Inventor Returns and Mobility*

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Abstract

We show that firm and industry, rather than inventor and invention factors, explain *more than half* of the variation in inventor returns in administrative employer-inventor-patent linked data from Germany. Between-firm variation in inventive rents is strongly associated with inventor mobility. Inventors are more likely to make a move just before a patent is filed than shortly thereafter and benefit from their move through a mobility-related marginal inventor return. Employers that pay inventor returns in excess of the expected return gain a favorable position in the market for inventive labor with subsequent increases in patent quality and quantity. Consistent with theoretical arguments, these results are sensitive to employers' technological complementarity and degree of competition, and invention quality.

Keywords: Inventor returns, labor mobility, patents, inventive productivity

JEL Codes: O31, J24, J62

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1 Introduction

Most inventions are generated by employed inventors and are then filed by their employers. Some jurisdictions have laws that govern the compensation of employed inventors for the invention of new technology. Employed inventor compensation laws are incomplete, reflecting the inherent complexity and uncertainty of the inventive process itself. In Germany, for example, employed inventors are entitled to participate in the invention's value-add commensurate with their relative inventive contribution, which, in turn, depends on qualitative factors like the inventor's initiative and autonomy during the inventive process. In spite of such attempts to regulate employed inventors' compensation, the marginal patent income is largely discretionary, i.e., determined by employers' practices. We are interested in whether employer's discretion in determining employed inventor compensation leads to between-firm heterogeneity in inventor returns, and whether such heterogeneity explains mobility patterns in the market for inventive labor.

The improved availability of administrative data at the individual inventor level has revived studies of inventive rents. Closest to ours are the seminal works by Toivanen and Väänänen (2012) and Aghion et al. (2018), which estimate the marginal income per patent for employed inventors in Finland. Given that most patenting activity in Finland is concentrated in one firm (i.e., Nokia Corporation)[1], their focus is on *within*-firm determinants of inventor returns, such as patent citations and inventor human capital.[2] We add to this literature by exploring the *between*-firm variation in inventor returns and its labor market consequences in a novel context.

We use novel data that link European Patent Office records with employer and employees' social security information from Germany. To estimate the marginal income per patent (henceforth, MIP), we first match inventors with *temporarily non-patenting inventors*[3] by age, education, work experience, current job description, geography, and industry.

[1]Intellectual property statistical country profile for Finland in 2022, retrieved December 17, 2023.
[2]A recent study by Aghion et al. (2022) examines inventive rent spillovers to inventors' coworkers.
[3]We do so because, unlike Finnish inventor data, see Aghion et al. (2018) and Toivanen and Väänänen

We identify matching non-patenting inventors for 22,450 patenting inventors from 7,365 unique firms for the 1998-2003 filing vintages. We then estimate a conditional difference-in-differences regression of the log daily wages of patenting and matched non-patenting inventors over the [–5, +10] years event window around the patent filing year, similar to Aghion et al. (2018), covering a 1993-2012 sample period.

Our estimated baseline MIP is 5.4% per annum over the event window. That is, the average patent yields a cumulative MIP of €58.1 k (deflated to 2015 values) over the full time window, which is close to an average annual wage among inventors in Germany. The MIP depends on patent citations in Germany as it does in Finland (Toivanen and Väänänen, 2012). The MIP on zero-citation patents is zero, while a non-zero-citation patent yields on average 9.4% annual MIP.

Importantly, we find that firm-level factors explain 52% of the variation in the MIP and industry explains 26%. Therefore, we explore two candidate between-firm determinants of the MIP: firm-level technological complementarity between the focal patent and the firm's overall patent stock and industry-level markups.

We show that our estimated baseline MIP depends dramatically on those two factors. A patent that is neither highly complementary to the existing patent stock, but in a high-markup industry yields no MIP, even if it generates forward citations. In contrast, zero-citation patents generate a sizeable 6.5% MIP if they are filed in firms with highly complementary patent stock, and the MIP is more than doubled if it is a non-zero-citation patent with a highly complementary patent stock. Zero-citation patents earn no MIP in high-markup industries, while non-zero-citation patents earn a 9.8% MIP. Overall, the conditional MIP in the presence of high technological complementarity is 10.5% and that in high-markup industries is 5.1%.

(2012), restrictions at the *Institut für Arbeitsmarkt- und Berufsforschung* (*IAB*) data center do not allow us to match inventor with non-inventor data. Therefore, our control group is sourced from the subsample of inventors who have not yet and will not for the subsequent eight years file a patent with respect to the patent filing year of the matched treated observation. While our approach might arguably increase precision over those that compare inventors to non-inventors, it comes at the cost of reduced sample size.

Turning to inventor mobility, inventors are 2.3 times as likely to switch employers in the two years before a patent filing than in the two years thereafter (and they do file the patent with the *new* employer). Inventors whose subsequent patent generates forward citations in the top-decile of the distribution are more than three-times more likely to switch employers two years prior to the filing year than after the filing. Thus, the data suggests that soon-to-be-inventors might increase their labor market mobility in expectation of an impactful invention. This begs the question whether such a move also generates an above-average MIP.

We run triple difference regressions to estimate the additional MIP associated with moving (pre-invention and post-invention within the observed treatment period), relative to non-movers. Zero-citation patents do not yield additional MIP related to moving pre- or post-invention. However, inventors of patents with forward citations earn an additional MIP of 7.9% for a total inventor return of 13.8% if they move *before* filing the patent. Strikingly, if they move *after* filing the patent, they do not earn a move-related additional MIP.

For patents with forward citations, the relation between inventor returns and mobility is contingent on the patents' technological complementarity and the new employers' industry markups. Importantly, irrespective of the complementarity or markup structure, inventors that move directly *after* filing a patent do not earn a move-related additional MIP. For pre-invention movers, however, the additional move-related MIP depends dramatically on the receiving employer and its industry. Inventors of patents that are highly complementary to the employer's previous patent stock strikingly earn an average total MIP of 29.2%, whereas those who have contributed to a low-complementarity patent earn only a 3.6% MIP. The difference in the mobility-related MIP between total high and low markup industries is less dramatic (10.9 and 6.3%, respectively). Although our tests are not designed to formally tease apart the degrees of which inventors move because of the soon-to-be-filed invention or the invention is driven by the move, our findings suggest that inventors' critical know-how may be highly valuable from a bargaining perspective and that the MIP serves as an effective device for sorting in the market for inventive labor.

Finally, given that German employers can and do exert great discretion in the MIP they pay their employed inventors, we explore whether a firm's history of compensating inventors in excess of the expected MIP influences firm-level invention outcomes in the future. We find that firms with high technological complementarity and high markups that pay, on average, a positive excess MIP are more likely to attract more inventors, increase their number of patent filings, and improve the number of forward citations these patents will generate.

2 Data

We create an annual employer-employee panel linked to patent filings by inventors employed by firms in Germany by merging three data files from the German Federal Employment Agency. The *Establishment History Panel* contains all business establishments in Germany with at least one employee liable to social security. The *Inventor Labor Market Biographies* file covers complete career paths of 152,350 inventors. The establishment and inventor data are constructed on the basis of administrative registers. They contain information on business establishments and detailed information on individual inventors' employment histories, salaries, job descriptions, and education, among others, extracted from social security records. The *Patent Filings* data list filed and granted inventions and invention quality proxies like citations with at least one inventor employed by an establishment in Germany, obtained from the German Patent and Trade Mark Office and the European Patent Office.[4]

We employ a matching strategy to generate two comparable groups of patenting and temporarily non-patenting employed inventors to isolate the marginal effect of a patent on

[4]For more descriptive information on the three datasets and the matching of employers, employed inventors, and patents, see Dorner et al. (2018).

an inventor's wage progression. Taking temporarily non-patenting inventors as the control group is different from the Finnish approach that takes non-inventors (Aghion et al., 2018; Toivanen and Väänänen, 2012). While both approaches have their relative merits, a strength of ours it that both treated and control observations should arguably have similar latent traits with regard to their propensity to invent *at some time*. Our approach is necessitated by a strict data protection policy at the Germany Federal Employment Agency that prohibits the combination of inventor and non-inventor data. To ensure that the temporarily non-patenting inventors' priority filings do not interfere with our estimation period for inventor returns to matched inventors, we require that they do not file patents in the period of five years before and eight years after the matched inventors' priority filing, with the latter cutoff representing the point in time when most EPO patents elapse due to a lack of renewal fee payment. Data availability and these matching restrictions lead to an estimation sample period between 1993 and 2012. We match patenting inventors with temporarily non-patenting inventors in the same state and the main NACE industry, with the same level of education (with or without university degree), and with a comparable level of job requirements (ranked from not complex to highly complex by the German Federal Employment Agency). Conditional on these categorical variables, we match using Coarsened Exact Matching (CEM) on inventors' age and tenure. We repeat this procedure for each of the filing-year cohorts and remove control group inventors that are already matched in a previous cohort.

This procedure yields a matched sample of 22,450 employed inventors at 7,365 different firms at the time of the priority filings, corresponding to 148,505 inventor-year observations in the treated and 156,121 inventor-year observations in the control group. Summary statistics in Table IA.1 in the Internet Appendix show that inventors in the treatment group and the matched control group are very similar in the pre-treatment year. The mean squared error is 0.61%. The sample inventors are, on average, 38 years old, have 6.2 years of tenure, are predominantly male (94.8%) with university diplomas (66.6%), and work in former West Germany (92.7%) as engineers (65.2%). Their patents are fairly evenly distributed across technology classes, with some clustering in transportation and electronics, which are important industries in Germany. On average, patenting inventors earn a 2015-deflated annual wage of 69,440 € at the time of patent filing.[5] Thus, compared to the most recent Finnish inventor sample (Aghion et al., 2022), our sample is slightly younger, less educated, and earns somewhat higher salaries. Given that our methodological approach restricts our matched sample, it is worth noting that the invention quality of sampled inventors is statistically not different from the average granted patent in Germany at that time (Table IA.6 in the Internet Appendix).

We provide more details on the institutional setting in Internet Appendix B, but note here that inventors in Germany are entitled to receive a compensation if their employers claim and use the invention, pursuant to the Employed Inventors Act (*Gesetz über die Arbeitnehmererfindungen*). There are also binding guidelines concerning the determination of inventor compensation (*Richtlinien für die Vergütung von Arbeitnehmererfindungen im privaten Dienst*). According to the guidelines, inventor compensation is the product of invention value and inventors' relative contribution. Importantly, the invention value is determined *in expectation* and the inventors' relative contribution is determined by three *qualitative factors*, including the inventor's initiative and relative share concerning the recognition of the need to invent ("*Stellung der Aufgabe*"), the inventor's autonomy vis-à-vis the inventor's dependence on the employer during the invention process ("*Lösung der Aufgabe*"), and the inventor's relative position within the firm with regard to the invention (i.e., designated inventors earn less for the same hypothetical invention than non-designated inventors, i.e., employees whose job is not strictly related to making the invention) ("*Aufgaben und Stellung des Arbeitnehmers im Betrieb*"). The guidelines state that the inventors' relative contribution should be in the range of 2 to 100%. As a result

[5]There is right-censoring of the daily wage variable due to a legally mandated cutoff in social security contributions ("Beitragsbemessungsgrenze"), which we address by following the correction in Card et al. (2013) and Dustmann et al. (2009).

of the guidelines' reliance on expectations and qualitative factors, employers have considerable discretion in determining inventor returns. Thus, our interest is in the extent to which inventor returns vary across firms and whether and how inventors act on such heterogeneity by becoming active in the market for inventive labor.

