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Inventor Returns and Mobility

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, effect sizes also depend on employer-inventor technological complementarity, degree of competition, and invention quality.

JEL-Codes: O310, J240, J620.

Keywords: inventor returns, labor mobility, patents, inventive productivity.

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1 Introduction

Most inventions are generated by employed inventors and are then filed by their employers (Harhoff and Hoisl, 2007). Some jurisdictions have laws that govern the marginal compensation of employed inventors for the invention of new technology, but 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 expected value-add commensurate with their relative inventive contribution. These may depend on qualitative factors like the inventor's initiative and autonomy during the inventive process. The purpose of our study is to investigate whether employers' discretion in determining employed inventors' marginal patent incomes 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 level of individual inventors has revived studies of inventive rents. Closest to ours are the seminal works by Toivanen and Väänänen (2012) and Aghion et al. (2018), which focus on the marginal income per patent for employed inventors in Finland.[1] Their focus is on *within*-firm determinants of inventor returns, such as patent citations and inventor human capital. We add to this literature by exploring the *between*-firm variation in inventor returns and the role of inventor mobility in a large labor market.[2] We show that inventor mobility transfers critical knowledge to employers which allows for above-average inventor returns and gains for employers in terms of patent quantity and quality.

We use novel register 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 inven-*

[1] A recent study by Aghion et al. (2024) also examines inventive rent spillovers to inventors' coworkers.

[2] Most patenting activity in Finland is concentrated in one firm (i.e., Nokia Corporation) while we can draw on a much broader firm and inventor population allowing us to study the impact of between-firm factors and inventor mobility. See Intellectual property statistical country profile for Finland in 2022, retrieved December 17, 2023.

tors[3] by age, education, work experience, current job description, geography, and industry. 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 €58.1k (deflated to 2015 values) over the full event window, which is close to one average annual wage payment among inventors in Germany. The MIP correlates with patent citations in Germany as it does in Finland (Toivanen and Väänänen, 2012). For patents that are never cited we find a zero MIP, while cited patents yield on average a 9.4% annual MIP.

Importantly, we find that firm-level factors account for 52% of the variation in the MIP and industry for 26%. Therefore, we explore technological complementarity between the patent and the filing employer's stock of patents in the technology class of the focal inventors' patents as a between-firm and product-market competition as a between-sector determinant of the MIP. The estimated baseline MIP depends dramatically on these two factors. A patent with low complementarity in a non-competitive industry yields no statistically discernable MIP, even if it generates forward citations. In contrast, even zero-citation patents generate a sizeable 4.5% MIP if they are filed in firms with highly complementary patent stock, and the MIP is almost tripled in these cases if it generates citations. In competitive industries, zero-citation patents earn no MIP, while cited patents earn a 10.3% MIP. Overall, the conditional MIP in the presence of high technological complementarity is 9.2% and that in relatively competitive product markets is 5.1%. These results provide

[3] We do so because, unlike Finnish inventor data, see Aghion et al. (2018) and Toivanen and Väänänen (2012), data privacy restrictions in Germany 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.

robust measures of the impact of complementarity and rivalry on the returns to invention.

Turning to inventor mobility, descriptive analyses suggest that inventors are 2.3 times as likely to switch employers in the two years prior to a patent filing than in the two years thereafter. Inventors whose subsequent patents generate forward citations in the top 15% of the distribution are more than three-times more likely to have switched employers two years prior to filing year than after filing. This raises the question of what role inventor mobility plays in the determination of returns to invention.

We run triple difference regressions to estimate the additional MIP associated with inventor mobility right before or after an invention, relative to non-movers. Neither pre- nor post-invention mobility is associated with an additional MIP for inventors of zero-citation patents. 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* the patent is filed. Strikingly, if they move *after* the filing of the patent, they do not earn a mobility-related additional MIP.

For patents with forward citations, the relation between inventor returns and mobility is contingent on technological complementarity and product-market competition. Importantly, irrespective of complementarity and competition, inventors that move directly *after* a patent has been filed do not earn a mobility-related MIP. For pre-invention movers, the additional mobility-related MIP can be large, but depends dramatically on characteristics of the new employer. Inventors whose earlier patents are highly complementary with the new employer's patent stock earn a staggering average total MIP of 24.3%, whereas inventors of patents with low complementarity do not earn any mobility-related MIP. The difference in the mobility-related MIP between high-competition and low-competition industries is smaller but still sizable (19.2 and 5.0%, respectively).

The findings suggest that inventors' critical know-how may be highly valuable from a bargaining perspective. We also show that the MIP serves as an effective device for sorting in the market for inventive labor by exploring the mobility patterns' impact on employer-employee match quality. Similar to the MIP-mobility regressions, inventors moving to a new employer shortly before a patent filing choose employers with substantially more (in absolute and relative terms) existing patents in the inventor's main technology class. For example, inventors of patents that will yield forward citations move to a new employer that has, on average, 11.1% more patents in the same technology class than the previous employer.

Finally, given our evidence that German employers can and do exert significant 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. The firm's inventor compensation policy appears to be highly relevant: firms that, on average, paid their inventors a positive excess MIP one decade earlier tend 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 firms that employ inventors 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 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 in four steps 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 with the current employer. 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 group. Summary statistics in Table IA.1 in the Internet Appendix

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

show that inventors in the treatment group and the matched control group are very similar in the pre-treatment year. The mean squared error over all covariates 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 concentration 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 ('FLEED') data (Aghion et al., 2024), our sample inventors are slightly younger, less likely academics, and earn somewhat higher salaries. Our sample comprises various firms and industries.

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.4 in the Internet Appendix).

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:

$$
\begin{aligned}
ln(\text{Wage}_{its}) = & \underbrace{\sum_{t=-4}^{T=10} \delta_t \times Inventor_i \times post_{it}}_{\text{Estimated MIP per annum w.r.t. priority filing year t=0}} + \\
& \alpha \times Inventor_i + \sum_{t=-4}^{T=10} \beta_t \times post_{it} + M_{it} \times \gamma + \theta_s + \epsilon_{its}
\end{aligned}
\tag{1}
$$

[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).

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 matching-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 captures pre-invention treatment effects for $t \in [-4, -3, -2, -1]$. As in Aghion et al. (2018, 2024), 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., 2024, p. 14). In fact, the evidence of the mobility-related MIP in Section 4 provides an explanation for anticipatory inventor returns.

