Scientific Labor Mobility, Market Value, and Knowledge Flows

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February 2014

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February 2014

Abstract

This paper studies the relationship between a firm's market value and the mobility of scientific and technical personnel in its sectoral and geographic proximity. I uncover distinct positive and negative effects of mobility on market value that operate through various channels. I document a positive effect of scientific labor mobility on market value through knowledge assets embedded within technologically similar firms: firms having large stocks of external knowledge in their disposal benefit from increased mobility of scientific and technical personnel. On the other hand, firms that lack large external stocks of knowledge suffer a negative effect. The detrimental effect of mobility is larger for firms in more competitive industries, supporting the hypothesis that estimates capture the losses due to outbound knowledge and human capital. However, such losses are not significantly different for firms with different levels of R&D intensity. The positive and negative effects of scientific labor mobility, on average, are of similar magnitudes, making the average firm "break even" in terms of its net impact. These results are consistent with previous findings, and provide further insight into why innovative firms cluster in industrial districts.

Keywords: Scientific labor mobility; Market value; Knowledge flows; R&D; Patents; Citations; GMM.

JEL Classification: O31, O32, O33, J62, L6, C23.

*A previous version of this study was circulated with the title "Intra-Industry Knowledge Spillovers and Scientific Labor Mobility."

1 Introduction

It has long been understood that the mobility of scientific and technical personnel is an important conduit for knowledge flows among innovating firms (Arrow, 1962; Almeida and Kogut, 1999; Singh and Agrawal, 2011). The mobility of scientific and technical personnel breaks down traditional firm boundaries, as employees carry specific or general human capital generated within the firm to other firms that may find its use profitable, and enjoy part of the ensuing rents. As a result, the movement of labor creates difficulties for firms in appropriating the returns to their R&D investments. On the other hand, intellectual capital of firms with related technologies or products become available to the firm simply by hiring former employees of a rival. Recent research on inventor mobility has shown that mobile inventors tend to produce innovations of higher quality than non-movers (Palomeras and Melero, 2010; Lenzi, 2013). Hence, knowledge flows that occur via personnel mobility are likely to be more valuable and critical than could otherwise occur, as scientists carry tacit, uncodifiable knowledge that can only be transferred as embedded in their human capital (Polanyi, 1966; Nelson and Winter, 1982).

The evidence that links scientific[1] labor mobility to knowledge flows rests on the methodology introduced by Jaffe et al. (1993), who trace knowledge flows by studying the frequency of patent citations between economic units. While this methodology is well-suited to study various causes and aspects of knowledge flows, it is naturally silent on the *value* of knowledge flows that occur as a result of the mobility of scientific personnel. Hence, little is known about the precise gains or loses faced by a firm due to increased labor mobility.

The current paper fills this gap by studying the relationship between scientific labor mobility in a firm's sectoral and geographic vicinity, and the firm's market value. The exercise is undertaken for a large panel of U.S. manufacturing firms, and documents both positive and negative effects of mobility on market value through various channels. I find that increased mobility of scientific personnel contributes to market value for firms that have access to large stocks of externally created knowledge assets. The magnitude of this effect is significant: a percentage point increase in the geographic (*resp.* sectoral) mobility rate increases market value by as much as 6.5% (*resp.* 3.1%) for a firm that has access to the mean external knowledge stock. On the other hand, a firm that lacks access to large stocks of external knowledge loses market value as a result of increased

[1] For fluidity, I often use the term "scientific" personnel instead of the more cumbersome "scientific and technical" personnel. These refer to a number of specific job classifications which will be introduced in Section 4.1.

scientific turnover. This could be interpreted as a loss due to outbound knowledge capital, looser appropriability conditions, and the loss of valuable human capital. Seeking further explanation for such losses, I find that they tend to be larger for firms operating in more competitive industries, which is in line with the interpretation attached to the estimates above. On average, the opposite effects of mobility are of similar magnitudes, and a firm that faces the mean stock of external knowledge approximately "breaks even" in terms of the net effect of labor turnover. However, I do not find any effect of mobility that operates through a firm's own R&D enterprise: Firms with larger R&D intensity do not suffer or gain more due to increased mobility.

My estimates also reveal that a significant portion of inter-firm transfers of knowledge can be explained by the mobility of scientific personnel. For instance, a one standard deviation increase in the rate of scientific mobility creates knowledge flows the value of which measure as much as 18% of the total spillover effect. The same percentage reaches levels as high as 43% if mobility increases from its minimum sample value to its sample average.

My measure of scientific labor mobility is taken from the U.S. Current Population Survey, which allows constructing mobility rates for specific job classifications at the industrial sector and state level. Knowledge flows due to personnel mobility are most likely to occur via hires from firms operating in the firm's own sectoral classification. Many scholars have also noted that knowledge flows tend to be geographically localized (Jaffe et al., 1993; Singh and Marx, 2013). Accordingly, the study exploits the variation in scientific mobility in a firm's geographic, as well as sectoral proximity. I address endogeneity concerns by adopting a GMM framework, and use additional instruments to account for the endogeneity of the mobility rate. Aside from various personal characteristics of the sample of scientific personnel (age, race, marital status, living situation) that have bearing on their mobility patterns, I also use the cross-sectional and longitudinal variation in the strictness of the enforcement of non-compete covenants (henceforth non-competes, or NCCs) across U.S. States as an instrument for state-level mobility. For this purpose, I use the coding of non-compete enforcement constructed by Garmaise (2011) and back-dated by Bird and Knopf (2010) to introduce exogenous shifts in the rate of observed job changes[2].

My analyses deal with the value of knowledge flows that occur through the movement of scientific labor. One may be tempted to consider such flows as externalities, but this view is misleading. Since the transfer of scientists and engineers is a market transaction, it is reasonable to expect the resulting knowledge flows to be priced, to the extent they can be predicted. Hence, knowledge flows

[2] I am grateful to Robert Bird and John Knopf for sharing their coding with me.

that are considered in this paper are most likely not pure knowledge externalities. Møen (2005) offers evidence that spillovers due to employer changes are at least *partially* internalized by labor markets. However, whether these flows are fully priced by the market is not clear, and it isn't straightforward to attach an externality interpretation to the paper's main results (on this point, also see Griliches, 1972; Zucker et al., 1998; Breschi and Lissoni, 2001).

The rest of the paper is structured as follows. Section 2 reviews the related strands of literature. Section 3 introduces the market value equation and describes the paper's main empirical model. Section 4 introduces the main data sources and details data-related issues. Section 5 deals with econometric inference and estimation and presents the paper's results. Section 6 concludes.

2 Literature

That the transfers of knowledge are facilitated by the movement of engineers has long been understood by researchers. Arrow (1962) emphasizes the public good properties of knowledge, and makes the aforementioned case for the mobility of engineers. Stephan (1996) mentions the then lack of empirical work on the sources of inter-firm knowledge spillovers, and suggests the mobility of scientists within the industrial sector as a potentially important channel to be investigated in future empirical work. Building on these ideas, many scholars performed empirical tests of the claim that mobility of technical personnel facilitates knowledge flows. Almeida and Kogut (1999), studying the mobility of patent holders, show that inter-firm movements of engineers influences the local transfer of knowledge. Song et al. (2003) study the patenting activities of engineers in the global semiconductor industry who moved from U.S. to non-U.S. firms to show that both domestic and international mobility of engineers are conducive to knowledge flows. Zucker and Darby (2009) argue that critical knowledge is transferred through the regional and national migration of "star" scientists. Studying the movements of a sample of elite life scientists, Azoulay et al. (2011) show that citations of scientific articles from the new to the old location significantly increase after a move. Lenzi (2010) provides evidence from Italian data that the mobility of inventors spurs cumulative knowledge building. Singh and Agrawal (2011) demonstrate that firms significantly increase the use of their new employees' prior inventions, which they interpret as evidence for "learning-by-hiring". Ejsing et al. (2013) study a matched employer-employee data for Danish firms to show that newcomers to the firm contribute more to innovation than long-term employees. A contrary result is produced by Stolpe (2002), who finds the mobility of inventors in LCD technology to be unrelated to knowledge flows. He argues that this is due to the largely codifiable, scientific knowledge base of LCD technology. Møen (2005) uses Norwegian data to test a model of human capital accumulation to show that engineers pay for the knowledge they accumulate early in their lives, indicating that knowledge externalities due to scientific mobility are (at least partially) internalized by the scientific labor market.

A similar line of literature studies knowledge flows that occur via mobility from multinational corporations (MNCs) to local firms. Görg and Strobl (2005) use a survey of manufacturing firms in Ghana to show that domestic firms whose owners has work experience in a multinational have higher productivity compared to other domestic firms. Balsvik (2011) shows that Norwegian workers that move from a MNC to a domestic firm contribute 20 to 25% more to the productivity of the host firm than workers without such experience. Poole (2013) demonstrates that worker mobility to domestic Brazilian firms from MNCs causes an increase in the wages of domestic workers, which she interprets as an effect due to knowledge spillovers.

Recruiting scientists from competitors is a wide-spread practice innovating firms rely on to gain access to rivals' innovations. Cassiman and Veugelers (2006) find that 42% of firms in a sample of Belgian manufacturing use hiring skilled personnel as a strategy to acquire new technologies. Hyde (2003) and Saxenian (1994) both emphasize Silicon Valley's highly mobile labor market that allows inter-firm knowledge transfers. Hyde (2003) provides several interviews with Silicon Valley scientists and CEOs that support this view. A particularly striking quote from the book is by a Silicon Valley CEO: "We don't do R&D, we do A&D, acquire and develop". Saxenian (1994) argues that the enormous success of Silicon Valley compared to Massachusetts's Route 128 lies in the former's tradition of loose employer-employee ties, open firm boundaries, and laws that protect employees' rights to move to rival firms or form rival start-ups. Carr and Gorman (2001) argue that firms that pursue trade secret litigation against former employees suffer serious reputational harm, and face a decline in their stock prices. Hyde (2003) adds that this hurts the company's recruitment efforts, since high quality job candidates are not willing to work for a firm that might limit their future prospects.

On the theory front, Pakes and Nitzan (1983) study employment contracts with scientists in an environment in which the scientist has the option to leave the employer with the knowledge of the innovations created within the firm. Kim and Marschke (2005) extend this model to incorporate the employer's patenting decision, and test its main implication that increased probability of misappropriation by the scientist increases the employer's propensity to patent innovations. Lewis and

Yao (2006) study a model of contracting and matching between firms and scientists to provide an equilibrium explanation for the mobility of scientists, and a rationale for open R&D environments. Their main results are driven by the incompleteness of employment contracts.