3 Inventor returns

We follow the seminal work by Aghion et al. (2018) and estimate the marginal income per patent (MIP) with a conditional difference-in-differences design on top of a Mincer (1958) earnings regression framework that fits inventors' deflated log daily wages, as follows:

$$\begin{aligned} ln(\text{Wage}_{its}) = \quad & \underbrace{\sum_{t=-4}^{T=10} \delta_t \times Inventor_i \times Post_{it}}_{\text{Estimated MIP per annum w.r.t. priority filing year}} \quad + \\ & \alpha \times Inventor_i + \sum_{t=-4}^{T=10} \beta_t \times Post_{it} + M_{it} \times \gamma + \theta_s + \epsilon_{its} \end{aligned} \tag{1}$$

where subscript i denotes inventor; subscript t denotes treatment year ($t = -4, -3, ..., 10$); and subscript s denotes the stratum of matched inventor pairs. Our specification includes stratum and treatment year fixed effects denoted by θ_s and β_t, respectively. We cluster robust standard errors at the inventor level.

Our dependent variable, $ln(\text{Wage}_{its})$, is the natural logarithm of inventor i's daily wage in year t (deflated with 2015 as the base year). The diff-in-diff estimator δ_t represents the estimated MIP per annum over the [–4, +10] years of the treatment period with respect to the priority patent filing year $t = 0$, and with $t = -5$ as the base year. The variable $Inventor_i$ is an indicator variable equal to one if individual i is a patenting inventor and zero if i is a temporarily non-patenting inventor. The variable $Post_{it}$ is an indicator variable that equals one for each running year t over the [–4, +10] treatment period for inventor i's invention. Our baseline specification includes, M_{it}, a matrix of Mincerian variables (education, potential experience, and squared potential experience) to control for standard cross-sectional determinants of income (Card, 1999; Heckman et al., 2006).

The MIP estimator δ_t also measures pre-invention treatment effects for $t \in [-4, -3, -2, -1]$. As in Aghion et al. (2018, 2022), pre-invention treatment effects preclude us from testing the parallel (pre-)trend assumption of our difference-in-differences model. Generally, non-parallel pre-trends do not necessarily reflect endogeneity; rather, they may be informative and necessary to avoid an underestimation of the total treatment effect in certain settings (Malani and Reif, 2015). In our specific setting, these pre-invention treatment effects may reflect "anticipatory effects of forward-looking firms" (Aghion et al., 2022, p. 14). In fact, the evidence of the mobility-induced marginal MIP in Section 4 provides an explanation for anticipatory inventor returns. Moreover, we note that the MIP pattern rises from statistically zero after $t = -1$ and subsides to statistically zero after $t = 9$ in Figure 1, suggesting that there are parallel pre- and post-trends outside the (empirical) treatment period.

Panel A of Figure 1 plots the MIP-related regression coefficients from Equation 1 (as tabulated in Table IA.5 in Internet Appendix C) (dark-blue line). The illustration suggests that Equation 1 captures inventor rents in Germany well. The estimated annual MIP is statistically non-significant and close to zero in $t = -4, -3$ and $t = 10$, indicating that inventive rents to employed inventors largely accrue over the years [–2, +9] around the priority filing year. There is a statistically significant anticipatory effect of 5.0% of the average annual wage in the year before the priority filing, then the MIP peaks in the two years after the priority filing with a maximum of 11.4%, and then it subsides. The Mincerian coefficients are consistent with expectations (Card, 1999; Heckman et al., 2006), with a positive effect of education and a positive, but marginally decreasing effect of potential experience on log daily wages. Our model fit is good, with an adjusted R-squared of 37.6% being roughly ten percentage points higher than in the FLEED data (Aghion et al., 2022).

Panel B of Figure 1 plots the nominal MIP accumulation over the [–5, +10] period. The total MIP at the end of the accumulation period is EUR 58.1k; hence, the average patent earns the average inventor an extra annual income. Inventors receive a non-trivial share of roughly 20% of the MIP as anticipatory earnings before the patent is actually filed. Our estimates resonate with those in related literature (e.g., Aghion et al., 2018; Kline et al., 2019). Going beyond prior work and looking at the MIP conditioned on firm factors, we modify Equation 1 by including fixed effects for the industry and firm. We find that EUR 30.3k of the total nominal MIP can be attributed as pay at the employer's discretion, that is, firm factors explain about 52% of the variation in the MIP.

[Place Figure 1 about here.]

While the estimation of annual treatment effects is the more precise measure of the MIP, we adopt Aghion et al.'s (2018, 2022) convention and consider time-invariant MIP estimates for the benefit of focusing our paper on variation in the treatment effect along other dimensions than time with respect to the patent filing.[6] To this end, we estimate the time-invariant average MIP Equation 2, as follows:

$$ln(Wage_{is}) = \delta' Inventor_i \times Post_i + \alpha' Inventor_i + \beta' Post_i + M_i\gamma' + \theta'_s + \epsilon_{is} \tag{2}$$

where δ' measures the average time-invariant MIP over the [–4, 10] accumulation period in years with respect to the year of patent filing, and all other variables are analogous to those defined for Equation 1.

The results are in Table 1, with coefficients for our Equation 2 baseline specification in Column (1). The MIP estimate is 0.054 (SE = 0.007), statistically highly significant with a p-value <1%. It indicates that the average inventor in Germany earns an average MIP of 5.4% per annum over the accumulation period, accumulating to an 81% total MIP over the [–4, 10] years of the treatment period. The adjusted R^2 is 34.3%, hence, it is slightly lower than for the model with the time-variant treatment effects. The Mincerian controls

[6]Comparing the MIP estimates from the two regression models suggests that the accumulated MIP is very similar (77.9% in Equation 1 and 81.0% in Equation 2). Thus, in the following, we rely on the short-form regression in reporting our results for ease of interpretation.

are as expected, as before (Table IA.7). We also experiment with different fixed effect specifications in Table IA.8 in the Internet Appendix and find that the average annual time-invariant MIP ranges across specifications between 7.6% (without any fixed effects) and 2.2% (with priority filing year and firm fixed effects). Our highly controlled specification with priority filing year, state, industry, and stratum fixed effects yields a robust average MIP of 4.0% per annum. Panels B and C of Table IA.8 also show that the main results are robust to excluding observations with imputed wages (see Card et al., 2013; Dustmann et al., 2009).

In line with Aghion et al. (2018), Kline et al. (2019), and Toivanen and Väänänen (2012), Columns (2) and (3) of Table 1 show that the MIP hinges on the patent quality, as proxied by forward citations. Zero-citation patents yield a statistically non-significant MIP, while the average MIP for non-zero-citation patents is sizable and highly significant, with an average annual time-invariant MIP of 0.094 (SE = 0.010). Robustness tests in Table IA.9 (Internet Appendix C) confirm that the MIP for zero-citation and non-zero-citation patents are statistically significantly different. Panel A of Figure IA.2 (Internet Appendix C) graphically illustrates the differences in MIP depending on different citation cohorts. To earn a statistically significant MIP, patents need to generate at least two forward citations. Patents with more than 25 forward citations can expect a MIP of as high as 24%, for a total of almost three extra annual salaries over the MIP accumulation period.

Unlike existing studies on inventor returns, we show that differences in the MIP are strongly related to measures for asset complementarity, as proxied by an employer's existing knowledge (i.e., patent) stock (Panel B of Figure IA.2), and the degree of product-market competition, as proxied by an employer's average industry markup (Panel C of Figure IA.2). Patents in the bottom two quintiles of the asset complementarity distribution earn a MIP that is statistically not different from zero, while those in the top-quintile earn a MIP as high as 20%. Similarly, employers in relatively uncompetitive product markets pay a MIP that is statistically not different from zero, while employers in the top-tercile competitive industries pay am average MIP of up to 11%. To test whether these patterns hold conditionally, we modify Equation 2 by interacting the treatment effect estimator $Inventor_i \times Post_i$ with proxies for asset complementarity and the degree of product-market competition in Columns 4-6 of Table 1. We test the new specification in the full, zero-citation, and non-zero-citation samples in Columns 4, 5, and 6, respectively. Strikingly, the baseline MIP estimate is non-significant in these specifications, suggesting that these two mechanisms absorb key variation in the MIP distribution. If inventors patent in a firm with highly complementary assets, they can expect an additional average annual MIP between 6.5% if their patent yields zero citations and 13.8% for non-zero-citation patents. Inventors employed by firms in sectors with high product-market competition earn non-significant MIP for zero-citation patents and a significant average annual MIP of 9.8% for non-zero-citation patents.

[Place Table 1 about here.]

Our results demonstrate that most of the MIP is determined at the employer level, with asset complementarity and product-market competition offered as two potential economic channels. In Internet Appendix C, we also show that the MIP varies across employed inventor characteristics. Table IA.10 displays heterogeneity in the MIP according to inventors' task complexity, job positions, and educational backgrounds. The estimations show that inventors in more complex jobs (excess MIP = 8.3%), especially engineers (excess MIP = 6.5%) and managers (excess MIP = 3.7%), and university educated inventors (excess MIP = 7.3%) earn higher inventor returns than the average inventor.

4 Inventor mobility

Given that the MIP is largely determined at the employer's discretion, we can expect patterns of inventive labor mobility that reflect the role of soon-to-be-filed inventions as a bargaining device. Indeed, we find that inventors' mobility rates are disproportionately higher *right before* a patent filing, and the pattern is more salient for inventors of high-quality patents. While the unconditional inventor turnover rate is 12.1% in our sample, the inventor turnover rate conditional on a patent filing in the next year is significantly higher at 20.0% for inventions in the top-15% of the forward citation distribution and 15.2% for all other patents (Panel A of Figure 2). Strikingly, we observe that (i) the turnover rate steadily increases in the five years prior to the patent filing and (ii) then, with the patent filing, immediately drops to or even below the sample average turnover rate over the MIP accumulation period, (iii) with also the mobility delta between high-quality and all other patents vanishing. For the majority of mobile inventors, a move leads to an ex-MIP wage increase of at least 5% per annum; however, the ex-MIP wage increase does not appear to be a key driver of the mobility patterns, as the patterns are consistent across the cross-section of wage increases (Figure IA.3, Internet Appendix C).

The mobility patterns lead to substantial differences in the MIP (Panel B of Figure 2). MIP estimates indicate that the average patent earns employed inventors who move to a new employer just before the patent filing, pre-movers, EUR 79.7k, post-movers EUR 58.3k, and non-movers EUR 20.5k. Thus, the mobility-related added MIP for a pre-mover relative to a non-mover yields a MIP that is almost four times higher. The patterns are slightly more salient for top inventors of patents in the top-15% of the forward citation distribution.

[Place Figure 2 about here.]

Although mobility is associated with a higher average MIP, not every move needs to automatically generate a higher MIP. To test contingency effects, we modify Equation 2 by adding two triple interactions: (i) $Inventor \times post \times pre\text{-}mover$ estimates the pre-filing mobility-related MIP add-on and (ii) $Inventor \times post \times post\text{-}mover$ the post-filing mobility-related MIP add-on for those inventors that move only once during the MIP accumulation period — that is, either before or after the priority filing, or never. Inventors with multiple moves could confound the results, although we show that the inclusion of multiple movers yields qualitatively similar results (Columns (1) and (2) in Table IA.11, Internet Appendix C).

