Erasmus
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Erasmus University Rotterdam

Bachelor Thesis International Business Economics and Economics

Do MNC's manage cross border labor mobility better?
The effect of labor mobility on individual performance across organizational types

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Date final version: [01-02-2022]

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Abstract

This paper explores the effects of labor mobility on individual inventors' performance measured in citation weighted patents. Using a 41 year long EPO panel dataset, three types of movers are investigated. Regular movers making a move to hiring firm, international movers who move to a firm abroad, and MNC movers who move to a different subsidiary of the same organization. Through a fixed effects estimation, regular movers are revealed to experience a reduced performance equal to about 9% of the mean citation weighted patents in the first 6 years at their new firm. This suggests the presence of Firm Specific Human Capital. MNC's manage labor mobility the best, with mobility increasing inventor performance by 5% of their average career performance, responsible for about 10% potential market value increase for the firm.

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1. Relevance and literature review

Knowledge is an intangible resource that inhibits nearly all human activity. In modern economics, the new growth theory recognizes knowledge as a key determinant to sustainable long run growth. As knowledge can be used endless times without depletion, it is a non-rival factor of production. Combining such a factor with rival ones leads to increasing returns to scale, implying economic growth. (Romer, 1989)

On a firm level knowledge is also recognized as a real resource. Acquiring knowledge can complement the rival factors of production and improve overall firm performance. Learning by Hiring (LbH) is a procedure where firms strategically hire human capital possessing new know-how, in order to diffuse this across the organization. LbH has received significant attention in scientific community, with results suggesting the process to be potentially beneficial for firms. LbH is found to have a positive effect on single worker productivity (Markusen & Trofimenko, 2009), knowledge diffusion and overall firm productivity (Parotta & Pozzoli, 2012) for the hiring firm. A major limitation of these findings is that they are sector and location contingent, challenging their external validity. (Rosenkopf & Almeida, 2003)

This concern in part is addressed by literature on knowledge spills. Knowledge spills are externalities, meaning that they are not valued by the open market as for instance the LbH process is. Such research often exploits patent citation data. Patent citation datasets contain detailed information about the patenting and citations activity, geographical location and collaborators of all inventors who apply for a patent at the corresponding patenting office. Analysing citation patterns gives an insight in the patterns of knowledge flows. Jaffe, Trajtenberg and Henderson pioneered this approach in their 1993 paper, analysing the role geographical proximity plays in mediating knowledge spills. Their findings suggest that knowledge spills are more likely to occur within a geographical proximity. This further rationalizes the existence of industry specialized clusters. (Baptista & Swann, 1998)

It is more abstract to draw conclusions based on such data on the firm or national level. The unit of analysis of such studies is patenting citations, which is complicated to evaluate from a firm perspective. Oettl and Agrawal face this exact problem in their 2008 paper. They investigate the knowledge flows resulting from international labour mobility on the firm and national levels. A conclusion of their paper is that further research is needed to aid the interpretation of their results measured in patenting citations. This paper's purpose is to function as such a work, while also extending on Oettl and Agrawal's final hypothesis. The final 'firm learning diaspora' hypothesis investigates the knowledge flow effects of within-firm international labour mobility. This type of mobility occurs when a patent producing scientist moves to a different subsidiary within the same multinational corporation (MNC). A higher level of knowledge flows was concluded for this hypothesis, suggesting that MNC's can manipulate knowledge flows to certain extent. Further investigation could reveal how big of a role knowledge flow management play in the rationale for the existence of MNC's. This paper furthers this conclusion specifically on the inventor level. Patenting literature often examines the effects of labour mobility from the firm's perspective. This leaves a gap from the inventors' perspectives: what impact does mobility have on their patenting performance? Such questions are usually addressed in narrower contexts. For example, in their 2008 paper Groysberg, Lee and Nanda estimate the performance decline of Fortune 500-star analysts as a result of a firm switch. They find a significant performance decline up to five years after their move. This finding suggests that for individual analysts' mobility has have adverse effects on performance. The scientific community has yet to generalize this finding over a broader set of employers. Patent producing inventors are ideal for this next step in generalization. First off, inventors are usually also high performing workers, often providing measurable gains in firm value. (Hall, Jaffe, & Trajtenberg, 2005) Secondly, patenting inventors are employed in a huge range of industries. Using patent citations data will hence extend the external validity of the findings. Synthesizing these reasons with the aim to further our understanding regarding MNC knowledge flow management results in the central question of this paper:

Can MNCs significantly reduce the settling period of inventors after a cross border move in comparison to generic cross border hires?

To fully understand the research question, it is essential to understand the theoretical framework of human capital. The Firm Specific Human Capital and General Human Capital theory are the most prominent theories in this regard, both having received an abundance of scientific backing in the past. These theories are born from a firm perspective but have important implications on knowledge flows. In the upcoming sections these underlying theories will be discussed in depth.

1.1 Firm-specific Human capital

Firm specific human capital poses that overall firm success in general is more dependent on organizational capital as opposed to employees their individual excellence. Such capital could include the management, bureaucratic infrastructure, core values and the culture of a firm. Organizational capital gives a structure to employees to perform their tasks in. This is seen as essential, in order to improve individual worker productivity. Workers need experience to build up a firm-specific skillset, which is purely the understanding how to use the organizational capital of their respective firm to their advantage. Human capital with this skillset has developed their capital in a firm-specific way. They can perform at a higher level within that specific firm, but their skill to exploit the organizational capital optimally is not applicable to other employers. Therefore, to achieve its overall goals, a firm should invest heavily organizational capital. It should then recruit and maintain stable workforce that builds up a firm-specific skillset working with the capital. This way the firm can enjoy the organizational and human capital synergies, boosting overall performance.

Highly relevant empirical support is provided by Huckman and Pisanos' 2006 paper, where freelance heart surgeons' performance is examined at various hospitals. Heart surgeries are a relatively repetitive and similar task, thus performance variation across hospitals is expected to be low. In contrary, surgeon performance is found to be dependent on the quantity of surgeries the surgeon accumulated at a specific institution. This is evidence of the surgeons building up an experience with the capital at specific hospitals, and becoming improving their abilities in the process. Surgeons work more effectively once they are more acquainted to the equipment and workforce at an institution. Altogether these points at the presence of a firm-specific ability surgeons build up over time, which boosts their performance.

A similar conclusion can be drawn from Groysberg, Lee and Nanda's 2008 article analyzing data of Fortune 500 star financial analysts. Performance is estimated through top rankings chosen by industry insiders. In the first section, firm switching analysts' rankings were compared non-switching ones. Switching stars were found to have a negative effect on their ranking, up to five years after the switch. The work analysts did at their new employers was essentially identical in nature, leaving the organizational capital attributable to the decline in performance.