The current study's emphasis on the geographic, as well as the sectoral dimension of labor mobility is inspired by the literature on the geography of spillovers, which has found physical geography to be an important impediment to knowledge flows[3]. Jaffe et al. (1993) show that citations to a patent are more likely to come from the same state and SMSA as the original patent, which they interpret as evidence for the localized nature of knowledge flows. Almeida and Kogut's (1999) study on the mobility of inventors reaches a similar conclusion. Singh and Marx (2013) find that country and state borders limit knowledge flows above and beyond physical distance. Singh (2005) and Breschi and Lissoni (2009) highlight that physical geography may be acting as a proxy for local scientific networks, in that the effect of distance diminishes once the effects of collaboration networks are controlled for. Mobility and network accounts of knowledge flows are intimately linked, in that the movements of scientists across firms and across space extend existing social networks, and are likely to be limited by them (Zellner and Fornahl, 2002). Agrawal et al. (2006) investigate such an aspect of labor mobility by studying social ties that survive geographic separation. They argue that connections that are conducive to knowledge flows are resistant to geographic separation, hence are likely to generate enduring links between the new and old firm or location of the moving scientist.

My results also provide further insight into why innovating firms cluster in industrial districts. The literature on agglomeration economies (Marshall, 1920; Krugman, 1991) puts special emphasis on labor pooling and local knowledge spillovers as critical determinants of firms' location choices. It has been recognized that firms locate near technically related rivals in order to gain access to essential resources that may otherwise be elusive (Marshall, 1920; Stuart and Sorenson, 2003). Stuart and Sorenson (2003) argue that industries cluster since entrepreneurs cannot mobilize essential resources without access to required social ties. Audretsch and Feldman (1996) find that the propensity to cluster is linked more closely to local spillovers than to advantages in production. Rosenthal and Strange (2001) use proxies for the common explanations of agglomeration, finding that the Ellison-Glaeser spatial concentration index (Ellison and Glaeser, 1997) is best explained by labor pooling motives at various geographic units. Ellison et al. (2010) find similar labor needs

[3] This is in contrast to early models that incorporated spillovers into economic analyses with the assumption that knowledge exhibited properties of pure public goods, as in models of endogenous growth (Romer, 1986; Lucas, 1988).

to be an important determinant of agglomeration, along with supplier relationships, spillovers, and shared natural advantages. The current paper's results build on these ideas, and have interesting implications for the individual, firm-level incentives to locate close to technically similar rivals. First, the paper's main result documents that the negative effects of labor mobility are large, but do not outweigh its benefits on average. In addition, the negative effect does not depend on the firm's own R&D intensity. These set of results jointly have two implications. First, disincentives for labor pooling are not strong enough to create *dis*agglomeration economies, as long as the firms in question are sufficiently innovative as a collective. Second, disincentives are not stronger for more innovative firms. Hence, results provide firm-level evidence for the labor pooling motivation for industrial agglomeration[4].

The current paper also draws from, and contributes to the literature on the measurement of spillover effects. The common methodology in this literature is to examine the effects of suitably aggregated stocks of external knowledge, termed "spillover pools", on a measure of performance or value, over and above those of the firm's own knowledge assets. I draw from the works of Jaffe (1986) and Bloom et al. (2013) in introducing spillover pools in typical market value equations. The preferred method is to build a weighted sum of external knowledge assets for each firm, where weights measure the technical proximity of the inventive activity of the firm with each remaining firm in the sample. I follow this approach, and also build and use measures of geographic concordance between the inventive activities of firms as weights in a similar aggregation procedure. This approach properly matches the units at which mobility rates are observed to the knowledge base most likely to be transferred by such mobility. Key results of the paper rely on interactions of the mobility rate with various other variables, including suitably constructed spillover pools. Estimates reveal that a significant portion of inter-firm transfers of knowledge can be explained by the mobility of scientific personnel. For instance, a one standard deviation increase in the rate of scientific mobility creates knowledge flows the value of which measure as much as 18% of total

[4] Obviously, I do not suggest that this is the primary reason for why agglomeration economies and industrial clusters exist, but propose this as one explanation for why they are robust and widespread. Even if a firm expects net losses due to the highly mobile labor market in a district, it may still find it imperative to locate close to it, since operation may be impossible without the spillovers discussed in this paper. This would be the case, for instance, if close proximity to the region is essential to gain access to the "tools of the trade". To understand the evolution of industrial districts, one must pay careful attention to the history and evolution of such districts, which tend to support the view that they are formed by the dissipation of essential knowledge through social networks, mobility, and spin-offs. In this regard, the evolution of high-tech districts such as Silicon Valley are not special cases, but examples of how a newfound "craft" creates local comperative advantages, and tends to keep and accumulate these advantages over time (Krugman, 1991). Historical accounts of how such crafts show similar patterns of knowledge localization are abundant.

spillovers, when spillover pools are held constant at the mean. The same percentage reaches levels as high as 43% if mobility increases from its minimum sample value to its sample average.

The variation in the enforcement of non-compete covenants enters as an instrument in the current paper's analyses. There is a burgeoning literature suggesting that stricter enforcement of NCCs significantly restrain employee mobility. Gilson (1999) argues that the initial condition for the success of Silicon Valley compared to Route 128 is the ban of non-competes in California. Marx et al. (2009), using Michigan's 1985 change of statute as a natural experiment, find that stricter non-compete enforcement reduces worker mobility, particularly for workers with firm-specific skills and in narrow technical fields. Marx et al. (2012) uncover a brain drain from states that enforce NCCs to states that do not. Marx (2011) finds that employees that are subject to non-competes commonly take career detours, i.e., they work outside their main field of expertise. For a review of the debate on NCC enforcement, and of the economic literature, see Marx and Fleming (2012).

3 Empirical Model

3.1 Market Value Equation

I start with a market value equation in the tradition of Griliches (1981). The market value of firm i at time t is assumed to take the form

$$V_{it} = q_t \left(A_{it} + \sum\nolimits_q \gamma_q K_{it,q} \right)^{\sigma} \tag{1}$$

where V_{it} is the market value of the firm (the sum of the values of common stock, preferred stock, and total debt net of assets), A_{it} is ordinary physical assets, and $K_{it,q}$, $q = 1, ...$ represent the firm's various knowledge (more generally, intangible) assets. Parameter σ allows for non-constant scale effects, and $\{\gamma_q\}$ measure the shadow value of knowledge assets relative to ordinary assets. From (1), dividing both sides with A_{it}, taking logs, imposing constant returns to scale, and using the linear approximation $\log(1 + \gamma x) \cong \gamma x$, we get

$$\log\left(\frac{V_{it}}{A_{it}}\right) = \log q_t + \sum\nolimits_q \gamma_q \frac{K_{it,q}}{A_{it}} \tag{2}$$

which can be interpreted as a regression specification with year-specific intercepts ($\log q_t$), and where the shadow values of intangibles $\{\gamma_q\}$ are coefficients to be estimated. The variable on the left hand side is the logarithm of Tobin's q, the market value of the firm relative to the replacement value of its physical assets, and q_t is interpreted as the average value of Tobin's q at year t. The motivation behind (2) is to look for sources of deviation from equilibrium ($q = 1$) in the firm's intangible knowledge assets[5].

In estimating variants of equation (2), knowledge assets are usually proxied by the firm's *stocks* of R&D, patents, and forward citations. I follow most of the literature in using the firm's R&D stock as a measure of its knowledge assets, which turns equation (2) into a regression with Tobin's q as the dependent variable and $\widetilde{R}_{it} = R_{it}/A_{it}$, R&D stock divided by assets as an independent variable. In addition, I follow Hall et al. (2005) in including $\widetilde{C}_{it} = C_{it}/P_{it}$, the firm's forward citation stock divided by its patent stock in the equation, as this variable captures the overall quality of the firm's stock of innovations (Trajtenberg, 1990; Albert et al., 1991; Harhoff et al., 1999; Giummo, 2003)[6]. All knowledge assets are used in *stock* form, calculated as perpetual inventories with 15% depreciation[7]. For instance, R_{it} is computed recursively by $R_{it} = r_{it} + .85 \times R_{it-1}$, where r_{it} represents firm i's R&D *expenditures* during year t. The computation of C_{it} and P_{it} are similar.

Following Jaffe (1986) and Bloom et al. (2013), I alter the market value equation by including measures of externally created knowledge (spillover pools)[8]. The spillover pool that is available to the firm ($SP^h_{K,it}$) is calculated as a weighted sum of knowledge assets for a set of external firms. Superscript h indicates the level of aggregation at which the variable is defined and measured (sector or geography), and subscript K the type of proxy for knowledge capital to be used in aggregation. In line with the paper's focus on sectoral and geographic mobility rates, two different aggregation procedures are employed, in order to match spillover pools to the relevant rate of labor mobility. These procedures will be detailed in the next subsection. At each aggregation level, I use three different indicators for the knowledge stocks of external firms, following conventional measures used to represent the firm's own knowledge assets. These are R&D stocks (R_{jt} for firm $j \neq i$), forward citation stocks (C_{jt}) and the ratio of forward citation stock to patent stock ($\widetilde{C}_{jt}$). In addition to

[5] A thorough discussion of the foundations of Tobin's q is outside the scope of the current paper, and the interested reader is referred to Hayashi (1982) and Wildasin (1984). Hall (1993) and Wernerfelt and Montgomery (1988) discuss various advantages of using market value compared to accounting measures of performance.

[6] A difference between the equation used here and that of Hall et al (2005) is that I exclude the firm's propensity to patent (Patent stock/R&D stock). This is because the coefficient for this term is statistically indistinguishable from zero in all specifications, which is consistent with the literature that precedes Hall et al (2005). They argue that this term partially controls for the effects of firm size, for which I control for using a direct measure, i.e, sales.

[7] This follows the convention in most of the previous literature. There is little known about the true depreciation rate of knowledge, and this has been a long lasting open question. Hall (2007) makes an extensive effort to estimate the rate of obsolescence of R&D investments, and finds estimates ranging from -6% to 40%, with implications of market value analysis being consistent with rates as high as 20-40%. Accordingly, I stick to the conventional depreciation rate of 15%, but test the robustness of my main results using various rates between 20-40% in unreported analysis.

[8] One way to motivate this is to assume that additional terms that are likely to affect market value enter through a a firm-year specific component of the intercept, which may be parametrized accordingly.

R&D stocks, the use of citations adjust for the quality of the inventive activity of external firms, which is intended to better capture the *value* of knowledge assets that can benefit remaining firms.

