The Effects of Inventions on Firms and Workers: Causal Evidence from Quasi-Random Patent Allocation*

Afroza Alam† André Diegmann‡

March 20, 2025

Abstract

This paper provides new evidence of patent-induced shocks on firm survival, growth, and productivity and how innovation shocks impact worker compensation and employment prospects. Using linked employer-employee data with newly linked German firm data and web-scraped patent documents, we leverage quasi-random assignment of patent applications to examiners. Patent allowance reduces market exit and increases firm productivity. This induces positive wage responses for lower wage jobs, in particular for administrative staff and skilled and unskilled manual and service employees. We present evidence that this result is likely driven by institutional feature of co-determination in the German labor market.

Keywords: Innovation, Firm Performance, Worker Compensation.

JEL classification: J01, O3, O34

*Acknowledgements and Disclosures: We thank Ufuk Akcigit, Laura Pohlan, Merih Sevilir, Daniel Streitz, Simon Wiederhold and numerous seminar and conference participants for constructive feedback and comments. For providing valuable support for data access and data expertise, we thank Sandra Gottschalk and Thorsten Doherr (Mannheim Enterprise Panel). We further thank Alexander Giebler for technical support with webscraping patent documents. We gratefully acknowledges financial support from the Leibniz Association Research Grant K525/2023. The views in this paper are solely the responsibility of the authors.

†Afroza Alam: Halle Institute for Economic Research (IWH). Email: aforza.alam@iwh-halle.de ‡André Diegmann: Halle Institute for Economic Research (IWH), Institute for Employment Research (IAB), ZEW – Leibniz Centre for European Economic Research. Email: andre.diegmann@iwh-halle.de.

1 Introduction

Innovation drives economic growth and subsequent welfare improvements in the long run. Key players in the innovation process are firms that invent the most superior product or production technology. In many advanced economies, the concentration of innovative firms, such as firms filing for patents, has increased considerably. Although overall patenting activity is increasing in countries like the U.S. and Germany throughout the last three decades, higher concentrated innovative activity indicates that rents from innovations become more concentrated with potential implications on inequality through differential worker compensation. For reasons that technological advances are typically not shared equally across society (Gordon 2016; Johnson and Acemoglu 2023), recent technological developments, such as automation and artificial intelligence, have sparked the public debate on government interference in the distribution of gains (Furman and Seamans 2019). To what extent and which type of workers benefit or lose under what conditions remains a central question.

This paper documents the disruptive nature of innovations on firms and workers. Exploiting variation in patent allowance generates a situation in which firms obtain monopoly rights and potentially extract economic rents. Thus, we first document how patent-induced shocks affect firm survival, employment and sales growth as well as productivity improvements measured by subsequent innovations. We then study the impact on employees by focusing on wage and bonus payment dynamics as well as worker reallocation and employment stability.

Our analysis relies on a new linkage of different datasets containing firms, establishments, and workers over the years between 2000 and 2021 (for a description of the linkage see Diegmann, Doherr, Hälbig, and Wolter 2024). 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 the fact that PATSTAT covers not only granted patents but also includes rejected patent applications. 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) allows us to measure worker compensation and the stability of employment. The data further contains detailed information at the worker level, including demographic characteristics and occupational information, which allows us to differentiate potential gains from innovations by studying wage developments and employment prospects for different groups of the workforce.

Identification of the causal effect of patent allowance on firms and workers suffers from selection bias. Firms with a patent granted are typically larger and more productive firms with better financial conditions and growth prospects. Although the data allows us to compare firms with granted patent applications with firms that receive a rejection, we show that major initial firm characteristics such as firm size, credit worthiness, and average real wage levels differ between assignees with granted and non-granted patents. This generates concerns in the parallel trends assumption even when pre-trends might be parallel (Kahn-Lang and Lang 2020). 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 preference 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 application numbers 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 to estimate the leniency of examiners to grant a patent. We further 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 empirical evidence that examiners typically examine 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. A complier in our setting is defined as a firm that would have received a different 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) and Humlum, Munch, and Rasmussen (2023) and provide empirical evidence that monotonicity holds. Finally, following Frandsen, Lefgren, and Leslie (2023), we implement pairwise monotonicity and exclusion text and fail to reject the joint null hypothesis thus hold pairwise monotonicity and exclusion text.

Pakes (1984) and Hall, Jaffe, and Trajtenberg (2001) have first provided 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. The sample of first time allowance or rejection of the patent application has arguable significant consequences on firm performance and subsequent worker compensation

and job stability.[1]

Using this data, we establish three distinct facts at the firm level. First, we show that winning a patent as compared to receiving a rejection affects the extensive margin of firm operation. One year after initial submission, the probability of market exit is reduced by 5% points and continues to decrease to 13% points five years post submission. Complier firms with a patent grant status have an exit rate of around 5% five years after the initial submission, whereas compliers with a non-granting patent status have an exit rate of 18%. We test alternative hypothesis that firm exits may be driven by M&A activity but do not find supporting evidence. Additionally, exploiting bankruptcy indicators supports the view of lower market exit rates. Second, we show that firm sales increase due to patent allowance. Surviving firms, however, do not grow in terms of employment, indicating higher labor productivity. Third, we provide evidence on follow-on patenting activity. In line with higher firm productivity, patent allowance induces cumulative research with a higher measured patent stock.

At the worker-level, firms with a successful patent application do not only become more productive and stay in the market, but also increase wages of workers observed initially in the firms. Five years after the initial submission, average wages of incumbent workers increase by 8.4%. This wage impact is not observed immediately but kicks in with a time lag of about three to four years. In contrast to U.S. evidence, we show that wage effects are driven by relatively lower wage jobs such as administration workers and employees in manual and service occupations as compared to managers. Surprisingly, technicians and engineers do not show significant wage impacts due to the successful applications, which likely represents regulation of inventor compensation.[2]

The worker-level results are heterogeneous across the firm size distribution, with larger firms driving the wage developments. One feature of the German labor market is that unions negotiate wage floors, but firms have considerable scope of wage-setting policies (Jäger, Schoefer, and Heining 2021).[3] Our estimates are consistent with the fact that larger firms have more leeway in the wage setting process. We further differentiate the sample by stock corporations and private partnerships, which, we argue, generates a distinction between lower and higher levels of within-firm co-determination. Gottschalk, Hauer, and Ahrens (2023) show that private partnerships are typically family-owned businesses with lower hierarchical layers, whereas public firms typically add hierarchy, leading to greater

[1]Patent applications in German firms are concentrated, with approximately 24,689 unique companies accounting for 357,309 patents filed with the EPO between 2000 and 2016 (applied in EPO). At the firm-year level, 37% of the firms submitted more than one patent. Focusing on first-time patenting firms, 83.5% apply for exactly one patent.

[2]In Germany, inventor compensation is regulated by the *Employee Inventions Act (1957)*. Evidence from Finland, a country with similar inventor regulations, Aghion, Akcigit, Hyytinen, and Toivanen (2018) show inventors receive only a small portion of the total gains from their inventions, whereas entrepreneurs benefit the most. Based on a setting without specific legal requirements for inventor compensation, Kline, Petkova, Williams, and Zidar (2019) shows for the U.S. that inventors account for the majority of pay increases.

[3]Sectoral bargaining under the *Collective Agreements Act (1969)* enables trade unions, employers, and employer associations to set industry-wide wage floors. However, since the beginning of 1990s, there has been a significant shift toward decentralization as employers demanded more firm-specific and differentiated regulations. This shift has been facilitated by "opening clauses", which allow individual firms to negotiate specific terms such as wages and working hours with their works councils under particular conditions (Jäger, Schoefer, and Heining 2021; Dustmann, Fitzenberger, Schönberg, and Spitz-Oener 2014). Additionally, the *Works Constitution Act (1952)* provides workers' rights through works councils, which actively participate in decisions on working hours, pay, workplace safety, and social matters within companies. Hübler and Jirjahn (2003) argue that in collective bargaining-covered establishments, works councils focus on boosting productivity, while in uncovered ones, they may engage more in securing wage benefits.

wage inequality by disproportionately increasing the productivity and wages of top employees (Bias, Lochner, Obernberger, and Sevilir 2022). Align with this, we show that managers employed in large stock corporations experience significant wage gains.[4] Five years after initial submission, wages increase by around 23%. Manual and service employees, in turn, experience a significant positive wage effects when employed in partnerships with arguably high levels of co-determination. These results suggest that institutional determinants are important drivers in distributing the gains from economic rents.

This paper first provides new causal evidence on the effects of innovations and firm performance. Early contributions in the field have documented robust positive correlations between innovation and firm performance, 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) uses 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 a lower cost of capital. 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 prevents from growing.[5] On the firm side, Kline, Petkova, Williams, and Zidar (2019) provide evidence for first-time applicants in the U.S. using a difference-in-difference setting and 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 lowers 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 that monopoly rights by patent allowance generate economic rents.

We further measure firm productivity by follow-on patenting activity thereby contributing to the literature on patenting activities and firm's future innovation. Cumulative research is a dominant feature of modern innovation. Sampat and Williams (2019), however, finds no effect on follow-on innovation in human genomes innovation activity. Galasso and Schankerman (2015) provide evidence on the impact of removing patent rights on cumulative innovation. Their results suggest that patent invalidation by courts significantly affects cumulative innovation with heterogeneous effects across technologies. Patent rights block downstream innovation in computers, electronics and medical instruments, but not in drugs, chemicals or mechanical technologies. In follow-up work, Galasso and Schankerman (2018) shows that removing patent rights reduces future patenting activities and

[4]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.

[5]Related to this line of research, Desai, Gavrilova, Silva, and Soares (2022) show the importance of trademarks for firm value and growth measured as firm-level employment, sales, and output.

increases the likelihood of market exit with the effects being driven by small- and medium-sized firms.[6] Our study contributes to the existing literature and shows that successful innovations not only engender future innovative endeavors but also contribute to cumulative innovation. Moreover, the technology composition relative to initial technology class do not differ between granted and non-granted patent. This provides descriptive evidence for cumulative research as the majority of new innovations fall in the technology class of the initial patent.

The unique worker-level evidence contribute to the literature that studies how shocks to firm performance propagate to workers. Numerous studies have documented that firm performance and worker compensation are strongly related (Card, Cardoso, Heining, and Kline 2018) and that more productive firms pay wage premia for 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) thereby contributing to aggregate wage inequality.[7] Kline, Petkova, Williams, and Zidar (2019) show in the difference-in-differences setting that patent allowance benefits inventors, firm officers and initially high-wage workers for ex ante valuable patents. Our setting allows us to further differentiate firm movers and stayers in which we can show that positive wage responses after successful patenting is driven by firm stayers. In contrast, new hires do not experience higher wages in firms with granted patents. Patent-induced shocks, therefore, propagate to incumbent workers. Although firms do not grow in terms of employment, we further document that worker composition is changing with higher inflow of technicians and engineers and lower inflow of administrative workers.

The remainder of this paper is organized as follows. In Section 2, we describe the data and provide descriptive statistics of the 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 6.1 reports our empirical results on firm performance. Sections 6.2 and 6.3 shows worker-level analysis. Section 7 concludes.

2 Data and Sample

2.1 Data

Firm-Level Data. The basis of our firm-level data is the *Mannheim Enterprise Panel* (MUP), panel data 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

[6] It is important to note that the paper by Galasso and Schankerman (2018) primarily hinges on the litigation of only valuable patents that make it to the U.S. Court of Appeals for the Federal Circuit. These patents may not represent an overall picture of innovation. Moreover, litigation typically ensues when the existing patent is only substituted with alternatives.

[7] Focusing on technology and inequality, Antonczyk, Fitzenberger, and Leuschner (2009) and Antonczyk, DeLeire, and Fitzenberger (2018) have found that technology-driven polarization in employment has led to wage inequality at the bottom of the wage distribution in Germany and the USA. In contrast, the adoption of digital technologies has been associated with enhanced employment stability, wage growth, and cumulative earnings, as shown by Genz, Gregory, Janser, Lehmer, and Matthes (2021)

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 variables 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. 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.

The basis in the linkage procedure contains all patents from Germany that have been applied to the EPO. The data is regularly updated by ZEW. We have patent applications available until 2019. Due to the fact that PATSTAT has time lags, we consider patent applications until 2016. Over the period between 1978 to 2016, we observe in total 617,673 patents applied in EPO, out of which around 90% are from firm assignees, 7% from individuals, 2% from 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. The match rate is considered to be high with around 94% of the patents being merged to the firm data. 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.

The characteristics of firms that engage in innovative activities are distinct, distinguishing them 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 innovation and patent activities are concentrated in the manufacturing, retail trade, and technical service sectors, offering unique insights into the innovation landscape in Germany. Appendix Table A.2 shows summary statistics of firms with their first patent application, which represents our baseline sample. Similarly to all firms with patent applications, this group of firms are larger and more productive compared to the average firm. However, compared to all innovative firms, first-time patenting firms younger, of lower size and slightly less productive,

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 covered by the MUP sample, we are able to extract examiner information for 255,420 applications over the years between 2000 to 2016.[8] Details about web-scraping and digitization process of the data are provided in Appendix B.

Additionally, we obtain the office information for the location where the application was submitted and the location where it is being evaluated.[9] We extract both locations because submitting the application at 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 Application for Each Office

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 the office information of our baseline sample. The office details of the examiners were extracted from the web-scraped PDF from Patentscope WIPO. Between 2000 and 2016, we managed to capture 255,420 applications. However, due to missing information, the total number represented in the table may not sum up to 255,420.

Linked Employer-Employee Data. We incorporate in our analysis data 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 Diegmann, Doherr, Hälbig, and Wolter

[8]Overall, the coverage rate varies around 76%. The years 2004 and 2005 are less well covered in the data.

[9]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.

(2024). 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.1. The top largest 10% of patenting firms contaminate 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 innovation on firm and worker outcomes.

To construct a clean analysis sample, we identify the first patent application event at the firm level and follow these firms over time. In total, we identify the year for 18,424 firms that are observed with its first application. Among them, the majority of 83.5% file for exactly one patent and 16.5% file for two or more patents.

In our analysis, we concentrate on a firm with first-time patent application.[10] 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. Appendix Figure A.2 shows the number of firms in our sample over time. On average, there are around 800 firms per year that fulfill the definition with slightly lower numbers towards the end of the sample period. 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. Similar to the overall sample, 57% of the applications receive a patent grant.

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 provides summary statistics for the year of the application, whereas Panels A2 and B2 provide information (outcome variables) five years after the first patent application. The average firm in our sample has about 167 employees and is about 14 years in the market at the time of the application. Both variables are right-skewed, i.e., 40% of the firms have fewer than 10 employees and 36% are younger than 5 years (with 10% being founded in the year of the application).

The industry affiliation is concentrated among four sectors. Similar to Appendix Table A.1, about every third firm is active in the manufacturing sector. The two second major industries are retail trade with 12% and technical service with 15%. About 4% of the firms are active in the information and communication industry. Over the course of five years (Panel A2), 13% of all firms exit the market. Conditional on survival, the average employment and revenue growth rate is about 38% to 43%.[11]

[10] Appendix Table A.2 shows that first-time patents have distinct characteristics from other innovative firms in the economy. Although being larger then a random firm in Germany, first time applicants are smaller in terms of employees and revenue, younger, and have a slightly better credit rating.

[11] When considering employment and revenue growth rate, we follow Davis and Haltiwanger (1999) and calculate the

Table 2: Summary Statistics: First-Time Patenting Firms

	N	Mean	SD	Minimum	Maximum
	(1)	(2)	(3)	(4)	(5)
		A: Firm-level Data			
A1: Initial year of patent application					
Employment	11,971	167.20	663.49	0.00	29,532
Log revenue	8,867	15.49	2.04	0.19	25.16
Firm age	11,970	14.16	11.30	0.00	42.00
New foundation	11,971	0.10	0.30	0.00	1.00
Average real daily wages	11,213	107.24	53.89	1.76	2,473.98
Credit rating index	8,683	235.85	53.88	100.00	600.00
Manufacturing	11,971	0.38	0.48	0.00	1.00
Retail trade	11,971	0.12	0.33	0.00	1.00
ICT	11,971	0.04	0.20	0.00	1.00
Technical service	11,971	0.15	0.35	0.00	1.00
A2: 5 years after patent application					
Firm exit	11,538	0.13	0.33	0.00	1.00
Employment growth	9,794	0.38	0.75	-1.99	2.00
Revenue growth	6,000	0.43	0.88	-2.00	2.00
Number of patents	11,971	1.76	7.31	0.00	375.00
Any patenting	11,971	0.42	0.49	0.00	1.00
Majority acquisition	11,971	0.23	0.42	0.00	1.00
		B: Individual-level Data			
B1: Initial year of patent application					
Female	1.72m	0.29	0.45	0.00	1.00
Age	1.72m	40.30	10.72	18.00	65.00
Nationality German	1.72m	0.91	0.29	0.00	1.00
Daily wages	1.72m	117.86	55.44	10.00	414.01
Bonus payments	1.72m	0.01	0.11	0.00	1.00
No vocational training	1.71m	0.13	0.33	0.00	1.00
Vocaltional training	1.71m	0.70	0.46	0.00	1.00
University	1.71m	0.17	0.38	0.00	1.00
Unskilled manual /service	1.70m	0.32	0.47	0.00	1.00
Skilled manual /service	1.70m	0.20	0.40	0.00	1.00
Administration	1.70m	0.21	0.41	0.00	1.00
Technicians/Engineers	1.70m	0.17	0.38	0.00	1.00
Manager	1.70m	0.03	0.17	0.00	1.00
B2: 5 years after patent application					
Employed	1.70m	0.83	0.38	0.00	1.00
Daily wages	1.41m	130.94	65.92	0.01	1450.47
Employed in same firm	1.41m	0.75	0.43	0.00	1.00

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

After the first patent filing event, 42% of the firms experience follow-up patents. Finally, we exploit ownership information to measure M&A activity. Around 23% experience a majority ownership change over the five years interval.

growth rate between two points in time as: $(L_{t+k} - L_t)/0.5(L_{t+k} + L_t)$. This measure bounds the distribution between -2 (firms with zero employment) and 2 (firms with initially zero employment).

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 insights from Lahorte (2018), more than half of examiners in EPO hold a doctorate, 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.[12] 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[13], 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 a preliminary opinion on patentability. This search report may also provide the applicant 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.

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

[13] 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 at the EPO.

The substantive examination carried out by the EPO involves a panel of three examiners, including the primary examiner who conducted 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 made through a 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. The case will be examined again by an EPO team of three examiners. In the event of an opposition, the EPO team of three examiners will examine the case again. The primary examiner of the examination division 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.