From the individual inventor perspective, it is clear that organizational capital plays a role in performance in certain industries. Thus, over time a firm-specific expertise is built up which is allows inventors to perform at their baseline level. Cross-firm mobility could hamper this performance since this firm-specific expertise needs to be re-learned at their new employer. Thus, our first hypothesis (H1) states:

Hypothesis 1 (H1): Firm switching inventors suffer a decline in patenting performance subsequently to their switch, marking an adjustment period

1.2 General Human capital

The general human capital theory places individual excellence at the center of an organization's success. Certain individuals, often referred to as stars seem to be naturally more productive and skilled as compared to others. Allowing these stars to excel without boundaries is the most effective way to benefit from such employees. Thus, developing extensive organizational capital could impede the performance of the workforce. Firms should instead focus on perfecting their recruitment and maintaining their current talent.

1.2.1 Knowledge mechanics

The underlying framework of the general human capital theory roots from the nature of knowledge and how it is shared. Knowledge can be distinguished into two types, namely codified and non-codified knowledge. The former is organized according to a certain standard, which makes its transfer relatively easy. Examples are a technical drawing following architectural standards, or a research article written according to the guidelines of the journal it is published in. Such codified knowledge is easy to understand and apply for colleagues and counterparts of the author of the drawer. This is because the knowledge is transformed into a communicable product, where it is described explicitly.

On the contrary non-codified knowledge is much more tacit in nature than codified knowledge. This makes it more difficult to codify, and thus more difficult to share. Examples could be the know-how of what spice a dish needs or how to shake a test tube to achieve a desired effect in a specific scientific experiment. It is possible to learn both these skills, but it requires experience and, often the physical presence of the holder of the knowledge. Much of this knowledge is implicit, making it difficult to describe and transfer.

The general human capital theory proposes that star employees possess such tacit knowledge. Such employees are naturally talented in their field and as such have more unique codified knowledge. Such information can be essential to firm success. If an employee has a superior skillset, it is in the firms' interest to diffuse this over the whole organization. While codifying knowledge can be a solution for this, it is a time intensive process, and in some cases impossible due to the very implicit nature of it. (Agrawal, 2006)

To effectively disseminate non-codified knowledge, one needs to engage with the owner of it. Empirical evidence shows that the aforementioned knowledge spills, occur in a highly localized pattern. Dissemination of existing knowledge is thus more likely to happen in the geographical proximity of the “holder” of this knowledge rather than further away. Knowledge spills are strongly concentrated in industry clusters, explaining the innovative capacity of regional clusters such as Silicon Valley. (Gleaser, Kallal, et al. 1992) This is because knowledge dissemination is strongly mediated by social relationships. It is much more likely that an idea a colleague or friend describes during lunch can be replicated successfully, opposing to an idea a professor across the globe describes in a scientific journal. Such conclusions have mostly been drawn from innovation intensive industries, exploiting patent citations data. (Jaffe et al. 1993; Thompson& Fox-Kean, 2005) (Almeida & Kogut 1999)
Hence, it is clear that social relationships, which are more likely to be maintained in a close proximity to a worker play role in the flow of knowledge. Literature has explored how these flows behave when a patent producing scientist makes a cross border move. In their previously mentioned 2008 paper, Oettl and Agrawal analyse knowledge flow trends of mobile inventors. For international movers, results show that the country of the hiring firm receives extensive knowledge flows from the previous ‘source’ firm the inventors worked at. Thus, knowledge flows are mediated by the social network an inventor builds up, and is not limited by firm boundaries.

The question that remains is how the moving inventors’ individual performance is affected in the process. An international move could disturb an inventor’s social life. On the one hand, due to the distance it is more difficult to engage with their previous circle, which is essential in acquiring new ideas which are essential in inventor performance. On the other hand, an international move does not only transcend firm and national boundaries, but also cultural ones. In a 1982 empirical analysis of 150 foreign language students in Britain Furnham and Bochner investigate the presence of a culture shocks in the visiting students. A culture shock in essence relates to the difficulty experienced by an individual when adapting to a new cultural context. The results found that the students experience a cultural shock which materializes in two ways. First off, they have a limited level of interaction with nationals from the host country. Secondly, such relationships that are maintained have a lower quality, meaning that they are of a functional rather than leisurely nature.

Internationally moving inventors are more likely to face such cultural contrasts after their move rather than regular interfirm movers. This could leave international movers more often isolated from a social circle, on the one hand leaving behind their old colleagues, and on the other struggling to integrate into their new social environment. This is likely to limit the effective transfer of know-how and ideas temporarily to the mover. With knowledge and know-how playing a central role in the performance of inventors, this will put international movers at a further disadvantage until a new

social network is built at their new firm. To counter this effect, hiring firms will likely make efforts to integrate foreign hires effectively into the organization. The effectiveness of such countermeasures is not conclusively clear yet, leading to our second hypothesis (H2):
(Oettl & Agrawal, 2008) (Singh & Agrawal, 2010)

<u>Hypothesis 2 (H2): Inventors moving to a firm abroad suffer a stronger decline in patenting performance on the short term after their switch than regular moving inventors</u>

1.3 MNC subsidiary mobility

So far it has become clear that switching firms for an inventor is likely to cause adverse performance effects due firm-specific human capital. Moving to a firm abroad likely leads to a more severe performance drop, due to the social network disruption of inventors. However, despite these costs borne by the individual employee, a cross border move still brings great benefits for the hiring firm[1]. Cites to new hires' previous patents are found to increase by 219% on average, showing evidence of effective learning by hiring. (Singh, & Agrawal, 2011)[2] Oettl and Agrawal in their 2008 paper found that more knowledge flows resulted from a cross-border within-firm move to the "source" firm. These moves occur between two subsidiaries of an MNC. Twice as many backwards knowledge flows were found to the source firm in the case of an MNC move compared to regular cross-border hires. This reveals that MNCs have the ability to better manage knowledge flows for workers moving internationally within their firm. The foremost underlying reason for this is the fact that MNC subsidiaries have a strong collaborative network with one another. As such, prior to the mobility of an inventor a cooperative relationship is possibly built up between the mover and the receiving subsidiary. Such relationships allow a mover to integrate more seamlessly into social environment of the hiring firm, allowing for more effective adaptation and knowledge dissemination. This is much less likely to occur on a systematic level for an interfirm cross-border movers.

The implications of this on individual performance is complex to extrapolate because of limited scientific research on the matter. However, the mechanics of the previously discussed determinants of individual performance can still be applied. Considering firm-specific human capital relating to H1, MNCs are a network of copies of the same firm transcending national borders. Significant efforts are made to keep the organizational capital constant across subsidiaries. Therefore,

[1] The source firm and country are found to benefit as well in terms of backwards knowledge flows. However, all knowledge flows are an unpriced externality and firms are highly unlikely to consider backwards flows. (Oettl, Agrawal, 2008)

specific skills built up by inventors at one subsidiary will be applicable at a different subsidiary. This is likely to reduce the intensity of adjustment periods of MNC movers.