Given previous findings on the relationship between scientific labor mobility and knowledge flows (Almeida and Kogut, 1999; Singh and Agrawal, 2011) we expect measures of scientific labor mobility (M) to be instrumental in drawing value from the spillover pool. This motivates the inclusion of an interaction of the spillover pool with a suitably matched measure of mobility ($M_{ht} \cdot SP^h_{K,it}$), where the level of aggregation (h) is common for both variables. As the mobility rate is expected to add or destroy value above and beyond that through external knowledge, I include a separate mobility term to pick up such effects. The main specification to be estimated therefore becomes

$$\begin{aligned} \log\left(\frac{V_{it}}{A_{it}}\right) \equiv\ & \log q_t + \gamma_R \widetilde{R}_{it} + \gamma_C \widetilde{C}_{it} \\ & + \gamma_S SP^h_{K,it} + \gamma_{MS} M_{ht} \cdot SP^h_{K,it} + \gamma_M M_{ht} \\ & + \mathbf{x}'_{it}\psi_K + \eta_i + \varepsilon_{it} \end{aligned} \tag{3}$$

A Box-Cox test indicates that the logarithm of the mobility rate gives a better fit to data, hence M_{ht} denotes the logarithm of the mobility rate of scientists and engineers at the aggregation unit h and year t. The sector classification for mobility closely follows Hall et al. (2005), and is described in Table 1. The time-specific intercept ($\log q_t$) is modelled using year dummies, and $\mathbf{x}_{it}$ is a vector of additional controls that will be introduced below. The error term $u_{it} = \eta_i + \varepsilon_{it}$ is the usual one-way error component specification, where ε_{it} is an i.i.d. error with zero mean, and η_i is the unobserved permanent effect for firm i.

3.2 Handling Sectors and Geography

I investigate scientific labor mobility at two different levels of aggregation, one at the level of industrial sectors, and another at the level of physical geography, i.e., states. This necessitates defining and computing spillover pools in a way that matches knowledge assets to the agents that are most likely to carry them as they move across firms. When interest lies on the mobility rate at the sector level, $SP^h_{K,it}$ is calculated as

$$SP^S_{K,it} = \log \textstyle\sum_{j \in \mathrm{SEC}(i),\, j \neq i} w_{ij} K_{jt} \tag{4}$$

where SEC(i) is the sector classification of firm i, and w_{ij} is a measure of the technical proximity between firms i and j. I restrict the summation to firms operating in the same sectoral classification to match the units at which mobility rates and external knowledge are observed. To construct each w_{ij}, I follow Jaffe (1986) and others in using the USPTO's (3-digit) technology classification system, in the following way. First, each firm (i) is assigned a vector T_i that contains the number of patents it was granted and classified in technology class $k \in \{1, \ldots, \kappa\}$ in its k^{th} element, where κ is the number of technology classes utilized. The technological proximity between firms i and j is calculated as the uncentered correlation between T_i and T_j. That is,

$$w_{ij} = \frac{T_i T_j'}{\|T_i\| \, \|T_j\|} \tag{5}$$

Note that w_{ij} equals one if the distributions of patents across technology classes perfectly coincide for the two firms, and it equals zero if the two firms never patent in the same USPTO technology class.

For the study of geographic labor mobility, firms are matched to geographic information using the rich detail of information contained in USPTO patent records. Firm activity often spans various states, and most firms in the sample patent under different assignee names and different locations. Each USPTO patent contains the state in which the patent application is filed. This allows observing the distribution of a the number of patents of the firm across US states. This information is used for two purposes. First, in order to match firms to data on geographic mobility, I assign each firm in the sample to the state in which its patents are most often classified[9]. Second, I use it to define and compute spillover pools in a way that is compatible with the geography of firm activity. For this purpose, I construct an index of geographical concordance using the overlap of firms' patenting activities across states. This is computed in similar vein to the technological proximity metric, using the spread of each firm's patents across U.S. states. For each firm, a 51-vector (G_i for firm i) is constructed that contains the number of patents of the firm in state s in its s^{th} element. Geographic concordance of firms i and j are then calculated as the uncentered correlation between G_i and G_j,

$$g_{ij} = \frac{G_i G_j'}{\|G_i\| \, \|G_j\|} \tag{6}$$

[9] An alternative to assigning a single state to each firm is to take weighted averages of state-level mobility rates for each firm, using the proportion of the firm's patents in each state as weights. I do not report results based on this method since the resulting firm-specific "mobility" variable does not have an obvious interpretation. This alternative "assignment" method does not change the main results of the paper.

and the corresponding spillover pool is computed as

$$SP^{G}_{K,it} = \log \sum\nolimits_{j \neq i} g_{ij} w_{ij} K_{jt} \tag{7}$$

Note that the technological proximity metric (w_{ij}) is incorporated into the computation of (7) as well, since the technical similarity between the two firms is important for generating spillovers beyond geography. Similar measures of geographic concordance are also used by Lychagin et al. (2010) and Bloom et al. (2013).

To summarize, two different aggregation procedures are used, and three knowledge indicators in each aggregation. Table 2 summarizes all six spillover variables, and Table 3 provides the names and description of all variables that are used in the paper.

4 Data Sources and Key Variables

The main data sources of the study are the NBER patents and citations data file (Hall et al, 2001) and the Current Population Survey (CPS). These are supplemented with a coding of the extent of non-compete enforcement across U.S. states constructed by Garmaise (2011) and Bird and Knopf (2010). Finally, I use the information on concentration indices across 4-digit SIC industry classifications made available by the Census Bureau's Economic Census.

4.1 Mobility of Scientists and Engineers

My source for the rate of scientific labor mobility is the Current Population Survey's Annual Demographic Files (March Supplement). The CPS March Supplement offers an annual, nationally representative sample of U.S. residents that consists of between 144,678 (in 1989) and 181,488 (1980) individual questionnaires. To construct mobility rates at various aggregations, I make use of information on the number of employers the respondent worked for in the year preceding the survey, the possible answers to which are $\{0, 1, 2, 3+\}$. I compute the fraction of scientific and technical personnel that changed employers during the year in question, aggregated at sectoral classifications (similar to the ones used in Hall et al., 2005), and across U.S. states. My sample of scientific and technical personnel follows the job classifications used by Kim and Marschke (2005), and are restricted to (Standard Occupation Codes in parentheses) engineers (044-059), mathematical and computer scientists (064-068), natural scientists (069-083), clinical laboratory technologists and technicians (203), engineering and related technologists and technicians (213-216), science technicians (223-225), and computer programmers (229).

Annual samples in the March Supplement contain between 2087 (in 1977) and 3181 (in 1990) scientific personnel (55,754 total responders), representing between 2.9 to 5.4 million such occupations, depending on the year. Between 225 and 427 sampled scientists changed jobs during the year in question. The mobility rate of scientific personnel moves between 9% (in 1993) and 14.4% (in 1990) over the sample period, which is lower than the mobility rate of the entire population (between 13.1% in 1983 and 17% in 1979). This is likely to result from higher specialization and job-specific knowledge of scientists and technicians.

The distribution of the sample of technical personnel into sectors and states is expectably uneven. For a few number of sector-year pairs, the number of individuals in the CPS sample that fall under the job classification used in the paper turn out to be quite low. This is especially true for electrical machinery, and to some extent for the oil sector, for which the annual number of scientific personnel frequently fall below 15. This produces a mobility rate that is unreliable, and is often equal to zero, since none of the few scientists in the sample have changed jobs. An additional 13 sector-year pairs produce a zero scientific mobility rate. These sector-year pairs are removed from the sample for the analyses on sectoral mobility. A similar situation exists for 41 state-year pairs, which are removed from the sample used for geographic analyses. Since the CPS is a representative sample of the entire U.S. residents, such cases indicate sectors and states that do not employ too many scientific personnel, nor are heavily represented in the sample of patenting firms. Thus, any sample selection bias due to these removals is likely to be negligible.

The CPS is useful in being a representative sample of scientists and engineers in the U.S. Admittedly, however, the CPS sample gives an aggregate and noisy indicator of scientific labor mobility. For instance, since my analyses focus on scientific personnel, the sample does not allow reliable aggregation at the level of finer industry classifications or finer geographic definitions, nor it allows an analysis of mobility rates for each sector at each state. For each of these levels of detail, the sample of scientists in the CPS becomes obstructively thin. An alternative to using the CPS measure is to study USPTO patent records and track mobile inventors as they patent under different affiliations (Singh and Agrawal, 2011; among others). However, inventors patent under different affiliations due to many reasons other than a change of employer. Laforgia and Lissoni (2009) find that only about 12% of inventors that have two or more affiliations in patent records can be classified as mobile, most multi-affiliation cases representing start-up ventures, mergers, acquisitions, contract research, or consulting. Another limitation of inventor records is that one can only observe technical personnel who has at least two patents (and patent under subsequent employers). The sample of such inventors is likely to be a non-random sample of all scientific personnel, introducing serious selection effects. The CPS sample of scientists, on the other hand, is representative of all scientists in the U.S. The current study complements the literature that uses USPTO inventor records by using an alternative data source on scientific mobility, as well as attempting to adress the provate value of scientific turnover.

Mobility is clearly pro-cyclical at the aggregate level. This is not surprising, but this will require some additional robustness tests to ensure that the cyclical nature of the data is not driving the main results.

4.2 Patents, Citations, and Firm Data

Patent and citation counts are taken from the NBER patent and citation database compiled by Hall et al. (2001), and firm variables come from the Compustat data file compiled by the same researchers. The NBER patent database consists of all patents granted by the USPTO between the years 1965 and 2002, and all citations received by these patents up to 2002. The Compustat data file consists of all manufacturing firms that are publicly traded in the U.S. The authors also match assignee names used by the USPTO to the CUSIP firm identifiers listed by Compustat for over 700,000 patents. For further details, see Hall et al. (2001) and Jaffe and Trajtenberg (2002).

Market value of the firm is the sum of common stock, preferred stock, and total debt net of assets. Recall that R&D, patent and citation stocks are computed as perpetual inventories with 15% annual depreciation. When computing stocks, I do not extrapolate the missing initial values to minus infinity, since stock variables are constructed beginning 1967, while the first year to be used in computations is 1976. Hence, the effect of the missing initial condition is likely to be negligible. This approach is preferred since it avoids the additional noise due to imposing aggregate growth rates for the variables in question on individual firms. Finally, citations are naturally truncated, as they will keep coming long after data collection. I correct citation counts for truncation using the correction weights given in Hall et al. (2001), which are obtained by estimating the citation lag distribution for the six main technology classes.

4.3 Competition

In order to obtain a measure of competition, I use measures of industry concentration in each U.S. manufacturing industry from the Economic Census of the U.S. Census Bureau. The census provides information on the Herfindahl-Hirschman index (HHI) and the 4-firm (CR4) and 20-firm (CR20) concentration ratios at the 4-digit SIC level. Concentration information for the paper's sample period is available in five year intervals, at 1977, 1982 and 1987. Remaining years in the dataset are assigned the concentration ratio in the earliest preceding survey year. The operations of some of the firms in Compustat span several 4-digit SIC classifications, and some operate in more than one 3-digit SIC class. For these firms, Compustat reports a primary SIC code that ends with one or two zeros, effectively indicating a classification of firm activity at the three or 2-digit SIC level. 40 firms in the final sample can be assigned a 2-digit SIC code, and 354 firms a 3-digit code. For these firms, I re-construct the HHI index at the 2 or 3 digit classification using the information on the corresponding 4-digit classification available in the Economic Census. Simple algebraic manipulation shows that the HHI concentration index in a 2-digit industry classification (HHI_{2d}) can be recovered from concentration indices of its 4-digit components ($HHI_{k,4d}$), if one has information on total sales in each 4-digit SIC category, as

$$HHI_{2d} = \left(\sum\nolimits_{k=1}^{n(2d)} S_k \right)^{-2} \sum\nolimits_{k=1}^{n(2d)} S_k^2 \cdot HHI_{k,4d} \tag{8}$$

where $n(2d)$ represents the number of 4-digit classifications in the relevant 2-digit category, and S_k and $HHI_{k,4d}$ are total sales (value of shipments) and industry concentration in the 4-digit classification $k = 1, ..., n(2d)$. The index at the necessary 3-digit classes are computed similarly. The only available option for obtaining CR4 and CS20 at higher aggregation levels than the 4-digit SIC is to take averages, or weighted averages of the index values for relevant sub-classes. Since the construction of the HHI is more reliable than taking averages, reported results use HHI. Finally, an index of competition is obtained by the logarithm of one minus the concentration index. Results that deal with competition are robust to alternative concentration measures.

