# Consequences of Lab Closures:

## Understanding Worker Mobility, Technological Trajectory and Productivity

Raphael Martins – NYU Stern[1]

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*Abstract*

*What are the consequences of R&D lab closures for inventor employer and geographical mobility, and for inventor productivity? This paper investigates this question in the context of the pharmaceutical industry, after firms decide to no longer have an R&D presence in a region and thus close their lab there. After analyzing a hand-collected sample of displaced inventors in the US in the last twenty years and examining employer and geographical mobility outcomes (move region only, move firm only, and move both region and firm), I find that: inventors that were more productive pre-closure are more likely to change both firm and region; they are also more likely to remain in the same technological trajectory; and inventors that change labs within the same firm see a drop in productivity. The paper offers two theoretical contributions to the knowledge worker mobility and productivity literatures: inventors' decisions on firm mobility, geographical mobility and technological trajectory should be analyzed jointly, since these three dimensions are often part of a trade-off; expanding on the concept of firm-specific human capital, I argue for the relevance of establishment-specific human capital.*

## 1. Introduction

In January of 2007, Pfizer's employees in its Ann Arbor R&D lab were given shocking news: the lab was being shut down. The company had been in crisis the prior few months due to an unfortunate sequence of events. It had acquired rival Pharmacia in 2003 in one of the largest M&A deals ever at the time, part of a strategy that aimed to find new sources of revenue, as drugs that were major sources of revenue were about to have their patents expire. Among them was Lipitor,

[1] rmartins@stern.nyu.edu.

the best-selling drug of all-time and one that was developed in the Ann Arbor lab. Additionally, millions of dollars had been poured into research on new drugs that could become blockbusters.

However, in December of 2006 it became official that torcetrapib, an experimental drug for heart disease upon which the company had invested close to one billion dollars, had failed its clinical trials. As the company was faced with a major financial crunch, it had to slash its R&D budget drastically. Since the Ann Arbor lab was considered the most productive and profitable one, its members were sure that they were not going to be significantly impacted, but at the end of day, company executives felt that shutting down the entire operation was the best course of action. Now inventors were faced with a mobility decision with implications for their geographical location, organizational tie and technological trajectory.

The anecdote illustrates the object of study of this paper: the closure of R&D labs. Firm closure in general is one of the most relevant phenomena of economic life, with significant repercussions for employees, firms and regions. Closures often lead to a major reshuffling of the competitive environment, with resources such as employees, clients and physical assets becoming available to the remaining firms (Hoetker and Agarwal 2007; Knott and Posen 2005), and to new ones (Carnahan 2017). Furthermore, when closure happens at the establishment level, it often implies a significant reorganization of production within firms. Expanding on previous research on the causes of firm closure (Mata and Portugal 2002; Geroski, Mata, and Portugal 2010), I am interested in the *consequences* of closure, with a particular focus on R&D labs and the human capital involved (Carnahan 2017). After such closures, with firms eliminating their R&D presence in that region, inventors are faced with three options: move firm (that is, staying local and finding a new job), move region (staying with the firm but in new location), or move both. My research examines how these three mobility outcomes are related to pre- and post-closure inventor productivity, since productivity helps understand who makes what choice (among other reasons because inventors will select into mobility outcomes with some understanding of the implications for changes in productivity). In particular, my research question is: What are the mobility and productivity consequences for inventors displaced by R&D lab closures, and how do they vary across pre-closure productivity levels? Aside from being a relevant phenomenon, lab closures are shocks that allow us to observe the relevance of geography and individual technological trajectory in mobility decisions, as well as how productivity changes after within-firm mobility.

The context which I analyze is the pharma industry. This is a relevant setting – aside from the fact that it being patent-intensive makes it convenient for studying innovation, it is an industry that has seen a lot of lab closures in the last 20-30 years due to mergers and to reorganizations. Thus, it is a prime candidate for the analysis of performance consequences of R&D lab closures. In this paper, I will study which workers decide to move to a different location within their original firm after a closure, which move to a new firm in their original region, and which change both firm and region. In particular, I am interested in how pre-closure productivity levels correlate with these choices, and how these choices are related to workers' technological trajectory post-closure – the expectation being that most productive inventors will prioritize their future productivity when making a mobility decision. Additionally, I will be examining pharma researchers' overall career trajectories after these closures compared to non-affected researchers, encompassing both treatment and selection effects – i.e., how many of them drop out of work on drug discovery post-closure, how this attrition is related to prior productivity, and what is their productivity post-closure. This analysis is particularly relevant given the issues around the decline of the productivity of R&D in pharma, which has led to a significant decline in approved drugs in the last few years.

My empirical approach involves hand-collected data on closures and on the careers of the individuals affected by 17 lab closures in the US between 2003 and 2014. My results show that more productive inventors are more likely to incur in the costs of finding new jobs and new homes to preserve their technological trajectory, and that after controlling for inventor fixed effects, these more mobile inventors see a decrease in performance, but not as large as the decrease for inventors that stay in the same firm. Conversely, less productive inventors are more likely to stay in the same region or firm, and to deviate from previous technological trajectory. In particular, I find that 1) inventors who change both firm and region after a closure are more likely to remain in the same technological trajectory (as measured by their patent classes); 2) the more productive inventors pre-closure tend to be those that change both firm and region and remain in the same technological trajectory; 3) inventors that change labs within the same firm (that is, only change region) see a decrease in performance, which I ascribe to the loss of establishment-specific human capital; 4) inventors that change both region and firm see a lower decrease in performance, which I interpret as the result of improved employer-employee matching making up for the loss of establishment-specific knowledge. These results are robust to controls for local geographical attachment, local labor market dynamism and nature of job post-closure. I also find that: results are not significantly altered by comobility; inventors that change both firm are region are more likely than others to take up research management roles in their next job; and that women's careers seem to be disproportionally affected by these closures.

I am interested in using the aftermath of lab closures as a lens through which I can develop the first main contribution of the paper: that knowledge workers' geographical mobility (Dahl and Sorenson 2010), workers' employment mobility (Carnahan, Agarwal, and Campbell 2012; Di Lorenzo and Almeida 2017), and technological capabilities (Garud and Rappa 1995; Myers 2020) are best understood when analyzed jointly, due to their significant interdependence. In other words, examining the interplay between these three dimensions enhances our understanding in a way that goes beyond what can be achieved when looking at them in isolation. This interdependence is a function of the trade-offs knowledge workers face when making decisions on their professional trajectories when their firms decide to change their (geographical) structure. In turn, how workers think about these trade-offs has impacts on employee retention (Campbell et al. 2012) and on innovation outcomes for the firms undergoing changes to their geographical presence (Argyres and Silverman 2004; Singh 2008). Lab closures provide a setting that puts in motion this interplay. One way to look at it is that prior to a closure, individuals are in equilibrium with respect to their location, employment, and technological trajectory decisions. After the closure they are pushed off that equilibrium and have to make decisions on these three aspects while valuing the trade-offs involved. The choices they make reveal important information about the preferences of firms and individuals that cannot be observed in the status quo that was prevalent prior to the closures.

In this sense, this paper builds on the labor mobility literature in strategy that investigates “what types of employees are most likely to leave”, and “what types of firms are they most likely to join” (Campbell *et al 2012*). While recent research has highlighted the relevance of factors such as absolute (Campbell *et al* 2012) and relative earnings (Carnahan *et al* 2012), and characteristics of knowledge (Palomeras and Melero 2010; Ganco 2013) in driving mobility, I emphasize that knowledge worker mobility is driven by the interaction of workers’ adherence to their technological trajectory (and thus the extent to which an employer allows them to do so) and their level of geographical attachment. In this sense, I attempt to answer recent calls in the mobility literature to: go beyond studying only treatment, and focus on improving our understanding of (self-)selection and sorting (Agarwal, Bidwell, Cirillo and Tzabbar 2020); and to “explore differences between the drivers of ‘pure’ geographical moves (knowledge workers who move locations but maintain knowledge focus) and those who jointly change geographical context and knowledge focus (e.g., knowledge workers who move to a different job in a new location)” (Wright, Tartari, Huang, Di Lorenzo and Bercovitz 2018).

As for a second contribution, recent literature in strategy has called attention to what is called the “paradox of portability of performance” – employees that see a drop in their performance when they move firms due to a loss of firm-specific human capital (Groysberg, Lee, and Nanda 2008; Raffiee and Byun 2019). This literature has established the importance of firm-specific human capital in individual performance (Huckman and Pisano 2006; Groysberg 2010), and how a significant element of firm-specific capital comes down to co-workers (Campbell, Saxton, and Banerjee 2014). By arguing that establishments are a relevant unit for the emergence of context-specific human capital (Ployhart and Moliterno 2011), I highlight the fact that firms often organize heterogeneously across establishments, especially when considering the interaction of factors such as historical inertia and M&A – as a firm incorporates new but pre-existing establishments, the latter may preserve routines and capabilities that are at dissonance from the rest of the firm (either due to firm strategy or to path dependence). In particular, in settings where firms have standalone R&D labs, such as the pharma industry, I argue that these differences across establishments can have important consequences for employee performance post-internal mobility – more specifically, that the ‘portability of performance paradox’ can also emerge within firm due to establishment-level human capital.

Finally, this paper contributes to the literature on the motivations and career choices of academic and industrial researchers. While previous work has emphasized the existence of a greater relative “taste for science” for academics and of greater relative financial motives for industrial researchers

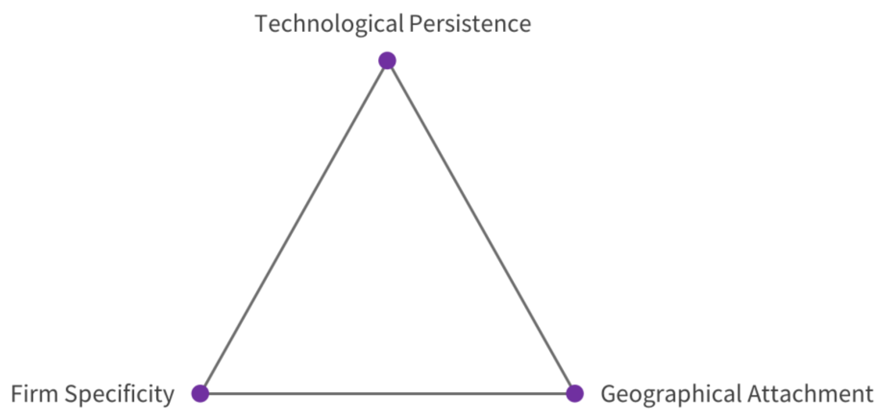
(Roach and Sauermann 2010; Sauermann and Cohen 2010; Agarwal and Ohyama 2013), this paper complements these results by highlighting that "taste for science" is still relevant for the career decisions of industrial researchers. Furthermore, it contributes to an emerging literature on intrafirm lateral mobility (e.g. Stadler, Helfat, and Verona 2021, Choudhury 2016, Chattopadhyay and Choudhury 2017)– while these papers highlight the positive aspects of such mobility, I argue that it can have a negative effect depending on circumstances associated with closures and reorganizations.