We identify three contingency factors that determine whether a move entails a significant MIP effect in Table 2. First, pre-filing mobility yields additional MIP only for patents that will generate non-zero forward citations; the mobility-related MIP for zero-citation patents is zero. The mobility-related MIP for non-zero-citation patents is 7.9%, amounting to a total MIP of 13.8% (base MIP of 5.9% plus mobility-realted MIP of 7.9%) per annum over the MIP accumulation period, or, in cumulative terms, to slightly more than two extra annual salaries. Second, and economically most significantly, a move to a new employer with high asset complementarity and a non-zero-citation invention in hand yields a mobility-related (total) MIP of 20.3% (29.2%) per annum. The corresponding cumulative MIP amounts to about 4.4 extra annual salaries, of which 3.1 are attributable to the pre-filing move. Inventors with soon-to-be-filed non-zero-citation patents moving to new employers with low asset complementarity still earn a base MIP of 3.6% per annum, but no mobility-related MIP. Third, the mobility-related (total) MIP for inventors with non-zero-citation patents is higher for moves to employers in relatively uncompetitive product markets, amounting to 10.9% (15.6%), relative to the 6.3% (12.8%) associated with moves to employers in relatively competitive product markets. Finally, note that none of these effects matter for inventors with zero-citation patents; zero-citation inventions do not yield a mobility-related MIP. Similarly, the timing of the move is crucial. Post-movers that move right after the priority filing never earn a mobility-related MIP. These results are qualitatively robust to different event windows in which inventor mobility is considered around the patent filing (Columns (3) to (10) in Table IA.11, Internet Appendix C).

[Place Table 2 about here.]

5 Firm-level implications

Do firm-specific MIP patterns impact firms' invention outcomes in the future? We consider whether a firm-specific history of paying excess MIP to employed inventors is related to the future rate of new inventor hiring (Panel A of Table 3), the number of future patents, and the number of forward citations on future patents (Panel B of Table 3). We define the firm-specific history of paying excess MIP as the average, time-invariant error term from the inventor-level MIP model in Equation 2 for each firm f, which we z-standardize for ease of interpretation and label *FS-MIP*.[7] Thus, an *FS-MIP* > 0 (< 0) indicates that employer f paid a MIP in excess of (lower than) the expected MIP to their employed inventors over the 1998-2003 estimation period. We use *FS-MIP* as an instrument to predict employer-level future invention outcomes.

Panel A of Table 3 shows results from a firm-year panel regression over the 2005-2014 period for the year-on-year relative change in the number of employed inventors per firm. The coefficient in Column (1) suggests that firms paying a MIP one standard deviation above the sample mean grow their R&D departments at a rate that is 55.0% higher than that for the sample mean. Columns (2) and (3) estimate the effects for samples split by the median of the asset complementarity proxy. High-complementarity employers' inventor growth rate is 126.6% if they pay a MIP that is one standard deviation higher than the sample mean, while that for low-complementarity employers is statistically not different from zero. Columns (4) and (5) estimate the effects for samples split by the median of the product-market competition proxy. Employers in highly competitive product markets hire inventors at a rate 69.4% higher than that of the sample mean. In contrast, employers in relatively uncompetitive product markets are not able to effectively use their MIP history as a hiring device. All documented patterns are robust to different model specifications and different fixed effects specifications, such as to the inclusion of firm, or state, industry, and year, or firm and industry-year fixed effects Table IA.12 (Internet Appendix C).

[7] Technically, *FS-MIP* $= \sum_{i \in f} \epsilon_{if}^{Equation\ 2} / i_f$ where i and f index inventors and employers, respectively.

Admittedly, these tests do not allow to make strict causal inferences; that is, they show that the historic excess *FS-MIP* is positively associated with firms' future inventor hiring rates, but they do not disentangle whether the positive association is driven by excess MIP attracting more inventors or firms with expansion plans offering more pay in general to effect firm growth. To address this point, Table IA.12 shows that *FS-MIP* is only informative for inventor hiring rates and not for non-inventor hiring rates, suggesting that it is unlikely that the identified association is driven by spurious correlation with a latent firm expansion policy.

Panel B of Table 3 presents results from a regression of the cumulative number of future patent filings (upper part of Panel B) and the cumulative number of forward citation-weighted future patent filings (lower part of Panel B) in the cross-section of firms, with both outcomes aggregated at the firm level over the 2008–2012 period. Controls include firm age, size, and firms' average initial patent stocks over the *FS-MIP* measurement period (i.e., 1998–2003). Column (1) in the upper part shows that the hypothetical increase in the firm-specific MIP by one standard deviation is associated with 7.6% (=exp(0.073)−1) more future patents filed in the decade after. Interestingly, this finding holds again only for high-complementarity firms and firms in highly competitive product markets. Note that the R^2 is almost thrice as large in those samples compared to the low-complementarity/low-competition counterparts. For example, the *FS-MIP* predicts future patent filings a decade later in firms in highly competitive product markets with an R^2 of 33.3%, while the same model yields an R^2 of only 11.8% in the sample of firms in less competitive product markets.

Similar patterns exist for the cumulative number of forward citation-weighted future patent filings (lower part of Panel B). The hypothetical increase in the firm-specific MIP by one standard deviation is associated with 6.8% (=exp(0.066)−1) more citation-weighted future patents in the decade after. Again, this result holds only in the high-complementarity/high-competition subsamples, and the R^2 in these subsamples is almost four to five times higher than in the low-complementarity/low-competition counterparts. Note that all results are robust to the choice of time windows (e.g., 2010–2014) or accounting for the zero-inflated patent outcome variable, using Poisson Pseudo Maximum Likelihood estimations (Table IA.13, Internet Appendix C).

Overall, the results in Section 3 show that the majority of the MIP is determined at the employer's discretion, and the results here show that firms can indeed pay excess MIP to employed inventors to positively impact future inventive productivity at the firm level.

[Place Table 3 about here.]

6 Conclusion

We explore novel data that link employer-employee data with patent records in Germany to shed new light on inventor returns and mobility. We find that most variation in inventor returns is *between*- rather than *within*-firm. Inventors exploit between-firm heterogeneity in expected inventor returns in the market for inventive labor. Bringing critical knowledge to new employers and contributing there to inventions that are complementary to the firm's prior patent stock and highly cited is associated with particularly high returns. Firms that offer above-expected inventor returns, in turn, are able to attract more inventors, leading to more and better inventions in the future. We show that these results hinge on patent quality, technological complementarity, and markups.

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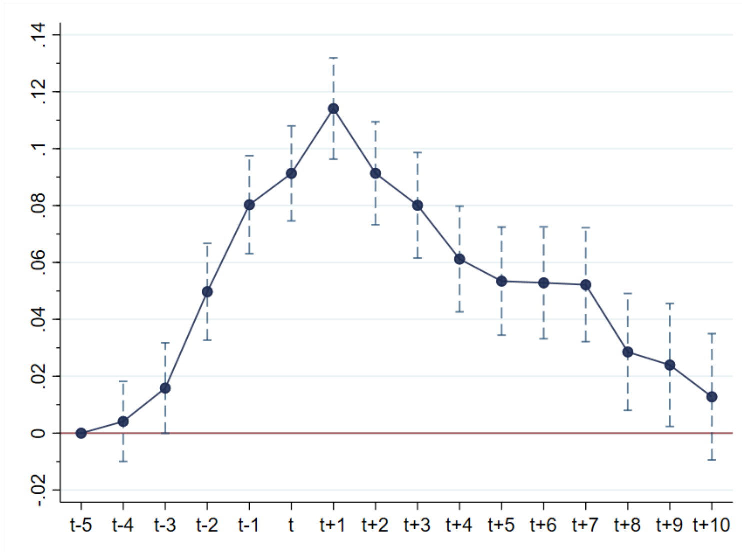
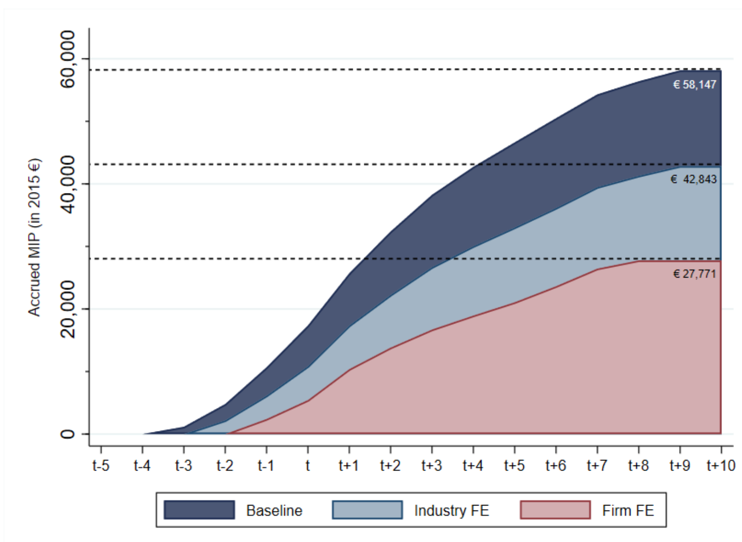
Exhibits of the main part

Figure 1: **Marginal Income per Patent (MIP) in Germany**

Panel A: Decomposition of MIP over time **Annual** MIP, in %



Panel B: Accumulated MIP over time (decomposed), in 2015 Euro values



Notes: The Figures display the differential wage progression of employee inventors in the main sample relative to the control group of temporarily non-patenting inventors. Panel A plots the estimated, annual marginal income per patent, i.e., δ_t in Equation 1. For details on the coefficients, we refer to Table IA.5 (Internet Appendix C). The whiskers span the 95 percent confidence intervals. Panel B plots the cumulative MIP, which is obtained using the δ_t coefficients from Panel A. We multiply respective coefficients, which indicate the percentage differential income of employee inventors relative to their matched control group inventors, with the average nominal daily income of all sample employees of 281,36 Euros (in 2015 Euro values), see Table IA.2 (**??**). The colored areas resemble the corresponding cumulative Euros, i.e., the aggregated MIP over time, decomposed into the three groups from Panel A. The dashed lines indicate the total accumulated MIP for each group at the end of the observation period.