4.4 Final Samples

Firms that have no patents at any point between 1976 and 1993 are removed from the sample, as well as sector-year or state-year pairs for which the sample of scientists and engineers in the CPS data are very low or no mobility is observed (section 4.1). One year of observations per firm is sacrificed in order to control for the pre-sample value, a lag of the dependent variable, and industry growth. After these removals, cleaning large outliers, deleting observations outside the desired time frame, and removing firms that appear only for a single year in the data, I am left with an unbalanced panel of 12802 observations (1280 firms) for the sectoral mobility sample, and 11442 observations (1239 firms) for the geographic mobility sample, spanning a 17 year interval from 1977 to 1993. The average number of years a firm appears in the former (*resp.* latter) sample data is 10 (*resp.* 9.23), with a standard deviation of 5.2 (*resp.* 4.2) years. Samples for the study of competition are further reduced to 12283 and 11002, respectively, due to missing values for the Herfindahl-Hirschman concentration index. Table 4 reports sample statistics for the main variables. Sample correlations between key variables are reported in Tables 5 and 6. All current dollar values are deflated using the GNP deflator. All "external" variables are computed by using the total sample of firms in Compustat, not just those that are in the final sample.

5 Estimation and Results

5.1 Econometric Issues

An important issue in the estimation of (3) is the presence of permanent firm effects that are correlated with independent variables. In general, controlling for permanent effects proves to be a difficult task in estimating variants of these equations, and the literature often resorts to pooled OLS without any attempt to account for them. There are numerous problems related to the presence of permanent firm effects, and methods that remove them. First, I have right hand side variables that are very persistent, both by their nature and also by construction. Thus, any method that directly eliminates permanent effects removes too much variation[10]. Second, R&D expenditures (therefore R&D stocks) are prone to measurement error for various reasons (Grilliches and Hausman, 1986), an important one being underreporting by firms. Any method that controls for fixed effects by differencing (first differencing, or differencing from means) is bound to exacerbate the bias due to measurement error. Third, most of the variation in the data set is in the cross section[11]. Due to these reasons, standard fixed effects methods tend to be uninformative. Standard GMM methods that

[10] In addition, Tobin's q is persistent in the long run as well. See Salinger (1984), who uses Tobin's q as a measure of long term monopoly power.

[11] Hall and Vopel (1997) make a case against controlling for unobserved firm effects by arguing that "most of the reasons why there exist permanent differences across firms in the market value equation can be attributed to R&D and/or market share (ed., one of their controls that is not the focus of the current paper), and we would like to measure these differences rather than simply differencing them away".

rely on differencing also produce unreliable results for similar reasons (Mairesse and Hall, 1996). Due to the persistence of right hand side variables, usual instruments tend to be weakly correlated with the endogenous variables in the first-differenced equation (Blundell and Bond, 2000).

To deal with these issues, I use a GMM-IV estimator in the tradition of Arellano and Bover (1995) and Blundell and Bond (1998, 2000). This method is particularly useful when one needs to control for individual effects in the presence of measurement error and persistent right hand side variables. It imposes weak restrictions on the permanent effects (i.e., *mean stationarity*) and makes use of the resulting moment conditions that allow the use of lagged differences as instruments for the equation in levels. Blundell and Bond (2000) argue that these additional instruments are particularly attractive under autoregressive errors, and report highly favorable Monte Carlo simulations, especially in cases where the standard first-differenced equation performs poorly[12]. The validity of the Arellano and Bover (1995) instruments critically rests on the lack of serial correlation in residuals. For this reason, I study regressions that condition on the immediate past by including a lagged dependent variable. The inclusion of the lagged dependent variable introduces well-known complications, and additional instruments need to be used to account for the endogeneity of the lagged dependent variable to obtain consistent estimates.

By instrumenting firm level variables, I also control for the potential endogeneity of the firm's own knowledge assets. It is easy to argue that R&D stock is endogenous in equation (3), since successful firms will adjust the intensity of their R&D efforts accordingly. Thus, market value causes R&D as well. Citation stocks (citation stock/patent stock in the regression equation) are less prone to such reverse causality since these capture the output of R&D activity, which has a large component that isn't in direct control of the firm, as indicated by the value distribution of patents and that of citations received.

5.2 Instruments for Mobility

There are numerous reasons to suspect the presence of reverse causality from market value to mobility, rendering the mobility term endogenous in equation (3). For instance, market value can directly cause labor mobility through increased layoffs during times of declining firm performance. More importantly, when firms in a given sector are doing collectively better, the average market

[12] For recent applications of this method in a similar framework, see Blundell, Griffith and Van Reenen (1999) and O'Mahony and Vecchi (2009) for an application of the system GMM estimator. The latter deals with the measurement of spillover effects in a production function framework. Also see Hahn (1999) for a discussion on the efficiency gains resulting from this method.

value of firms can cause higher mobility due to increased on-the-job search. In order to achieve the causal relationship in the direction I seek, additional instruments are employed for the sectoral and geographic mobility rates, in addition to the GMM procedure described above. For sectoral mobility rates, I follow Kim and Marschke (2005) in using the logarithms of the fraction of male and white scientists and the average age of scientists as instruments for the mobility rate. Additionally, I use the fraction of scientists in the sector that are married, and the fraction that do not live alone as instruments.

For the geographic mobility variable, I also use the cross-sectional and longitudinal variation in the extent of non-compete enforcement across and within U.S. states as an instrument, in addition to the personal characteristics (gender, race, age, marital status and living situation) of the sample of scientists at the state level. Garmaise (2011) constructs an index that measures the strictness of NCC enforcement in each state (and DC) for each year between 1992 and 2004. To construct the index, Garmaise uses a set of 12 questions taken from Malsberger (2004), and assigns 1 point to the state if the aspect of NCC enforcement addressed by the question exceeds a given threshold[13]. Bird and Knopf (2010) use the same methodology to extend the Garmaise index to cover the period 1976-1994. The index takes integer values between 0 and 12. Two states (California and North Dakota) whose legal codes ban the enforcement of these contracts are assigned the lowest score of 0, while the highest enforcement score over the sample period 1977 to 1993 is 7 (Missouri, Tennessee, DC, and Florida after 1991). The variation in enforcement stems from the differences in the *scope* of enforcement, i.e., conditions under which state statute and courts uphold the contract, and the index reflects this variation. Various changes in enforcement are observed during the sample period, most significant ones of which occurred in Michigan (0 to 5 in 1985) and Louisiana (1 to 4 in 1989). There are minor disagreements between the Bird and Knopf (2010) and Garmaise (2011) codings, but using alternative codings do not alter the results presented in the current paper. Reported results use the former (Bird and Knopf) coding in cases of disagreement.

The validity of these instruments are easy to demonstrate. A regression of M_{ht} on the set of instruments reveal that they are significant individually and collectively, with F-statistic above 100 for both the sectoral and geographic mobility rates, and jointly explain around 10% of the variation in sectoral labor mobility. A similar exercise is also undertaken using the original respondents as units, where "having changed employer" is a dichotomous binary variable. These analysis confirm the same result, with F-statistics above 300. The strictness of non-compete enforcement reduces

[13] See Garmaise (2011) Appendix for the list of questions and corresponding thresholds.

mobility. Older and married scientific personnel, and those living with someone are less mobile, while males and whites change employers more frequently. The validity of instruments will be demonstrated by the Sargan test of overidentifying restrictions. Results are also robust to using subsets of instruments in each regression.

5.3 Alternative Explanations and Confounders

Drawing from the literature on the sources of knowledge flows, a central interest of the paper is the value of knowledge flows that occur via scientific labor mobility. On the other hand, labor mobility can affect market value through various additional mechanisms. First, the loss of a critical scientist doesn't only represent loss of knowledge, but also of *human capital*. Second, under loose employer-employee ties, employees may be less inclined to invest in firm-specific skills, understanding that their careers are only weakly tied to their current employer (Fallick et al., 2006). Since controlling for direct measures of human capital or employee investment is elusive, the current paper does not make an attempt to disentangle the separate effects through each of these channels, but report a joint estimate of all. On the other hand, increased labor mobility can have additional benefits for the firm as the costs of searching for and finding talent will be lower, and critical vacancies can be filled sooner. My estimates are likely to partially reflect the quality of the labor force in question, as the prospect of mobility may attract more talented personnel from other sectoral (Marx, 2011) or geographic markets (Marx et al., 2012). To address these possibilities, I estimate additional specifications that include the rate of *aggregate* labor mobility (mobility rate of all employed, excluding scientists and engineers) in the relevant labor market as an additional regressor. The estimated negative effects of mobility, on the other hand, include the joint effects of misappropriation, outbound human capital, and other effects of loose employer-employee ties.

In addition, mobility can affect market value by altering the productivity of the firm's own R&D capital. As internal R&D capital gets larger, so would the detrimental effects of misappropriation due to mobility. On the other hand, the firm's R&D capital presumably increases the firm's absorptive capacity (Cohen and Levinthal, 1990). I investigate the overall effects of mobility due to such channels by estimating additional regressions that include an interaction of mobility with internal R&D stock/Assets ($\widetilde{R}_{it}$). The choice of $\widetilde{R}_{it}$ as opposed to directly using R&D stock or annual R&D expenditures owes to the specification of the market value equations (2) and (3) in which $\widetilde{R}_{it}$ is the proper measure of internal R&D capital.

5.4 Additional Issues

Equation (3) is motivated by resorting to the argument that external knowledge assets create value for firms, and scientific mobility is expected to be instrumental in drawing value from external knowledge. A strict interpretation of the market value equation, however, reveals a set of underlying assumptions that are not completely realistic: that inventors observe external knowledge assets and the mobility rate in relevant labor markets, and price the firm's assets accordingly. My defense against this is two-fold. First, differences over time and across markets in the rate of scientific mobility may reflect observable knowledge-diffusing attributes of sectoral and geographic labor markets in question. Therefore, the potential for knowledge flows, and channels by which they occur can be treated as an important intangible asset for the firm. For instance, mobility may act as insurance against lagging behind competitors and signal a competitive technological position for the future to potential investors. Second, mobility does not create a one-time transfer of knowledge, but creates long-lasting links between the source and the target (Agrawal et al., 2003), which renders its effects to some extent observable.

