicians	383,929	0.10	0.30	0.00	1.00
Administration	383,929	0.19	0.39	0.00	1.00
Manager	383929	0.03	0.18	0.00	1.00
B2: 5 years after patent application					
Employed	383,929	0.81	0.39	0.00	1.00
Daily wages	310,189	125.82	60.00	0.06	1,058.5
Employed in same firm	310,189	0.76	0.42	0.00	1.00

Notes: The table shows summary statistics of first-time patent applicants in Germany between 2000 and 2016. Panel (A) displays summary statistics at the firm-level. Panel (B) displays summary statistics at the worker-level.

and wage information. To calculate meaningful average firm-level wages and labor productivity figures, we select firms with at least five employees before the patent application. This sample, therefore, represents active firms that engage in innovative activity and likely excludes spin-offs and newly founded firms for which we cannot observe the evolution before the first application and for which information on revenue is typically very limited. In total, we identify 3,453 companies that are observed with their first application. Among them, the majority of 80.6% file for exactly one patent and 14% file for two patents (the remaining 5% file for more than two patents). Between 2000 and 2015, we observe on average 290 firms per year as first-time patenting firms with 70% in each year receiving a grant status.[8]

By focusing on the first patent application, we obtain a clean measure of first-time innovation that is comparable to the existing literature in this field. Kline, Petkova, Williams, and Zidar (2019) analyze a firm's first patent application, whereas Farre-Mensa, Hegde, and Ljungqvist (2020) focus on first applications among startups. One of the major advantages of the data compared to other patent data such as the USPTO is the fact that we observe the granting status of the patent application.

Table 2 displays summary statistics of firm-level characteristics (Panel A) and worker-level characteristics (Panel B) for two different points in time. Panels A1 and B1 provide summary statistics for the year before the application, while Panels A2 and B2 provide information on outcome variables six years after the first patent application. The average firm in our sample has about 138 employees and is on average 19 years in the market at the time of the application.

In terms of industry affiliation, the sample is concentrated among four sectors. Similar to Appendix Table A.1 (all patenting firms in Germany), more than every second firm is active in the manufacturing sector. The two second major industries are retail trade with 15% and technical service with 12%. About 4% of the firms are active in the information and communication industry. Over the course of six years (Panel A2), 7% of all firms exit the market. Conditional on firm survival, average firm size, revenue and real wages grow. Moreover, we observe about 40% of the firms with follow-up patent filing events after the first submission. Finally, we exploit ownership information to measure M&A activity. This includes changes in the ownership structure of existing firms, profit takeover agreements, as well as merges that result in an exit of the firm ID. Approximately 27% experience a change in majority ownership in the six-year interval. Profit takeover agreements and merges are observed for 6% and 5% of the firms, respectively.

3 Institutional Background

3.1 Patent Examiner and Examination Process

The European Patent Office (EPO) has established a three-member panel of examiners to conduct a comprehensive review and examination of patents. The panel comprises a primary examiner who performs the initial search, a second examiner, and a chairman. Over their working career, an examiner can work as a primary examiner in one examination process and as, e.g, a chairman in other cases. Over the lifetime of patent examinations, the majority of 5,340 examiners served in all three positions as primary and second examiner as well as the chairman. 1,309 examiners serve as both primary and second examiners, and 865 examiners stay as primary examiners only. All examiners are highly specialized and work within specific technical fields. Based on

[8]Information on revenue is available since 2000, for which reason we drop patenting events in 2000 and 2001 when conditioning on non-missing revenue numbers two years before the submission

insights from Lahorte (2018), more than half of EPO examiners hold a doctorate degree, and many bring valuable prior professional expertise. Additionally, they are multilingual and capable of working in the EPO's three official languages (English, German, and French) as well as their native language.

Examining patent applications at the EPO involves several steps that ensure a thorough assessment of the invention.[9] Figure 1 presents a simplified depiction of the examination process. After the application, the first step is to conduct a formal examination, which ensures that all necessary documents, such as descriptions, claims, drawings, and abstracts are provided. After the formality of the examination is completed and the filing date is assigned[10], the application is handed over to the primary examiner, who evaluates it comprehensively. The primary examiner is responsible for assessing the patent application until a decision is made to either grant or refuse it. The examiner conducts initial research on the innovation and compiles a comprehensive search report. The search report is based on the patent claims but also incorporates the description and drawings. Furthermore, the examiner evaluates the clarity of the claims, the technical contribution of the invention, the scope of the claims, and provides a preliminary opinion on patentability. This search report may also provide the applicant with a clear indication of the application's prospects, allowing them to make informed decisions about their application. In some cases, applicants may withdraw the application if they believe it has no chance of success. In this process, if objections or a lack of unity exist, the examiner communicates their findings to the applicant and requests a response within a specified deadline, typically four months. If the applicant responds, the application undergoes re-examination to address any objections raised through amendments or explanations. After this process is complete, the EPO publishes the application with the search report, usually within 18 months of the filing date. The applicant then has six months to decide whether to continue with the application and request a more detailed (substantive) examination or to designate additional countries for patent protection. If the applicant fails to do so, the application is deemed to be withdrawn. Two types of patents are considered non-grant: (i) patents that were rejected after the examination and (ii) patents that the applicant withdraws.

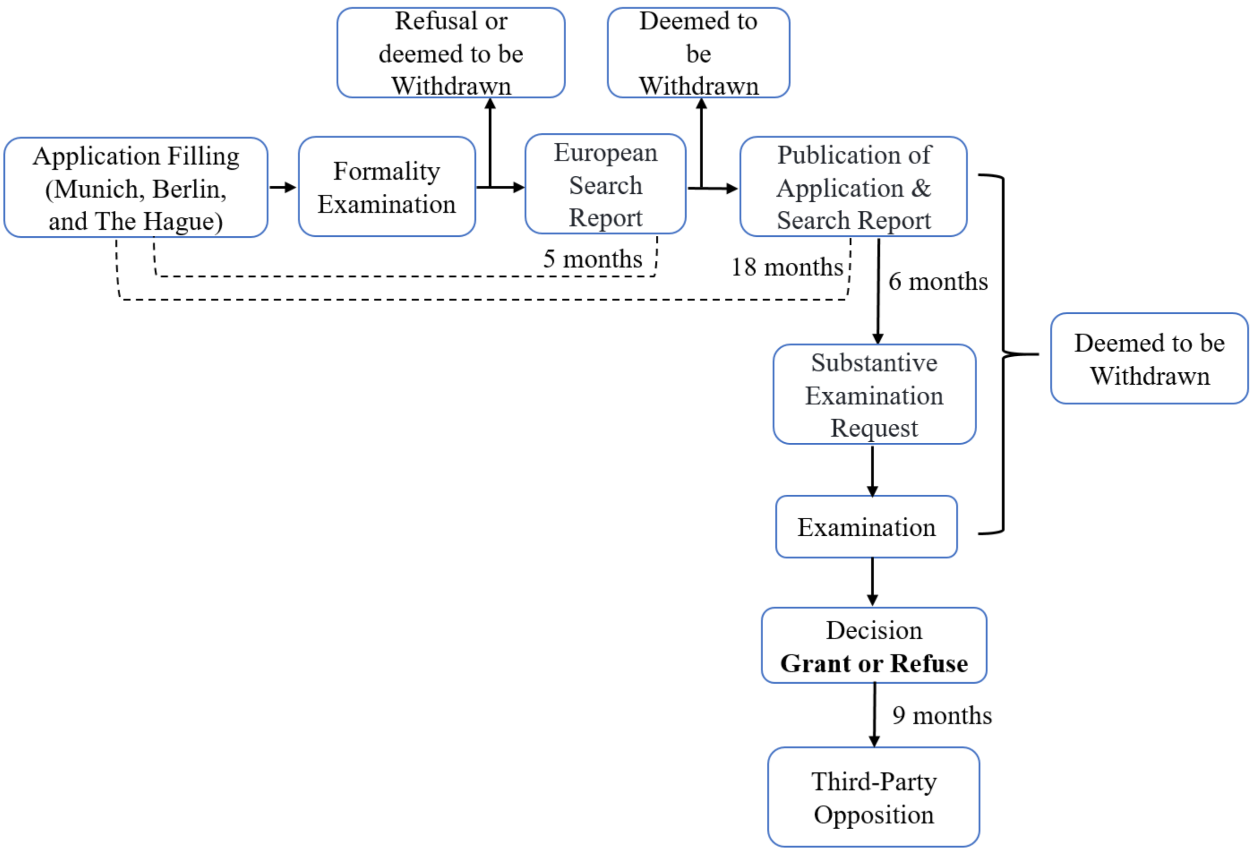
The substantive examination carried out by the EPO involves a panel of three examiners, including the primary examiner who conducts the initial search. Together, they assess whether the application and invention meet the European Patent Convention (EPC) requirements and determine its patentability based on the search report. Decisions are taken by majority vote, and in case of a tie, the chair of the division casts the deciding vote. If the examiners decide to grant a patent and all fees have been paid, along with any required claims translations, the decision is published in the European Patent Bulletin. However, if someone wishes to challenge the validity of the granted patent, they can oppose it with arguments and evidence within nine months of the grant being reported in the bulletin. In the event of an opposition, the EPO team of three examiners will re-examine the case. The primary examiner of the examination division

[9] Information on the application and examination process are gathered from EPO 2023 and EPO 2024 guidelines.

[10] The filing date is the date when applications are submitted electronically or received by post at the EPO. Within two months from the date of filing, the applicant can add or submit any missing part of the application. In that case, the date of filing will be adjusted to the day on which the missing parts are received by the EPO.

frequently participates in the opposition proceeding of the same patent (Gaessler, Harhoff, and Sorg 2019). It is worth noting that only a small percentage of around 3-4% of granted patents are opposed. Among the opposed cases, 34.1% are amended, 34.8% are revoked, and 31.1% are upheld.

Figure 1: Overview of the European patent application process



Notes: The figures depict the standard patent application process at the European Patent Office (EPO). Following the formalities examination, each application is initially reviewed by a single examiner (the primary examiner). Once the applicant requests substantive examination, the application is assessed by a panel of three examiners, including the primary examiner. On average, the entire process takes approximately four to four and a half years to complete.

3.2 Patent Rejection Grounds

A European patent application undergoes rigorous examination processes under § 94 EPC, where the examining division evaluates the application with legal standards established by the EPC. A decision to grant or reject an application must be legally justified, with the grounds or acts for rejection clearly stated by § 97 EPC.

In this context, applications are primarily rejected due to a lack of novelty or inventiveness. According to the European Patent Convention (EPC), if an idea has already been publicly disclosed or is deemed obvious to professionals in the field, it fails the novelty (§ 54 EPC) or inventive step (§ 56 EPC) tests cannot be patented.[11] Furthermore, the EPC specifies certain types of ideas

[11] The novelty requirement under § 54 EPC ensures that patents are only granted for inventions, not already part of

that are not eligible for patents at all, such as purely abstract algorithms, mathematical formulas, aesthetic designs, or business methods without technical application, as outlined in § 52 EPC.[12] These boundaries help maintain the focus of patent law on genuine technical innovations rather than on broadly defined concepts or non-technical ideas.

Beyond the substance of an invention, procedural and formal issues also play a key role in the approval process. Patent applications must be clearly written and detailed enough for an expert to replicate the invention without needing to invent anything themselves, as required under § 83 EPC. Ambiguous language, inconsistent claims, or combining unrelated ideas into one application can all lead to rejections under §§ 82 and 84 EPC. Timely responses to examiner communications and payment of required fees are also essential; missed deadlines may result in the application being considered withdrawn under §§ 121, and 86 EPC. Even after a patent is granted, it can still be revoked if challenged successfully during the opposition process, particularly if the original patent fails to meet the core requirements outlined in § 100 EPC.[13]

3.3 Allocation of Patents to Examiners

In our identification strategy, we exploit the allocation of patents to examiners. The allocation process is a priori not random, because to be able to examine a potentially new invention, examiners need knowledge and expertise of the respective technology.

Based on USPTO data, Righi and Simcoe (2019) show that matching patent applications to examiners is based on examiner specialization. Once applications arrive at the patent office, they are divided into technology classes (International Patent Classification, IPC), or art units. Each application is then allocated to an examiner within that unit. Lemley and Sampat (2012) have first provided evidence that patent application assignments are random within the art unit for the U.S. Patent and Trademark Office.

At the EPO, Lahorte (2018) reports that examiners are specialized and work within technical sectors. Similarly, we observe that patent applications are not randomly allocated to examiners within the EPO but rather based on the art unit or IPC class. To provide a visual representation of this allocation process, Figure 2 illustrates how applications are allocated to examiners within different technology classes. For this purpose, we construct the IPC class at the 2-digit level and either take into account that patents can have multiple IPC classes (red bars) or assign the main IPC class to one patent (green bars). We then define the mode IPC class for each examiner and plot the distribution of assigned IPC classes for each examiner accordingly. The mode of IPC class, therefore, serves as our measure for technology specialization, which we label as technology expertise. For example, the upper left corner of Figure 2 shows that examiners who are defined in our data-driven way as specialized in technology class A (human necessities) typically receive patent applications within the same category A. This pattern is consistent across all eight broad

the "state of the art." The inventive step under § 56 EPC demands that the invention not be obvious to a "person skilled in the art" based on prior knowledge.

[12] § 52(2) EPC explicitly excludes discoveries, scientific theories, mathematical methods, aesthetic creations, schemes, rules and methods for performing mental acts, playing games or doing business, and programs for computers—unless they produce a technical effect.

[13] Opposition grounds under § 100 EPC include lack of novelty, lack of inventive step, and insufficiency of disclosure. Revocation proceedings under § 101 EPC are conducted before the EPO's Opposition Division.

technology classes.[14]

Within each defined technological specialization, we observe deviations as examiners evaluate patents outside their defined field of expertise. For example, an examiner specialized in IPC class G (physics; in the lower left corner of the figure) is also observed to evaluate patents in other IPC classes such as B (performing operations, transporting) and C (chemistry, metallurgy). This is, to some extent, because patents have multiple IPC classes which is why the green bars are more concentrated within the respective field of specialization. It may also happen because of endogenous reasons such as match effects. To circumvent potential endogenous deviations, we base our identification strategy on the IPC specialization of examiners, thus exclusively using the quasi-random variation within the technological specialization.

4 Empirical Strategy

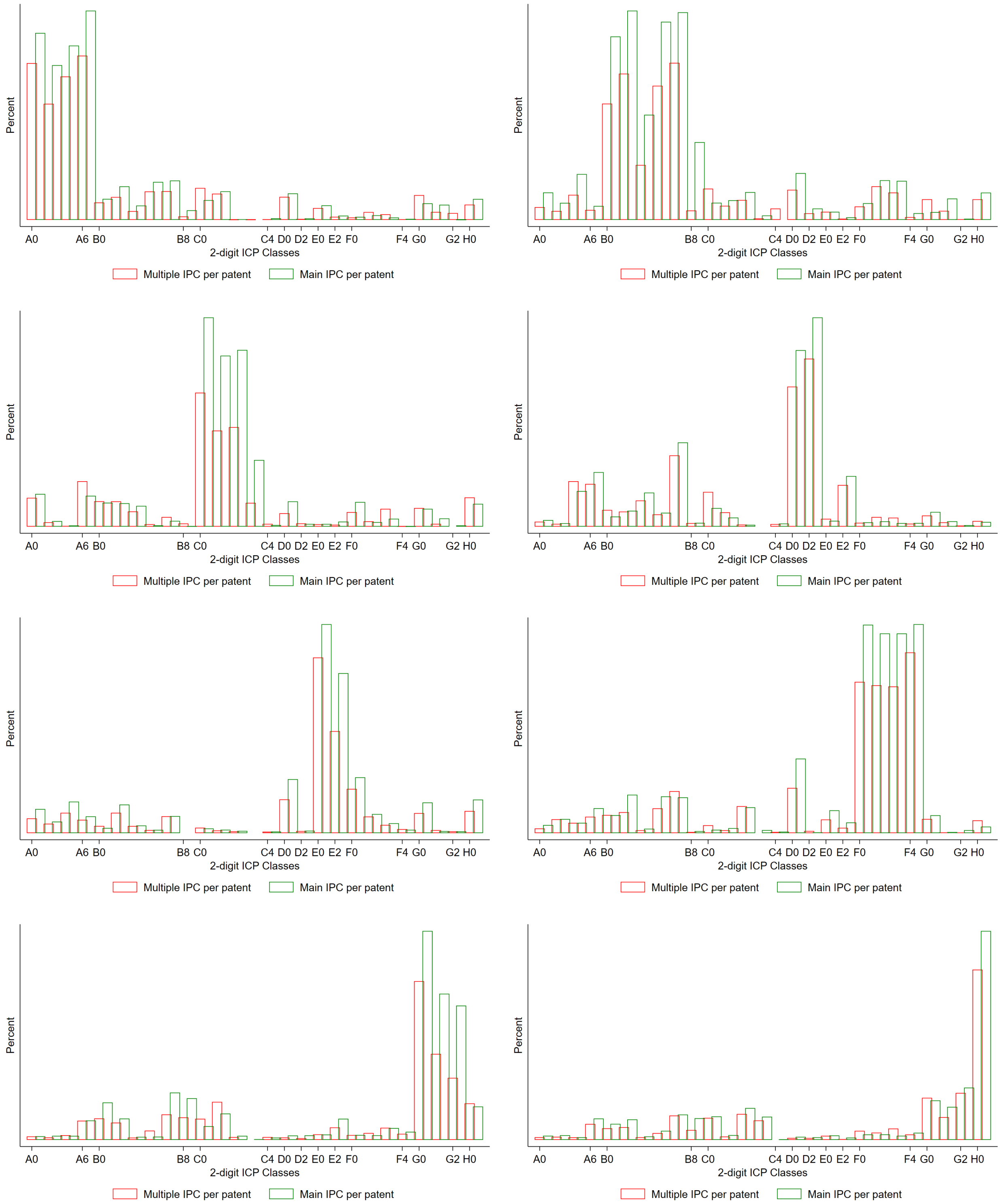
The objective of this paper is to estimate the causal effects of patent allowance on firm- and worker-level outcomes. Identifying causal effects is challenging because of unobserved heterogeneity. For example, examiners may be less hesitant to assign a patent to be granted if the firms signal follow-up innovations. Similarly, firms with deep pockets that hire lawyers to support the application process might be more likely to receive a positive decision. This type of information may be revealed to the examiner during previews and meetings, but it is unobserved to the econometrician. Furthermore, it is unclear whether controlling for observables of the firm such as firm size eliminates this type of bias because firms of similar size or sector affiliation could face different growth prospects that are not recorded in our administrative data.

To address these empirical challenges, we follow the judge-IV literature and develop examiner-stringency instruments for the assignment of patents to be granted. This approach has been used in the empirical crime literature (Bhuller, Dahl, Løken, and Mogstad 2020; Agan, Doleac, and Harvey 2023), bankruptcy regulations (Dobbie, Goldin, and Yang 2018; Sampat and Williams 2019; Bernstein, Colonnelli, Giroud, and Iverson 2019; Kleiner and Hüther 2025), and patent and trademark evaluations (Farre-Mensa, Hegde, and Ljungqvist 2020; **?**; Hege, Pouget, and Zhang 2024; Aneja, Reshef, and Subramani 2024). The main purpose of this approach is to estimate fixed traits of decision-makers – referred to as leniency or stringency – regarding outcomes. By combining these estimates of fixed traits with the quasi-random allocation to decision-makers, an exogenous shifter is generated that helps mitigate potential biases. In our setting, we depart from the canonical judge-IV setting by taking into account that patent applications are allocated to examiners based on the examiner's field of specialization.

The first step in the empirical analysis is to construct a measure for examiner's stringency in assigning the patent to be granted or rejected. When constructing the instrument, we focus on the primary examiner, who is responsible for searching, providing initial feedback, and communicating with the applicant for any required modifications. One reason is that, in cases of rejection, we can find the information for the chairman and second examiners, but we cannot get the name of

[14] All eight broad technology classes are (A) Human necessities; (B) Performing Operations, Transporting; (C) Chemistry, Metallurgy; (D) Textiles, Paper; (E) Fixed Constructions; (F) Mechanical Engineering, Lighting, Heating, Weapons, Blasting; (G) Physics; (H) Electricity

Figure 2: Allocation of patent application to examiner based on examiner specialization



Notes: The figures illustrate the allocation of patent applications to primary examiners across different technology classes. IPC classes are constructed at the 2-digit level. The red bars account for patents with multiple IPC classifications, while the green bars represent the main IPC class assigned to each patent. The technology classes are defined as follows: A—Human Necessities; B—Performing Operations, Transporting; C—Chemistry, Metallurgy; D—Textiles, Paper; E—Fixed Constructions; F—Mechanical Engineering, Lighting, Heating, Weapons, Blasting; G—Physics; H—Electricity.

the chairman and second examiner when the application is withdrawn.

The construction of the instrument must address the own-observation issue that arises due to a mechanical correlation in finite samples between the ongoing patent evaluation and the estimation of the examiner preference. We follow the literature by estimating a leave-one-out measure of granting a patent, i.e., by removing the considered examination case from the estimation of the stringency measure. We further normalize examiners' preferences within the three observed EPO offices. In other words, we measure an examiner's stringency on granting patents relative to the average stringency of cases handled in that office. We thus obtain:

$$Z_{fioj} = \frac{1}{n_{oj}-1}\left(\sum_{k=1}^{n_{oj}}(D_{k \notin f}) - D_{fi}\right) - \frac{1}{n_o - 1}\left(\sum_{k=1}^{n_o}(D_{k \notin f}) - D_{fi}\right) \tag{1}$$

where f denotes the firm, i the patent, o the EPO office, and j the assigned examiner. For example, $D_{fi} = 1$ indicates that the patent i submitted from firm f was granted. When estimating examiner j's leniency to grant a patent, we make use of all decisions observed in the constructed dataset. Because firms may submit multiple patent applications over time that are assigned to the same examiner, examiner decisions may be correlated. To mitigate this concern, we construct the examiner's average decision using only patents filed by other firms ($k \notin f$), excluding those submitted by the focal firm.

Measures of firm-level performance we consider include market exit, employment, revenue, wage, and subsequent innovations. At the worker-level, we focus on wage dynamics (including bonus payments) and employment stability. Let Y_{ft} denote the outcome of firm f in period t relative to the publication year of the first patent. The 2SLS specification can be written as:

$$\mathrm{D}_{fi} = \delta_{q(f)} + \delta_1 Z_{f(j)} + \theta_1 X_f + \epsilon_{1f} \tag{2}$$

$$\mathrm{Y}_{ft} = \beta_{q(f)t} + \beta_2 D_{fi} + \theta_2 X_f + \epsilon_{2f} \tag{3}$$

where $q(f)$ are EPO-office-by-year combinations, the units wherein our randomization takes place. Hence, we compare firms filing for patents in the same office and year. The coefficient of interest is β_2, the causal effect of patent allowance on firm and worker dynamics. In the baseline specification, we assign a value of one if at least one of the submitted patents gets granted and zero otherwise. Alternatively, we calculate the share of granted patents.[15] The vector X contains two further variables. First, we include initial firm characteristics in terms of employment, revenue and average wage level which accounts for potential level differences and allows for interpreting estimated coefficients in terms of growth. We further include the field of specialization of the assigned examiner, taking into account the quasi-random nature of allocating patents to examiners.[16] We cluster standard errors at the level of the patent examiner.

At the worker level, we provide two ways of identifying the impact of patent allowance. In the baseline, we pool all workers and run the first stage on the pooled sample. Alternatively, we estimate the first stage at the firm level and use predicted values in the pooled worker level

[15] Note that the instrument Z is unaffected by multiple patent submissions because the construction of the instrument only uses applications by other firms.