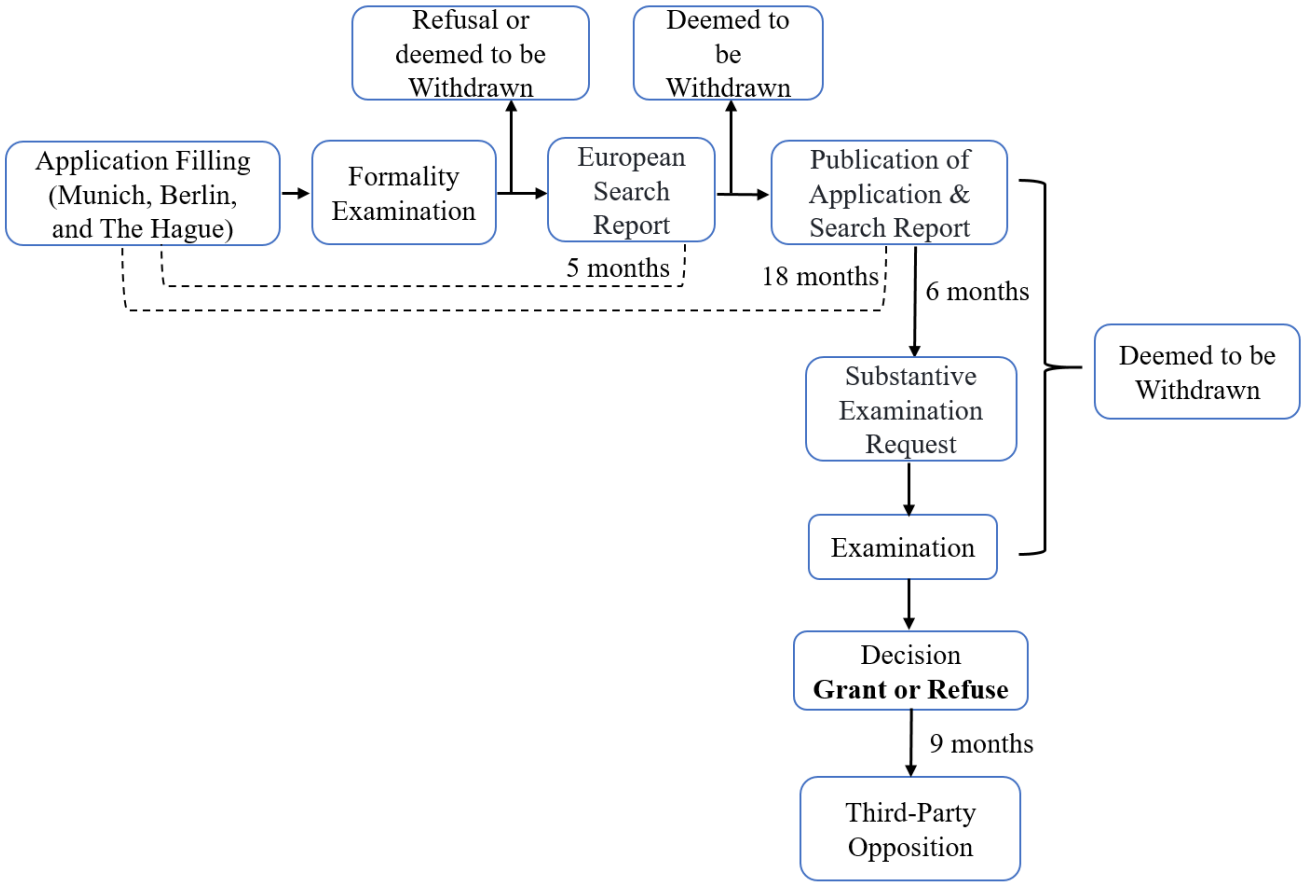


Figure 1: Overview of European patent application process

3.2 Allocation of Patents to Examiners

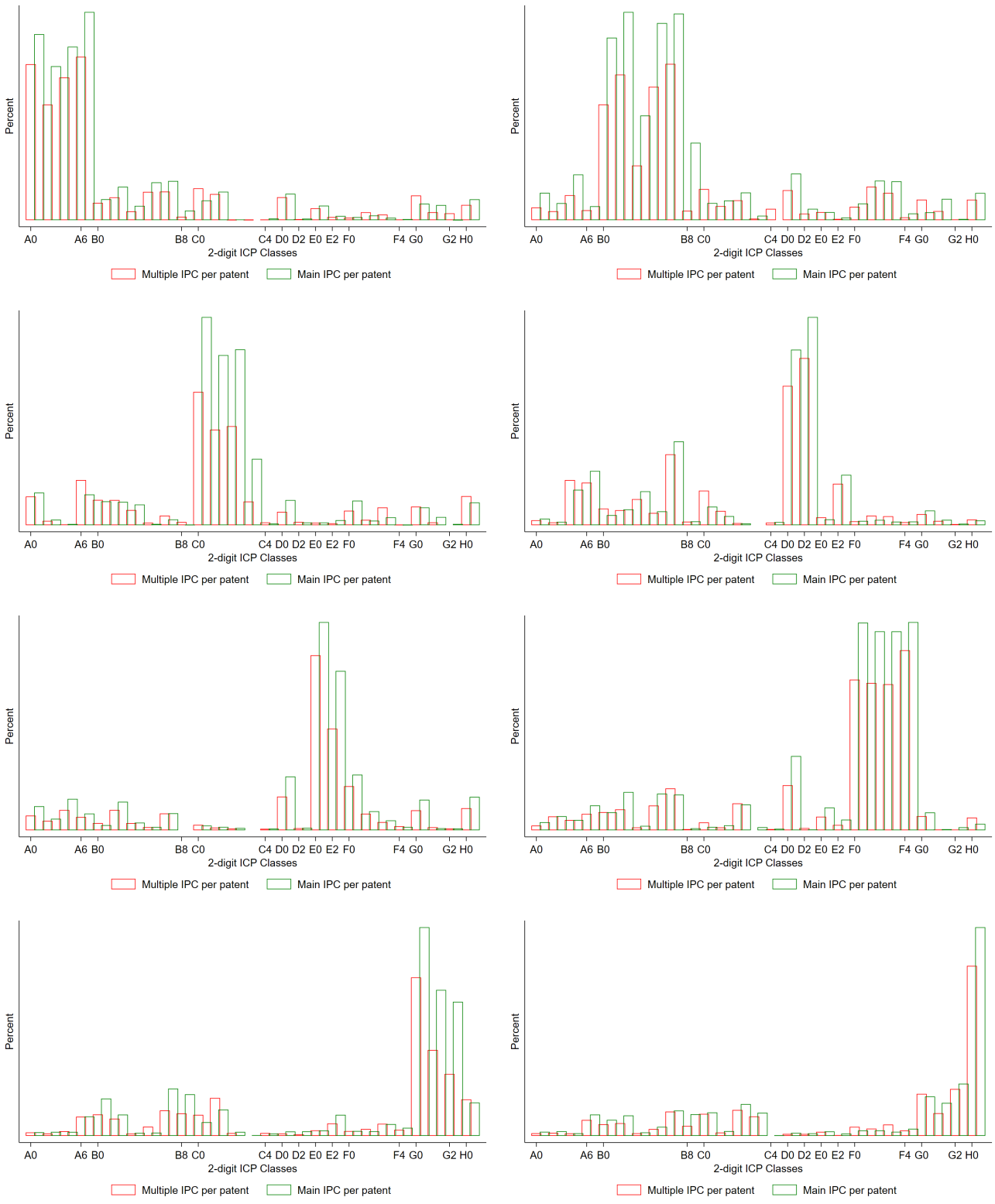
In our identification strategy, we exploit the allocation of patents to examiners. The allocation process is á priori not random, because to be able to examine a potentially new invention, examiners need knowledge and expertise of the respective technology.

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 European Patent Office, Lahorte (2018) report that examiners are specialized and work in narrow technical sectors. Similarly, we observe that patent applications are not randomly allocated to examiners within the European Patent Office 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 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 technology classes.[14]

Within each defined technological specialization, we observe deviations as examiners evaluating patents outside their defined field of expertise. For example, an examiner specialized in IPC class G (physics in the lower left corner) 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 out of which reason 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.

[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



Notes: Figures show the applications are assigned to examiners within different technology classes. It shows the allocation of applications to primary examiners. IPC classes are constructed at the 2-digit level. The red bar shows the patents with multiple IPC classes, and the green bars show the main IPC class that examiners are assigned. Here, 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

4 Empirical Strategy

The goal of this paper is to estimate the causal effects of a successful innovation as opposed to a rejected application measured as firms' patenting activity on firm and worker-level outcomes. Identifying these 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 if 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) and patent and trademark evaluations (Farre-Mensa, Hegde, and Ljungqvist 2020; Hege, Pouget, and Zhang 2024; Aneja, Reshef, and Subramani 2024; Desai, Gavrilova, Silva, and Soares 2022). 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 main purpose of the 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 of decision-makers, an exogenous shifter is generated that helps mitigate potential biases.

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 in cases of rejections, we can find the information for the chairman and second examiners, but we cannot get the name of 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's 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:

$$Z_{fioj} = \frac{1}{n_{oj}-1}\left(\sum_{k=1}^{n_{oj}}(D_{k\not\in f}) - D_{fi}\right) - \frac{1}{n_o-1}\left(\sum_{k=1}^{n_o}(D_{k\not\in f}) - D_{fi}\right) \tag{1}$$

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. Given that over time, firms may submit multiple patents assigned to the same examiner which my cause a correlation of decisions. For this reason, the average decision of the examiner only contains other patent decisions not submitted by the same firm.

We estimate the dynamic effects of patent allowance on firm dynamics and worker performance. At the firm level, we consider market exit, employment and revenue growth and subsequent innovations. At the worker level, we focus on wage dynamics 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 EOP-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 our sample of first-time patenting firms, around 16.5% of the firms submit more than one patent. In the baseline specification, we assign a value of one if at least one of the submitted patents get granted and zero otherwise. Alternatively, we calculate the share of granted patents.[15] The vector X contains two further variables. First, we include initial measures of firm size in terms of employment and revenue which results in a normalization of estimated growth rate effects. 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. When considering worker-level outcomes, we cluster the standard errors at the firm and examiner level.

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). Our identification strategy departs from earlier judge-IV designs regarding the allocation mechanism to patents, which comes from the quasi-random assignment of the patent within the art unit or IPC class. We exploit all available information of examiners decision making over the years between 1990 to 2016. Since the outcome variables are only available from 2000 onwards, we provide independence and monotonicity tests for the years 2000 to 2016.

[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) emphasized the use of class or subclass fixed effect as the patent applications to examiners are based on examiner specialization.

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 regression. The figure delivers two takeaways. 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, an assigned patent to an examiner at the 90th percentile of the leniency distribution has a probability of around 75% to receive a grant status. In contrast, the probability of receiving a grant status is below 55% for patents assigned to examiners at the 10th percentile of the leniency distribution.



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 examiner leniency (left y-axis). The figure is constructed by conditioning of having handled at least five patent applications per examiner.

FIGURE 3: FIRST-STAGE ANALYSIS

We further observe consistent patterns in patent-granting behavior among examiners. Appendix Figure C.11 indicates by 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 0.97. Our first stage analysis is robust when constructing our instrument for the second examiner or for the chairman, as well as when considering the formation of teams (see Appendix Figure C.12).

5.2 Independence

For our instrument to be valid, it must fulfill the independence assumption. We provide evidence that this assumption holds in Table 3. To test for the independence assumption, 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. The independent variable is an indicator if the patent will be granted. Each line represent a single regression controlling for the filing year and office fixed-effects. 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 result shows that the granted status is endogenous. In particular larger firms of higher age and with better credit ratings are more likely to get the patent granted. This finding might reflect the fact that larger firms more often employ of specialized individuals who can organize the patent submission process more efficiently.

Table 3: Test of Random Assignment of Firms to Examiners

	Granted		Leniency		Dep. variables		
	Coefficient	*p*-value	Coefficient	*p*-value	Mean	SD	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Employment							
Log employees	0.102	0.014	-0.037	0.772	3.910	1.796	8,476
Small firm < 5 employees	-0.016	0.105	-0.015	0.611	0.206	0.404	8,476
Big firm > 100 employees	0.024	0.016	-0.006	0.849	0.226	0.418	8,476
Revenue							
Log sales	0.080	0.113	-0.131	0.388	15.460	2.038	7,989
Sales < p25	-0.016	0.146	0.044	0.190	0.250	0.434	7,989
Sales > p90	0.004	0.603	-0.005	0.812	0.100	0.300	7,989
Productivity							
Log labor productivity	0.012	0.736	-0.049	0.632	12.152	1.316	7,737
Labor productivity < p25	-0.007	0.530	0.051	0.128	0.250	0.434	7,737
Labor productivity > p90	-0.012	0.132	-0.027	0.263	0.100	0.300	7,737
Median firm real wage	-0.021	0.033	-0.019	0.517	5.264	0.382	7,842
Credit worthiness							
Good Credit Index	0.012	0.231	0.011	0.716	0.220	0.414	7,821
Bad Credit Index	-0.029	0.000	-0.011	0.602	0.080	0.270	7,821
Firm Age & Legal Form							
Firm age < 5 years	-0.057	0.000	-0.032	0.377	0.278	0.448	6,853
LLC	0.001	0.909	0.009	0.806	0.702	0.458	6,853
Stock corporation	-0.012	0.074	-0.031	0.137	0.056	0.230	6,853

Notes: All explanatory variables listed in the table refer to the initial firm observation. Each line represents a single regression of the explanatory variable on the leniency measure that takes values between 0 (minimum) and 1 (maximum) controlling for examiner office-year and technology fixed effect. *p*-values calculated based on robust standard errors. *p<0.1, **p<0.05, ***p<0.01.

Column (3) of the table performs the same regressions but testing the leniency measure, 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 assigning the granting status to a patent.

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. 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.

Table 4: Exclusion Test

	Summary			Leniency	
	N	Mean	SD	Coeff	*p*-value
	(1)	(2)	(3)	(4)	(5)
Experience	4,626	18.382	4.676	-0.172	0.166
Workload	4,626	8.460	6.078	0.040	0.808
Interaction with applicant	280,580	1.490	0.896	0.000	0.989
Application decision duration	244,376	4.136	1.498	-0.016	0.440
Application publication duration	278,276	1.456	0.876	0.041	0.487

Notes: This table shows summary statistics of examiner characteristics and the correlation between examiner leniency and these characteristics. We conditioned the examiner to handle 15 patents. The characteristics include work experience, workload, interaction with the applicant, duration of the patent decision (we exclude if the duration is more than 7 years; 90% of the application takes 1 to 7 years), and duration of the first publication of the patent. Experience and workload are measured at the examiner level. Interaction with the applicant and the duration are measured at the patent level. Each line represents a single regression of the explanatory variable on the leniency measure that takes values between 0 (minimum) and 1 (maximum), controlling for examiner office-year and technology class fixed effect. *p*-values calculated based on robust standard errors.

We provide a test for the exclusion restriction by collecting further information describing the examiner. 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 might provide more chances for amendment than others or that examiners that are inclined to grant more patents when they have more workload. Lahorte and Preller (2023) also states that effective communication and interaction with the applicant accelerate the processing of the application.

The basic idea, thus, is that our instrument should also be uncorrelated with examiner's other characteristics that we can observe. The data allows us to construct the number of applications the examiner is handling, which serves as a proxy for workload. We can further measure the experience with patent applications by calculating the number of years we observe an examiner since the first occurrence in the data. The number of times the examiner provides feedback or asks for the amendment of the application is considered as a proxy that describes the interaction with the applicant. We also consider the duration of the first publication of the application when the application and search report become public as the applicant can get the indication if the patent is successful or unsuccessful. Lastly, we consider the duration until the application reaches a decision. Table 4 provides the results. The table first shows that the average examiner has 18 years of experience and a current workload of 8.5 patents. The average examiner interacts 1.5 times with the assignee, the average patent application

has a duration of 4.2 years, and 1.5 years for the patent application to become public. The last two columns provide the results on the correlation between our instrument and the constructed variables. In all cases, the leniency measure is uncorrelated with the variables suggesting that the exclusion restriction holds.

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 the patent granted with lenient examiners. This assumption ensures the 2SLS estimand can be a local average treatment effect interpretation, i.e., it is an average causal effect among the subgroup that could have received a different decision if the application is 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 (Bhuller, Dahl, Løken, and Mogstad 2020; Dobbie, Goldin, and Yang 2018). To do this, we construct sub-samples with respect to firm size, firm age, sales, sector affiliation, productivity (labor productivity and AKM effects), and credit ratings measured at the initial year of 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 shown in column (4). As expected under the assumption of average monotonicity, all first-stage (as per Equation (2)) coefficients are positive and statistically significant.

Table 5: First Stage Results by Sub-Samples

		Mean			
	N	Granted	Leniency	Coeff	p-value
	(1)	(2)	(3)	(4)	(5)
Small firm < 10 employees	2,655	0.572	0.618	0.507	0.000
Big firm > 100 employees	1,924	0.658	0.654	0.516	0.000
Firm age < 5 years	2,488	0.562	0.618	0.490	0.000
Sales < p25	1,998	0.578	0.618	0.442	0.000
Sales > p75	1,997	0.628	0.650	0.542	0.000
Labor productivity < p25	1,935	0.596	0.626	0.568	0.000
Labor productivity > p75	1,935	0.602	0.638	0.597	0.000
Good Credit Index	1,723	0.650	0.656	0.565	0.000
Bad Credit Index	621	0.468	0.600	0.432	0.002
High AKM	1,610	0.662	0.656	0.482	0.000
Low AKM	3,946	0.590	0.626	0.548	0.000
Manufacturing	4,031	0.650	0.658	0.498	0.000
Retail trade	1,353	0.644	0.656	0.413	0.000
ICT	470	0.460	0.528	0.549	0.000
Technical service	1,558	0.562	0.606	0.449	0.000

Notes: All explanatory variables refer to the initial year of the patent application. Each line represents the set of firms for which the condition holds. We regress granted patent on examiner leniency for each sub-group, controlling for examiner office-year and technology fixed effect (Eq. 2). p-values calculated based on robust standard errors.

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

2023). 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 a slightly increasing first-stage coefficient. 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.

Table 6: Testing for Monotonicity with the Baseline Instrument

	Predicted Probability Percentiles		
	1 – 33	34 – 66	67 – 100
	(1)	(2)	(3)
Leniency	0.485	0.545	0.496
p-value	0.000	0.000	0.000
Observations	2,437	2,436	2,363
Mean	0.388	0.656	0.786
SD	0.480	0.466	0.404

Notes: This table implements a monotonicity test for patent grant decisions. 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 times year FE, and technology FE. p-values calculated based on robust standard errors.

Finally, following Frandsen, Lefgren, and Leslie (2023), we also test and fail to reject the combined null hypothesis that pairwise monotonicity and exclusion hold (Appendix Table C.3).[17]

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 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 $\underline{Z}$ examiner by the first percentile and the 99th 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. Our estimation suggests that around 42%

[17] Frandsen, Lefgren, and Leslie (2023) show that one can relax the strict (pair-wise) monotonicity assumption of the original LATE framework to an average monotonicity assumption under which IV still converges to a proper weighted average of treatment effects. They also provide a test for the joint null hypothesis that the exclusion and monotonicity assumptions hold (there is a continuous relationship between judge leniency and case outcomes (averaged at the judge level)). The test for the joint null hypothesis is performed for different numbers of knots and Bonferroni weights using the suggested quadratic spline.

of our sample are compliers, which means that 42% of the firms would have obtained different results if assigned to different examiners. In our sample, 44% are always takers who would receive positive decisions no matter which examiners are assigned to them. Consequently, 16% of the sample consists of never-takers.

6 Empirical Results

In this section, we present empirical results using the constructed instrument and compare the findings with the OLS results. We present the findings of our baseline sample, consisting of firms that submitted their initial patent application between 2000 and 2016. All estimations cover up to five years after the application year. We start by presenting findings on firm outcomes including market exit, employment and sales growth and future productivity measured as future patenting activities. We then extend our analysis to the individual level, focusing on wage and employment effects of winning a patent as compared to rejections. We examine how rents are shared between employees according to age, gender, and occupation. Additionally, we explore job relocation responses as firms might change the composition of the workforce after successfully winning a patent.

6.1 Winning Patent and Firm Outcomes

Market Exit. Table 7 presents the results of winning a patent on the probability to exit the market up to five years after the application. Panel A provides OLS estimates, while Panels B and C provide IV and first stage estimates, respectively.

Based on OLS results, Panel A shows a negative correlation between the patent granting status and firm exit. Winning a patent reduces market exit by about 2.3% points one year after the application. This effect accumulates to 10% points five years after and represents a sizeable impact relative to the mean exit rates presented in the middle part of the table. Panel B shows the IV results confirming the negative impact of winning a patent on the probability to exit the market. In line with the discussion on the relevance of the instrument, we observe a strong first stage coefficient (Panel C) with the Kleinbergen-Paap F-statistics rejecting the hypothesis of weak instruments with values ranging between 216 and 233. Thus, weak identification issues do not apply in our setting. Compared to the OLS results, the IV estimates suggest that the causal effect of winning the first patent on firm exit is slightly larger compared to the OLS results. Five years after the application, our LATE estimate indicates that the probability to exit the market reduces by 13% points.