Another important problem is how one should interpret significant coefficients for the spillover and mobility terms. A significant coefficient for the interaction term, or the mobility term can result from potential co-movements within an industry, or patterns of change in technological opportunities in the same industry over time. To account for these possibilities, I include the total sales within the 4-digit SIC class, which controls for demand effects and for changes in various industrial conditions. Permanent industry effects are controlled by dummies for sectors. I also include the logarithm of the firm's own sales to account for possible size effects. Also, the coefficient of the interaction term in (3) may be positive if either component picks up the effects of aggregate or industrial economic conditions (Grilliches, 1992). Recall that labor mobility is pro-cyclical, and the sizes of spillover pools may also correlate with business cycles. In order to address these issues, I check the robustness of coefficients to the inclusion of the growth rate in the industry (current or lagged), and GDP growth rate in the U.S. during the year in question. Results also hold when these terms are interacted with labor mobility and spillover pools to further test whether they will pick up the variation formerly explained by mobility terms (See Appendix).

A final caveat for the methodology that I use is that coefficients of spillover terms are likely include the effects of positive spillovers as well as negative competitive effects. These coefficients reflect the combination of both, and they will at best be *lower bounds* for the true spillover effect.

Bloom et al (2013) attempt to identify these two effects, using the Jaffe (1986) technological proximity metric along with a measure of product market closeness between any two firms. They find that both effects are present, but the negative effect due to product market competition tends to be much lower than positive spillover effects.

Table A1 in the Appendix walks the reader through a specification search, by reporting relevant regression results at each step towards the final specification. These analyses demonstrate the need for each of the decisions made, and illustrate the robustness of the paper's main results to alternative estimation strategies.

5.5 Results

Table 7 reports estimates for the main specification in equation (3). Columns 1 through 3 study scientific mobility at the sectoral level, while columns 4 through 6 turn to geographic labor mobility. Each column uses one of the six spillover measures that were previously introduced. All regressions include a full set of year dummies, and dummies for industry sectors. Columns 4 through 6 additionally employ state dummies. All estimates are from two-step GMM[14].

In all regressions, the spillover pools, the interaction between mobility and the spillover pool, and the separate mobility term are statistically significant at all reasonable levels of significance. The estimated coefficient of the interaction term has a positive sign, while the mobility term alone has a negative sign in all specifications. This is consistent with the expected effects of labor mobility on firm performance, and the trade-offs discussed in the Introduction can be observed in regression results. The positive sign of the interaction term indicates that firms with a high amount of externally created knowledge in their disposal benefit from increased labor turnover, while the negative sign of the mobility term shows that there is an adverse effect of mobility to firms that lack large external knowledge stocks. The latter adverse effect is likely to stem from looser appropriability conditions in a highly mobile scientific labor market and the resulting outbound intellectual and human capital. Note that this is true holding key industry characteristics constant, and with the presence of year and sector dummies[15].

[14] OLS estimates for all specifications are available upon request from the author.

[15] The coefficients of either mobility term do not change considerably with the inclusion of industry characteristics and sector/state dummies, indicating that these coefficients are not affected by sector and year effects. Results are also robust to the use of industry dummies at the 4-digit SIC level instead of sector dummies. In OLS regressions, I also observe that further controlling for dummies for each sector-year pair reduces the (negative) coefficient of the separate mobility term, while not affecting the interaction term significantly. These interaction dummies are not used in main results since they make the inversion of the second stage GMM instrument matrix problematic.

The elasticity of Tobin's q with respect to mobility is given by (note that the mobility term is already in logs)

$$\frac{\partial \log q_{it}}{\partial M_{ht}} = \underbrace{\widehat{\gamma}_{MS} SP^h_{K,it}}_{+} + \underbrace{\widehat{\gamma}_{M}}_{-} \tag{9}$$

which can be used to calculate marginal effects of the mobility rate for different values of $SP^h_{K,it}$. It is instructive to look at the composition of the elasticity (9) into its positive (from the interaction term) and negative (from the separate mobility term) components. I interpret the former as the increase in market value due to the spillovers that occur through labor mobility, while the latter represents losses endured due to increased mobility. Evaluated at the mean spillover pool, the former ranges from 0.101 (column 1) to 0.314 (column 6). These are the contributions of the interaction term alone on the elasticity above. The contribution of the standalone mobility term on (9) ranges from -0.196 (column 1) to -0.754 (column 5). To put more substance into these numbers, note that the mean sectoral (*resp.* geographic) mobility rate over the entire sample is 0.101 (*resp.* 0.116). Thus, if one wants to convert the elasticity values above to the effects of a percentage point increase in the mobility rate (i.e., the effects of one additional job change for every 100 scientist), they need to be multiplied by $(0.101)^{-1}$ for the sectoral rate, and by $(0.116)^{-1}$ for the geographic rate, to get the aforementioned value at mean mobility. This implies that the positive impact of a percentage point increase in the mobility rate on market value ranges from 1.98% to 6.51%, with the corresponding negative impacts having magnitudes -1.94% and -6.79%. The positive and negative portions of (9) are very close to one another for sectoral mobility, and *net* effects remain between 0.04% (column 1) and 0.16% (column 2). For the geographic rates (and matching spillover pools) the wedge between the two are larger, but net effects remain much smaller than the magnitudes of each, which is between -0.27% (column 5) and -0.48% (column 6). It appears that the impact of labor mobility through spillovers is substantial, but is countered by a negative effect of similar magnitude. Net effects remain small, if not negligible. The effects implied by geographic mobility (and the relevant spillover pools) are larger than the corresponding effects for sectoral mobility. Geographic mobility rates also give negative net effects that are larger in magnitude. These marginal effects for all six specifications from Table 7 are summarized at Table 8.

To get a more complete picture, one can look at marginal effects at different quintiles of the spillover pools. For instance, a firm that has access to the spillover pool at the third quartile enjoys net returns as high as 1.01% of market value, due to the aforementioned increase in labor mobility. The same return from sectoral mobility range between 0.12% and 0.53%, while geographic aggregation produces net effects in between 0.66% and 1.01%. At the 90^{th} percentile of the spillover pool, net effects measure as high as 1.55% (column 6, geographic mobility) of market value. Net effects due to geographic mobility, again, are larger than those due to sectoral mobility.

Finally, using estimated coefficients in Table 7, it is also possible to compute the fraction of the overall spillover effect $\left(\widehat{\gamma}_S SP^h_{K,it} + \widehat{\gamma}_{MS} M_{ht} \cdot SP^h_{K,it}\right)$ that occurs due to scientific mobility. Holding spillover pools constant at the mean, a one standard deviation increase in the rate of scientific mobility creates spillovers that measure as much as 17.6% (column 1) of the total spillover effect. This minimum value for this percentage is 13.6% (column 5). This percentage reaches levels as high as 42.7% (column 4) if the mobility rate increases from its minimum sample value to its sample average.

The negative effect of mobility reported in Table 7 deserves further scrutiny. Table 9 investigates the potential sources of this negative effect, and provides some additional robustness checks. I have interpreted the negative effect of the standalone mobility terms in Table 7 as the loss of critical knowledge and human capital via scientific mobility. If this interpretation is correct, then one would also expect losing critical knowledge assets and human capital to a close competitor to be more harmful than it is to a non-rival company. Hence, holding positive spillover effects constant, we expect the detrimental effect to be larger in industries with more head-to-head competition. Columns 1 (sectoral mobility) and 4 (geographic mobility) in Table 9 test this prediction by including the interaction of scientific mobility with a measure of competition at the relevant SIC class for each firm. I measure competition by (the logarithm of) one minus the Herfindahl-Hirschman index of concentration. As expected, the interaction term has a negative and significant coefficient in both specifications. Hence, the negative effect of scientific mobility is more pronounced for firms operating in more competitive environments, supporting the hypothesis that my estimates capture the effects of misappropriation and the loss of critical resources.

The results of the paper rely on measures of mobility computed for specific job classifications, representing the sample of scientific and technical personnel in the Current Population Survey. While results are robust to controlling for industrial and aggregate economic fluctuations (Table A1), it is still possible that the scientific mobility rate acts as a proxy for the aggregate rate of mobility in the relevant sector or state. In order to make sure that estimates are due to the mobility of *scientific* personnel, columns 2 and 5 include (the logarithm of) the *aggregate* rate of employer-to-employer mobility in the relevant sector-year or the state-year. Aggregate mobility also controls for the potential benefits of a mobile labor market, such as lower costs and delays for filling vacancies, and the overall quality of the relevant labor force. This rate is computed for all employed personnel in the CPS sample, excluding the sample of scientists and engineers. The sign of the aggregate mobility rate is negative and statistically insignificant in both specifications, and does not alter the coefficient of either mobility term significantly.

Furthermore, it is possible to expect scientific mobility to create or destroy firm value by operating through the firm's *own* R&D effort, for two reasons. First, the larger the firm's own R&D capital, the larger the potential for loss due to looser appropriability conditions as scientific labor markets become more mobile. Second, the firm's R&D stock may increase the firm's ability to internalize and use external knowledge (Cohen and Levinthal, 1990). Thus, the potential effect of an interaction of mobility with a measure of internal R&D capital is theoretically ambiguous. The net effect of such a variable is investigated in columns 3 and 6 of Table 9, by including the interaction of scientific mobility with $\widetilde{R}_{it}$ (R&D stock/Assets). In general, I find that estimation with additional terms including the firm's endogenous internal assets tend to be complicated, and it is difficult to keep the parameters of diagnostic tests within acceptable limits. Note that a major difficulty in the estimation of (3) is the instrumentation of R&D stocks (Appendix), hence it is not surprising that further parameters including an interaction with this variable creates additional difficulties. For this reason, I seek the effect of a mobility $\times$ $\widetilde{R}_{it-1}$ interaction, with the R&D variable lagged for one year. Even with this specification, estimation proves difficult, and I can reject serial correlation in residuals only at the 7 or 8% significance ($p = 0.075$ in column 3 and 0.061 in column 6). The coefficient of this interaction term is positive but it is insignificant at all reasonable levels of statistical significance. It may be the case that the beneficial (absorptive capacity) and detrimental (larger loss potential) effects for firms with larger R&D intensities are present, but cancel each other out. Nevertheless, it is clear that firms with larger R&D intensity do not benefit or lose more due to an increase in the rate of scientific mobility.