[16] While using examiner characteristics as instrumental variables, Righi and Simcoe (2019) emphasize the use of class or subclass fixed effect as the allocation of the patent applications to examiners are based on examiner specialization.

sample. Considering standard errors, the first approach clusters standard errors at the examiner level, whereas in the second approach we provide clustered bootstrapped standard errors.

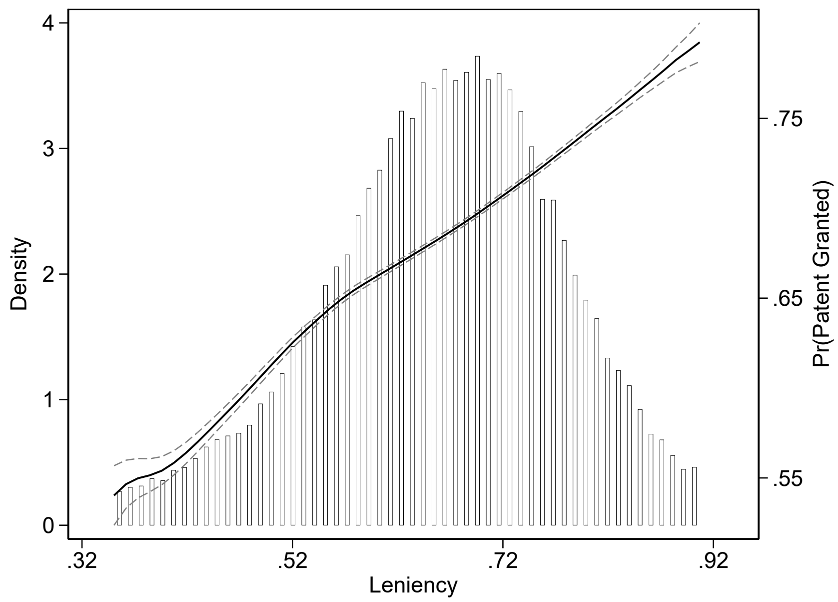
5 Instrument Diagnostics

In this section, we assess the examiner's leniency as our instrument and provide evidence that they meet the relevance, independence, exclusion, and monotonicity conditions, enabling us to interpret our IV estimates as local average treatment effects (LATE).

5.1 Instrument Relevance

Figure 3 shows the graphical representation of the first stage by plotting the relationship between the probability of granting patents and the estimated examiner preferences based on a local linear

FIGURE 3: FIRST-STAGE ANALYSIS



Notes: The figure plots the probability of granting a patent against the leave-one-out mean examiner leniency. The plotted solid line corresponds to a local linear regression of granting a patent on the examiner's leniency. The two dashed lines show the corresponding 90% CI. All plotted values in the local linear regression are mean-standardized residuals from regressions on patent office times year fixed effects and technology of the examiner fixed effects. The histogram shows the density of examiner leniency (left y-axis). The figure is constructed by conditioning of having handled at least ten patent applications per examiner.

regression. The figure provides two key insights. The tendency of a patent examiner has a strong impact on the assignment to grant a patent. Our first stage analysis shows that the probability of granting a patent increases continuously along the leniency measure based on the primary examiner. The density plot highlights considerable variation in how examiners impose decisions. It reveals a widespread tendency of examiners to grant a patent. For example, a patent assigned to an examiner at the 75th percentile of the leniency distribution has an average grant probability of approximately 72%. In contrast, patents reviewed by examiners at the 25th percentile face a grant probability of less than 65%.

We further observe consistent patterns in patent-granting behavior among examiners. Appendix Figure B.1 Panel A documents high persistence in granting behavior by plotting the correlation coefficient between the leave-one-out measure in the previous case (measured by the date of the application) and the leave-one-out measure in the current case, which is 0.98. Panel B further shows that the leave-one-out measure remains persistent over the career of examiners.

5.2 Independence

For our instrument to be valid, it must satisfy the independence assumption. We provide evidence that this assumption holds in Table 3. To test for the independence, we follow the logic that if patent applications are allocated on a quasi-random pattern, the instrument should not be able to predict initial firm characteristics. Table 3 first shows in Column (1) a coefficient estimate and the corresponding *p*-value in Column (2), with the dependent variable being the list of firm characteristics measured in the initial year of the patent application.

TABLE 3: TEST OF RANDOM ASSIGNMENT OF FIRMS TO EXAMINERS

	Granted		Leniency		Dep. variables		
	Coefficient (1)	*p*-value (2)	Coefficient (3)	*p*-value (4)	Mean (5)	SD (6)	N (7)
Employment							
Log employees	0.041	0.383	-0.068	0.657	4.500	1.268	3,323
Big firm > p90	-0.000	0.982	-0.045	0.210	0.100	0.300	3,323
Employment growth t-2 -> t-1	-0.015	0.072	0.021	0.347	0.138	0.196	3,323
Employment growth t-3 -> t-1	-0.044	0.009	0.016	0.730	0.298	0.392	3,220
Revenue							
Log sales	0.025	0.695	-0.032	0.878	16.226	1.644	3,323
Sales > p90	0.011	0.348	-0.028	0.438	0.100	0.300	3,323
Sales growth t-2 -> t-1	-0.020	0.378	0.064	0.340	0.076	0.636	3,323
Sales growth t-3 -> t-1	-0.090	0.018	-0.043	0.687	0.158	0.860	2,896
Productivity							
Log labor productivity	-0.016	0.734	0.036	0.803	12.418	1.142	3,323
Labor productivity > p90	-0.021	0.081	-0.017	0.652	0.100	0.300	3,323
Growth t-2 -> t-1	-0.005	0.822	0.044	0.532	-0.062	0.650	3,323
Growth t-3 -> t-1	-0.038	0.318	-0.028	0.788	-0.136	0.832	2,858
High AKM firm FE	0.011	0.477	-0.077	0.129	0.200	0.400	3,316
Low AKM firm FE	0.017	0.365	0.014	0.819	0.490	0.500	3,316
Firm Age							
Young firms below 5 years	-0.013	0.223	0.000	0.990	0.074	0.262	3,323
Firm age > 15 years	0.037	0.035	0.024	0.658	0.736	0.442	3,323

Notes: All explanatory variables listed in the table refer to the year before the patent application. Each line represents a single regression of the explanatory variable on the grant indicator in Column (1) and the leniency measure in Column (2) controlling for examiner fully interacted office-year and technology fixed effect. *p*-values calculated based on standard errors clustered at the examiner level.

The independent variable is an indicator of whether the patent is granted. Each line represents a single regression controlling for the filing year and office fixed-effects (fully interacted). We also include broad sector dummies measured at the 1-digit level, essentially capturing if the firm operates in manufacturing, retail trade, ICT or technical services (representing 88% of the firms in our sample). The table first of all shows that the granted status indicator is endogenous. In particular, the dynamics of firm growth prior to the patent application, as well as firm age correlate with the grant status.

Column (3) of the table performs the same regressions but testing the leniency measure instead of the grant status, taking into account the assigned IPC class knowledge of the examiner. These results provide evidence that the constructed instrument is uncorrelated with baseline firm characteristics. The evidence suggests that the leniency of a patent examiner (within the IPC-expertise) is indeed an exogenous shifter in determining a patent's granting status.

5.3 Exclusion

To interpret our IV estimates as the causal effect of winning a patent requires an exclusion restriction. In our case it means that the tendency to grant a patent only affects firm outcomes through the assignment of the application and not in any other way. Although the final decision to a patent application is either granted or rejected, examiners can, for example, interact in different ways with the assignee to influence the final decision. Lahorte and Preller (2023) state that effective communication and interaction with the applicant accelerate the processing of the application, thus, emphasizing the role of communication during the application process. If lenient examiners or examiners with less workload provide more feedback during the application period, the final results of the decision and potential firm outcomes might not be the results of the patent granting status. Lemley and Sampat (2012) show that more experienced examiners are more inclined to grant patents without any rejections, or they can make faster decisions than less experienced colleagues (Lahorte 2018). It might also be plausible that lenient examiners provide more opportunities for amendment than others, or that examiners with a higher workload are more inclined to grant patents.

Table 4: Exclusion Test

	Summary			Leniency	
	N (1)	Mean (2)	SD (3)	Coeff (4)	*p*-value (5)
Experience	5,403	17.754	4.878	-2.926	0.110
Workload	5,403	7.686	5.960	1.483	0.285
Interaction with applicant	289,317	1.488	0.894	0.002	0.919
Application decision duration	251,823	4.138	1.498	-0.005	0.793
Application publication duration	286,966	1.454	0.874	0.043	0.455

Notes: This table shows summary statistics of examiner characteristics and the correlation between examiner leniency and these characteristics. We conditioned the examiner to handle ten patents. The characteristics include work experience, workload (average number of applications per year), interaction with the applicant, duration of the patent decision (we exclude patents if the duration is more than 7 years; 90% of the application takes 1 to 7 years), and the duration of the first publication of the patent. Experience and workload are measured at the examiner level. Interaction with the applicant and the duration variables are measured at the patent level. Each line represents a single regression of the explanatory variable on the leniency measure controlling for examiner office-year and technology class fixed effect. For experience and workload, estimates are controlled for the examiner's office and the technology class fixed effect. *p*-values calculated based on standard errors clustered at the examiner level.

We assess the validity of the exclusion restriction by incorporating additional information on examiner characteristics. The central premise is that our instrument should be uncorrelated with other observable attributes of examiners. The data allow us to construct several such measures. First, we proxy examiner workload by the number of applications currently assigned to an examiner. Second, we measure examiner experience by calculating the number of years observed since the examiner's first appearance in the data.[17] Third, we proxy examiner–applicant interaction us-

[17]We exploit all available information of examiners decision making over the years between 1990 to 2016.

ing the number of times the examiner issues feedback or requests amendments to the application. We also consider the time to first publication—when the application and search report become public—which provides applicants with an early signal of the likelihood of grant. Finally, we examine the total duration until the application reaches a final decision.

Table 4 reports the results. On average, examiners have 18 years of experience and handle 8.5 applications. Examiners interact with assignees 1.5 times on average, the mean application duration is 4.2 years, and the average time to first publication is 1.5 years. The final two Columns present correlations between our instrument and these constructed variables. Across all specifications, the leniency measure is uncorrelated with examiner characteristics and application outcomes, providing support for the validity of the exclusion restriction.

5.4 Monotonicity

Under heterogeneous effects, the interpretation of our instrumental variable estimates relies on the validity of the exclusion restriction and the monotonicity assumption. In our context, the monotonicity condition implies that patents that were granted with strict examiners will also get granted with lenient examiners. This assumption ensures the 2SLS estimand can be interpreted as a local average treatment effect (LATE), i.e., it is an average causal effect among the subgroup who could have received a different decision had the application been assigned to a different examiner.

We apply two different approaches to test the assumption. First, the monotonicity assumption implies that the first-stage estimates should be non-negative for any sub-sample (Dobbie, Goldin, and Yang 2018; Bhuller, Dahl, Løken, and Mogstad 2020). To do this, we construct sub-samples with respect to firm size, firm age, sales, sector affiliation, and productivity (labor productivity and AKM effects) measured one year before the application. To perform this test, we still construct the instrument based on the full sample of all available cases. Table 5 shows the results with the first stage coefficient presented in Column (4). As expected under the assumption of average monotonicity, all first-stage (as per Equation (2)) coefficients are positive and statistically significant.

Second, we estimate the propensity to receive a grant status for the patent based on observable characteristics of the firm (Bhuller, Dahl, Løken, and Mogstad 2020; Humlum, Munch, and Rasmussen 2025). Variables include firm size and firm sales measured in deciles, firm age in year dummies, 2-digit sector dummies, credit rating dummies, the legal form, average wages, as well as year and patent offices dummies. With the set of variables, we run a lasso model to predict the outcome of the patent to be granted. Based on these propensities, we separate the sample into three sub-samples and run the first stage regression in each of them. Table 6 shows the first-stage estimates for the three sub-samples with relatively stable first-stage coefficients. The table provides evidence that lenient examiners are more likely to grant patents in sub-samples with low and high probabilities of patents being granted. Taken together, these results support the validity of the monotonicity assumption.

Finally, we implement the test proposed by Frandsen, Lefgren, and Leslie (2023). The authors show that one can relax the strict (pairwise) monotonicity assumption of the original LATE frame-

Table 5: First Stage Results by Sub-Samples

	N	Mean: Granted	Mean: Leniency	Coeff	p-value
	(1)	(2)	(3)	(4)	(5)
Small firm < 10 employees	444	0.692	0.632	0.646	0.000
Big firm > 100 employees	854	0.714	0.656	0.509	0.000
Firm age < 5 years	248	0.678	0.646	0.630	0.008
Firm age > 15 years	2,444	0.722	0.658	0.514	0.000
Sales < p25	831	0.684	0.632	0.614	0.000
Sales > p75	830	0.710	0.652	0.482	0.000
Labor productivity < p25	831	0.690	0.638	0.523	0.000
Labor productivity > p75	831	0.706	0.654	0.808	0.000
Good Credit Index	995	0.720	0.664	0.505	0.000
Bad Credit Index	117	0.650	0.628	0.440	0.233
High AKM firm FE	663	0.736	0.658	0.532	0.000
Low AKM firm FE	1,625	0.712	0.648	0.594	0.000
Manufacturing	1,923	0.736	0.670	0.440	0.000
Retail trade	496	0.742	0.672	0.528	0.000
ICT	109	0.568	0.524	0.968	0.002
Technical service	400	0.626	0.602	0.657	0.000

Notes: All explanatory variables refer to the initial year before the patent application. Each line represents the set of firms for which the condition holds. We regress patent grants on examiner leniency within each sub-group, controlling for examiner fully interacted office-year and Tech.-exp. FE (Eq. 2). p-values calculated based on standard errors clustered at the examiner level.

Table 6: Testing for Monotonicity

	Predicted Probability Percentiles: 1 – 33	34 – 66	67 – 100
	(1)	(2)	(3)
Leniency	0.544	0.378	0.620
p-value	0.000	0.000	0.000
Observations	1,100	1,105	1,118
Mean granted probability	0.566	0.754	0.808
SD	0.496	0.430	0.394

Notes: This table shows first-stage regression results by predicted grant probability sub-samples. The sample is partitioned into 3 sub-samples based on predicted decision to grant a patent, resulting from a lasso model based on predetermined firm characteristics. These characteristics include employment, revenue, productivity, firm age, credit score, legal form, average wages, and sector dummies. Each Column shows the estimated first-stage coefficient including examiner office-by-year FE, and technology FE. p-values calculated based on standard errors clustered at the examiner level.

work to an average monotonicity assumption under which IV still converges to a proper weighted average of treatment effects. Appendix Table B.1 fails to reject the combined null hypothesis that pairwise monotonicity and the exclusion restriction hold.[18]

5.5 Compliance

To provide more insights and learn more about our sample of firms, we calculate the share of always takers, never takers, and compliers by following Dahl, Kostøl, and Mogstad (2014). In our situation, a complier is a firm that would have received a different decision had they been examined by a different examiner. In case of a binary instrument, the share of compliers can be calculated as $E[D_i|Z_i = 1] - E[D_i|Z_i = 0]$ (Abadie 2003). Calculating the share of compliers in

[18] The test for the joint null hypothesis is performed for different numbers of knots and Bonferroni weights using the suggested quadratic spline.

the sample for a continuous instrument is extended by defining the "most lenient", $\bar{Z}$, and the "strictest", $\underline{Z}$, examiner. We approximate $\bar{Z}$ and $\underline{Z}$ examiners by the 2nd and the 98th percentile of the leniency distribution and calculate the share of compliers as $\pi_c = \hat{\gamma}(\bar{Z} - \underline{Z})$, where $\hat{\gamma}$ is the estimated first stage coefficient. Always takers are firms that receive patent allowance regardless of the assigned examiner. Due to monotonicity, the share of always takers can be calculated as $\pi_a = \hat{\alpha} + \hat{\gamma}\underline{Z}$. The share of never takers is calculated as the remaining group of firms. Conditional on firm survival, our estimation suggests that around 25.6% of our sample are compliers, which means that 25.6% of the firms would have obtained different results if assigned to different examiners. Furthermore, 57% are always takers who would receive positive decisions regardless of the assigned examiner. Consequently, 17.4% of the sample consists of never takers.

5.6 Examiner Leniency and Patent Rejection Grounds

In Section 3.2, we outlined the legal bases for patent rejection under the European Patent Convention (EPC). In this section, we examine how examiner leniency correlates with the specific legal provisions cited in rejection decisions. Patent examination involves a degree of subjective interpretation, particularly when assessing claim scope, inventive step, clarity, sufficiency of disclosure, and applicant correspondence. This interpretive flexibility means that examiner discretion can influence outcomes. To assess this relationship, we classify examiners into three categories based on their leniency scores: (i) low leniency (bottom 10th percentile), (ii) moderate leniency (50th–75th percentile), and (iii) high leniency (top 10th percentile). For each group, we identify rejected applications in which the examiner explicitly cites legal grounds, using a targeted web-scraping methodology to retrieve the relevant documentation (see Appendix B.2 for details on the data collection process).

While all examiner groups reference broadly similar legal grounds for rejection, the frequency and emphasis of these citations differ substantially across the leniency spectrum (see Appendix Table B.2). Examiners in the low-leniency group more frequently invoke substantive grounds, such as subject-matter ineligibility (§ 52 EPC), lack of inventive step (§ 56 EPC), and insufficient clarity (§ 84 EPC), indicating a more stringent threshold for patentability. Their decisions often reflect a narrow interpretation of what constitutes a patentable invention, emphasizing technical contribution and novelty. By contrast, examiners with moderate leniency exhibit a more balanced approach. While they continue to enforce core patentability standards (e.g., novelty under § 54 EPC), they also more frequently cite procedural deficiencies, including missed deadlines (§ 121 EPC) and non-compliant amendments (§ 123(2) and (3) EPC). High-leniency examiners rarely issue rejections, and when they do, these are typically grounded in core substantive issues such as novelty, inventive step, or subject-matter eligibility. They seldom invoke procedural grounds, suggesting a more permissive or applicant-friendly interpretation of the EPC's formal requirements.

6 Patent Allowance and Firm Dynamics

This section provides OLS and IV estimation results covering up to six years after the application year. We present estimation results of patent allowance on firm outcomes including market exit, employment, revenue, labor productivity and future patenting activity as well as average wage dynamics.

6.1 Market Exit

The first two Columns in Table 7 present results of patent allowance on financial distress measure by an indictor if the firm experiences credit defaults over the next six years after patent submission. OLS results in Column (1) indicates a 1% point reduction in the default probability. Column (2) shows the IV results confirming the negative impact of winning a patent on the default probability. In line with the discussion on the relevance of the instrument, we observe a strong first stage coefficient with the Kleibergen-Paap F-Statistics rejecting the hypothesis of weak instruments with values of 98. Thus, weak identification issues do not apply in our setting. The identified LATE implies that a patent grant status reduces financial distress by 6.5% points (a discussion on complies is provided in Section 6.5).

This result is consistent with the view that access to finance improves after successful patenting; a result consistent with evidence for innovative activity in general (Bai and Tian 2020) and start-ups in particular (Farre-Mensa, Hegde, and Ljungqvist 2020).[19]

Table 7: Regression Results: The Effect of Patent Allowance on Financial Distress & Exit

	Financial distress		Market exit	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Patent Granted	-0.010**	-0.065**	-0.070***	-0.128**
	(0.005)	(0.031)	(0.011)	(0.061)
F-Statistic		97.71		97.71
Observations	3,323	3,323	3,323	3,323
Dep. var. mean	0.012	0.012	0.07	0.07
Granted	0.710	0.710	0.710	0.710
Office × year FE	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of financial distress and market exit indicators on patent grant six years after the patent application. Financial distress is measured by an indicator variable equal to 1 if the firm experienced bankruptcy and zero otherwise. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year FE, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

As firms are less likely to file for bankruptcy, our results show that successful patent applications impact the probability to exit the market. Table 7 Column (3) shows a negative correlation between the patent granting status and firm exit rates over the next six years post submission. Winning a patent reduces market exit by about 7.0% points. Column (4) shows the IV results

[19] Eisdorfer and Hsu (2011) demonstrate that companies are more likely to go bankrupt if they fall behind competitors in patent competition.

confirming the negative impact of winning a patent on the probability of exiting the market. Similarly, the IV estimates suggest a downward bias in OLS coefficients. Six years after the application, the LATE indicates that the probability of exiting the market reduces by 12.8% points.[20]

Although the market exit variable is based on employment information (economic active firms) and is considered to be of high quality, the estimated coefficients are economically large given the resources invested by firms with and without granted applications. One possible explanation behind these results might be that the exit indicator of unsuccessful firms might be affected by M&A, which could generate artificial firm exits. According to the M&A literature, R&D-intensive firms with slow growth in patent output are more likely to be target firms (Bena and Li 2014 and Sevilir and Tian 2012). Therefore, we examine whether patent allowance has an impact on M&A events. For this, we are able to measure three different types of M&A events: (i) minority acquisition, (ii) majority acquisition of existing and new owner, (iii) profit take-over agreements and merger contracts. Appendix Table B.4 presents the IV results. The estimates do not provide evidence that patent allowance affects variables capturing M&A events. If anything, we document a positive coefficient on the probability that new owners with a majority share enter the firm if the patent application was successful. Therefore, M&A activity is unlikely to explain the exit results.

6.2 Employment & Revenue Dynamics

Employment. Table 8 reports the effect of patent allowance on firm size, measured as average employment over the six years following the initial patent application. Columns (1) and (2) present results for all workers, while Columns (3) and (4) focus on full-time employees.

The OLS estimates in Columns (1) and (3) suggest a small positive relationship between patent allowance and firm size; however, these effects are statistically insignificant. The IV estimates in Columns (2) and (4) are close to zero and likewise statistically insignificant. Taken together, the results provide no evidence that patent allowance leads to an expansion in employment, either along the extensive margin (total workforce) or when restricting the sample to full-time employees.

Figure 4 complements these findings by presenting dynamic estimates of employment effects before and after patent submission. (Results for full-time employees are shown in Appendix Figure B.3). First, consistent with the identification strategy, the IV estimates (blue dots) exhibit no systematic differences prior to the patent application, supporting the absence of pre-trends. Second, post-submission coefficients remain close to zero and statistically insignificant throughout the observation window. Finally, the figure presents difference-in-differences IV estimates (in blue in the lower right corner), constructed by comparing average employment levels before and after the application year by stacking both observations for each firm. The coefficient is estimated to be close to zero and statistically insignificant. Overall, the evidence consistently indicates that patent allowance has no effect on firm size.

[20] For robustness, we provide IV probit results in Appendix Table B.3, confirming the causal effects of patent allowance on financial distress and market exit. For reasons of convergence, we reduce the high number of fixed-effects in the IV-probit specification by excluding fully interacted office time year FE. Sector FE are aggregated for cells with low occupancy.