Panel A of Figure 1 plots the annual MIP (regression coefficients from Equation 1, as tabulated in Table IA.5 in the Internet Appendix) (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 parallel pre- and post-treatment trends and that inventive rents to employed inventors largely accrue over the years [–2, +9] around the priority filing year. There is a statistically significant anticipatory MIP of 8.0% in the year before the priority filing, then the annual MIP peaks in the two years after the priority filing with a maximum of 11.4% before 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., 2024).

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 18.3% 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 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, 2024) 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

[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.

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 Mincerian controls are as expected (documented in Table IA.7) and the adjusted R^2 is 34.3%. We also experiment with different fixed effect specifications in Table IA.6 in the Internet Appendix and find that the average annual time-invariant MIP ranges across specifications between 7.6% (without any fixed effects) and 2.8% (with priority filing year and firm fixed effects). Our highly controlled specification with priority filing year and stratum fixed effects (i.e., which also capture amongst others industry- and location-specific effects) yields a robust average MIP of 5.6% per annum. Panels B and C of Table IA.6 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.8 in the Internet Appendix confirm that the MIP for zero-citation and non-zero-citation patents are statistically significantly different. Panel A of Figure IA.2 in the Internet Appendix 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. Inventors of patents with more than 25 forward citations can expect a MIP of as high as 24%, for a total nominal MIP 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, even before conditioning on other covariates, strongly related to measures for technological complementarity, as proxied by an employer's existing knowledge stock relevant for the focal inventor, i.e., the stock of patents in the same industry class (Panel B of Figure IA.2), and the degree of product-market competition, as proxied by average industry markups (Panel C of Figure IA.2). Patents in the bottom tercile of the technological complementarity distribution do not earn an additional MIP, while those in the top-tercile earn a MIP as high as 8%. These findings are in line with related findings, inter alia, that technological complementarity may enhance worker productivity in innovative settings (Goldin and Katz, 1998), increase firms' absorptive capacities of new knowledge (Cohen and Levinthal, 1990), and value creation from innovation (Hottenrott and Peters, 2012; Teece, 2010). Similarly, employers in relatively uncompetitive product markets pay a MIP that is statistically not different from zero, while employers in competitive product markets pay an average MIP of up to 11%. A positive correlation between the MIP and product-market competition is consistent with numerous theoretical arguments, including technology races (Lerner, 1997), employer-employee rent sharing from enhanced market power (Bloom et al., 2013), and the strategic prevention of future technology licensing costs (Moreira et al., 2020).

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 technological 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 ($Inventor \times post$) 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 high complementarity, they can expect an additional average annual MIP between 4.5% if their patent yields zero citations and 12.7% for non-zero-citation patents. Inventors employed by firms in competitive product markets earn non-significant MIP for zero-citation patents and a significant average annual MIP of 10.3% 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 technological complementarity and product-market competition offered as two economic channels. In Internet Appendix C, we show that the MIP also varies across employed inventor characteristics. Table IA.9 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.

Another notable difference between our German and the Finnish inventor data pertains to inventive rent spillovers to inventors' coworkers. Aghion et al. (2018) estimate an annual MIP spillover effect to inventors' white- and blue-collar coworkers of 1–2% of their annual wage. In contrast, we find that the estimated MIP is consistently higher when we match our inventors with coworkers compared to outside-firm non-coworkers (Table IA.10 in the Internet Appendix). A potential explanation for the discrepancy is that, unlike Aghion et al. (2018), our matched temporarily non-patenting coworkers work in the same R&D department as the patenting inventors and they compete for variable compensation from the same bonus pool, which might lead to higher relative wage differentials between the two employee groups (Giummo, 2010).[7] Thus, our result that inventions might put non-inventing coworkers at a disadvantage is more in line with Aghion et al.'s (2024) finding of non-employment risk for some coworker types.

4 Inventor mobility

Given that the MIP is largely determined at the employer's discretion, we can expect that a relatively efficient market for inventive labor reflects between-firm MIP heterogeneity in its mobility patterns. As a motivational analog for marginal income-driven inventor mobility, Akcigit et al. (2016) show that "superstar" inventors' relocation choices are determined by top-tax-rate heterogeneity across countries. Therefore, as a first step, we explore patterns in inventor mobility right before and after patent filings. We find that inventors' mobility rates are disproportionately higher *right before* a patent filing, and the pattern is more salient for high-quality inventions.

While the unconditional inventor turnover rate is 12.1% in our sample, the inventor turnover rate conditional on filing a patent one year later is significantly higher at 20.0% for inventions in the top-15% of the forward citation distribution and 15.2% for all other patents. Strikingly, we observe in Panel A of Figure 2 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 other patents vanishing. These patterns suggest that inventive labor may be responsive to the anticipation of employer-varying MIP, and that inventors are much less inclined to switch employers right after filing a patent when they still accumulate their MIP.[8]

[7]Panel B of Table IA.10 also shows that the size of the MIP is not statistically different for solo-inventors or inventor teams of varying sizes.

[8]We are hesitant to interpret the inventor mobility patterns as evidence of job market signaling and bargaining in the Spence (1973) sense because of the significant pre-filing mobility rate. However, related work allows for pre-filing inventor mobility, as information about an ongoing inventive process may leak (d'Andria, 2016). We are precluded from testing whether pre-filing information leakage (e.g., in the form

It is noteworthy that, for the majority of mobile inventors, a move leads to an increase in inventors' base pay of at least 5% per annum excluding the future MIP; but, this 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 for mobile inventors in Germany (Panel B of Figure IA.3 in the Internet Appendix).

Therefore, as a second step, we investigate whether inventor mobility is driven by MIP-related wage increases, that is, a higher expected MIP at the new employer. We find that the mobility patterns lead to substantial differences in the MIP (Panel B of Figure 2). Our MIP estimates indicate that the average patent earns inventors who move to a new employer just before the patent filing (*pre-movers*) EUR 79.7k, right after a patent filing (*post-movers*) EUR 58.3k, and employed inventors who stay at the same employer over the entire MIP accumulation period (*non-movers*) earn EUR 20.5k. Thus, the mobility-related added MIP for a pre-mover relative to a non-mover 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. We exclude inventors with multiple moves to eliminate a potential source of bias, although we show in the Internet Appendix that the inclusion of multiple movers does not materially change our results (Columns (1) and (2) in Table IA.11).

of working papers or conference presentations) constitute a public signal due to privacy restrictions on our data.