6 Conclusion

This paper studied the relationship between scientific labor mobility and market value, producing, for the first time, estimates of the net value of the mobility of scientific personnel, as well as the resulting knowledge flows. I document distinct positive and negative effects of scientific mobility on market value, and discuss the implications of each. The private value of knowledge transfers that occur through labor mobility is statistically and economically significant. According to my estimates, private gains due to knowledge flows associated with one job movement per 100 scientists are between about 2% and 6.5% of the firm's market value, depending on the specification used. Another question of interest is the net private returns, or losses to innovative firms that operate in industries with highly mobile labor markets. It has been considered puzzling that highly innovative firms choose to locate in close proximity to their rivals, facilitating the transfer of their scientific labor force to competitors. I find negative effects of mobility that are likely to represent such losses, which are of similar magnitudes to the positive effects of knowledge flows. Hence, my results suggest that on average, firms tend to "break even" if the labor market they hire from becomes more mobile. While the negative effect of mobility is higher for firms in more competitive industries, firms with larger internal R&D do not suffer or gain more due to labor mobility, compared to others. These results highlight individual, firm-level incentives for operating in a highly mobile labor market, and provide firm-level evidence for the labor pooling motivation for industrial agglomeration. In terms of its policy implications, the evidence is supportive of legal remedies that facilitate the mobility of employees, as previous evidence has repeatedly suggested.

I have taken care to exclude alternative explanations for the main results of the paper. Most importantly, my main results and arguments remain valid when potential effects of industrial and aggregate economic conditions are accounted for, and the rate of scientific labor mobility rate is instrumented. This suggests that estimated coefficients and elasticities are, to a large extent, due to the mobility of engineers and scientists in the firm's immediate sectoral environment, rather than being artifacts of external economic conditions, such as recessions and booms, or industrial expansion and decline.

My estimates are obtained using a large panel of U.S. manufacturing firms that spans a large variety of 4-digit SIC classifications. One would expect the impact of labor mobility to be higher for high-tech and R&D intensive industries, and industries that are at earlier stages of their life cycle. Gaining insight about these additional hypotheses require more detailed data on scientist turnover, and are exciting avenues of research in this area.

Acknowledgement: TBA.

7 Appendix

- Table A1 here -

Table A1 progressively reports estimates from various methods, in order to illustrate the problems in estimating (3) and how each of these problems are dealt with. I present these results also to illustrate the performance of the various methods used, their effect on model parameters, and the robustness of the paper's main results to various empirical choices made. All regressions use the sectoral mobility rate and $SP^S_{CITE,it}$ as a measure for the spillover pool, but the progression of estimates is similar for other specifications. Columns 1 through 3 in Table 6 treat the mobility rate as exogenous, while columns 4 through 8 treat it as an endogenous variable. I explore different GMM specifications that instrument firm level variables with appropriate lags of either levels or differences of regressors. In particular, columns 3 through 8 use the Arellano and Bover (1995) suggestion of instrumenting the levels equation by lags of differences of endogenous regressors. In all specifications I assume external and industry-level variables to be exogenous. Indicators of the firm's internal knowledge assets treated as endogenous in all columns. All estimates use two-step GMM.

Column 1 uses lagged levels dated $t-2$ through $t-8$ of firm level variables as instruments for the levels equation. An important feature of these estimates (and also those in the main text) is that the coefficient of the R&D term is lower than its estimates from the literature that estimate similar specifications for U.S. data (for a review of the pre-1999 literature and estimated coefficients, see Hall, 1999) by an order of multiple magnitudes. There is a similar situation for the coefficient of citation stock/patent stock ratio. However, the Sargan test statistic strongly rejects the validity of these instruments ($\chi^2_{(165)} = 231.88$, $p = 0.00$). In particular, no subset of lagged levels proves to be a valid instrument set for the R&D term. The implied correlation between lagged levels and residuals suggest that permanent firm effects are present, and that they are not fully accounted for. On a side note, the mobility terms have comparable signs and magnitudes with t-statistics similar to those in the paper's main results.

Column 2 reports results from an extended system-GMM estimation that estimates a stacked system of equations including both the levels equation and the equation in first differences, with the instrumentation methodology described above. This method results in somewhat different estimates for the coefficients of key variables, but the set of instruments are strongly rejected by the Sargan test ($\chi^2_{(292)} = 389.98$, $p = 0.00$). This is mainly due to the fact that finding valid instruments for the differenced R&D term proves to be elusive.

Column 3 uses lagged differences (dated $t-2$ through $t-8$) of the main firm level variables as instruments in the levels equation. I observe that lagged differences dated $t-1$ are never valid instruments, while the validity of differences dated $t-2$ is also rejected in some specifications. These observations are consistent with the presence of measurement error.

To justify the use of lagged differences as instruments in the levels equation, Arellano and Bover (1995) make the stationarity assumption

$$E(x_{it}\eta_i) = w_i \neq 0 \quad \text{for} \quad t = 1, 2, ..., T \tag{10}$$

where x_{it} denotes a generic regressor. That is, regressors are allowed to be correlated with permanent effects, but their covariance is assumed to be constant over time. Then, (10) implies the set of moment conditions

$$E[\Delta x_{it}\eta_i] = w_i - w_i = 0 \tag{11}$$

which suggests the instrumentation discussed above. Note that (10) can also be expressed as a restriction on the initial condition alone. For an extended discussion on this assumption, see Arellano and Bover (1995), and Arellano (2003).

These additional instruments are not rejected by the Sargan test statistic ($\chi^2_{(166)} = 154.97$, $p = 0.418$). Therefore, this methodology is adopted as the preferred estimator for the rest of paper. The lack of correlation between lagged differences and residuals, along with the apparent correlation between lagged *levels* and residuals indicates that fixed effects are indeed present and are not accounted for in the previous specifications. On the other hand, it should be noted that the m_1 and m_2 test statistics (Arellano and Bond, 1991) suggest that there is still autocorrelation in the residuals, which can arise due to the presence of permanent firm effects. Thus, further attention to the serial correlation properties of errors is called for. This point will be discussed in further detail below.

To deal with the potential endogeneity of the mobility term, column 4 instruments the mobility term in addition to the firm level variables. Additional instruments used are the logarithm of the average age of scientists working in the industry sector, and the logarithms of the fraction of males, and the fraction of those that are married and do not live alone. These additional instruments prove to be valid ($\chi^2_{(154)} = 165.60$, $p = 0.247$). Interestingly, this method gives coefficients for the mobility and interaction terms that are higher in magnitude than previous estimates, confirming the suspicion that there exists positive reverse causality from market value to mobility.

A potentially important problem with the regressions in columns 1 through 4 is that the error term is serially correlated, as indicated by the m_1 and m_2 test statistics of Arellano and Bond

(1991). These are tests for the lack of first and second order serial correlation in the first-differenced residuals, respectively. If model residuals are not serially correlated, we would expect to see strong evidence for negative first order serial correlation ($cov\left(\Delta u_{it}, \Delta u_{it-1}\right) = -var\left(u_{it-1}\right)$), but no evidence for second order serial correlation in the first-differenced residuals ($cov\left(\Delta u_{it}, \Delta u_{it-2}\right) = 0$ if $E\left(u_{it}u_{it-\tau}\right) = 0$ for all $\tau > 0$). Note that serially correlated residuals in panel data can arise if there are permanent effects that are not fully accounted for. Hence, this issue needs to be addressed in order to achieve consistent estimates.

To account for the serial correlation in the residuals, column 5 introduces a pre-sample value of the dependent variable as an additional regressor. While the pre-sample value of $\log q$ is highly significant, this makes little difference in the test statistics m_1 and m_2. Column 6 includes a lagged dependent variable for the same purpose, which is instrumented by its lagged differences dated $t-2$ and $t-3$. The set of instruments are still jointly valid ($\chi^2_{(179)} = 199.31$, $p = 0.142$), while residuals do not show any sign of serial correlation. First-differenced residuals exhibit strong negative serial correlation. As opposed to the estimates in columns 1-5, no evidence is found for second order serial correlation in the first-differenced residuals, indicating that all permanent effects have been properly accounted for. The signs and significance of main coefficients of interest remain robust to the inclusion of $\log q_{i,t-1}$.

As previously argued, main results of the paper can be driven by aggregate or industrial economic conditions if either the mobility rate or spillover pools pick up effects due to business cycles, or industrial expansion or decline. In addition to the controls previously described to control for such effects (section 5.4), columns 7 and 8 provide additional robustness tests on the specification in column 6. Column 7 includes the aggregate GDP growth rate in United States during the relevant year, while column 8 includes terms that interact GDP growth with mobility and the spillover pool. The aim is to see whether these additional interactions will pick up the variation previously explained by mobility-spillover interactions. Results in column 6 remain robust to the inclusion of these terms, but the magnitudes of the coefficients of both mobility terms are smaller. Similar observations apply when the industrial growth rate is used in interaction terms instead of GDP growth.

Finally, the specification in column 7 of Table A1 is used in all main regressions reported in the paper.

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Table 1
Sector classifications for the mobility variable

Sector	1	Paper and Printing
	2	Chemicals (excluding Drugs)
	3	Rubber
	4	Wood and Miscellaneous Manufacturing
	5	Primary Metal
	6	Fabricated Metal
	7	Machinery
	8	Electrical Machinery
	9	Autos
	10	Air & Boat
	11	Textiles and Leather
	12	Drugs
	13	Food
	14	Computers and Instruments
	15	Oil

Table 2
Summary of external knowledge assets (spillover pools) used

	Sectoral Aggregation: Uses technological proximity	Geographic Aggregation: Uses geographic and technological proximity
R&D Stock	$SP^{S}_{R\&D,it} = \sum_{j\in \mathbf{SEC}(i), j\neq i} w_{ij} \cdot R_{jt}$	$SP^{G}_{R\&D,it} = \sum_{j\neq i} g_{ij} \cdot w_{ij} \cdot R_{jt}$
Citation Stock	$SP^{S}_{CITE,it} = \sum_{j\in \mathbf{SEC}(i), j\neq i} w_{ij} \cdot C_{jt}$	$SP^{G}_{CITE,it} = \sum_{j\neq i} g_{ij} \cdot w_{ij} \cdot C_{jt}$
Citation St./ Patent St.	$SP^{S}_{CP,it} = \sum_{j\in \mathbf{SEC}(i), j\neq i} w_{ij} \cdot \left(\frac{C}{P}\right)_{jt}$	$SP^{G}_{CP,it} = \sum_{j\neq i} g_{ij} \cdot w_{ij} \cdot \left(\frac{C}{P}\right)_{jt}$

Table 3
Variable names and definitions

V_{it}	Market value (of firm i at year t)
K_{it}	Knowledge assets, generic
A_{it}	Ordinary physical assets
q_{it}	Tobin's Q
σ	Returns to assets
γ	Shadow value of knowledge assets relative to ordinary assets
R_{it}	R&D stock
r_{it}	R&D expenditures (flow)
P_{it}	Patent stock
C_{it}	Citation stock
$\tilde{R}_{it}$	R&D stock/Assets
$\tilde{C}_{it}$	Citation stock/Patent stock
SP_{it}^{h}	Spillover pool available to firm i at year t, at aggregation level h
	All use technological proximity, along with geographic concordance metrics or sector restrictions:
$SP_{R\&D,it}^{S}$	External R&D stock, within sector
$SP_{CITE,it}^{S}$	External citation stock, within sector
$SP_{CP,it}^{S}$	External citation yield, within sector
$SP_{R\&D,it}^{G}$	External R&D stock, agg. w.r.t. tech. and geog. proximity
$SP_{CITE,it}^{G}$	External citation stock, agg. w.r.t. tech. and geog. proximity
$SP_{CP,it}^{G}$	External citation yield, agg. w.r.t. tech. and geog. proximity
M_{ht}	Logarithm of the scientific mobility rate (sector or state h at year t)