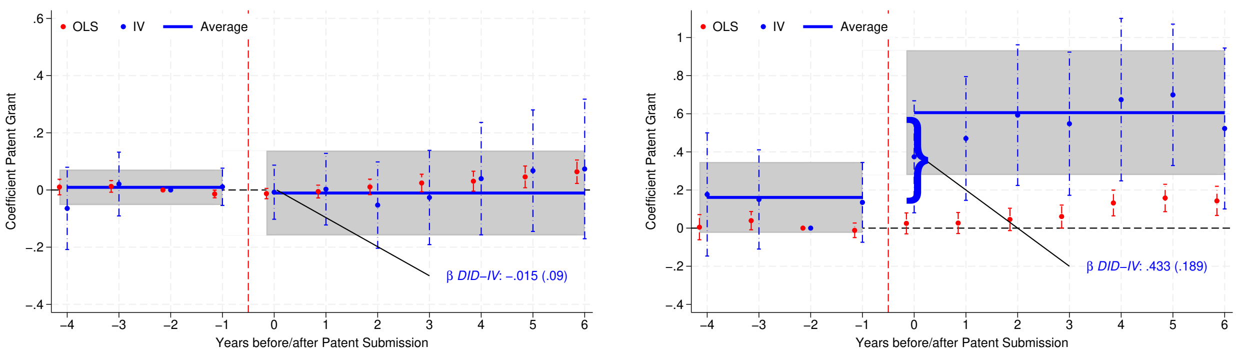
Table 8: Regression Results: The Effect of Patent Allowance on Employment & Revenue

	Log Employment				Log Revenue			
	All workers		Full-time		Mean		Aggregate	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patent Granted	0.020	-0.011	0.021	0.006	0.072**	0.606***	0.085**	0.669***
	(0.016)	(0.090)	(0.017)	(0.095)	(0.032)	(0.199)	(0.034)	(0.209)
F-Statistic		87.18		87.21		84.41		84.41
Observations	3,034	3,034	3,034	3,034	3,024	3,024	3,024	3,024
Dep. var. mean	4.074	4.074	3.942	3.942	16.492	16.492	18.376	18.376
Granted	0.728	0.728	0.728	0.728	0.728	0.728	0.728	0.728
Office × year FE	✓	✓	✓	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of (log) average employment of all workers and full-time workers, and (log) average and aggregate revenue during the six years post patent application on patent grant. Aggregate indicates the sum of revenue over the post-application period from year one to six. Columns (1) and (2) report (log) employment results based on all workers. Columns (3) and (4) report (log) employment results based on full-time workers. Columns (5) to (6) report results on average (log) revenue, and Columns (7) and (8) report the results on (log) aggregate revenue. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

Figure 4: Employment Dynamics before/after Patent Submission

(a) Employment (b) Revenue



Notes: The figure shows estimation results along with 95% confidence intervals of the effect of a patent allowance on (log) employment and (log) revenue four years before and six years after the patent application. Panel (A) provides results measuring employment by all employed workers. Panel (B) provides results on revenue. Red dots and blue dots represent OLS and IV estimates, respectively. In Panel (A) the solid blue horizontal lines show IV results on average employment before and after the submission of the patent application. In Panel (B) the solid blue horizontal lines show IV results on average revenue before and after the submission of the patent application. Results are normalized to two years before the patent submission.

Workforce Composition. Although patent allowance does not affect overall employment levels, it may still influence the composition of the workforce through selective hiring or separation. Such compositional changes could, in principle, other outcome variables such as survival, productivity, and wages if firms disproportionately retain or attract more skilled workers.

Appendix Table B.5 examines this mechanism by reporting IV estimates of the effect of patent allowance on hiring and job separation across occupational groups, including managers, technicians, administrative staff, service workers, and manual workers. Panel A focuses on hiring probabilities, while Panel B considers job separation. Across all specifications, we find no statistically significant differences in hiring or separation patterns between firms with successful and unsuccessful patent applications. Moreover, Column (7) shows no differential effect on workers' estimated AKM person effects, based on the measures provided by Lochner, Seth, and Wolter (2023). This further indicates that firms do not systematically upgrade worker quality following a successful patent application.

Revenue. Columns (5)–(8) of Table 8 report the effect of patent allowance on firm revenue using two alternative measures. First, we consider average firm revenue over the post-treatment period (in logs). Second, we construct aggregate revenue by summing revenues over the same period and then taking logs.

The OLS estimates in Columns (5) and (7) indicate a positive and statistically significant association between patent allowance and revenue, with coefficients of 0.072 and 0.085 log points, respectively. In contrast, the IV estimates in Columns (6) and (8) are substantially larger and highly statistically significant. These results imply that patent allowance leads to sizable increases in firm revenue. The somewhat larger effect on aggregate revenue suggests that these gains accumulate over time, pointing to dynamic effects following a successful patent application.

The gap between OLS and IV estimates is considerable, indicating a downward bias in the OLS results. One potential reason for the downward bias of the OLS estimates is that firms with lower growth dynamics are more likely to receive a grant status on their submission as documented in Table 3 (Columns 1 and 2).

Panel B of Figure 4 complements these findings by presenting dynamic IV estimates before and after the patent application. The pre-treatment coefficients are small and statistically insignificant, providing no evidence of differential trends prior to treatment. Following the patent application, the IV estimates turn positive and gradually increase, peaking around four years after treatment. While the pre-treatment coefficients are not precisely zero, their average remains small and statistically insignificant (approximately 0.17 log points). The implied difference-in-differences IV estimate is about 0.43 log points, reinforcing the conclusion that patent allowance leads to substantial and persistent increases in firm revenue.

6.3 Productivity Dynamics

Due to the lack of data on capital and firm-level inputs, we are unable to compute total factor productivity (TFP) at the firm level. Instead, we rely on two proxy measures of productivity. First, we measure labor productivity as the ratio of revenue to employment. Second, we capture firm-level productivity through future innovative activity, measured by patenting behavior over the six years following the initial patent application.

Table 9 reports OLS and IV estimates of the effect of patent allowance on these productivity measures. Columns (1)–(4) present results for log labor productivity, distinguishing between mean and aggregate measures. Columns (5)–(8) report results on future patenting activity. Specifically, Columns (5) and (6) examine the number of patent applications filed (transformed using the inverse hyperbolic sine transformation), while Columns (7) and (8) focus on the number of patents granted within six years of the initial application.

Table 9: Regression Results: The Effect of Patent Allowance on Firm Productivity Measures

	Log Labor Productivity				Future Patenting			
	Mean		Aggregate		All submissions		Granted applications	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patent Granted	0.052*	0.607***	0.065**	0.671***	0.161***	0.391*	0.186***	0.378**
	(0.029)	(0.190)	(0.031)	(0.197)	(0.038)	(0.219)	(0.029)	(0.173)
F-Statistic		84.41		84.41		87.18		87.18
Observations	3,024	3,024	3,024	3,024	3,034	3,034	3,034	3,034
Dep. var. mean	12.418	12.418	12.356	12.356	1.784	1.784	0.982	0.982
Granted	0.728	0.728	0.728	0.728	0.728	0.728	0.728	0.728
Office $\times$ year FE	✓	✓	✓	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of (log) average and aggregate labor productivity and future patenting activity during the six years post patent application on patent grant. Labor productivity is calculated by revenue over employment. Aggregate indicate the sum of revenue and employment over the post application period. Columns (1) to (4) report results on labor productivity. Outcome variables in Columns (5) and (6) are actual numbers of patent applications transformed by the inverse hyperbolic sine transformation. Outcome variables in Columns (7) and (8) are actual numbers of granted patent applications transformed by the inverse hyperbolic sine transformation. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

The results indicate that obtaining a first patent leads to a significant increase in both firm productivity and subsequent innovation. Focusing first on labor productivity, the OLS estimates in Columns (1) and (3) show a positive and statistically significant association between patent allowance and log labor productivity, with coefficients of 0.052 and 0.065, respectively. Again, IV estimates in Columns (2) and (4) are substantially larger—0.607 and 0.671, respectively—and highly statistically significant. These coefficients imply economically large effects, indicating that patent grants causally increase firm productivity. The consistency of these results across both mean and aggregate measures suggests that the effect is not driven by short-term fluctuations, but reflects a sustained improvement in firm performance, as indicated by Appendix Figure B.4 that provides the results at the yearly level before and after the patent submission.

Turning to future innovation outcomes, the OLS estimates in Columns (5) and (7) show a positive and statistically significant association between patent allowance and subsequent patenting activity. The IV results confirm a causal interpretation of this relationship. Quantitatively, the IV estimate in Column (6) indicates that firms receiving their first patent experience a substantial increase in subsequent patent applications. Similarly, Column (8) shows that successful initial applicants also obtain significantly more granted patents in the following years.

Overall, the findings suggest that patent success enhances both firm productivity and innovative activity. The substantially larger IV estimates relative to OLS point to the presence of attenuation or selection biases in the OLS specifications. Moreover, the stronger effects on revenue-based productivity compared to employment are consistent with the interpretation that patent protection primarily boosts firm performance through increased revenues rather than workforce expansion.

An important question related to patenting activity is whether firms' subsequent patent applications are primarily strategic, aimed at protecting their initial inventions. Prior research suggests that patents driven by strategic motives—such as blocking, exchange, or portfolio expansion—tend to receive fewer forward citations, reflecting a more limited contribution to subsequent innovation and the clustering of patents around a core technology (Blind, Cremers, and Mueller 2009).

We provide descriptive evidence on this issue in Appendix Figure B.5, which compares the technological proximity of future patent applications to the initial one. Specifically, we compute the share of assignees whose subsequent patents fall within the same IPC class as the initial application, as well as the share entering entirely new IPC classes. The figure shows that approximately 40% of firms continue to patent within their original technology class, with no meaningful differences between firms whose initial applications were granted and those whose applications were rejected.

Further evidence is provided in Appendix Table B.6, which examines self-citations and forward citations of new applications. The IV estimates (conditional on future patent submissions) reveal no differential effects in citation patterns that would be consistent with increased strategic patenting. If anything, the probability of self-citing the initial patent declines by around 10 percentage points, while the total number of citations received increases by approximately 38%.

Taken together, these findings provide little support for the view that firms with successful initial patent applications engage more intensively in strategic follow-on patenting. Instead, the evidence is more consistent with genuine increases in innovative activity.

6.4 Wages Dynamics

As successful innovation increases both firm revenue and labor productivity, a natural question is whether these gains are shared with workers in the form of higher wages.

Table 10 reports the effect of patent allowance on firm-level wages, distinguishing between all workers and firm stayers. Columns (1) and (2) present results for the full workforce, while Columns (3) and (4) restrict the sample to employees who remain with the firm over the observation period. The OLS estimates in Columns (1) and (3) indicate a positive and statistically significant association between patent allowance and wages. For all workers, a granted patent is associated with an increase in wages of approximately 1.6%, while for firm stayers the corresponding estimate is 1.5%.

The IV estimates are substantially larger in magnitude. Column (2) shows that, for all workers, obtaining a patent increases wages by about 6.1%, while Column (4) reports an increase of 5.7% for firm stayers. The similarity of the effects across both groups suggests that wage gains are broadly shared within firms and are not solely driven by worker composition or turnover.

Figure 5 complements these findings by presenting dynamic treatment effects before and after patent submission using a difference-in-differences IV framework. The pre-treatment coefficients are small and statistically insignificant, indicating no evidence of differential wage trends prior to the patent application and supporting the validity of the identification strategy. Following submission, wages increase gradually for firms with successful applications. The average post-

Table 10: Regression Results: The Effect of Patent Allowance on Wages

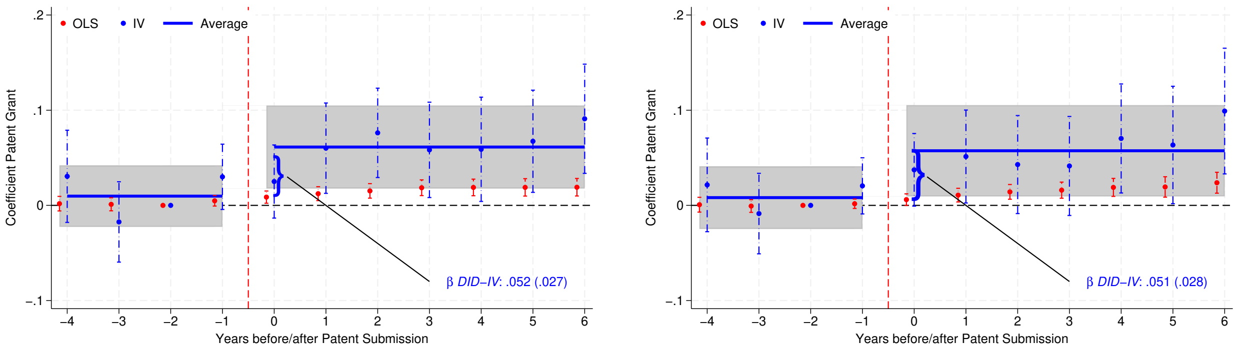
	All workers		Firm Stayer	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Patent Granted	0.016***	0.061**	0.015***	0.057**
	(0.004)	(0.027)	(0.005)	(0.029)
F-Statistic		87.30		87.18
Observations	3,034	3,034	3,034	3,034
Dep. var. mean	4.71	4.71	4.786	4.786
Granted	0.728	0.728	0.728	0.728
Office × year FE	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of (log) average real daily wages among full-time employees during the six years post patent application on patent grant. The first two Columns report results based on all workers. The last two Columns report results based on firm stayers. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

submission DID-IV effect amounts to approximately 5.2% for both all workers and firm stayers, reinforcing the conclusion that patent-induced productivity gains translate into meaningful wage increases.

Figure 5: Wage Dynamics before/after Patent Submission

(a) All Workers (b) Stayer



Notes: The figure shows estimation results along with 95% confidence intervals of the effect of a patent allowance on (log) real daily wages among full-time workers four years before and six years after the patent application. Panel (A) provides results measuring wages for all employed workers. Panel (B) provides results measuring wages for firm stayer. Red dots and blue dots represent OLS and IV estimates, respectively. The solid blue horizontal lines show IV results on average wages before and after the submission of the patent application. Results are normalized to two years before the patent submission.

Wages by Worker Inflows. Appendix Table B.7 reports IV estimates using average wages of newly hired workers as the outcome variable. Column (1) shows that patent allowance has a positive and statistically significant effect on the wages of new hires, indicating that wage gains are not limited to incumbent employees. Importantly, this effect does not appear to be driven by changes in worker composition through the hiring of higher-quality workers. Column (7) of Appendix Table B.5 shows no statistically significant impact of patent allowance on the average AKM person effect, suggesting that firms do not systematically upgrade worker quality following a successful patent application.

Consistent with this interpretation, Column (2) of Appendix Table B.7 examines the wage share—defined as the ratio of average wages of new hires to those of incumbent workers. The estimated effect is small and statistically insignificant, indicating that wages increase proportionally for both groups. Taken together, these findings suggest that the wage gains associated with successful patenting are broadly shared across workers rather than being concentrated among incumbents. This contrasts with evidence from the U.S., where Kline, Petkova, Williams, and Zidar (2019) find that wage gains from successful patenting accrue primarily to incumbent workers, with no effects for new hires.

Selective Outflow. Appendix Table B.8 investigates whether the observed wage increases are driven by changes in workforce composition rather than genuine wage growth. In principle, average wages could rise if lower-paid workers are more likely to leave the firm, thereby mechanically increasing the average wage of the remaining workforce. However, we find no evidence supporting this mechanism. Specifically, patent allowance has no statistically significant effect on the outflow of low-wage workers, whether defined relative to the median wage or the firm-specific average wage. This suggests that the estimated wage increases reflect genuine improvements in worker compensation rather than compositional changes in the workforce.

6.5 Potential Outcomes

The IV estimates represents a local average treatment effect (LATE) among compliers, i.e., firms that would have received a different decision had they been examined by a different examiner. To better understand this LATE, we follow the work of Imbens and Rubin (1997) and Dahl, Kostøl, and Mogstad (2014) and applied more recently in Bhuller, Dahl, Løken, and Mogstad (2020) to decompose the IV estimates into the average potential outcomes if the compliers would have been granted and if they would have been rejected. Based on the estimated sample shares of compliers, always takers and never-takers, we can calculate average outcomes by treatment status and instrument ("most lenient"/"strictest"). For example, $E[Y_i|D_i = 1, Z_i = most\ \ lenient]$ consists of average outcomes of always takers and compliers. With this logic, we calculate average outcomes of compliers, i.e., $E[Y|D = 0, \text{Complier}]$ and $E[Y|D = 1, \text{Complier}]$.

Table 11 reports revenue, employment, and real daily wages among compliers. Columns (1) to (3) in the upper panel show the results averaging over the six years post submission. Columns (4) to (6) report the results with revenue, employment, and wage information at year six after patent submission. For example, $(E[Rev|D = 0, Complier])$ reveals average revenues for firms that did not win a patent, whereas $(E[Rev|D = 1, Complier])$ are revenue numbers for complier firms winning a patent. The difference shown in Column (3) indicates that revenue increases by 10.6 million Euros – an increase of 86% – if the firm wins the patent. With only minor differences in average firm size, average revenue per employee increases due to patent allowance by about 218 thousand Euros.[21]

[21]Exit rates among compliers that win a patent are 1% six years after the application. The rejection of the patent causes market exit. Six years after treatment, the share of firms that exit the market is around 12%.

Table 11: Potential Outcomes | Complier

	Average during six years post submission			At year six post submission		
	$E[Y\|D=1]$	$E[Y\|D=0]$	Δ	$E[Y\|D=1]$	$E[Y\|D=0]$	Δ
	(1)	(2)	(3)	(4)	(5)	(6)
Revenue	22,86m	12,28m	10,57m	22,14m	12,91m	9,23m
Firm size	50.73	52.80	-2.08	48.47	47.29	-1.17
Rev./head	450,710	232,672	218,037	456,796	272,870	183,925
Daily wages	131.19	122.54	8.64	143.34	127.73	15.60
W.-bill/head	34,109	31,860	2,249	37,074	33,212	3,861
Rent sharing elasticity			0.103			0.213

	Difference-in-differences IV				
	$E[Y\|D=1, pre]$	$E[Y\|D=0, pre]$	$E[Y\|D=1, post]$	$E[Y\|D=0, post]$	DID-IV
Revenue	14,09m	11,60m	22,86m	12,28m	8,09m
Firm size	32.83	33.84	50.73	52.80	-1.06
Rev./head	327,293	283,614	450,710	232,672	174,359
Daily wages	116.05	114.01	131.19	122.54	6.61
W.-bill/head	29,456	29,222	34,109	31,860	2,015
Rent sharing elasticity					0.110

Notes: The table shows potential outcomes of revenue, employment, revenue per worker, daily wages, and the wage bill per worker for firms that win a patent and firms that receive a rejection among the group of compliers. The strictest and the most lenient examiner are approximated by the 2nd and 98th percentile of the leniency distribution.

Average real daily wages increase by 8.64 Euros indicating an increase of about 1 Euro per hour (assuming 8 hours per day). With these estimates we calculate the wage bill per employee by multiplying daily wages times 260 working days per year. The differential wage bill per workers $E[WageBill(1) - WageBill(0)|\text{Complier}]$, therefore, amounts to around 2,249 Euros.

The increase in wages relative to the increase in labor productivity represents our estimated rent sharing elasticity. Our results imply a rent sharing elasticity of 0.10, indicating that a 10% increase in labor productivity increases average wages by 1%. Following the same logic for revenue, employment, and wages at year six post application, the rent sharing elasticity estimate increases to 0.21. This is because wage responses take time and are not visible during the early years after patent submission.

Similarly, the lower part of the table shows rent sharing parameters following the difference-in-differences approach. Although statistically insignificant, taking into account pre-submission differences in outcomes generates a rent sharing elasticity estimate of 0.11.

6.6 Heterogeneity Results

This section presents heterogeneity results by firm and patent characteristics.

Product vs Process Innovations. Documented firm dynamics might be driven by the invention of new products and/or new processes. Tham, Baslandze, Liu, and Sojli (2026) found that both product and process innovations significantly improve firm performance in terms of profits, sales, and TFP, whereas Bena, Ortiz-Molina, and Simintzi (2022) showed that the role of process innovation sustains or increases output by improving production efficiency and lowering costs.

Aligned with the literature, Panel A of Appendix Table B.9 distinguishes the sample of firms with successful innovations into product or process innovations following the methodology proposed by Heinrich, Seliger, and Wörter (2022).[22] Panel A shows that both types of innovations exhibit higher revenue and labor productivity growth with slightly more pronounced point estimates for process innovations in the case of wages.[23]. This generates higher rent sharing elasticities of around 0.33 for process innovations vs. around 0.14 for product innovations at year six after the patent submission (see Appendix Figure B.6).

Legal form. Panel B of Table B.9 distinguish the sample by the legal form of the firms. We provide results for stock corporations and non-traded firms, which mainly consist of limited liability companies (LLCs). German LLCs differ from the U.S., as the shares cannot be traded on a stock exchange.[24] Gottschalk, Hauer, and Ahrens (2023) provide average statistics on family-owned businesses by legal firm types. Following these estimates, LLCs are typically characterized as family businesses. The share corresponds to around 80% of the firms being family-owned. In contrast, 27% of stock companies are family-owned. Family-owned businesses represent a typical business model in Germany, persist across the firm-size distribution, and maintain a distinctive labor relations culture. These firms are characterized by higher workforce attachment (Rammer and Spielkamp 2019, Schenkenhofer 2022), commitment to job security (Kölling 2020, Sommer 2023), active engagement in workforce development (Gottschalk, Hauer, and Ahrens 2023, Schenkenhofer 2022, Rammer and Spielkamp 2019, Simon 2009), close relationships between owner-managers and employees (Kölling 2020, Schenkenhofer 2022), and strong internal cohesion (Rammer and Spielkamp 2019, Simon 2009). Thus, we argue that differentiating firms by their legal form serves as a proxy for differential employer-employee relationships and provide insight into institutional determinants.

The results in Panel B indicate that both firm types, LLCs and stock corporations experience a boost in revenue and labor productivity dynamics, with employment responses being insignificant. For stock corporations, point estimates on revenue and productivity turn slightly higher but are relatively imprecisely estimated due to low sample size. In terms of wages, however, only LLCs are observed with wages improvements. If anything, the coefficient of patent grant on wages for stock corporation turn negative. This implies, on average, negative rent sharing estimates for stock corporations and slightly higher rent sharing estimates for family-oriented businesses compared to the baseline numbers of 0.21 (see Appendix Figure B.6).

[22] Heinrich, Seliger, and Wörter (2022) classify patents into product, process, and mixed innovations using claim-based information, but the coverage of their classification declines after 2010. To ensure complete coverage of the patents in our sample, we train a supervised machine learning model (DistilBERT) using patent titles and abstracts as inputs, while employing the claim-based classifications from the authors as labels. We then apply this trained model to the titles and abstracts of unclassified patent. The model achieves an overall accuracy of 83%.

[23] This results potentially highlights the role of lowering marginal costs after implementing process innovations (Aghion, Akcigit, Hyytinen, and Toivanen 2024)

[24] Non-traded corporations consist of single-owned companies, limited partnerships, and limited liability companies. In our sample, 78% of the firms are *GmbHs* and 17% are *GmbH & Co KGs*. Stock corporations include associations. Associations are organized, represented and managed by an executive board. The board is elected by the members of the association. In contrast to stock corporations, the executive board is controlled by the General Assembly of Members. In our sample of corporations and non-partnerships, 90% of the firms are stock corporations.

Industry Affiliation. Panel C of Table B.9 provides further results differentiating for firms in the manufacturing sector – in which 50% of the sample consists of – and all other sectors. Revenue responses and subsequent productivity improvements are estimated to be lower for manufacturing firms. However, wage responses are more pronounced, leading rent sharing estimates of 0.3 in the manufacturing sector (see Appendix Figure B.6).

Follow-On Patenting. Panel D of Table B.9 provides the results based on future patenting events (we acknowledge that this is conditioning on future outcomes). Both type of firms show similar dynamics for revenue and labor productivity improvements. Positive wage dynamics are documented to be more pronounced for firms with follow-on patenting, generating rent sharing estimates of more than 0.35 compared to around 0.12 for firms without further patenting activity (see Appendix Figure B.6).