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 at least some 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-related 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 technological complementarity yields a mobility-related (total) MIP of 15.0% (24.3%) per annum for patents that generate forward citations. The corresponding cumulative MIP amounts to about 4.5 extra annual salaries, of which 2.8 are attributable to the pre-filing move and 1.7 to the invention itself. Inventors contributing to non-zero-citation patents at new employers with low technological complementarity earn 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 competitive product markets, amounting to 12.2% (19.2%), relative to no mobility-related MIP (12.8%) associated with moves to employers in relatively uncompetitive product markets. Finally, note that none of these effects matter for inventors with zero-citation patents; the average zero-citation invention does not yield a mobility-related MIP. Similarly, the timing of the move is crucial. Moves right after the patent filing do not earn their inventors any 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 in the Internet Appendix).

[Place Table 2 about here.]

These results are indicative of the MIP potentially functioning as a sorting device to improve the employer-employee match quality in the market for inventive labor. As a more direct test, we explore whether inventor mobility improves technological complementarity between the inventor's earlier patent filings and the employer's existing patent stock. To that end, we modify the MIP-mobility regression framework from Table 2 by replacing the MIP as the dependent variable with two proxies for inventor-employer technological complementarity: (i) the natural logarithm of the total number of patents the employer has in the technology class of the focal inventor and (ii) the share of patents in the focal inventor's technology class in the employer's total patent stock. The results in Table IA.14 in the Internet Appendix are consistent with the MIP-mobility regression results in Table 2, suggesting that pre-movers mostly move to new employers with higher technological complementarity for both non-zero- and zero-citation patents, albeit the treatment effect for the latter is halved. For poxy (ii), pre-movers only improve technological complementarity when the mobility is associated with a patent that generates forward citations. Economically, pre-movers with non-zero-citation patents move, on average, to new employers with an 11.1% higher share of patents in the corresponding technology class compared to the previous employer, suggesting a substantially improved employer-inventor match. Interestingly, the mobility of post-movers who depart right after a patent filing and before the MIP accumulation period ends always leads to a reduction in the average technological complementarity.

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 associated with 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 proxy the firm-specific history of paying excess MIP with the average, time-invariant error term from the inventor-level MIP regressions in Equation 2 for each firm f, which we z-standardize for ease of interpretation and label *FS-MIP*.[9] 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.

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. That is, the average inventor employment growth rate is 2.3% in our sample and employers with an average historic MIP one standard deviation above the mean grow their R&D departments at 3.6% per annum. Columns (2) and (3) estimate the effects for samples split by the median of the technological complementarity proxy. High-complementarity employers' inventor growth rate is 4.1% (80.3% above the sample mean) if they pay a MIP one standard deviation above the sample mean, while that for low-complementarity employers is statistically not different from zero, suggesting that low-complementary employers are not able to effectively use their MIP history as an inventor hiring device. Columns (4) and (5) estimate the effects for samples split by the median of the product-market competition proxy. Employers in relatively competitive product markets hire inventors at an annual 3.9% growth rate (71.0% above the sample mean). In contrast, employers' inventor growth rate of 3.0% is only weakly significant and much lower (32.3% above the sample mean) for employers in non-competitive product markets. 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 in the Internet Appendix).

These tests show that the historic MIP firms have paid in excess of market expectation is positively associated with firms' future inventor hiring rates. The results may suggest that industrial researchers who are known to have stronger preferences for income than aca-

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

demic researchers (Roach and Sauermann, 2010; Sauermann and Cohen, 2010) have indeed higher mobility elasticities to between-employer MIP heterogeneity (d'Andria, 2016); a similar finding is established for cross-country inventor mobility and between-jurisdiction tax heterogeneity (Akcigit et al., 2016). A limitation of our regression framework is that it does not disentangle whether the positive association is driven by excess MIP attracting more inventors or firms with expansion plans offering ex-ante more pay in general to stimulate 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) on *FS-MIP* in the cross-section of firms, with both outcomes aggregated at the firm level over the 2008–2012 period. The two measures comprise important dimensions in predicting firm dynamics and growth (Balasubramanian and Sivadasan, 2011). 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 a hypothetical increase in the firm-specific MIP by one standard deviation is associated with 7.6% (=exp(0.073)−1) more future patents filed one decade later. Reinforcing the relevance of our identified contingency factors, this finding holds again only for high-complementarity employers. Note that the the explained variation in the data is almost four times as large in high-complementary (R^2=32.0%) compared the low-complementarity counterparts (R^2=8.3%). The difference between relatively competitive (8.3%) and uncompetitive (5.1%) product markets is consistent with the aforementioned patterns.

Similar patterns exist for the cumulative number of forward citation-weighted future patent filings (lower part of Panel B). A hypothetical increase in the firm-specific MIP component by one standard deviation is associated with 6.8% (=exp(0.066)−1) more citation-weighted future patents one decade later. Again, the result holds only in the high-technological complementarity subsample, and the R^2 in the subsample is much higher than in the low-technological complementarity counterpart. The pattern is similar for employer subsamples split by the level of product-market competition, albeit less dramatically so. 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 in the Internet Appendix). Our aggregate results at the employer level are reminiscent of inventor-level evidence that links pay to inventive productivity (Sauermann and Cohen, 2010).

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 utilize their discretion 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 often comes along with mobility-related additional 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. These results depend crucially on patent quality, technological complementarity, and product-market competition.