## 2. The role of technological persistence, firm specificity and geographical attachment in understanding inventor mobility and technological trajectories

A long tradition in strategy research posits that knowledge embedded in individuals and combined in social settings is the basis for the development of competitive advantage (Nelson and Winter 1982; Grant 1996). It follows that understanding worker mobility – and in particular, knowledge worker mobility – is important for its strategic implications. Thinking about mobility in the context of R&D lab closures, I will analyze to what regions and firms do scientists go after lab closures, and how are these mobility patterns related to their technological trajectories; and how do these mobility patterns interact with inventor performance pre-closure.

In predicting what happens to scientists after lab closures, my starting point is to posit that decisions on firm mobility, geographical mobility, and technological trajectory are interdependent. I first will argue for the relevance of firm specificity, geographical attachment, and technological persistence of individuals in general, and of inventors in particular. Then I will argue that given these three realities, it follows that a lab closure will force displaced inventors to make mobility decisions in which these three elements will be in a trade-off with one another – that is, for example an inventor that decides to prioritize staying in her technological trajectory may have to give up on firm specificity and/or geographical attachment. Figure 1 illustrates the interplay of these three factors driving mobility:

**Figure 1: Drivers of labor mobility**




*2.1 Individual technological persistence*

Literature from economics of innovation shows that scientists and inventors tend to persist in their technological trajectories over time. In other words, after starting to develop an area of expertise, they tend to persist in it, since "persistence is required to develop requisite competencies" and "understand the social structure of the technological field" (Garud and Rappa 1995, p. 532). Garud and Rappa (1995) find that, in the context of research on cochlear implants, the longer a researcher works on a field, the less likely it is that she will leave it, with her first and fifth year of involvement being the critical years. This is how the authors rationalize the result:

> "Over time, researchers develop technology-specific competencies. These competencies expand in a path-dependent manner (Cohen and Levinthal, 1990; Dosi, 1982; David, 1985; Arthur, 1988) as earlier technological choices direct future options and solutions. As competencies become specialized to particular technological trajectories, researchers find it increasingly difficult to redeploy themselves to pursue other trajectories, or to pursue other technological paradigms. As a consequence, there are powerful incentives, which increase over time, for researchers to persist with a trajectory. Thus, an important determinant of persistence is the longevity of association with the technology itself." (p. 535).

Garud and Rappa (1995) also investigate what determines the persistence of researchers in the context of an emerging technological field. Persistence was positively correlated with the cochlear implant field becoming legitimized; researchers being associated with an institution that received NIH funding; the attainment of a critical mass of researchers; the accumulation of knowledge in the field, as measured by the cumulative number of publications; and the demand for cochlear implants.

Furman, Murray, and Stern (2012) also find that researchers persist in their technological trajectories. After the US federal government enacted a policy that made it more difficult for researchers to get access to resources to engage in human embryonic stem cell research, researchers proved nevertheless to be resilient in their trajectories. After an initial decline in stem cell related research output from US scientists in the first few years following the enactment of the policy, there was a research rebound. The authors conclude that the extent of researchers' technological persistence is indirect evidence of how difficult, and costly, for funders and policymakers to shape the national research portfolio.

In an attempt to quantify the extent of this difficulty, Myers (2020) analyzes NIH data on targeted funding for one-time proposals on specific diseases, populations or methodologies to investigate how costly it is to incentivize a scientist studying one disease to study another. He finds that the implied cost of attracting a marginal application to targeted funding competitions is three times greater than the expected value of entry for marginal entrants. This number puts into perspective the significant inertia that characterizes the technological trajectory of scientists and inventors.

Furthermore, scientists and inventors are motivated by non-pecuniary factors – such as intellectual pursuit, recognition - that are closely related to constant technological trajectory (Roach and Sauermann 2010; Agarwal and Ohyama 2013). For example, Sauermann and Cohen (2010) find that non-pecuniary motives such as intellectual challenge and independence have a strong positive relationship with innovative output.

*2.2 Firm Specificity*

Turnover is a relatively infrequent event, and research from labor economics shows that it becomes even more infrequent as the levels of education, age and tenure go up, and it is more frequent for women and production workers (Jovanovic 1979). Out of all these variables, tenure is the one that shows the strongest correlation – which can be rationalized by a model of labor market matching where assessment of the quality of the match is done over time, as both parties experience it (Jovanovic 1979). This means that R&D workers, who tend to be male and highly educated, are even less at risk for turnover, and in particular for quitting their jobs. In other words, because these workers are more dependent than others on good matching between employee and employer to be productive, they will be more likely to want to preserve a good match once they find it.

This argument is reinforced by the strategy literature that analyzes the relationship between employee productivity, complementary assets, firm rent sharing and turnover. As argued by Campbell, Ganco, Franco and Agarwal (2012), the amount of value created and captured by human resources depends on the level of human capital, the importance of complementary assets and how transferable these assets are in a mobility event. Employees with higher levels of human capital will generate more value, especially when considering the interaction of this human capital with the firm's complementary assets – "organizational knowledge (e.g., codified routines, knowledge embodied in products and processes, and intellectual property rights), nonhuman complementary assets (e.g., physical capital, contractual relationships with buyers/suppliers, brand equity, and reputation), and human complementary assets (e.g., tacit knowledge embodied in other employees)" (Campbell, Ganco, Franco and Agarwal 2012, p. 67). While their reliance on complementary assets to generate value may reduce their bargaining power that would enable greater quasi-rent appropriation, high human capital employees tend to be able to replicate the assets in other firms. This explains why they tend to capture a greater share of quasi-rents, both in pecuniary and in non-pecuniary forms. These efforts on the part of employers to retain these employees result in a lower level of turnover, as reflected in the empirical analysis.

The above arguments are particularly applicable to R&D workers, who tend to be the highest-paid employees in pharmaceutical firms. In sum, their level of firm specificity leads them to be particularly attached to their jobs in normal times. But as I will argue below, this level of attachment decreases when they are faced with a lab closure, since it has important implications for their employer-employee matching were they to remain with the firm in a different lab.

### *2.3 Geographical Attachment*

Moving to a different city or region is in general a costly endeavor, both financially and psychologically. This results in migration being a relatively infrequent phenomenon. While the US has one of the highest internal migration rates in the world, within a 5-year span only 9% of the population will change states – and this number has been dropping (Molloy, Smith, and Wozniak 2011). Coate and Mangum (2019) estimate a structural model of migration and find that this declining rate can be mostly attributed to "increasing home attachment": as US cities and regions that were major sources of gross migration flows over the decades consolidated a local population, these newly generated "locals" became attached to these areas in a way that previous generations of residents were not.

Dahl and Sorenson (2010) illustrate the same principle but using Danish microdata and focusing on technical workers – engineers and scientists. Their results reveal that "Danish technical workers place very high weights on social factors when considering where to work. From most to least important, those educated as scientists and engineers care about proximity to their current residence, proximity to their parents, the number of high school classmates in a region, the number of college classmates in a region, proximity to past places they have lived, and income. For the typical Danish scientist, engineer or medical worker, social factors swamp economic considerations in their choices of where to work" (Dahl and Sorenson 2010, p. 44). While it is often the case that the American R&D workers in my sample will face displacement in a region that is not their original home region, since many of them had already moved for school and/or work, the primacy of proximity to current residence in the Danish results is yet another indication that individuals tend to be in general geographically bound.

*2.4 Putting it all together*

Taking these three elements into account, in predicting what happens to scientists after lab closures, my starting point is to posit that decisions on firm mobility, geographical mobility, and technological trajectory are interdependent. This interdependence arises from the fact that because these workers develop very narrow technological specializations over time, local labor markets will be too thin for inventors to be able to accommodate these three dimensions. For example, pharma researchers specialize along many dimensions, such as: diagnostic areas (e.g., cardiovascular disease, cancer, etc.); drug R&D approaches (rDNA, combinatorial chemistry, genomics, etc.); R&D stages (target identification and validation; lead identification and optimization; pre-clinical development). Thus, the local labor market for each one of the possible combinations of specializations will likely be very thin.

Given that the labor market is often not thick enough to accommodate these three aspects of the job search (at least outside of major centers such as Boston), inventors often face a trade-off among these three dimensions, and those that place greater weight in one dimension will compensate by giving less priority to the others. This is because individuals tend to show a large amount of geographical attachment to their home region (Dahl and Sorenson 2010; Coate and Mangum 2019), while at the same time showing a large degree of persistence in their technological trajectories when working as researchers (Garud and Rappa 1995; Furman, Murray, and Stern 2012; Myers 2020). In other words, displaced inventors in the pharma industry that want to keep researching a certain therapeutic area, and additionally want to keep working in a specific function such as target or lead discovery, may need to change region and firm in order to do so. These workers Yang, Nugent, and Fuchs (2016) show preliminary qualitative evidence that geographical attachment and technological persistence became conflicting impulses for individuals within the context of optoelectronic component manufacturing – in a US labor market thinned out by outsourcing, individuals had to decide whether they should uproot themselves to keep working in their technological area, or to change technological area and stay in the same region. Furthermore, individuals that change labs within the same firm often will be faced with changes to their research program dictated by strategic decisions associated with the closure of their previous lab.

Thus, I posit the following hypothesis:

*H1: Individuals who change both region and firm post-closure change their technological trajectory less than individuals that only change region or firm.*

Who are the individuals that decide to prioritize their original technological trajectory while changing region and firm? Previous literature in strategy and innovation has shown that more productive, higher-paid employees are less likely to change firms (Hoisl 2007; Carnahan, Agarwal, and Campbell 2012; Di Lorenzo and Almeida 2017). This can be explained by various factors: high status, which increases the individual's motivation to stay with the organization; firm-level routines and capabilities which could play a significant role in the individual's success; preventive action in the part of the firm in the form of greater sharing of rents (salary, profit sharing); and in the case of researchers, desire on their part to keep working in their current technological area.

However, a lab closure changes the scenario, since it eliminates or diminishes the effect of all four mechanisms tying highly productive employees to their current firm. That original technological trajectory in the firm may no longer be available, since lab closures often represent firms moving away from a therapeutic area, for instance. Inventors may also feel that the establishment-level skills that catapulted them to higher productivity will no longer exist in a new lab within the restructuring firm, which would make them more inclined to search for other matches. Additionally, the higher status the researcher had obtained in the closed lab may get downgraded when moving to a different lab within the firm, which would possibly make her indifferent between staying or not in the same firm when it came to that margin. Finally, since remaining with the firm now means that inventors will have to move regions, the geographical attachment that might have played a role in tying these inventors to their employers is no longer a relevant factor. All these factors may not get sufficiently compensated by management's efforts to maintain the inventor in the form of higher wages and other amenities. On the hiring firm's side, its incentive will be to keep the inventor in a trajectory in which she was already productive pre-hire.