Assigning Zero for Exiting Firms. Finally, we provide a way of taking into account differential exit rates by assigning a zero for revenue, employment and wages in the year the firms is exiting the market and beyond (Appendix Table B.10). All point estimates increase in magnitude which results in substantially higher rent sharing elasticities of up to 0.3 six years post submission. The reason for this increase is partly due to higher wages payments relative to revenue per worker figures.

7 Patent Allowance and Worker-Level Dynamics

7.1 Wages Dynamics

Wages. In this section, we provide worker-level evidence distinguishing by demographic characteristics and, in particular, by tasks performed on the job. Before digging into different subsamples, we provide results using the pooled worker sample to confirm estimation results at the firm level. Panel A of Appendix Figure B.7 shows OLS and IV results of patent allowance on log real daily wages for the pooled sample of all full-time workers who stay in the same firm over the entire period. In each specification, we additionally control for workers initial wage level. The results confirm the presented results using average firm wages in Figure 5, i.e., patent allowance increases wages by about 6% with stronger results towards the end of the observation window. Interestingly, Panel B confirms the results by using a two-sample approach estimating the first stage at the firm level and using predicted values in the second stage at the worker level.

Average wage responses might alter different benefits for different groups of employees. One first candidate to distinguish the workforce is the gender dimension. The literature on gender differences in rent sharing shows that males typically receive higher rents, which is one reason for observed gender wage gaps (Card, Cardoso, and Kline 2016). Kline, Petkova, Williams, and Zidar (2019) show that earnings of male workers increase in response to patent allowance, whereas the earnings of female workers do not. Similar to the findings from the U.S., our estimates show that male wages increase in response to patent allowance by 12.2%. The point estimate among female workers turn insignificant (Column (2) of Appendix Table B.11).[25]

We further take advantage of the richness of the data and provide estimation results by occupational groups, differentiating between manual and service tasks, technicians, administrators, and managers. We provide results based on the fully nested IV specification in Panel A of Table 12. F-Statistics turn reasonable high among all five groups but manual tasks with a F-Statistics of 5.7. For this reason, we provide results based on the two-sample 2SLS approach running the first stage using the full firm sample and predicted values in the second stage (Panel B). In this setting, we provide clustered bootstrapped 90% CI in squared brackets.

Table 12: Regression Results: The Effect of Patent Allowance on wages by Occupations

	Six Years after Patent Application				
	Manual task (1)	Service task (2)	Technicians (3)	Administration (4)	Manager (5)
Panel A: IV Results					
Patent Granted	0.216*	0.024	0.174**	0.069**	0.165*
	(0.121)	(0.036)	(0.072)	(0.033)	(0.093)
F-Statistic	5.782	40.88	15.98	58.99	15.84
Panel B: 2S2SLS Results					
Patent Granted	0.121***	0.036	0.157***	0.106**	0.158**
	(0.040)	(0.054)	(0.050)	(0.050)	(0.078)
	[0.035;0.193]	[-0.07;0.121]	[0.05;0.244]	[-0.02;0.174]	[0.022;0.331]
Observations	94,707	24,691	20,520	32,827	4,871
Dep. var. mean	4.63	4.508	4.944	4.804	5.116
Granted	0.776	0.76	0.746	0.694	0.686
Office × year FE	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows IV and 2S2SLS regression results of log real daily wages on patent grant six years after the patent application among incumbent workers initially employed in the firm differentiated by occupational groups. Panel A shows the IV results. Panel B shows the 2S2SLS results. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. Squared brackets indicate 90% bootstrap CI clustered at the examiner level using 1,000 replications. *p<0.1, **p<0.05, ***p<0.01.

In contrast to US evidence – where only higher-level employees benefit in terms of wage gains[26] – our results in Table 12 show that patent allowance significantly raise wages across occupational groups except for service tasks.[27] The strongest impact is observed for the group of technicians, who are most likely among the inventors of the technology, and managers with point

[25] In addition to gender differences, Appendix Table B.11 shows that younger workers aged below up to 30 years have slightly higher point estimates (0.15 vs 0.10 log points for age groups above 30), consistent with Aghion, Akcigit, Hyytinen, and Toivanen (2024) who document that younger workers receive significantly higher post-invention wage premia than their senior counterparts. Point estimates by nationality are rather similar. Finally, our results show that wages for workers with a vocational degree respond strongest with slightly negative and insignificant point estimates for workers without a formal education (Columns (8)-(10) of Appendix Table B.11). The two-sample approach in Panel B delivers quantitatively similar results.

[26] Kline, Petkova, Williams, and Zidar (2019) find significant disparities in earnings responses: gains are concentrated among inventors and top-quartile earners within firms. Based on a conditional a differences-in-differences approach, Aghion, Akcigit, Hyytinen, and Toivanen (2018) have found that both inventing and non-inventing coworkers and entrepreneurs benefit from innovation, although the entrepreneurs capture the largest share.

[27] Appendix Table B.12 shows results for one to six years post patent submission.

estimates around 0.16 log points.[28]

Bonus Payments. Daily wages in the data consist of permanent wages and potential bonus payments, such as end-of-year payments or other non-regular compensation payments. Paying bonuses might be a flexible way to compensate employees.[29] Panel A of Appendix Table B.14 shows the results of patent allowance on a dummy variable equal to 1 if the employee received a bonus payment in a given year and zero otherwise. In Panel B, we show the results calculating the bonus share as the Euro value of bonus payments relative to the total. In both cases, patent allowance does not impact the probability of bonus payment nor the share of bonus payments. This suggests that wages responses are driven by permanent wage increases.

7.2 Employment Stability

In addition to higher wage growth, workers may also benefit from increased employment stability. To address the question of whether patents impact the probability of future employment, we define a dummy variable equal to 1 if the worker who was initially employed at the firm remains employed (in the same firm or in any other firm).

In our sample, on average, about 82% of employees remain employed six years after the initial patent submission. Appendix Table B.15 shows the employment results by occupational groups. Across all groups, except administrative workers, the probability of being employed is unaffected by the patent allowance status. Administrative workers, however, are around 5.1% points more likely to be employed.

7.3 Robustness Checks

A main concern when analyzing wages based on social security data is the fact that raw wage information are right-censored at the social security limit. This might be a concern, in particular, for managers, as this group earns relatively high wages from the onset. For this reason, we provide robustness checks in Appendix Table B.16. Panel A specifies the outcome variable equal to one if wages earned six years post patent application are above the censoring limit and zero otherwise. The probability of becoming censored in the data is not affected by the patent grant status. Next, Panel B conditions the sample on workers initially earning below the censoring limit with similar results across the six occupational groups.

[28] According to the *Employee Inventions Act (1957)* in Germany, employees are required to report any innovation they develop during their employment to their employer. If the employer claims the invention, the employee is entitled to adequate and reasonable compensation. This regulation is supposed to benefit both parties: employers gain access to valuable innovations, and inventors receive appropriate recognition and financial rewards for their contributions. Our sample consists of firms being the assignees of the patents, which, according to the act, indicates that a claim of the employer for the invention has been taken place. In contrast, if the employer waives the claim, the employee is free to use the invention independently. However, issues such as unclear compensation guidelines, payment delays, and challenges in equitable compensation distribution among co-inventors often lead to disputes (Brockhoff 1997). Comparable legal regulations exist in Denmark, Finland, Norway, and Sweden, and other European countries have their own national patent laws governing employee innovations. In contrast, there are no legal requirements for inventor compensation in the U.S. and Canada (Harhoff and Hoisl 2007).

[29] Bonus payments represent a small fraction of wages with around 2.5% of workers on our sample receive such payments.

A second concern arises from potential working time adjustments. If employees in firms with rejected patents are more likely to reduce working hours, positive wage effects might reflect working time adjustments rather than true wage gains. The worker-level data contains information on part-time employment. Appendix Table B.17 provides the results analyzing the probability of part-time employment six years post patent submission across the occupational groups. We find no evidence of significant working-time adjustments for most occupations. The only exception is administrative workers, whose probability of transitioning from full-time to part-time employment increases slightly by 4.2% points, which would downward bias results on wage payments.

Lastly, we provide results on wages for movers at the time of the new job in Appendix Table B.18. Albeit sizable coefficients among technicians, administrative workers and manager, wages among movers do not significantly differ between workers from firms with granted vs non-granted patents.

7.4 Heterogeneity by Firm Types

A striking result at the firm level is the observation that wages in stock companies are, on average, not affected by patent grant status. We provide further evidence on wages across the occupational groups by the type of firms in Appendix Table B.19.[30] Most interestingly, management compensation is particularly pronounced among stock corporations, which holds also true for workers in manual task occupations (Panel B).[31] Point estimates among technicians and service employees in stock companies even turn negative and insignificant. Part of the increase in wages among managers in stock corporations is driven by bonus payments, as shown in Panel B of Appendix Table B.21. The management staff in stock corporations is also positively effected in terms of employment. Successful patent allowance substantially increases their employment probability by around 20% points (Panel B of Appendix Table B.23).[32]

In terms of sector difference, Panels C and D of Appendix Table B.19 show that managers and administrative workers have slightly more pronounced and more precisely estimated point estimates in non-manufacturing sectors (primarily in retail trade, technical services and ICT). The baseline results among manual task workers is driven by manufacturing firms.

Panels E and F of Appendix Table B.19 differentiate by product and process innovations. Except for managers, wage increase are found to be relatively similar. Managers, however, experience higher wage gains when the patent is a process innovation.

These results suggest that the organizational structure of the firm and the type of the new technology rewards different groups differently. Businesses that can be classified as more family-

[30] The table provides full nested IV results at the worker level. Results based on the two sample approach using the firm level in the first stage is shown in Appendix Table B.20. Appendix Table B.22 and Appendix Table B.24 show the results for bonus shares and employment probabilities, respectively.

[31] Appendix Tables B.25 and B.26 provide the results on wages for each year since the patent application for non-traded firms and stock corporations, respectively. For managers in stock corporations, wages start to increase after year two. In non-traded firms, we observe significant estimates for technicians and manual workers from year three onward. Manager wages turn significant in year six.

[32] These results are not driven by the fact that stock corporations differ in size or sector composition. Appendix Table B.27 shows the results for limited liability companies, re-weighting the regressions to mimic stock corporations in terms of employment size, revenue, average wages, sector composition, and year and office of patent submission. Point estimates decrease slightly but remain at similar levels suggesting that differences in observables among the two groups do not drive the findings.

oriented in the manufacturing sector seem to benefit not only the management but also lower-level wage jobs. Stock companies direct a larger proportion to their management.

8 Conclusion

This paper provides estimates of how patent-induced shocks impact firm performance and affect worker-level wages and employment stability using a new linkage of patent applications of German firms with social security data. Based on an examiner-IV design, exploiting patent examiner preferences for patent allowance, we show that successful applications significantly enhance firm survival, productivity, and wage payment to its employees. Our baseline estimates suggest that an increase in revenue per worker by 10% increases earnings by 1%. With these estimates, we provide new causal evidence that idiosyncratic variability in firm performance is central for worker compensation. We further show that not only incumbent workers benefit but also new hires experience higher wages when entering firms with successful patent applications. This suggests that inequality between incumbent workers and new hires is not amplified due to higher firm productivity.

Our estimated rent sharing elasticities are substantially lower compared to similar empirical settings in the U.S., where Van Reenen (1996) and Kline, Petkova, Williams, and Zidar (2019) show elasticities of approximately 0.5. In the German context and in stark contrast to worker-level evidence from the U.S., we document that wage gains are broadly shared across the different task spectrum.

Our results are heterogeneous across institutional characteristics of firms and by the type of inventions. In particular, our results provide evidence that institutional characteristics have differential effects on the distribution of economic rents. Consistent with higher levels of employer-employee relations, we show that family-oriented private businesses, as compared to stock corporations, benefit low- and medium-wage employees. Managers in stock corporations are among the group who gain the most, with part of the wage increase coming from bonus payments. Therefore, our study emphasizes the pivotal role of innovation in driving firm competitiveness and economic growth, while also contributing to a more nuanced understanding of how the benefits of productivity shocks are distributed among different types of workers and firms.

Bibliography

Abadie, A. (2003): "Semiparametric instrumental variable estimation of treatment response models," *Journal of Econometrics*, 113(2), 231–263.

Abowd, J. M., F. Kramarz, and D. N. Margolis (1999): "High wage workers and high wage firms," *Econometrica*, 67(2), 251–333.

Abowd, J. M., and T. Lemieux (1993): "The effects of product market competition on collective bargaining agreements: The case of foreign competition in Canada," *The Quarterly Journal of Economics*, 108(4), 983–1014.

Abowd, J. M., K. L. McKinney, and N. L. Zhao (2018): "Earnings inequality and mobility trends in the United States: Nationally representative estimates from longitudinally linked employer-employee data," *Journal of Labor Economics*, 36(S1), S183–S300.

Acemoglu, D., A. He, and D. le Maire (2022): "Eclipse of rent-sharing: The effects of managers' business education on wages and the labor share in the US and Denmark," NBER Working Paper 29874, National Bureau of Economic Research.

Agan, A., J. L. Doleac, and A. Harvey (2023): "Misdemeanor prosecution," *The Quarterly Journal of Economics*, 138(3), 1453–1505.

Aghion, P., U. Akcigit, A. Hyytinen, and O. Toivanen (2018): "On the returns to invention within firms: Evidence from Finland," *AEA Papers and Proceedings*, 108, 208–212.

——— (2024): "A year older, a year wiser (and farther from frontier): Invention rents and human capital depreciation," *Review of Economics and Statistics*, 106(4), 974–982.

Aneja, A., O. Reshef, and G. Subramani (2024): "Attrition and the gender patenting gap," *The Review of Economics and Statistics*, pp. 1–31.

Arai, M., and F. Heyman (2009): "Microdata evidence on rent sharing," *Applied Economics*, 41(23), 2965–2976.

Audretsch, D. B., E. E. Lehmann, and J. Schenkenhofer (2018): "Internationalization strategies of hidden champions: Lessons from Germany," *Multinational Business Review*, 26(1), 2–24.

Bagger, J., B. J. Christensen, and D. T. Mortensen (2014): "Wage and labor productivity dispersion: The roles of total factor productivity, labor quality, capital intensity, and rent sharing," Mimeo, Royal Holloway, University of London.

Bai, Q., and S. Tian (2020): "Innovate or die: Corporate innovation and bankruptcy forecasts," *Journal of Empirical Finance*, 59, 88–108.

Barth, E., A. Bryson, J. C. Davis, and R. B. Freeman (2016): "It's where you work: Increases in the dispersion of earnings across establishments and individuals in the United States," *Journal of Labor Economics*, 34(S2), S67–S97.

Bena, J., and K. Li (2014): "Corporate innovations and mergers and acquisitions," *The Journal of Finance*, 69(5), 1923–1960.

Bena, J., H. Ortiz-Molina, and E. Simintzi (2022): "Shielding firm value: Employment protection and process innovation," *Journal of Financial Economics*, 146(2), 637–664.

Bernstein, S., E. Colonnelli, X. Giroud, and B. Iverson (2019): "Bankruptcy spillovers," *Journal of Financial Economics*, 133(3), 608–633.

Bersch, J., S. Gottschalk, B. Müller, and M. Niefert (2014): "The Mannheim Enterprise Panel (MUP) and Firm Statistics for Germany," *ZEW-Centre for European Economic Research Discussion Paper*, (14-104).

Bessen, J., and E. Maskin (2009): "Sequential innovation, patents, and imitation," *RAND Journal of Economics*, 40(4), 611–635.

Bhuller, M., G. B. Dahl, K. V. Løken, and M. Mogstad (2020): "Incarceration, recidivism, and employment," *Journal of Political Economy*, 128(4).

Bias, D., B. Lochner, S. Obernberger, and M. Sevilir (2026): "Going public and the internal organization of the firm," *The Journal of Finance*, 81(1), 459–505.

Biondi, F., S. Inferrera, M. Mertens, and J. Miranda (2025): "Declining job reallocation in Europe: The role of shocks, market power, and technology," Discussion paper, Jena Economic Research Papers.

Blanchflower, D. G., A. J. Oswald, and P. Sanfey (1996): "Wages, profits, and rent-sharing," *The Quarterly Journal of Economics*, 111(1), 227–251.

Blind, K., K. Cremers, and E. Mueller (2009): "The influence of strategic patenting on companies' patent portfolios," *Research Policy*, 38(3), 428–436.

Brockhoff, K. (1997): "Ist die kollektive Regelung einer Vergütung von Arbeitnehmererfindungen wirksam und nötig?," *Zeitschrift für Betriebswirtschaft*, 67(7), 677–687.

Card, D., A. R. Cardoso, J. Heining, and P. Kline (2018): "Firms and labor market inequality: Evidence and some theory," *Journal of Labor Economics*, 36(S1).

Card, D., A. R. Cardoso, and P. Kline (2016): "Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women," *The Quarterly Journal of Economics*, 131(2), 633–686.

Card, D., F. Devicienti, and A. Maida (2014): "Rent-sharing, hold-up, and wages: Evidence from matched panel data," *Review of Economic Studies*, 81(1), 84–111.

Card, D., J. Heining, and P. Kline (2013): "Workplace heterogeneity and the rise of West German wage inequality," *The Quarterly Journal of Economics*, 128(3), 967–1015.

Carlsson, M., J. Messina, and O. N. Skans (2016): "Wage adjustment and productivity shocks," *The Economic Journal*, 126(595), 1739–1773.

Cho, H.-J., and V. Pucik (2005): "Relationship between innovativeness, quality, growth, profitability, and market value," *Strategic Management Journal*, 26(6), 555–575.

Christofides, L. N., and A. J. Oswald (1992): "Real wage determination and rent-sharing in collective bargaining agreements," *The Quarterly Journal of Economics*, 107(3), 985–1002.

Czarnitzki, D., and K. Kraft (2004): "Innovation indicators and corporate credit ratings: Evidence from German firms," *Journal of Economics and Business*, 82(3), 377–384.

——— (2010): "On the profitability of innovative assets," *Applied Economics*, 42(15), 1941–1953.

Dahl, G. B., A. R. Kostøl, and M. Mogstad (2014): "Family welfare cultures," *The Quarterly Journal of Economics*, 129(4), 1711–1752.

Decker, R. A., J. Haltiwanger, R. S. Jarmin, and J. Miranda (2020): "Changing business dynamism and productivity: Shocks versus responsiveness," *American Economic Review*, 110(12), 3952–3990.

Desai, P., E. Gavrilova, R. C. Silva, and M. Soares (forthcoming): "The Value of Trademarks," *Journal of Financial Economics*, Accepted for publication.

Diegmann, A., T. Doherr, M. Hälbig, and S. Wolter (2025): "Linking the Mannheim Enterprise Panel (MUP) with Administrative Establishment Data of IAB–an update," Discussion paper, Institut für Arbeitsmarkt-und Berufsforschung (IAB), Nürnberg.

Diegmann, A., S. Gottschalk, M. Hälbig, A. Schmucker, S. Wolter, and F. Zimmermann (2026): "MUP-BHP–Enriching Administrative Establishment Data with Commercial Enterprise Data," *Jahrbücher für Nationalökonomie und Statistik*, (0).

Dobbie, W., J. Goldin, and C. S. Yang (2018): "The effects of pretrial detention on conviction, future crime, and employment: Evidence from randomly assigned judges," *American Economic Review*, 108(2), 201–240.

Doherr, T. (2023): "The Search Engine: A Holistic Approach to Matching," Discussion Paper 23-001, ZEW -Centre for European Economic Research, Mannheim.

Du Caju, P., F. Rycx, and I. Tojerow (2011): "Inter-industry wage differentials: How much does rent sharing matter?," *The Manchester School*, 79(4), 691–717.

Dustmann, C., J. Ludsteck, and U. Schönberg (2009): "Revisiting the German wage structure," *The Quarterly Journal of Economics*, 124(2), 843–881.

Eisdorfer, A., and P.-H. Hsu (2011): "Innovate to survive: The effect of technology competition on corporate bankruptcy," *Financial Management*, 40(4), 1087–1117.

EPO (2023): *European Patent Guide: How to Get a European Patent*. European Patent Office, Munich, Germany, 23rd edn., Edited and published by the European Patent Office.

——— (2024): *Guidelines for Examination in the European Patent Office*. European Patent Office, Munich, Germany.

Estevão, M., and S. Tevlin (2003): "Do firms share their success with workers? The response of wages to product market conditions," *Economica*, 70(280).

Farre-Mensa, J., D. Hegde, and A. Ljungqvist (2020): "What is a patent worth? Evidence from the U.S. Patent "Lottery."," *The Journal of Finance*, 75(2), 639–682.

Frandsen, B., L. Lefgren, and E. Leslie (2023): "Judging judge fixed effects," *American Economic Review*, 113(1), 253–77.

Furman, J., and R. Seamans (2019): "AI and the Economy," *Innovation policy and the economy*, 19(1), 161–191.

Gaessler, F., D. Harhoff, and S. Sorg (2019): "Bargaining failure and freedom to operate: Re-evaluating the effect of patents on cumulative innovation," Discussion Paper 19-11, Max Planck Institute for Innovation & Competition.

Galasso, A., and M. Schankerman (2015): "Patents and cumulative innovation: Causal evidence from the courts," *The Quarterly Journal of Economics*, 130(1), 317–369.

——— (2018): "Patent rights, innovation, and firm exit," *The RAND Journal of Economics*, 49(1), 64–86.

Garin, A., and F. Silvério (2024): "How responsive are wages to firm-specific changes in labour demand? Evidence from idiosyncratic export demand shocks," *The Review of Economic Studies*, 91(3), 1671–1710.

Gordon, R. J. (2016): "Perspectives on the rise and fall of American growth," *American Economic Review*, 106(5), 72–76.

Gottschalk, S., A. Hauer, and J.-P. Ahrens (2023): *Die volkswirtschaftliche Bedeutung der Familienunternehmen: 6. Auflage und Schwerpunkt" Ausbildungsengagement"*. München: Stiftung Familienunternehmen.

Green, J. R., and S. Scotchmer (1995): "On the division of profit in sequential innovation," *RAND Journal of Economics*, 26(1), 20–33.

Gürtzgen, N. (2009): "Rent-sharing and collective bargaining coverage: Evidence from linked employer–employee data," *The Scandinavian Journal of Economics*, 111(2), 323–349.

Hall, B. H., A. B. Jaffe, and M. Trajtenberg (2001): "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools," NBER Working Paper 8498, National Bureau of Economic Research.

Harhoff, D., and K. Hoisl (2007): "Institutionalized incentives for ingenuity—Patent value and the German Employees' Inventions Act," *Research Policy*, 36(8), 1143–1162.

Hege, U., S. Pouget, and Y. Zhang (2024): "Climate patents and financial markets," Finance Working Paper 961/2024.

Heinrich, S., F. Seliger, and M. Wörter (2022): "Appropriability and basicness of R&D: Identifying and characterising product and process inventions in patent data," *PLOS ONE*, 17(8), e0272225.

Hildreth, A. K. G. (1998): "Rent-sharing and wages: Product demand or technology driven premia?," *Economics of Innovation and New Technology*, 5(2–4), 199–226.

Hildreth, A. K. G., and A. J. Oswald (1997): "Rent-sharing and wages: Evidence from company and establishment panels," *Journal of Labor Economics*, 15(2), 318–337.

Humlum, A., J. Munch, and M. Rasmussen (2025): "What works for the unemployed? Evidence from quasi-random caseworker assignments," NBER Working Paper 33807, National Bureau of Economic Research.

Imbens, G. W., and D. B. Rubin (1997): "Estimating outcome distributions for compliers in instrumental variables models," *The Review of Economic Studies*, 64(4), 555–574.

