Intra-Industry Knowledge Spillovers and Scientific Labor Mobility

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Abstract

I test the hypothesis that the mobility of scientific and technical personnel is a conduit for knowledge spillovers among innovative firms. Using a variant of the standard Tobin's Q equation, I show that firms who have access to large pools of externally created knowledge in their industrial and technological neighborhoods enjoy additional market value as a result of higher scientific labor mobility, while they suffer from higher mobility whenever external knowledge is limited. Specifically, a percentage point increase in the mobility rate (one additional job change for each 100 scientists) increases market value by 1% to 3.1% through spillovers for a firm that has access to the mean spillover pool. This effect is largely offset by the standalone negative impact of labor mobility on market value, thus the firm breaks even in terms of the net private value of increased labor turnover. These results are consistent with previous findings and anecdotal evidence, and provide further insight into why innovative firms cluster in industrial districts.

Keywords: Knowledge Spillovers, Labor Mobility, R&D, Patents, Citations, Market Value, Panel Data, GMM.

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1 Introduction

The majority of R&D activity in the U.S. takes place within private corporations, with industrial R&D comprising an estimated 71% of total R&D expenditures in 2006. Despite brief periods of fluctuations, the share of private R&D in national R&D has been rapidly increasing since 1950s (National Science Board, Science and Engineering Indicators, 2002, 2008), a trend that makes all aspects of privately performed R&D of particular interest to economists.

The output of private R&D efforts is the knowledge and know-how created within the company's own research enterprise. Knowledge is an intangible asset that can be replicated at relatively low cost, and it can easily travel through firm boundaries, making it difficult for firms to appropriate the returns to their own investments. Knowledge spillovers among private firms, industries, regions, and countries have been intensively studied by economists. Particular attention has been given to the measurement of such effects, albeit with limited success and agreement regarding their magnitude. The major obstacles still lie with the measurement of knowledge, which is a difficult task itself, and that of tracing the externalities that follow. Since spillovers are not directly observable, and do not leave hard trails which we can observe, their measurement is only possible by examining their indirect impact on observable economic indicators. Griliches (1992, 1995), Carter (2007), Ratanawaraha and Polenske (2007), and Kuznets (1962) offer treatments of the various methodological problems in this line of inquiry.

On the other hand, while the measurement of spillovers received substantial effort, little work has been done to highlight and understand the mechanisms by which spillovers actually occur. The question of how knowledge diffuses is crucial for a complete understanding and treatment of spillovers effects, due to various reasons. Most importantly, we cannot prescribe policy before understanding these mechanisms. Also, mechanisms that cause or facilitate spillovers must be exactly those that also constrain them (Audretsch and Keilbach, 2005), thus studying these mechanisms is important to understand not only how spillovers occur, but also how they are limited by economic, institutional and other factors. Earlier models that have incorporated spillovers into economic analysis assumed that knowledge exhibits properties of pure public goods, and that it becomes available for wider use as soon as it is produced. Models of endogenous growth (Romer, 1986); Lucas ,1988) formalized the argument that spillovers are endogenous sources of increasing returns. On the other hand, it took little time for researchers to point out that spillovers are bound by various factors. Most importantly, spillovers have been found to be geographically limited (Jaffe, A. Trajtenberg and Henderson, 1993). This observation and the literature that follows is supportive of the idea that local factors influence the spread of knowledge, and these factors require further investigation.

One important channel by which spillovers occur is believed to be the transfer of key scientific and engineering personnel among firms. Higher employee turnover breaks down traditional firm boundaries since the scientist carries firm-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. Thus, intellectual capital of firms with related technologies or products become available simply by hiring former employees of a rival.

That interfirm transfers of knowledge are facilitated by the movement of engineers has long been understood by researchers. Arrow (1962) writes that knowledge exhibits properties of a public good, and makes the aforementioned case for the mobility of engineers. Almeida and Kogut (1999), studying the mobility of patent holders, show that interfirm movements of engineers influences the local transfer of knowledge. Stephan (1996) writes "future work should also focus on the role mobility within the industrial sector plays in facilitating spillovers". Moen (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, and thus knowledge externalities are (at least partially) internalized by the scientific labor market. 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.

It is also worth mentioning that the role of scientific networks in the knowledge economy, particularly for spillovers and local industrial clusters has spawned a large literature. Following Polanyi (1966), Nelson and Winter (1982), and others, this literature emphasizes the difference between codifiable and uncodifiable, i.e., tacit knowledge. The latter can only be transferred among economic agents through direct contact with the possessor of such knowledge, hence its transmission is limited by the (often informal) scientific network of its creator. Note that scientific labor mobility and scientific networks are two distinct phenomena, but they are related in a very essential way: they both underscore the importance of local, often personal relationships for the transfer of knowledge, and their implications for innovation at large.

Anecdotal evidence regarding many aspects of scientific labor mobility and its impact on innovation are abundant. Recruiting scientists from competitors is a wide-spread practice innovating firms rely on to gain access to rivals' innovations. This is nowhere more transparent than Silicon Valley of California, an area with the highest employee turnover rates on earth. Hyde (2003) and Saxenian (1994), in their detailed case studies of the labor market in Silicon Valley, both place very strong emphasis on the loose employer-employee ties that facilitate the transfer of knowledge. Hyde (2003) contains several anecdotes, and 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".

From the point of view of an innovating firm, the downside of higher mobility rates is that protecting one's own knowledge capital becomes increasingly difficult, or simply impossible. As a result, firms rely on alternative protection mechanisms against employee departures, or may simply under-invest in R&D. This brings forth questions regarding the design of the R&D organization, and in particular, whether or not higher employee turnover presents poor incentives for firms to invest in R&D activity. It is reasonable to suspect that serious agency problems within the innovating firm, or market failures in innovative markets may be present when labor turnover is high.