This IV estimate 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

Table 7: Regression Result: The Effect of Successful Innovation on Market Exit

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
Panel A: OLS Results					
Patent Granted (0/1)	-0.0229***	-0.0415***	-0.0582***	-0.0869***	-0.1062***
	(0.004)	(0.006)	(0.007)	(0.008)	(0.009)
Panel B: IV Results					
Patent Granted (0/1)	-0.0531**	-0.0570*	-0.0837**	-0.0665	-0.1290**
	(0.025)	(0.034)	(0.041)	(0.045)	(0.050)
Panel C: First Stage					
Leniency	0.5123***	0.5123***	0.5123***	0.5244***	0.5391***
	(0.034)	(0.034)	(0.034)	(0.035)	(0.037)
F-Statistic	233.8	233.8	233.8	221.1	216.7
Observations	8,045	8,045	8,045	7,619	7,146
Mean outcome	0.024	0.042	0.066	0.09	0.108
Granted	0.594	0.594	0.594	0.616	0.634
Office × year FE	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

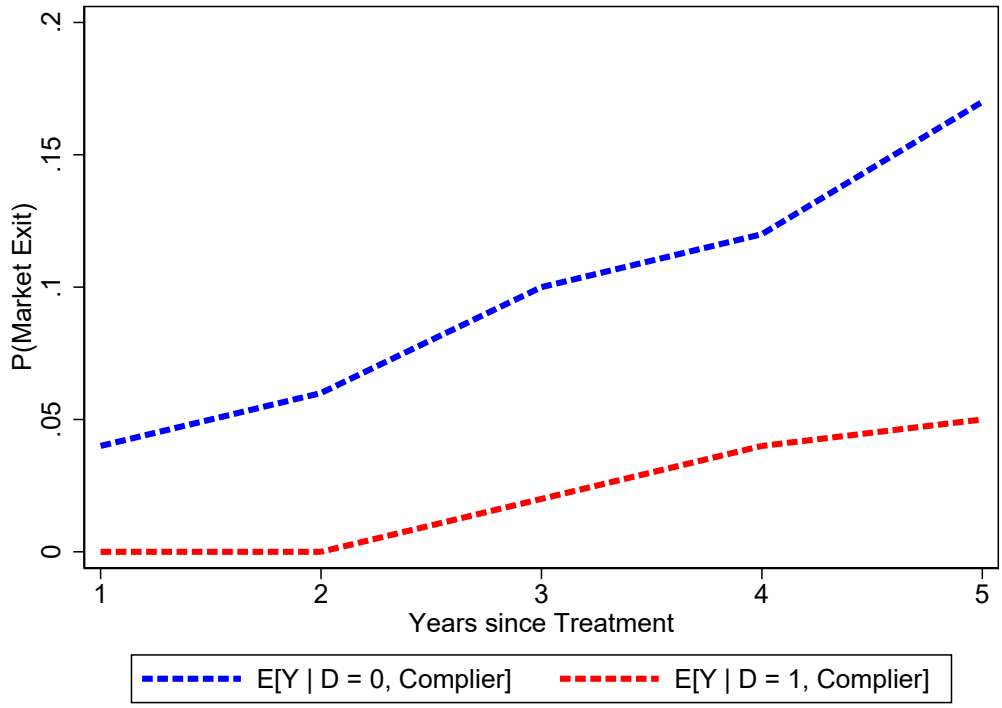
Notes: The table shows OLS, first stage, and IV regression results of market exit on patent grant one to five years after the patent application. Panel A shows the OLS results, Panel B shows IV results, and Panel C shows the first stage results. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

lenient"/"strictest"). For example, $E[Y_i|D_i = 1, Z_i = most\ lenient]$ consist of average outcomes of always-takes and compilers. With this logic, we calculate average outcomes of compliers, i.e., $E[Y|D = 0, \text{Complier}]$ and $E[Y|D = 1, \text{Complier}]$.

Figure 4 plots market exit rates among compliers. $(E[Y|D = 0, Complier])$ reveals average market exit rates for firms that did not win a patent, whereas $(E[Y|D = 1, Complier])$ are average exit rates for complier firms winning a patent. Winning a patent among compliers causes a close to zero exit rate during the first two years after the application. The exit probability increases to about 4% five years after the application. The rejection of the patent immediately causes some firms to exit the market. Five years after treatment, the probability to exit the market is around 17%. The difference between the two lines represents the causal impact presented in Table 7.

Although the market exit variable is based on employment numbers and is considered to be of high quality, the estimated coefficients are economically high given the resources invested by these firms. One possible explanation behind these results might be that the exit indicator of unsuccessful firms might be affected by Mergers and Acquisitions (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 (see, for example, Bena and Li 2014 and Sevilir and Tian 2012). Therefore, we examine whether a causal link exists between winning or failing to obtain the first patent and M&A events. For this, we are able to measure three different types of M&A events: (i) minority acquisition of a new owner, (ii) majority acquisition of a new owner, and (iii) profit-takeover

agreement.



Notes: The figure plots the probability of market exit for firms that win a patent and firms that receive a rejection among the group of compliers up to five years after the treatment.

Figure 4: Potential Outcomes: Firm Exit

Appendix Table D.4 presents the results. First of all, the table shows that around 13.6% of the firms experience a majority acquisition event over the next five years after the submission of the patent. The OLS estimates in Panel A exhibit a positive statistical significant correlation between the three types of M&A deals (columns (1) to (3)). However, the IV estimates in Panel B indicate no causal relationship between any type of M&A events and the patent status. Based on these results, we do not find supporting evidence for a potential different interpretation of the market exit results. Further, we endorse the interpretation that market exit and firm failure are significantly influenced by financial distress, as evidenced by the credit rating information available in the MUP data. Column (4) shows that winning a patent reduces the probability that the firm will experience a bankruptcy event during the following five years. The IV estimate is, similar to the results in Table 7, larger in absolute terms compared to OLS. According to our estimation, firms are 4.1% points less likely to go bankrupt if their first patent application gets granted than those whose first patent gets rejected.

This result is consistent with the literature on insolvency and patent competition. Eisdorfer and Hsu (2011) demonstrate that companies are more likely to go bankrupt if they fall behind competitors in patent competition. Supporting their findings, Bai and Tian (2020) also show that firms generating more high-value patents are less likely to file for bankruptcy in the future. Overall, our results provide evidence that winning a patent generates an economically strong survival advantage by lowering the

probability to exit the market.

Employment & Revenue Dynamics. Table 8 shows the results of winning a patent on employment (Panel A) and revenue (Panel B) growth dynamics over a 5-year period following the application year. The growth rate at each point in time is calculated with the initial value at the time of the patent application. We condition the sample on surviving firms and devote the results including firms that exit the market to the Appendix Table D.5. In the case when a firm is experiencing an exit event, the growth rate takes the value of -2.

In both cases, OLS results indicate a positive and increasing impact of the patent on firm growth over time. IV results in Table 8 (Panels A2 and B2), however, show that a successful invention does not generate employment growth, with precisely estimated coefficients. Revenue growth estimates are overall positive and economically significant. Estimating potential outcomes among compliers shows that in $t = 2$ revenue growth amounts to about 43% among firms receiving the patent, whereas revenue growth is about 22% if the firm would not have received the patent.[18]

Together, the results indicate that firm-level productivity – measured as labor productivity, i.e., revenue over employment – increases after initial patent allowance. This increase is driven by an increase in revenues. A further way to investigate productivity responses is to test if initial allowance affects the future patenting activity.

Future Patenting. We therefore examine firm productivity by measuring firm's future patenting at the intensive and extensive margin over the following five years after the initial patent application. In Table 9, columns (1) and (2) present OLS and IV results with the outcome variable being a dummy equal to 1 if the firms is filing for at least one patent after the initial application and zero otherwise. Columns (3) and (4) indicate the number of patents (transformed by the inverse hyperbolic sign transformation) the firms files for during this period. Finally, column (5) displays IV results on the number of patents conditioning on survival five years after initial submission.

The table demonstrates that winning the first patent causes a subsequent increase in patent applications compared to those whose first applications are not granted. The OLS results in columns (1) and (3) illustrate the positive and significant correlation between granting a first patent application and future innovation. Our IV estimation results confirm the significant causal relationship between firms' follow-up innovation if their first application is successful. According to our IV estimation in column (3), firms that obtain the first patent are 21% points more likely to apply for future patents compared to firms whose first application got rejected. The results are confirm by looking at the intensive margin in columns (3) to (5). Winning the first patent increases the number of future patent applications by approximately 39-43% points compared to the situation when the application is de-

[18]Including firm exits, our analysis indicates that successful invention has a positive and significant impact on both employment and revenue growth five years following the initial patent application. Among compliers, those receiving the patent experienced 56% increase in revenue growth, while patent-rejected firms saw an 8.8% decline. A similar trend is also observed in employment growth results, firms receiving the patent grow by 30% whereas 1.6% decrease in employment growth for patent-rejected firms (See Appendix Table D.5)

Table 8: Regression Result: The Effect of Successful Innovation on Firm Growth

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
			A: Employment Growth		
Panel A1: OLS Results					
Patent Granted (0/1)	0.0034	0.0259**	0.0378***	0.0479***	0.0606***
	(0.009)	(0.011)	(0.012)	(0.014)	(0.015)
Panel A2: IV Results					
Patent Granted (0/1)	-0.0062	-0.0060	-0.0346	0.0113	0.0036
	(0.055)	(0.062)	(0.070)	(0.079)	(0.084)
F-Statistic	235.6	231.2	222.2	204	192.6
Observations	7,821	7,656	7,440	6,840	6,272
Mean outcome	0.338	0.358	0.364	0.378	0.384
E[Y | D = 0, Complier]	0.255	0.276	0.305	0.307	0.295
E[Y | D = 1, Complier]	0.225	0.247	0.251	0.300	0.276
			B: Revenue Growth		
Panel B1: OLS Results					
Patent Granted (0/1)	0.0196	0.0401**	0.0614***	0.0813***	0.1055***
	(0.015)	(0.017)	(0.019)	(0.021)	(0.023)
Panel B2: IV Results					
Patent Granted (0/1)	0.1808**	0.2146**	0.1459	0.1595	0.2492**
	(0.087)	(0.095)	(0.104)	(0.115)	(0.126)
F-Statistic	205.1	200.6	177.6	154.5	143.4
Observations	6,815	6,467	5,896	5,321	4,832
Mean outcome	0.294	0.33	0.362	0.384	0.400
E[Y | D = 0, Complier]	0.211	0.221	0.291	0.259	0.288
E[Y | D = 1, Complier]	0.390	0.429	0.430	0.397	0.531
Office × year FE	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of employment (Panel A) and revenue growth (Panel B) on first patent grant one to five years after the patent application condition on firm surviving. Panels A1 and B1 show the OLS results. Panels A2 and B2 show the IV results. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

nied. These results indicate high firm productivity which is in line with the finding on the impact of winning the patent in revenue relative to employment effects. The findings differ from previous findings provided by Sampat and Williams (2019). They found no follow-on patents in the field of human genomes based on successful and unsuccessful gene patents.

One question related to the patenting activity is whether future patents applications differ relative to the initial patent. We provide descriptive evidence in Appendix Figure D.13 by comparing technology class differences of the new patent applications with the first ones. Specifically, we calculate the share of assignees who's future inventions IPC classes match perfectly with the initial one as well as the share with completely new IPC classes. The figure reveals that most firms remain in their existing technology class for their future innovations. More than 40% of the firms are patenting exactly within their initial IPC classes with the differences between initially granted vs not granted assignees being unpronounced. We therefore conclude that future patenting activity is not associated with a different

Table 9: Regression Result: The Effect of Successful Innovation on Future Innovation

	Future patenting		Number of patents		
			Full sample		Survival
	OLS	IV	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)
Patent Granted (0/1)	0.1221***	0.2140***	0.2184***	0.4297***	0.3921***
	(0.011)	(0.067)	(0.022)	(0.123)	(0.147)
F-Statistic		233.8		234.2	189.7
Observations	8,045	8,045	7,977	7,977	6,315
Mean outcome	0.414	0.414	0.664	0.664	0.756
Granted	0.594	0.594	0.594	0.594	0.658
Office × year FE	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of future patenting activity on patent grant over the fives years following the initial application. Columns (1) and (2) contain a dummy equal to 1 if the firm produced at least 1 follow-on patent application. Columns (3) to (5) contains the actual number of patent applications transformed by the inverse hyperbolic sign transformation. Column (5) conditions on firm survival five years after the initial patent application. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

degree of diversification in their technology class.

6.2 Wage Responses & Worker Reallocation: Worker-Level Analysis

Wages. The firm-level findings from the previous section indicate that firms that are awarded first patents experience better firm performance indicated by lower market exit rates, higher revenue growth and a higher follow-on patent intensity. Based on the match of the firm-level data to social security data, we will test how wages of workers in firms with granted vs. non-granted patents develop after the initial application.

Table 10 shows OLS and IV results of log real daily wages estimated at the worker level. We condition the sample on workers employed in the firms that submit the patent in the initial year and follow these workers over time. In each specification, we additionally control for workers initial wage level and baseline characteristics such as age, gender, nationality, and educational level. Due to multiple observations per firm, we cluster the standard errors at the examiner and firm level. The table shows that wages start to respond positively with a time lag. OLS results indicate a 0.8% increase in wages already two years after the application with an increase to 2% four years after. IV coefficient estimates tend to be larger compared to OLS but are accompanied by higher standard errors. Four years after the initial event, wages increase by 6.5% (significant at the 5% level) and continue to increase to 8.4% five years after.

Workforce Composition. Although employment numbers of firms winning a patent do not grow stronger compared to the firms that receive a rejection, the composition of the workforce might change due to selective hiring and firing. This might partly contribute to higher wages if better individuals

Table 10: Regression Result: The Effect of Successful Innovation on Wage

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
Panel A: OLS Results					
Patent Granted (0/1)	0.0039	0.0083**	0.0129**	0.0203***	0.0259***
	(0.002)	(0.004)	(0.005)	(0.006)	(0.007)
Panel B: IV Results					
Patent Granted (0/1)	0.0258*	0.0236	0.0445	0.0650**	0.0839**
	(0.015)	(0.022)	(0.027)	(0.032)	(0.035)
F-Statistic	30.95	31.89	32.62	32.57	32.11
Observations	740,674	711,618	690,722	671,436	653,968
Mean outcome	4.644	4.662	4.678	4.688	4.698
Granted	0.684	0.684	0.684	0.684	0.684
Office × year FE	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of log real daily wages on patent grant one to five years after the patent application among incumbent workers initially employed in the firm. Panel A shows the OLS results. Panel B shows the IV results. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles, and at the worker level, of initial log wages, and baseline demographics. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

with higher human capital are hired who might have positive spillover effects on the initial workforce of stayers within the firm.

Panels C2 of Appendix Tables D.6 and D.7 show hiring and separation effects of occupational groups distinguishing between managers, technicians/engineers, administration, and skilled and unskilled manual and service workers. The tables do show three distinguished results. First, firms with positive patent evaluations are less likely to hire workers of administration occupations but this group is also less likely to be among workers leaving the firm. This result suggests that the existing workforce of administrative workers remains more stable among firms with granted patents. Second, firms with granted patents are more likely to hire technicians and engineers. Panel B2 of Appendix Table D.6 shows that when a firm's initial patent application is accepted, the probability of hiring new technicians and engineers increases by 9.5% after three years, and this probability increases to 12% by five years of initial submission. In turn, we do not observe an effect of job separations (Table D.7). This result is consistent with an increased patenting activity after the initial application as this group of workers are likely among actual inventors. Third, unskilled manual and service workers are most significantly impacted by job loss. The acceptance of the patent increases the likelihood of job separation by 17% points five years after the application.

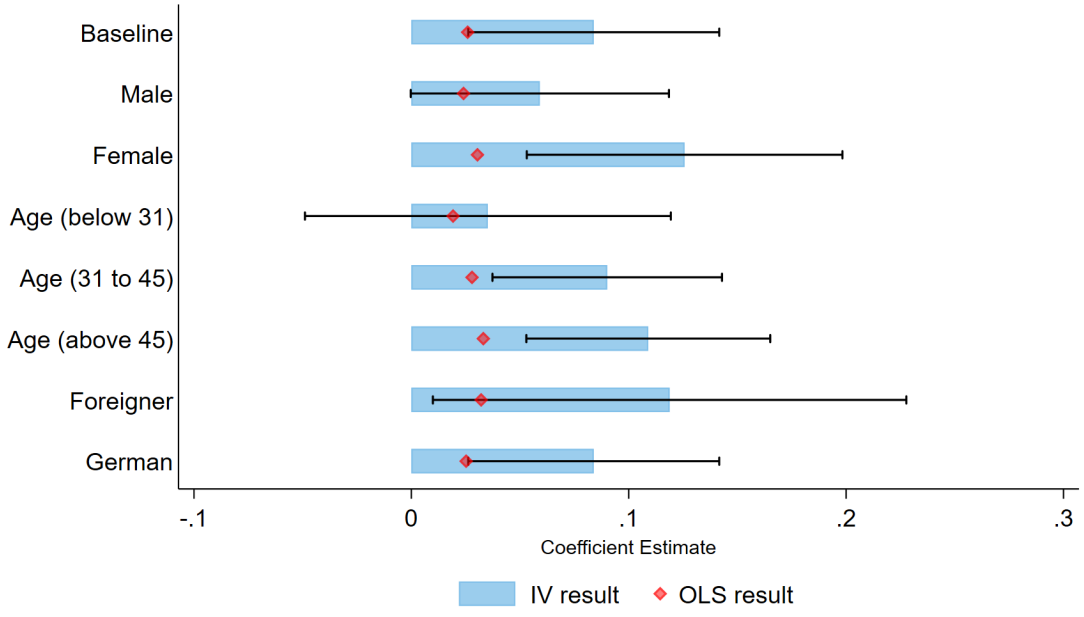
These results imply that the composition of the firm is affected by patent allowance. Patent allowance increase the stability of the organization of the firm measured by administrative workers and leads to an increased inflow of highly skilled workers measured as technicians and engineers. This result is supported by a subsequent analysis studying worker-fixed effects (based on AKM-style

wage regressions before the hire that control for worker and establishment effects and are estimated using seven-year windows) of new hires in Appendix Table D.8. The table shows that successful innovations increases the probability that the new hire is in the upper decile of the AKM distribution. This supports the view that new hires of firms with initial patent allowance are of higher quality.

6.3 Who Benefits from Inventions? Wage and Employment Responses by Sub-Groups

Wages. Average wage responses might alter different benefits for different groups of employees. One first candidate to distinguish the workforce might be the gender dimension. The literature on gender differences in rent sharing shows that males typically receive higher rents, which is one reason for 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. In this section, we first examine wage effects distinguishing by gender, age, and nationality of workers. We further take advantage of the richness of the data and provide estimates by occupational groups differentiating between managers, administrators, engineers, as well as skilled and unskilled manual and service tasks.

Figure 5 shows the wage results five years after the initial year of application. In contrast to



Notes: The figure plots coefficient estimates of winning a patent on log real daily wages by sub-groups five years after the initial patent submission. The black lines represent the 90% CI around the IV estimate. The red dot represents the OLS point estimate. Details estimations for one to five years for all groups are shown in Appendix Table D.9

FIGURE 5: REAL WAGE EFFECTS BY SUB-GROUPS

findings from the U.S., our estimates show female workers benefit from patent allowance more than men. Moreover, we observe an increasing point estimate by initial worker age. Workers up to 30 years

of age show a positive but insignificant effect. The highest point estimate is observed for workers in the age group above 45 (more details can be find in Appendix Table D.9, Panel D2 and E2). Finally, the results point towards slightly higher wage responses for workers of foreign nationality.