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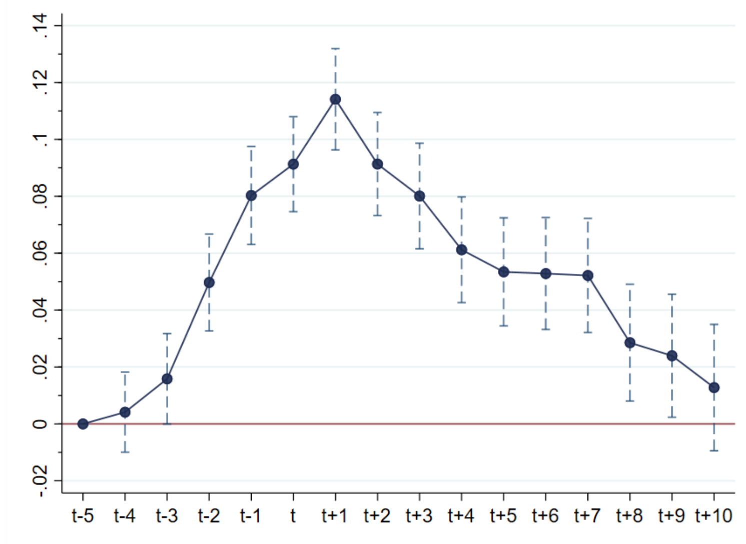
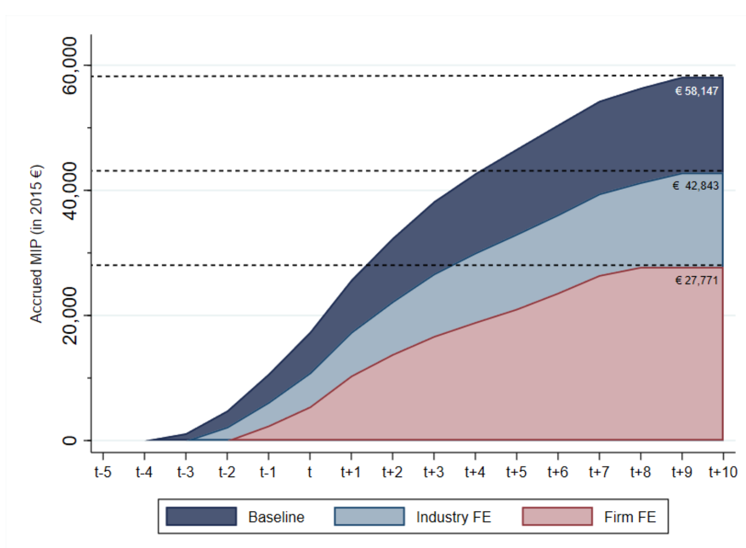
Exhibits of the main part

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: Panel A plots the estimated MIP per annum from Equation 1 over the 15-year accumulation period relative to the priority filing year t=0, with 95%-confidence intervals. Corresponding regression results are in Table IA.5 in Internet Appendix C. Panel B plots the cumulative MIP over the 15-year accumulation period as a nominal amount in EUR deflated to 2015, stacking the MIP portions attributable to firm, industry, and baseline (i.e., inventor and invention) factors. Marginal effects for the MIP decomposition into firm, industry, and other factors are in Figure IA.1 in Internet Appendix C.

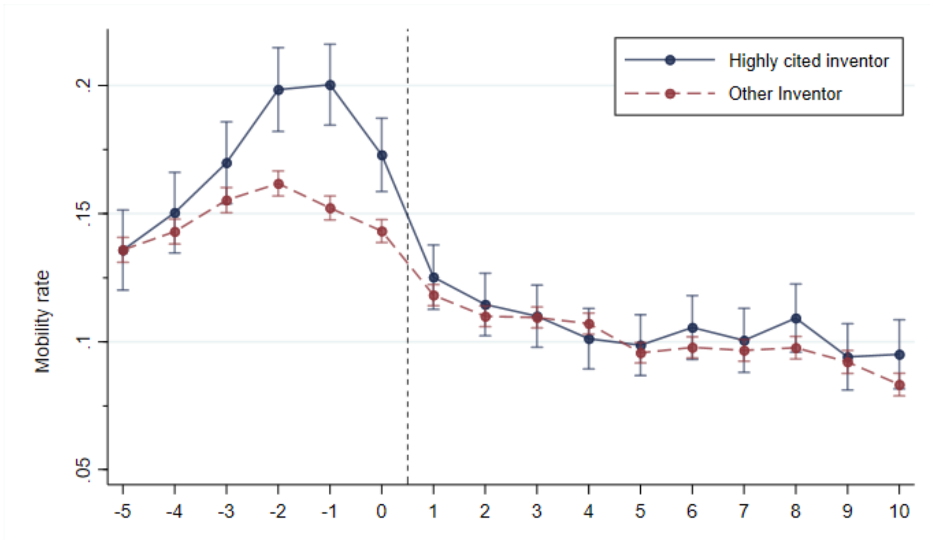
Table 1: Inventor returns, conditioning on technological complementarity and industry-level competition

Dependent variable:	*ln*(Wage)					
	Baseline estimation			Conditioning on technological complementarity and competition		
	(1)	(2)	(3)	(4)	(5)	(6)
Inventor × post	0.054***	0.002	0.094***	–0.015	–0.024	–0.015
	(0.007)	(0.011)	(0.010)	(0.011)	(0.017)	(0.016)
Inventor × post × complementarity				0.092***	0.045*	0.127***
				(0.015)	(0.023)	(0.021)
Inventor × post × competition				0.051***	0.001	0.103***
				(0.016)	(0.023)	(0.022)
Citation cohorts:	*All patents*	*Zero-citation*	*Non-zero-citation*	*All patents*	*Zero-citation*	*Non-zero-citation*
Mincer controls	✓	✓	✓	✓	✓	✓
Strata FE	✓	✓	✓	✓	✓	✓
Interaction components	✓	✓	✓	✓	✓	✓
Observations	304,626	143,458	161,161	300,773	141,644	159,129
Adj. R^2	0.343	0.368	0.353	0.347	0.371	0.358