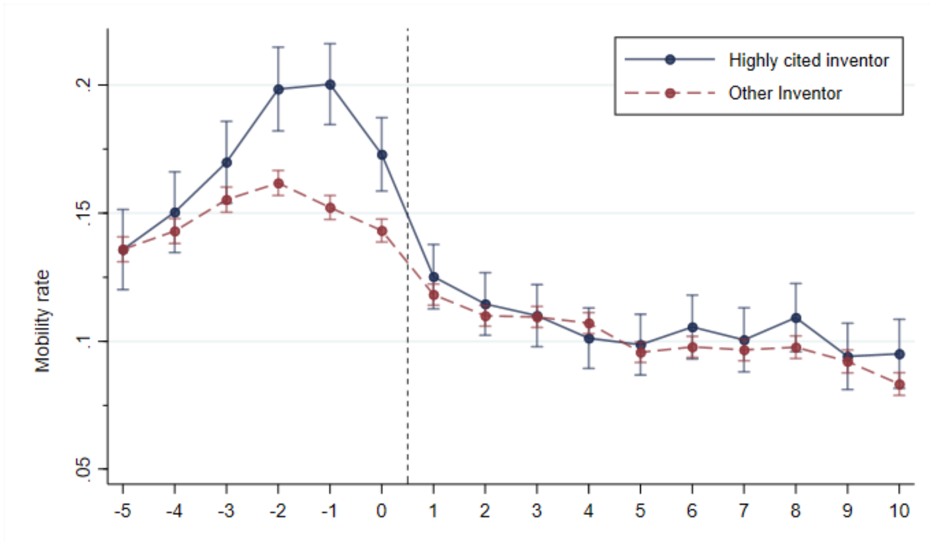
Table 1: Inventor returns, conditioning on technological complementarity and markups

Dependent variable:	*ln*(Wage)					
	Baseline estimation			Conditioning on technological complementarity and markups		
	All patents	*Zero-citation*	*Non-zero-citation*	*All patents*	*Zero-citation*	*Non-zero-citation*
Inventor × post	0.054***	0.002	0.094***	–0.004	–0.021	0.002
	(0.007)	(0.011)	(0.010)	(0.010)	(0.015)	(0.015)
Inventor × post × complementarity				0.105***	0.065**	0.138***
				(0.017)	(0.028)	(0.022)
Inventor × post × markups				0.051***	0.002	0.098***
				(0.016)	(0.023)	(0.022)
Mincer controls	✓	✓	✓	✓	✓	✓
Strata FE	✓	✓	✓	✓	✓	✓
Interaction components	✓	✓	✓	✓	✓	✓
Observations	304,626	143,458	161,161	304,626	143,458	161,161
Adjusted R^2	0.343	0.368	0.353	0.348	0.372	0.358

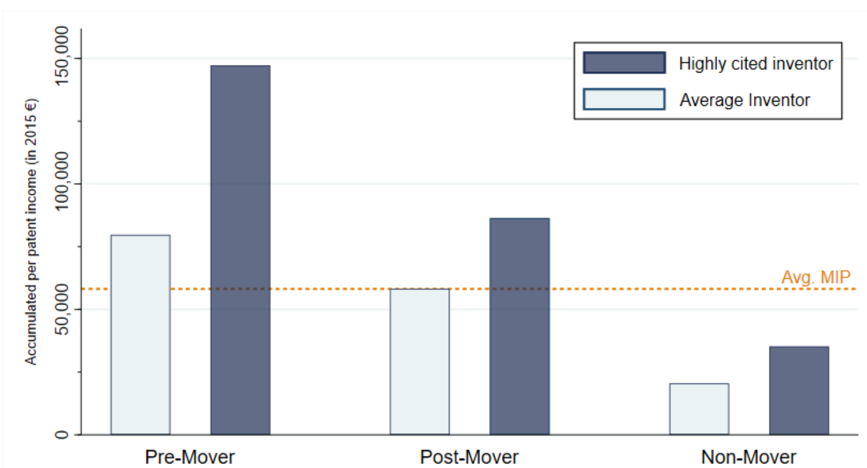
Notes: The table displays estimates of different variants of Equation 2. Column 1 is the baseline estimation. Columns 2 and 3 repeat this specification for subsamples of inventors without and with citations, respectively. All specifications include Mincer controls (i.e., tenure, tenure squared, and education), strata fixed effects, and the base components of the DD estimators. The use of these covariates is indicated in the bottom of the table but the output is suppressed. For details on respective coefficients, we refer to Table IA.7 (Internet Appendix C). Columns 4-6 repeat the first three columns but add triple interactions. Complementarity is equal to one for all inventors employed at a firm with high technological complementarity of their patent stock and zero otherwise. Markups is equal to one for all inventors employed in a sector in the top tercile of the firm-level mark-ups, i.e., highly competitive environments. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the inventor level. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Figure 2: **Mobility patterns**

Panel A: Annual share of inventors changing employer, by inventor type



Panel B: Total accrued MIP, by mover and inventor type



Notes: This figure displays mobility patterns of sample inventors and differences in individual inventors' returns in the context of mobility patterns. Panel A displays the share of inventors that change their inventor, measured for each year relative to the patent filing year. The solid blue line resembles all inventors with a patent in the top 15% of the overall citation distribution, i.e., highly cited inventors. The dashed red line resembles all remaining inventors. We refer to Figure IA.3 for robustness tests on the mover and comparison group definitions. Whiskers span the 95 percent confidence intervals. Panel B displays the average accrued earnings accumulated from individual MIPs, distinguishing three types of inventors: those that switch employers before (1) or after (2) the patent filing and those that never change their employer (3). The light blue bars resemble the average accumulated MIP in 2015 Euros for the average inventor within these subgroups. The dark blue bars refer only to inventors with highly cited patents, as defined in Panel A. As a reference, the dashed line references the accumulated MIP of an average inventor.

Table 2: **MIP and Mobility**

Dependent variable:	*ln*(Wage)									
			Complementarity		Markups		Complementarity		Markups	
			Hi	Lo	Hi	Lo	Hi	Lo	Hi	Lo
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Inventor × post × pre-mover	0.079***	0.008	0.203***	0.034	0.109***	0.063***	-0.071	0.034	-0.034	0.050
	(0.025)	(0.026)	(0.047)	(0.029)	(0.042)	(0.031)	(0.059)	(0.028)	(0.040)	(0.034)
Inventor × post × post-mover	-0.038	0.041	0.040	-0.063	0.029	-0.064	0.011	0.060	0.038	0.052
	(0.033)	(0.037)	(0.054)	(0.041)	(0.058)	(0.039)	(0.081)	(0.042)	(0.062)	(0.046)
Inventor × post	0.059***	-0.006	0.089***	0.036**	0.047*	0.065***	0.051*	-0.037**	0.002	-0.019
	(0.014)	(0.014)	(0.023)	(0.017)	(0.025)	(0.017)	(0.030)	(0.016)	(0.024)	(0.018)
Citation cohorts:	Non-zero-cit.	Zero-cit.	Non-zero-citations				Zero-citations			
Prob. > Chi^2:	0.0587		0.0115		0.5177		0.0848		0.2157	
Strata FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mincer controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	139,273	124,144	43,433	94,073	52,808	84,698	30,135	92,421	48,291	74,265
R^2	0.370	0.385	0.363	0.378	0.389	0.380	0.373	0.382	0.411	0.396

Notes: This table presents estimates on the additional effect of inventor mobility on their marginal income per patent. The estimation specification follows the time-invariant MIP Equation 2, only here the MIP is separately estimated for inventors that changed their employer before or after the initial patent filing using triple interactions in which $Inventor \times Post$ is multiplied with either one of the indicators $pre - mover$ or $post - mover$. Pre-movers are all inventors that change their employer at any year before the patent filing (i.e., between t-5 and t-1). Post-movers are all inventors that change their employer in any later year. The sample excludes inventors that change employers before and after the filing. For a robustness test on this simplification, see Table IA.11. The specification is separately estimated for split samples, delineating inventors with at least one citation (Columns 1 and 3-6) and inventors without any citations (Columns 2 and 7-10). Columns 3-4 and 7-8 further distinguish inventors that file patents at firms with high or low technological complementarity. Columns 5-6 and 9-10 distinguish inventors that file patents at firms in high or low competitive industries. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the inventor level. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 3: **Discretionary ex-ante excess MIP attracts more inventors**

	Complementarity		Competition	
	Hi	Lo	Hi	Lo
Panel A: Firms' renumeration patterns and future inventor growth				
Dependent variable:		Δ inventors		
	(1)	(2)	(3)	(4)	(5)
FS-MIP, z.	0.550***	1.266***	0.208	0.694***	0.305
	(0.122)	(0.268)	(0.140)	(0.162)	(0.184)
Firm-level controls	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
# Firm-year obs.	14,630	6,397	8,170	10,618	3,947
R^2	0.046	0.077	0.020	0.058	0.010
Panel B: Firms' renumeration patterns and future inventive output					
Dependent variable:		# future patent filings (in logs)			
	(1)	(2)	(3)	(4)	(5)
FS-MIP, z.	0.073***	0.119***	0.029	0.091***	0.037
	(0.018)	(0.033)	(0.018)	(0.024)	(0.029)
# Firm obs.	2,825	1,106	1,697	1,922	874
R^2	0.277	0.360	0.146	0.333	0.118
Dependent variable:		# citations on future patent filings (in logs)			
	(1)	(2)	(3)	(4)	(5)
FS-MIP, z.	0.066***	0.139***	0.015	0.075**	0.038
	(0.021)	(0.044)	(0.010)	(0.029)	(0.033)
# Firm obs.	2,825	1,106	1,697	1,922	874
R^2	0.202	0.248	0.066	0.245	0.053
Controls in both sets of estimations:					
Firm-level controls	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓

Notes: The table presents estimates on the relationship between firms ex-ante compensation patterns and their propensity to hire inventors (Panel A) as well as their future inventive output (Panel B). The firm-level samples cover all firms for which we obtain at least one MIP estimate from out baseline estimation displayed in Table 1. Panel A uses a firm-year sample comprising the years 2005-2014. The dependent variable, $\Delta inventors$, is the year-over-year growth rate in firms' employee inventors. The main regressor, FS-MIP, is the z-standardized excess MIP that a firm pays between 1998 and 2002. Firm-level control variables are firm age, firm age squared, and firm size (the log. of the total number of employees). Further, the regressions control for state, industry, and calendar year fixed effects. Panel B is a firm-level cross sectional data set. The dependent variable is firms' cumulative patent filings between 2008 and 2012 (and the number of citations in the second row). Again, the main regressor is firms' z-standardized excess MIP estimated between 1998 and 2002. The control variables are time-invariant mean values of firm age, firm age squared, and firm size for the years 2008 until 2012. Regressions also control for firms' initial patent stock, measured as the total number of patent filings between 1998 and 2002, and state and industry fixed effects. We use robust standard errors (in parentheses below coefficients). *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

INTERNET APPENDICES

D. Harhoff, D. Heller and P. Momtaz

Inventor Returns and Mobility

Internet Appendix A: Institutional Context

The law for inventions of employed inventors (*Gesetz über die Arbeitnehmererfindungen*, abbreviated *ArbnErfG*) regulates rights and obligations, especially the monetary rewards to employed inventors for each invention, in Germany. The law is in effect since October 1, 1957, and has experienced only minor revisions since then. The law is applicable to all non-managerial inventors with social security obligations in Germany (§1).[8] The *ArbnErfG* reconciles two colliding statutory principles in the German legal system. It reconciles the principle in German employment law that all tangible or intangible products that result from work for an employer are the property of the employer and not of the employee if the employee was assigned to this task and received a salary with the principle in German invention law that the inventor owns all rights pertaining to the invention. The *ArbnErfG* rules that employed inventors' inventions ("*Diensterfindungen*") routinely become property of the employer, while the employed inventor is entitle to a monetary compensation.

The *ArbnErfG* entitles employed inventors to a monetary compensation if their employer uses the invention (§9) and refers to guidelines to set the right amount for the compensation (§11). The guidelines ("*Richtlinien für die Vergütung von Arbeitnehmererfindungen im privaten Dienst*, abbreviated *RiLis*") were published on July 20, 1959, and amended on September 1, 1983. The *RiLis* are not regulatorily binding ("*Kann-Bestimmung*"), however, they are relevant because, in case of a dispute about the compensation, the patent chambers at the local District Courts will only make a final judgement if the conflicting parties have first consulted the board of arbitration at the German Patent and Trademark Office (DPMA), which, in turn, relies in its recommendations on the *RiLis*.