Furthermore, higher productivity inventors should exhibit a greater technological persistence/geographical attachment ratio than other inventors. This is because they have more to lose in terms of productivity if they change technological trajectory, and because presumably on average they give greater relative priority to their career as opposed to their personal lives compared to other inventors, as reflected in their higher productivity. Therefore, given that inventors that stick closer to their trajectories will be more mobile (i.e. H1), we should expect that higher firm mobility for inventors with higher pre-closure productivity should be associated with higher geographical mobility as well:

*H2: Higher pre-closure productivity increases the likelihood that a given inventor changes both firm and location*.

**Inventor productivity after closures: the role of establishment-specific human capital**

How do lab closures and the subsequent mobility affect scientists' productivity? As firms decide to restructure their geographical R&D layout, it is imperative to understand how productive inventors that move to a different lab within the firm can remain at least as productive as before. Similarly, firms that take on displaced researchers – be they firms in the same or in a different region – hope that the newcomers can maintain or improve their previous performance. From a societal point of view, it could be argued that the "excessive churn" in the pharmaceutical industry in the last few decades – represented by the countless number of mergers and acquisitions and overall restructurings – may have been the cause of the industry's R&D productivity downturn, a phenomenon documented by authors who have also offered different explanations for it (Bunnage 2011; Scannell et al. 2012).

Previous literature which has examined the impact of restructuring associated with M&A on inventors' performance has found that key inventors of the acquired company often have their performance negatively impacted (Ernst and Vitt 2000; Kapoor and Lim 2007; Hussinger 2012). What is more, these effects are worse for inventors who had more extensive preacquisition collaborations and for inventors whose research expertise differed the most from the core areas of the acquiring firm (Paruchuri, Nerkar, and Hambrick 2006). A related literature has examined the changes in inventor productivity after mobility events. Results show that on average productivity increases after a move (Hoisl 2007) and this effect is especially pronounced for inventors at the top quintile of the productivity distribution (Hoisl 2009). By examining the productivity performance of inventors after their lab closes, I aim to increase our understanding of inventor productivity, and whether firms should seek to retain employees if they have to relocate.

What should we expect in terms of within-inventor changes in productivity outcomes? To analyze this, I introduce the concept of establishment-level human capital (ESHC), which is analog to the concept of firm-specific human capital (FSHC). FSHC is an understanding of organizational procedures and policies that is necessary for the value creation activities and is crucial for the development of competitive advantage, and that becomes irrelevant when employees switch firms (Coff 1997; Hatch and Dyer 2004).

In his exploration of performance portability in the context of equity research, Groysberg (2010) provides a good overview of the elements that comprise FSHC. The element most discussed in the literature is complementarity and familiarity between members of a team – that is, "team human capital" comprised of common language, knowing who to contact, knowing strengths and weakness of co-workers (Huckman and Pisano 2006; Campbell, Saxton, and Banerjee 2014). It should be noted that "team human capital" encompasses many dimensions – aside from coworkers that are directly working together on the same tasks, also included are support/junior staff, supervisory/senior staff and staff across other functions in the organization. In the case of equity analysts, Groysberg (2010) illustrates how: junior analysts were often considered senior analysts' source of competitive advantage; research directors were able to galvanize a team of analysts and protect their intellectual freedom, leading to better performance; and how the banks' traders, technical analysts, portfolio strategists and sales force helped improve the final product with their inputs, with the latter also helping in marketing it to their clients. Furthermore, FSHC can be derived from firm-specific processes and rules (e.g., investment committees that sharpen analysts' arguments), firm-specific capabilities (e.g., sophisticated IT platforms and corporate systems that optimize analysts' access to information) and firm-specific training (which increases performance by creating further synergies between employees' human capital and firm-specific capabilities)[2].

Thus, the concept of FSHC implies both that some of employees (high) performance can be attributed to firm-related attributes, and that by changing firms employees may see a reduction in their performance. The latter is in fact an empirical result of the literature on the "paradox of portability of performance" (Groysberg, Lee, and Nanda 2008; Raffiee and Byun 2019). It stands to reason then that we can expand the concept of FSHC to the level of the establishment. That is, establishments within the same firm could be highly unique in terms of their routines and capabilities, and this feature could drive differential employee performance across establishments within the firm. Such heterogeneity of routines, capabilities, and therefore ESHC, could be a consequence of historical processes – different establishments have different starting points in terms of how their initial routines, and since routines "build on the past" and their development "is a function of where they have started out from" (see Becker (2004) for a review of the path dependence nature of routine evolution), establishments within the same firm can have different routine trajectories due to path dependence. Firms may decide to preserve this heterogeneity as a strategic choice, but even when they don't, they are limited in the extent to which they are able to achieve homogeneity (Szulanski 1996). Even if two establishments begin with individuals endowed with the same context-generic knowledge, skills, abilities and other characteristics (KSAOs), they are likely to develop two distinct, context-specific human capital resources at the

[2] Huckman and Pisano (2006) describe another potential source of FSHC - differences in employee status across firms, which allows for command of production process and preferential access to resources.

unit (establishment) level, due to emergent processes filled with path dependence, social complexity and causal ambiguity  (Ployhart and Moliterno 2011).

Thus, industries that have establishments which are dedicated to R&D – such as pharma – are prime candidates for ESHC playing a significant role. Consequently, the dismantling of a lab would in principle wipe out most of the knowledge in terms of innovation processes that had been developed at the establishment and team levels – such processes are not easily transferrable across establishments even within the same firm. This would imply lower performance for inventors that move regions to stay in the same firm, in a different establishment:

*H3: Researchers who change to a different lab within the same firm will see a decrease in their performance*

Inventors who change both firm and region are of course exposed to the loss of both ESHC and FSHC. Yet, in their case a countervailing positive effect on their productivity would be their improved employer-employee matching (Jovanovic 1979; Hoisl 2007). This improved matching could be due to: knowledge spillovers from new colleagues; monetary incentives; career advancement; new areas of application for existing knowledge (Hoisl 2009). This improved matching would at least compensate for the decline in performance due to the loss of establishment-specific human capital:

*H4: Inventors who change both firm and region will have a smaller decline in performance than inventors who change region only.*

While H3 and H4 have behind them a treatment rationale to explain performance post-closure, there is also a selection story that can be told. For simplicity, the rest of the paper will proceed operating under the treatment arguments, and section 5.3.1 will argue that ESHC is a relevant component of both the treatment and selection stories.

## 3. Data, variables and methods

The data set required to test these hypothesis needs to fulfill some requirements. Firstly, I need data on R&D lab closures, but not just any closures, but those that represent the exit of the focal firm from the region in terms of R&D activities. For example, Pfizer's shut down of its Ann Arbor lab meant that the company no longer had any R&D activity in that commuting zone. This exit requirement is needed to set up the trade-off expressed in the three mobility outcomes (Move Region, Move Firm, Move Region and Firm): if the firm still had R&D operations in the region after the closure, the option "move neither region nor firm" would be available to the employee. For this reason, certain closures could not be used – the most conspicuous example being Merck shutting down its big operations in NJ, since it still had R&D units in NYC afterwards. A second requirement was to prioritize accuracy over scale in building the data. Thus, it was important to find closures which not only represented the exit from a region, but also where the shutdown from announcement to conclusion was quick and straightforward. Relatedly, I included in the sample inventors which I could precisely identify as having worked in the lab, and leaving at the time of the closure. These requirements have left me with a smaller sample, but one which is accurate.

Previous research has highlighted the difficulty in observing data on R&D units (Argyres and Silverman 2004; Argyres, Rios, and Silverman 2020). Thus, my starting point is searching for closure events of standalone R&D labs that represented the exit of the focal firm from the region in terms of R&D activities. The main data sources were company reports, news articles, and Web Archive. The next step was to identify inventors impacted by closures, and while patent data is a useful starting point, recent work has shown it is a very noisy measure of mobility (Ge, Huang, and Png 2016). After listing the inventors assigned to patents by the closing firm in the region of the closed lab, I search for their profiles on LinkedIn, as well as for complementary career information on Google Scholar and ResearchGate. For those that I can verify were working at the lab at the time of the closure, I code their mobility and control variables, and collect their complete patent data from PatentsView. Current treatment sample is comprised of 17 closures and 426 displaced inventors.

Aside from the treatment sample, I also build a control sample of 504 inventors who were working at the same firm as the treated ones at the time of the closure, but in different labs (and did not leave at the time of the lab closure). For most lab closures, I was able to find at least as many control inventors as treated ones. However, for four labs this was not possible. In these cases, I removed from the sample enough treated inventors so as to equal the number of control inventors for that lab, leaving me with 360 treated inventors, and 864 inventors total. To remove treated inventors, first I find the control inventor that has the shortest patent portfolio distance to each of the treated inventors, then I remove the treated inventors that have the highest maximum distance to a control inventor until I have at least the same number of treated and control inventors for each lab. Because the control sample is designed so as it is comprised only of inventors who remained in the firm after the closure, I use it only for the technological trajectory and productivity regressions. This provides a comparison for the ex post tech changes and production that the treated inventors observe, to reduce concerns about (for example) declines in productivity in specific sub-fields.

I use the following variables in the regressions:

- Post-closure technological distance: I create a dummy to identify each patent class that shows up in the inventor's portfolio and calculate what are the percentages of each class in that portfolio. I then calculate the Euclidean distance between the portfolio in the years post-closure and the portfolio in the 5-year window leading up to the closure. The greater the distance, the more the inventor has moved away for her technological trajectory post-closure (Benner and Waldfogel 2008).

- Pre-closure technological distance: same as above but comparing the five years prior to the closure to the previous five years.
- Gender: dummy equals 1 for women
- Move Region, Move Firm, and Move Region and Firm: dummy that equals 1 for each mobility outcome
- PhD: dummy that equals 1 for PhD holders
- Tenure: length of tenure at the firm, in years, prior to the closure
- Career Length: length of career, in years, prior to the closure
- Pre-Closure Productivity: log of number of patents in the 5-year window prior to the closure
- Post-Closure Productivity: log of number of patents in the 5-year window after the closure

Determinants of mobility outcomes are measured using a multinomial logit model, since there are three possible outcomes (Move Region, Move Firm, and Move Region and Firm). Technological trajectory and ex-post productivity are modeled by OLS regressions where the variables of interest are the three mobility outcomes, with ex-post productivity also being modeled by Poisson panel data models with inventor fixed effects - time periods being 5-year windows prior to the closure and the full window after the closure. The inclusion of inventor fixed effects allows for statements on changes in individual productivity after the closures, going beyond a simple comparison of ex-post productivity across groups. Additionally, while OLS models looking at the first difference are informative, their limitation is the lack of a comparison group for the three outcomes. Thus, I also run models that include a control sample of non-displaced inventors working in different labs within the firm that give me a comparison group of inventors that changed neither region nor firm[3].