Regarding social network effects, MNC subsidiaries generally collaborate more frequently with one another as compared to two randomly chosen firms with varying nationalities. This gives MNC inventors opportunities to acquaint themselves with future colleagues prior to their move. MNCs also maintain global employee network, in order to encourage collaboration and knowledge transfer across subsidiaries. (Oettl & Agrawal, 2008) These will possibly allow an MNC hire to integrate into the social network of the hiring subsidiary more easily, hence diminishing social network effects. Altogether this leads to the third and final hypothesis (H3).

<u>Hypothesis 3 (H3): MNC cross-border hires suffer from less severe adjustment periods in comparison with inter-firm cross border hires</u>

2 Research methodology

2.1 Data

The data source used for the empirical analysis is the OECD REGPAT March 2018 database. This is comprised from multiple existing patent databases published by the European Patenting Office (EPO). It contains detailed information regarding patents applied for between 1977 and 2018. Due to the vast size of the full REGPAT file, only specific sections of the available data are acquired which are then merged. For patents' inventor specific information including the address, name and patenting share the OECD inventor source file is used. For information relating to the firm that the patent is applied for, the EPO International Patent Classification (IPC) and the application registry files are used. These files reveal the geographical location of each firm, and the technological IPC classification of each patent. (www.wipo.int) At last, in order to gauge the significance or value of patents, the citation statistics per patent as of 2018 were merged to the dataset.

These operations resulted in a forty-one yearlong panel dataset, giving insights in 3,569,530 inventors who have filed for over 83,400,000 patents in this period, affiliated to 309,587 firms located in 228 countries. In the upcoming section the necessary data transformations are described, to fit the exact purposes of this paper.

2.2 Sampling

In order to avoid errors in the analysis certain sections of the aforementioned dataset are excluded from the final sample in the analysis.

Initially, all patents with missing inventor names are dropped from the sample. To judge the development of the performance through their careers, identifying the correct individual is of essence, leaving no room for error. Another requirement for this is that inventors appear multiple times in the sample, to follow their performance over time. Hence, inventors in the sample must be affiliated with multiple patents. As such, all inventors who appear only once in the whole dataset are excluded. This implies that inventors only affiliated with only 1 (share) of a patent are dropped. With these two operations over 1,261,177 inventors remain in the final sample, amounting to about 35% of the initial amount. After these sampling steps the variables for the empirical model are constructed.

2.3 Variables

2.3.1 Dependent variables

The key requirement the dependent variable needs to fulfil is its ability to capture the individual performance of inventors. Considering the chosen dataset, the yearly citations weighted patenting output of each inventor is used for this purpose. Research has previously underlined that not all patents are of the same in their value to a firm. Patents and their significance can vary tremendously, conditional on many variables, some of which unobservable. This exact concern is addressed by Hall, B. H., Jaffe, A., & Trajtenberg, M. in their 2005 paper. Building an empirical market valuation model, using patent, citation, and market value data they find a 3% increase in market value per citation. Hence, citation counts offer somewhat of an indication of a patent's value. Thus, by weighing patenting output by citations a more accurate insight can be gained about the value which an affiliated scientist delivered for his/her firm. This variable is very simple to obtain from the dataset. The patent shares each inventor holds, which is one (the patent) divided by the total quantity of its inventors, is multiplied by the total citation count. This is repeated for each patent an inventor is affiliated with, revealing to citation weighed patenting activity of all individuals. This is summed on a yearly basis, holding the patent application year as a reference. Through this procedure we arrive at our dependent variable, citation weighted yearly patents, which serves as a proxy for performance.

Another trend visible in the data is missing years for inventors, where they were not affiliated with any patents. These years are simply not observed in the sample, leaving only patent productive years as observations. Rather than "completing" the panel by filling in zeroes for non-productive years, the sample is left as it is. The reasoning behind this is the chosen empirical model, which will be discussed in the upcoming sections.

2.3.2 Independent variables

Considering that all hypotheses include labor mobility as independent variable, the general procedure in obtaining them is very similar. In the process of finding our independent variable, the data is converted to a long panel format. This format observes each individual inventor for each year that they have invented a patent. Thus, by chronologically testing whether the companies affiliated with the individual's patents change throughout the panel could reveal various kinds of mobility. Table 1 gives a comprehensive overview for all subgroups the inventors are classified in.

If the previous year's affiliated company name does not match the current, then in the current year a move is recorded. As an example, if an inventor invents a patent in 2006 for Royal Philips N.V., and in his/her next year of patenting activity, in 2008, an invention is made for Akzo Nobel, the *move* variable indicates a 1 in 2008. In all years where the inventor invents a patent for the same affiliated firm the, the *move* variable indicates a 0. For interfirm mobility used in the analysis for H1, this methodology results to 4,289,396 moves.

For H2, in order to detect international moves the same procedure is applied, only matching the country codes in which the companies are registered. As an example, if an inventor invents a patent in 2006 for any firm with a Dutch country code, and in his/her next year of patenting activity, in 2008, an invention is made for a firm with a French country code, the *move_international* variable indicates a 1 in 2008. In all years where the inventor invents a patent for the same affiliated firm the, the *move_international* variable indicates a 0. Over 172,679 international moves are detected throughout the sample, marking cross border mobility.

H3 requires the identification of MNC movers. Hence a move that is made across borders, but within the same firm. In this case the international moves methodology was combined with the requirement that the company name remains constant despite the new geographical location from which the patent is applied. Thus, if an inventor invents a patent in 2006 for Royal Philips N.V. with a Dutch country code, and in his/her next year of patenting activity, in 2008, an invention is made for for Royal Philips N.V. with a French country code, the *move_MNC* variable indicates a 1 in 2008. In all years where the inventor invents a patent for the same affiliated firm the, the *move_MNC* variable indicates a 0. Over 71,181 MNC moves are identified throughout the sample marking within firm cross border labor mobility.

		Move across countries?	
		Yes	**No**
Move across firms?	**Yes**	*International Move* *(172,679)*	*Move* *(4,289,396)*
	No	*MNC Move* *(71,181)*	*No Move*

Table 1: Inventor classification overview *Note: Below the variable specifications the quantity of the respective variables in the sample is shown.*

To better understand the effects of mobility performance adjustment periods, variables are constructed to evaluate the long-term effects of mobility. Delayed variables for each move type are generated. As an example, for H1, delayed move variables *move(t+1)* up to *move(t+5)* are constructed for each year. These dependent variables mirror their corresponding move variable, but shift it ahead by their indicated years. Hence, if an inventor is detected to be at a new firm in 2006, then the *move* variable indicates a 1 for 2006, and 0 for the previous and upcoming years. *Move(t+1)* indicates a 1 for

2007, *move(t+2)* for 2008, etc. This is repeated for all move types to gain a comparable insight in the adjustment periods of mobile workers.