Table 11 provides the wage results differentiating by occupational groups. The literature on task-biased technological change provides evidence for job polarization due to technological progress with a reduction in demand for middle-wage jobs but an increase in labor demand for non-routine jobs at the tails of the job-wage distribution (Katz, Kearney, et al. 2005; Autor and Dorn 2013). The literature on skill-biased technological change points to the fact that with the adaptation of new technology, the economy generates higher rewards for skilled/highly educated workers compared to unskilled/less educated workers (Acemoglu 1998; Dustmann, Ludsteck, and Schönberg 2009). New inventions and subsequent follow-on innovations might change the within-firm demand for certain tasks. Patent-level evidence from the U.S. provided by Kline, Petkova, Williams, and Zidar (2019) suggests that higher-level employees such as officers and initially high-wage workers benefit the most in terms of wage growth. In contrast, our results show that inventions has significant wage gains across lower level occupations such as administration, skilled, and unskilled workers but we fail to document significant effect for managers and the employees of technical occupations such as technicians and engineers.[19] The null effect, in particular for technicians and engineers, is surprising as this group is most likely generating the inventions. It is likely that this result reflects the fact that inventor compensations are tightly regulated in Germany. The *Employee Inventions Act* gives employers the right to claim the invention, obliging them to compensate inventors based on the invention's value. This regulation is supposed to benefit both parties: employers gain access to valuable innovations, and inventors receive appropriate recognition and financial reward 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. Thus, differential compensation in our empirical setting in rather unlikely.[20]

Bonus Payments. The data allows us to distinguish between wages and bonus payment, such as end-of-year payments or other non-regular compensation. Paying bonuses might be a flexible way to compensate employees. Bonus payment represent only a small fraction of wages and only around 2.5% of workers on our sample receive such payments. For this reason, we analyze bonus payment

[19] Appendix Table D.10 shows results for one to five years. It demonstrates positive and significant wage responses to patent allowance for workers in administrative occupations. Specifically, administrative workers experience a 5.1% increase in wages three years after the initial patent submission, with the increase reaching 8.0% by the fifth year if the patent is granted, compared to those patents being rejected. Similarly, skilled and unskilled workers also see significant wage gains. Five years after the initial submission, earnings for skilled and unskilled workers rise by 13.2% and 15%, respectively, when the patent is accepted compared to when it is rejected.

[20] According to the *Employee Inventions Act (1957)*, employees are required to report any innovations they develop during their employment to their employer. If the employer claims the invention, the employee is entitled to adequate and reasonable compensation. 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).

Table 11: Regression Result: The Effect of Successful Innovation on wage: Subgroup-Occupations

	Five Years after Patent Application				
	Unskilled	Skilled	Administration	Technicians and Engineers	Manager
	(1)	(2)	(3)	(4)	(5)
Panel A1: OLS Results					
Patent Granted (0/1)	0.0384***	0.0400***	0.0299***	0.0254***	-0.0005
	(0.008)	(0.007)	(0.007)	(0.006)	(0.010)
Panel A2: IV Results					
Patent Granted (0/1)	0.1495**	0.1322***	0.0797***	0.0571	0.0192
	(0.059)	(0.042)	(0.029)	(0.044)	(0.050)
F-Statistic	15.58	28.28	57.79	15.15	47.79
Observations	192,623	127,032	145,465	104,002	23,479
Mean outcome	4.466	4.648	4.762	5.000	5.116
Office × year FE	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of log real daily wages on patent grant five years after the patent application among incumbent workers initially employed in the firm and differentiated by occupational groups. Panel A shows the OLS results. Panel B shows the IV results. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles, and at the worker level, of initial log wages, and baseline demographics. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

as dummy equal to one if an employees received bonus payment in a given year and zero otherwise. Appendix Table D.11 reveal no significant impact of successful innovation on bonuses across all occupations, except for administrative and unskilled workers. For administration employees, the likelihood of receiving a bonus increases by 6.5% points three years after a patent submission and by 7.6% points five years post-submission if the patent is granted, compared to when it is rejected. Analyzing bonus payments in levels (inverse hyperbolic sign transformed), confirms the results and shows that bonuses of administrative workers increase by 16.2% points five years after the initial submission of the patent if that patent got accepted. Similarly, for unskilled workers, the likelihood of receiving a bonus increases by 6.7% points five years post-submission if the patent is granted and 13% in levels.

Robustness. 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 and engineers, as these groups earn relatively high wages to begin with. For this reason, we provide a series of robustness checks in Appendix Table D.12. For comparison, the table first shows the baseline coefficient five years after patent submission in column (1). Column (2) controls at the individual level for initial censoring. Column (3) conditions the sample on workers with initial wages below the censoring limit. Finally, column (4) analyzes the probability of moving beyond the censoring limit five years after patent submission. Throughout the specifications, we

confirm the baseline results.

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 then true wage gains. The worker-level data contains information on part-time employment. Appendix Table D.13 provides the results analyzing the probability of part-time employment five years post patent submission for the full sample and occupational groups. On average in the overall sample, 14% of the incumbent employees work in part-time five years post submission. The coefficient of the patent grant status is 0.0004 and insignificant providing evidence that working time adjustments are unlikely to drive the results. The insignificant effect on part-time employment is confirmed for all occupational sub-groups in columns (2) to (6).

Heterogeneity. One important distinction when analyzing wages is to differentiate between firm movers and stayers. A first notable result in this regard is the fact that the event of granting a patent increases the probability of staying in the firm up to five years after initial application by about 22.4% points (see Appendix Table D.14). This is consistent with the market exit results from Section 6.1, where we have shown that patent allowance reduces market exit by up to 13% points. This result is important to understand as conditioning on movers and stayers generates a selected sample of surviving firms. Appendix Table D.16 shows the wage results one, three, and five years after the application for job switchers and stayers. The table only shows significant wage gains for administrative, skilled, and unskilled workers observed among employees who remain with the same firm. These results suggest that patent-induced shocks at the firm level propagate to incumbent workers in relatively lower paying occupations.

Appendix Table D.17 further distinguishes the wage results five years after the submission by initial firm size and the legal form. We provide split-sample estimates by showing results for initially small/large firms below/above 150 employees. Columns (1) and (2) of the table provide evidence that the documented positive wage effects are driven by larger firms, whereas none of the estimates are significant for employees initially employed in smaller firms. This result suggests that the wage-setting policy, with larger firms having more leeway in setting wages, plays a crucial role in distributing gains in the form of higher wages.

We further distinguish the sample by legal forms of stock corporations and private partnerships.[21] Gottschalk, Hauer, and Ahrens (2023) provide average statistics on family-owned business by legal firm types. Following these estimates, partnerships are typically characterized as family businesses. The share corresponds to around 80% of the firms being family-owned. Among stock companies, 27% are family-owned. Family-owned business is a typical business model in Germany and even persist along the firm-size distribution. These firms are characterized by lower hierarchical levels

[21] Private partnerships consist of single-owned companies, limited partnerships, and limited liability companies. German LLCs differ compared to the U.S. as the shares cannot be traded on a stock exchange. In our sample of partnerships, 78% of the firms are *GmbHs* and 17% as *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/non-partnerships, 90% of the firms are stock corporations.

and arguably more co-determination, for which reason the distinction offers insight into institutional determinants of distributing gains. Following these institutional features, columns (3) and (4) of Appendix Table D.17 show that skilled and unskilled manual and service employees in partnerships are driven the positive wage results. This is particularly true for larger firms (column (5)). Administrative workers experience similar wage effects in both types of firms. Manager compensation is particularly driven by large stock corporations with, on average, 23% wage increases as public firms tend to create more hierarchical organizations, which disproportionately benefit top employees (Garicano and Rossi-Hansberg 2006; Bias, Lochner, Obernberger, and Sevilir 2022). [22]

Employment Stability. Besides benefiting in terms of higher wage growth, workers could benefit from higher employment stability. In order to answer the question whether patents impact the probability of being employed, we specify a dummy variable equal to 1 if the worker who was initially employed in the firm is employed one to five years afterwards and zero in the case of un/non-employment. Appendix Table D.19 provides the results one to five years after the initial patent application. In our sample, on average, about 82% of employees remain employed five years after the initial patent application. Overall, the probability of being employed increases by 5.1% points for employees in firms that win the patent. Similar to the findings on wage effects, the impact is more pronounced among older workers, particularly those aged 31 years and above. In contrast, no significant differences are observed based on gender. However, nationality appears to play a role, as employment stability is significantly higher for German workers compared to foreign workers.

Table 12 shows the employment results by occupational groups. Panel B shows that after five years of initial application, the likelihood of being employed increases by 6.2% points and 4.8% points for unskilled and skilled employees, respectively, in firms that win the patent compared to rejections. A similar result is also observed for administration staff, with an increase in the probability of being employed by 6.6% points for employees in a patent-winning firm. For technicians and engineers as well as managers, no significant difference is found between patent-winning and rejected firms in terms of employment (see Appendix Table D.20 for yearly results). The employment dimension, therefore, is found to be of significant importance in terms of rent extraction for lower-skilled groups.[23]

7 Conclusions

Innovations and technological progress are driving economic development and welfare. This paper provides estimates of how patent-induced shocks impact firm performance and affect worker-level wages and employment stability. Based on an examiner-IV design, exploiting patent examiner pref-

[22] The higher likelihood of receiving a bonus for administrative workers remains consistent when the results are distinguished based on firm size and legal form, as shown in Appendix Table D.18. Furthermore, the estimations segmented by initial firm size and legal form reveal that employees in large stock companies are significantly more likely to receive bonuses across all occupations, including technicians and engineers, administrative workers, skilled (manual and service), and unskilled (manual and service) workers.

[23] Appendix Table D.21 shows that the employment results among unskilled employees are driven by larger firms. For administrative workers, no significant differences in job stability are observed across firms of varying sizes or legal forms.

Table 12: Regression Result: The Effect of Successful Innovation on employment: Subgroup-Occupations

	Five Years after Patent Application				
	Unskilled	Skilled	Administration	Technicians and Engineers	Manager
	(1)	(2)	(3)	(4)	(5)
Panel A: OLS Results					
Patent Granted (0/1)	0.0223***	0.0093**	0.0130***	0.0200***	0.0264***
	(0.006)	(0.004)	(0.004)	(0.005)	(0.008)
Panel B: IV Results					
Patent Granted (0/1)	0.0615**	0.0480**	0.0655***	0.0601	0.0132
	(0.030)	(0.024)	(0.016)	(0.046)	(0.038)
F-Statistic	17.85	30.20	56.18	11.62	51.42
Observations	233,562	147,999	175,808	124,768	30,994
Mean outcome	.824	.858	.826	.832	.756
Office × year FE	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of being employed on patent grant five years after the patent application among incumbent workers initially employed in the firm and differentiated by occupational groups. Panel B shows the OLS results. Panel B shows the IV results. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles, and at the worker level, of initial log wages, and baseline demographics. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

erences for granting patents, we show that successful patent applications significantly enhance firm survival and sales growth, while also inducing follow-on innovations.

In our setting, we are able to provide evidence that idiosyncratic variation in firm performance has an impact on workers. The improved firm performance and higher productivity propagate to workers in different ways. Wages of incumbent workers start to increase slowly and reach 7% five years after the initial patent submission. These results are heterogeneous across the occupational distribution. Administrative workers and skilled and unskilled (manual and service) employees experience wage gains. In contrast to previous U.S. evidence (Kline, Petkova, Williams, and Zidar 2019), our results highlight that the benefits of innovation are more broadly shared in the German labor market.

In particular, our results provide evidence that institutional characteristics have differential effects on the distribution of economic rents. Consistent with higher levels of co-determination, we show that partnerships as compared to stock corporations benefit medium-wage job employees. Large stock corporations seem to have a particular positive impacts on managers. 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 innovation are distributed among different types of workers and firms.

References

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., 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. (1998): "Why do new technologies complement skills? Directed technical change and wage inequality," *The Quarterly Journal of Economics*, 113(4), 1055–1089.

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.

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

Antonczyk, D., T. DeLeire, and B. Fitzenberger (2018): "Polarization and rising wage inequality: Comparing the US and Germany," *Econometrics*, 6(2), 1–33.

Antonczyk, D., B. Fitzenberger, and U. Leuschner (2009): "Can a Task-Based Approach Explain the Recent Changes in the German Wage Structure?," *Yearbooks for National Economy and Statistics*, 229(2-3), 214–238.

Autor, D. H., and D. Dorn (2013): "The growth of low-skill service jobs and the polarization of the US labor market," *American economic review*, 103(5), 1553–1597.

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

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

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).

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 (2022): "Going Public and the Internal Organization of the Firm," in *Proceedings of the EUROFIDAI-ESSEC Paris December Finance Meeting 2022*. Available at SSRN: https://ssrn.com/abstract=4112225 or http://dx.doi.org/10.2139/ssrn.4112225.

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., 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.

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

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.

Davis, S. J., and J. Haltiwanger (1999): "Gross job flows," *Handbook of Labor Economics*, 3, 2711–2805.

Desai, P., E. Gavrilova, R. Silva, and M. Soares (2022): "The Value of Trademarks," *SSRN Electronic Journal*, Available at SSRN: https://ssrn.com/abstract=4280505 or http://dx.doi.org/10.2139/ssrn.4280505.

Diegmann, A., T. Doherr, M. Hälbig, and S. Wolter (2024): "Linking the Mannheim Enterprise Panel (MUP) with Administrative Establishment Data of IAB," Discussion paper, Institut für Arbeitsmarkt-und Berufsforschung (IAB), Nürnberg [Institute for ....

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 SearchEngine: A holistic approach to matching," *ZEW-Centre for European Economic Research Discussion Paper*, (23-001).

Dustmann, C., B. Fitzenberger, U. Schönberg, and A. Spitz-Oener (2014): "From Sick Man of Europe to Economic Superstar: Germany's Resurgent Economy," *Journal of Economic Perspectives*, 28(1), 167–188.

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.

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," *RAND Journal of Economics*, 49(1), 64–86.

Garicano, L., and E. Rossi-Hansberg (2006): "Organization and Inequality in a Knowledge Economy," *Quarterly Journal of Economics*, 121(4), 1383–1435.

Genz, S., T. Gregory, M. Janser, F. Lehmer, and B. Matthes (2021): "How Do Workers Adjust When Firms Adopt New Technologies?," *ZEW - Centre for European Economic Research Discussion Paper*, (21-073).

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.

Hall, B. H., A. B. Jaffe, and M. Trajtenberg (2001): "The NBER patent citation data file: Lessons, insights and methodological tools," .

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.

Hübler, O., and U. Jirjahn (2003): "Works Councils and Collective Bargaining in Germany: The Impact on Productivity and Wages," *Scottish Journal of Political Economy*, 50(4), 471–491.

Humlum, A., J. Munch, and M. Rasmussen (2023): "What Works for the Unemployed? Evidence from Quasi-Random Caseworker Assignments," Working Paper 2023-43, University of Chicago, Becker Friedman Institute for Economics, 114 Pages.

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, and J. Heining (2021): "Labor in the Boardroom," *The Quarterly Journal of Economics*, 136(2), 669–725.

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

Kahn-Lang, A., and K. Lang (2020): "The promise and pitfalls of differences-in-differences: Reflections on 16 and pregnant and other applications," *Journal of Business & Economic Statistics*, 38(3), 613–620.

Katz, L. F., M. S. Kearney, et al. (2005): "Trends in US Wage Inequality: Re-Assessing the Revisionists," *NBER Working Paper Series*, p. 11627.

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, 665–712.

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.

Pakes, A. (1984): "Patents as options: Some estimates of the value of holding European patent stocks," Discussion paper, National Bureau of Economic Research.

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.

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

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.

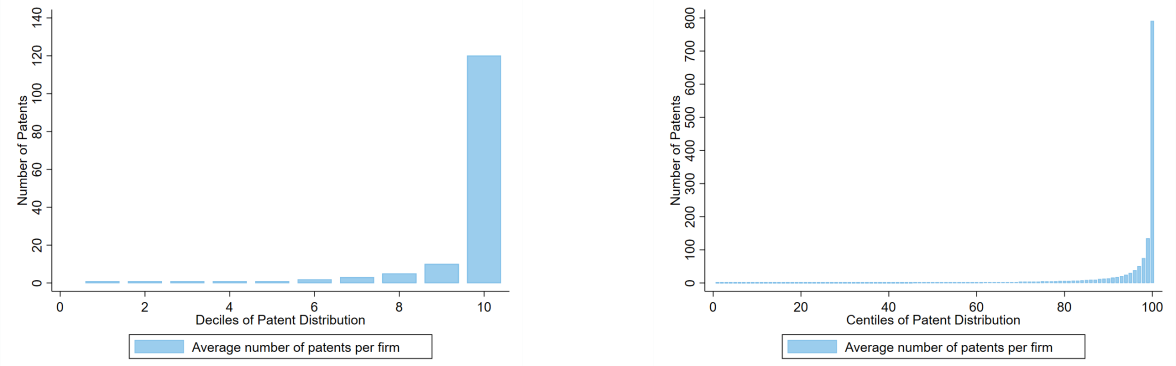
Supplementary Appendix

A Patent Statistics

Table A.1: Summary Statistic - All firms Vs. innovative firms characteristics

	Overall Firm-Random Sample			Innovative Firm			
	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
Hotelling	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, maintainance	1,285,163	0.018	0.134	32,000	0.002	0.037	0.000

Notes: The table represents the mean characteristics of all innovative firms compared to all enterprises in the economy. A firm is considered innovative, conditional on having one patent. T-test is performed to determine the difference in their mean characteristics. *p<0.1, **p<0.05, ***p<0.01.

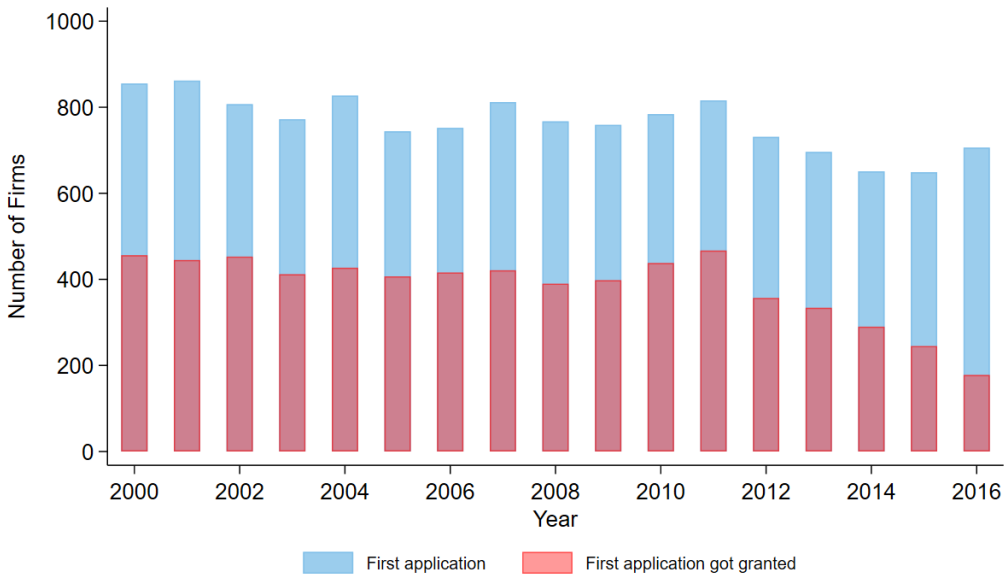


A: Distribution of firms: top decile

B: Distribution of firms: top centile

Notes: Distribution of the average number of patents per firm based on all MUP-EPO patents (total 357,309 applications) from 2000 to 2016. A) Average number of patents per firm for each decile. It shows the average number of patents (120 patents) per firm is concentrated on the top 10 patent-producing firms and The top largest 10% of patenting firms contaminate 83% of all applications. B) Average number of patents per firm for each centile. It shows the average number of patents (791 patents) per firm is concentrated on the top 1% of patent-producing firms.