Jäger, S., B. Schoefer, S. Young, and J. Zweimüller (2020): "Wages and the value of nonemployment," *The Quarterly Journal of Economics*, 135(4), 1905–1963.

Johnson, S., and D. Acemoglu (2023): *Power and progress: Our thousand-year struggle over technology and prosperity*. Hachette UK.

Kleiner, K., and N. Hüther (2025): "Justice good as random?," *The Journal of Finance*, Forthcoming.

Kline, P., N. Petkova, H. Williams, and O. Zidar (2019): "Who profits from patents? Rent-sharing at innovative firms," *The Quarterly Journal of Economics*, 134(3), 1343–1404.

Kogan, L., D. Papanikolaou, A. Seru, and N. Stoffman (2017): "Technological innovation, resource allocation and growth," *The Quarterly Journal of Economics*, 132(2), 665–712.

Kölling, A. (2020): "Employment in family firms: Less but safe? Analyzing labor demand of German family firms with a treatment model for panel data," *Bulletin of Economic Research*, 72(1), 14–32.

Lahorte, P. (2018): "Inside the mind of an EPO examiner," *World Patent Information*, 54, S18–S22, Supplement issue.

Lahorte, P., and D. Preller (2023): "What Entrepreneurs Can Expect from EPO Patent Examiners," in *Winning with IP: Managing Intellectual Property Today*, ed. by A. Jolly, pp. [98–109]. Novaro Publishing, 4th edn.

Lemley, M. A., and B. Sampat (2012): "Examiner characteristics and patent office outcomes," *The Review of Economics and Statistics*, 94(3), 817–827.

Lochner, B., S. Seth, and S. Wolter (2023): "AKM effects for German labour market data 1985-2021," Discussion paper, Institut für Arbeitsmarkt-und Berufsforschung (IAB), Nürnberg.

Martins, P. S. (2009): "Rent sharing before and after the wage bill," *Applied Economics*, 41(17), 2133–2151.

Mertens, M., S. Mueller, and G. Neuschaeffer (2026): "Identifying rent-sharing using firms' energy input mix," *Journal of the European Economic Association*, p. jvag006.

Pakes, A. (1986): "Patents as options: Some estimates of the value of holding European patent stocks," *Econometrica*, 54(4), 755–784.

Rammer, C., and A. Spielkamp (2019): "The distinct features of hidden champions in Germany: A dynamic capabilities view," Discussion Paper Discussion Paper No. 19-012, ZEW - Leibniz Centre for European Economic Research, Available at: https://ssrn.com/abstract=3381500.

Righi, C., and T. Simcoe (2019): "Patent examiner specialization," *Research Policy*, 48(1), 137–148.

Roberts, P. W. (1999): "Product innovation, product-market competition and persistent profitability in the U.S. pharmaceutical industry," *Strategic Management Journal*, 20(7), 655–670.

Sampat, B., and H. L. Williams (2019): "How Do Patents Affect Follow-On Innovation? Evidence from the Human Genome," *American Economic Review*, 109(1), 203–236.

Schenkenhofer, J. (2022): "Hidden champions: a review of the literature and future research avenues," *Management Review Quarterly*, 72, 417–482.

Schlömer-Laufen, N., R. Kay, and M. Holz (2014): "Works Councils in Family Businesses in Germany – Why Are There So Few?," Discussion Paper Working Paper 03/14, Institut für Mittelstandsforschung Bonn (IfM).

Scotchmer, S. (1991): "Standing on the shoulders of giants: Cumulative research and the patent law," *Journal of Economic Perspectives*, 5(1), 29–41.

Sevilir, M., and X. Tian (2012): "Acquiring Innovation," AFA 2012 Chicago Meetings Paper, 45 Pages. Posted: 28 Dec 2010, Last revised: 26 Oct 2014.

Simon, H. (2009): *Hidden Champions of the Twenty-First Century: Success Strategies of Unknown World Market Leaders*. Springer, New York.

Sommer, M. (2023): *Familienunternehmen als Wohlstandsgaranten Eine Repräsentativbefragung der deutschen Bevölkerung*. München: Stiftung Familienunternehmen.

Song, J., D. J. Price, F. Guvenen, N. Bloom, and T. Von Wachter (2019): "Firming up inequality," *The Quarterly Journal of Economics*, 134(1), 1–50.

Sorkin, I. (2018): "Ranking firms using revealed preference," *The Quarterly Journal of Economics*, 133(3), 1331–1393.

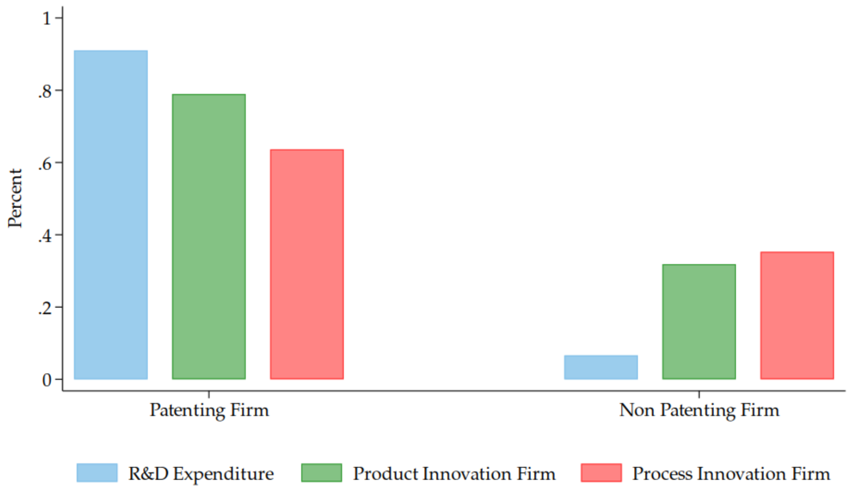
Tham, W. W., S. Baslandze, L. Liu, and E. Sojli (2026): "Foundational processes and growth," *Journal of Financial Economics*, 180.

Van Reenen, J. (1996): "The creation and capture of rents: wages and innovation in a panel of UK companies," *The Quarterly Journal of Economics*, 111(1), 195–226.

Supplementary Appendix

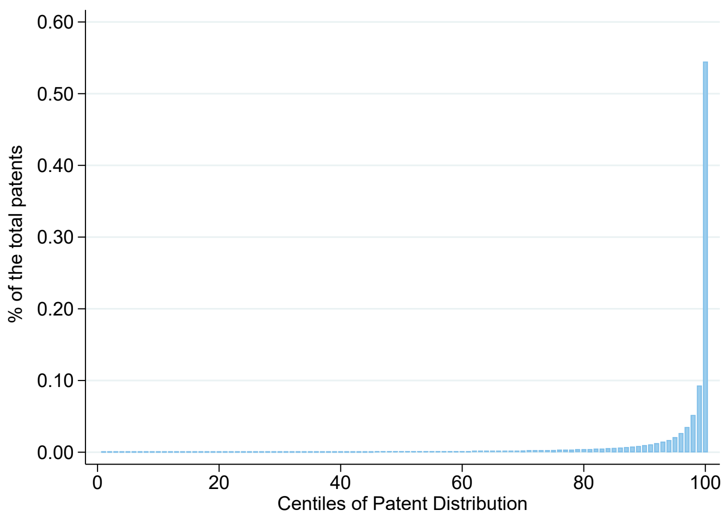
A Descriptive Statistics of Patenting Firms in Germany

Figure A.1: R&D Expenditure and Innovation Activity at the Firm-Level



Notes: The figure is based on the Mannheim Innovation Panel (MIP) and shows the differences in terms of R&D expenditures, reported product innovations and process innovations by firms with vs without patent applications. R&D expenditures refer to the sum of all expenditures within each group.
Source: Mannheim Innovation Panel (MIP) 2015, 2017, 2019

Figure A.2: Distribution of Patents per Firm Across Percentiles



Notes: This figure shows the distribution of patents across firm centiles. Each bar represents the share of total patents held by firms within a given centile. The sample consists of 357,309 MUP–EPO patent applications filed between 2000 and 2016.

Table A.1: Summary Statistics - All Firms vs. Firms with Patents

	Overall Firm-Random Sample			Patenting Firms			
	N	Mean	SD	N	Mean	SD	p-value
Log employees	1,249,959	1.286	0.980	30,550	3.174	2.028	0.000
Log sales	1,225,024	13.112	1.422	29,604	15.595	2.126	0.000
Productivity	1,235,836	11.832	1.132	29,541	12.403	1.081	0.000
Firm age	1,286,854	21.838	36.664	33,490	33.599	45.667	0.000
Credit rating index	1,252,863	287.794	86.184	30,885	248.256	68.276	0.000
Agriculture	1,285,163	0.012	0.112	32,000	0.002	0.039	0.000
Stone	1,285,163	0.002	0.034	32,000	0.003	0.053	0.000
Manufacturing	1,285,163	0.094	0.290	32,000	0.483	0.486	0.000
Energy	1,285,163	0.002	0.052	32,000	0.005	0.065	0.000
Water	1,285,163	0.004	0.068	32,000	0.006	0.075	0.000
Construction	1,285,163	0.136	0.342	32,000	0.028	0.159	0.000
Retail trade	1,285,163	0.224	0.416	32,000	0.145	0.340	0.000
Transportation, storage	1,285,163	0.040	0.194	32,000	0.006	0.073	0.000
Accommodation	1,285,163	0.072	0.258	32,000	0.000	0.016	0.000
ICT	1,285,163	0.030	0.168	32,000	0.036	0.180	0.000
Banking, insurance	1,285,163	0.026	0.158	32,000	0.009	0.087	0.000
Housing	1,285,163	0.038	0.192	32,000	0.016	0.119	0.000
Technical service	1,285,163	0.116	0.320	32,000	0.194	0.380	0.000
Business service	1,285,163	0.056	0.230	32,000	0.030	0.157	0.000
Public, social, health	1,285,163	0.072	0.258	32,000	0.010	0.101	0.000
Art, maintenance	1,285,163	0.018	0.134	32,000	0.002	0.037	0.000

Notes: The table shows mean characteristics of firms with patenting activity compared to all firms in Germany. p-values relate to a standard t-test to determine the difference in mean characteristics.

B Further Empirical Results

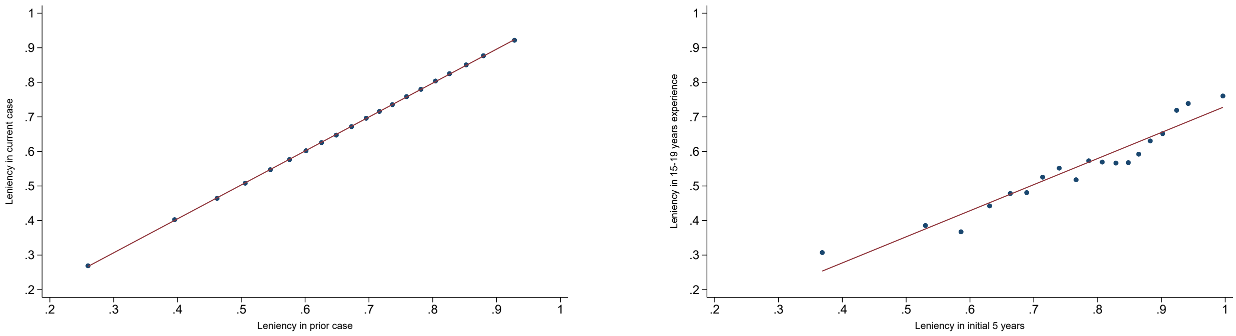
B.1 Extension of Instrument Validity

Table B.1: Test of Joint Null of Monotonicity & Exclusion

	15 knots				20 knots			
	ω=1	ω=0.8	ω=0.5	ω=0.3	ω=1	ω=0.8	ω=0.5	ω=0.3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Test statistic	280	280	280	280	281	281	281	281
d.f.	1739	1739	1739	1739	1734	1734	1734	1734
P-values	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Notes: The table presents results from the test proposed in Frandsen, Lefgren, and Leslie (2023) for the joint null hypothesis that the monotonicity and exclusion restrictions hold. We test this null using office times year fixed effects conditional on having handled at least ten examinations. Columns (1) to (4) provide the results imposing 15 knots in the quadratic spline function. Columns (5) to (8) provide the results imposing 20 knots in the quadratic spline function. Each Column is associated with different weighting schemes between the fit and slope components of the test. A failure to reject the null implies that we cannot reject the hypothesis that the monotonicity and exclusion restrictions jointly hold. The test was implemented in STATA via the package `testjfe`.

Figure B.1: Persistency in Examiners' Leniency



A: Short-Run Persistence

B: Long-Run Persistence

Notes: Panel (A) plots the examiner's current leave-one-out measure vs. lagged leave-one-out measure based on the date of the patent submission. The correlation coefficient between the leave-one-out measure in the previous case and the leave-one-out measure in the current case is equal to 0.98. Panel (B) plots the examiner's average leave-one-out measure during the first 5 years vs. the leave-one-out measure during 15 to 19 years of experience. The estimated correlation coefficient is equal to 0.47.

B.2 Examiner Leniency and Patent Rejection Grounds

Table B.2: Legal Grounds Cited in Rejection Letters by Examiner Leniency Groups

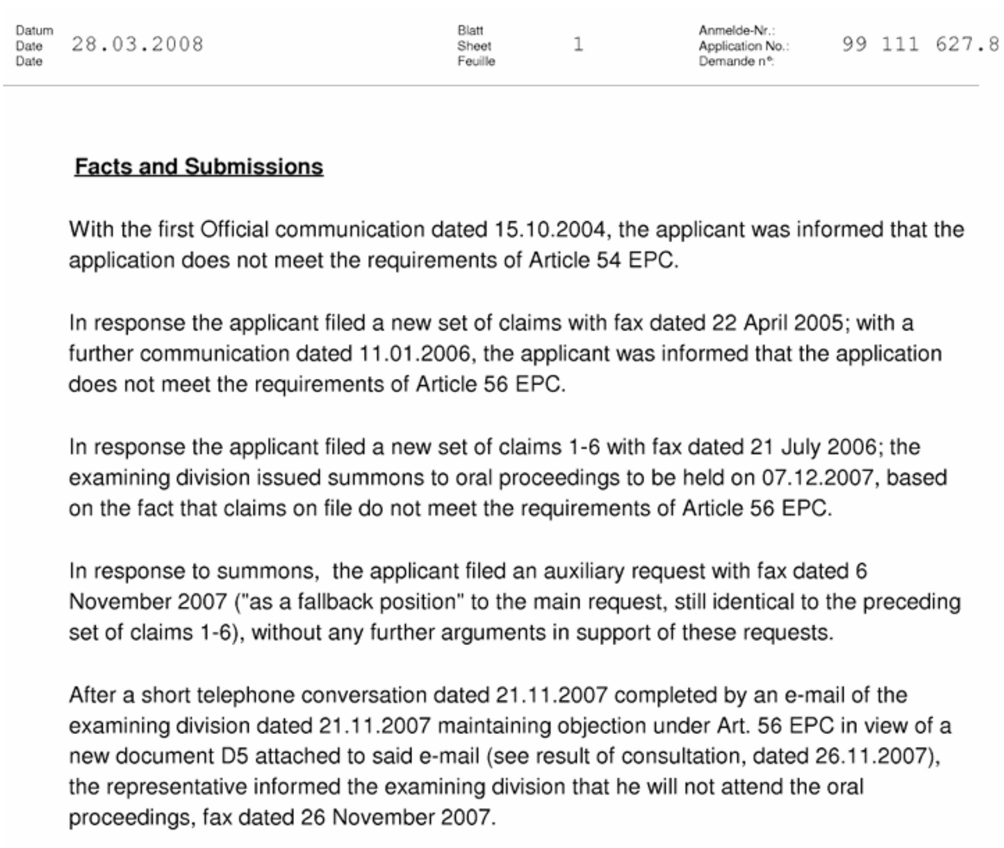
Legal Ground	Description	% of Applications
	Low Leniency (Bottom 10th Percentile), based on 434 application documents	
§ 52	Not a patentable invention and excluded from subject matter (e.g., business methods, mathematical methods, or computer programs without technical effect)	54%
§ 56	Lack of inventive steps	49%
§ 54	Lack of novelty	41%
§ 84	Unclear and ambiguous claims	32%
§ 123(2 & 3)	Amendment contains new claims not supported by original application	28%
§ 121	Missed the deadline to communicate	21%
§ 83	Lack of disclosure	12%
§ 71(7)	Not paying the fee	5%
§ 82	Lack of unity in claims	3%
§ 101(2 & 3(b))	Filing of opposition	2%
	Medium Leniency (50th–75th Percentile), based on 438 application documents	
§ 54	Lack of novelty	40%
§ 121	Missed the deadline to communicate	34%
§ 56	Lack of inventive steps	24%
§ 123(2 & 3)	Amendment contains new claims not supported by original application	18%
§ 52	Not a patentable invention and excluded from subject matter (e.g., business methods, mathematical methods, or computer programs without technical effect)	18%
§ 84	Unclear and ambiguous claims	17%
§ 71(7)	Not paying the fee	12%
§ 83	Lack of disclosure	8%
§ 101(2 & 3(b))	Filing of opposition	6%
§ 82	Lack of unity in claims	2%
	High Leniency (Top 10th Percentile), based on 228 application documents	
§ 54	Lack of novelty	49%
§ 52	Not a patentable invention and excluded from subject matter (e.g., business methods, mathematical methods, or computer programs without technical effect)	36%
§ 56	Lack of inventive steps	36%
§ 123(2 & 3)	Amendment contains new claims not supported by original application	19%
§ 84	Unclear and ambiguous claims	18%
§ 121	Missed the deadline to communicate	17%
§ 83	Lack of disclosure	5%
§ 71(7)	Not paying the fee	4%
§ 101(2 & 3(b))	Filing of opposition	3%
§ 82	Lack of unity in claims	2%

To investigate the relationship between examiner leniency and the citation of legal grounds in patent rejections, we classified examiners into three groups based on their leniency scores: (i) Low Leniency – examiners in the bottom 10th percentile of the leniency distribution; (ii) Medium Leniency – examiners between the 50th and 75th percentiles; and (iii) High Leniency – examiners in the top 10th percentile. From these groups, we randomly selected 7,565 rejected applications for analysis. Using automated web crawling and scraping methods, we locate each application in the European Patent Register. For each case, we attempted to retrieve the PDF file titled "Grounds for the Decision (Annex)", which contains the examiner's detailed reasoning for the rejection (See figure B.2). If this document was unavailable, we downloaded the most recent alternative file, which provided the procedural status of the application (including withdrawn or closed cases).

Of the total sample, "Grounds for the Decision (Annex)" documents were successfully retrieved for 1,100 cases in which the legal grounds for rejection were explicitly cited. Within this subset, 434 cases were reviewed by low leniency examiners, 438 by medium leniency examiners, and 228 by high leniency examiners. The relatively small number of high leniency cases reflects their higher overall acceptance rates.

From these documents, we extracted all European Patent Convention (EPC) legal articles cited by examiners and analyzed both the types and frequencies of legal grounds referenced across the three leniency groups.

Figure B.2: Snapshot of a "Grounds for the Decision (Annex)"



Datum Date Date 28.03.2008 | Blatt Sheet Feuille 1 | Anmelde-Nr.: Application No.: Demande n°: 99 111 627.8

Facts and Submissions

With the first Official communication dated 15.10.2004, the applicant was informed that the application does not meet the requirements of Article 54 EPC.

In response the applicant filed a new set of claims with fax dated 22 April 2005; with a further communication dated 11.01.2006, the applicant was informed that the application does not meet the requirements of Article 56 EPC.

In response the applicant filed a new set of claims 1-6 with fax dated 21 July 2006; the examining division issued summons to oral proceedings to be held on 07.12.2007, based on the fact that claims on file do not meet the requirements of Article 56 EPC.

In response to summons, the applicant filed an auxiliary request with fax dated 6 November 2007 ("as a fallback position" to the main request, still identical to the preceding set of claims 1-6), without any further arguments in support of these requests.

After a short telephone conversation dated 21.11.2007 completed by an e-mail of the examining division dated 21.11.2007 maintaining objection under Art. 56 EPC in view of a new document D5 attached to said e-mail (see result of consultation, dated 26.11.2007), the representative informed the examining division that he will not attend the oral proceedings, fax dated 26 November 2007.

Notes: Snapshot of a "Grounds for the Decision (Annex)" document which describes the rejection reasons and legal grounds for an application based on the European Patent Convention.