The generation of these variables brings up a key concern. The *move(t+n)* variable records diminishing observations the higher the delay gets. This is to be expected, as the likelihood of movement occurring over time increases, leaving the subsequent delay variable from previous move irrelevant. Therefore, the delay variables are reset when a new move is made. Rapid mobility can thus have effects on the significance of our delayed findings by reducing the sample size but does not inhibit our sample with errors. What however does, is the select group of rapidly moving inventors, who in certain cases recorded a move in each year of their activity. Because of their behavior it is impossible to gauge the longer-term effects of a move on their performance, as they constantly move away very rapidly. In the most extreme cases of this, inventors move to a new firm each year throughout all of their observable career. These inventors will be referred to as freelance inventors. In most cases, only during a specific part of an inventor's career such rapid movement is observable. Hence for certain parts of their observable career they stay at the same firm for a longer period. Considering that those years are relevant to the analysis, as for example the counterfactual in H1, the decision was made to only drop pure freelancers from the dataset. A minimum of 3-year long tenures subsequent to the move was chosen for this purpose. In appendix table A.2 the sensitivity analysis required for this decision is performed. Summary statistics of the sample with the freelancers is shown in table 2 and without in table 3 below.

2.3.3 Control variables

To isolate the dependent variables' effects on the independent variable, potentially confounding variables are identified and constructed. For this purpose, econometric theory opts for the use of variables that are determined before the treatment and differ significantly between the treated and the control groups. Initially the year control is used. This variable comes in the form of a yearly dummy controlling for year specific trends.

The second control variable is the experience of the inventors. More experience in his/her respective field can mean a more extensive patenting stock and social network an inventor has accumulated. The latter clearly can have an effect on the independent variable, as an inventor integrated in the community of his/her field is more likely to be referred to and cited by colleagues, than someone who is not so well integrated. The former increases the value of an inventor to a hiring firm, as the patenting stock of a new hire can be effectively exploited and diffuse across it.
(Singh & Agrawal, 2011). Thus, by accumulating all years of activity in the sample the yearly *experience* variable is constructed.

At last, the sector and the firm specific controls were constructed. Both these variables can be potential confounders. At firms with more developed organizational capital a higher yearly citation weighed patenting performance could be reached by inventors, while the benefits of this could discourage employees from moving to other firms. As for the sectors, certain disciplines have a higher propensity to patent, which could affect the importance of attracting star inventors. Hence both the firm and the sector in which an inventor works can be correlated to the *move* variables and the citation weighed patents. The firm control is constructed by generating unique identifiers for each *applicant name,* through which the patent is applied for by the inventor. The same procedure holds for the sector control, converting the firms' respective IPC numbers to identifiers. The overview of all constructed variables is visible in tables 2, 3 and 4 below.

Variable	Number of observations	Mean	Standard Deviation	Minimum	Maximum
1. Citation weighted patents	3,576,577	8.198	23.030	0	9,178.578
2. Move	3,576,577	0.257	0.437	0	1
3. International Move	3,576,577	0.022	0.145	0	1
4. MNC Move	3,576,577	0.006	0.078	0	1
5. Experience	3,576,578	1.507	2.983	0	38
6. Sector	3,575,735	-	-	1	63,410
7. Firm	3,575,723	-	-	1	272,091

Table 2: Summary statistics of full sample

Variable	Number of observations	Mean	Standard Deviation	Minimum	Maximum
1. Citation weighted patents	1,340,900	8.959	25.360	0	9,178.578
2. Move	1,340,900	0.146	0.353	0	1
3. International Move	1,340,900	0.013	0.114	0	1
4. MNC Move	1,340,900	0.007	0.085	0	1
5. Experience	1,340,900	3.610	4.017	0	38
6. Sector	1,340,900	-	-	1	63,410
7. Firm	1,340,900	-	-	1	272,091

Table 3: Summary statistics of sample used for final analysis

Variable	1.	2.	3.	4.	5.
1. Citation weighted patents	-				
2. Move	-0.039***	-			
3. International Move	-0.015***	0.101***	-		
4. MNC Move	-0.009***	-0.036***	0.739***	-	
5. Experience	-0.006***	-0.019***	0.011***	0.022***	-

Table 4: Correlations of all key variables (Robust standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1)

2.4 Empirical model

The empirical model for the analysis requires to deepen our understanding about the relationship (1) below.

$$Citation\ Weighed\ Patents = f(Labor\ Mobility) \quad (1)$$

$$Y_{it} = \alpha_i + \rho T_{it} + \beta X_{it} + \gamma_t + \varepsilon_{it} \quad (2)$$

Considering that the data a is a panel with abundant years of observation for each individual, a fixed effects regression is used in the analysis. This econometric approach is widely accepted in the scientific community for such datatypes. (Wooldridge, 2010) Therefore, the regression (2) is estimated. The main advantage of this model is the unique constant α_i accounting for individual pre-treatment effects for all inventors. Many unobserved confounders are filtered out through this method, improving this paper's internal validity. The treatment effect of a move, conditional on the hypothesis is estimated through the ρ variable. This estimation is an Average Treatment effect on the Treated, referred to as the ATT. The fixed effects estimation cannot account for time variant confounders. These variables influence the likelihood of an inventor to move, and his/her citation weighed patenting behavior. Within this context examples could be the inventor in question becoming a parent or government grants triggering huge investments into R&D in a specific country. Such factors are time-variant, hence not accounted for in the fixed-effects estimation, and not observed in the data. The potential to such variables has a significant impact on the internal validity of the analysis, which will be further discussed in the conclusion. To minimize the potential of such confounders, time variant control variables are added to the regression. The effects of which, denoted by β in equation 2 are hence accounted for in the estimation. The year dummies accounts for the temporal variation represented by γ. At last, the standard errors will be clustered by individual, and will be time specific.

Considering the aforementioned concern of missing years of observation for scientists, the fixed effects model can account for such inconsistencies. The model detects the application year of patents as the year id, and performs reliable regressions on the basis of this unbalanced panel. Sensitivity checks were performed with a complete and incomplete panel in the appendix table A.1.