*3.1 Treatment x selection*

What role does causality and identification play in this paper? To answer this question, I should differentiate between the mobility/trajectory results, and the ex-post productivity results. Papers in the firm/establishment closure literature that attempt to isolate causal mechanisms operating at the individual level usually rely on the assumption, which would also be applicable here, that such closures are exogenous to individuals (e.g. Dahl and Sorenson 2010, p. 37). Yet, in my mobility/trajectory results, I am less concerned with identifying causality than with empirically describing the selection processes underlying observed outcomes. In this, I follow recent remarks made by two prominent mobility scholars, Rajshree Agarwal and Matthew Bidwell, in a volume where they debated where the literature was headed (Agarwal et al. 2020). In it, Agarwal states that:

> "In my view, the biggest challenge for research in mobility is our implicit theoretical lens, where we focus on a treatment view of the world instead of incorporating a selection view along with a treatment view. We don't necessarily think: 'Who are the people who are moving, why are they moving, and what are the selection pressures as opposed to the treatment pressures?' (…) What is the role of sorting and selection, and fit?"

Bidwell agrees that "unbundling the selection and treatment views is virtually impossible", and that "this is a field where causality is hard to ascertain", and Agarwal goes further by saying "Not only is causality hard, I don't even think that that's the right approach. What Matthew's alluding to is that these career decisions are fundamentally endogenous. (…) if you're truly interested in

[3] This control sample is not used in the multinomial logit models for mobility because it only contains inventors that kept working in the firm after the lab closure.

charting career pathways and the evolutions of careers, then we must embrace selection, which is not what causal studies and identification do very well."

My analysis of inventors' (firm and geographical) mobility and technological trajectory basically follows the principles laid out in this dialogue. The concern is not so much with treatment/causal effects, because mobility and technological trajectory decisions are "fundamentally endogenous" – it is almost impossible, and for the most part undesirable, to get rid of the selection effects, since doing so would fundamentally disfigure the phenomenon being analyzed. Instead, the concern is with understanding "who are the people moving, and why" – in other words, "what is the role of sorting and selection, and fit". In this vein, the argument I make in this analysis of mobility can be summarized as "people who were more productive prior to the closure (that is, the 'who') decide to change both firm and region (that is, they sort/select into these outcomes) as a way to better preserve their technological trajectory, despite eventual losses of firm specificity and geographical attachment (that is, the 'why')".

As for the analysis of inventors' ex-post productivity. so far the arguments have followed the logic of a treatment effect: as inventors get displaced, their performance in their new jobs will be differentially affected by the treatment associated with the loss of ESHC, with those that stay in the same firm eventually seeing the biggest decrease in performance. However, there is also a selection story that could be playing out: as inventors get displaced, those that expect to perform poorly in the future select into staying in the firm.

One possible way to reconcile these two arguments is to note that part of why these inventors expect to perform worse going forward is precisely the knowledge of the importance that ESHC has in their performance. As they get displaced, they realize that without access to past coinventors, routines and processes, their performance will decline, so they might as well hold on to their current job, even if that means geographical displacement. It is thus difficult to tease apart treatment from selection in this case, since they are intertwined, and both come down to productivity – this gets us back to Bidwell's argument that when it comes to mobility, it is virtually impossible to unbundle selection and treatment views. More importantly, in both the treatment and the selection accounts, I argue that ESHC would play a significant role in productivity trajectories, and it is thus a phenomenon that managers and employees making intrafirm mobility decisions must contend with.

## 4. Main results

Tables 1 and 2 below show respectively the summary statistics and the pairwise correlations of the variables included in the empirical analysis of the treated sample. In terms of mobility outcomes, 18% of the sample changed region only, 56% changed firm only, and 27% changed both firm and region. Additionally, 76% of the sample is male, 65% has a PhD, and the average career length prior to the closure is 14 years.

**Table 1: Descriptive Statistics**

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Distance Pre-Closure | 0.49 | 0.29 | 0.02 | 1.41 |
| Distance Post-Closure | 0.70 | 0.34 | 0.06 | 1.41 |
| Gender | 0.24 | 0.43 | 0.00 | 1.00 |
| Move Region | 0.18 | 0.38 | 0.00 | 1.00 |
| Move Firm | 0.56 | 0.50 | 0.00 | 1.00 |
| Move Region and Firm | 0.27 | 0.44 | 0.00 | 1.00 |
| PhD | 0.65 | 0.48 | 0.00 | 1.00 |
| Tenure | 10.35 | 5.65 | 1.00 | 34.00 |
| Career Length | 14.19 | 6.89 | 2.00 | 44.00 |
| Pre-Closure Productivity | 1.26 | 0.91 | 0.00 | 4.28 |
| Post-Closure Productivity | 1.31 | 1.05 | 0.00 | 3.71 |

## Table 2: Pairwise Correlations

| | Distance Pre-Closure | Distance Post-Closure | Gender | Move Region | Move Firm | Move Region and Firm | PhD | Tenure | Career Length | Productivity Pre-Closure | Productivity Post-Closure |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Distance Pre-Closure | 1.000 | | | | | | | | | | |
| Distance Post-Closure | 0.087 | 1.000 | | | | | | | | | |
| Gender | 0.051 | -0.059 | 1.000 | | | | | | | | |
| Move Region | 0.057 | -0.001 | -0.082 | 1.000 | | | | | | | |
| Move Firm | 0.034 | 0.118 | 0.072 | -0.517 | 1.000 | | | | | | |
| Move Region and Firm | -0.089 | -0.127 | -0.010 | -0.280 | -0.677 | 1.000 | | | | | |
| PhD | 0.005 | 0.001 | -0.262 | 0.081 | -0.102 | 0.044 | 1.000 | | | | |
| Tenure | -0.066 | 0.024 | -0.061 | 0.000 | 0.031 | -0.034 | -0.094 | 1.000 | | | |
| Career Length | 0.025 | 0.156 | -0.115 | 0.022 | 0.062 | -0.088 | 0.003 | 0.694 | 1.000 | | |
| Productivity Pre-Closure | -0.393 | -0.373 | -0.048 | -0.088 | -0.019 | 0.097 | 0.082 | 0.030 | 0.019 | 1.000 | |
| Productivity Post-Closure | 0.003 | -0.367 | -0.013 | -0.128 | 0.080 | 0.020 | -0.034 | -0.155 | -0.251 | 0.254 | 1.000 |

The main regression results follow below, split into the three main outcomes of interest: geographical and firm mobility; technological trajectory; and ex-post productivity.

*5.1 Geographical and firm mobility*

Table 3 shows some initial results from a multinomial logit for the three main mobility outcomes post-closure: change region only; change firm only (base outcome); and change both firm and region. Examining the marginal effects of the pre-closure productivity variable (measured in terms of number of patents in the 5-year window leading up to the closure), we see in Column 4 that it seems to be associated with a higher likelihood of changing both region and firm (p-value = .05). A 50% increase in patenting activity in the pre-closure period is associated with an increase of two percentage points in the probability of moving both firm and region – this is an increase of 7% compared to the sample average of 27%. This result does not hold up when looking at changing only region (Column 3) – in fact, the negative coefficient on productivity is indicative that firms extended offers to less productive inventors. The data is consistent with more productive inventors seeming to be more willing to incur in the costs of finding new jobs and new homes – not only because they have the opportunity, but also because their preferences place greater weight on their work life. Table A1 in the appendix shows the OLS results for each of the three outcomes.

**Table 3: Determinants of mobility post-closure**

| Variables | Coefficients | | Marginal Effects | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Move Region | Move Region and Firm | Move Firm | Move Region | Move Region and Firm |
| Productivity Pre-Closure | -0.198 | 0.177 | -0.008 | -0.037* | 0.046* |
| | [0.157] | [0.131] | [0.028] | [0.022] | [0.025] |
| Gender | -0.482 | -0.104 | 0.059 | -0.060 | 0.001 |
| | [0.379] | [0.293] | [0.063] | [0.045] | [0.057] |
| PhD | 0.543* | 0.265 | -0.091 | 0.063 | 0.028 |
| | [0.319] | [0.263] | [0.055] | [0.040] | [0.050] |
| Tenure | -0.002 | 0.010 | -0.001 | -0.001 | 0.002 |
| | [0.034] | [0.031] | [0.006] | [0.005] | [0.006] |
| Career Length Pre | -0.003 | -0.030 | 0.005 | 0.001 | -0.006 |
| | [0.028] | [0.026] | [0.005] | [0.004] | [0.005] |
| Observations | 397 | 397 | 397 | 397 | 397 |

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 4 includes mobility results for changes in technological trajectory when considering measures of local attachment. My measure is whether the inventor went to college in the same area as the lab she was working in prior to the closure. The mobility results show that inventors that went to college in the area are less likely to leave the region to stay in the same firm, and that more productive inventors are still more likely to change both firm and region (p-value = 0.12). This is consistent with the idea that while some inventors prioritize local attachment, others make it secondary to reoptimizing their employment fit.

**Table 4: Determinants of mobility post-closure, controlling for local attachment**

| Variables | Coefficients | | Marginal Effects | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Move Region | Move Region and Firm | Move Firm | Move Region | Move Region and Firm |
| Productivity Pre-Closure | -0.181 | 0.157 | -0.009 | -0.031 | 0.040 |
| | [0.168] | [0.135] | [0.029] | [0.021] | [0.026] |
| Gender | -0.603 | -0.210 | 0.083 | -0.065 | -0.018 |
| | [0.413] | [0.301] | [0.064] | [0.043] | [0.058] |
| PhD | 0.518 | 0.172 | -0.071 | 0.058 | 0.013 |
| | [0.356] | [0.276] | [0.059] | [0.041] | [0.054] |
| Tenure | -0.007 | 0.013 | -0.001 | -0.001 | 0.003 |
| | [0.037] | [0.031] | [0.007] | [0.005] | [0.006] |
| Career Length Pre | 0.000 | -0.029 | 0.005 | 0.001 | -0.006 |
| | [0.030] | [0.026] | [0.005] | [0.004] | [0.005] |
| College in Area | -0.923 | -0.286 | 0.115 | -0.090* | -0.025 |
| | [0.570] | [0.378] | [0.078] | [0.047] | [0.073] |
| Observations | 379 | 379 | 379 | 379 | 379 |

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

An important regional determinant of mobility is the dynamism of the local labor market. I incorporate a measure of this for mobility results in Table 5. The variable "Growth Local Establishments" uses County Business Patterns data from the US Census, and it is built by calculating the average growth of number of R&D establishments in physical, engineering and life sciences in the region in the three years preceding each closure (including the year of the closure)[4]. Results show that, as expected, labor market dynamism has a very large effect on the three mobility outcomes. Also as expected, inventors are more likely to change region and firm, and less likely to change only firm, the more dynamic the local labor market is at the time of the closure. The

[4] Ideally this variable would be constructed using number of R&D employees in the region, but information on number of employees is not available for closures in the early 2000s.

results on pre-closure productivity remain the same: more productive inventors are more likely to change both region and firm, and less productive inventors are more likely to stay with the firm.