Table 4
Sample Statistics

		Mean	Median	St. Dev.	Min	Max
Market Value		1303.68	146.64	4756.07	0.16	120756.52
Net Capital		1262.25	120.84	4904.05	0.39	106569.91
Tobin's q		1.553	1.086	1.547	0.002	14.942
R&D Stock		189.74	12.88	998.01	0	25763.63
Patent Stock		84.49	7.6	289.41	0	5849.16
Citation Stock		1012.39	86.67	4246.46	0	140330.78
R&D/Assets		0.26	0.121	0.533	0	16.617
Citation Stock/Patent Stock		11.716	9.484	11.115	0	174.4
Sectoral Mobility		0.101	0.102	0.041	0.021	0.381
Geographic Mobility		0.116	0.111	0.041	0.019	0.364
Aggregate Mobility (Sectoral)		0.118	0.118	0.031	0.042	0.278
Aggregate Mobility (Geographical)		0.148	0.146	0.027	0.088	0.240
Spillover Pools (in logs)						
Sector (Tech. Proximity)	*R&D Stock*	7.011	7.397	2.022	-1.614	10.789
	Citation Stock	8.842	9.062	1.846	1.373	12.685
	Citation St./Patent St.	4.391	4.425	1.312	-3.073	7.090
Geography (Tech and Geog. Proximity)	*R&D Stock*	7.052	7.294	1.611	-1.674	10.457
	Citation Stock	8.744	9.001	1.481	-2.416	11.849
	Citation St./Patent St.	3.745	3.934	1.337	-8.819	12.092
Sales		1749.82	220.37	6893.08	0.33	164933.14
Industry Sales		21457.75	4868.13	71771.53	50.49	752738.16
Industry Growth		0.03	0.028	0.209	-0.839	8.627
I (R&D Expenditures=0) (*flow*)		0.204	0	0.403	0	1
Competition (1 - HHI)		0.94	0.96	0.06	0.73	0.99
Instruments (Geographic Aggregates)						
	NCC Enforcement	3.74	4	2.12	0	7
	Age	37.92	37.93	1.57	28.42	43.79
	Male	0.78	0.79	0.06	0.42	0.95
	White	0.90	0.91	0.06	0.27	1
	Married	0.69	0.69	0.07	0.30	0.93
	Not alone	0.68	0.68	0.07	0.30	0.93
CPS Sample *From individual survey data, sample of scientists and engineers.*						
	Mobility	0.11	0	0.32	0	1
	Age	38.05	36	11.49	14	90
	Male	0.78	1	0.42	0	1
	White	0.9	1	0.3	0	1
	Married	0.7	1	0.46	0	1
	Not alone	0.69	1	0.46	0	1

NOTES: All dollar values are in millions of 1992 dollars, deflated using the GNP deflator. All logarithms are natural logs. Sample size: 12802 for the sectoral, and 11442 for the geographic mobility samples. Sample period: 1977-1993. Only geographic aggregates of main instruments are reported to save space.

Table 5
Sample correlations between key variables

Variables	**Abbr.**	$\tilde{R}$	$\tilde{C}$	$SP^G_{R\&D}$	M_{St}	M_{Gt}	MA_{St}	MA_{Gt}	*Comp*	*logS*	*logIS*	*IG*
log (q)	*log (q)*	0,272	0,287	0,094	0,043	0,037	-0,089	0,065	-0,012	-0,153	-0,085	0,114
R&D/Assets	$\tilde{R}$	.	0,259	0,178	0,044	0,004	-0,120	0,032	-0,098	-0,204	-0,055	0,065
Citation Stock/Patent Stock	$\tilde{C}$		.	0,167	0,038	0,014	-0,065	0,044	-0,021	-0,073	-0,066	0,080
Spillover Pool: Geog. R&D	$SP^G_{R\&D}$			.	-0,036	-0,098	-0,212	-0,099	-0,135	0,265	0,168	0,022
Scientific Mobility (Sector)	M_{St}				.	0,121	0,424	0,162	0,071	-0,073	-0,087	0,038
Scientific Mobility (State)	M_{Gt}					.	0,149	0,469	-0,036	0,003	0,021	0,016
Aggregate Mobility (Sector)	MA_{St}						.	0,278	0,157	-0,023	-0,150	0,045
Aggregate Mobility (State)	MA_{Gt}							.	-0,046	0,020	0,044	0,040
Competition: log (1-HHI)	*Comp*								.	-0,074	-0,243	-0,023
log (Sales)	*logS*									.	0,475	-0,042
log (Industry Sales)	*logIS*										.	-0,008
Industry Growth	*IG*											.

NOTE: Only one spillover pool measure in included, external R&D stocks aggregated using geographical and technological proximity ($SP^G_{R\&D}$).

Table 6
Sample correlations between measures for the spillover pool

	Technological Aggregates (within sector)			**Technological and Geographic Aggregates**		
	R&D Stock	Citation Stock	Citation St./ Patent St.	R&D Stock	Citation Stock	Citation St./ Patent St.
Technological Aggregates (within sector)						
R&D Stock	.	0.975	0.759	0,582	0,579	0,489
Citation Stock		.	0.817	0,577	0,592	0,509
Citation St./Patent St.			.	0,469	0,493	0,527
Tech. and Geographic Aggregates						
R&D Stock				.	0,972	0,881
Citation Stock					.	0,919
Citation St./Patent St.						.

Table 7
GMM regressions
Dependent variable: log (V_{it}/A_{it})

	Sectoral Mobility of Scientific Personnel			Geographic Mobility of Scientific Personnel		
	Spillover pools are aggregated within sector, using technological proximity			Spillover pools are aggregated using technological and geographic proximity		
	(1) SP = $SP^{S}_{R\&D,it}$	(2) SP = $SP^{S}_{CITES,it}$	(3) SP = $SP^{S}_{CP,it}$	(4) SP = $SP^{G}_{R\&D,it}$	(5) SP = $SP^{G}_{CITES,it}$	(6) SP = $SP^{G}_{CP,it}$
R&D / Assets	0.04040 (9.83)	0.04016 (9.80)	0.04059 (9.97)	0.04326 (8.59)	0.04493 (8.69)	0.04382 (8.20)
Citations / Patents	-0.00161 (-2.26)	-0.00153 (-2.16)	-0.00157 (-2.18)	-0.00076 (-1.04)	-0.00058 (-0.81)	-0.00064 (-0.90)
Spillover Pool	0.06068 (2.94)	0.07903 (3.11)	0.17275 (3.83)	0.15200 (3.63)	0.19546 (3.64)	0.22194 (4.09)
Scientific Mobility × Spillover Pool	**0.02849** **(3.32)**	**0.03428** **(3.26)**	**0.07154** **(3.85)**	**0.06550** **(3.43)**	**0.08269** **(3.65)**	**0.09473** **(4.13)**
Scientific Mobility	**-0.19580** **(-3.27)**	**-0.28686** **(-3.24)**	**-0.30977** **(-3.85)**	**-0.49921** **(-3.45)**	**-0.75380** **(-3.66)**	**-0.40784** **(-4.18)**
log (Sales)	-0.00171 (-0.83)	-0.00281 (-1.37)	-0.00351 (-1.74)	-0.00228 (-0.91)	-0.00290 (-1.61)	-0.00244 (-0.99)
log (Industry Sales)	-0.00744 (-3.06)	-0.00790 (-3.26)	-0.00823 (-3.39)	-0.00529 (-1.84)	-0.00495 (-1.71)	-0.00503 (-1.74)
Industry Sales Growth	0.07370 (4.24)	0.07183 (4.18)	0.07069 (4.11)	0.05433 (2.74)	0.05496 (2.77)	0.05315 (2.62)
log (q) | *t* - 1	0.84676 (65.4)	0.84870 (65.3)	0.85045 (64.9)	0.85745 (65.27)	0.85930 (65.74)	0.85859 (66.32)
GDP Growth	-0.05984 (-1.10)	-0.14815 (-1.84)	-0.16383 (-2.35)	-0.26098 (-2.39)	-0.48159 (-2.99)	-0.16832 (-2.41)
Sargan	185.01 (165) (p = 0.136)	186.17 (165) (p = 0.124)	181.94 (165) (p = 0.174)	151.00 (134) (p = 0.150)	152.04 (134) (p = 0.136)	154.50 (134) (p = 0.109)
Arellano-Bond (m_1)	-2.38 (p = 0.018)	-2.46 (p = 0.010)	-2.55 (p = 0.011)	-2.50 (p = 0.012)	-2.51 (p = 0.012)	-2.49 (p = 0.013)
Arellano-Bond (m_2)	-0.079 (p = 0.484)	-0.80 (p = 0.424)	-0.801 (p = 0.423)	-0.725 (p = 0.468)	-0.619 (p = 0.536)	-0.465 (p = 0.642)
Sample size	12802	12802	12802	11442	11442	11442

NOTES:

(1) Standard errors are robust to arbitrary forms of heteroscedasticity, *t*-statistics are in parentheses.
(2) All columns include year dummies, dummies for sectors, and a dummy for having zero R&D expenditures (flow) that year (coefficients not reported). Columns 4 through 6 additionally include state dummies.
(3) Instruments used for firm-level variables are combinations of lagged differences dated *t* – 2 through *t* – 10;
(4) Instruments for the mobility rate (in *all columns*) are the logarithm of the average age of scientists in the industry sector, logarithms of the fraction of scientists that are male, and the fraction of those that are married and do not live alone. Columns 4 through 6 additionally use the coding for NCC enforcement by Garmaise (2011) and Bird and Knopf (2010) as an instrument.
(5) Instruments for $\log q_{i,t-1}$ (in all columns) are lagged differences of $\log q_{it}$, dated *t* – 3 and *t* – 4;
(6) Degrees of freedom for the Sargan test of overidentifying restrictions is given in parenthesis.