3 Results

3.1 Specific Human Capital (H1)

Below in Table 4 the fixed effects regression results are shown for H1. H1 anticipated mobile inventors to have a performance decline due to the adjustment periods to their new organizational. To set a baseline, in model 1, the yearly citation weighed patents of inventors are regressed on the move variables. The initial *Move* variable represents the first year in which an inventor is affiliated to a patent at a new firm. The delayed move variables *Move t+1* up to *Move t+5* are delayed move dummies, allowing the judgement of the intensity and duration of adjustment periods. Move coefficients can be interpreted in the unit of the dependent variable, which is yearly citation weighted patents. The move coefficient in the year of the move is strongly negative at about 3.3 less citations on average for moving inventors and is statistically significant at the 95 level ($p<0.05$). Regarding the adjustment period, the move effect initially seems to diminish, but picks up again in the third year after the year of the move. In the five subsequent years to the move this effect stabilizes around 1 less yearly citation on average for moving inventors because of the move. Noticeable is that this effect seems to somewhat fluctuate, seemingly picking up in the fifth year after the move.

In model 2 the year dummies are included in the model specification. The initial effect of a move is slightly less negative now, at about 3 less patent citations for the first year of the move. Beyond the insignificantly negative effects in the first two years after the move, between the third and fifth year a significantly at the 99 level ($p<0.01$) negative effect can be seen of around 0.5 citation for each year. Again, the adverse performance effect picks up at the fifth subsequent year to the move.
The *move* coefficients are interpreted in terms of patenting performance, the unit of which is yearly citation weighted patents. Therefore, a firm switch leads to a significant decline of about 5[3] citation weighted patents over their year of move and the five subsequent ones.

At last, model 3 is the complete one from the analysis. All time variant controls described in the variables section are added along with the year dummies. The performance dip in the year of the move has picked up to about 3 less patent citations as compared to model 2. The first two years after the move show less significant and insignificant negative coefficients. A slightly more severe performance drop is noticeable in the third up to the fifth year after the move, as compared to model 2. This now fluctuates around 0.4 less patent citations picking up to 0.7 in the fifth year and is significant at the 99 level ($p<0.01$).

This suggest that inventors that switched firms in our sample can expect a severe dip of about 3 patent citations in their first year at their new firm. In the upcoming two years, this on average

[3] Summation of all significant (minimum $p<0.05$) move (and delay) coefficients.

diminishes to slightly negative to insignificantly negative values. In the third to fifth subsequent years to the move the move, the adverse effect still picks up, and reduces inventors' performance by about half a patent citation each year.

Citation Weighted Patents	Model 1	Model 2	Model 3
Move	-3.322***	-2.895***	-3.003***
	(0.081)	(0.079)	(0.078)
Move t+1	-0.768***	-0.045	-0.145*
	(0.080)	(0.081)	(0.082)
Move t+2	-0.782***	-0.053	-0.140
	(0.131)	(0.138)	(0.148)
Move t+3	-1.038***	-0.347***	-0.407***
	(0.114)	(0.112)	(0.111)
Move t+4	-0.982***	-0.341**	-0.380***
	(0.137)	(0.135)	(0.137)
Move t+5	-1.376***	-0.696***	-0.719***
	(0.172)	(0.169)	(0.170)
Year		Yes	Yes
Experience			Yes
Firm			Yes
Sector			Yes
Inventor fixed effects	Yes	Yes	Yes
Observations	1,340,899	1,340,899	1,339,718
R-squared	0.002	0.005	0.005
Number of inventors	372,045	372,045	371,485

Table 4: H1 Individual fixed effects results. *Note: The table above displays the developing effect of a firm switch by inventors in the sample, holding individual inventor fixed effects constant. The independent variable 'Move' denotes the year of the move, with 'Move t+1' up to t+5 the subsequent years. Hence chronologically developing patenting performance effects can be read from top to bottom in each column. The three models are identical, except for their control variables. In model 1, only the move variables are tested. Model 2 includes a year dummy controlling for time fixed effects. Model 3 also controls for inventors' experience, firm, and firm sector fixed effects. Due to some missing variables, the number of observations fall slightly as more controls are added. The Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

In the context of H1, specific human capital seems to play a role in the performance of the chosen sample of EPO inventors. Moving to a new firm clearly results to a negative shock in patent citations. Thus, there is not enough evidence to reject H1.

The adverse performance effect fluctuates throughout the first five subsequent years of their move, impacting movers negatively. This suggests that adjusting to new organizational capital can be quiet a lengthy procedure, taking over five full years. Quantifying the cost of a move in terms of citations, in total a move costs inventors around 4.5 average patent citation in their first six years at their new firm. Interpreting this from the inventor perspective value is rather difficult. Inventors most likely value citations to a varying extent, depending on their individual characteristics. As an example, an inventor with a relatively low number of patent citations attaches much more value to one additional citation than one with hundreds.

In an attempt to generalize however, in the 41-year panel the mean citation weighted patent production is about 50. For the average inventor this puts the cost of moving at about 9% of their careers captured in the sample. This value is quite significant and highlights the serious costs inventors incur due to interfirm mobility. Important to note is however, that this is likely to be a high estimate. Inventors often apply for patents outside of the EPO, and the panel is more likely to capture only a fragment of their career rather than the full picture. As such, the real average career citation weighted patent output is likely to be above the 50 in this sample, pushing the 9% effect down as well.

Individual performance declines also have an adverse effect on firm performance. Taking the previously mentioned 3% market value increase a patent citation can give a firm, a potential 14%[4] market value increase potential can be missed by the hiring firm, assuming all of these citations would have been made on patents affiliated with the inventors hiring firm. This value is about 7% when the assumption loosened, to half of these citations corresponding to the hiring firm. Taking the value between the two, a roughly 10% of market value regular productive capacity of patenting inventors can be expected by hiring firms. (Hall, Jaffe, & Trajtenberg, 2005)

3.2 Social network effects (H2)

The empirical results of H2 are shown below table 5. H2 anticipates international movers to have a more severe shock in their performance due to the physical distance from their old social network. The sample is unchanged, keeping non-movers as the baseline.

Model 1 displays the simplest estimation, only including the dependent and independent variables. International movers on average suffer a penalty on their citation weighted patenting performance in their move year of about 2.5 (significant at the 99 level, p<0.01). Surprisingly a positive and significant at the 99 level (p<0.01) coefficients can be read for the first up to the fifth years proceeding the move. The net effect of moving internationally as compared to nationally is positive, suggesting that interfirm movers on average suffer more in terms of patent weighted citation performance from the simplest model’s estimation.