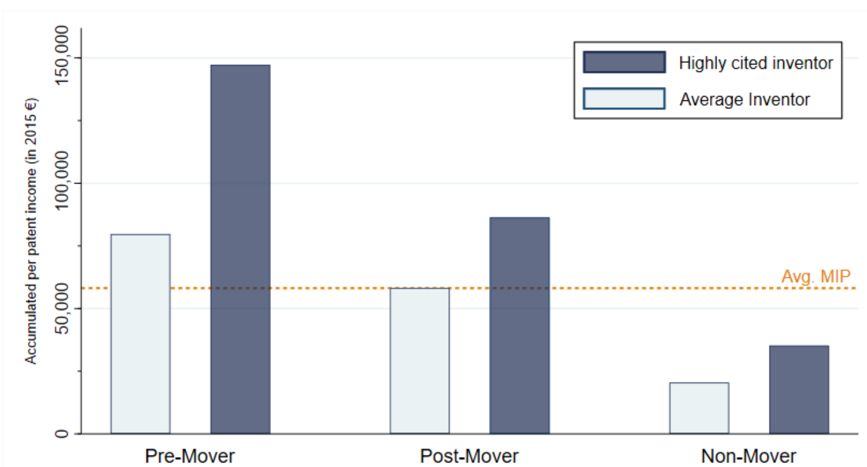
Notes: Regression results from Equation 2 are in columns (1), (2), and (3) for the full sample, zero-citation, and non-zero-citation patents, respectively. Regression results for a modified regression that estimates marginal MIP effects of technological complementarity and product-market competition are in Columns (4), (5), and (6). We proxy complementarity with an indicator variable for whether an employer has an above-median patent stock in the employed inventor patent's technology class measured at the beginning of each year. We proxy competitive industries with an indicator variable for whether an employer operates in a product market with below-median markups. Markups are firm-level differences in costs of goods sold and their production costs measured in the three years before the focal year, and aggregated on the 2-digit NACE level. Coefficients on suppressed covariates are in Table IA.7 in Internet Appendix C. Standard errors in parentheses below coefficients are heteroscedasticity-adjusted and clustered at the inventor level. *, **, and *** denote significance at the 10%, 5%, and 1% 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: Panel A shows the annual rate of inventors moving to a new employer over the [−5, 10] event period in years with respect to the priority filing year t=0 among high-quality inventors in the top 15% of the forward citation distribution (solid line) and other inventors (dashed line). Mobility patterns for different inventor classifications are in Figure IA.3. Panel B plots the estimated cumulative MIP as a nominal amount in EUR deflated to 2015 for high-quality inventors (dark bars, as defined before) and the average inventor (light bars) that move right before a patent filing (*pre-movers*), after a patent filing (*post-movers*), or stay at the same employer over the MIP accumulation period (*non-movers*).

Table 2: **MIP and Mobility**

Dependent variable:	*ln*(Wage)									
			Complementarity		Competition		Complementarity		Competition	
			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	0.150***	0.042	0.122***	0.007	-0.013	0.033	-0.071*	0.077**
	(0.025)	(0.026)	(0.040)	(0.032)	(0.041)	(0.031)	(0.048)	(0.031)	(0.040)	(0.040)
Inventor × post × post-mover	-0.038	0.041	-0.011	-0.047	-0.007	-0.052	-0.028	0.094*	0.059	0.052
	(0.033)	(0.037)	(0.046)	(0.046)	(0.060)	(0.038)	(0.057)	(0.049)	(0.066)	(0.043)
Inventor × post	0.059***	-0.006	0.093***	0.014	0.070***	0.050***	0.026	-0.042**	0.014	-0.020
	(0.014)	(0.014)	(0.019)	(0.020)	(0.025)	(0.016)	(0.023)	(0.018)	(0.024)	(0.017)
Citation cohorts:	Non-zero-cit.	Zero-cit.	Non-zero-citations				Zero-citations			
Strata FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mincer controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Interaction components	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	139,273	124,144	64,973	72,533	55,435	83,772	45,294	77,262	49,172	74,922
Adj. R^2	0.370	0.385	0.365	0.388	0.378	0.394	0.377	0.390	0.406	0.415

Notes: Regression results for the mobility-related MIP are in columns (1) and (2) for non-zero-citation and zero-citation patents, respectively. The MIP estimator is interacted with *pre-mover* and *post-mover* dummies to indicate whether inventors moved to a new employer right before or after a priority filing, respectively, relative to *non-movers* who stayed at the same employer over the MIP accumulation period. For non-zero-citation patents, the mobility-related MIP is estimated in columns (3) and (4) for employers with high and low technological complementarity and in columns (5) and (6) for product markets with high and low competition, respectively. For zero-citation patents, the mobility-related MIP is estimated in columns (7) and (8) for employers with high and low technological complementarity and in columns (9) and (10) for product markets with high and low competition, respectively. Robustness tests for different mobility windows around the priority filing year are in Table IA.11 in Internet Appendix C. Standard errors in parentheses below coefficients are heteroscedasticity-adjusted and clustered at the inventor level. *, **, and *** denote significance at the 10%, 5%, and 1% 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***	0.803***	0.127	0.710***	0.323*
	(0.122)	(0.181)	(0.182)	(0.179)	(0.164)
Firm-level controls	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
# Firm-year obs.	14,630	10,285	4,281	6,409	8,219
Adj. R^2	0.046	0.060	0.014	0.076	0.016
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***	0.112***	0.024	0.083***	0.051*
	(0.018)	(0.027)	(0.021)	(0.023)	(0.029)
# Firm obs.	2,825	1,780	1,025	1,282	1,537
Adj. R^2	0.230	0.320	0.083	0.312	0.287
Dependent variable:	# citations on future patent filings (in logs)				
	(1)	(2)	(3)	(4)	(5)
FS-MIP, z.	0.066***	0.121***	0.011	0.068**	0.050
	(0.021)	(0.034)	(0.026)	(0.029)	(0.033)
# Firm obs.	2,825	1,780	1,025	1,282	1,537
Adj. R^2	0.202	0.233	0.025	0.221	0.215
Controls in both sets of estimations:					
Firm-level controls	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓

Notes: Panel A shows results from regressions of the employers' year-on-year employed inventors growth rate on the employers' average historic MIP in excess of market expectation in a firm-year panel for the 2005-14 period. The firm-specific MIP (henceforth, *FS-MIP*) is calculated as the z-standardized average ϵ_{is} from Equation 2 over all patents filed by employer i in the past. Table IA.12 in Internet Appendix C shows that *FS-MIP* does not predict employers' employed *non*-inventors growth rates. Panel B shows results from regressions of the employers' number of patent filings (upper part) and forward citations (lower part) accumulated over the 2008-12 period on the employers' *FS-MIP* over the 1998-2002 period. Results in columns (1), (2) and (3), and (4) and (5) are for the full sample, employers with high and low technological complementarity, and employers in product markets with high and low levels of competition, respectively. Standard errors in parentheses below coefficients are heteroscedasticity-adjusted and clustered at the inventor level. *, **, and *** denote significance at the 10%, 5%, and 1% 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).[10] 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):

$$\underbrace{V}_{\text{Compensation (``\textit{\textbf{V}ergütung}'')}} = \underbrace{E}_{\text{Invention's value (``\textit{\textbf{E}rfindungswert}'')}} \times \underbrace{A}_{\text{Inventor's relative contribution (``\textit{\textbf{A}nteilsfaktor}'')}} \tag{3}$$

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 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.

[10] 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.