**Table 5: Determinants of mobility post-closure, controlling for labor market dynamism**

| **Variables** | **Coefficients** | | **Marginal Effects** | | |
|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** |
| | Move Region | Move Region and Firm | Move Firm | Move Region | Move Region and Firm |
| Productivity Pre-Closure | -0.178 | 0.238* | -0.018 | -0.038* | 0.056** |
| | [0.158] | [0.135] | [0.029] | [0.022] | [0.026] |
| Gender | -0.457 | -0.035 | 0.047 | -0.060 | 0.013 |
| | [0.380] | [0.298] | {0.064] | [0.045] | [0.058] |
| PhD | 0.576* | 0.342 | -0.106* | 0.065 | 0.041 |
| | [0.321] | [0.266] | [0.055] | [0.041] | [0.049] |
| Tenure | -0.006 | -0.001 | 0.001 | -0.001 | 0.000 |
| | [0.034] | [0.031] | [0.006] | [0.005] | [0.006] |
| Career Length Pre | -0.004 | -0.034 | 0.005 | 0.001 | -0.007 |
| | [0.028] | [0.026] | [0.005] | [0.004] | [0.005] |
| Growth Local Establishments | -0.732 | -2.484*** | 0.445*** | 0.015 | -0.460*** |
| | [0.804] | [0.896] | [0.166] | [0.117] | [0.172] |
| Observations | 397 | 397 | 397 | 397 | 397 |

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

*5.2 Technological trajectory*

The results from Tables 3, 4 and 5 suggest that since more productive inventors are more willing to change region and firm, they would be less likely to change their technological trajectory, which would be consistent with their preferences placing more weight on their work life. Table 6 shows results that are consistent with this premise. The dependent variable in these regressions is a measure of change in the researcher’s technological trajectory.

**Table 6: Relationship between mobility outcomes and technological trajectory**

| VARIABLES | (1)<br>Distance Post-Closure | (2)<br>Distance Post-Closure | (3)<br>Distance Post-Closure | (4)<br>Distance Pre-Closure |
|---|---|---|---|---|
| Move Firm | 0.039 | 0.064 | 0.091 | 0.005 |
| | [0.061] | [0.052] | [0.056] | [0.042] |
| Move Region and Firm | -0.064 | -0.013 | 0.016 | -0.038 |
| | [0.066] | [0.058] | [0.060] | [0.044] |
| Productivity Pre-Closure | | -0.132*** | -0.149*** | -0.158*** |
| | | [0.022] | [0.024] | [0.016] |
| Gender | | | -0.101* | 0.011 |
| | | | [0.056] | [0.041] |
| PhD | | | -0.025 | 0.061 |
| | | | [0.056] | [0.039] |
| Tenure | | | -0.011* | -0.004 |
| | | | [0.006] | [0.003] |
| Career Length Pre | | | 0.020*** | 0.009*** |
| | | | [0.005] | [0.003] |
| Observations | 214 | 214 | 213 | 247 |
| R-squared | 0.018 | 0.151 | 0.225 | 0.301 |

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Column 1 in Table 6 shows a negative correlation between this distance and having moved both firm and region. When I add other covariates in Columns 2 and 3, including productivity in the pre-closure window, the result holds up – in the complete specification in Column 3, moving only firm is associated with an 9% increase in the distance between the inventor's pre-closure and post-closure portfolios compared to the omitted category, move only region (p-value = 0.10). Moving both has no statistical difference with moving only region. These results validate the hypothesis that inventors that change both firm and region stick closer to their technological trajectory, while inventors that prioritize their geographical attachment deviate more. Column 4 shows a placebo regression that uses as dependent variable the difference between two time windows that are pre-closure, and the coefficient on Move Region and Firm is statistically close to zero. Thus, the results in Tables 3, 4, 5 and 6 are consistent with Hypotheses 1 and 2.

Table 7 shows results for technological trajectory of inventors post-closure, with a sample that incorporates control inventors who stayed in the same firm and region. Since these inventors are now the omitted category, we can now observe changes in technological trajectory for the three mobility outcomes in comparison to the control sample. In the complete specification of column 3, we see the same pattern as before: inventors who change firms and stay in the same region deviate from their previous technological trajectory in a significant way. Comparing these results with the ones from Table 6, which contained only the treated sample, we see that the size of the coefficient is mostly the same, but the increased sample size has reduced the standard errors significantly. The placebo regression in Column 4 again eliminates the effect.

**Table 7: Relationship between mobility and technological trajectory, with control sample**

| Variables | (1)<br>Distance Post-Closure | (2)<br>Distance Post-Closure | (3)<br>Distance Post-Closure | (4)<br>Distance Pre-Closure |
|---|---|---|---|---|
| Move Region | 0.039 | 0.040 | 0.024 | -0.056 |
| | [0.058] | [0.049] | [0.051] | [0.042] |
| Move Firm | 0.071* | 0.095** | 0.103*** | -0.047 |
| | [0.042] | [0.039] | [0.039] | [0.030] |
| Move Region and Firm | -0.081 | -0.035 | -0.033 | -0.101*** |
| | [0.053] | [0.050] | [0.047] | [0.034] |
| Productivity Pre-Closure | | -0.117*** | -0.126*** | -0.142*** |
| | | [0.015] | [0.016] | [0.012] |
| Gender | | | -0.096** | -0.015 |
| | | | [0.039] | [0.029] |
| PhD | | | 0.011 | 0.024 |
| | | | [0.034] | [0.025] |
| Tenure | | | -0.002 | -0.001 |
| | | | [0.004] | [0.003] |
| Career Length Pre | | | 0.012*** | 0.005** |
| | | | [0.003] | [0.002] |
| Observations | 418 | 418 | 417 | 471 |
| R-squared | 0.017 | 0.133 | 0.182 | 0.259 |

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

The results above may include control inventors whose research are too distant from their treated counterparts in terms of their patent portfolio. Table 8 shows results for the distance regression that limit the control sample to inventors whose maximum distance to a treated inventor in the same firm is less than 0.15. The results are qualitatively similar. Tables A2 and A3 in the Appendix perform the same exercise with distance thresholds of 0.2 and 0.3.

**Table 8: Relationship between mobility outcomes and technological trajectory, with control sample limited to maximum distance threshold = 0.15**

| Variables | (1) Distance Post-Closure | (2) Distance Post-Closure | (3) Distance Post-Closure | (4) Distance Pre-Closure |
|---|---|---|---|---|
| Move Region | 0.047 | 0.053 | 0.034 | -0.013 |
| | [0.063] | [0.054] | [0.057] | [0.044] |
| Move Firm | 0.079* | 0.110** | 0.113** | 0.000 |
| | [0.048] | [0.046] | [0.045] | [0.032] |
| Move Region and Firm | -0.073 | -0.018 | -0.017 | -0.058 |
| | [0.058] | [0.056] | [0.053] | [0.036] |
| Productivity Pre-Closure | | -0.126*** | -0.137*** | -0.138*** |
| | | [0.020] | [0.020] | [0.013] |
| Gender | | | -0.081* | -0.014 |
| | | | [0.046] | [0.032] |
| PhD | | | 0.014 | 0.020 |
| | | | [0.045] | [0.028] |
| Tenure | | | -0.006 | -0.004 |
| | | | [0.005] | [0.003] |
| Career Length Pre | | | 0.016*** | 0.005* |
| | | | [0.004] | [0.003] |
| Observations | 296 | 296 | 295 | 335 |
| R-squared | 0.024 | 0.135 | 0.196 | 0.256 |

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 9 replicates the exercise of Table 4 of including measures of local attachment, but looking at changes in technological trajectory. This specification includes a second measure of local attachment, which is a dummy that equal 1 if the inventor went to college in the area, or spent more than four years in the area prior to the closure. While this operationalization does not yield results (Column 2), in Column 1 the interaction between going to school in the area and Move Firm has similar size as the Move Firm coefficient, but with opposite sign (p-value = 0.12), which is indicative that inventors that went to school in the area and stayed there after the closure do not deviate their trajectory significantly. There are at least two explanations for this. Firstly, inventors just stay in their research trajectories because the schools they went, and the local firms they went to, do the same research. Secondly, inventors more embedded in the local environment (because they went to school there) have more opportunities available to them due to lower information asymmetries, so they do not need to deviate as much.

**Table 9: Relationship between mobility outcomes and technological trajectory, controlling for local attachment**

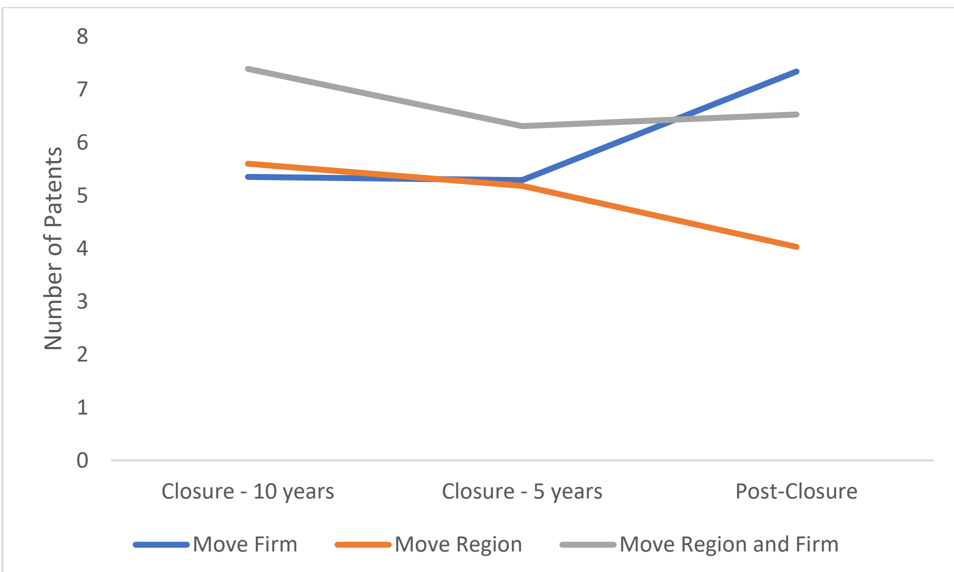
| **Variables** | **(1)**<br>Distance Post-Closure | **(2)**<br>Distance Post-Closure |
|---|---|---|
| Move Firm | 0.098 | 0.177* |
| | [0.063] | [0.104] |
| Move Region and Firm | 0.008 | 0.020 |
| | [0.063] | [0.060] |
| Productivity Pre-Closure | -0.146*** | -0.150*** |
| | [0.026] | [0.025] |
| Gender | -0.077 | -0.097* |
| | [0.057] | [0.057] |
| PhD | -0.022 | -0.025 |
| | [0.059] | [0.056] |
| Tenure | -0.009 | -0.011* |
| | [0.007] | [0.006] |
| Career Length Pre | 0.020*** | 0.019*** |
| | [0.005] | [0.005] |
| College in Area | 0.057 | |
| | [0.106] | |
| Move Firm*College in Area | -0.120 | |
| | [0.077] | |
| Local | | 0.123 |
| | | [0.082] |
| Move Firm*Local | | -0.089 |
| | | [0.109] |
| Observations | 202 | 213 |
| R-squared | 0.232 | 0.231 |

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

*5.3 Ex-post productivity*

Moving to the analysis of post-closure productivity, Figure 2 shows the consolidated productivity trajectory (measured in raw number of patents) of the three mobility groups across three periods: the 5-year window starting at 10 years prior to the closure; the 5-year window immediately preceding the closure; and the years post-closure. The graph shows that inventors in the Move Region group suffer a distinct decline in productivity after the closures when compared to the other two groups.