B.3 Firm-Level Empirical Results

TABLE B.3: IV-PROBIT RESULTS: THE EFFECT OF PATENT ALLOWANCE ON FINANCIAL DISTRESS & EXIT

	Financial distress			Market exit		
	Probit	IV-Probit	IV-Probit	Probit	IV-Probit	IV-Probit
	(1)	(2)	(3)	(4)	(5)	(6)
Patent Granted	-0.333***	-1.377***	-1.620***	-0.517***	-0.827**	-0.741*
	(0.120)	(0.357)	(0.312)	(0.071)	(0.358)	(0.428)
Observations	3,323	3,323	2,042	3,323	3,323	3,286
Office year FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
Tech.-exp. FE			✓			✓

Notes: The table shows probit and IV-probit regression results of financial distress and market exit indicators on patent grant six years after the patent application. Financial distress is measured by an indicator variable equal to 1 if the firm experienced bankruptcy and zero otherwise. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. All specifications control for office, year, and sector FE, initial employment, revenue, and wage levels measured in logs. Columns (3) and (6) additionally control for technology class FE of the examiner. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

TABLE B.4: IV RESULTS: THE EFFECT OF PATENT ALLOWANCE ON M&A

	Minority acquisition	Majority acquisition existing owner	Majority acquisition new owner	Profit take-over agreement	Mergers
	(1)	(2)	(3)	(4)	(5)
Patent Granted	-0.0637	-0.0428	0.1885**	-0.0135	0.0681
	(0.071)	(0.069)	(0.086)	(0.047)	(0.053)
F-Statistic	87.18	87.18	87.18	87.18	87.18
Observations	3,323	3,323	3,323	3,323	3,323
Dep. var. mean	0.108	0.108	0.202	0.056	0.052
Granted	0.71	0.71	0.71	0.71	0.71
Office × year FE	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

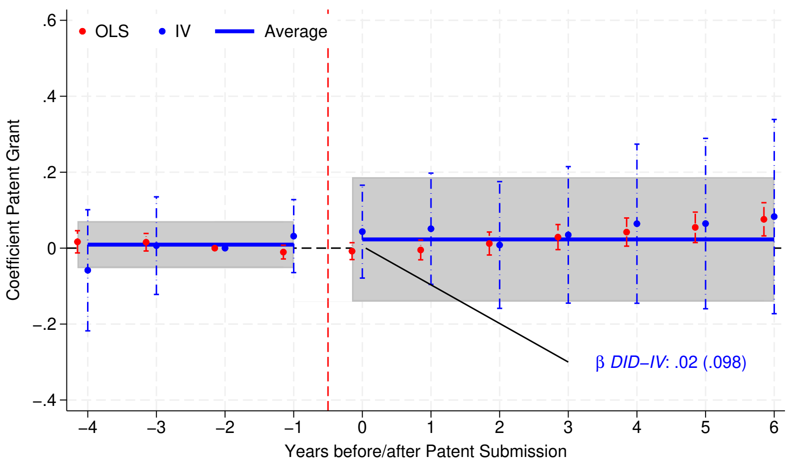
Notes: The table shows IV regression results of M&A events within six years following the patent application. Outcome variables represent dummy variable and refer to merger and acquisition events including minority and majority (of existing and new owners) acquisition, profit take-over agreements and merger. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

Table B.5: IV Results: The Effect of Patent Allowance on New Hire & Job separation

	Total # over initial size (1)	Manual task (2)	Service task (3)	Technicians (4)	Admin (5)	Manager (6)	AKM person FE (7)
			A: New Hire				
Patent Granted	-0.095	0.014	-0.003	0.004	0.012	0.002	0.015
	(0.584)	(0.056)	(0.037)	(0.028)	(0.049)	(0.020)	(0.031)
F-Statistic	88.14	88.50	88.50	88.50	88.50	88.50	88.31
Observations	3,034	3,017	3,017	3,017	3,017	3,017	3,008
Dep. var. mean	1.326	0.388	0.122	0.096	0.236	0.04	4.506
			B: Job separation				
Patent Granted	0.027	-0.029	0.052	-0.053	0.057	-0.033	-0.056
	(0.095)	(0.060)	(0.040)	(0.040)	(0.054)	(0.025)	(0.049)
F-Statistic	88.14	89.21	89.21	89.21	89.21	89.21	85.20
Observations	3,034	2,985	2,985	2,985	2,985	2,985	2,929
Dep. var. mean	0.344	0.39	0.122	0.104	0.232	0.048	4.59
Office × year FE	✓	✓	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓

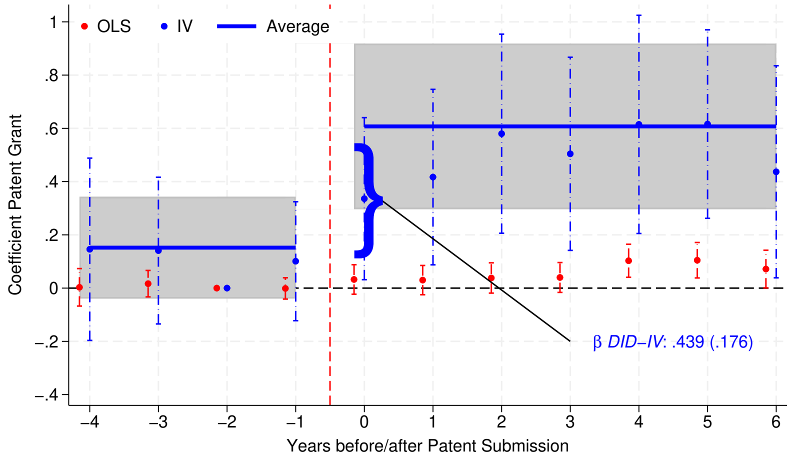
Notes: The table shows IV regression results of the firm's hiring (Panel A) and separation activities on patent grant status six years after the patent application. Column (1) shows the total number of hiring (Panel A) and separations (Panel B) relative to the initial workforce. Columns (2)-(6) refer to indicators equal to 1 if the respective occupational groups are hired/separated (conditional on hiring/separation). Column (7) reports the average AKM person FE. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

Figure B.3: Full-time Employment Dynamics before/after Patent Submission



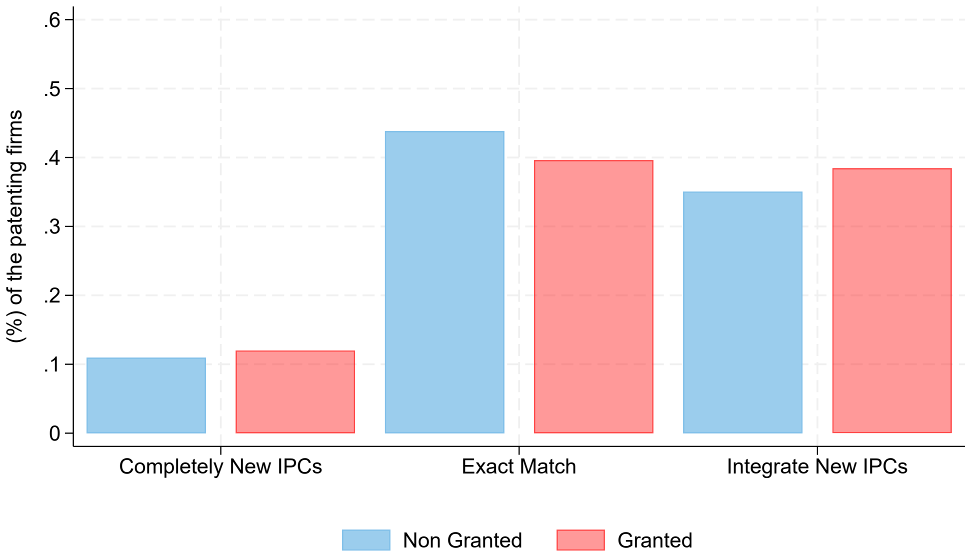
Notes: The figure shows estimation results along with 95% confidence intervals of the effect of a patent allowance on (log) full-time employment four years before and six years after the patent application. Red dots and blue dots represent OLS and IV estimates, respectively. The solid blue horizontal lines show IV results on average employment before and after the submission of the patent application. Results are normalized to two years before the patent submission.

FIGURE B.4: LABOR PRODUCTIVITY DYNAMICS BEFORE/AFTER PATENT SUBMISSION



Notes: The figure shows estimation results along with 95% confidence intervals of the effect of a patent allowance on (log) labor productivity four years before and six years after the patent application. Red dots and blue dots represent OLS and IV estimates, respectively. The solid blue horizontal lines show IV results on average labor productivity before and after the submission of the patent application. Results are normalized to two years before the patent submission.

FIGURE B.5: FIRMS' INNOVATION DIVERSIFICATION CONDITIONAL ON FUTURE PATENTING ACTIVITIES



Notes: The figure shows the innovation diversification of firms' future patenting activities, distinguishing between firms whose initial patent application was granted and those whose application was not granted. "Completely New IPCs" refers to firms that, within six years of their first application, file patents in entirely new technology classes. "Exact Match" refers to firms that file subsequent patents within the same technology class as their initial application. "Integrate New IPCs" refers to firms that file new patents that combine the original technology class with additional, new IPC classes. All measures are constructed using the 2-digit IPC level.

Table B.6: Regression Results: The Effect of Patent Allowance on Future Patent Quality

	1(Self-Citation)		Number of Citations		1(At least 1 Citations)	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Patent Granted	-0.029	-0.108	-0.061	0.385	-0.060*	0.032
	(0.021)	(0.120)	(0.075)	(0.463)	(0.035)	(0.214)
F-Statistic		25.85		25.85		25.85
Observations	1,255	1,255	1,255	1,255	1,255	1,255
Dep. var. mean	0.088	0.088	0.774	0.774	0.424	0.424
Granted	0.768	0.768	0.768	0.768	0.768	0.768
Office × year FE	✓	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Notes: This table shows OLS and IV regression estimates of the effect of patent allowance on future patent quality (measured by citations), for any subsequent patent filed within five years of a firm's first patent. Outcome variables in Columns (1) and (2) represent an indicator variable equal to 1 if self-citing its first application and zero otherwise. Outcome variables in Columns (3) and (4) represent the total number of citations (transformed by the inverse hyperbolic sine transformation) received by the firm's future patents. Outcome variables in Columns (5) and (6) represents an indicator equal to 1 if the future patent(s) receive at least one citation. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

Table B.7: IV Results: The Effect of Patent Allowance on Wages of New Hires

	Log Wage	Wage Share
	(1)	(2)
Patent Granted	0.149**	0.039
	(0.070)	(0.042)
F-Statistic	87.52	87.52
Observations	3,017	3,017
Dep. var. mean	4.362	0.728
Office × year FE	✓	✓
Tech.-exp. FE	✓	✓
Sector FE	✓	✓

Notes: The table shows IV regression results of (log) wages for new hires (Column 1) and the wage share of new hire calculated by average wages of new hires divided by average wages of stayers (Column 2) on patent grants over the six years following the initial application. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

Table B.8: Regression Results: The Effect of Patent Allowance on Selective Outflow

	Wage ≤ Median Firm			Wage ≤ Average Firm		
	Period 1-6 yrs		6 yrs. post	Period 1-6 yrs		6 yrs. post
	OLS	IV	IV	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Patent Granted	-0.002	-0.015	-0.018*	-0.001	-0.010	-0.012
	(0.002)	(0.009)	(0.010)	(0.002)	(0.010)	(0.011)
F-Statistic		87.18	87.18		87.18	87.18
Observations	3,034	3,034	3,034	3,034	3,034	3,034
Dep. var. mean	0.008	0.008	0.010	0.008	0.008	0.010
Granted	0.728	0.728	0.728	0.728	0.728	0.728
Office × year FE	✓	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

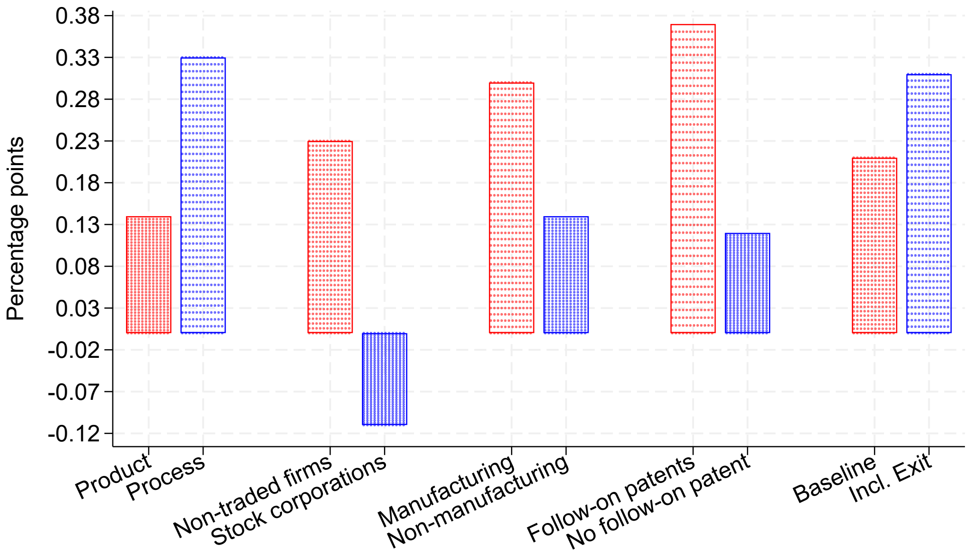
Notes: The table shows OLS and IV regression results of the number of job separations with low wages relative to the initial workforce on patent grant over the six years after the patent application. Columns (1) to (3) define low wage job separations relative to the median firm wage. Columns (4) to (6) define low wage job separations relative to the average firm wage. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

Table B.9: IV Results: Heterogeneity by Firm & Patent Types

	Employment		Revenue		Labor Productivity		Wage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			A: Product vs. Process Innovations					
	Product	Process	Product	Process	Product	Process	Product	Process
Patent Granted	-0.069	-0.111	0.684***	0.503**	0.745***	0.612***	0.082*	0.117**
	(0.107)	(0.108)	(0.249)	(0.233)	(0.237)	(0.223)	(0.044)	(0.048)
F-Statistic	60.80	73.10	57.95	70.92	57.95	70.92	60.80	73.10
Observations	2,665	1,518	2,655	1,512	2,655	1,512	2,665	1,518
			B: Family-oriented companies (LLC) vs. Stock Corporations					
	Family	Stock	Family	Stock	Family	Stock	Family	Stock
Patent Granted	-0.016	-0.027	0.593***	0.792	0.599***	0.819	0.123***	-0.149
	(0.096)	(0.337)	(0.216)	(0.562)	(0.207)	(0.506)	(0.043)	(0.123)
F-Statistic	73.66	12.42	70.98	12.42	70.98	12.42	73.66	12.42
Observations	2,850	176	2,840	176	2,840	176	2,850	176
			C: Manufacturing vs. Other Sectors					
	Manuf.	Other	Manuf.	Other	Manuf.	Other	Manuf.	Other
Patent Granted	-0.037	0.001	0.431*	0.688**	0.455**	0.685**	0.127**	0.075
	(0.138)	(0.121)	(0.247)	(0.316)	(0.231)	(0.297)	(0.063)	(0.059)
F-Statistic	30.27	49.51	29.66	47.87	29.66	47.87	30.27	49.51
Observations	1,783	1,243	1,778	1,238	1,778	1,238	1,783	1,243
			D: Future Patent Submission vs. No					
	Yes	No	Yes	No	Yes	No	Yes	No
Patent Granted	-0.155	0.026	0.498	0.656**	0.644*	0.621**	0.148**	0.069
	(0.164)	(0.118)	(0.344)	(0.271)	(0.338)	(0.255)	(0.067)	(0.057)
F-Statistic	25.85	52.23	24.82	50.95	24.82	50.95	25.85	52.23
Observations	1,255	1,773	1,251	1,767	1,251	1,767	1,255	1,773
Office $\times$ year FE	✓	✓	✓	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table shows IV regression results of (log) employment, (log) revenue, (log) labor productivity, and (log) wage six years after the patent application by firms and patent types. Labor productivity is calculated by revenue over employment. Panel A differentiates by product vs process innovations. Panel B differentiates by non-traded firms vs stock corporations. Panel C differentiates by manufacturing vs firms in other industries. Panel D differentiates by future patenting activity. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

Figure B.6: Rent sharing Elasticity by Firm & Patent Types



Notes: The figure shows rent-sharing elasticities for different sub-samples. The first two bars differentiate by product and process innovations. The second two bars differentiate by non-trade firms and stock corporations. The third two bars differentiate by manufacturing firms and all other firms. The fourth two bars differentiate by follow-on patent applications. The last two bars provide the baseline results and elasticities including zeros in employment, revenue, and wages for firms exiting the market. Elasticity is calculated as the log difference in revenue per employee divided by the log difference in wages per employee. Results refer to year six after the initial patent application assuming no difference in employment growth between firms with granted and non-granted patents due to insignificant coefficients estimate.

Table B.10: Regression Results: Including Zeros for Exiting Firms

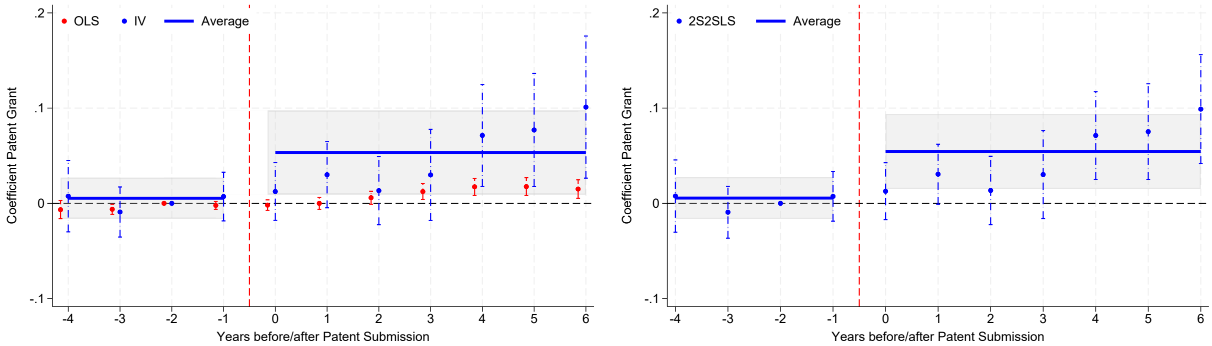
	Employment		Revenue		Lab. Prod.		Wages	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patent Granted	0.099***	0.186*	0.154***	0.639***	0.054*	0.470**	0.077***	0.182***
	(0.020)	(0.108)	(0.033)	(0.226)	(0.028)	(0.190)	(0.012)	(0.065)
F-Statistic		97.71		94.67		94.67		97.71
Observations	3,323	3,323	3,313	3,313	3,313	3,313	3,323	3,323
Dep. var. mean	3.966	3.966	17.086	17.086	13.122	13.122	5.436	5.436
Granted	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71
Office $\times$ year FE	✓	✓	✓	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of (log) employment, (log) revenue, (log) labor productivity, and (log) wage six years after the patent application assigning zero values in the outcome variable once the firm is exiting the market. Labor productivity is calculated by revenue over employment. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

B.4 Worker-Level Empirical Results

Figure B.7: Wage Dynamics before/after Patent Submission, Worker Level for stayers

(a) IV Results (b) Two-sample 2SLS



Notes: The figure shows estimation results along with 95% confidence intervals of the effect of a patent allowance on (log) real daily wages for firm stayers four years before and six years after the patent application. Panel (A) provides results based on fully nested IV estimation. Red dots and blue dots represent OLS and IV estimates, respectively. Panel (B) provides results based on a two-sample approach with predicted values from the firm-level first stage regression. The solid blue horizontal lines show IV results on average wages before and after the submission of the patent application. Results are normalized to two years before the patent submission.

Table B.11: Regression Results: The Effect of Patent Allowance on Wages by Demographic Groups

	Male	Female	Age bellow 31	Age 31–45	Age above 45	Foreigner	German	No Education	Vocational Training	University Degree
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: IV Results										
Patent Granted	0.122**	0.067	0.151**	0.100**	0.100**	0.119*	0.105**	-0.014	0.112**	0.057
	(0.054)	(0.047)	(0.060)	(0.050)	(0.040)	(0.066)	(0.047)	(0.081)	(0.047)	(0.037)
F-Statistic	17.85	22.05	21.09	16.89	25.62	15.30	19.63	7.677	18.60	38.72
Panel B: 2S2SLS Results										
Patent Granted	0.111***	0.076	0.154***	0.092**	0.108***	0.115**	0.102***	-0.010	0.106***	0.078
	(0.036)	(0.049)	(0.045)	(0.036)	(0.037)	(0.056)	(0.035)	(0.055)	(0.034)	(0.048)
Observations	151,101	43,998	39,046	106,112	49,941	14,368	180,730	18,435	156,071	19,852
Dep. var. mean	4.852	4.614	4.748	4.824	4.782	4.714	4.804	4.578	4.788	5.080
Office × year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table shows IV and 2S2SLS regression results of (log) real daily wages on patent grant six years after the patent application among incumbent workers initially employed in the firm, differentiated by demographic groups including gender, age, nationality, and education. 2S2SLS results in Panel B is based on a two-sample approach with predicted values from the firm-level first stage regression. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

TABLE B.12: IV RESULTS: THE EFFECT OF PATENT ALLOWANCE ON WAGES OVER TIME BY OCCUPATIONS

	Years After Patent Application					
	t_1	t_2	t_3	t_4	t_5	t_6
			A: Manager			
Patent Granted	-0.006	-0.015	0.063	-0.003	0.030	0.165*
	(0.051)	(0.056)	(0.069)	(0.064)	(0.065)	(0.093)
F-Statistic	21.94	20.27	19.12	17.49	17.04	15.84
Observations	6,227	5,919	5,600	5,340	5,097	4,871
Dep. var. mean	5.022	5.070	5.088	5.104	5.114	5.116
			B: Administration			
Patent Granted	0.037**	0.023	0.062**	0.078***	0.069**	0.069**
	(0.018)	(0.020)	(0.025)	(0.029)	(0.030)	(0.033)
F-Statistic	58.93	60.04	60.02	59.78	57.37	58.99
Observations	38,762	37,485	36,387	35,216	34,028	32,827
Dep. var. mean	4.756	4.768	4.780	4.788	4.796	4.804
			C: Technicians			
Patent Granted	0.071*	0.032	0.080	0.120**	0.131**	0.174**
	(0.041)	(0.043)	(0.049)	(0.057)	(0.060)	(0.072)
F-Statistic	16.73	16.38	16.47	16.43	15.81	15.98
Observations	24,233	23,528	22,814	22,072	21,300	20,520
Dep. var. mean	4.898	4.910	4.920	4.928	4.938	4.944
			D: Service Task			
Patent Granted	-0.001	-0.013	-0.020	0.003	0.009	0.024
	(0.022)	(0.025)	(0.026)	(0.028)	(0.033)	(0.036)
F-Statistic	41.92	41.31	41.34	39.90	39.77	40.88
Observations	29,477	28,419	27,478	26,530	25,594	24,691
Dep. var. mean	4.484	4.488	4.492	4.496	4.500	4.508
			E: Manual Task			
Patent Granted	0.084	0.061	0.044	0.140*	0.151*	0.216*
	(0.054)	(0.051)	(0.061)	(0.081)	(0.089)	(0.121)
F-Statistic	6.771	6.579	6.310	6.317	5.822	5.782
Observations	109,715	106,890	103,991	101,017	98,013	94,707
Dep. var. mean	4.602	4.606	4.614	4.622	4.632	4.630
Office × year FE	✓	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Notes: The table shows IV regression results of (log) real daily wages on patent grant one to six years after the patent application among incumbent workers initially employed in the firm, differentiated by subgroups of occupational tasks. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

Table B.13: 2S2SLS Results: The Effect of Patent Allowance on Wages over Time by Occupations

	Years After Patent Application					
	t_1	t_2	t_3	t_4	t_5	t_6
			A: Manager			
Patent Granted	-0.007	-0.016	0.065	-0.003	0.029	0.158**
	(0.054)	(0.058)	(0.068)	(0.063)	(0.063)	(0.078)
Observations	6,227	5,919	5,600	5,340	5,097	4,871
Dep. var. mean	5.022	5.070	5.088	5.104	5.114	5.116
			B: Administration			
Patent Granted	0.057**	0.036	0.095**	0.120***	0.104**	0.106**
	(0.026)	(0.030)	(0.039)	(0.045)	(0.046)	(0.050)
Observations	38,762	37,485	36,387	35,216	34,028	32,827
Dep. var. mean	4.756	4.768	4.780	4.788	4.796	4.804
			C: Technicians			
Patent Granted	0.066*	0.029	0.073*	0.109***	0.117**	0.157***
	(0.034)	(0.039)	(0.040)	(0.042)	(0.046)	(0.050)
Observations	24,233	23,528	22,814	22,072	21,300	20,520
Dep. var. mean	4.898	4.910	4.920	4.928	4.938	4.944
			D: Service Task			
Patent Granted	-0.002	-0.021	-0.031	0.004	0.013	0.036
	(0.033)	(0.038)	(0.040)	(0.042)	(0.050)	(0.054)
Observations	29,477	28,419	27,478	26,530	25,594	24,691
Dep. var. mean	4.484	4.488	4.492	4.496	4.500	4.508
			E: Manual Task			
Patent Granted	0.050**	0.036	0.026	0.082**	0.085**	0.121***
	(0.025)	(0.030)	(0.033)	(0.034)	(0.035)	(0.040)
Observations	109,715	106,890	103,991	101,017	98,013	94,707
Dep. var. mean	4.602	4.606	4.614	4.622	4.632	4.630
Office × year FE	✓	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Notes: The table shows 2S2SLS regression results of (log) real daily wages on patent grant one to six years after the patent application among incumbent workers initially employed in the firm, differentiated by subgroups of occupational tasks. Each specification is based on a two-sample approach with predicted values from the firm-level first stage regression. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

Table B.14: Regression Results: The Effect of Patent Allowance on Bonuses by Occupations

	Six Years after Patent Application				
	Manual task	Service task	Technicians	Administration	Manager
	(1)	(2)	(3)	(4)	(5)
		Panel A: Probability of getting Bonus payment			
Panel A1: IV Results					
Patent Granted	0.080	-0.008	0.047	-0.003	-0.042
	(0.082)	(0.028)	(0.070)	(0.022)	(0.093)
F-Statistic	5.782	40.88	15.98	58.99	15.84
Panel A2: 2S2SLS Results					
Patent Granted	0.045	-0.013	0.042	-0.004	-0.040
	(0.040)	(0.043)	(0.061)	(0.034)	(0.088)
	[-.02;.121]	[-.094;.066]	[-.066;.154]	[-.071;.057]	[-.176;.148]
Observations	94,707	24,691	20,520	32,827	4,871
Dep. var. mean	0.054	0.034	0.058	0.052	0.072
		Panel B: Bonus payment Share			
Panel B1: IV Results					
Patent Granted	-0.000	-0.002	-0.001	-0.004	0.005
	(0.004)	(0.003)	(0.004)	(0.002)	(0.006)
F-Statistic	5.782	40.88	15.98	58.99	15.84
Panel B2: 2S2SLS Results					
Patent Granted	-0.000	-0.003	-0.000	-0.006*	0.005
	(0.002)	(0.004)	(0.004)	(0.003)	(0.006)
	[-.005;.004]	[-.010;.006]	[-.008;.006]	[-.014;.000]	[-.004;.019]
Observations	94,707	24,691	20,520	32,827	4,871
Dep. var. mean	0.004	0.004	0.002	0.004	0.004
Office × year FE	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows IV and 2S2SLS regression results of bonus payment on patent grant for subgroups of occupations six years after the patent application. The outcome variable in Panel A are dummy variables equal to 1 if the individual gets bonus payments and zero otherwise. The outcome variable in Panel B are bonus shares calculated as bonus amount relative to total wage payments. 2S2SLS results in Panels A2 and B2 are based on a two-sample approach with predicted values from the firm-level first stage regression. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. Squared brackets indicate 90% bootstrap CI clustered at the examiner level using 1,000 replications. *p<0.1, **p<0.05, ***p<0.01.