The *RiLis* propose the following formula to determine the compensation to employed inventors per invention (Point 39):

$$\underbrace{V}_{\text{Compensation ("\textit{Vergütung}")}} = \underbrace{E}_{\text{Invention's value ("\textit{Erfindungswert}")}} \times \underbrace{A}_{\text{Inventor's relative contribution ("\textit{Anteilsfaktor}")}} \tag{3}$$

where E can be approximated by expected licensing fees (Points 6-11), the expected accounting difference between profits and losses attributable to the invention (Point 12), or simply by estimating the price the employer would have to pay if it had to source the invention from a third-party (Point 13). A, in turn, depends on three separate factors. The first factor is the inventor's initiative and relative share concerning the recognition of the need to invent ("*Stellung der Aufgabe*") (Point 31), the second is inventor's autonomy

[8] For inventors in managerial positions, the law does not apply automatically, however, it is often the case that employer and managerial employee agree on a voluntary, contractual basis to abide by the law.

vis-'a-vis the inventor's dependence on the employer during the invention process ("*Lösung der Aufgabe*") (Point 32), and the third is the inventor's relative position within the firm with regard to the invention (i.e., designated inventors earn less for the same hypothetical invention than non-designated inventors, i.e., employees whose job is not strictly related to making the invention) ("*Aufgaben und Stellung des Arbeitnehmers im Betrieb*") (Points 33-36). A can range from 2% to 100%. If the relative contribution among multiple inventors cannot be separated, A is equally divided by the number of inventors per patent.

Inventors are entitled to receive a compensation for the time the patent protection is valid, which is often less than the patent's maximum lifetime. For example, the *RiLis* also discuss the case of a lump-sum compensation payment at the patent filing date. In this case, the *RiLis* assume that the *expected* patent protection is six years (Point 41), hence significantly below the maximum lifetime.

Internet Appendix B : Data, matching, descriptives

Original data sources: Data on companies, inventors, and patents comes from three novel administrative datasets made available through the Research Data Center (FDZ) of the German Federal Employment Agency (BA) at the Institute of Employment Research (IAB). The first dataset is Establishment History Panel (the administrative reference is "BHP"). It contains all establishments in Germany with at least one employee liable to social security on the reference date, i.e., June 30^{th} of every year (Ganzer et al., 2020). The data is available as of 1992 and 1975 for East and West Germany, respectively. It reports establishments' information, including their industry, location, wage statistics for full-time employees, and employee counts both in total and broken down by gender, age, occupational status, qualification, and nationality.

The second dataset is labor market biographies of inventors ("INV-SIAB"). It records complete biographies of 152,350 inventors over the 1980–2014 period listed on patent filings at the European Patent Office (EPO) or the German Patent and Trademark Office (DPMA) between 1999 and 2011. It comprises information extracted from social security filings, such as an inventor's employer, wage, and job title as well as many other detailed biographic information, such as age, tenure, education, gender, nationality, or marital status. This information is essential as it allows us to analyze the marginal income per patent using a matching strategy based on individual inventors' characteristics.

The third dataset is the inventor patent file ("INV-PAT"). It covers all patents filed by inventors between 1980 and 2014 once the inventor is included in the INV-SIAB data. Inventor refers to all individuals that are listed on the patent application as "inventor". Given the link to the INV-SIAB data, all these individuals are inventors who are employed at a company at one point in time. The patent data comprises the most important bibliographic information, such as the application and grant dates or the patent family, and information on the technological quality of the patent, including different levels of citation data. For data protection reasons, the time-relevant information in the patent data is compressed to quarter-year observations. In total, this dataset covers 235,933 patents and 148,743 unique inventors. In our analysis, we only consider granted patents.

Matching approach: We merge the three data sources described above, following a standardized procedure. It adjusts overlapping and redundant employment spells, links employee inventors' bibliographic data to respective employers, and aggregates the data to an inventor-year panel. This preliminary data contains all potential focal inventors and the control group candidates, spanning the years 1980 to 2014, and constitutes the basis for creating the matched sample of patent-filing employee inventors and the non-filing comparison group. Hence, unlike data samples in related studies, it only contains information about inventors and does not use non-inventors for comparisons (e.g., Aghion et al., 2018; Akcigit et al., 2017; Toivanen and Väänänen, 2012). For consistency, we consider only individuals at least 18 or, at maximum, 64 years of age who are full-time employed and that can be linked to a firm with no missing location data.

We construct a unique treatment-control matching that satisfies several important restrictions. First, we focus on inventor-year observations without patent applications five years before and eight years after the respective filing. Following this, all treated candidates are investors with priority filings in the year cohorts: 1998, 1999, 2000, 2001, or 2002. The threshold of five years before the application is given by construction since the BHP data only covers employees from East and West Germany as of 1992. We experimented with the other threshold for the subsequent years after filing. Our main results are robust to applying any threshold between six and ten years. As the preferred specification, we chose the threshold of eight years as it resembles the average lifespan of a patent in Europe (Gill and Heller, 2024). Relevant control candidates are any inventors without patent filings in the respective timeframe.

As a final step, we isolate relevant inventor pairs that share similar characteristics using Coarsened Exact Matching (CEM): Treated and control group candidates have to work in the same state and industry, have the same level of education (university or not), and have a comparable job. Jobs are classified using the four-tier categorization of IAB that distinguishes different levels of work requirement. Conditional on sharing these characteristics, we match patenting and non-patenting inventors based on their age and tenure. We repeat this procedure for each of the filing year cohorts and exclude control group inventors that are already matched in a previous cohort. This procedure results in a matched sample of individual employees listed as inventors in at least one patent filed either at the German or European Patent Office in the years 1998-2002 as well as their matched non-patenting inventor counterpart, covering 304,626 inventor-year observations on 22,302 individual employee inventors working at 17,621 individual German firms in the private sector during the years 1993 and 2012.

Main dependent variable and summary statistics: Our main dependent variable is the the natural logarithm of daily wages for each inventor per year. The information on daily wages are directly obtained from the INV-SIAB data. However, to ensure consistency of the data, several adjustments are needed. First, we adjust the original wage information by deflating the nominal wages to 2015 values. Second, we exclude part-time jobs which: The wage data allows us to identify marginal part-time income as the corresponding thresholds are known. Third, we need to adjust for the right-censoring of the wage data. In Germany, the contribution assessment ceiling ("Beitragsbemessungsgrenze") constitutes a legal cap on the mandatory wage reportings in Germany. We follow well-established approaches in the literature to impute these wages (e.g., Card et al., 2013; Dustmann et al., 2009). Importantly, the empirical analyses will show that the main results are robust to omitting this step and to excluding inventor pairs with earnings close to the reporting thresholds. Hence, the main dependent variable, $ln(Wage)$, is the imputed and deflated wages (in logs) of full-time employee inventors in Germany. Tables IA.1 – IA.4 display summary statistics for the main sample.

Table IA.1: **Summary statistics, inventors and matched non-inventing inventors (in the final year before the priority patent filing)**

	Mean values		
	Inventor sample	Matched sample	Δ Mean
Age	38.459	38.317	0.142
Experience, years	10.125	10.928	-0.803
Experience, years in current job	6.192	6.918	-0.727
Job - highly complex (1/0)	0.622	0.561	0.061
Job - complex (1/0)	0.231	0.243	-0.012
Job - manager (1/0)	0.194	0.181	0.013
Job - engineer (1/0)	0.658	0.639	0.019
University (1/0)	0.686	0.620	0.066
East German (1/0)	0.083	0.070	0.013
Any pre-move (1/0)	0.460	0.430	0.030
Any post-move (1/0)	0.244	0.256	-0.012
Daily wage (in Euros)	267.08	261.49	5.584
ln(Wage)	5.405	5.334	0.071
Firm-specific variables:			
Firm age	17.689	18.136	-0.447
Number employees	4,208	3,631	577
Industry: manufacturing (1/0)	0.243	0.254	-0.011
Industry: capital goods (1/0)	0.511	0.504	0.007
Industry: IT/finance (1/0)	0.131	0.119	0.012
High complementarity (1/0)	0.308	0.244	0.064
High competition (1/0)	0.401	0.398	0.003

Table IA.2: **Summary statistics, final sample (matched and pooled)**

	Obs.	Mean	Std. dev.	q25	q50	q75	Min.	Max.
Inventor-specific variables:								
Age	304,626	41.466	8.912	35	41	47	18	64
Experience, years	304,626	13.804	7.351	8.033	13.507	19.216	0.003	32.521
Experience, years in current job	304,626	8.095	7.006	2.496	6.003	12.258	0.003	32.521
Job - highly complex (1/0)	304,626	0.589	0.492	0	1	1	0	1
Job - complex (1/0)	304,626	0.233	0.423	0	0	0	0	1
Job - unskilled (1/0)	304,626	0.166	0.372	0	0	0	0	1
Job - manager (1/0)	304,626	0.187	0.390	0	0	1	0	1
Job - engineer (1/0)	304,626	0.652	0.476	0	1	1	0	1
Job - technical job (1/0)	304,626	0.889	0.476	1	1	1	0	1
East German (1/0)	304,626	0.077	0.267	0	0	0	0	1
Any move (1/0)	304,595	0.634	0.482	0	1	1	0	1
Any pre-move (1/0)	304,595	0.430	0.495	0	0	0	0	1
Any post-move (1/0)	304,595	0.256	0.436	0	0	0	0	1
Daily wage (in Euros)	304,626	281.360	181.810	156.763	224.825	355.907	37.747	933.335
ln(Wage)	304,626	5.458	0.637	5.061	5.420	5.877	3.502	6.892
University (1/0)	304,626	0.666	0.472	0	1	1	0	1
Female (1/0)	304,626	0.052	0.222	0	0	0	0	1
Firm-specific variables:								
Firm age	304,626	19.780	10.436	10	22	28	0	37
Number employees	304,626	3,804.3	8,436.9	202	736	2,590	1	55,220
Employment growth	300,457	0.018	0.213	-0.055	0.002	0.065	-0.790	5.319
Inventor growth	300,457	0.023	0.116	-0.030	0.012	0.062	-0.500	1.500
Patents filed p.a.	300,576	19.890	61.018	0	0	6	0	517
Patent stock p.a.	300,576	140.054	475.091	0	3	34	0	3,913
Industry: manufacturing (1/0)	304,626	0.245	0.430	0	0	0	0	1
Industry: capital goods (1/0)	304,626	0.515	0.500	0	1	1	0	1
Industry: IT/finance (1/0)	304,626	0.128	0.334	0	0	0	0	1
High complementarity (1/0)	300,773	0.275	0.446	0	0	1	0	1
High competition (1/0)	300,773	0.398	0.489	0	0	1	0	1

Table IA.3: **Firm-level descriptive statistics, full sample: locations and industries**