**Figure 2: Productivity Trajectories for the Three Mobility Outcomes**




As for the regression analysis, in Table 10 we see some initial validation of hypotheses 3 and 4. Column 1 of Table 10 shows that when comparing the productivity outcomes of the three mobility options amongst one another, moving only region is the option that performs worse. As expected, the persistence factor, represented by the coefficient of the productivity in the time window immediately prior to the closure, is strongly positive. Column 2 includes other controls, and there is positive correlation between ex-post productivity and having a PhD, and a negative correlation between productivity and career length prior to the closure.

Column 3 shows the results of a panel regression with inventor fixed effects – whereas the previous two regressions were at the inventor level, Column 3 is at the inventor-period level. Each inventor's career was split into 5-year time windows dummies for the years pre-closure, and a dummy for the entire post-closure period. The regression includes time period dummies (omitting the first period) and interactions between the last period dummy and the 'Move Region' and 'Move Region and Firm' outcomes, with the other control variables being wiped out by the inventor fixed effect. Consistent with Hypotheses 3 and 4, we see that scientists who changed labs within the same firm see a significant drop-off in performance post-closure, while those who changed both region and firm remain on the same productivity trajectory (i.e., there is no statistically significant change).

**Table 10: Ex-Post Productivity**

| | Cross section | | Panel with FE |
|---|---|---|---|
| **Variables** | **(1)** | **(2)** | **(3)** |
| | Productivity Post | | |
| Move Region | -1.844*** | -1.600*** | |
| | [0.562] | [0.440] | |
| Move Region and Firm | -0.363 | -0.432 | |
| | [0.606] | [0.471] | |
| Productivity Pre-Closure | 0.143*** | 0.129*** | |
| | [0.024] | [0.020] | |
| Gender | | -0.399 | |
| | | [0.513] | |
| PhD | | 0.976** | |
| | | [0.405] | |
| Tenure | | -0.057 | |
| | | [0.067] | |
| Career Length Pre | | -0.193*** | |
| | | [0.047] | |
| Move Region*Post-Closure Dummy | | | -0.542** |
| | | | [0.264] |
| Move Region and Firm*Post-Closure Dummy | | | -0.222 |
| | | | [0.217] |
| Observations | 425 | 424 | 2,550 |
| R-squared | 0.110 | 0.210 | |

Panel regression includes dummies for 5-years time windows and inventor FE
Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 11 runs the same specifications, now including the control sample. Column 2 again shows a negative effect associated with the Move Region outcome, as well as with the Career Length Pre-Closure variable (PhD is no longer significant). Furthermore, Gender is now associated with a negative effect – women seem to be less productive after closures, as the burden on families affected by these displacements seem to fall proportionally more to female scientists then to male scientists. Looking at Column 3 for the results with inventor fixed effects, we find that, consistent with Hypothesis 3, inventors who changed region to stay in the same firm see a decrease in their performance (p-value = 0.14), and consistent with Hypothesis 4, the coefficient on Move Region is larger in absolute value than the coefficient on Move Region and Firm, and the high p-value of the latter is indicative of a null effect. Thus, it would seem that inventors that stay in the same firm see a decline in performance, while inventors who change both firm and region maintain the same productivity trajectory.

**Table 11: Ex-Post Productivity, including control sample**

| | Cross section | | Panel with FE |
|---|---|---|---|
| **Variables** | **(1)** | **(2)** | **(3)** |
| | Productivity Post | | |
| Move Region | -1.672*** | -1.410*** | |
| | [0.529] | [0.383] | |
| Move Firm | -0.123 | 0.045 | |
| | [0.633] | [0.461] | |
| Move Region & Firm | -0.467 | -0.306 | |
| | [0.729] | [0.547] | |
| Productivity Pre-Closure | | 0.061*** | |
| | | [0.007] | |
| Gender | | -1.627*** | |
| | | [0.499] | |
| PhD | | 0.568 | |
| | | [0.538] | |
| Tenure | | -0.114** | |
| | | [0.054] | |
| Career Length Pre | | -0.174*** | |
| | | [0.044] | |
| Move Firm*Post-Closure Dummy | | | 0.147 |
| | | | [0.185] |
| Move Region*Post-Closure Dummy | | | -0.389 |
| | | | [0.263] |
| Move Region and Firm*Post-Closure Dummy | | | -0.183 |
| | | | [0.220] |
| Observations | 862 | 861 | 5,172 |
| R-squared | 0.130 | 0.240 | |

Panel regression includes dummies for 5-years time windows and inventor FE
Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Similar to Table 8, Table 12 limits the control sample to inventors that have a maximum distance threshold to the closest treated inventor of 0.15. Results are qualitatively similar, but with stronger statistical power, especially when the distance threshold is 0.2 (possibly the optimal combination of sample size and treatment/control sample comparability).

**Table 12: Ex-Post Productivity, including control sample limited to maximum distance threshold = 0.15**

| | Cross section | | Panel with FE |
|---|---|---|---|
| **Variables** | **(1)** | **(2)** | **(3)** |
| | Productivity Post | | |
| Move Region | -3.903*** | -3.773*** | |
| | [0.987] | [0.886] | |
| Move Firm | 0.554 | 0.561 | |
| | [1.108] | [0.966] | |
| Move Firm and Region | -1.386 | -1.327 | |
| | [1.236] | [1.081] | |
| Productivity Pre-Closure | 0.228*** | 0.237*** | |
| | [0.045] | [0.045] | |
| Gender | | -1.036 | |
| | | [0.973] | |
| PhD | | 1.455 | |
| | | [0.916] | |
| Tenure | | 0.026 | |
| | | [0.111] | |
| Career Length Pre | | -0.312*** | |
| | | [0.089] | |
| Move Firm*Post-Closure Dummy | | | 0.185 |
| | | | [0.170] |
| Move Region*Post-Closure Dummy | | | -0.604** |
| | | | [0.247] |
| Move Region and Firm*Post-Closure Dummy | | | -0.220 |
| | | | [0.231] |
| Observations | 299 | 298 | 1,632 |
| R-squared | 0.100 | 0.160 | |

Panel regression includes dummies for 5-years time windows and inventor FE
Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

One possible explanation for the results above is that inventors that change establishments within the same firm post-closure are more likely to take up a non-research role in the new job (such as regulatory affairs, management of contract research organizations, etc.). In this scenario, the greater decline in productivity observed for inventors in the Move Region category would not be explained by loss of establishment-specific routines and processes, but by inventors simply no longer engaging in research. Table 13 replicates the analysis for ex-post productivity for a subsample comprised only of inventors that had a research role in their next jobs after the closure, either in direct research or in a managerial role (as coded from their LinkedIn profiles). Around 80% of treated inventors in the original sample fit this criterion. Column 3 shows that the decline in productivity for inventors in the Move Region category is robust to this analysis.

**Table 13: Ex-Post Productivity, research roles subsample**

| | **Cross section** | | **Panel with FE** |
|---|---|---|---|
| **Variables** | **(1)** | **(2)** | **(3)** |
| | Productivity Post | | |
| Move Region | -2.441*** | -2.164*** | |
| | [0.678] | [0.568] | |
| Move Region and Firm | -0.373 | -0.442 | |
| | [0.710] | [0.590] | |
| Productivity Pre-Closure | 0.168*** | 0.159*** | |
| | [0.036] | [0.032] | |
| Gender | | -0.014 | |
| | | [0.673] | |
| PhD | | 1.073** | |
| | | [0.484] | |
| Tenure | | -0.044 | |
| | | [0.085] | |
| Career Length Pre | | -0.230*** | |
| | | [0.063] | |
| Move Region*Post-Closure Dummy | | | -0.691** |
| | | | [0.282] |
| Move Region and Firm*Post-Closure Dummy | | | -0.310 |
| | | | [0.233] |
| Observations | 339 | 338 | 2,034 |
| R-squared | 0.100 | 0.190 | |

Panel regression includes dummies for 5-years time windows and inventor FE
Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

If performance post-closure decreases due to loss of ESHC, we should see this loss being positively correlated with variables associated with more developed ESHC. Table 14 adds some additional interactions to the ex-post productivity regressions to test for this consistency. In particular, inventors with more ESHC should be inventors that: had longer tenure at the firm prior to the closure; worked in bigger labs (in my sample this is measured as number of inventors present in the sample for each lab); and had a greater number of coinventors prior to the closure. The negative coefficients for the mobility outcomes interacted with tenure (for both the treatment sample only and the addition of the control sample) and lab size are consistent with this story. I find no results for number of coinventors pre-closure.

**Table 14: Ex-Post Productivity, additional interactions**

| **Variables** | **(1)** | **(2)** | **(3)** | **(4)** |
|---|---|---|---|---|
| | | Treatment Sample | | Control Sample |
| Move Firm | | | | 1.941*** |
| | | | | [0.347] |
| Move Region | 0.528 | 0.394 | -0.255 | 0.641 |
| | [0.471] | [0.604] | [0.308] | [0.475] |
| Move Firm and Region | 0.687* | -0.550 | -0.125 | 0.579 |
| | [0.395] | [0.624] | [0.294] | [0.423] |
| Move Firm*Tenure | | | | -0.175*** |
| | | | | [0.037] |
| Move Region*Tenure | -0.100*** | | | -0.099*** |
| | [0.033] | | | [0.034] |
| Move Firm and Region*Tenure | -0.084*** | | | -0.068** |
| | [0.032] | | | [0.031] |
| Move Region*Lab Size | | -0.023* | | |
| | | [0.013] | | |
| Move Firm and Region*Lab Size | | 0.008 | | |
| | | [0.013] | | |
| Move Region*Number of Coinventors in Old Job | | | -0.039 | |
| | | | [0.031] | |
| Move Firm and Region*Number of Coinventors in Old Job | | | -0.009 | |
| | | | [0.018] | |
| Observations | 2,544 | 2,550 | 2,550 | 5,166 |

Panel regression includes dummies for 5-years time windows and inventor FE
Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

## 6. Additional analysis

### *6.1 Lab fixed effects*

Table 15 includes results for the treated inventors with lab fixed effects for each of the 17 closures. Column 1 shows that inventors that were in regions that had less dynamic pharmaceutical clusters (WA, IL, MI) were more likely to move both firm and region than inventors who were in more dynamic clusters (such as the ones in CA). After taking these effects into account, prior productivity becomes less relevant to explain regional and firm mobility. Column 2 shows that the results for technological trajectory are similar to previous ones.