Table B.15: Regression Results: The Effect of Patent Allowance on Employment by Occupations

	Six Years after Patent Application				
	Manual task	Service task	Technicians	Administration	Manager
	(1)	(2)	(3)	(4)	(5)
Panel A: IV Results					
Patent Granted	0.066	-0.009	0.040	0.051**	0.035
	(0.044)	(0.028)	(0.041)	(0.020)	(0.077)
F-Statistic	9.679	43.74	20.40	70.56	23.21
Panel B: 2S2SLS Results					
Patent Granted	0.045	-0.014	0.040	0.081**	0.037
	(0.030)	(0.043)	(0.042)	(0.031)	(0.080)
	[-.004;.102]	[-.088;.081]	[-.042;.11]	[.014;.142]	[-.123;.174]
Observations	139,838	38,897	32,016	53,718	8,964
Dep. var. mean	0.828	0.792	0.818	0.812	0.724
Granted	0.776	0.760	0.746	0.694	0.686
Office × year FE	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows IV and 2S2SLS regression results of an indicator variable equal to 1 if employed on patent grant six years after the patent application among incumbent workers initially employed in the firm, differentiated by occupational groups. Panel A shows the IV results. 2S2SLS results in Panel B is based on a two-sample approach with predicted values from the firm-level first stage regression. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. Squared brackets indicate 90% bootstrap CI clustered at the examiner level using 1,000 replications. *p<0.1, **p<0.05, ***p<0.01.

Table B.16: Robustness Results: Censored Wages

	Six Years after Patent Application				
	Manual task	Service task	Technicians	Administration	Manager
	(1)	(2)	(3)	(4)	(5)
	A: Probability of censored wages at t=6				
Panel A1: IV Results					
Patent Granted	-0.000	-0.050	0.066	0.044	0.052
	(0.029)	(0.031)	(0.071)	(0.042)	(0.097)
F-Statistic	5.872	41.60	15.67	59.76	16.24
Panel A2: 2S2SLS Results					
Patent Granted	-0.000	-0.077	0.058	0.067	0.050
	(0.017)	(0.048)	(0.061)	(0.066)	(0.090)
	[-.028;.037]	[-.16;.025]	[-.054;.167]	[-.09;.156]	[-.102;.254]
Observations	96,710	25,317	20,834	33,468	4,969
Dep. var. mean	0.024	0.048	0.184	0.142	0.386
	B: Sample of uncensored wages at t=0				
Panel B1: IV Results					
Patent Granted	0.222*	0.026	0.175**	0.084**	0.253**
	(0.124)	(0.038)	(0.076)	(0.037)	(0.123)
F-Statistic	5.706	37.32	15.23	58.75	12.40
Panel B2: 2S2SLS Results					
Patent Granted	0.124***	0.039	0.154***	0.127**	0.238**
	(0.041)	(0.056)	(0.053)	(0.055)	(0.099)
	[.043;.195]	[-.073;.138]	[.041;.238]	[-.015;.208]	[.076;.492]
Observations	93,491	23,539	17,523	28,704	2,920
Dep. var. mean	4.61	4.488	4.92	4.778	5.072
Office × year FE	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows robustness checks of the baseline sample specification with respect to the censoring of the wage data at the social security limit. Panel A specifies an indicator equal to 1 if individual *i*'s wage six years after the patent application is above the censoring limit. Panel B conditions the sample on workers initially earning below the censoring limit. 2S2SLS results in Panels A2 and B2 are based on a two-sample approach with predicted values from the firm-level first stage regression. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. Squared brackets indicate 90% bootstrap CI clustered at the examiner level using 1,000 replications. *p<0.1, **p<0.05, ***p<0.01.

Table B.17: Regression Results: The Effect of Patent Allowance on Part-time Employment by Occupations

	Six Years after Patent Application				
	Manual task (1)	Service task (2)	Technicians (3)	Administration (4)	Manager (5)
Panel A: IV Results					
Patent Granted	0.061	-0.000	-0.010	0.042*	-0.059
	(0.058)	(0.025)	(0.033)	(0.022)	(0.070)
F-Statistic	5.872	41.60	15.67	59.76	16.24
Panel B: 2S2SLS Results					
Patent Granted	0.034	-0.000	-0.009	0.064**	-0.056
	(0.024)	(0.038)	(0.030)	(0.032)	(0.066)
	[-.023;.071]	[-.10;.06]	[-.063;.045]	[.003;.122]	[-.162;.082]
Observations	96,710	25,317	20,834	33,468	4,969
Dep. var. mean	0.06	0.216	0.102	0.21	0.128
Granted	0.776	0.760	0.746	0.692	0.686
Office × year FE	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows IV and 2S2SLS regression results of part-time employment on patent grant six years after the patent application among incumbent workers initially employed in the firm, differentiated by occupational groups. 2S2SLS results in Panel B is based on a two-sample approach with predicted values from the firm-level first stage regression. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. Squared brackets indicate 90% bootstrap CI clustered at the examiner level using 1,000 replications. *p<0.1, **p<0.05, ***p<0.01.

Table B.18: Regression Results: The Effect of Patent Allowance on Mover Wage by Occupations

	Six Years after Patent Application				
	Manual task (1)	Service task (2)	Technicians (3)	Administration (4)	Manager (5)
Panel A: IV Results					
Patent Granted	0.025	-0.022	0.130	0.134*	0.107
	(0.091)	(0.120)	(0.100)	(0.070)	(0.216)
F-Statistic	18.05	23.04	19.61	57.12	11.15
Panel B: 2S2SLS Results					
Patent Granted	0.027	-0.028	0.145	0.208*	0.106
	(0.098)	(0.156)	(0.108)	(0.109)	(0.217)
Observations	21,482	6,334	5,901	10,993	1,847
Dep. var. mean	4.474	4.368	4.882	4.72	5.02
Granted	0.73	0.76	0.734	0.644	0.616
Office × year FE	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows IV and 2S2SLS regression results of log wages among movers after the patent application, differentiated by occupational groups. 2S2SLS results in Panel B is based on a two-sample approach with predicted values from the firm-level first stage regression. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

Table B.19: IV Results: The Effect of Patent Allowance on Wages by Occupations: Firm & Patent Types

	Six Years after Patent Application				
	Manual task (1)	Service task (2)	Technicians (3)	Administration (4)	Manager (5)
A: Family-oriented companies					
Patent Granted	0.243	0.045	0.200**	0.047	0.150
	(0.148)	(0.041)	(0.081)	(0.034)	(0.097)
F-Statistic	4.353	31.61	12.92	37.13	14.49
Observations	84,144	16,715	18,774	28,278	4,075
Dep. var. mean	4.598	4.458	4.918	4.754	5.054
B: Stock companies					
Patent Granted	4.297	-0.152	-0.066	0.039	0.488***
	(15.636)	(0.118)	(0.166)	(0.065)	(0.181)
F-Statistic	0.0903	20.22	4.977	31.68	29.87
Observations	10,562	7,976	1,741	4,548	791
Dep. var. mean	4.712	4.574	4.946	4.918	5.202
C: Manufacturing Sectors					
Patent Granted	0.369	0.019	0.223	0.059	0.221
	(0.399)	(0.075)	(0.149)	(0.116)	(0.206)
F-Statistic	1.165	9.092	4.922	6.677	5.766
Observations	68,680	8,918	11,889	13,844	1,889
Dep. var. mean	4.582	4.564	4.968	4.758	5.184
D: Non-Manufacturing Sectors					
Patent Granted	0.079	0.035	0.087	0.071**	0.242**
	(0.070)	(0.051)	(0.069)	(0.032)	(0.118)
F-Statistic	11.60	22.82	14.87	59.95	11.29
Observations	26,027	15,769	8,627	18,982	2,979
Dep. var. mean	4.676	4.452	4.868	4.790	5.020
E: Product Innovation					
Patent Granted	0.199	0.015	0.182*	0.072*	0.120
	(0.121)	(0.051)	(0.096)	(0.042)	(0.088)
F-Statistic	5.553	21.72	9.789	40.37	17.46
Observations	85,331	18,001	18,310	28,715	4,370
Dep. var. mean	4.606	4.464	4.920	4.784	5.066
F: Process Innovation					
Patent Granted	0.297	-0.002	0.105**	0.055*	0.278**
	(0.181)	(0.038)	(0.050)	(0.031)	(0.111)
F-Statistic	3.331	51.35	20.19	45.45	15.03
Observations	47,014	14,873	11,545	18,911	2,876
Dep. var. mean	4.630	4.558	4.908	4.792	5.020
G: Firms with Follow-on Innovation					
Patent Granted	0.411	0.040	0.409	0.189	0.912
	(0.392)	(0.072)	(0.329)	(0.150)	(1.235)
F-Statistic	1.537	13.05	2.033	4.870	0.636
Observations	51,873	13,184	12,112	15,502	2,149
Dep. var. mean	4.638	4.554	4.932	4.778	4.988
H: Firms without Follow-on Innovation					
Patent Granted	0.136	0.009	0.064	0.052	0.218**
	(0.089)	(0.056)	(0.060)	(0.034)	(0.102)
F-Statistic	8.123	26.09	22.97	107	24.89
Observations	42,832	11,504	8,406	17,324	2,716
Dep. var. mean	4.580	4.428	4.906	4.776	5.174
Office × year FE	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows IV regression results of the impact of patent grants on (log) real daily wages measured six years after the patent application of incumbent workers, differentiated by occupational groups across firms and patent types. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

Table B.20: 2S2SLS Results: The Effect of Patent Allowance on Wages by Occupations: Firm & Patent Types

	Six Years after Patent Application				
	Manual task (1)	Service task (2)	Technicians (3)	Administration (4)	Manager (5)
	A: Family-oriented companies				
Patent Granted	0.122***	0.064	0.169***	0.062	0.141*
	(0.041)	(0.055)	(0.049)	(0.044)	(0.081)
Observations	84,144	16,715	18,774	28,278	4,075
Dep. var. mean	4.598	4.458	4.918	4.754	5.054
	B: Stock companies				
Patent Granted	0.571*	-0.319	-0.065	0.084	1.071***
	(0.322)	(0.271)	(0.158)	(0.142)	(0.333)
Observations	10,562	7,976	1,741	4,548	791
Dep. var. mean	4.712	4.574	4.946	4.918	5.202
	C: Manufacturing Sectors				
Patent Granted	0.107**	0.017	0.123**	0.037	0.157
	(0.048)	(0.068)	(0.059)	(0.067)	(0.123)
Observations	68,680	8,918	11,889	13,844	1,889
Dep. var. mean	4.582	4.564	4.968	4.758	5.184
	D: Non-Manufacturing Sectors				
Patent Granted	0.090	0.054	0.103	0.124**	0.248**
	(0.071)	(0.081)	(0.079)	(0.052)	(0.099)
Observations	26,027	15,769	8,627	18,982	2,979
Dep. var. mean	4.676	4.452	4.868	4.790	5.020
	E: Product Innovation				
Patent Granted	0.113***	0.018	0.136**	0.098*	0.127
	(0.043)	(0.061)	(0.054)	(0.055)	(0.082)
Observations	85,331	18,001	18,310	28,715	4,370
Dep. var. mean	4.606	4.464	4.920	4.784	5.066
	F: Process Innovation				
Patent Granted	0.161***	-0.004	0.143**	0.088*	0.284***
	(0.050)	(0.068)	(0.065)	(0.048)	(0.093)
Observations	47,014	14,873	11,545	18,911	2,876
Dep. var. mean	4.630	4.558	4.908	4.792	5.020
	G: Firms with Follow-on Innovation				
Patent Granted	0.138**	0.038	0.154**	0.103*	0.234*
	(0.059)	(0.065)	(0.067)	(0.062)	(0.139)
Observations	51,873	13,184	12,112	15,502	2,149
Dep. var. mean	4.638	4.554	4.932	4.778	4.988
	H: Firms without Follow-on Innovation				
Patent Granted	0.094*	0.013	0.076	0.092	0.269***
	(0.053)	(0.080)	(0.070)	(0.061)	(0.103)
Observations	42,832	11,504	8,406	17,324	2,716
Dep. var. mean	4.580	4.428	4.906	4.776	5.174
Office × year FE	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows 2S2SLS regression results of the impact of patent grants on (log) real daily wages measured six years after the patent application of incumbent workers, differentiated by occupational groups across firms and patent types. Each specification is based on a two-sample approach with predicted values from the firm-level first stage regression. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

Table B.21: IV Results: The Effect of Patent Allowance on Bonus Share by Occupations: Firm & Patent Types

	Six Years after Patent Application				
	Manual task (1)	Service task (2)	Technicians (3)	Administration (4)	Manager (5)
		A: Family-oriented companies			
Patent Granted	-0.000	0.000	-0.001	-0.005	0.003
	(0.004)	(0.003)	(0.004)	(0.003)	(0.006)
F-Statistic	4.353	31.61	12.92	37.13	14.49
Observations	84,144	16,715	18,774	28,278	4,075
Dep. var. mean	0.004	0.004	0.002	0.004	0.004
		B: Stock companies			
Patent Granted	-0.048	-0.005	-0.032	0.003	0.010***
	(0.176)	(0.007)	(0.022)	(0.006)	(0.003)
F-Statistic	0.0903	20.22	4.977	31.68	29.87
Observations	10,562	7,976	1,741	4,548	791
Dep. var. mean	0.004	0.002	0.006	0.004	0.002
		C: Manufacturing Sectors			
Patent Granted	-0.006	-0.000	-0.015*	-0.030	0.012
	(0.011)	(0.008)	(0.009)	(0.019)	(0.014)
F-Statistic	1.165	9.092	4.922	6.677	5.766
Observations	68,680	8,918	11,889	13,844	1,889
Dep. var. mean	0.004	0.004	0.004	0.004	0.004
		D: Non-Manufacturing Sectors			
Patent Granted	0.009**	-0.003	0.009	0.001	-0.000
	(0.004)	(0.003)	(0.006)	(0.002)	(0.007)
F-Statistic	11.60	22.82	14.87	59.95	11.29
Observations	26,027	15,769	8,627	18,982	2,979
Dep. var. mean	0.002	0.002	0.002	0.004	0.004
		E: Product Innovation			
Patent Granted	0.000	-0.003	-0.004	-0.003	0.003
	(0.004)	(0.004)	(0.006)	(0.003)	(0.006)
F-Statistic	5.553	21.72	9.789	40.37	17.46
Observations	85,331	18,001	18,310	28,715	4,370
Dep. var. mean	0.004	0.004	0.002	0.004	0.004
		F: Process Innovation			
Patent Granted	-0.002	0.004	-0.004	-0.006**	0.014
	(0.007)	(0.004)	(0.004)	(0.003)	(0.009)
F-Statistic	3.331	51.35	20.19	45.45	15.03
Observations	47,014	14,873	11,545	18,911	2,876
Dep. var. mean	0.004	0.004	0.004	0.004	0.004
		G: Firms with Follow-on Innovation			
Patent Granted	0.009	-0.007	-0.000	-0.016	0.033
	(0.011)	(0.006)	(0.007)	(0.016)	(0.061)
F-Statistic	1.537	13.05	2.033	4.870	0.636
Observations	51,873	13,184	12,112	15,502	2,149
Dep. var. mean	0.002	0.002	0.002	0.004	0.004
		H: Firms without Follow-on Innovation			
Patent Granted	-0.003	0.003	-0.005	-0.005**	0.007*
	(0.007)	(0.005)	(0.006)	(0.002)	(0.004)
F-Statistic	8.123	26.09	22.97	107	24.89
Observations	42,832	11,504	8,406	17,324	2,716
Dep. var. mean	0.004	0.004	0.004	0.004	0.002
Office × year FE	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows IV regression results of bonus share on patent grant, differentiated by occupational groups across firms and patent types. The outcome variable bonus share which is calculated bonus amount relative to wages. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

Table B.22: 2S2SLS Results: The Effect of Patent Allowance on Bonus Share by Occupations: Firm & Patent Types

	Six Years after Patent Application				
	Manual task (1)	Service task (2)	Technicians (3)	Administration (4)	Manager (5)
	A: Family-oriented companies				
Patent Granted	-0.000	0.000	-0.001	-0.007*	0.003
	(0.002)	(0.005)	(0.004)	(0.004)	(0.006)
Observations	84,144	16,715	18,774	28,278	4,075
Dep. var. mean	0.004	0.004	0.002	0.004	0.004
	B: Stock companies				
Patent Granted	-0.006	-0.010	-0.031*	0.006	0.022***
	(0.011)	(0.013)	(0.018)	(0.012)	(0.007)
Observations	10,562	7,976	1,741	4,548	791
Dep. var. mean	0.004	0.002	0.006	0.004	0.002
	C: Manufacturing Sectors				
Patent Granted	-0.002	-0.000	-0.008*	-0.019**	0.008
	(0.003)	(0.007)	(0.004)	(0.008)	(0.009)
Observations	68,680	8,918	11,889	13,844	1,889
Dep. var. mean	0.004	0.004	0.004	0.004	0.004
	D: Non-Manufacturing Sectors				
Patent Granted	0.011***	-0.005	0.011	0.002	-0.000
	(0.004)	(0.005)	(0.007)	(0.003)	(0.007)
Observations	26,027	15,769	8,627	18,982	2,979
Dep. var. mean	0.002	0.002	0.002	0.004	0.004
	E: Product Innovation				
Patent Granted	0.000	-0.004	-0.003	-0.004	0.003
	(0.002)	(0.005)	(0.004)	(0.004)	(0.006)
Observations	85,331	18,001	18,310	28,715	4,370
Dep. var. mean	0.004	0.004	0.002	0.004	0.004
	F: Process Innovation				
Patent Granted	-0.001	0.007	-0.005	-0.010**	0.015*
	(0.004)	(0.007)	(0.006)	(0.004)	(0.008)
Observations	47,014	14,873	11,545	18,911	2,876
Dep. var. mean	0.004	0.004	0.004	0.004	0.004
	G: Firms with Follow-on Innovation				
Patent Granted	0.003	-0.007	-0.000	-0.009	0.008
	(0.003)	(0.005)	(0.003)	(0.007)	(0.011)
Observations	51,873	13,184	12,112	15,502	2,149
Dep. var. mean	0.002	0.002	0.002	0.004	0.004
	H: Firms without Follow-on Innovation				
Patent Granted	-0.002	0.005	-0.006	-0.008**	0.009*
	(0.004)	(0.007)	(0.007)	(0.004)	(0.005)
Observations	42,832	11,504	8,406	17,324	2,716
Dep. var. mean	0.004	0.004	0.004	0.004	0.002
Office × year FE	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows 2S2SLS regression results of bonus share on patent grant, differentiated by occupational groups across firms and patent types. The outcome variable bonus share which is calculated bonus amount relative to wage. Each specification is based on a two-sample approach with predicted values from the firm-level first stage regression. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

Table B.23: IV Results: The Effect of Patent Allowance on employment by Occupations: Firms & Patent Types

	Six Years after Patent Application				
	Manual task (1)	Service task (2)	Technicians (3)	Administration (4)	Manager (5)
	A: Family-oriented companies				
Patent Granted	0.066	0.001	0.015	0.029	-0.013
	(0.044)	(0.030)	(0.046)	(0.023)	(0.078)
F-Statistic	9.557	37.58	15.77	49.06	23.46
Observations	124,438	27,355	29,131	45,991	7,656
Dep. var. mean	0.826	0.778	0.818	0.808	0.712
	B: Stock companies				
Patent Granted	-0.030	0.046	0.101	0.114***	0.217**
	(0.203)	(0.157)	(0.195)	(0.043)	(0.087)
F-Statistic	1.612	2.362	2.986	18.31	19.94
Observations	15,400	11,541	2,884	7,727	1,306
Dep. var. mean	0.842	0.840	0.820	0.84	0.804
	C: Manufacturing Sectors				
Patent Granted	0.061	0.007	-0.022	0.057	-0.116
	(0.079)	(0.064)	(0.093)	(0.061)	(0.180)
F-Statistic	2.676	10.01	4.656	8.361	5.492
Observations	100,015	13,797	17,518	21,856	3,518
Dep. var. mean	0.830	0.78	0.834	0.824	0.738
	D: Non-Manufacturing Sectors				
Patent Granted	0.058	-0.034	0.093*	0.061**	0.070
	(0.046)	(0.035)	(0.052)	(0.024)	(0.094)
F-Statistic	15.36	25.31	21.70	72.47	16.72
Observations	39,822	25,099	14,496	31,861	5,443
Dep. var. mean	0.824	0.798	0.800	0.806	0.718
	E: Product Innovation				
Patent Granted	0.021	-0.036	0.050	0.059**	0.036
	(0.045)	(0.039)	(0.054)	(0.025)	(0.082)
F-Statistic	7.535	23.95	11.77	44.65	22.80
Observations	125,076	28,320	27,815	46,095	7,983
Dep. var. mean	0.830	0.786	0.820	0.814	0.722
	F: Process Innovation				
Patent Granted	0.144*	-0.023	0.030	0.054**	0.059
	(0.075)	(0.032)	(0.039)	(0.025)	(0.090)
F-Statistic	5.887	47.36	22.42	52.80	20.16
Observations	68,665	23,007	17,940	30,890	5,355
Dep. var. mean	0.830	0.796	0.816	0.812	0.714
	G: Firms with Follow-on Innovation				
Patent Granted	-0.011	0.008	0.045	0.049	0.645
	(0.093)	(0.086)	(0.103)	(0.070)	(0.794)
F-Statistic	2.290	9.161	3.087	7.101	0.943
Observations	73,114	20,131	18,612	25,011	4,191
Dep. var. mean	0.834	0.802	0.8160	0.804	0.6880
	H: Firms without Follow-on Innovation				
Patent Granted	0.130**	-0.003	0.063	0.085***	-0.022
	(0.057)	(0.034)	(0.046)	(0.020)	(0.074)
F-Statistic	12.20	34.60	28.57	106.3	28.62
Observations	66,721	18,764	13,403	28,707	4,767
Dep. var. mean	0.820	0.786	0.822	0.820	0.768
Office × year FE	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows IV regression results of employment on patent grant, differentiated by occupational groups across firms and patent types. The outcome variable is a dummy variable equal to 1 if the individual is still employed and zero otherwise. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