Panel A: Locations

NUTS-1 region	Corresponding state	Observations (share in %)	Population share (2022, in %)	East = 1
DE1	Baden-Württemberg	23.1	13.3	0
DE2	Bavaria	21.6	15.9	0
DE3	Berlin	2.5	4.5	1
DE4	Brandenburg	0.8	3.1	1
DE5	Bremen	0.5	0.8	0
DE6	Hamburg	2.2	2.2	0
DE7	Hesse	9.6	7.6	0
DE8	Mecklenburg-Vorpommern	0.3	1.9	1
DE9	Lower Saxony	6.5	9.7	0
DEA	North Rhine-Westphalia	21.8	21.5	0
DEB	Rhineland-Palatinate	4.6	4.9	0
DEC	Saarland	0.6	1.2	0
DED	Saxony	2.3	4.8	1
DEE	Saxony-Anhalt	0.6	2.6	1
DEF	Schleswig-Holstein	1.7	3.5	0
DEG	Thuringia	1.3	2.5	1

Panel B: Main industry classes

	IAB establishment main category	Share (in %)
1	Agriculture, electricity, gas/water	0.42
2	Manufacture of food consumer products	0.09
3	Manufacture of non-food consumer products	0.51
4	Manufacture of industrial goods	24.69
5	Manufacture of capital and consumer goods	51.02
6	Construction	0.65
7	Hotel/restaurants, trade/maintenance	4.20
8	Transport/storage, IT, finance, real estate	13.20
9	Education, health, social work, public sector	5.21

Table IA.4: **Patent-level descriptive statistics, full sample: technology classes**

	Tech-class	Obs.	Share	Cumul.
1	Electrics/energy	735	6.84	6.84
2	Audiovisual	188	1.75	8.59
3	Telecommunication	425	3.96	12.55
4	Digital communication	221	2.06	14.61
5	Basic communication process	81	0.75	15.36
6	Computer techniques	351	3.27	18.63
7	IT methods	25	0.23	18.86
8	Semiconductors	153	1.42	20.29
9	Optics	191	1.78	22.06
10	Measurement	631	5.87	27.94
11	Analysis of bio-materials	90	0.84	28.78
12	Control	236	2.20	30.97
13	Medical techniques	332	3.09	34.07
14	Organic chemistry	360	3.35	37.42
15	Biotechnology	284	2.64	40.06
16	Pharmaceuticals	208	1.94	42.00
17	Polymers	287	2.67	44.67
18	Food & chemistry	59	0.55	45.22
19	Materials & chemistry	264	2.46	47.68
20	Materials & metallurgy	286	2.66	50.34
21	Surface techniques	230	2.14	52.48
22	Chemical engineering	364	3.39	55.87
23	Environmental techniques	155	1.44	57.31
24	Handling	435	4.05	61.36
25	Machine tools	496	4.62	65.98
26	Engines/pumps/turbines	496	4.62	70.60
27	Textiles/paper-machines	283	2.63	73.23
28	Other machines	410	3.82	77.05
29	Therm processes	194	1.81	78.86
30	Mechanical elements	647	6.02	84.88
31	Transport	1,053	9.80	94.68
32	Furniture/games	84	0.78	95.47
33	Other consumer goods	142	1.32	96.79
34	Civil engineering	345	3.21	100.00

Internet Appendix C

Additional Analyses and Robustness Tests

Below, we display several additional analyses and robustness tests that are references in the main text. More specifically, Table IA.5 reports the full set of coefficients obtained from estimating Equation 1. Table IA.6 shows that the quality of sample patents is similar to all other patents filed in the same time frame in Germany. Tables IA.7 – IA.9 report robustness tests on the main MIP estimations, including a detailed display on the effects of patent quality differences as well as tests on alternative combinations of fixed effects (see also Figure IA.1), wage imputations, or other variants in the model specifications.

Table IA.10 and Figure IA.2 show how variation in the MIP related to observable inventor characteristics. Table IA.11 and Figure IA.3 illustrate that the observed mobility patterns are consistent when investigating different types of inventors. Finally, Tables IA.12 and IA.13 display robustness tests on the implications of differences in firms' remuneration patterns (i.e., how much MIP they offer) on the long-run firm-level employee growth and patenting activity.

Table IA.5: **Marginal inventor returns over a patent's lifecycle**

Dependent variable: ln (wage)			
Difference-in-differences estimators:		***Years w.r.t. patent filing:***	
Inventor × $\mathbb{1}_{t=-5}$	.	$\mathbb{1}_{t=-5}$	.
Inventor × $\mathbb{1}_{t=-4}$	0.0041 (s.e.=0.0106)	$\mathbb{1}_{t=-4}$	0.0185** (0.0074)
Inventor × $\mathbb{1}_{t=-3}$	0.0158 (0.0107)	$\mathbb{1}_{t=-3}$	0.0720*** (0.0075)
Inventor × $\mathbb{1}_{t=-2}$	0.0497*** (0.0106)	$\mathbb{1}_{t=-2}$	0.1089*** (0.0075)
Inventor × $\mathbb{1}_{t=-1}$	0.0803*** (0.0103)	$\mathbb{1}_{t=-1}$	0.1798*** (0.0073)
Inventor × $\mathbb{1}_{t=0}$	0.0913*** (0.0098)	$\mathbb{1}_{t=0}$	0.2525*** (0.0069)
Inventor × $\mathbb{1}_{t=1}$	0.1141*** (0.0101)	$\mathbb{1}_{t=1}$	0.2565*** (0.0072)
Inventor × $\mathbb{1}_{t=2}$	0.0913*** (0.0101)	$\mathbb{1}_{t=2}$	0.2936*** (0.0072)
Inventor × $\mathbb{1}_{t=3}$	0.0801*** (0.0103)	$\mathbb{1}_{t=3}$	0.3175*** (0.0073)
Inventor × $\mathbb{1}_{t=4}$	0.0612*** (0.0102)	$\mathbb{1}_{t=4}$	0.3226*** (0.0072)
Inventor × $\mathbb{1}_{t=5}$	0.0534*** (0.0103)	$\mathbb{1}_{t=5}$	0.3292*** (0.0073)
Inventor × $\mathbb{1}_{t=6}$	0.0528*** (0.0106)	$\mathbb{1}_{t=6}$	0.3610*** (0.0074)
Inventor × $\mathbb{1}_{t=7}$	0.0522*** (0.0107)	$\mathbb{1}_{t=7}$	0.3810*** (0.0074)
Inventor × $\mathbb{1}_{t=8}$	0.0286*** (0.0109)	$\mathbb{1}_{t=8}$	0.4133*** (0.0075)
Inventor × $\mathbb{1}_{t=9}$	0.0240** (0.0113)	$\mathbb{1}_{t=9}$	0.4413*** (0.0079)
Inventor × $\mathbb{1}_{t=10}$	0.0128 (0.0116)	$\mathbb{1}_{t=10}$	0.4624*** (0.0082)
Mincer controls:		***Base variables:***	
Education	0.0363*** (0.0006)	Inventor	−0.0353*** (0.0076)
Experience	0.0446*** (0.0005)	Constant	4.7022*** (0.0075)
Experience^2	−0.0016*** (0.00002)		
# obs. = 304,626		Adjusted R^2 = 0.3756	

Notes: The table reports the full set of regression coefficients obtained from estimating Equation 1. This comprises all MIP components, including the lower term components of the interaction terms, and all control variables. The regressions further include strata fixed effects. We deploy robust standard errors (in parentheses below coefficients). *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table IA.6: **Comparing patent quality: sample vs. out-of-sample patents**

Dependent variables:	*ln*(Citations)					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample patent (=1)	0.153***	0.000	-0.020	0.120***	-0.006	-0.012
	(0.012)	(0.015)	(0.013)	(0.009)	(0.009)	(0.009)
Granted		0.257***			0.220***	
		(0.021)			(0.005)	
Estimation method:	*OLS*			*PPQML*		
Granted only:			✓			✓
Additional controls:						
Filing year FE	✓	✓	✓	✓	✓	✓
Tech. class FE	✓	✓	✓	✓	✓	✓
# inventors	✓	✓	✓	✓	✓	✓
Observations	157,581	157,581	70,845	157,581	157,581	70,845
Adjusted R^2	0.061	0.071	0.075			
Wald Chi^2				3,010	4,704	1,523

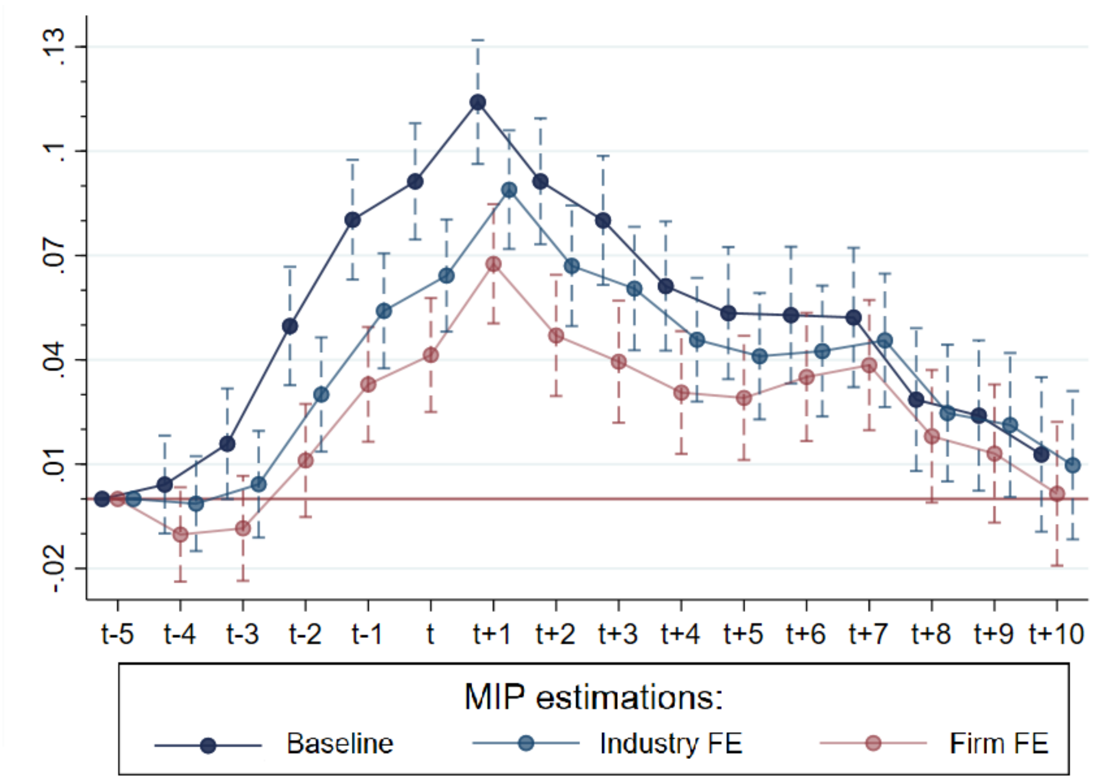
Notes: The table displays estimates on differences in patent quality of sample patents filed by employee inventors in the treatment group and all other patents filed in the same year cohorts, i.e., between 1998 and 2003, by any out-of-sample inventor in Germany. The dependent variable is the logarithm of citations received by each patent within the first ten years after filing. The indicator of interest is $Samplepatent$, equals one for all patents filed by sample inventors and zero otherwise. Note, these patents are eventually granted by definition. Columns 2 and 3 thus account for patent grants in the out-of-sample patents. Columns 4-6 repeat the first three specifications using Poisson Pseudo Maximum Likelihood estimations to account for potential zero-inflation in the outcome variable. All regressions control for filing year and technology class fixed effects as well as the number of co-inventors. We deploy robust standard errors (in parentheses below coefficients). *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table IA.7: **Treatment Effects interact with patent quality**