**Table 15: Lab fixed effects**

| VARIABLES | (1) Move Region and Firm | (2) Distance Post-Closure |
|---|---|---|
| Move Firm | | 0.126** |
| | | [0.062] |
| Move Region and Firm | | 0.026 |
| | | [0.062] |
| Productivity Pre-Closure | 0.032 | -0.130*** |
| | [0.027] | [0.025] |
| Gender | 0.046 | -0.085 |
| | [0.057] | [0.062] |
| PhD | 0.079 | -0.020 |
| | [0.050] | [0.058] |
| Tenure | -0.002 | -0.005 |
| | [0.006] | [0.007] |
| Career Length Pre | -0.004 | 0.011** |
| | [0.005] | [0.004] |
| Amgen WA | 0.149** | -0.496*** |
| | [0.071] | [0.154] |
| Astrazeneca DE | 0.306*** | -0.180 |
| | [0.088] | [0.161] |
| Bayer CT | 0.478*** | -0.473*** |
| | [0.093] | [0.130] |
| Eli Lilly NC | 0.123 | -0.736*** |
| | [0.177] | [0.183] |
| Eli Lilly WA | 0.074 | -0.427*** |
| | [0.096] | [0.160] |
| GSK WA | 0.288** | -0.385** |
| | [0.116] | [0.160] |
| Merck San Diego | 0.064 | -0.676*** |
| | [0.088] | [0.127] |
| Merck WA | 0.376*** | -0.442*** |
| | [0.128] | [0.144] |
| Millennium San Francisco | -0.023 | -0.643*** |
| | [0.089] | [0.139] |
| Novartis MD | 0.245 | -0.430** |
| | [0.159] | [0.168] |
| Pfizer San Francisco | 0.077 | -0.430*** |
| | [0.081] | [0.151] |
| Pfizer IL | 0.335*** | -0.555*** |
| | [0.087] | [0.130] |
| Pfizer MI | 0.268*** | -0.453*** |
| | [0.077] | [0.131] |
| Pfizer PA | 0.229*** | -0.301** |
| | [0.075] | [0.139] |
| Takeda San Francisco | 0.076 | -0.228 |
| | [0.182] | [0.155] |
| Biogen San Diego | 0.055 | |
| | [0.093] | |
| Observations | 397 | 213 |
| R-squared | 0.106 | 0.355 |

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

### *6.2 Research roles and mobility outcomes*

Going back to the data on job nature post-closure that I explored in Table 13, I now use this information as the dependent variable to analyze how it is related to the three mobility outcomes.

Column 1 of Table 16 is a regression of a dummy indicating whether the inventor had a research role after closure on the three mobility outcome variables, plus controls. While no patterns emerge in this specification, for Columns 2 and 3 I recode the dependent variable as dummies for direct research roles or research management roles, respectively. For the former, results show that inventors in the Move Region category are significantly more likely (both in statistical and in economic terms) to take up a direct research role when they move to a new lab within the firm than inventors in the other two mobility outcomes. This result is consistent with the idea that the negative ex-post productivity results for More Region are not driven by inventors taking non-research roles when they move labs with the firm after the closure. The results for Column 3, for the dummy for research management roles, show that inventors in the Move Region and Firm category are more likely than the others to work in a research management role after closure. This result is consistent with the idea that inventors that decide to give up on their geographical attachment and firm specificity are looking to improve their career prospects. Finally, Table 16 again shows how the negative effects of closures fall disproportionately to women, who seem to be more likely to drop out of research roles after displacement.

## Table 16: Research roles and mobility outcomes

| Variables | (1) Research Role Post-Closure | (2) Direct Research Role Post-Closure | (3) Research Management Role Post-Closure |
|---|---|---|---|
| Move Firm | -0.044 | -0.174*** | 0.076 |
| | [0.051] | [0.064] | [0.061] |
| Move Firm and Region | -0.026 | -0.196*** | 0.125* |
| | [0.057] | [0.072] | [0.068] |
| Productivity Pre-Closure | 0.029 | 0.026 | 0.003 |
| | [0.022] | [0.026] | [0.025] |
| Gender | -0.111** | -0.108** | 0.011 |
| | [0.055] | [0.060] | [0.051] |
| PhD | 0.015 | -0.345*** | 0.351*** |
| | [0.046] | [0.050] | [0.041] |
| Tenure | -0.008 | -0.001 | -0.005 |
| | [0.006] | [0.006] | [0.006] |
| Career Length Pre | -0.003 | -0.013*** | 0.009* |
| | [0.005] | [0.005] | [0.005] |
| Observations | 397 | 381 | 380 |
| R-squared | 0.042 | 0.144 | 0.147 |

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 17 shows more results consistent with the idea that the negative effects on productivity for people in the Move Region category are not driven by these scientists no longer engaging in scientific research. The table shows a Logit regression that has as its dependent variable whether inventors had a patent or not after getting displaced, with Column 1 including only the treatment sample, and Column 2 adding the control sample. In the latter, we see that out of the 3 mobility outcomes, Move Region is the only one that does not have a negative significant coefficient – as was the case with the prior table, it is evident in fact that if anything people in the Move Region category were *more* likely to continue working on research after the closures.

**Table 17: Patenting outcomes post-closure, extensive margin (binary DV)**

| Variables | (1) | (2) |
|---|---|---|
| | Productivity Post | |
| Move Region | 0.044 | -0.093 |
| | [0.077] | [0.078] |
| Move Firm | | -0.185*** |
| | | [0.046] |
| Move Firm and Region | 0.021 | -0.191*** |
| | [0.060] | [0.061] |
| Productivity Pre-Closure | 0.038*** | 0.047*** |
| | [0.007] | [0.006] |
| Gender | -0.055 | -0.069 |
| | [0.068] | [0.044] |
| PhD | 0.135** | 0.078** |
| | [0.057] | [0.037] |
| Tenure | -0.015** | -0.005 |
| | [0.007] | [0.004] |
| Career Length Pre | -0.015*** | -0.014*** |
| | [0.006] | [0.004] |
| Observations | 424 | 861 |

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

*6.3 Comobility*

Recent literature in strategy has emphasized the importance of comobility in facilitating smoother processes of job changes (Groysberg, Lee, and Nanda 2008; Campbell, Saxton, and Banerjee 2014; Marx and Timmermans 2017). In the context of this paper, one would expect that, *ceteris paribus*, inventors that move to new labs (regardless of location and firm) with former colleagues should stick closer to their technological trajectories and suffer a smaller performance decrease than those that move solo. To verify this, I construct a variable that measures the number of coinventors from her previous job the focal inventor works with in her new job. The mean number of coinventors in the new job is 0.48, with standard deviation close to 1, with the number ranging from 0 to 6. Tables

18 and 19 show results for changes in technological trajectory and productivity controlling for this variable, and for its interactions with mobility outcomes. For the former, the coefficient on the interaction between number of coinventors and Move Firm shows that moving to a new firm in the same region with former colleagues ameliorates the deviation from technological trajectory we observed on these inventors that decided to prioritize geographical attachment over career concerns. For the latter, moving with coinventors does not seem to alter ex-post productivity outcomes in a significant way.

**Table 18: Comobility and technological trajectory**

| **Variables** | **(1)** | **(2)** | **(3)** |
|---|---|---|---|
| | | Distance Post-Closure | |
| Move Firm | 0.091 | 0.094* | 0.139** |
| | [0.056] | [0.055] | [0.060] |
| Move Region and Firm | 0.016 | 0.023 | 0.002 |
| | [0.060] | [0.060] | [0.064] |
| Productivity Pre-Closure | -0.149*** | -0.132*** | -0.126*** |
| | [0.024] | [0.031] | [0.031] |
| Gender | -0.101* | -0.108* | -0.087 |
| | [0.056] | [0.058] | [0.059] |
| PhD | -0.025 | -0.035 | -0.016 |
| | [0.056] | [0.057] | [0.059] |
| Tenure | -0.011* | -0.010 | -0.011* |
| | [0.006] | [0.006] | [0.006] |
| Career Length Pre | 0.020*** | 0.019*** | 0.018*** |
| | [0.005] | [0.005] | [0.005] |
| Number of Coinventors | | -0.005 | -0.007 |
| | | [0.005] | [0.005] |
| Move Firm*Number of Coinventors | | | -0.050*** |
| | | | [0.016] |
| Move Region and Firm*Number of Coinventors | | | 0.015 |
| | | | [0.042] |
| Observations | 213 | 213 | 199 |
| R-squared | 0.225 | 0.229 | 0.275 |

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

**Table 19: Comobility and ex-post productivity**

| Variables | Cross section (1) | (2) | Panel with FE (3) |
|---|---|---|---|
| | Productivity Post | | |
| Move Region | -1.308*** | -1.277** | |
| | [0.494] | [0.639] | |
| Move Firm | 0.446 | -0.346 | |
| | [0.501] | [0.631] | |
| Productivity Pre-Closure | 0.129*** | 0.120*** | |
| | [0.020] | [0.019] | |
| Gender | -0.399 | -0.743* | |
| | [0.513] | [0.447] | |
| PhD | 0.976** | 0.787* | |
| | [0.405] | [0.417] | |
| Tenure | -0.057 | -0.038 | |
| | [0.067] | [0.063] | |
| Career Length Pre | -0.193*** | -0.152*** | |
| | [0.047] | [0.054] | |
| Number of Coinventors in New Job | | 0.837*** | |
| | | [0.143] | |
| Move Region*Number of Coinventors in New Job | | -0.673 | |
| | | [0.712] | |
| Move Firm and Region*Number of Coinventors in New Job | | -0.237 | |
| | | [0.645] | |
| Move Region*Post-Closure Dummy | | | -0.823** |
| | | | [0.365] |
| Move Region and Firm*Post-Closure Dummy | | | -0.207 |
| | | | [0.241] |
| Move Region*Post-Closure Dummy*Number of Coinventors in New Job | | | 0.373 |
| | | | [0.300] |
| Move Region and Firm*Post-Closure Dummy*Number of Coinventors in New Job | | | -0.102 |
| | | | [0.089] |
| Observations | 424 | 377 | 2,268 |
| R-squared | 0.210 | 0.280 | |

Panel regression includes dummies for 5-years time windows and inventor FE
Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

## 6 Conclusion and Next Steps

This paper examines the consequences of R&D lab closures for inventors in the pharmaceutical industry. It finds that: 1) inventors who change both firm and region after a closure are more likely to remain in the same technological trajectory (as measured by their patent classes); 2) the more productive inventors pre-closure tend to be those that change both firm and region and remain in the same technological trajectory; 3) inventors that change labs within the same firm (that is, only change region) see a decrease in performance, which I ascribe to the loss of establishment-specific human capital; 4) inventors that change both region and firm see a non-decrease in performance, which I interpret as the result of improved employer-employee matching making up for the loss of establishment-specific knowledge.