Figure A.1: Distribution of the average number of patents per firm



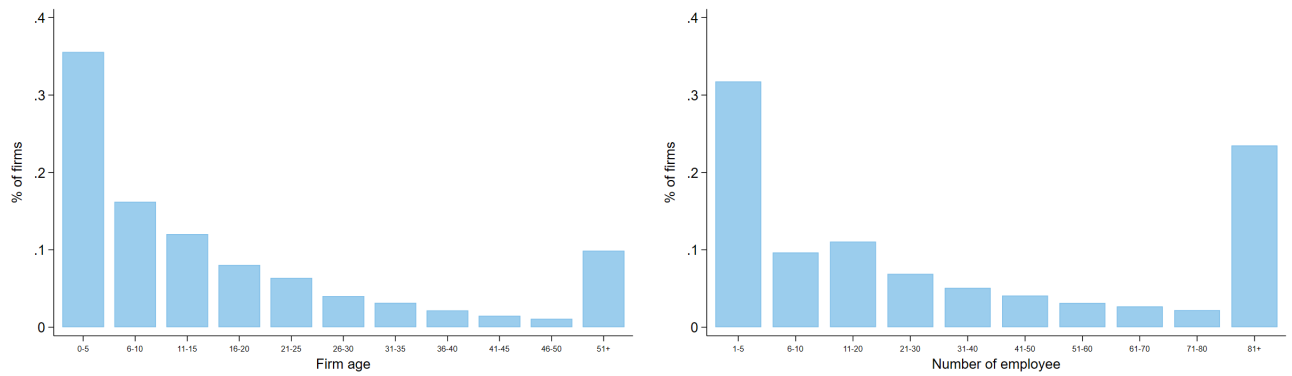
Notes: The figure shows the number of firms apply for their first patent. The red bar shows the number of firms whose first application was accepted.

Figure A.2: Number of firms with first patent

Table A.2: Summary Statistic -Innovative firms Vs Baseline sample characteristics

	Innovative Firm			Baseline Sample			
	N.	Mean	SD.	N	Mean	SD	p-value
Log employees	30,550	3.174	2.028	10,198	2.898	1.959	0.000
Log sales	29,604	15.595	2.126	9,888	15.254	2.150	0.000
Productivity	29,541	12.403	1.081	9,796	12.337	1.290	0.000
Firm age	33,490	33.599	45.667	10,870	20.999	33.652	0.000
Credit rating index	30,885	248.256	68.276	9,710	242.656	58.639	0.000
Agriculture	32,000	0.002	0.039	10,771	0.002	0.043	0.550
Stone	32,000	0.003	0.053	10,771	0.003	0.054	0.409
Manufacturing	32,000	0.483	0.486	10,771	0.440	0.496	0.000
Energy	32,000	0.005	0.065	10,771	0.005	0.073	0.356
Water	32,000	0.006	0.075	10,771	0.005	0.070	0.172
Construction	32,000	0.028	0.159	10,771	0.027	0.162	0.684
Retail trade	32,000	0.145	0.340	10,771	0.155	0.362	0.015
Transportation, storage	32,000	0.006	0.073	10,771	0.005	0.074	0.810
Hotelling	32,000	0.000	0.016	10,771	0.000	0.022	0.492
ICT	32,000	0.036	0.180	10,771	0.055	0.228	0.000
Banking, insurance	32,000	0.009	0.087	10,771	0.009	0.093	0.496
Housing	32,000	0.016	0.119	10,771	0.009	0.092	0.000
Technical service	32,000	0.194	0.380	10,771	0.211	0.408	0.000
Business service	32,000	0.030	0.157	10,771	0.031	0.173	0.742
Public, social, health	32,000	0.010	0.101	10,771	0.016	0.126	0.000
Art, maintainance	32,000	0.002	0.037	10,771	0.002	0.040	0.945

Notes: The table represents the' mean characteristics of our baseline sample (firm with first application, after linking with the examiner information) compared to all innovative firms in the economy. A T-test is performed to determine the difference in their mean characteristics. *p<0.1, **p<0.05, ***p<0.01.

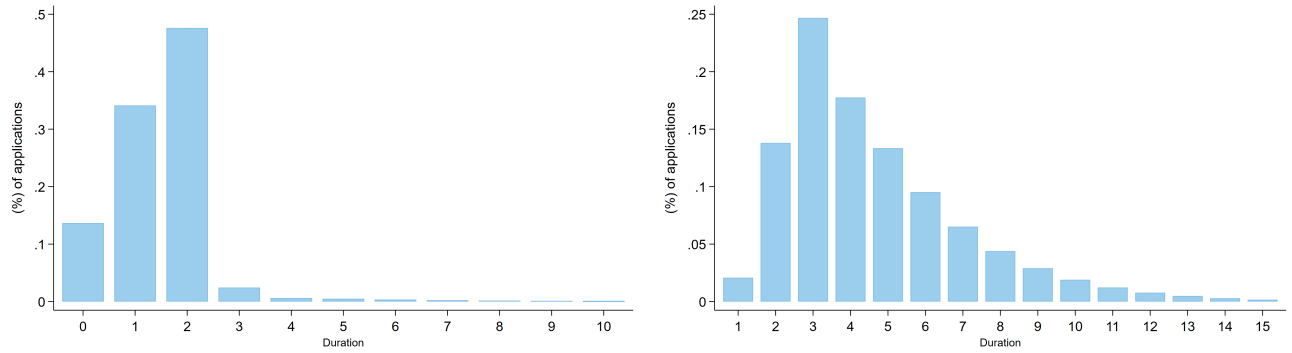


A: Distribution of firms by age

B: Distribution of firms by employee

Notes: A and B show the number of patent generating firms based on firm age and size, respectively, for our baseline sample of 10,873 firms from 2000 to 2016 (firm with first application, after linking with the examiner information)

Figure A.3: Distribution of firms based on age and size



A: Duration to patent publication

B: Duration to get decision

Notes: Based on all MUP-EPO patents (total 357,309 applications) from 2000 to 2016. A) Duration to patent publication refers to the time from the submission of the application to when it is publicly published along with the examiner's search report. B) Duration to patent decision represents the period examiners take to either approve or reject the patent application. Since the decision year is not directly specified in PATSTAT, we rely on the legal event titles from EPO worldwide legal event data (INPADOC). We use the dates associated with key legal events, such as "IP RIGHT GRANT" and "APPLICATION DISCONTINUATION," to determine the decision date.

Figure A.4: Duration of patent publication and decision

B EPO Patent Examiner: Web Scraping and Digitization

The PATSTAT database does not contain any information on patient examiners. To overcome this issue, 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, in the search section, we can search any patent using the application number provided by the EPO authority (Figure B.5). This search could return multiple results; however, we select only the EP-level application, which indicates that it was submitted at the EPO office (Figure B.6). When we select the application, we can see all the documentation related to a certain patent, such as the description, patent claims, and any drawings or figures. The documents section contains all the PDF files that are associated with the patents (refer to Figure B.7 and B.8). Among all these records, only a couple of these documents contain the names of the examiners.



Figure B.5: Patentscope search option

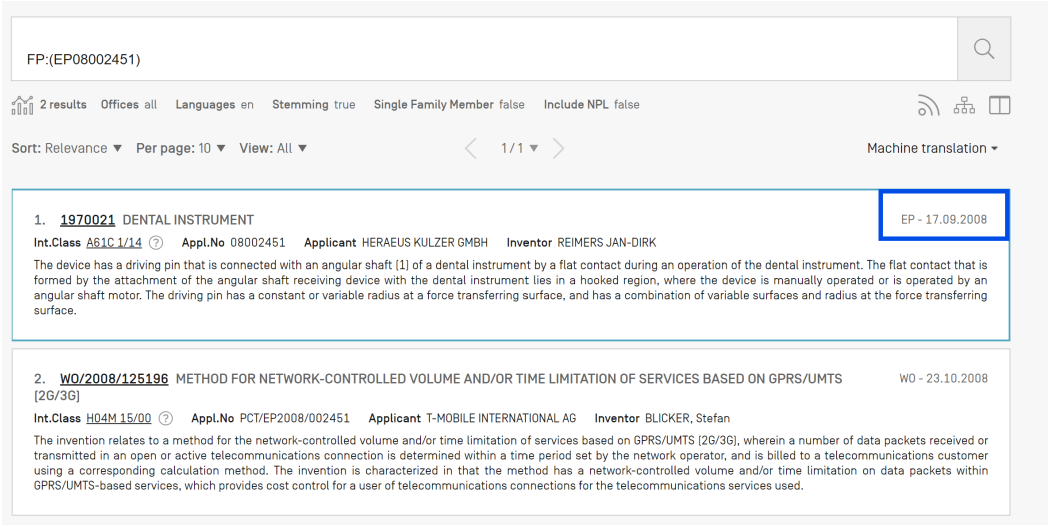


Figure B.6: Search Result

At the EPO, a three-member panel of examiners conducts a thorough assessment and examination

of a patient. After the applicant submits an application, a formalities officer reviews all the 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 applicant. 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 as "Communication from the Examining Division" (see to Figure B.8). This communication document also provides the location of the application submission, the site of evaluation, the date of communication, and the name of the primary examiner (see to Figure B.9 for an example of the communication docs). Another 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 chairman, the first examiner, and the second examiner (Figure B.10). In the majority of cases, the name of the primary or first examiner was available. However, we were unable to obtain the second examiner and chairman information for certain cases due to missing documents for non-granted patents and patent applications that were withdrawn.

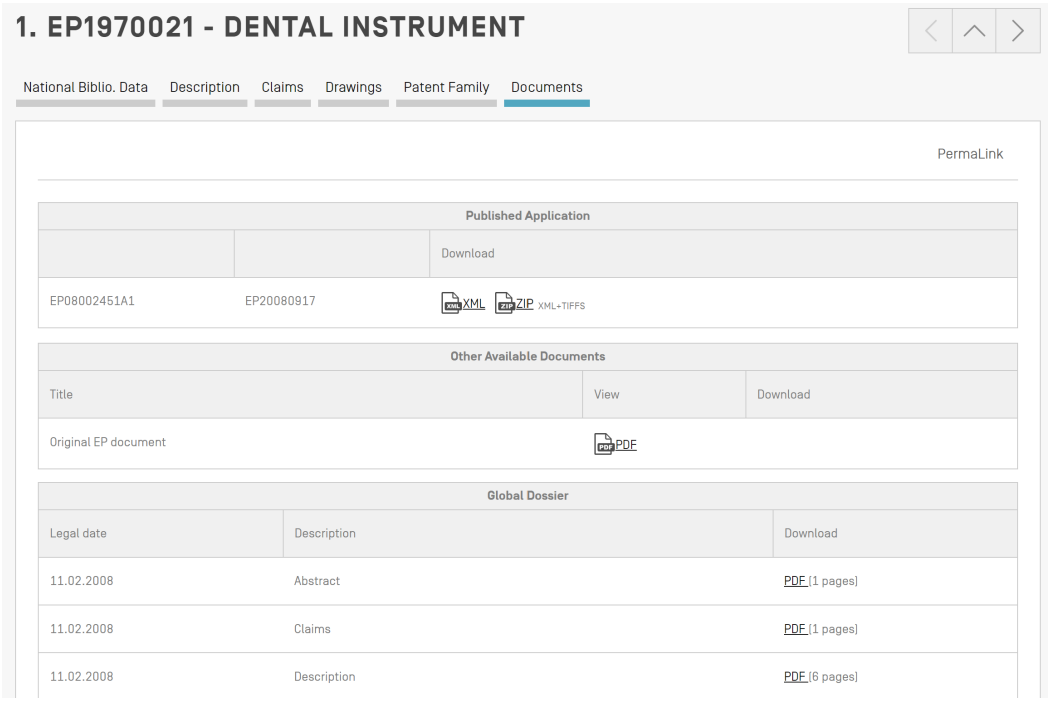


Figure B.7: Documents of the Patent

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 B.8: Documents of the Patent



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

Application office

Europäisches Patentamt | European Patent Office | Office européen des brevets

Generaldirektion 2 | Directorate General 2 | 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 B.9: Communication Documents

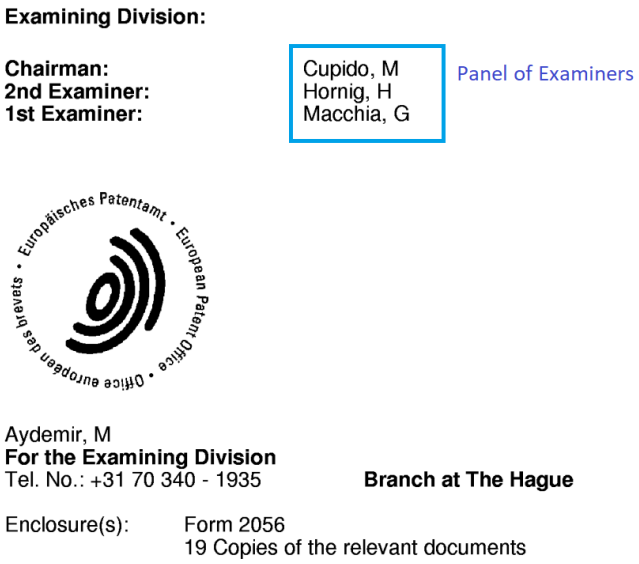
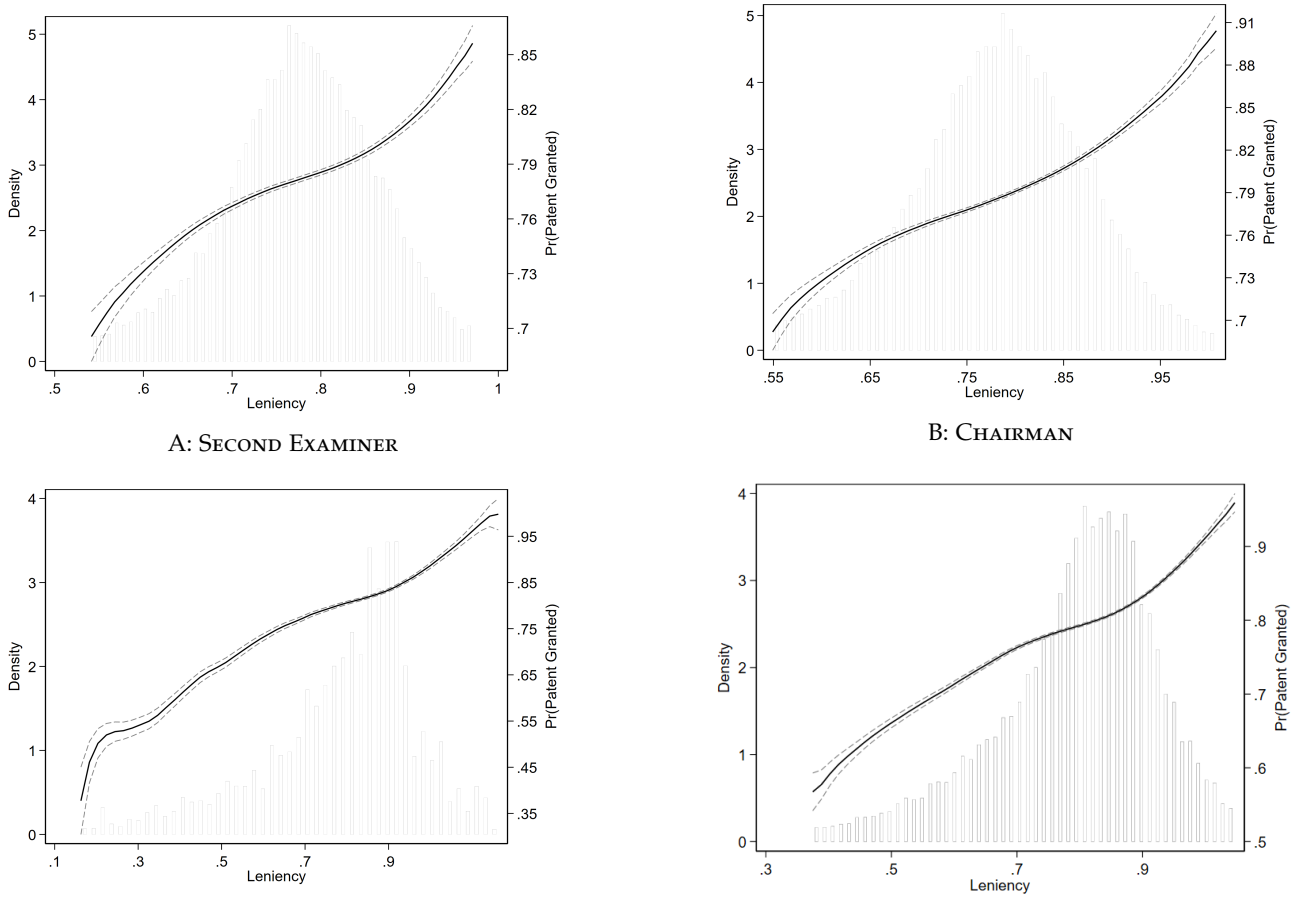


Figure B.10: Examiners' Names

In the first phase, we used the web-scraping approach (using Python) to collect all of the 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)." At this stage, we have retrieved approximately 623,858 PDF documents corresponding to 330,237 patent application IDs since 1981, representing 58% of all patents from MUP linkage. For our sample period from 2000 to 2016, we downloaded 255,420 applications, covering 73% of the patents from the MUP link, which resulted in 9,068 examiners.

In the second phase, we digitize the names of all examiners from the downloaded documents. We extracted the names of the primary examiner, the secondary examiner, and the chairman. 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 ensure that information is retrieved even if the papers are in a different foreign language. While extracting the names, it occasionally extracted special characters, such as a hyphen (), comma (,), and others. 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 "SACHRÜFNNGAFRAGEN" and "RÉPUTÉE RETIRÉE" which was extracted along with the name. 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.

C Extension of Instrument Validity



A: Second Examiner

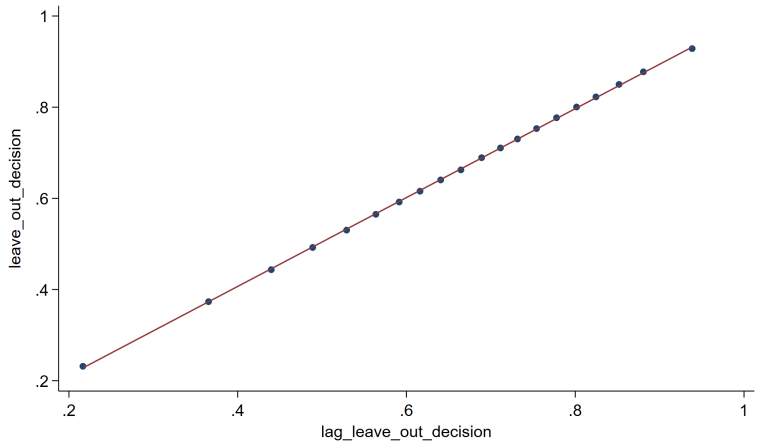
B: Chairman

C: Team of same three examiners

D: Team of same two examiners

Notes: All four figures plot the probability of granting a patent against the leave-one-out mean examiner leniency (× 100) on the right y-axis. The plotted solid line corresponds to a local linear regression of granting a patent on the examiner 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 of examiner fixed effects and technology of the examiner fixed effects. The histogram shows the density examiner leniency (left y-axis). The figure is also constructed by the conditioning of having handled at least 15 patents, which left us to have 4230-second examiners with 225,617 applications and 3700 chairman with 229,914 applications. The variability of leniency is very low when we consider them as a team of three, meaning the same three people come together as a panel of three examiners. This results in nearly 150,692 teams, with 73% of the teams appearing together only once. There are 27 teams that appear more than 50 times, with a maximum of one team appearing together 158 times. For a team of two, we consider them as a team of two if two people come together in a panel of three. This results in around 132,141 teams, with 38% of the teams of two appearing only once. 25% of the team of two appeared more than 5 times, with a maximum of one team appearing together 379 times.

Figure C.11: First-stage Analysis



Notes: Correlation between examiner present and past decisions shows examiners are persistent with their decisions. This explains if the examiner grants the previous case, s/he will grant the current case. The correlation coefficient between the leave-one-out measure in the previous case and the leave-one-out measure in the current case which is 0.97.