Table B.24: 2S2SLS Results: The Effect of Patent Allowance on Employment by Occupations: Firm & Patent Types

	Six Years after Patent Application				
	Manual task (1)	Service task (2)	Technicians (3)	Administration (4)	Manager (5)
		A: Family-oriented companies			
Patent Granted	0.047	0.002	0.014	0.041	-0.015
	(0.031)	(0.045)	(0.043)	(0.033)	(0.087)
Observations	124,438	27,355	29,131	45,991	7,656
Dep. var. mean	0.826	0.778	0.818	0.808	0.712
		B: Stock companies			
Patent Granted	0.022	0.042	0.089	0.249***	0.476**
	(0.153)	(0.146)	(0.176)	(0.088)	(0.194)
Observations	15,400	11,541	2,884	7,727	1,306
Dep. var. mean	0.842	0.840	0.820	0.84	0.804
		C: Manufacturing Sectors			
Patent Granted	0.025	0.006	-0.012	0.038	-0.075
	(0.031)	(0.058)	(0.047)	(0.040)	(0.109)
Observations	100,015	13,797	17,518	21,856	3,518
Dep. var. mean	0.830	0.78	0.834	0.824	0.738
		D: Non-Manufacturing Sectors			
Patent Granted	0.074	-0.055	0.129*	0.111**	0.084
	(0.059)	(0.057)	(0.070)	(0.045)	(0.108)
Observations	39,822	25,099	14,496	31,861	5,443
Dep. var. mean	0.824	0.798	0.800	0.806	0.718
		E: Product Innovation			
Patent Granted	0.013	-0.043	0.039	0.078**	0.039
	(0.028)	(0.047)	(0.042)	(0.032)	(0.088)
Observations	125,076	28,320	27,815	46,095	7,983
Dep. var. mean	0.830	0.786	0.820	0.814	0.722
		F: Process Innovation			
Patent Granted	0.103**	-0.042	0.042	0.089**	0.065
	(0.044)	(0.058)	(0.055)	(0.043)	(0.099)
Observations	68,665	23,007	17,940	30,890	5,355
Dep. var. mean	0.830	0.796	0.816	0.812	0.714
		G: Firms with Follow-on Innovation			
Patent Granted	-0.004	0.006	0.021	0.033	0.172
	(0.036)	(0.068)	(0.050)	(0.046)	(0.131)
Observations	73,114	20,131	18,612	25,011	4,191
Dep. var. mean	0.834	0.802	0.8160	0.804	0.6880
		H: Firms without Follow-on Innovation			
Patent Granted	0.109***	-0.005	0.081	0.155***	-0.028
	(0.040)	(0.054)	(0.060)	(0.036)	(0.092)
Observations	66,721	18,764	13,403	28,707	4,767
Dep. var. mean	0.820	0.786	0.822	0.820	0.768
Office $\times$ year FE	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows 2S2SLS regression results of employment on patent grant, differentiated by occupational groups across firms and patent types. The outcome variable is a dummy variable equal to 1 if the individual is still employed and zero otherwise. Each specification is based on a two-sample approach with predicted values from the firm-level first-stage regression. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

TABLE B.25: IV RESULTS: THE EFFECT OF PATENT ALLOWANCE ON WAGES BY OCCUPATIONS & TIME—NON-TRADED FIRMS

	Years After Patent Application					
	t_1	t_2	t_3	t_4	t_5	t_6
			A: Manager			
Patent Granted	-0.006	-0.032	0.035	-0.016	0.012	0.141*
	(0.057)	(0.061)	(0.072)	(0.066)	(0.069)	(0.081)
Observations	5,295	5,019	4,723	4,487	4,276	4,075
Dep. var. mean	5.000	5.052	5.070	5.088	5.100	5.102
			B: Administration			
Patent Granted	0.048*	0.012	0.055*	0.080**	0.062	0.062
	(0.027)	(0.028)	(0.033)	(0.038)	(0.041)	(0.044)
Observations	33,547	32,446	31,454	30,408	29,374	28,278
Dep. var. mean	4.732	4.746	4.754	4.764	4.772	4.778
			C: Technicians			
Patent Granted	0.065*	0.036	0.079*	0.114***	0.122**	0.169***
	(0.036)	(0.040)	(0.042)	(0.043)	(0.047)	(0.049)
Observations	22,170	21,534	20,880	20,190	19,479	18,774
Dep. var. mean	4.894	4.906	4.918	4.926	4.936	4.942
			D: Service Task			
Patent Granted	-0.001	-0.011	-0.020	0.011	0.025	0.064
	(0.033)	(0.037)	(0.039)	(0.042)	(0.049)	(0.055)
Observations	20,377	19,614	18,897	18,112	17,402	16,715
Dep. var. mean	4.444	4.454	4.460	4.470	4.476	4.480
			E: Manual Task			
Patent Granted	0.043*	0.032	0.020	0.078**	0.079**	0.122***
	(0.026)	(0.030)	(0.034)	(0.033)	(0.035)	(0.041)
Observations	97,618	95,087	92,504	89,844	87,125	84,144
Dep. var. mean	4.590	4.594	4.602	4.610	4.620	4.620
Office × year FE	✓	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Notes: The table shows 2S2SLS regression results of (log) real daily wages on patent grant one to six years after the patent application among incumbent workers initially employed in the firm and differentiated by subgroups of occupation for non-traded firms. Each specification is based on a two-sample approach with predicted values from the firm-level first-stage regression. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

Table B.26: IV Results: The Effect of Patent Allowance on Wages by Occupations & Time—Stock Corporations

	Years After Patent Application					
	t_1	t_2	t_3	t_4	t_5	t_6
			A: Manager			
Patent Granted	-0.144	0.262	0.561**	0.790***	0.792***	1.071***
	(0.182)	(0.195)	(0.236)	(0.227)	(0.221)	(0.333)
Observations	928	895	872	847	814	791
Dep. var. mean	5.170	5.178	5.200	5.206	5.198	5.200
			B: Administration			
Patent Granted	0.024	0.098	0.125	0.092	0.174	0.084
	(0.092)	(0.097)	(0.118)	(0.130)	(0.152)	(0.142)
Observations	5,214	5,037	4,931	4,807	4,654	4,548
Dep. var. mean	4.892	4.904	4.924	4.924	4.934	4.950
			C: Technicians			
Patent Granted	0.028	0.129	-0.150	0.149	0.081	-0.065
	(0.097)	(0.112)	(0.123)	(0.132)	(0.155)	(0.158)
Observations	2,061	1,991	1,930	1,878	1,817	1,741
Dep. var. mean	4.928	4.934	4.944	4.952	4.958	4.962
			D: Service Task			
Patent Granted	0.031	-0.044	0.120	0.131	0.094	-0.319
	(0.109)	(0.125)	(0.178)	(0.172)	(0.253)	(0.271)
Observations	9,100	8,805	8,581	8,418	8,191	7,976
Dep. var. mean	4.600	4.588	4.580	4.568	4.568	4.580
			E: Manual Task			
Patent Granted	0.427**	0.417*	0.268	0.251	0.343	0.571*
	(0.212)	(0.244)	(0.318)	(0.281)	(0.277)	(0.322)
Observations	12,097	11,803	11,486	11,172	10,887	10,562
Dep. var. mean	4.712	4.716	4.714	4.718	4.722	4.722
Office × year FE	✓	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Notes: The table shows 2S2SLS regression results of (log) real daily wages on patent grant one to six years after the patent application among incumbent workers initially employed in the firm and differentiated by subgroups of occupation for stock corporation. Each specification is based on a two-sample approach with predicted values from the firm-level first-stage regression. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

Table B.27: IV Results for Family-oriented Companies Re-weighted to Stock Corporations

	Six Years after Patent Application				
	Manual task (1)	Service task (2)	Technicians (3)	Administration (4)	Manager (5)
Panel A: Wages					
Patent Granted	0.208**	0.056	0.119*	0.054**	0.141*
	(0.092)	(0.041)	(0.062)	(0.027)	(0.080)
F-Statistic	8.204	31.56	14.42	45.63	21.23
Observations	84,144	16,715	18,774	28,278	4,075
Panel B: Bonus Share					
Patent Granted	-0.001	-0.000	-0.001	-0.002	-0.002
	(0.004)	(0.003)	(0.003)	(0.002)	(0.007)
F-Statistic	8.204	31.56	14.42	45.63	21.23
Observations	84,144	16,715	18,774	28,278	4,075
Panel C: Employment					
Patent Granted	0.021	-0.025	-0.063	-0.017	-0.083
	(0.037)	(0.032)	(0.051)	(0.029)	(0.097)
F-Statistic	11.61	32.99	15.34	45.04	25.15
Observations	124,438	27,355	29,131	45,991	7,656
Office $\times$ year FE	✓	✓	✓	✓	✓
Tech.-exp. FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows IV regression results of workers employed in limited liability companies of the impact of patent grants on (log) real daily wages, bonus share, and employment measured six years after the patent application of incumbent workers, differentiated by occupational groups. All regressions re-weight the sample to mimic observables of stock corporations in terms of employment, revenue, average wages (all measured before the submission), industry, year of patent submission, and office of patent submission. All specifications are conditional on having at least ten examinations per examiner. Instrument refers to the leave-one-out measure of assigning grant status. *F*-Statistic refers to the Kleibergen-Paap *F*-Statistic. All specifications control for fully interacted office and year fixed effects, technology class FE of the examiner, sector FE, initial employment, revenue, and wage levels (of the firm and the individual worker) measured in logs. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

C Online Data Addendum: Web Scraping & Digitization of EPO Examiner

The PATSTAT database does not contain information on patent examiners. To overcome this limitation, we deploy patent documents accessible on Patentscope from the World Intellectual Property Organization (WIPO). Patentscope is a database that allows users to access all patent-related documents from participating national and regional offices. Here, we can search for any patent using the application number provided by the EPO authority as visualized in Appendix Figure C.1. Although a search may return multiple results, we focus exclusively on EP-level applications, which indicate submission to the EPO as outlined in Appendix Figure C.2. Once an application is selected, the full set of associated documents becomes available, including descriptions, claims, drawings, and other supporting materials. The "Documents" section contains all PDF files linked to the patent (see Appendix Figures C.3 and C.4). Among all these records, selected documents contain the names of the examiners.

At the EPO, a three-member panel of examiners conducts a thorough assessment and examination of a patent. Following submission, a formalities officer reviews all necessary requirements and transfers the application to the primary examiner. The primary examiner is responsible for evaluating the patent, preparing preliminary search reports, and communicating with the applicants. Therefore, the primary examiner's name appears in the search report as well as in all correspondence between the examiner and the applicants. These communication documents are labeled "Communication from the Examining Division" (see Appendix Figure C.4). The communication documents also provide additional details, such as the filing location, examination site, communication date, and the name of the primary examiner (see Appendix Figure C.5 for an example of a communication document). Another key document, titled "Communication about the intention to grant a European Patent" or "Decision to refuse the application (examining division)" contains the names of all three examiners: the first examiner, the second examiner, and the chairman (see Appendix Figure C.6). In the majority of cases, the name of the primary or first examiner is available. However, information on the second examiner and chairman is not always available, particularly for non-granted or withdrawn applications where the relevant documents are often missing.

Figure C.1: Patentscope search option

Figure C.2: Search Result

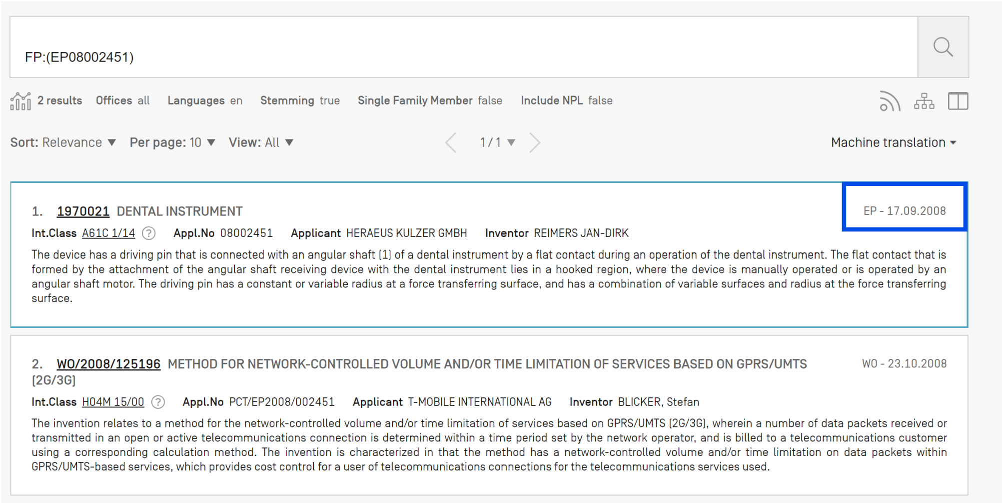


Figure C.3: Documents of the Patent (1/2)

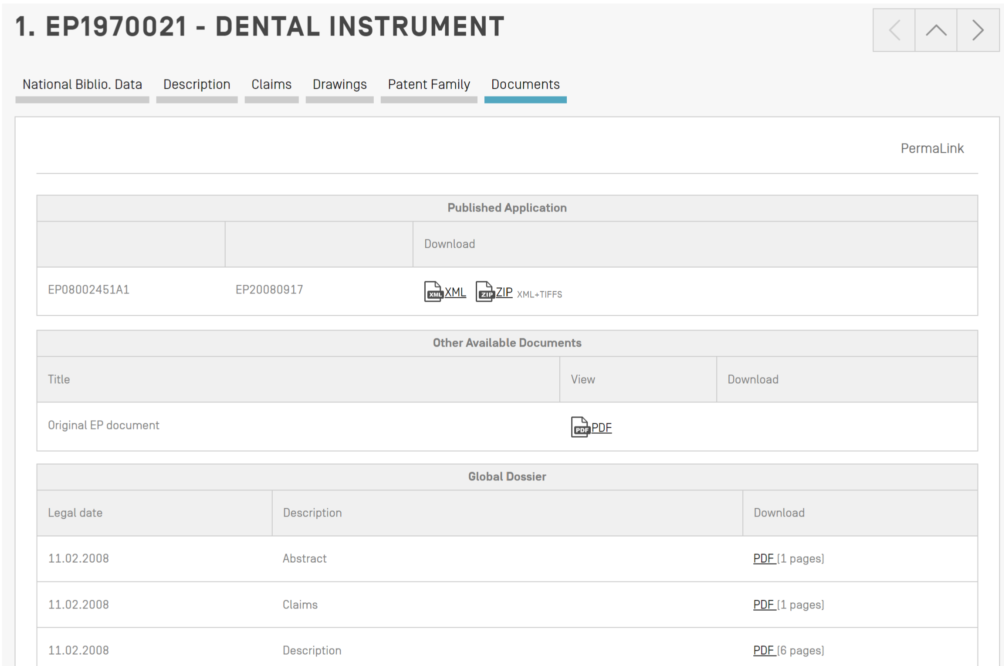
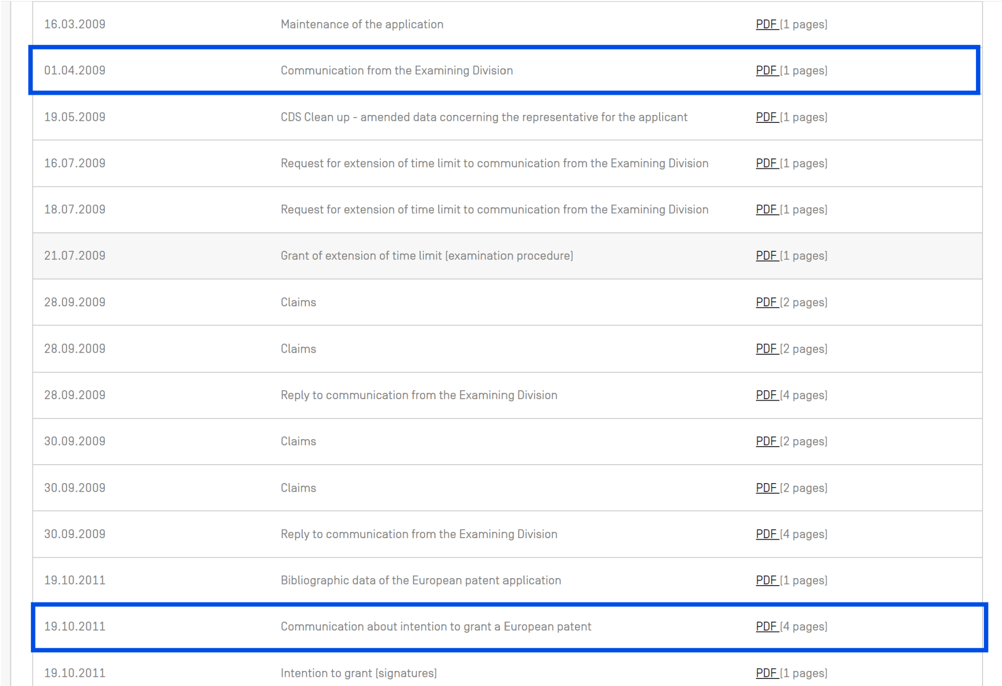


Figure C.4: Documents of the Patent (2/2)



16.03.2009	Maintenance of the application	PDF (1 pages)
01.04.2009	Communication from the Examining Division	PDF (1 pages)
19.05.2009	CDS Clean up - amended data concerning the representative for the applicant	PDF (1 pages)
16.07.2009	Request for extension of time limit to communication from the Examining Division	PDF (1 pages)
18.07.2009	Request for extension of time limit to communication from the Examining Division	PDF (1 pages)
21.07.2009	Grant of extension of time limit (examination procedure)	PDF (1 pages)
28.09.2009	Claims	PDF (2 pages)
28.09.2009	Claims	PDF (2 pages)
28.09.2009	Reply to communication from the Examining Division	PDF (4 pages)
30.09.2009	Claims	PDF (2 pages)
30.09.2009	Claims	PDF (2 pages)
30.09.2009	Reply to communication from the Examining Division	PDF (4 pages)
19.10.2011	Bibliographic data of the European patent application	PDF (1 pages)
19.10.2011	Communication about intention to grant a European patent	PDF (4 pages)
19.10.2011	Intention to grant (signatures)	PDF (1 pages)

FIGURE C.5: COMMUNICATION DOCUMENTS

EPA/EPO/OEB
D-80298 München
+49 89 2399-0
TX 523 656 epmu d
FAX +49 89 2399-4465

Application office

Europäisches Patentamt — Generaldirektion 2
European Patent Office — Directorate General 2
Office européen des brevets — Direction Générale 2

Bayer HealthCare AG
Law and Patents
Patents and Licensing
51368 Leverkusen
ALLEMAGNE

Examination Office

Telephone numbers:	Branch at The Hague
Primary Examiner (substantive examination)	+31 70 340-4078
Formalities Officer / Assistant (Formalities and other matters)	+31 70 340-2667

Application No.	Ref.	Date
00 100 129.6 - 1212	LEA033409-EP 01	23.06.2005
Applicant: Bayer HealthCare AG		

Communication pursuant to Article 96(2) EPC

The examination of the above-identified application has revealed that it does not meet the requirements of the European Patent Convention for the reasons enclosed herewith. If the deficiencies indicated are not rectified the application may be refused pursuant to Article 97(1) EPC.

You are invited to file your observations and insofar as the deficiencies are such as to be rectifiable, to correct the indicated deficiencies within a period

of 4 months

from the notification of this communication, this period being computed in accordance with Rules 78(2) and 83(2) and (4) EPC.

One set of amendments to the description, claims and drawings is to be filed within the said period on separate sheets (Rule 36(1) EPC).

Failure to comply with this invitation in due time will result in the application being deemed to be withdrawn (Article 96(3) EPC).

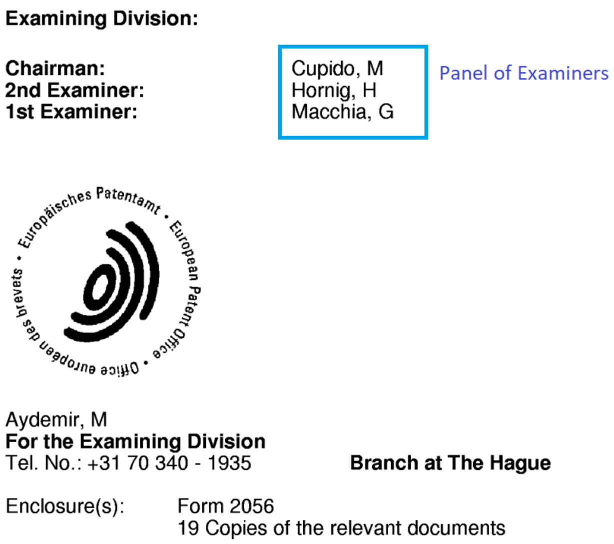
Europäisches Patentamt • European Patent Office • Office européen des brevets

Macchia, G
Primary Examiner
for the Examining Division

Primary examiner's name

Enclosure(s): 7 page/s reasons (Form 2906)

Figure C.6: Examiners' Names



Examining Division:

Chairman:	Cupido, M	Panel of Examiners
2nd Examiner:	Hornig, H	
1st Examiner:	Macchia, G	

Aydemir, M
For the Examining Division
Tel. No.: +31 70 340 - 1935 **Branch at The Hague**

Enclosure(s): Form 2056
19 Copies of the relevant documents

In order to extract information, we first used Python to web scrape and collect all PDF documents titled "Communication from the Examining Division", "Communication about the intention to grant a European Patent", and "Decision to refuse the application (examining division)". In total, we obtain approximately 623,858 PDF documents corresponding to 330,237 patent application IDs since 1981, representing 58% of all patents available in the MUP-EPO data. For our sample period from 2000 to 2016, we managed to download PDF documents for 255,420 patent applications, covering 73% of the patents from the MUP-EPO data. Behind these patent applications, we extracted 9,068 unique examiners.

In the second step, we digitized the names of all examiners from the downloaded documents. We extracted the names of the primary examiner, second examiner, and the chairman. Additionally, we extracted the location of the application and examination office. Not all of the documents are in English; the majority are in German, while a few are in French. During the text extraction process from documents, we ensured that information is retrieved even if the documents are in a different foreign language. During extraction of names, we occasionally extracted special characters, such as hyphens ($-$) and commas (,). Consequently, we removed all special characters and numbers from the names ([\&#$^+,:"£;=?@|'<>.-*()%] and 0 through 9). Additionally, we replaced letters for German Umlauts, such as *ä* to *ae*, *ö* to *oe*, and *ü* to *ue*. Furthermore, we eliminated additional German and French articles from the name, including DEN, DI, LE, LA, VON, DER, DAS, DEL, DE, and DA. We also removed some irrelevant text like "SACHPRÜFUNGSFRAGEN" and "RÉPUTÉE RETIRÉE" which was extracted along with the name for some cases. The full name of the individual is often not visible in the documents. Sometimes the person's whole name is mentioned, and occasionally it is just the last name and the first name's initial. To maintain consistency, we retained the individual's surname and the initial of their first name. We have also assigned each examiner a unique ID for analytical purposes.

In order to digitized the location of the patent office, the documents do not always report precise geographic information. In such cases, we infered location using the telephone number of the primary examiner. Similar to the names, we removed all special characters from the telephone numbers to ensure consistency and used the first four digits of the calling code to determine locations, such as 4989 corresponds to Munich, 4930 to Berlin, and 3170 to The Hague.

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https://www.ssrn.com/link/ZEW-Ctr-Euro-Econ-Research.html
https://ideas.repec.org/s/zbw/zewdip.html

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