The paper seeks to make the following contributions. Firstly, it enhances our understanding of the geographical context of the mobility of knowledge workers by incorporating their technological trajectory into the picture. In this sense, it answers the call made by the editors of a 2018 volume on knowledge worker mobility: "An assumption, oftentimes implicit, is that the workers are simply moving to another location to carry on the same work based on the same set of knowledge attributes. However, this may not necessarily be the case. Knowledge workers may or may not be called upon to make direct use of their pre-existing knowledge when they move to a new geographical context and in some instances they may need to substantially adapt their knowledge assets. Further research is therefore needed to explore differences between the drivers of 'pure' geographical moves (KWs who move locations but maintain knowledge focus) and those who jointly change geographical context and knowledge focus (e.g., KWs who move to a different job in a new location)." (Wright et al. 2018, p. 15-16). Secondly, it brings considerations of employee turnover and geography into the reorganization literature (Karim 2006), and in particular the R&D organization literature (Argyres and Silverman 2004; Singh 2008; Arora, Belenzon, and Rios 2014). Thirdly, it contributes to the literature on inventor productivity and mobility (Hoisl 2007; 2009) by incorporating within-firm mobility events as another relevant instance of mobility that can influence patenting outcomes, as well as the literature on inventors motivations and career choice (Roach and Sauermann 2010; Sauermann and Cohen 2010; Agarwal and Ohyama 2013) by highlighting the role of "taste for science" for industrial researchers. Finally, this research contributes to the literature on firm-specific capabilities (Huckman and Pisano 2006; Groysberg, Lee, and Nanda 2008) by highlighting the importance of establishment-level capabilities.

The empirical work presented above will be extended in the following ways. Firstly, inventor performance will include patent citation measures, as well as restricting the post-closure window to five years. Secondly, a lab fixed effects model which incorporates the control sample. Finally, I will use patent data to examine: what other firms had filed patents close to each affected inventor in her region; the patent portfolio of the firm/lab she moved to; the extent to which inventors being more or less generalist affect the outcomes analyzed in this paper; the role of overlap of technological trajectories of incoming inventors with new colleagues; and the performance of treatment and control labs prior to the closure.

*6.1 Managerial and policy implications*

This research has important implications for managers and policymakers. It is a cautionary tale for the former, in the sense that talent retention in a firm that is undergoing significant geographical reorganization (coupled with changes in its areas of focus) may become an issue. As firms decide to reduce their geographical footprint by eliminating establishments, its expectation that it would be able to retain the best workers being displaced may prove unwarranted, despite its best efforts. After such displacement events, these workers' attachment to their employer will decrease, for two reasons: 1) because their geographical attachment could be high enough to prevent them from moving to a different establishment in a new area; 2) and because if they are willing to move to a new area, this opens up a myriad of job opportunities to be explored in other companies – and such opportunities may allow them to preserve their technological trajectories in ways that may not be available with their current employer. Another reason why it is a cautionary tale is that retained workers may no longer be as productive as they were before, due to among other reasons the loss of establishment-specific human capital. Thus, one needs to be careful about the idea that human capital can be moved around establishments and geographies with no major repercussions to their performance.

For policymakers, this paper highlights the importance of a dense labor market for regional talent management strategies. If a region lose an important establishment, such as a local anchor tenant, and this region does not have a dense enough local labor market to accommodate workers that want to preserve their technological trajectories, it will possibly suffer from regional brain drain. To be sure, many workers will remain in the region due to their geographical attachment – again, place matters – but the most talented and productive ones may move to regions where they can keep their career on track. Furthermore, this paper points to the importance of establishments that are particularly productive from a social standpoint, and that may not be replicated if they are closed down. When firms' individual strategies regarding establishment closure may lead to outcomes that make financial sense for them, but that could lead to loss of socially valuable productive knowledge, governments may be justified in stepping in to keep these units functioning.

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## Appendix

### Table A1: Mobility OLS Regressions

| VARIABLES | (1)<br>Move Region | (2)<br>Move Firm | (3)<br>Move Region and Firm |
|---|---|---|---|
| Productivity Pre-Closure | -0.041 | -0.008 | 0.049 |
| | [0.022] | [0.028] | [0.025] |
| Gender | -0.061 | 0.058 | 0.003 |
| | [0.044] | [0.063] | [0.057] |
| PhD | 0.059 | -0.091 | 0.032 |
| | [0.040] | [0.055] | [0.049] |
| Tenure | -0.001 | -0.001 | 0.002 |
| | [0.005] | [0.006] | [0.005] |
| Career Length Pre | 0.002 | 0.005 | -0.007 |
| | [0.004] | [0.005] | [0.004] |
| Observations | 397 | 397 | 397 |
| R-squared | 0.021 | 0.014 | 0.019 |

Robust standard errors in brackets

### Table A2: Relationship between mobility outcomes and technological trajectory, with control sample limited to maximum distance threshold = 0.2

| **Variables** | **(1)**<br>Distance Post-Closure | **(2)**<br>Distance Post-Closure | **(3)**<br>Distance Post-Closure | **(4)**<br>Distance Pre-Closure |
|---|---|---|---|---|
| Move Region | 0.057 | 0.064 | 0.050 | -0.013 |
| | [0.060] | [0.052] | [0.054] | [0.043] |
| Move Firm | 0.089** | 0.119*** | 0.123*** | -0.003 |
| | [0.044] | [0.042] | [0.042] | [0.031] |
| Move Region and Firm | -0.063 | -0.012 | -0.008 | -0.060* |
| | [0.055] | [0.053] | [0.051] | [0.035] |
| Productivity Pre-Closure | | -0.115*** | -0.123*** | -0.135*** |
| | | [0.019] | [0.019] | [0.013] |
| Gender | | | -0.066 | -0.004 |
| | | | [0.044] | [0.031] |
| PhD | | | 0.001 | 0.023 |
| | | | [0.041] | [0.028] |
| Tenure | | | -0.005 | -0.002 |
| | | | [0.004] | [0.003] |
| Career Length Pre | | | 0.014*** | 0.003 |
| | | | [0.004] | [0.002] |
| Observations | 332 | 332 | 331 | 373 |
| R-squared | 0.024 | 0.119 | 0.168 | 0.235 |

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

**Table A3: Relationship between mobility outcomes and technological trajectory, with control sample limited to maximum distance threshold = 0.3**

| **Variables** | **(1)** Distance Post-Closure | **(2)** Distance Post-Closure | **(3)** Distance Post-Closure | **(4)** Distance Pre-Closure |
|---|---|---|---|---|
| Move Region | 0.051 | 0.053 | 0.036 | -0.045 |
| | [0.059] | [0.051] | [0.053] | [0.043] |
| Move Firm | 0.083* | 0.107*** | 0.111*** | -0.037 |
| | [0.043] | [0.040] | [0.040] | [0.031] |
| Move Region and Firm | -0.069 | -0.024 | -0.022 | -0.092*** |
| | [0.053] | [0.051] | [0.048] | [0.034] |
| Productivity Pre-Closure | | -0.111*** | -0.120*** | -0.141*** |
| | | [0.017] | [0.017] | [0.013] |
| Gender | | | -0.082** | -0.009 |
| | | | [0.041] | [0.030] |
| PhD | | | -0.004 | 0.022 |
| | | | [0.037] | [0.026] |
| Tenure | | | -0.004 | -0.001 |
| | | | [0.004] | [0.003] |
| Career Length Pre | | | 0.014*** | 0.004* |
| | | | [0.004] | [0.002] |
| Observations | 377 | 377 | 376 | 427 |
| R-squared | 0.02 | 0.123 | 0.18 | 0.246 |

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

**Table A4: Ex-Post Productivity, including control sample limited to maximum distance threshold = 0.2**

| | Cross section | | Panel with FE |
|---|---|---|---|
| **Variables** | **(1)** | **(2)** | **(3)** |
| | Productivity Post | | |
| Move Region | -3.875*** | -3.786*** | |
| | [0.916] | [0.829] | |
| Move Firm | 0.595 | 0.49 | |
| | [1.009] | [0.881] | |
| Move Firm and Region | -1.372 | -1.380 | |
| | [1.152] | [1.015] | |
| Productivity Pre-Closure | 0.232*** | 0.243*** | |
| | [0.044] | [0.044] | |
| Gender | | -0.796 | |
| | | [0.914] | |
| PhD | | 1.335 | |
| | | [0.843] | |
| Tenure | | -0.001 | |
| | | [0.101] | |
| Career Length Pre | | -0.284*** | |
| | | [0.082] | |
| Move Firm*Post-Closure Dummy | | | 0.172 |
| | | | [0.151] |
| Move Region*Post-Closure Dummy | | | -0.618*** |
| | | | [0.233] |
| Move Region and Firm*Post-Closure Dummy | | | -0.232 |
| | | | [0.217] |
| Observations | 336 | 335 | 1,897 |
| R-squared | 0.100 | 0.160 | |

Panel regression includes dummies for 5-years time windows and inventor FE
Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

**Table A5: Ex-Post Productivity, including control sample limited to maximum distance threshold = 0.3**

| | **Cross section** | | **Panel with FE** |
|---|---|---|---|
| **Variables** | **(1)** | **(2)** | **(3)** |
| | Productivity Post | | |
| Move Region | -3.338*** | -3.273*** | |
| | [0.849] | [0.769] | |
| Move Firm | 0.847 | 0.548 | |
| | [1.115] | [0.998] | |
| Move Firm and Region | -0.708 | -0.893 | |
| | [1.215] | [1.085] | |
| Productivity Pre-Closure | 0.081*** | 0.092*** | |
| | [0.010] | [0.009] | |
| Gender | | -1.477 | |
| | | [1.001] | |
| PhD | | 1.664* | |
| | | [0.979] | |
| Tenure | | -0.081 | |
| | | [0.123] | |
| Career Length Pre | | -0.205** | |
| | | [0.084] | |
| Move Firm*Post-Closure Dummy | | | 0.201 |
| | | | [0.158] |
| Move Region*Post-Closure Dummy | | | -0.589** |
| | | | [0.239] |
| Move Region and Firm*Post-Closure Dummy | | | -0.216 |
| | | | [0.219] |
| Observations | 388 | 387 | 2,206 |
| R-squared | 0.130 | 0.180 | |

Panel regression includes dummies for 5-years time windows and inventor FE
Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1