Figure C.12: correlation between examiner present and past decision

Table C.3: Test of Joint Null of Monotonicity and 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)
				Employment growth				
Test statistic	458	458	458	458	427	427	427	427
d.f.	(439)	(439)	(439)	(439)	(434)	(434)	(434)	(434)
P-value	[0.258]	[0.322]	[0.516]	[0.860]	[0.579]	[0.724]	[1.000]	[1.000]
				Revenue growth				
Test statistic	444	444	444	444	380	380	380	380
d.f.	(439)	(439)	(439)	(439)	(434)	(434)	(434)	(434)
P-value	[0.429]	[0.536]	[0.858]	[1.000]	[0.971]	[1.000]	[1.000]	[1.000]
				Firm Exit				
Test statistic	355	355	355	355	323	323	323	323
d.f.	(442)	(442)	(442)	(442)	(437)	(437)	(437)	(437)
P-value	[0.999]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]

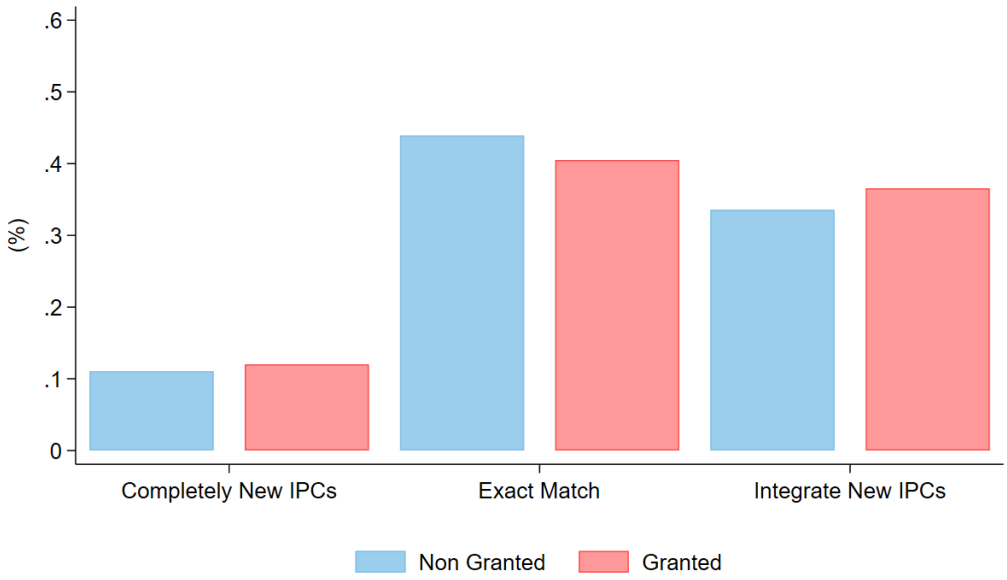
Notes: The table presents results from the test proposed in Frandsen, Lefgren, and Leslie (2023) for the joint null hypothesis that the monotonicity and exclusion restrictions hold for the outcome variables employment growth, revenue growth, and exit five year after the application. We test this null using office times year fixed effects conditional on having handled at least 5 patents. 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 the monotonicity and exclusion restrictions jointly hold. The test was implemented in Stata via the package testjfe.

D Further Empirical Results

Table D.4: Regression Result: The Effect of Successful Innovation on M&A and Bankruptcy

	Minority acquisition (1)	Majority acquisition (2)	Profit take-over agreement (3)	Bankruptcy (4)
Panel A: OLS Results				
Patent Granted (0/1)	0.0134**	0.0167**	0.0121**	-0.0167***
	(0.007)	(0.008)	(0.005)	(0.004)
Panel B: IV Results				
Patent Granted (0/1)	-0.0401	0.0585	-0.0079	-0.0410**
	(0.040)	(0.049)	(0.027)	(0.019)
F-Statistic	233.8	233.8	233.8	235.1
Observations	8,045	8,045	8,045	7,900
Mean outcome	0.084	0.136	0.05	0.014
Granted	0.594	0.594	0.594	0.594
Office × year FE	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of M&A and Bank bankruptcy events on patent grants over the five years following the initial application. Panel A shows the OLS results. Panel B shows the IV results. It contains a dummy equal to 1 if the firm experienced any of these M&A and bank bankruptcy events within five years following the initial application. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.



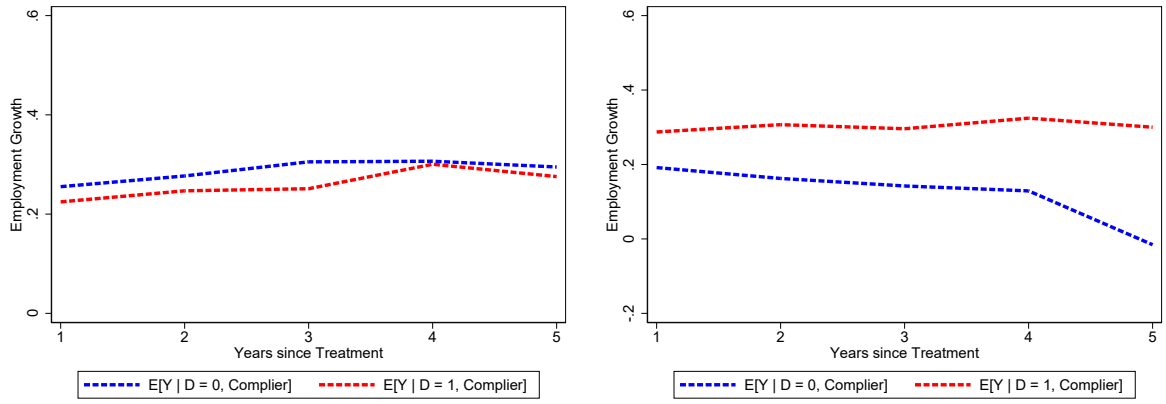
Notes: The figure shows the technology class of a firm's future innovations within five years of the initial application. It indicates that, within this period, if the firm develops a new innovation, the technology class remains the same, regardless of whether the original patent was granted or not.

Figure D.13: Firms' innovation diversification conditional on future patenting activities

Table D.5: Regression Result: The Effect of Successful Innovation on Firm Growth

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
	A: Employment Growth				
Panel A1: OLS Results					
Patent Granted (0/1)	0.0411***	0.1029***	0.1517***	0.2211***	0.2787***
	(0.013)	(0.016)	(0.019)	(0.022)	(0.024)
Panel A2: IV Results					
Patent Granted (0/1)	0.1112	0.1566*	0.1585	0.1877	0.3202**
	(0.074)	(0.094)	(0.110)	(0.123)	(0.137)
F-Statistic	233.6	233.1	233.6	222.5	217.3
Observations	8,037	8,018	8,001	7,569	7,095
Mean outcome	0.294	0.286	0.252	0.222	0.194
Granted	0.594	0.594	0.594	0.616	0.634
E[Y | D = 0, Complier]	0.192	0.162	0.142	0.129	-0.016
E[Y | D = 1, Complier]	0.287	0.307	0.296	0.325	0.300
	B: Revenue Growth				
Panel B1: OLS Results					
Patent Granted (0/1)	0.0608***	0.1289***	0.2054***	0.2828***	0.3422***
	(0.017)	(0.020)	(0.024)	(0.027)	(0.030)
Panel B2: IV Results					
Patent Granted (0/1)	0.2609***	0.3899***	0.3709***	0.4018**	0.6395***
	(0.101)	(0.118)	(0.138)	(0.158)	(0.176)
F-Statistic	201.7	203.9	186.6	167	166.7
Observations	7,019	6,812	6,431	6,020	5,633
Mean outcome	0.26	0.264	0.246	0.21	0.178
Granted	0.594	0.594	0.594	0.616	0.634
E[Y | D = 0, Complier]	0.157	0.111	0.106	.078	-0.088
E[Y | D = 1, Complier]	0.421	0.498	0.495	0.509	0.559
Office × year FE	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of employment (Panel A) and revenue growth (Panel B) on patent grant one to five years after the patent application. Here, we also include the firms that exit the market, and the growth rate takes the value of -2 for the exiting firm. Panels A1 and B1 show the OLS results. Panels A2 and B2 show the IV results. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles. Robust standard errors clustered at the examiner level. *p<0.1, **p<0.05, ***p<0.01.

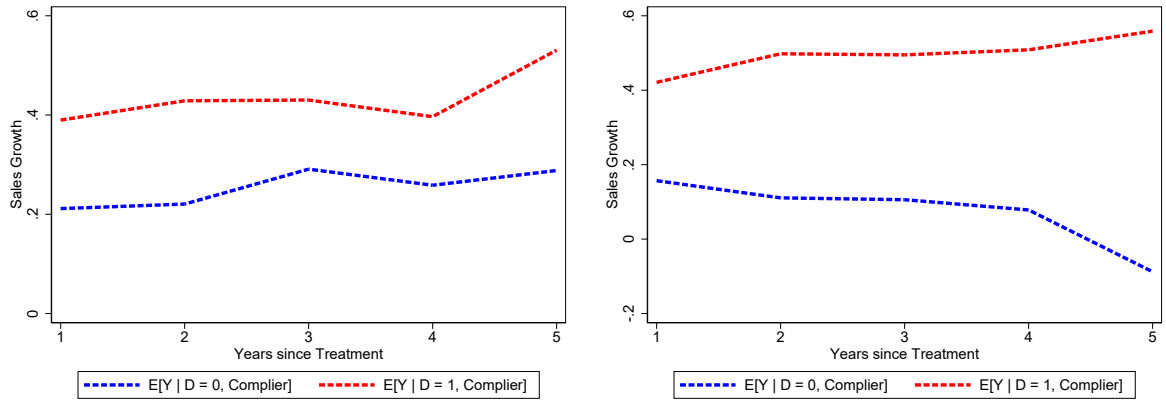


A: Employment growth conditional on survival

B: Employment growth

Notes: The figures plot the potential outcome (PO) of the employment growth for firms that win a patent and firms that receive a rejection among the group of compliers up to five years after the treatment. A) Condition on firms' survival. B) Including firms' exit, and the growth rate takes the value of -2 for the exiting firm.

Figure D.14: potential outcome (PO) among compliers: Employment Growth



A: Revenue growth conditional on survival

B: Revenue growth

Notes: The figures plot the potential outcome (PO) of the revenue growth for firms that win a patent and firms that receive a rejection among the group of compliers up to five years after the treatment. A) Condition on firms' survival. B) Including firms' exit, and the growth rate takes the value of -2 for the exiting firm.

Figure D.15: potential outcome (PO) among compliers: revenue Growth

Table D.6: Regression Result: The Effect of Successful Innovation on Hiring by occupations

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
	A: Manager				
Panel A1: OLS Results					
Patent Granted (0/1)	-0.0289**	-0.0295**	-0.0276*	-0.0275**	-0.0184**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.008)
Panel A2: IV Results					

Table D.6: Regression Result: The Effect of Successful Innovation on Hiring by occupations

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
Patent Granted (0/1)	0.0375	0.0265	0.0368	0.0356	0.0554
	(0.051)	(0.043)	(0.043)	(0.052)	(0.055)
F-Statistic	28.67	40.17	39.85	30.85	27.61
Observations	121,633	187,603	231,797	272,433	305,403
Mean Outcome	0.050	0.054	0.056	0.054	0.052
B: Technicians and Engineers					
Panel B1: OLS Results					
Patent Granted (0/1)	-0.0026	-0.0033	-0.0055	-0.0032	-0.0027
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Panel B2: IV Results					
Patent Granted (0/1)	0.0724	0.0712	0.0951*	0.0975*	0.1229**
	(0.056)	(0.050)	(0.051)	(0.055)	(0.062)
F-Statistic	28.67	40.17	39.85	30.85	27.61
Observations	121,633	187,603	231,797	272,433	305,403
Mean Outcome	0.158	0.172	0.178	0.178	0.178
C: Administration					
Panel C1: OLS Results					
Patent Granted (0/1)	-0.0213*	-0.0271**	-0.0335***	-0.0338***	-0.0262**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)
Panel C2: IV Results					
Patent Granted (0/1)	-0.1066	-0.1188*	-0.1824***	-0.1923***	-0.1707**
	(0.072)	(0.063)	(0.067)	(0.075)	(0.076)
F-Statistic	28.67	40.17	39.85	30.85	27.61
Observations	121,633	187,603	231,797	272,433	305,403
Mean Outcome	0.228	0.234	0.234	0.234	0.236
D: Skilled (Manual & Service)					
Panel D1: OLS Results					
Patent Granted (0/1)	0.0122	0.0150**	0.0150**	0.0158**	0.0159*
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)
Panel D2: IV Results					
Patent Granted (0/1)	0.0409	0.0564	0.0113	0.0231	0.0164
	(0.043)	(0.037)	(0.037)	(0.044)	(0.051)
F-Statistic	28.67	40.17	39.85	30.85	27.61
Observations	121,633	187,603	231,797	272,433	305,403
Mean Outcome	0.146	0.144	0.140	0.138	0.136
E: Unskilled (Manual & Service)					
Panel E1: OLS Results					
Patent Granted (0/1)	0.0023	0.0108	0.0196*	0.0240**	0.0174
	(0.014)	(0.013)	(0.012)	(0.011)	(0.012)
Panel E2: IV Results					
Patent Granted (0/1)	-0.1184	-0.0911	-0.0130	0.0280	0.0114
	(0.073)	(0.062)	(0.055)	(0.059)	(0.075)
F-Statistic	28.67	40.17	39.85	30.85	27.61
Observations	121,633	187,603	231,797	272,433	305,403

Table D.6: Regression Result: The Effect of Successful Innovation on Hiring by occupations

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
Mean Outcome	0.256	0.238	0.236	0.230	0.228
Office × year FE	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of firm's new hire on patent grant one to five years after the patent application among incumbent workers initially employed in the firm and differentiated by subgroups occupation. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

Table D.7: Regression Result: The Effect of Successful Innovation on Job Separation by Occupations

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
	A: Manager				
Panel A1: OLS Results					
Patent Granted (0/1)	-0.0258**	-0.0245*	-0.0174	-0.0150	-0.0115
	(0.013)	(0.013)	(0.011)	(0.011)	(0.008)
Panel A2: IV Results					
Patent Granted (0/1)	0.0469	0.0231	0.0130	0.0136	-0.0220
	(0.050)	(0.048)	(0.039)	(0.034)	(0.026)
F-Statistic	23.67	16.90	30.07	29.45	33.63
Observations	107,627	79,450	61,528	56,719	54,357
Mean Outcome	0.058	0.052	0.050	0.046	0.044
	B: Technicians and Engineers				
Panel B1: OLS Results					
Patent Granted (0/1)	0.0037	-0.0070	-0.0001	0.0112	-0.0021
	(0.009)	(0.011)	(0.010)	(0.010)	(0.009)
Panel B2: IV Results					
Patent Granted (0/1)	0.0323	-0.0008	0.0093	0.0142	-0.0679
	(0.053)	(0.075)	(0.057)	(0.057)	(0.054)
F-Statistic	23.67	16.90	30.07	29.45	33.63
Observations	107,627	79,450	61,528	56,719	54,357
Mean Outcome	0.174	0.174	0.192	0.168	0.166
	C: Administration				
Panel C1: OLS Results					
Patent Granted (0/1)	-0.0100	-0.0120	-0.0350***	-0.0390***	-0.0266**
	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)
Panel C2: IV Results					
Patent Granted (0/1)	-0.0493	-0.1879*	-0.1444**	-0.2323***	-0.1362*
	(0.067)	(0.098)	(0.066)	(0.073)	(0.077)

Table D.7: Regression Result: The Effect of Successful Innovation on Job Separation by Occupations

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
F-Statistic	23.67	16.90	30.07	29.45	33.63
Observations	107,627	79,450	61,528	56,719	54,357
Mean Outcome	0.230	0.222	0.232	0.230	0.230
	D: Skilled (Manual & Service)				
Panel D1: OLS Results					
Patent Granted (0/1)	-0.0028	0.0148*	0.0079	0.0286***	0.0040
	(0.007)	(0.009)	(0.009)	(0.009)	(0.013)
Panel D2: IV Results					
Patent Granted (0/1)	-0.0032	0.0152	0.1152**	0.0514	-0.0400
	(0.043)	(0.055)	(0.048)	(0.051)	(0.066)
F-Statistic	23.67	16.90	30.07	29.45	33.63
Observations	107,627	79,450	61,528	56,719	54,357
Mean Outcome	0.144	0.152	0.158	0.172	0.194
	E: Unskilled (Manual & Service)				
Panel E1: OLS Results					
Patent Granted (0/1)	0.0128	0.0090	0.0264**	-0.0006	0.0234
	(0.013)	(0.012)	(0.012)	(0.014)	(0.017)
Panel E2: IV Results					
Patent Granted (0/1)	-0.1470*	0.0519	-0.0347	0.0476	0.1720**
	(0.089)	(0.088)	(0.069)	(0.071)	(0.083)
F-Statistic	23.67	16.90	30.07	29.45	33.63
Observations	107,627	79,450	61,528	56,719	54,357
Mean Outcome	0.240	0.240	0.254	0.276	0.274
Office × year FE	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of worker's job separation on patent grant one to five years after the patent application among incumbent workers initially employed in the firm and differentiated by subgroups occupation. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

Table D.8: Regression Result: The Effect of Successful Innovation on Talent Acquisition & Wages

	AKM (Top Decile)	Log Wages of	
	New Hire (before)	New Hire (in t=5)	Separation (in t=0)
	(1)	(2)	(3)
Patent Granted (0/1)	0.0351*	0.0999	0.0239
	(0.018)	(0.071)	(0.126)
F-Statistic	43.71	43.38	23.68
Observations	123,709	187,992	93,939
Mean outcome	.088	4.432	4.608
Office × year FE	✓	✓	✓
Technology-expertise FE	✓	✓	✓
Sector FE	✓	✓	✓

Notes: The table shows IV regression results of firms' new hires and separations on patent grants. The outcome variables in column (1) is a dummy variable equal to one if the individual AKM fixed-effect is in the upper decile of the AKM distribution and zero otherwise. The outcome variable in column (2) is log daily wages of new hires five years after the patent submission. The sample includes all new hires one to five years post patent application. The outcomes variable in column (3) is log initial daily wages of separations. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

Table D.9: Regression Result: The Effect of Successful Innovation on Wage by Demographics

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
			A: Male		
Panel A1: OLS Results					
Patent Granted (0/1)	0.0049*	0.0099**	0.0124**	0.0191***	0.0240***
	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)
Panel A2: IV Results					
Patent Granted (0/1)	0.0231	0.0207	0.0299	0.0432	0.0591
	(0.016)	(0.024)	(0.028)	(0.033)	(0.036)
F-Statistic	32.14	33.16	33.86	33.80	33.16
Observations	509,162	491,183	477,763	464,796	453,194
Mean Outcome	4.766	4.784	4.798	4.810	4.820
			B: Female		
Panel B1: OLS Results					
Patent Granted (0/1)	0.0014	0.0047	0.0134**	0.0223***	0.0304***
	(0.003)	(0.004)	(0.006)	(0.007)	(0.008)
Panel B2: IV Results					
Patent Granted (0/1)	0.0260	0.0269	0.0652**	0.1015***	0.1257***
	(0.018)	(0.024)	(0.033)	(0.039)	(0.044)
F-Statistic	24.27	24.79	25.18	25.18	24.97
Observations	231,512	220,435	212,959	206,640	200,774
Mean Outcome	4.382	4.400	4.412	4.426	4.426
			C: Age (below 31)		

Table D.9: Regression Result: The Effect of Successful Innovation on Wage by Demographics