Dependent variable:	*ln(Wage)*					
Diff-in-diff variables:						
Inventor × Post	0.054***	0.002	0.094***	-0.004	-0.021	0.002
	(0.007)	(0.011)	(0.010)	(0.010)	(0.015)	(0.015)
Inventor	-0.039***	0.016	-0.094***	0.022**	0.032**	0.008
	(0.008)	(0.012)	(0.011)	(0.007)	(0.016)	(0.015)
Post	0.244***	0.259***	0.223***	0.215***	0.212***	0.219***
	(0.005)	(0.007)	(0.008)	(0.007)	(0.009)	(0.011)
Interact with MIP determinants:						
complementarity				0.077***	0.034*	0.115***
				(0.013)	(0.019)	(0.018)
Inventor × complementarity				-0.129***	-0.071**	-0.174***
				(0.018)	(0.029)	(0.024)
Post × complementarity				0.002	0.038**	-0.034**
				(0.012)	(0.017)	(0.017)
Inventor × Post ×complementarity				0.105***	0.065***	0.138***
				(0.017)	(0.028)	(0.022)
markups				-0.142***	-0.161***	-0.115***
				(0.011)	(0.015)	(0.018)
Inventor × markups				-0.050***	0.009	-0.103***
				(0.016)	(0.024)	(0.022)
Post × markups				0.065***	0.087***	0.032*
				(0.011)	(0.014)	(0.017)
Inventor × Post ×markups				0.051***	0.002	0.098***
				(0.016)	(0.023)	(0.022)
Mincer controls:						
Education	0.040***	0.042***	0.038***	0.040***	0.041***	0.038***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Experience	0.049***	0.048***	0.050***	0.048***	0.047***	0.049***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	4.646***	4.599***	4.709***	4.690***	4.664***	4.727***
	(0.011)	(0.015)	(0.016)	(0.012)	(0.016)	(0.018)
Sample (citations):	*All*	*Zero*	*Non-zero*	*All*	*Zero*	*Non-zero*
Strata FE:	✓	✓	✓	✓	✓	✓
Observations	304,626	143,458	161,161	304,626	143,458	161,161
Adjusted R^2	0.343	0.368	0.353	0.348	0.372	0.358

Notes: The table reports all coefficients of regression specifications that are displayed in Table 1. Specifically, in addition to the main coefficients, this table also reports the full set of coefficient estimates for the control variables, i.e., labeled as *Mincer controls* and *Interaction components* in Table 1. We deploy robust standard errors (in parentheses below coefficients). *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Figure IA.1: **Decomposing the MIP: industry- and firm-specific factors**



Notes: The Figures display the differential wage progression of employee inventors in the main sample relative to the control group of temporarily non-patenting inventors, similar to Panel A Figure 1. Only here, three separately estimated regressions are displayed. The dark blue coefficients are equivalent to those reported in Panel A of Figure 1. Moreover, the light blue and red coefficients are obtained from repeating the baseline equation as defined in Equation 1 but adding granular industry- (light blue line) or firm fixed effects (red line), respectively. The whiskers span the 95 percent confidence intervals.

Table IA.8: **Robustness tests average MIP estimations**

Panel A: Testing different fixed effect specifications

Dependent variable:	*ln*(Wage)					
	(1)	(2)	(3)	(4)	(5)	(6)
Inventor × post	0.076***	0.071***	0.054***	0.056***	0.029***	0.028***
	(0.008)	(0.008)	(0.006)	(0.007)	(0.007)	(0.007)
Additional controls:						
Mincer controls	✓	✓	✓	✓	✓	✓
Interaction components	✓	✓	✓	✓	✓	✓
Year FE		✓	✓	✓		✓
State FE		✓	✓			
Industry FE			✓			
Strata FE				✓		
Firm FE					✓	✓
Observations	304,626	304,626	304,599	304,626	300,965	300,965
Adjusted R^2	0.219	0.283	0.325	0.380	0.507	0.518

Panel B: Testing sensitivity to the wage imputation

Dependent variable:	*ln*(Wage)			
	(1)	(2)	(3)	(4)
Inventor × post	0.055***	0.055***	0.058***	0.057***
	(0.007)	(0.008)	(0.008)	(0.009)
Sample:	excl. +/-1 %	excl. +/-2 %	excl. +/-5 %	excl. +/-10 %
Additional controls:				
Mincer controls	✓	✓	✓	✓
Interaction components	✓	✓	✓	✓
Strata FE	✓	✓	✓	✓
Observations	299,349	294,008	274,398	214,971
R^2	0.348	0.350	0.356	0.372

(*Continued on next page*)

Table IA.8 *continued*

Panel C: Testing sensitivity to the high earning inventors

Dependent variable:	ln(Wage)			
	(1)	(2)	(3)	(4)
Inventor × post	0.053***	0.052***	0.049***	0.041***
	(0.007)	(0.007)	(0.007)	(0.007)
Sample:	excl. top 1%	excl. top 2%	excl. top 5%	excl. top 10%
Additional controls:				
Mincer controls	✓	✓	✓	✓
Interaction components	✓	✓	✓	✓
Strata FE	✓	✓	✓	✓
Observations	301,580	298,534	289,395	274,164
R^2	0.340	0.341	0.332	0.318

Notes: The table displays robustness tests on the main results of the aggregated MIP estimations in Table 1 (Column 1). The tables show regression estimates using different variants of Equation 2. In Panel A, we explore different combinations of fixed effects, as indicated at the bottom of the table. States are all NUTS-1 regions in Germany, equivalent to the sixteen federal states. Industries are defined according to the 1-digit WZ classification scheme used in the IAB establishment panel and are comparable to the NACE main classes. In Panel B, we test the main results' sensitivity to the wage imputation that we implemented, following related literature (i.e., Card et al., 2013; Dustmann et al., 2009. In Columns 1-4, we exclude observations close to the time-varying reporting threshold. Specifically, we exclude any observation within 1-, 2-, 5-, and 10-percent around the cutoff, respectively. In Panel C, we test for the sensitivity of the main results regarding inventors with particularly high income. The regressions exclude all observations of the inventors in the top 1-, 2-, 5-, 10- income distribution. Other than this, all regressions are defined equivalent to those defined in Equation 2. Standard errors (in parentheses below coefficients) are heteroscadisticity and clustered on the inventor level. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

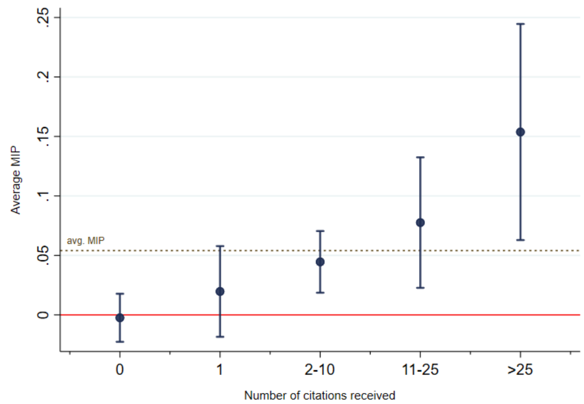
Table IA.9: **Robustness tests for the baseline estimates: Triple-interactions**

Dependent variable:	*ln*(Wage)				
	(1)	(2)	(3)	(4)	(5)
Inventor × post	0.003	-0.004	-0.058	-0.052	-0.043
	(0.011)	(0.010)	(0.014)	(0.013)	(0.013)
Inventor × post × Non-zero-citations	0.092***		0.100***	0.091***	0.088**
	(0.015)		(0.016)	(0.016)	(0.015)
log(Citations)		0.010***			
		(0.002)			
Inventor × post × complementarity		0.105***	0.127***	0.124***	0.109**
		(0.017)	(0.018)	(0.018)	(0.018)
Inventor × post × markups		0.051***	0.048***	0.060***	0.054***
		(0.016)	(0.016)	(0.016)	(0.016)
Mincer controls	✓	✓	✓	✓	✓
Interaction components	✓	✓	✓	✓	✓
Strata FE	✓	✓	✓	✓	✓
Firm- and industry controls				✓	✓
Year FE					✓
Observations	304,626	304,626	304,626	300,457	300,457
Adjusted R^2	0.343	0.348	0.299	0.327	0.377

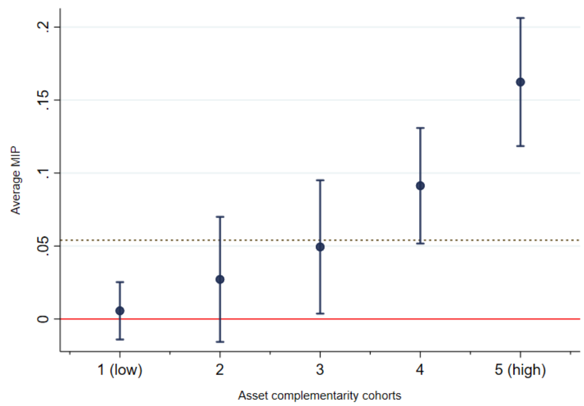
Notes: The table displays robustness tests on the baseline findings displayed in Table 1. Different to before, the estimations include interactions with the *Non-zero-citations* dummy refering to all inventors with patent filings that receive at lease one citation within the first ten years after filing. Further, the specifications test different sets of additional controls and fixed effects. Firm- and industry controls refer to the variables firm age, firm size, $Bundesland$ (state) fixed effects, and industry-year specific changes in employment. The use of these covariates is indicated in the bottom of the table but the output is suppressed. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the inventor level. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Figure IA.2: **Heterogeneity in the average treatment effect**

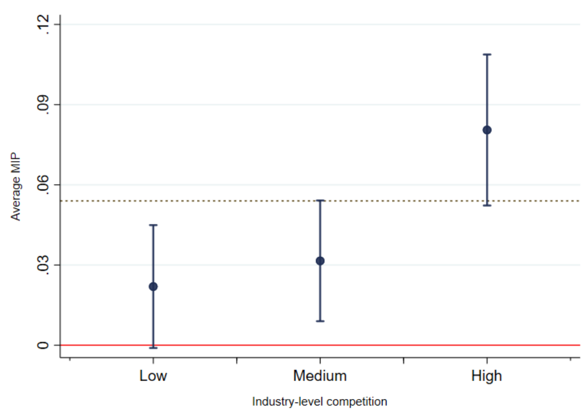
Panel A: Citation cohorts



Panel B: Firm-level complementarity cohorts



Panel C: Industry-level markup cohorts



Notes: The Figures display the DID coefficient of the time-invariant average MIP estimation, δ' in Equation 2, for different subsamples. In Panel A, the sample is split according to the number of forward citations received within the first ten years after initial filing. In Panel B, the sample is split into 20-percentile bins of the focal employers' asset complementarity distribution at the time of the patent filing. Complementarity is measured by the size of the patent stock. In Panel C, the sample is split into three equally sized bins of industry-specific ex-ante average markups. The whiskers span the 95 percent confidence intervals. The dashed line serves as a reference, indicating the average MIP (of 5.4%).