Table 8
Labor mobility, additional calculations (using estimates in Table 7)

	Sectoral Mobility of Scientific Personnel			Geographic Mobility of Scientific Personnel		
	Spillover pools are aggregated within sector, using technological proximity			Spillover pools are aggregated using technological and geographic proximity		
(A) Percentage change in market value as a result of a percentage point increase in the mobility rate						
	SP = $SP^{S}_{R\&D,it}$	SP = $SP^{S}_{CITE,it}$	SP = $SP^{S}_{CP,it}$	SP = $SP^{G}_{R\&D,it}$	SP = $SP^{G}_{CITE,it}$	SP = $SP^{G}_{CP,it}$
Positive effect (interaction term)	1.978 %	3.001 %	3.110 %	4.161 %	6.514 %	3.196 %
Negative effect (mobility term)	-1.939 %	-2.840 %	-3.067 %	-4.497 %	-6.791 %	-3.674 %
Net effect	0.039 %	0.161 %	0.043 %	-0.336 %	-0.277 %	-0.478 %
(B) Percentage of the overall spillover effect, as mobility rate changes…						
	SP = $SP^{S}_{R\&D,it}$	SP = $SP^{S}_{CITE,it}$	SP = $SP^{S}_{CP,it}$	SP = $SP^{G}_{R\&D,it}$	SP = $SP^{G}_{CITE,it}$	SP = $SP^{G}_{CP,it}$
…by one standard deviation	17,66 %	16,54 %	15,91 %	13,81 %	13,59 %	13,70 %
…from minimum to mean	40,77 %	38,87 %	37,78 %	42,73 %	42,28 %	42,50 %

NOTE: Positive and negative effects may not add to the net effect exactly, due to rounding.

Table 9
GMM regressions
Dependent variable: log (V_{it}/A_{it})

	Sectoral Mobility of Scientific Personnel			**Geographic Mobility of Scientific Personnel**		
	Spillover pools are aggregated within sector, using technological proximity			Spillover pools are aggregated using technological and geographic proximity		
	(1) SP = $SP^{S}_{CITES,it}$	(2) SP = $SP^{S}_{CITES,it}$	(3) SP = $SP^{S}_{CITES,it}$	(4) SP =$SP^{G}_{CITES,it}$	(5) SP =$SP^{G}_{CITES,it}$	(6) SP =$SP^{G}_{CITES,it}$
R&D / Assets	0.03845 (9.59)	0.03676 (9.10)	0.05593 (6.19)	0.04199 (8.14)	0.04243 (8.26)	0.06931 (2.73)
Citations / Patents	-0.00189 (-2.59)	-0.00199 (-2.64)	-0.00174 (-2.23)	-0.00096 (-1.00)	-0.00097 (-1.01)	-0.00116 (-1.41)
Spillover Pool	0.09777 (3.45)	0.09614 (2.67)	0.13377 (3.78)	0.12004 (2.23)	0.12591 (2.33)	0.13211 (2.26)
Scientific Mobility × Spillover Pool	**0.04241 (3.64)**	**0.04163 (4.23)**	**0.05784 (3.95)**	**0.05163 (2.25)**	**0.05427 (2.36)**	**0.05476 (2.23)**
Scientific Mobility × Competition	**-0.05688 (-2.40)**	**-0.06485 (-2.64)**	**-0.07450 (-2.90)**	**-0.09691 (-3.54)**	**-0.09674 (-3.51)**	**-0.07811 (-2.62)**
Scientific Mobility × (R&D / Assets)			**0.00646 (1.55)**			**0.01026 (-1.01)**
Scientific Mobility	**-0.35630 (-3.64)**	**-0.34816 (-3.44)**	**-0.49249 (-3.99)**	**-0.47367 (-2.27)**	**-0.49568 (-2.37)**	**-0.50402 (-2.25)**
Aggregate Mobility		**-0.04031 (-1.59)**	**-0.02964 (-1.10)**		**-0.04210 (-1.24)**	**-0.03087 (-0.81)**
log (Sales)	-0.00422 (2.00)	-0.00361 (-1.71)	-0.00249 (-1.15)	-0.00215 (-0.82)	-0.00201 (-0.76)	-0.00303 (-1.09)
log (Industry Sales)	-0.00722 (-2.84)	-0.00750 (-2.94)	-0.00787 (-2.94)	-0.00521 (-1.72)	-0.00538 (-1.77)	-0.00660 (-2.01)
Industry Sales Growth	-0.14592 (-2.08)	0.07149 (3.96)	0.07906 (4.11)	0.06068 (3.08)	0.06011 (3.04)	0.07155 (3.25)
log (q) | t - 1	0.85021 (62.87)	0.84253 (65.05)	0.83310 (63.95)	0.84060 (63.26)	0.84160 (62.07)	0.83479 (55.87)
GDP Growth	-0.19292 (-2.17)	-0.22240 (-2.21)	-0.34124 (-2.81)	-0.24576 (-1.51)	-0.28903 (-1.77)	-0.28734 (-1.63)
Sargan	182.32 (164) (p = 0.156)	184.94 (165) (p = 0.137)	179.03 (164) (p = 0.200)	144.55 (131) (p = 0.197)	144.66 (131) (p = 0.196)	135.01 (121) (p = 0.181)
Arellano-Bond (m_1)	-2.22 (p = 0.026)	-2.26 (p = 0.024)	-1.78 (p = 0.075)	-2.37 (p = 0.018)	-2.38 (p = 0.017)	-1.87 (p = 0.061)
Arellano-Bond (m_2)	-1.200 (p = 0.230)	-0.608 (p = 0.543)	-0.128 (p = 0.898)	-0.228 (p = 0.820)	-0.248 (p = 0.804)	-0.002 (p = 0.998)
Sample size	12283	12283	11052	11002	11002	9809

NOTES:

(1) Standard errors are robust to arbitrary forms of heteroscedasticity, t-statistics are in parentheses.
(2) All columns include year dummies, dummies for sectors, and a dummy for having zero R&D expenditures (flow) that year (coefficients not reported). Columns 4 through 6 additionally include state dummies.
(3) Instruments used for firm-level variables are combinations of lagged differences dated t – 2 through t – 10;
(4) Instruments for the mobility rate (in *all columns*) are the logarithm of the average age of scientists in the industry sector, logarithms of the fraction of scientists that are male, and the fraction of those that are married and do not live alone. Columns 4 through 6 additionally use the coding for NCC enforcement by Garmaise (2011) and Bird and Knopf (2010) as an instrument.
(5) Instruments for $\log q_{i,t-1}$ (in all columns) are lagged differences of $\log q_{it}$, dated t – 3 and t – 4;
(6) Degrees of freedom for the Sargan test of overidentifying restrictions is given in parenthesis.

Table A1
GMM regressions – Specification search
Dependent variable: log (q).
Mobility: Sectoral Mobility. Spillover pool: $SP^{S}_{CITES,it}$

	(1) GMM Levels	**(2) SYSTEM GMM**	**(3) GMM Levels**	**(4) GMM Levels**	**(5) GMM Levels**	**(6) GMM Levels**	**(7) GMM Levels**	**(8) GMM Levels**
R&D / Assets	0.05426	0.03473	0.03565	0.03909	0.02419	0.03418	0.04016	0.03888
	(5.03)	(9.07)	(4.92)	(5.42)	(2.75)	(9.03)	(9.80)	(9.49)
Citations / Patents	0.00437	0.00333	0.00193	0.00162	-0.00251	-0.00015	-0.00153	-0.00154
	(4.10)	(4.73)	(1.28)	(1.08)	(-1.48)	(-0.26)	(-2.16)	(-2.18)
Spillover Pool	-0.03720	-0.00961	0.04089	0.09037	0.07410	0.09735	0.07903	0.08360
	(-1.27)	(-0.63)	(1.90)	(2.79)	(2.23)	(4.12)	(3.11)	(3.12)
Sectoral Mobility × Spillover Pool	**0.02621**	**0.01430**	**0.02413**	**0.04583**	**0.04739**	**0.04218**	**0.03428**	**0.03225**
	(3.60)	**(4.47)**	**(3.85)**	**(3.82)**	**(3.66)**	**(4.34)**	**(3.26)**	**(2.96)**
Sectoral Mobility	**-0.17210**	**-0.09883**	**-0.17624**	**-0.35793**	**-0.37400**	**-0.35142**	**-0.28686**	**-0.28568**
	(-2.89)	**(-3.68)**	**(-3.36)**	**(-3.50)**	**(-3.40)**	**(-4.28)**	**(-3.24)**	**(-2.77)**
log (Sales)	0.02190	-0.01182	-0.01114	-0.01280	-0.00207	-0.00275	-0.00281	-0.00279
	(1.94)	(-1.74)	(-1.31)	(-1.52)	(-0.29)	(-1.37)	(-1.37)	(-1.37)
log (Industry Sales)	0.05175	-0.02466	-0.02385	-0.02664	-0.03008	-0.00769	-0.00790	-0.00798
	(3.12)	(-2.88)	(-2.26)	(-2.52)	(-3.24)	(-3.24)	(-3.26)	(-3.30)
Industry Sales Growth	0.25878	0.16487	0.21040	0.21756	0.18442	0.07260	0.07183	0.06973
	(6.25)	(8.01)	(5.63)	(5.83)	(5.06)	(4.31)	(4.18)	(4.14)
log (q) | pre-sample					0.40576			
					(23.4)			
log (q) | t - 1						0.84871	0.84870	0.85095
						(73.0)	(65.3)	(65.4)
GDP Growth							-0.14815	-0.13475
							(-1.84)	(-1.61)
Sectoral Mobility × GDP Gr.								0.00591
								(1.28)
Spillover Pool × GDP Gr.								-0.00312
								(-4.80)
Sargan	231.88 (165)	389.98 (292)	**154.97 (152)**	**165.60 (154)**	**150.58 (140)**	**199.32 (179)**	**186.17 (165)**	**184.95 (165)**
	(p = 0.000)	(p = 0.000)	**(p = 0.418)**	**(p = 0.247)**	**(p = 0.256)**	**(p = 0.142)**	**(p=0.124)**	**(p = 0.137)**
Arellano-Bond (m_1)	17.11	-5.01	20.06	20.05	18.92	**-2.74**	**-2.46**	**-2.50**
	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.000)	**(p = 0.006)**	**(p = 0.014)**	**(p = 0.013)**
Arellano-Bond (m_2)	15.47	-4.38	18.04	18.04	17.15	**-1.10**	**-0.80**	**-0.97**
	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.000)	**(p = 0.271)**	**(p = 0.424)**	**(p = 0.334)**
Sample size	12802	12802	12802	12802	12802	12802	12802	12802

NOTES:

(1) All equations include a complete set of year dummies, except columns 7 and 8, where one dummy is suppressed to avoid perfect multicollinearity. All columns include dummies for industry sectors, and a dummy for having zero R&D expenditures that year (coefficients not reported). Standard errors are robust to arbitrary form of heteroscedasticity, *t*-statistics are in parenthesis.

(2) Instruments used for firm-level variables are,

Column 1: lagged levels dated $t-2$ through $t-8$;

Column 2: lagged levels dated $t-3$ through $t-8$ in the equation for differences, and lagged differences of the same dates in the levels equation.

Columns 3-8: combinations lagged differences dated $t-2$ through $t-10$.

(3) Instruments for the mobility rate (in *columns 4-8*) are the logarithm of the average age of scientists in the industry sector, logarithms of the fraction of scientists that are male, and the fraction of those that are married and do not live alone.

(4) Instruments for $\log q_{i,t-1}$ (in columns 6-8) are lagged differences of $\log q_{it}$, dated $t-3$ and $t-4$;

(5) Degrees of freedom for the Sargan test of overidentifying restrictions is given in parenthesis.