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
Panel C1: OLS Results					
Patent Granted (0/1)	-0.0006	0.0055	0.0112	0.0145	0.0192*
	(0.005)	(0.007)	(0.009)	(0.009)	(0.010)
Panel C2: IV Results					
Patent Granted (0/1)	0.0279	-0.0011	0.0125	0.0317	0.0352
	(0.029)	(0.040)	(0.046)	(0.049)	(0.051)
F-Statistic	26.10	28.85	29.97	29.78	29.88
Observations	140,271	134,703	132,098	130,465	129,176
Mean Outcome	4.400	4.476	4.540	4.592	4.634
	D: Age (31 to 45)				
Panel D1: OLS Results					
Patent Granted (0/1)	0.0059***	0.0104***	0.0170***	0.0231***	0.0279***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.005)
Panel D2: IV Results					
Patent Granted (0/1)	0.0229	0.0259	0.0576**	0.0696**	0.0901***
	(0.015)	(0.019)	(0.024)	(0.028)	(0.032)
F-Statistic	29.39	30.18	30.40	30.31	29.84
Observations	323,933	315,911	311,810	308,505	306,409
Mean Outcome	4.708	4.722	4.732	4.740	4.748
	E: Age (above 45)				
Panel E1: OLS Results					
Patent Granted (0/1)	0.0046**	0.0100***	0.0137***	0.0255***	0.0331***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)
Panel E2: IV Results					
Patent Granted (0/1)	0.0199	0.0248	0.0410*	0.0716***	0.1090***
	(0.013)	(0.017)	(0.023)	(0.028)	(0.034)
F-Statistic	29.81	29.79	30.60	30.63	29.87
Observations	276,470	261,004	246,814	232,466	218,383
Mean Outcome	4.692	4.688	4.682	4.674	4.664
	F: Foreigner				
Panel F1: OLS Results					
Patent Granted (0/1)	0.0062	0.0130*	0.0185*	0.0261**	0.0321***
	(0.005)	(0.008)	(0.010)	(0.010)	(0.012)
Panel F2: IV Results					
Patent Granted (0/1)	0.0213	0.0045	0.0278	0.0750	0.1188*
	(0.035)	(0.048)	(0.053)	(0.062)	(0.066)
F-Statistic	16.63	18.16	19.24	19.52	18.97
Observation	58,673	55,157	52,806	50,621	49,008
Mean Outcome	4.566	4.584	4.600	4.606	4.618
	G: German				
Panel G1: OLS Results					
Patent Granted (0/1)	0.0036	0.0078**	0.0124**	0.0197***	0.0252***
	(0.002)	(0.004)	(0.005)	(0.006)	(0.007)

Table D.9: Regression Result: The Effect of Successful Innovation on Wage by Demographics

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
Panel G2: IV Results					
Patent Granted (0/1)	0.0258*	0.0265	0.0480*	0.0667**	0.0839**
	(0.015)	(0.021)	(0.027)	(0.031)	(0.035)
F-Statistic	31.42	32.24	32.87	32.74	32.27
Observations	682,000	656,460	637,915	620,814	604,959
Mean Outcome	4.65	4.67	4.684	4.694	4.704
Office × year FE	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of log real daily wages on patent grant one to five years after the patent application among incumbent workers initially employed in the firm and differentiated by subgroups like gender, age, and nationality. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles, and at the worker level, of initial log wages, and baseline demographics. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

Table D.10: Regression Result: The Effect of Successful Innovation on Wage by Occupations

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
	A: Managers				
Panel A1: OLS Results					
Patent Granted (0/1)	-0.0027	-0.0095	-0.0095	-0.0188**	-0.0005
	(0.005)	(0.007)	(0.008)	(0.008)	(0.010)
Panel A2: IV Results					
Patent Granted (0/1)	-0.0217	-0.0255	0.0049	0.0240	0.0192
	(0.023)	(0.032)	(0.037)	(0.042)	(0.050)
F-Statistic	47.79	49.78	48.65	46.71	47.79
Observations	28,128	26,472	25,228	24,329	23,479
Mean Outcome	4.996	5.046	5.076	5.100	5.116
	B: Technicians and Engineers				
Panel B1: OLS Results					
Patent Granted (0/1)	0.0073**	0.0104***	0.0189***	0.0225***	0.0254***
	(0.003)	(0.004)	(0.005)	(0.006)	(0.006)
Panel B2: IV Results					
Patent Granted (0/1)	0.0112	-0.0008	0.0312	0.0356	0.0571
	(0.022)	(0.029)	(0.034)	(0.041)	(0.044)
F-Statistic	15.15	14.34	15.08	15.30	15.15
Observations	118,160	113,882	110,121	106,938	104,002
Mean Outcome	4.94	4.96	4.974	4.986	5.00
	C: Administration				
Panel C1: OLS Results					

Table D.10: Regression Result: The Effect of Successful Innovation on Wage by Occupations

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
Patent Granted (0/1)	0.0021	0.0077*	0.0187***	0.0251***	0.0299***
	(0.003)	(0.004)	(0.006)	(0.007)	(0.007)
Panel C2: IV Results					
Patent Granted (0/1)	0.0116	0.0214	0.0506**	0.0662**	0.0797***
	(0.011)	(0.017)	(0.024)	(0.026)	(0.029)
F-Statistic	57.79	57.54	58.39	58.09	57.79
Observations	164,336	158,075	153,517	149,415	145,465
Mean Outcome	4.71	4.73	4.742	4.752	4.762
D: Skilled (Manual & Service)					
Panel D1: OLS Results					
Patent Granted (0/1)	0.0071**	0.0123***	0.0222***	0.0298***	0.0400***
	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)
Panel D2: IV Results					
Patent Granted (0/1)	0.0522***	0.0394	0.0511*	0.0910***	0.1322***
	(0.018)	(0.024)	(0.029)	(0.034)	(0.042)
F-Statistic	28.28	28.92	28.89	28.75	28.28
Observations	140,136	135,929	132,885	130,035	127,032
Mean Outcome	4.63	4.634	4.64	4.644	4.648
E: Unskilled (Manual & Service)					
Panel E1: OLS Results					
Patent Granted (0/1)	0.0063*	0.0159***	0.0137**	0.0313***	0.0384***
	(0.004)	(0.005)	(0.006)	(0.007)	(0.008)
Panel E2: IV Results					
Patent Granted (0/1)	0.0558**	0.0688**	0.0645	0.1118**	0.1495**
	(0.025)	(0.032)	(0.040)	(0.050)	(0.059)
F-Statistic	15.58	16.21	16.38	16.44	15.58
Observations	218,089	209,886	204,050	197,707	192,623
Mean Outcome	4.462	4.464	4.466	4.466	4.466
Office × year FE	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of log real daily wages on patent grant one to five years after the patent application among incumbent workers initially employed in the firm and differentiated by subgroups occupation. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles, and at the worker level, of initial log wages, and baseline demographics. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

Table D.11: Regression Result: The Effect of Successful Innovation on Bonus by Occupations

	Years after Patent Application			
	t1	t3	t5	t5
	(1)	(2)	(3)	(4)
	A: Manager			
Patent Granted (0/1)	-0.0068	0.0104	0.0373	0.0533
	(0.023)	(0.027)	(0.031)	(0.084)
F-Statistic	53.24	50.75	49.69	49.69
Observations	28,128	25,228	23,479	23,479
Mean outcome	0.032	0.048	0.068	0.112
	B: Technicians and Engineers			
Patent Granted (0/1)	-0.0456	0.0031	0.0483	0.0595
	(0.032)	(0.026)	(0.030)	(0.057)
F-Statistic	14.46	17.07	17.08	17.08
Observations	118,160	110,121	104,002	104,002
Mean outcome	0.026	0.036	0.05	0.092
	C: Administration			
Patent Granted (0/1)	0.0253	0.0646***	0.0758***	0.1622***
	(0.016)	(0.023)	(0.022)	(0.051)
F-Statistic	58.57	59.75	59.12	59.12
Observations	164,336	153,517	145,465	145,465
Mean outcome	0.028	0.038	0.05	0.108
	D: Skilled (Manual & Service)			
Patent Granted (0/1)	-0.0623**	-0.0248	0.0495*	0.0921
	(0.031)	(0.022)	(0.030)	(0.059)
F-Statistic	29.17	29.08	28.76	28.76
Observations	140,136	132,885	127,032	127,032
Mean outcome	0.024	0.032	0.048	0.086
	E: Unskilled (Manual & Service)			
Patent Granted (0/1)	-0.0372	0.0212	0.0674**	0.1301*
	(0.031)	(0.017)	(0.034)	(0.070)
F-Statistic	20.96	20.85	19.90	19.90
Observations	218,089	204,050	192,623	192,623
Mean outcome	0.02	0.026	0.034	0.068
Office × year FE	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓

Notes: The table shows IV regression results of bonus payment on patent grant first, third, and fifth years after the patent application at extensive (column (1) to (3) and intensive margin (column (4) among incumbent workers initially employed in the firm and differentiated by subgroups occupation. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles, and at the worker level, of initial log wages, and baseline demographics. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

Table D.12: Regression Result: Robustness censored wage by Occupations

	Years after Patent Application			
	Baseline	Control for censoring dummy	Uncensored sample in t=0	1(wage in t=5 censored)
	(1)	(2)	(3)	(4)
		A: Manager		
Patent Granted (0/1)	-0.0222	-0.0388	-0.0636	0.0486
	(0.048)	(0.045)	(0.064)	(0.058)
F-Statistic	49.69	50.66	44.05	49.69
Observations	23,479	23,479	14,615	23,479
Mean outcome	5.116	5.116	4.914	.422
		B: Technicians and Engineers		
Patent Granted (0/1)	0.0584	0.0484	0.0362	0.0314
	(0.042)	(0.042)	(0.044)	(0.048)
F-Statistic	17.08	17.08	14.99	17.08
Observations	104,002	104,002	82,854	104,002
Mean outcome	5.00	5.00	4.89	.25
		C: Administration		
Patent Granted (0/1)	0.0717**	0.0704**	0.0779**	0.0120
	(0.030)	(0.029)	(0.031)	(0.026)
F-Statistic	59.12	59.12	55.19	59.12
Observations	145,465	145,465	127,212	145,465
Mean outcome	4.762	4.762	4.668	.156
		D: Skilled (Manual & Service)		
Patent Granted (0/1)	0.0961**	0.0981**	0.1014**	-0.0177
	(0.039)	(0.039)	(0.040)	(0.017)
F-Statistic	28.76	28.77	28.05	28.76
Observations	127,032	127,032	124,205	127,032
Mean outcome	4.648	4.648	4.634	.028
		E: Unskilled (Manual & Service)		
Patent Granted (0/1)	0.1172**	0.1191**	0.1166**	-0.0198*
	(0.050)	(0.050)	(0.050)	(0.011)
F-Statistic	19.90	19.90	19.77	19.90
Observations	192,623	192,623	190,866	192,623
Mean outcome	4.466	4.466	4.46	.012
Office × year FE	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓

Notes: The table shows robustness specification with respect to the censoring of the wage data at the social security limit five years after the patent application among incumbent workers initially employed in the firm differentiated by occupational subgroups. Column (1) presents the baseline results. In column (2), the regression specification controls for a dummy variable equal to one if individual *i*'s initial wage was above the limit and zero otherwise. Column (3) conditions the sample on workers initially earning below the censoring limit. Column (4) specifies the outcome variable equal to one if wages earned five years post patent application is above the censoring limit and zero otherwise. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles, and at the worker level, of initial log wages, and baseline demographics. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

Table D.13: IV Regression Result: The Effect of Successful Innovation on Part-time Employment

	Full	Unskilled	Skilled	Administration	Technicians	Manager
	(1)	(2)	(3)	(4)	(5)	(6)
Patent Granted (0/1)	0.0004	0.0044	0.0071	0.0106	-0.0256	-0.0489**
	(0.023)	(0.057)	(0.030)	(0.020)	(0.025)	(0.023)
Observations	680,079	202,929	131,183	150,449	106,852	24,476
Mean outcome	.144	.106	.086	.236	.120	.162
Office × year FE	✓	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Notes: The table shows IV regression results of part-time employment on patent grant one to five years after the patent application among incumbent workers initially employed in the firm for the full sample and differentiated by occupational subgroups. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles, and at the worker level, of initial log wages, and baseline demographics. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

Table D.14: Regression Result: The Effect of Successful Innovation on staying in the same firm by Demographics

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
			A: Overall		
Panel A1: OLS Results					
Patent Granted (0/1)	0.0132**	0.0207***	0.0267***	0.0452***	0.0671***
	(0.006)	(0.008)	(0.009)	(0.012)	(0.014)
Panel A2: IV Results					
Patent Granted (0/1)	0.0665	0.0871*	0.1047*	0.1551**	0.2240***
	(0.042)	(0.052)	(0.060)	(0.068)	(0.079)
F-Statistic	30.95	31.89	32.62	32.57	32.11
Observations	740,674	711,618	690,722	671,436	653,968
Mean Outcome	0.92	0.854	0.808	0.76	0.712
			B: Male		
Panel B1: OLS Results					
Patent Granted (0/1)	0.0173***	0.0268***	0.0343***	0.0497***	0.0724***
	(0.006)	(0.008)	(0.009)	(0.012)	(0.014)
Panel B2: IV Results					
Patent Granted (0/1)	0.0767	0.0875	0.0959	0.1444**	0.2190***
	(0.048)	(0.057)	(0.061)	(0.069)	(0.082)
F-Statistic	32.14	33.16	33.86	33.80	33.16
Observations	509,162	491,183	477,763	464,796	453,194
Mean Outcome	0.92	0.862	0.814	0.768	0.718
			C: Female		
Panel C1: OLS Results					
Patent Granted (0/1)	0.0038	0.0060	0.0085	0.0303**	0.0491***
	(0.006)	(0.008)	(0.009)	(0.013)	(0.015)

Table D.14: Regression Result: The Effect of Successful Innovation on staying in the same firm by Demographics

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
Panel C2: IV Results					
Patent Granted (0/1)	0.0352	0.0604	0.0763	0.1268*	0.1911**
	(0.035)	(0.046)	(0.058)	(0.068)	(0.080)
F-Statistic	24.27	24.79	25.18	25.18	24.97
Observations	231,512	220,435	212,959	206,640	200,774
Mean Outcome	0.918	0.842	0.790	0.744	0.702
D: Age (below 31)					
Panel D1: OLS Results					
Patent Granted (0/1)	0.0194***	0.0257***	0.0291***	0.0425***	0.0646***
	(0.007)	(0.009)	(0.010)	(0.011)	(0.013)
Panel D2: IV Results					
Patent Granted (0/1)	0.1239**	0.1310**	0.1173*	0.1282**	0.1911***
	(0.055)	(0.062)	(0.062)	(0.063)	(0.070)
F-Statistic	26.10	28.85	29.97	29.78	29.88
Observations	140,271	134,703	132,098	130,465	129,176
Mean Outcome	0.846	0.732	0.654	0.586	0.528
E: Age (31 to 45)					
Panel E1: OLS Results					
Patent Granted (0/1)	0.0142**	0.0225***	0.0319***	0.0506***	0.0698***
	(0.006)	(0.008)	(0.009)	(0.013)	(0.015)
Panel E2: IV Results					
Patent Granted (0/1)	0.0810*	0.1057*	0.1321**	0.1909**	0.2574***
	(0.045)	(0.057)	(0.066)	(0.075)	(0.085)
F-Statistic	29.39	30.18	30.40	30.31	29.84
Observations	323,933	315,911	311,810	308,505	306,409
Mean Outcome	0.918	0.854	0.808	0.764	0.720
F: Age (above 45)					
Panel F1: OLS Results					
Patent Granted (0/1)	0.0067	0.0124*	0.0149*	0.0345***	0.0597***
	(0.006)	(0.007)	(0.008)	(0.013)	(0.014)
Panel F2: IV Results					
Patent Granted (0/1)	0.0085	0.0213	0.0410	0.0943	0.1662*
	(0.040)	(0.049)	(0.061)	(0.074)	(0.091)
F-Statistic	29.81	29.79	30.60	30.63	29.87
Observations	276,470	261,004	246,814	232,466	218,383
Mean Outcome	0.960	0.920	0.888	0.856	0.814
G: Foreigner					
Panel G1: OLS Results					
Patent Granted (0/1)	0.0126*	0.0251**	0.0354***	0.0519***	0.0636***

Table D.14: Regression Result: The Effect of Successful Innovation on staying in the same firm by Demographics

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
	(0.007)	(0.012)	(0.013)	(0.018)	(0.020)
Panel G2: IV Results					
Patent Granted (0/1)	0.1080	0.1386*	0.1995**	0.2910***	0.3093**
	(0.067)	(0.081)	(0.096)	(0.111)	(0.122)
F-Statistic	16.63	18.16	19.24	19.52	18.97
Observations	58,673	55,157	52,806	50,621	49,008
Mean Outcome	0.920	0.854	0.808	0.756	0.710
	H: German				
Panel H1: OLS Results					
Patent Granted (0/1)	0.0131**	0.0203***	0.0258***	0.0444***	0.0670***
	(0.005)	(0.007)	(0.009)	(0.012)	(0.013)
Panel H2: IV Results					
Patent Granted (0/1)	0.0603	0.0817	0.0965*	0.1434**	0.2173***
	(0.040)	(0.051)	(0.058)	(0.067)	(0.078)
F-Statistic	31.42	32.24	32.87	32.74	32.27
Observations	682,000	656,460	637,915	620,814	604,959
Mean Outcome	0.920	0.856	0.808	0.762	0.712
Office × year FE	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of being employed at the same firm on patent grant among incumbent workers initially employed in the firm and differentiated by occupational groups from one to five years. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles, and at the worker level, of initial log wages, and baseline demographics. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

Table D.15: Regression Result: The Effect of Successful Innovation on Staying in the same firm by Occupations

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
	A: Managers				
Panel A1: OLS Results					
Patent Granted (0/1)	0.0218**	0.0484***	0.0540***	0.0722***	0.0970***
	(0.009)	(0.012)	(0.013)	(0.016)	(0.017)
Panel A2: IV Results					
Patent Granted (0/1)	0.0074	0.0086	0.0086	0.0027	0.0767
	(0.036)	(0.055)	(0.072)	(0.081)	(0.092)
F-Statistics	51.00	49.78	48.65	46.71	47.79

Table D.15: Regression Result: The Effect of Successful Innovation on staying in the same firm by Occupations

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
Observations	28,128	26,472	25,228	24,329	23,479
Mean Outcome	0.880	0.784	0.704	0.632	0.564
B: Technicians and Engineers					
Panel B1: OLS Results					
Patent Granted (0/1)	0.0174***	0.0345***	0.0419***	0.0528***	0.0767***
	(0.006)	(0.010)	(0.011)	(0.012)	(0.014)
Panel B2: IV Results					
Patent Granted (0/1)	0.0899	0.1109	0.0756	0.1162	0.2855**
	(0.055)	(0.081)	(0.083)	(0.091)	(0.117)
F-Statistics	12.88	14.34	15.08	15.30	15.15
Observations	118,160	113,882	110,121	106,938	104,002
Mean Outcome	0.910	0.838	0.788	0.740	0.690
C: Administration					
Panel C1: OLS Results					
Patent Granted (0/1)	0.0086	0.0130	0.0235**	0.0505***	0.0733***
	(0.006)	(0.008)	(0.010)	(0.013)	(0.015)
Panel C2: IV Results					
Patent Granted (0/1)	0.0007	-0.0069	0.0140	0.0764	0.1272**
	(0.024)	(0.035)	(0.046)	(0.055)	(0.065)
F-Statistics	57.11	57.54	58.39	58.09	57.79
Observations	164,336	158,075	153,517	149,415	145,465
Mean Outcome	0.914	0.846	0.792	0.742	0.690
D: Skilled (Manual & Service)					
Panel D1: OLS Results					
Patent Granted (0/1)	0.0185***	0.0238***	0.0293***	0.0307**	0.0616***
	(0.007)	(0.008)	(0.011)	(0.014)	(0.018)
Panel D2: IV Results					
Patent Granted (0/1)	0.0972*	0.1515**	0.0958	0.1242	0.2500**
	(0.053)	(0.064)	(0.073)	(0.088)	(0.113)
F-Statistics	29.16	28.92	28.89	28.75	28.28
Observations	140,136	135,929	132,885	130,035	127,032
Mean Outcome	0.942	0.896	0.860	0.820	0.774
E: Unskilled (Manual & Service)					
Panel E1: OLS Results					
Patent Granted (0/1)	0.0101	0.0141	0.0167	0.0458***	0.0629***
	(0.009)	(0.011)	(0.013)	(0.017)	(0.018)