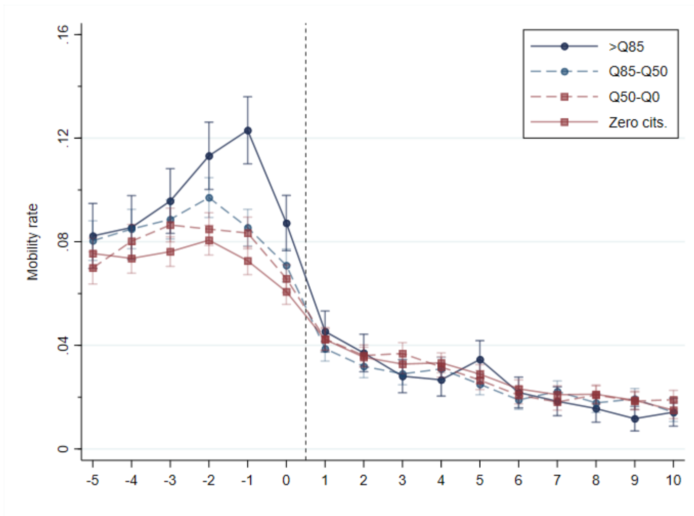
Table IA.10: **Heterogeneity in inventor returns across different inventor characteristics**

Dependent variable:	*ln*(Wage)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inventor × post	0.001	0.057***	-0.022	0.052***	0.050***	-0.018	0.059***	-0.013
	(0.012)	(0.010)	(0.015)	(0.016)	(0.015)	(0.010)	(0.009)	(0.010)
Inventor × post × Complex job			0.024					
			(0.019)					
Inventor × post × Highly complex job			0.083***					
			(0.018)					
Inventor × post × Manager						0.037**		
						(0.019)		
Inventor × post × Engineer						0.065***		
						(0.013)		
Inventor × post × University degree								0.073***
								(0.014)
Sample (job/inventor types):	*Complex*	*Highly complex*	*All*	*Manager*	*Engineer*	*All*	*University degree*	*All*
Mincer controls	✓	✓	✓	✓	✓	✓	✓	✓
Strata FE	✓	✓	✓	✓	✓	✓	✓	✓
MIP determinants	✓	✓	✓	✓	✓	✓	✓	✓
Interaction components	✓	✓	✓	✓	✓	✓	✓	✓
Observations	69,260	176,486	304,626	54,738	192,507	304,626	197,000	294,420
Adjusted R^2	0.282	0.306	0.353	0.371	0.338	0.358	0.295	0.385

Notes: This table shows how the MIP varies depending on certain inventor characteristics. The regressions estimate Equation 2 using different subsamples, depending on the job complexity, inventor jobs, and inventor education. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the inventor level. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

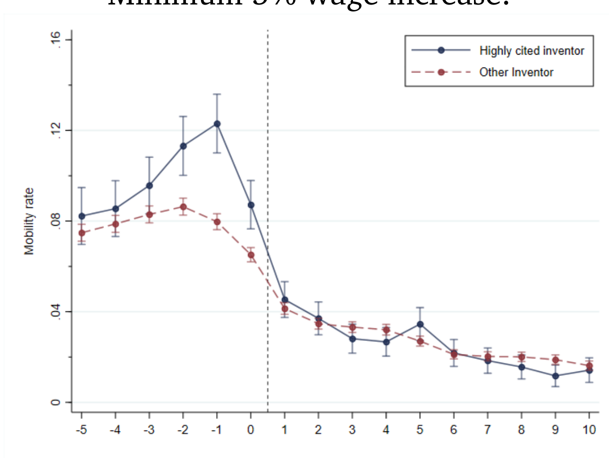
Figure IA.3: **Robustness tests on mobility patterns**

Panel A: Alternative definition of citation cohorts

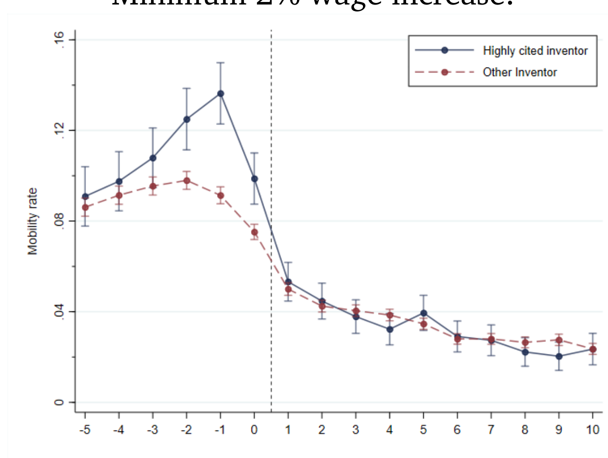


Panel B: *Voluntary* employer changes

Minimum 5% wage increase:



Minimum 2% wage increase:



Notes: The Figures display mobility patterns of employee inventors, relative to the year of their initial patent filing. Specifically, it displays the annual share of inventors changing their employer similar to Figure 2 (Panel A), using distinguishing inventors by different attributes. Here, Panel A distinguishes four inventor types, depending on the citations their focal patent received: 1. zero, 2. non-zero but below median, 3. above median but below the 85^{th}-percentile, and 4. in the top 15^{th}-percentile. Panel B distinguishes highly cited inventors just like in Panel A of Figure 2, but here we only consider *voluntary* movers, i.e., employees whose job change is accompanied by a salary increase of at least 5% (left graph) or 2% (right graph) in year-over-year comparison), respectively. The whiskers span the 95 percent confidence intervals.

Table IA.11: **Robustness tests - MIP and Mobility**

Dependent variable:	*ln*(Wage)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Inventor × post	0.059***	-0.002	0.071***	0.009	0.046***	0.002	0.059***	0.015	0.045***	0.005
	(0.013)	(0.014)	(0.013)	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)	(0.015)
Inventor × post × pre-mover	0.086***	0.000			0.087***	0.001				
	(0.021)	(0.023)			(0.024)	(0.025)				
Inventor × post × post-mover	-0.031	0.009	-0.050	0.025						
	(0.025)	(0.028)	(0.033)	(0.037)						
Inventor × post × pre-mover$^{[-3,-1]}$			0.070**	-0.037			0.075***	-0.042	0.066***	-0.048
			(0.027)	(0.029)			(0.027)	(0.028)	(0.027)	(0.029)
Inventor × post × post-mover$^{[0,4]}$					0.021	0.001	0.016	-0.001	0.010	-0.002
					(0.025)	(0.028)	(0.025)	(0.028)	(0.026)	(0.028)
Inventor × post × pre-mover$^{[-5,-4]}$									0.063***	0.029
									(0.034)	(0.033)
Inventor × post × post-mover$^{[5,10]}$									0.008	0.011
									(0.026)	(0.027)
Citation cohorts:	Non-zero-cit.	Zero-cit.	Non-zero-cit.	Zero-cit.	Non-zero-cit.	Zero-cit.	Non-zero-cit.	Zero-cit.	Non-zero-cit.	Zero-cit.
Strata FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mincer controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	161,146	143,443	139,273	124,144	139,273	124,144	139,273	124,144	139,273	124,144
R^2	0.355	0.370	0.369	0.384	0.370	0.386	0.370	0.386	0.372	0.387

Notes: This table displays robustness tests on the main findings about inventors' MIP depending on inventors different mobility patterns. Columns 1 and 2 are similar to Columns 1 and 2 in Table 2, only here the sample includes inventors that move before and after their initial patent filing. Columns 3-10 are similar to Columns 1 and 2 in Table 2, only here the mover indicators are defined differently. Pre-moves only consider moves in the three years before the patent filing (Columns 3, 4, 7, and 8). Post-moves only consider moves in the five years after the patent filing (Columns 5, 6, 7, and 8). Columns 9 and 10 further add interactions with pre movers in the four and five years before the patent filing and post movers in any year later than the first five years after the filing. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the inventor level. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table IA.12: **Robustness tests: compensation patterns and firm-level employee growth**

Panel A: Triple interactions and non-inventor employee growth

Dependent variables:	Δ inventors			Δ non-inventor employees		
	(1)	(2)	(3)	(4)	(5)	(6)
FS-MIP, z.	0.233*	0.292	0.054	0.032	-0.033	0.269
	(0.136)	(0.180)	(0.183)	(0.127)	(0.148)	(0.209)
Complementarity^{hi}	-0.611***		-0.626***		-0.202	
	(0.211)		(0.215)		(0.221)	
FS-MIP, z. $\times$ Complementarity^{hi}	1.031***		1.004***		0.235	
	(0.122)		(0.242)		(0.246)	
Markup^{hi}		0.001	0.107			0.310
		(0.230)	(0.234)			(0.238)
FS-MIP, z. $\times$ Markup^{hi}		0.394*	0.278			-0.353
		(0.229)	(0.229)			(0.258)
Firm-level controls	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
# Firm-year obs.	14,567	14,567	14,567	14,630	14,567	14,567
$Adj.R^2$	0.048	0.046	0.048	0.067	0.067	0.067

Panel B: Testing different layers of fixed effects

Dependent variables:	Δ inventors			
	(1)	(2)	(3)	(4)
FS-MIP, z.	1.210***	0.434***	0.550***	0.550***
	(0.112)	(0.122)	(0.122)	(0.121)
Firm-level controls	✓	✓	✓	✓
State FE		✓	✓	✓
Industry FE		✓	✓	
Year FE			✓	
Industry-Year FE				✓
# Firm-year obs.	14,633	14,630	14,630	14,630
$Adj.R^2$	0.013	0.036	0.046	0.053

Notes: The table displays robustness tests on the baseline findings on firms' renumeration patterns and future inventor growth rates. In Panel A, regressions are similar to those in Column 1 of Table 3, only here the Columns 1-3 add interaction terms with indicators for firms with high asset complementarity (Columns 1 and 3) or those active in highly competitive industries (Columns 2 and 3). In Columns 4-6, the dependent variable are non-inventor employee growth rates. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the inventor level. Panel B displays regression estimates for specifications similar to those in Column 1 of Table 3, only here we use different combinations of fixed effects. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table IA.13: **Robustness tests: compensation patterns and firm-level patenting output**

Panel A: Measuring patent output in 2010-2014

		Complementarity		Competition	
		Hi	Lo	Hi	Lo
Dependent variable:	# future patent filings (in logs)				
	(1)	(2)	(3)	(4)	(5)
FS-MIP, z.	0.049***	0.061***	0.026*	0.053***	0.041*
	(0.014)	(0.033)	(0.018)	(0.019)	(0.023)
Firm-level controls	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
# Firm obs.	2,690	1,042	1,626	1,836	825
$Adj.R^2$	0.271	0.341	0.079	0.320	0.116

Panel B: Using Poisson Pseudo Maximum Likelihood Estimations

		Complementarity		Competition	
		Hi	Lo	Hi	Lo
Dependent variable:	# future patent filings				
	(1)	(2)	(3)	(4)	(5)
FS-MIP, z.	0.096***	0.130***	0.051	0.112***	0.055
	(0.025)	(0.039)	(0.035)	(0.030)	(0.047)
Firm-level controls	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
# Firm obs.	2,666	1,037	1,601	1,822	802
Wald Chi^2	563.65	328.82	225.71	509.86	95.29

Notes: The tables display robustness tests on Panel B of Table 3. Specifically, Panel A repeats is similar to before, only here all future outcomes (i.e., the dependent variable and firm-level controls) are measured during the years 2010-2014 (instead of 2008-2012). Panel B uses Poisson Pseudo Maximum Likelihood estimations in order to account for potential zero-inflation in the outcome variable.