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.3 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)**

	∅ 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	0.406	0.491	0	0	1	0	1
High competition (1/0)	300,773	0.405	0.491	0	0	1	0	1

Table IA.3: **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. Table IA.4 shows that the quality of sample patents is similar to all other patents filed in the same time frame in Germany. Table IA.5 reports the full set of coefficients obtained from estimating Equation 1. Tables IA.7 – IA.8 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.9 and Figure IA.2 show how variation in the MIP related to observable inventor characteristics. Similarly, Table IA.10 reports how the MIP differs for inventors that work in the same company as the control group inventors. Further, it shows that the main effects are stable across different team sizes. 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.4: **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

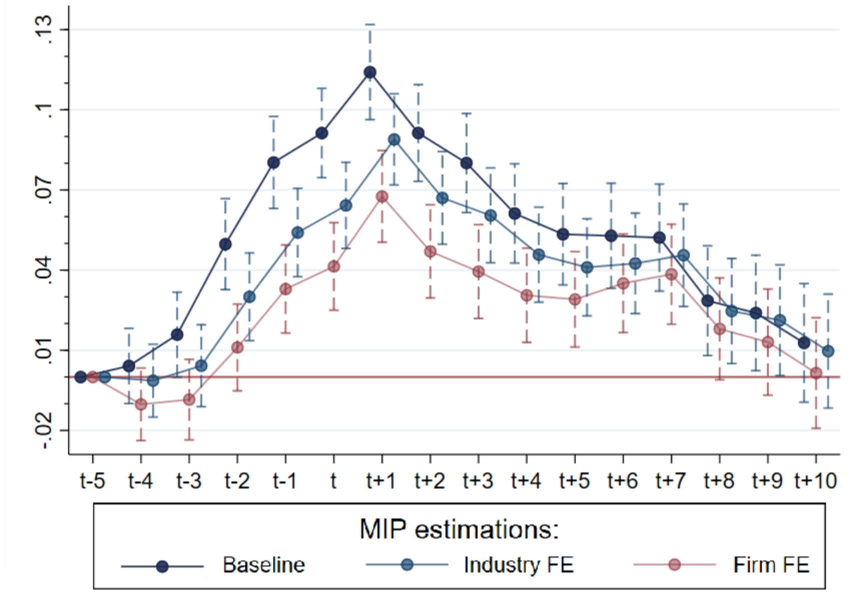
Notes:
The table displays estimates on differences in patent quality of sample patents filed by employee inventors in the treatment group and all other patents filed in the same year cohorts, i.e., between 1998 and 2003, by any out-of-sample inventor in Germany. The dependent variable is the logarithm 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.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.

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.6: **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)
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

(*Continued on next page*)

Table IA.6 *continued*

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 %
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

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%
Strata FE	✓	✓	✓	✓
Mincer controls	✓	✓	✓	✓
Interaction components	✓	✓	✓	✓
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.7: **Treatment Effects interact with patent quality**

Dependent variable:	*ln(Wage)*					
	(1)	(2)	(3)	(4)	(5)	(6)
Diff-in-diff variables:						
Inventor × post	0.054***	0.002	0.094***	–0.015	–0.024	–0.015
	(0.007)	(0.011)	(0.010)	(0.011)	(0.017)	(0.016)
Inventor	-0.039***	0.016	-0.094***	0.037***	0.042**	0.029*
	(0.008)	(0.012)	(0.011)	(0.012)	(0.018)	(0.017)
Post	0.244***	0.259***	0.223***	0.219***	0.216***	0.225***
	(0.005)	(0.007)	(0.008)	(0.008)	(0.010)	(0.012)
Interact with MIP determinants:						
complementarity				0.065***	0.037**	0.090***
				(0.012)	(0.016)	(0.017)
Inventor × complementarity				-0.118***	-0.064***	-0.162***
				(0.016)	(0.025)	(0.022)
Post × complementarity				-0.010	0.014	-0.038**
				(0.011)	(0.015)	(0.016)
Inventor × post × complementarity				0.092***	0.045*	0.127***
				(0.015)	(0.023)	(0.021)
competition				-0.137***	-0.160***	-0.107***
				(0.011)	(0.015)	(0.018)
Inventor × competition				-0.052***	0.009	-0.108***
				(0.016)	(0.024)	(0.023)
Post × competition				0.061***	0.085***	0.026
				(0.011)	(0.014)	(0.017)
Inventor × post × competition				0.051***	0.001	0.103***
				(0.016)	(0.023)	(0.022)
Mincer controls:						
Education	0.040***	0.042***	0.038***	0.041***	0.043***	0.039***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Experience	0.049***	0.048***	0.050***	0.048***	0.047***	0.048***
	(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***	4.684***	4.654***	4.720***
	(0.011)	(0.015)	(0.016)	(0.012)	(0.017)	(0.019)
Sample (citations):	*All*	*Zero*	*Non-zero*	*All*	*Zero*	*Non-zero*
Strata FE:	✓	✓	✓	✓	✓	✓
Observations	304,626	143,458	161,161	300,773	141,644	159,129
Adjusted R^2	0.343	0.368	0.353	0.347	0.371	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.

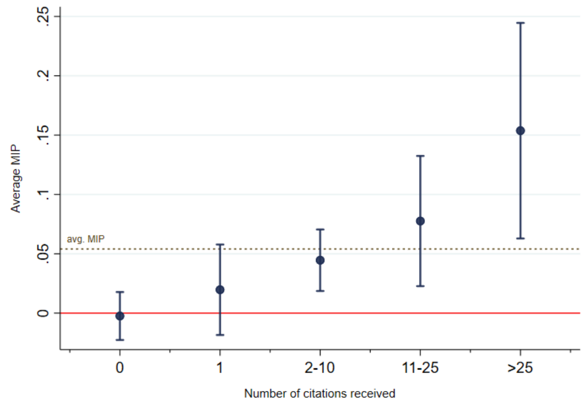
Table IA.8: **Robustness tests for the baseline estimates: Triple-interactions**