Table D.15: Regression Result: The Effect of Successful Innovation on staying in the same firm by Occupations

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
Panel E2: IV Results					
Patent Granted (0/1)	0.0907	0.0874	0.2173*	0.2588**	0.2579*
	(0.079)	(0.091)	(0.121)	(0.126)	(0.136)
F-Statistics	16.60	16.21	16.38	16.44	15.58
Observations	218,089	209,886	204,050	197,707	192,623
Mean Outcome	0.938	0.890	0.852	0.810	0.768
Office × year FE	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of being employed at the same firm on patent grant among incumbent workers initially employed in the firm and differentiated by occupational groups from one to five years. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles, and at the worker level, of initial log wages, and baseline demographics. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

Table D.16: IV Results: The Impact of Successful Innovation on Wages by Movers/Stayers and Occupations

	Job Changers			Stayers		
	t1	t3	t5	t1	t3	t5
	(1)	(2)	(3)	(4)	(5)	(6)
			A: Manager			
Patent Granted (0/1)	-0.0136	0.0607	0.1612	-0.0113	0.0107	-0.0146
	(0.123)	(0.106)	(0.103)	(0.023)	(0.032)	(0.039)
F-Statistic	28.03	32.12	38.62	48.54	43.24	41.86
Observations	3,307	7,399	10,184	24,811	17,385	12,619
Mean Outcome	4.966	5.062	5.102	5.026	5.12	5.172
			B: Technicians and Engineers			
Patent Granted (0/1)	0.1103	0.0344	-0.0088	0.0132	0.0377	0.0583
	(0.130)	(0.118)	(0.101)	(0.021)	(0.032)	(0.043)
F-Statistic	8.433	6.466	8.389	12.54	18.09	18.10
Observations	10,196	22,612	31,728	107,963	86,190	69,913
Mean Outcome	4.896	4.962	5.002	4.944	4.982	5.016
			C: Administration			
Patent Granted (0/1)	0.0542	0.0514	0.0603	0.0066	0.0495**	0.0602**
	(0.050)	(0.050)	(0.049)	(0.010)	(0.021)	(0.026)
F-Statistic	90.22	82.60	78.28	51.83	47.55	40.48
Observations	13,702	31,186	44,589	150,633	119,990	96,295
Mean Outcome	4.588	4.678	4.71	4.728	4.772	4.808
			D: Skilled (Manual & Service)			
Patent Granted (0/1)	0.0400	0.1623*	0.0455	0.0383**	0.0126	0.0771*
	(0.114)	(0.098)	(0.068)	(0.017)	(0.026)	(0.044)
F-Statistic	42.33	38.44	49.42	25.29	24.35	15.67
Observations	8,047	18,208	28,258	132,084	112,733	95,198
Mean Outcome	4.344	4.422	4.47	4.638	4.67	4.688
			E: Unskilled (Manual & Service)			
Patent Granted (0/1)	0.1997	0.0061	-0.0815	0.0233	0.0105	0.1258*
	(0.133)	(0.119)	(0.096)	(0.022)	(0.036)	(0.073)
F-Statistic	37.55	37.93	34.5	13.03	10.52	8.204
Observations	13,460	30,171	44,596	204,629	171,004	142,838
Mean Outcome	4.042	4.142	4.18	4.498	4.534	4.562

Notes: All explanatory variables listed in the table refer to the initial firm observation. Each line represents a single regression of the explanatory variable on the leniency measure that takes values between 0 (minimum) and 1 (maximum). All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles, and at the worker level, of initial log wages, and baseline demographics. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

Table D.17: IV Regression Result: The Effect of Successful Innovation on Wage by Firm Size & Legal Form

					Large firms	
	Small	Large	Partnership	Stock company	Partnership	Stock company
	(1)	(2)	(3)	(4)	(5)	(6)
			A: Manager			
Patent Granted (0/1)	-0.0102	0.0623	-0.0075	0.1702	0.0176	0.2330**
	(0.072)	(0.056)	(0.050)	(0.115)	(0.062)	(0.102)
Observations	7,557	16,840	21,074	3,321	14,390	2,449
Mean outcome	5.13	5.088	5.084	5.202	5.062	5.24
			B: Technicians and Engineers			
Patent Granted (0/1)	-0.0061	0.0611	0.0630*	-0.0311	0.0932*	0.0753
	(0.041)	(0.049)	(0.036)	(0.094)	(0.051)	(0.173)
Observations	32,729	71,273	93,130	10,868	62,561	8,712
Mean outcome	4.972	5.012	4.994	5.042	5.004	5.072
			C: Administration			
Patent Granted (0/1)	-0.0002	0.1296**	0.1059***	0.0182	0.1389**	0.1374
	(0.040)	(0.054)	(0.040)	(0.085)	(0.057)	(0.113)
Observations	44,674	100,790	124,825	20,637	83,951	16,839
Mean outcome	4.702	4.788	4.74	4.89	4.762	4.916
			D: Skilled (Manual & Service)			
Patent Granted (0/1)	0.0122	0.1573***	0.1090***	0.0986	0.1470***	0.1140
	(0.045)	(0.050)	(0.040)	(0.099)	(0.055)	(0.079)
Observations	33,928	93,101	107,053	19,974	74,135	18,966
Mean outcome	4.612	4.66	4.648	4.644	4.664	4.65
			E: Unskilled (Manual & Service)			
Patent Granted (0/1)	0.0515	0.1575***	0.1018**	0.0367	0.1514**	-0.0527
	(0.046)	(0.056)	(0.043)	(0.101)	(0.060)	(0.113)
Observations	49,072	143,549	172,473	20,146	124,895	18,653
Mean outcome	4.368	4.5	4.462	4.502	4.498	4.524
Office × year FE	✓	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Notes: The table presents IV regression results of the impact of patent grants on log real daily wages, measured five years after the patent application of incumbent workers, initially employed by the firm, differentiated by occupational groups and firm size/legal form. Small and large firms are defined as those with fewer than or more than 150 employees, respectively. Each specification uses the predicted values from the overall first-stage regression using the full sample. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles, and at the worker level, of initial log wages, and baseline demographics. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

Table D.18: IV Regression Result: The Effect of Successful Innovation on Bonus by Occupations

					Large firm	
	Small	Large	Partnership	Stock company	Partnership	Stock company
	(1)	(2)	(3)	(4)	(5)	(6)
			A: Manager			
Patent Granted (0/1)	0.0194	0.0522	0.0178	-0.0309	0.0094	0.0682
	(0.055)	(0.046)	(0.039)	(0.066)	(0.050)	(0.059)
Observations	7,241	16,233	20,270	3,203	13,861	2,371
Mean outcome	0.062	0.05	0.05	0.078	0.044	0.084
			B: Technicians and Engineers			
Patent Granted (0/1)	0.0444*	0.0507	0.0324	0.2044**	0.0247	0.5792***
	(0.025)	(0.035)	(0.024)	(0.083)	(0.034)	(0.147)
Observations	32,729	71,273	93,130	10,868	62,561	8,712
Mean outcome	.054	.044	.046	.05	.042	.052
			C: Administration			
Patent Granted (0/1)	0.0936***	0.1145***	0.0894***	0.2241***	0.0865**	0.2829***
	(0.027)	(0.039)	(0.027)	(0.085)	(0.037)	(0.085)
Observations	44,674	100,790	124,825	20,637	83,951	16,839
Mean outcome	.054	.046	.048	.056	.044	.056
			D: Skilled (Manual & Service)			
Patent Granted (0/1)	-0.0202	0.0855**	0.0346	0.2517*	0.0660	0.5417***
	(0.028)	(0.043)	(0.027)	(0.148)	(0.041)	(0.144)
Observations	33,928	93,101	107,053	19,974	74,135	18,966
Mean outcome	.04	.05	.048	.048	.052	.048
			E: Unskilled (Manual & Service)			
Patent Granted (0/1)	0.0130	0.0644	0.0227	0.2181***	0.0253	0.2678***
	(0.023)	(0.041)	(0.022)	(0.060)	(0.033)	(0.088)
Observations	49,072	143,549	172,473	20,146	124,895	18,653
Mean outcome	0.022	0.038	0.032	0.058	0.036	0.062
Office × year FE	✓	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Notes: The table presents IV regression results of the impact of patent grants on bonus payment in extensive margin(dummy=1 if workers get bonus or zero otherwise), measured five years after the patent application of incumbent workers, initially employed by the firm, differentiated by occupational groups and firm size/legal form. Small and large firms are defined as those with fewer than or more than 150 employees, respectively. Each specification uses the predicted values from the overall first-stage regression using the full sample. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles, and at the worker level, of initial log wages, and baseline demographics. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

Table D.19: Regression Result: The Effect of Successful Innovation on Employment by Demographics

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
			A: Overall		
Panel A1: OLS Results					
Patent Granted (0/1)	0.0062***	0.0104***	0.0111***	0.0120***	0.0164***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Panel A2: IV Results					
Patent Granted (0/1)	0.0293*	0.0142	0.0254	0.0275	0.0510***
	(0.015)	(0.016)	(0.016)	(0.019)	(0.019)
F-Statistic	29.26	29.29	29.32	29.33	29.38
Observations	798,333	797,688	797,166	796,620	796,141
Mean Outcome	0.926	0.892	0.866	0.842	0.820
			B: Male		
Panel B1: OLS Results					
Patent Granted (0/1)	0.0076***	0.0115***	0.0110***	0.0121***	0.0156***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
Panel B2: IV Results					
Patent Granted (0/1)	0.0384**	0.0224	0.0317*	0.0354	0.0506**
	(0.017)	(0.018)	(0.019)	(0.023)	(0.022)
F-Statistic	30.79	30.85	30.86	30.87	30.90
Observations	543,315	542,876	542,526	542,105	541,768
Mean Outcome	0.936	0.904	0.880	0.856	0.836
			C: Female		
Panel C1: OLS Results					
Patent Granted (0/1)	0.0018	0.0067**	0.0093***	0.0093***	0.0157***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
Panel C2: IV Results					
Patent Granted (0/1)	0.0135	0.0001	0.0164	0.0167	0.0503***
	(0.014)	(0.017)	(0.016)	(0.019)	(0.019)
F-Statistic	22.86	22.87	22.89	22.88	22.96
Observations	255,018	254,812	254,640	254,515	254,373
Mean Outcome	0.908	0.864	0.836	0.812	0.788
			D: Age (below 31)		
Panel D1: OLS Results					
Patent Granted (0/1)	0.0083**	0.0092***	0.0091***	0.0088**	0.0115***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Panel D2: IV Results					
Patent Granted (0/1)	0.0286	-0.0031	-0.0152	-0.0060	0.0132
	(0.023)	(0.023)	(0.024)	(0.025)	(0.022)
F-Statistic	21.65	21.72	21.69	21.71	21.86
Observations	158,933	158,747	158,614	158,526	158,435
Mean Outcome	0.880	0.846	0.832	0.822	0.814

Table D.19: Regression Result: The Effect of Successful Innovation on Employment by Demographics

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
		E: Age (31 to 45)			
Panel E1: OLS Results					
Patent Granted (0/1)	0.0062***	0.0092***	0.0094***	0.0108***	0.0137***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Panel E2: IV Results					
Patent Granted (0/1)	0.0267*	-0.0050	0.0212	0.0158	0.0313*
	(0.015)	(0.018)	(0.016)	(0.018)	(0.016)
F-Statistic	28.38	28.42	28.49	28.47	28.49
Observations	341,795	341,512	341,369	341,168	340,999
Mean Outcome	0.946	0.924	0.912	0.904	0.898
		F: Age (above 45)			
Panel F1: OLS Results					
Patent Granted (0/1)	0.0021	0.0097***	0.0115***	0.0125**	0.0201***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.007)
Panel F2: IV Results					
Patent Granted (0/1)	0.0265**	0.0393*	0.0409*	0.0464	0.0826**
	(0.014)	(0.021)	(0.024)	(0.031)	(0.035)
F-Statistic	29.76	29.77	29.77	29.80	29.77
Observations	297,605	297,429	297,183	296,926	296,707
Mean Outcome	0.928	0.876	0.830	0.782	0.734
		G: Foreigner			
Panel G1: OLS Results					
Patent Granted (0/1)	0.0094**	0.0110*	0.0078	0.0067	0.0183**
	(0.004)	(0.006)	(0.007)	(0.008)	(0.008)
Panel G2: IV Results					
Patent Granted (0/1)	0.0057	-0.0619	-0.0294	-0.0378	0.0069
	(0.039)	(0.052)	(0.052)	(0.064)	(0.059)
F-Statistic	14.86	14.93	14.98	14.93	14.98
Observations	65,183	65,122	65,090	65,044	65,007
Mean Outcome	0.896	0.842	0.806	0.772	0.748
		H: German			
Panel H1: OLS Results					
Patent Granted (0/1)	0.0059***	0.0102***	0.0112***	0.0120***	0.0159***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Panel H2: IV Results					
Patent Granted (0/1)	0.0307**	0.0198	0.0299*	0.0319*	0.0545***
	(0.014)	(0.015)	(0.015)	(0.018)	(0.018)
F-Statistic	30.03	30.05	30.07	30.09	30.14
Observations	733,150	732,566	732,076	731,576	731,134

Table D.19: Regression Result: The Effect of Successful Innovation on Employment by Demographics

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
Mean Outcome	0.930	0.896	0.870	0.848	0.828
Office × year FE	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of being employed on patent grant among incumbent workers initially employed in the firm and differentiated by occupational groups from one to five years. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles, and at the worker level, of initial log wages, and baseline demographics. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

Table D.20: Regression Result: The Effect of Successful Innovation on Employment by Occupations

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
	A: Managers				
Panel A1: OLS Results					
Patent Granted (0/1)	0.0048	0.0200***	0.0251***	0.0172**	0.0264***
	(0.004)	(0.005)	(0.006)	(0.007)	(0.008)
Panel A2: IV Results					
Patent Granted (0/1)	0.0243	0.0104	0.0067	-0.0175	0.0132
	(0.023)	(0.030)	(0.035)	(0.037)	(0.038)
F-Statistic	50.71	51.30	51.38	51.54	51.42
Observations	31,181	31,120	31,073	31,034	30,994
Mean Outcome	0.902	0.850	0.812	0.784	0.756
	B: Technicians and Engineers				
Panel B1: OLS Results					
Patent Granted (0/1)	0.0044	0.0141***	0.0142***	0.0147***	0.0200***
	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
Panel B2: IV Results					
Patent Granted (0/1)	0.0040	-0.0124	0.0323	0.0322	0.0601
	(0.021)	(0.037)	(0.038)	(0.046)	(0.046)
F-Statistic	11.50	11.49	11.54	11.58	11.62
Observations	125,331	125,185	125,050	124,922	124,768
Mean Outcome	0.942	0.908	0.880	0.856	0.832
	C: Administration				
Panel C1: OLS Results					
Patent Granted (0/1)	0.0010	0.0059**	0.0074**	0.0100***	0.0130***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)

Table D.20: Regression Result: The Effect of Successful Innovation on Employment by Occupations

	Years after Patent Application				
	t1	t2	t3	t4	t5
	(1)	(2)	(3)	(4)	(5)
Panel C2: IV Results					
Patent Granted (0/1)	0.0132	0.0160	0.0297**	0.0385***	0.0655***
	(0.010)	(0.012)	(0.013)	(0.014)	(0.016)
F-Statistic	56.20	56.22	56.21	56.16	56.18
Observations	176,269	176,120	176,018	175,928	175,808
Mean Outcome	0.932	0.896	0.872	0.848	0.826
	D: Skilled (Manual & Service)				
Panel D1: OLS Results					
Patent Granted (0/1)	0.0030	0.0056*	0.0115***	0.0095**	0.0093**
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Panel D2: IV Results					
Patent Granted (0/1)	0.0230	0.0214	0.0420*	0.0466**	0.0480**
	(0.016)	(0.021)	(0.024)	(0.024)	(0.024)
F-Statistic	30.12	30.16	30.14	30.14	30.20
Observations	148,249	148,197	148,124	148,053	147,999
Mean Outcome	0.944	0.916	0.896	0.876	0.858
	E: Unskilled (Manual & Service)				
Panel E1: OLS Results					
Patent Granted (0/1)	0.0066**	0.0112***	0.0098***	0.0146***	0.0223***
	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)
Panel E2: IV Results					
Patent Granted (0/1)	0.0521**	0.0312	0.0254	0.0414	0.0615**
	(0.024)	(0.029)	(0.027)	(0.035)	(0.030)
F-Statistic	17.86	17.87	17.87	17.86	17.85
Observations	233,878	233,799	233,725	233,594	233,562
Mean Outcome	0.932	0.896	0.872	0.846	0.824
Office × year FE	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓

Notes: The table shows OLS and IV regression results of being employed on patent grant among incumbent workers initially employed in the firm and differentiated by occupational groups from one to five years. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles, and at the worker level, of initial log wages, and baseline demographics. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.

Table D.21: IV Regression Result: The Effect of Successful Innovation on Employment by Firm Size & Legal Form

					Large firms	
	Small	Large	Partnership	Stock company	Partnership	Stock company
	(1)	(2)	(3)	(4)	(5)	(6)
			A: Manager			
Patent Granted (0/1)	-0.0521	0.0149	0.0054	0.0020	-0.0202	-0.0346
	(0.057)	(0.066)	(0.049)	(0.090)	(0.072)	(0.172)
Observations	9,224	21,767	27,086	3,904	18,936	2,831
Mean outcome	.782	.746	.748	.818	.734	.834
			B: Technicians and Engineers			
Patent Granted (0/1)	0.0033	0.0491	0.0327	0.0721	0.0497	-0.1231
	(0.027)	(0.048)	(0.032)	(0.067)	(0.045)	(0.156)
Observations	38,247	86,520	111,612	13,152	75,909	10,611
Mean outcome	.854	.824	.834	.826	.824	.822
			C: Administration			
Patent Granted (0/1)	0.0786***	0.0899***	0.0678***	0.1126***	0.0660**	0.1800***
	(0.026)	(0.026)	(0.021)	(0.042)	(0.030)	(0.043)
Observations	53,759	122,049	151,217	24,588	102,104	19,945
Mean outcome	0.828	0.826	0.824	0.840	0.822	0.846
			D: Skilled (Manual & Service)			
Patent Granted (0/1)	0.0414	0.0525*	0.0361	0.0676	0.0445	0.0172
	(0.031)	(0.032)	(0.025)	(0.075)	(0.033)	(0.097)
Observations	39,500	108,496	124,934	23,062	86,627	21,869
Mean outcome	.858	.856	.856	.866	.854	.866
			E: Unskilled (Manual & Service)			
Patent Granted (0/1)	0.0188	0.0681*	0.0364	0.1060	0.0539	0.1001
	(0.030)	(0.037)	(0.026)	(0.067)	(0.036)	(0.088)
Observations	59,862	173,699	209,274	24,284	151,272	22,427
Mean outcome	0.818	0.826	0.822	0.830	0.824	0.832
Office × year FE	✓	✓	✓	✓	✓	✓
Technology-expertise FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓

Notes: The table presents IV regression results of the impact of patent grants on the employment status of incumbent workers, initially employed by the firm, differentiated by occupational groups and firm size/legal form. Small and large firms are defined as those with fewer than or more than 150 employees, respectively. Each specification uses the predicted values from the overall first-stage regression using the full sample. All specifications control for fully interacted office and year fixed effects and are conditional on having at least five 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 technology class FE, sector FE, initial employment and revenue deciles, and at the worker level, of initial log wages, and baseline demographics. Robust standard errors two-way clustered at the examiner and firm level. *p<0.1, **p<0.05, ***p<0.01.