In model 2 the year dummy is added. The move year international move coefficient is still significant on the 99 level (p<0.01) but more negative, at around 3 citation weighted patents. The following show slightly positive and mostly insignificant coefficients. In the first two years after the move, some of the performance loss is recouped, cross border movers outperforming withi border

[4] $= 1.03^{4.5}$ each citation has the theoretical ability to increase the firm’s market value by 3%, considering a penalty of about 45 citations

interfirm movers by about 1 citation weighted patent (minimum significance at the 90 level (p<0.1). Overall, in model 2 the net effect of an international move is a negative 2 citation weighed patents over the five-year period as compared to within border interfirm movers (excluding insignificant coefficients).

Model 3 is the most complete model, once again adding all controls along with the year dummies. In this case however the decision has been made to exclude the sector control, as the vast majority of these effects are already accounted for by the firm dummy. In appendix table A.4 the sensitivity analysis verifying this is visible. The model 3 results are approximately in line with those of model 2. The coefficients mostly display similar results and significance. A negative effect of about three less citation weighed patent in the move year is compensated by a positive effect of a similar magnitude in the following two years, though these coefficients are less significant. The following period shows insignificant slightly positive coefficients up to the fifth year after the move. Here the most pronounced negative effect hits in, with an on average negative 1.7 citation weighed patent penalty of moving internationally as compared to nationally. The net effect throughout the years is the same negative 2 citation weighed patent as found in model 2.

Citation Weighted Patents	Model 1	Model 2	Model 3
International Move	-2.386***	-2.608***	-2.596***
	(0.198)	(0.199)	(0.199)
International Move t+1	1.318***	0.461*	0.461*
	(0.256)	(0.258)	(0.258)
International Move t+2	1.628***	0.654**	0.674**
	(0.307)	(0.309)	(0.309)
International Move t+3	1.342***	0.154	0.204
	(0.373)	(0.376)	(0.377)
International Move t+4	1.595***	0.197	0.272
	(0.474)	(0.477)	(0.479)
International Move t+5	2.493***	0.824	0.903
	(0.726)	(0.726)	(0.727)
Year		Yes	Yes
Experience			Yes
Firm			Yes
Inventor Fixed Effects	Yes	Yes	Yes
Observations	1,340,899	1,340,899	1,339,718
R-squared	0.000	0.004	0.004
Number of inventors	372,045	372,045	371,485

Table 5: H2 individual fixed effects results *Note: The table above displays the developing effect of an international move by inventors in the full inventor sample. The independent variable 'International Move' denotes the first year in which the inventor has invented a patent at his/her hiring firm, with 'Move t+1' up to t+5 denoting the subsequent years. Hence chronologically developing patenting performance effects can be read from top to bottom in each column. The three models are identical, except for their control variables. In model 1, only the move variables are tested. Model 2 includes a year dummy controlling for time fixed effects. Model 3*

*also controls for inventors' experience, firm, and firm sector fixed effects. Due to some missing variables, the number of observations fall slightly as more controls are added. The Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

Considering H2, international movers overall suffer less severe performance decline as compared to regular movers. Hence, there is sufficient evidence to reject H2. Over the six-year analysis, moving internationally costs inventors 2 citation weighted patents as opposed to a within border interfirm movers' loss of 4.5. This can be contextualized in terms of inventor career output from the previously mentioned average of 50 citation weighted patents per inventor career. This puts the performance drop to about 4% of their output over the whole analysed career.

From a hiring firms' perspective, the results can be interpreted similarly to H1. Maintaining the same assumptions, the 1.6 citation weighed patent could lead to an additionally missed market value expansion of 2%[5] of international hires in comparison to regular hires.

The significantly negative performance effect can be traced to two separate effects. On the one hand firm-specific human capital still plays a role as has been confirmed in H1. The vast majority of international movers in the sample also switch firms as visible in table 1. This means most international movers have to adjust to the new organizational capital subsequent to their moves, which has been demonstrated to reduce productive capacity in H1. On the other hand, social network losses can also be held responsible for some of this performance loss. Leaving behind one's social network through an international move could come at a cost, reducing knowledge flows quantified by patenting citations to the inventor in question. It remains surprising how two potential factors for performance loss (H2) cause for a less severe effect than only one (H1). Implications of this finding will be further discussed in the conclusion.

3.3 MNC subsidiary mobility (H3)

Finally, the H3 empirical results are displayed in table 6 below. H3 expected MNC movers to have a milder adverse performance shock due to the similarity of the organizational capital at their new firm, and the existing firm-wide network they were able to build up. The same sample is used as for the previously tested hypotheses.

Starting with model 1, which regresses citation weighted patents onto the MNC move, immediately a negative and significant on the 95 level (p<0.01) effect of about one citation weighted patent is noticeable in the move year. The delay variables show positive and generally significant results on at least the 90 level (p<0.05) of a similar magnitude. According to model 1, the

[5] $= 1.03^{0.8}$ assuming that 50% of the citation weighted patent penalty of 1.6 is associated to patents at previous firms

comparatively worse performance in the move year of MNC movers is more than compensated in subsequent years after the move. A net surplus is built in the following years resulting to roughly 8 citation weighted patents marking an “MNC surplus”. A similar calculation for cross border movers results in a negative 1.5 citation weighted patent over the six years of analysis.

The results of model 2 show a bleaker picture for MNC movers. Having added the year dummies, the move year coefficient is identical to that of model 1, roughly negative one, and significant on the 95 level ($p<0.01$). All delay variables from the third year after the move onwards become insignificant. The positive delay coefficients in the first and second year after the move also fall to about half of the model 1 readings. In comparison with model 1, an MNC move still seems on average to have a net positive effect in terms of citation weighted patenting performance as compared to non-movers. However, this MNC surplus has vastly fallen in magnitude to a net value of about 0.7 citations weighted patents over the first three years of the move.

Model 3 estimates the same dependent variable on the independent ones, adding all available control variables, except the sector one. The results are strikingly similar to model 2, with the first three move variables remaining significant (at least at the 95-level $p<0.05$). The magnitudes and signs of the coefficients are also nearly unchanged. The MNC surplus remains mostly unchanged as well at the previously found 0.7 citation weighted patents. The delay *MNC move* coefficients remain positive and insignificant as well. This indicates that on average in our sample, from the third year after the move onwards MNC movers do not have a significant performance differential compared to non-movers, or international movers[6].

[6] Regular movers have significantly negative coefficients for the *Move(t+3)* up to *Move(t+5)* variables.