Dependent variable:	*ln*(Wage)				
	(1)	(2)	(3)	(4)	(5)
Inventor $\times$ post	0.003	-0.016	-0.066***	-0.058***	-0.049***
	(0.011)	(0.011)	(0.014)	(0.014)	(0.014)
Inventor $\times$ post $\times$ Non-zero-citations	0.092***		0.101***	0.093***	0.090***
	(0.015)		(0.016)	(0.016)	(0.015)
log(Citations)		0.010***			
		(0.002)			
Inventor $\times$ post $\times$ complementarity		0.092***	0.101***	0.098***	0.085***
		(0.015)	(0.016)	(0.016)	(0.016)
Inventor $\times$ post $\times$ competition		0.052***	0.048***	0.058***	0.052***
		(0.016)	(0.017)	(0.016)	(0.016)
Strata FE	✓	✓	✓	✓	✓
Mincer controls	✓	✓	✓	✓	✓
Interaction components	✓	✓	✓	✓	✓
Firm- and industry controls				✓	✓
Year FE					✓
Observations	304,626	300,773	300,773	296,796	296,796
Adjusted R^2	0.343	0.347	0.300	0.328	0.377

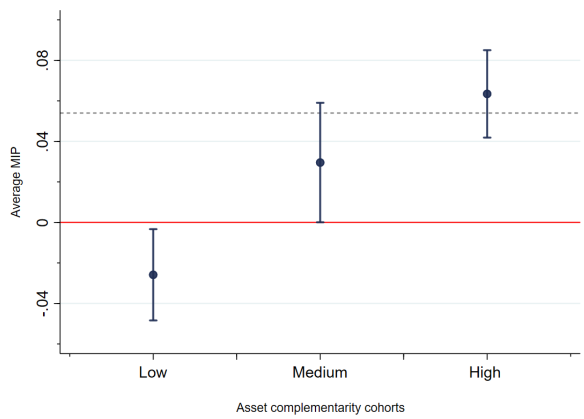
Notes: The table displays robustness tests on the baseline findings displayed in Table 1. Different to before, the estimations include interactions with the *Non-zero-citations* dummy referring to all inventors with patent filings that receive at lease one citation within the first ten years after filing. 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**

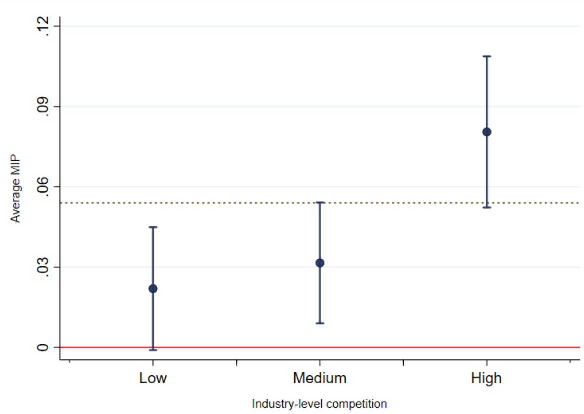
Panel A: Citation cohorts



Panel B: Firm-level complementarity cohorts



Panel C: Industry-level competition 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 three groups of the focal employers' asset complementarity distribution. Complementarity is measured by the size of the patent stock in the technology class of the focal inventor. 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.9: **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.

Table IA.10: **Treatment heterogeneity: team structure**

Panel A: Within- and across firm inventor returns

Dependent variable:	*ln*(Wage)					
	Colleagues as controls			Firm-outsiders as controls		
	(1)	(2)	(3)	(4)	(5)	(6)
Inventor × post	0.109***	0.054**	0.149***	0.020**	–0.030*	0.062***
	(0.013)	(0.022)	(0.018)	(0.009)	(0.013)	(0.013)
Citation cohorts:	*All patents*	*Zero-citation*	*Non-zero-citation*	*All patents*	*Zero-citation*	*Non-zero-citation*
Mincer controls	✓	✓	✓	✓	✓	✓
Strata FE	✓	✓	✓	✓	✓	✓
Interaction components	✓	✓	✓	✓	✓	✓
Observations	100,382	41,022	59,360	200,391	100,622	99,769
Adjusted R^2	0.310	0.332	0.316	0.344	0.371	0.369

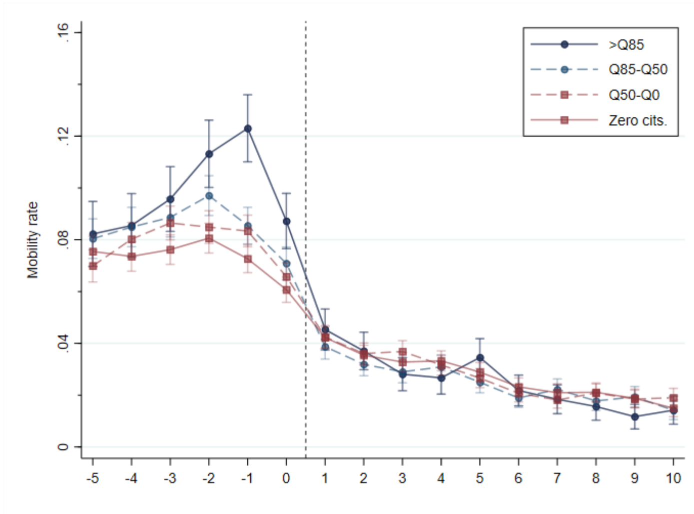
Panel B: Team size - the number of co-inventors and the MIP

Dependent variable:	*ln*(Wage)					
	(1)	(2)	(3)	(4)	(5)	(6)
Inventor × post	0.037*	0.054***	0.057***	0.055***	0.056***	0.059***
	(0.020)	(0.009)	(0.015)	(0.008)	(0.009)	(0.011)
Inventor × post × $\text{Team}^{\text{solo}}$				–0.013		–0.017
				(0.022)		(0.023)
Inventor × post × $\text{Team}^{\text{large}}$					–0.006	–0.010
					(0.015)	(0.016)
Team size (nbr. inventors)	Solo (1)	Medium (2-4)	Large ($\geq$ 5)	Any		
Mincer controls	✓	✓	✓	✓	✓	✓
Strata FE	✓	✓	✓	✓	✓	✓
Interaction components	✓	✓	✓	✓	✓	✓
Observations	39,683	191,054	73,880	304,626	304,626	304,626
Adjusted R^2	0.411	0.356	0.381	0.343	0.343	0.343

Notes: Panel A displays how the baseline estimates vary, depending on whether treated and control group inventors work for the same employer. Specifically, Columns 1-3 and Columns 4-6 repeat Columns 1-3 from Table 1 for two different subsamples. Columns 1-3 use only inventors who work at the same firm as their matched control group inventor at the time of the patent filing. Columns 4-6 use only inventors and their matched control group peers that do not work in the same company in the year of the patent filing. Panel B displays the absence of significant treatment heterogeneity across inventor team sizes, measured by the number of co-inventors on the focal patent. In the sample, the average (median) team size is 3.6 (3). The regressions are similar to the baseline specification in Column 1 of Table 1. Columns 1-3 use different subsamples depending on the number of inventors on the focal patent, distinguishing solo inventors (Column 1), teams of 2-4 inventors (Column 2), and teams of at least five inventors (Column 3). Columns 4-6 use the full sample, but add a different sets of triple interaction terms, estimating the additional effect of solo inventors ($\text{Team}^{\text{solo}}$, Column 4), large inventor groups of at least five inventors ($\text{Team}^{\text{large}}$, Column 5), or both effects simultaneously (Column 6), respectively. In both panels, all regressions control for the interaction components without displaying the estimated coefficients. 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.

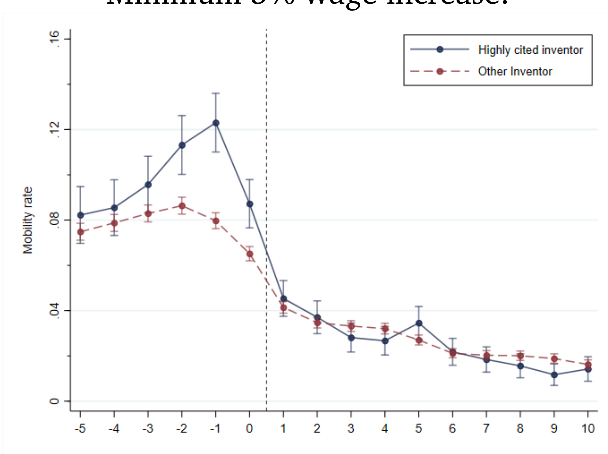
Figure IA.3: **Robustness tests on mobility patterns**

Panel A: Alternative definition of citation cohorts

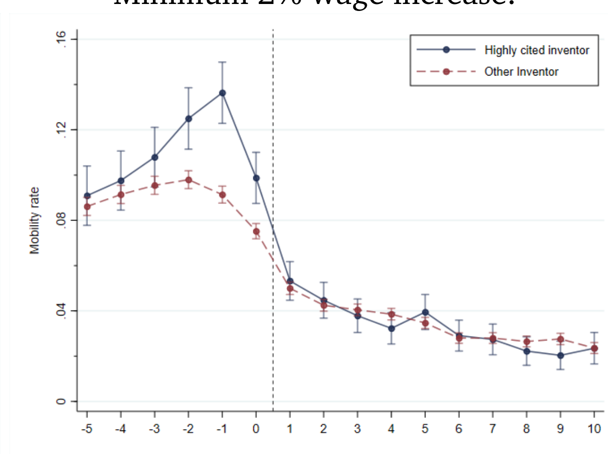


Panel B: *Voluntary* employer changes

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 $\times$ 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 $\times$ post $\times$ pre-mover	0.086***	0.000			0.087***	0.001				
	(0.021)	(0.023)			(0.024)	(0.025)				
Inventor $\times$ post $\times$ post-mover	-0.031	0.009	-0.050	0.025						
	(0.025)	(0.028)	(0.033)	(0.037)						
Inventor $\times$ post $\times$ 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 $\times$ post $\times$ 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 $\times$ post $\times$ pre-mover$^{[-5,-4]}$									0.063***	0.029
									(0.034)	(0.033)
Inventor $\times$ post $\times$ 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.	0.164	0.223	-0.135	0.032	-0.136	0.077
	(0.169)	(0.159)	(0.163)	(0.127)	(0.188)	(0.160)
complementarity	-0.998***		-0.969***		-1.042***	
	(0.214)		(0.215)		(0.222)	
FS-MIP, z. × complementarity	0.715***		0.709***		0.326	
	(0.229)		(0.229)		(0.246)	
competition		-2.155***	-2.106***			1.781**
		(0.647)	(0.650)			(0.759)
FS-MIP, z. × competition		0.606***	0.566**			-0.061
		(0.223)	(0.223)			(0.235)
Firm-level controls	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
# Firm-year obs.	14,567	14,567	14,567	14,567	14,567	14,567
$Adj.R^2$	0.048	0.047	0.048	0.067	0.068	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***	0.073***	0.014	0.051***	0.038*
	(0.014)	(0.021)	(0.018)	(0.018)	(0.021)
Firm-level controls	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
# Firm obs.	2,690	1,692	977	1,233	1,451
$Adj.R^2$	0.271	0.305	0.017	0.282	0.264

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***	0.147***	0.058	0.150***	0.047
	(0.025)	(0.039)	(0.043)	(0.035)	(0.036)
Firm-level controls	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
# Firm obs.	2,666	1,765	1,002	1,265	1,531
Wald Chi^2	563.65	352.50	46.58	207.82	430.09

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.

Table IA.14: **Mobility and Complementary Assets**

Dependent variable:	Complementary assets			
	Total (in logs)		Share of total	
	(1)	(2)	(3)	(4)
Inventor × post × pre-mover	0.360***	0.173**	0.025***	-0.013
	(0.083)	(0.087)	(0.009)	(0.010)
Inventor × post × post-mover	-0.324***	-0.390***	-0.065***	-0.053***
	(0.112)	(0.116)	(0.012)	(0.015)
Inventor × post	0.306***	0.158***	0.035***	0.023***
	(0.036)	(0.069)	(0.005)	(0.006)
Citation cohorts:	Non-zero-cit.	Zero-cit.	Non-zero-cit.	Zero-cit.
Mean dep. variable:	2.986	2.557	0.225	0.214
Strata FE	✓	✓	✓	✓
Mincer controls	✓	✓	✓	✓
Interaction components	✓	✓	✓	✓
Observations	139,273	124,144	139,273	124,144
Adj. R^2	0.325	0.324	0.151	0.156

Notes: This table presents estimates on the effect of inventor mobility on their employer's complementary asset stock. The dependent variable, inventor-employer asset complementarity, is measures as the total number of patents (1+logs.) in the technology class of the focal inventor (Columns 1-2) or the share of respective patents among the total patent stock of the employer (Columns 3-4). The estimation specification is equivalent to Columns 1-2 of Table 2, distinguishing inventors with and without cited patents. 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.