Citation Weighted Patents	Model 1	Model 2	Model 3
MNC Move	-1.097***	-1.297***	-1.271***
	(0.294)	(0.293)	(0.293)
MNC Move (t+1)	1.602***	0.759**	0.736**
	(0.341)	(0.340)	(0.340)
MNC Move (t+2)	2.116***	1.152***	1.144***
	(0.402)	(0.401)	(0.401)
MNC Move (t+3)	2.031***	0.800	0.810
	(0.576)	(0.578)	(0.578)
MNC Move (t+4)	1.656***	0.189	0.216
	(0.616)	(0.614)	(0.614)
MNC Move (t+5)	3.073***	1.404	1.445
	(1.142)	(1.143)	(1.143)
Year		Yes	Yes
Experience			Yes
Firm			Yes
Inventor Fixed Effects	Yes	Yes	Yes
Observations	1,340,899	1,340,899	1,340,045
R-squared	0.000	0.004	0.004
Number of inventors	372,045	372,045	371,485

Table 6: H3 individual fixed effects results *Note: The table above displays the developing effect of an MNC move by inventors in the full sample of patenting inventors. The independent variable 'MNC Move' denotes the first year in which the inventor has invented a patent at his/her hiring firm, with 'Move t+1' up to t+5 denoting the subsequent years. Hence chronologically developing patenting performance effects can be read from top to bottom in each column. The three models are identical, except for their control variables. In model 1, only the MNC move variables are tested. Model 2 includes a year dummy controlling for time fixed effects. Model 3 also controls for inventors' experience and firm fixed effects. Due to some missing variables, the number of observations fall slightly as more controls are added. The Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

Hence on average MNC movers gain over 0.7 citation weighted patents over the 6 years of analysis around their move. Considering that this value is a loss of over 2 citation weighted patents for regular international movers there is insufficient evidence to reject Hypothesis 3.

From an individual inventor's perspective this has ambiguous implications. The net gain in MNC moving over interfirm international moves is over 2.7 citation weighted patents. This once again will be valued differently by different inventors. The percentage from the average career citation weighted patenting output this is about 5% of an inventor's career output. Following the previous methodology of market valuations potential of patent citations, MNC's on average can gain about 8% additional market value from a within firm international hire as compared to an external international one. This is 10% better from firms engaging in international LbH. Hence MNC's movers on average gain a boost in performance due to the move, vastly outperforming interfirm international movers, and slightly outperforming within border interfirm movers in this regard.

4 Conclusion

This paper investigates whether MNC's can reduce the intensity of the settling periods of individual inventors in comparison to interfirm cross border hires. This central question is approached in 3 steps.

First off, the effect of interfirm labor mobility on inventor performance are addressed in H1. Here firm-specific human capital is identified as a factor that is likely to lead to a settling period for movers in comparison to non-movers. The empirical results confirm this expectation. Movers underperform by 4.5 citation weighted patents over the six analysed years subsequent to their move in comparison to non-movers. This is roughly 9% of the average inventor's career patenting performance in the sample. For firms this means a 10% reduction in potential market value generated by the new hire. Thus, there is not enough evidence to reject H1. Firm specific human capital is found to play a significantly negative role in the performance of interfirm movers, also impacting the firm.

Then, H2 specifically investigates the settling periods of cross-border hires. Along with firm-specific human capital, the disruption of inventor social networks rationalizes the anticipation of more intense settling periods for such movers in comparison to regular within border interfirm movers. From an identical methodology the conclusion is drawn that such movers on average have a more modest settling period of about 2 citation weighted patenting in the six analysed years. This is about 4% of their career output and a 2% loss in potential market value for the firm. Notably these figures are below the results from H1, meaning cross border hires face less severe adjustment periods in comparison with regular interfirm hires. Thus, H2 is rejected.

At last, H3 takes the final step in narrowing down the paper to MNC subsidiary hires. MNC hires are expected to have less severe settling periods than interfirm cross border hires. Across subsidiaries the organizational capital is theoretically constant, diminishing the firm-specific human capital effects. In line with expectations, MNC movers tend to perform better than regular cross border hires during their adjustment periods. Moreover, their adjustment period is not of a negative nature, but sees them outperforming non-movers by 0.7 citation weighted patents in the six analyzed years. This result puts MNC movers 2.7 citation weighted patents ahead of interfirm cross border hires (H2), which is 5% of the average inventor "career", responsible for a missed 10% potential market value increase for the hiring firm. As such, there is not enough evidence to reject H3. MNC's are better able to manage the settling periods of international hires.

A remarkable result is that cross border movers outperform regular interfirm movers in their adjustment periods. The latter group is anticipated to be negatively impacted by one factor, namely firm specific human capital effects. Along with this, the former is also expected to be negatively affected by social network effects. Logically a group affected by two adverse factors should underperform to one affected by only one of these. An explanation for this seemingly counter intuitive result could be that one of the effects is milder for the cross-border movers. A factor where this could be the case is the specific human capital effect. For this to have a milder impact on the group, there should be an abundance of MNC movers which would dilute the cross border interfirm moving group with less severe to no specific human capital effects[7]. Considering the mover group sizes in table 1, over 41% of international movers make an MNC move. With such a high fraction of MNC movers in the sample potential dilution of the international mover's sample is highly likely. With such a large fraction of international movers not actually being affected by firm-specific human capital, the rejection of H2 can be somewhat rationalized. Almost half of the group does theoretically not face any firm specific human capital performance declines, which is found to have strongest negative performance effects in H1. This explains the surprising rejection of H2. The implications of this will be further discussed below in the suggestions for further research section. Overall this also clarifies that MNC's play a mediating role in mediating international inventor mobility, being responsible for 40% of this in the sample.

Furthermore, another remarkable result is that of H3, where MNC movers outperform non-movers. This means that MNC's succeed in minimizing specific human capital effects, and optimize the social network effects of new hires to an extent where a move is beneficial to the individual performance of an inventor. This sheds further light on the inherent benefits going global could have for a firm. When following a certain strategy, transferring inventors across subsidiaries on average has a beneficial effect for the inventor and thus also firm performance. This falls somewhat in line with the preliminary findings by Oettl and Agrawal in their 2008 paper where MNC's are found to be double as good at managing knowledge flows as compared to interfirm cross-border hires.

These findings have significant implications on the individual inventor, the hiring firm and society. From the individual inventor's perspective, it is clear that moving across firms is a costly process in terms of performance. Depending on the importance they attach to their citation weighted patenting performance, these results could discourage such a move. Alternatively, inventors might opt to recognize this cost in the labor market more consciously, demanding higher wages in order to compensate for their losses from interfirm mobility. Based on the previously mentioned concerns regarding H2, it is hard to make a judgement on cross border interfirm hires. What is clear however, is that inventors can even benefit from MNC subsidiary moves. Inventors should opt to make such moves rather than interfirm cross border ones if they want to for instance improve their individual performance while gaining work experience abroad. From the firms' perspective this paper clarifies that LbH comes at a clear cost, in the form of individual inventor performance. This cost may or may

[7] Because MNC movers are theorized to make a move to a subsidiary with close to identical organizational capital. Hence firm-specific human capital effects play less to no role.

not be already recognized in the recognized by firms engaging in the activity. The H3 results further rationalize the existence of MNC's and could be seen as a clear reason for firms to go global in the future. MNC's manage to extract value from cross border labor mobility. While this has positive effects on market value, this makes attracting inventors who value their individual performance highly cheaper. From the social perspective, the beneficial process of knowledge sharing is found to have a clear cost in the H1 results. Hence this paper provides nuance to the benefits of knowledge sharing. These costs should certainly be adapted optimizing public policy as well. Further from H3, governing bodies could better understand that MNC's manage human capital well. Taxation systems could better recognize the societal benefit of knowledge sharing MNC are capable to bring about.

While making considerable progress, this paper calls the need for further research in this topic. This in part comes as a result of paper's limitations. In particular, the methodology of inventor performance identification can be improved. A clear problem in this paper is that the fraction of MNC movers of the cross border moving sample is rather high. Hence MNC specific effects can confound the results drawn about cross border moves. This could be overcome by splitting up the sample, excluding MNC movers, and only examining interfirm cross-border movers. This could give us a better understanding of that specific move type. Further, certain inventors in the sample apply for patents under slightly different name permutations. In this paper no fitting solution was found to group these permutations together under one inventor identifier. This leads to significant random errors. Inventors could be identified as multiple individuals who never existed, reducing the reliability of the results. Overcoming this permutation problem, in a methodology similar to Thompson, and Fox-Kean's 2005 paper could improve the precision and reliability of the findings in this paper. Further, the completeness of the sample can be improved. In this paper only EPO patents and citations are used, which does not capture the full careers of inventors. However, inventors can have patents at completely different patenting offices. Therefore, this paper potentially neglects entire sections of potential inventor performance, resulting to systematic errors. This could be overcome by merging multiple datasets from different patenting offices. As such, inventors could be tracked more accurately over their careers. A paper pursuing this would give a more accurate glimpse into the true cost of labor mobility.

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6 Appendix

Citation Weighted Patents	Incomplete panel	Complete panel
move	-2.895***	-2.895***
	(0.079)	(0.079)
move_t1	-0.045	-0.045
	(0.081)	(0.081)
move_t2	-0.054	-0.054
	(0.138)	(0.138)
move_t3	-0.345***	-0.345***
	(0.112)	(0.112)
move_t4	-0.341**	-0.341**
	(0.135)	(0.135)
move_t5	-0.696***	-0.696***
	(0.169)	(0.169)
Year	Yes	Yes
Experience		
Firm		
Sector		
Inventor Fixed Effects	Yes	Yes
Observations	1,340,899	1,340,899
R-squared	0.005	0.005
Number of inventors	372,045	372,045

Table A.1: Incomplete versus completed sample sensitivity analysis *Note: The table above displays the sensitivity analysis at the rationalizing the use of an incomplete panel in the results section. The Move and its delay variables were regressed side by side. The rightmost model shows the effects of a completed panel, where all missing observation years have been filled with zeroes. This gives a technically more accurate view of the inventor performance throughout the panel, explicitly recognizing unproductive years. In the middle column this procedure is not performed. The comparison of the results concludes that the methodologies do not influence the final outcome, and that the fixed effects regression is not affected in its results by an incomplete panel. This provides the necessary evidence to work with incomplete panels in all of the results section. The Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

Citation Weighted Patents	Full sample	Min 3 year tenure	Min 6 year tenure
Move	-3.598***	-2.842***	-3.034***
	(0.036)	(0.078)	(0.114)
Move t+1	-0.281***	-0.014	0.210*
	(0.036)	(0.078)	(0.115)
Move t+2	-0.032	0.078	0.169
	(0.048)	(0.105)	(0.162)
Move t+3	0.029	-0.151	-0.174
	(0.051)	(0.093)	(0.128)
Move t+4	-0.022	-0.254**	0.018
	(0.063)	(0.100)	(0.133)
Move t+5	-0.091	-0.265**	-0.076
	-3.598***	-2.842***	-3.034***
Year		Yes	Yes
Experience			No
Firm			No
Sector			No
Inventor fixed effects	Yes	Yes	Yes
Observations	3,576,577	1,340,899	721,424
R-squared	0.008	0.005	0.005
Number of inventors	1,261,177	372,045	173,030

Table A.2: Tenure length sensitivity analysis. *Note: The table above displays the sensitivity analysis regarding the minimum tenure inventors are required to have at the same firm to stay in the sample. In the 2nd column from the left the full sample is used including rapidly moving inventors. The 3rd column only includes inventors with a minimum tenure of 3 years at the same firm, and column four 6 years. The relatively similar results (for H1) provide sufficient evidence that a minimum tenure of three years is the most reasonable estimate. This balances the internal validity and sample size of the empirical analysis. The Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

Citation Weighted Patents	Regular SE	Inventor clustered SE
Move	-2.895***	-2.895***
	(0.079)	(0.079)
Move t+1	-0.045	-0.045
	(0.081)	(0.081)
Move t+2	-0.053	-0.053
	(0.138)	(0.138)
Move t+3	-0.347***	-0.347***
	(0.112)	(0.112)
Move t+4	-0.341**	-0.341**
	(0.135)	(0.135)
Move t+5	-0.696***	-0.696***
	(0.169)	(0.169)
Year	Yes	Yes
Experience		
Firm		
Sector		
Inventor fixed effects	Yes	Yes
Observations	1,339,718	1,339,718
R-squared	0.005	0.005
Number of inventors	371,485	371,485

Table A.3: Standard error clustering sensitivity analysis. *Note: The table above displays the sensitivity analysis for the choice to use inventor clustered standard errors. On the left column no clustered standard errors are used, while on the right they are. With identical results, clustered standard errors were chosen to use throughout the paper. The Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

Citation Weighted Patents	Sector and firm control	Firm control only
Move	-2.915***	-2.915***
	(0.080)	(0.080)
Move t+1	-0.071	-0.071
	(0.081)	(0.081)
Move t+2	-0.088	-0.088
	(0.142)	(0.142)
Move t+3	-0.389***	-0.389***
	(0.112)	(0.112)
Move t+4	-0.394***	-0.394***
	(0.136)	(0.136)
Move t+5	-0.758***	-0.758***
	(0.167)	(0.167)
Year	Yes	Yes
Experience	Yes	Yes
Firm	Yes	Yes
Sector	Yes	No
Inventor fixed effects	Yes	Yes
Observations	1,339,718	1,339,718
R-squared	0.005	0.005
Number of inventors	371,485	371,485

Table A.4: Control variables selection sensitivity analysis. *Note: The table above displays the sensitivity analysis for the choice to exclude sectoral controls from the regression. The control is included in the second column from the left and excluded in the 3rd column. As no significant difference can be seen between the two results, the control is chosen not to be included in the majority of the models. The Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*