It is important to note, however, that a significant body of studies point out that higher mobility rates tend to foster innovation rather than impede it. 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-up companies themselves. California courts do not enforce non-compete covenants, as opposed to those of Massachusetts. Also, mechanisms seems to have evolved that reduce the likelihood of trade secret litigation against departing employees. 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 reputational harm hurts the company's recruitment efforts in the labor market, since high quality job candidates are not willing to work for a firm that might limit their future prospects [1]. According to Saxenian (1994), therefore, the ensuing mobility of its labor market is the key factor that explains the success of Silicon Valley compared to elsewhere. If this is indeed

[1] See Hyde (2003) for an extended discussion.

true, policies that tend to limit labor turnover, such as the strict enforcement of the Uniform Trade Secrets Act, as well as non-compete covenants, may be wildly misplaced.

Despite the body of theoretical explorations, case studies and anecdotal evidence, no empirical evidence that documents the significance of the relationship between scientific labor mobility and spillovers has yet been produced. Another question of importance is the net private returns, or losses to innovative firms due to higher mobility rates, which has not been subject to empirical investigation. This paper is an attempt to fill these gaps in the literature. My primary objective, therefore, is to inquire to what extent labor mobility is conducive to value transfers among firms in the same industry, and how mobility rates affect firm performance. I study the potential impact of increased labor mobility in a firm's immediate industrial and technological neighborhood on its market value, and estimate the related elasticities of market value with respect to the observed mobility rates. More specifically, I estimate a variant of the standard Tobin's q equation using measures of internally and externally created knowledge, with additional controls and instruments to seek the causal impact of industrial labor mobility on market value.

My results confirm that the mobility of scientists within the industry facilitates the interfirm transfer of knowledge to a significant extent. Furthermore, the presence and respective sizes of the two counteracting effects discussed above can be seen from regression results. Firms that have access to a large body of externally created knowledge enjoy increased market value as a result of higher labor mobility, while firms that lack sizable external knowledge pools suffer a negative impact. For an average firm, the two effects approximately cancel each other out, or have little overall impact on market value, hence the firm "breaks even". This finding explains the seemingly paradoxical behavior of many innovative firms to cluster around their immediate rivals in industrial districts, thus facilitating the transfer of employees to their rivals[2].

The rest of the paper is organized as follows. Section 2 presents the model and empirical

[2] I do not suggest that this is the primary reason for why such districts exist, but propose this as an additional 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. 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. Historical accounts of how many crafts show similar patterns of knowledge localization are abundant.

strategy employed, section 3 presents the data and the construction of main variables, section 4 discusses the econometric issues and the estimation methodology, section 5 presents the results, and section 6 concludes.

2 Model and Empirical Strategy

2.1 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

$$V_{it} = q_t \left(A_{it} + \gamma K_{it}^{*}\right)^{\sigma} \tag{1}$$

where V_{it} is the market value of the firm, A_{it} is ordinary physical assets, and K_{it}^{*} represents effective knowledge assets. Parameter σ allows for non-constant scale effects, and γ measures the shadow value of knowledge assets relative to ordinary assets. Parameter q_t is a time-specific intercept that is interpreted as the average value of Tobin's q for each given year. I write K_{it}^{*} simply as

$$K_{it}^{*} \equiv K_{it} + \alpha SP_{it}$$

where K_{it} is the stock of firm i's own knowledge assets and SP_{it} is a measure of the knowledge that is external to the firm, henceforth called the "spillover pool". Thus, K_{it}^{*} is the total stock of knowledge at the firm's disposal, including knowledge produced inside and potentially drawn from outside the firm. This formulation implicitly assumes that (A1) spillover pool enters the effective knowledge stock additively, (A2) spillover pool does not interact with firm's own knowledge assets[3], and (A3) α, the fraction of outside knowledge eventually capitalized is identical for all subsets of firms[4].

[3] I stick to (A2) throughout the paper, but also investigate whether alternative formulations that allow the possibility for an absorptive capacity effect can perform better. I observe that additional regressors that interact a firm's own knowledge assets with the spillover pool tend to be statistically insignificant for a wide range of spillover measures used in this paper. This is in contrast to Jaffe (1986), who finds that firms with higher R&D stocks benefit more from knowledge externalities. These results are not reported.

[4] Using simple dummy interactions for industry sectors (results not reported), I observe that there is substantial inter-industry heterogeneity in ways firms draw value from other firms' knowledge assets. This issue is left aside for the moment since having reliable mobility measures for smaller industry classes is elusive. It is worth noting that this heterogeneity is an under-investigated aspect of spillovers between private firms.

From (1), taking logs and imposing constant returns to scale, we get

$$\log\left(\frac{V_{it}}{A_{it}}\right) = \log q_t + \log\left(1+\gamma\left(\frac{K^*_{it}}{A_{it}}\right)\right) \tag{2}$$

The variable on the left hand side is the logarithm of what is known as Tobin's q, the market value of the firm relative to the replacement value of its physical assets. The tradition in the literature is to use the approximation $\log(1+\gamma K^*_{it}/A_{it}) \cong \gamma K^*_{it}/A_{it}$, which leads to a linear specification that can be estimated by avoiding complications due to non-linearity[5]. Since some of the methods used in the current paper require a linear specification, I only report results that use the linear approximation. Regarding the results of the current article on labor mobility, the nonlinear form gives results that are qualitatively and quantitatively similar to those given by the linear model[6].

I use R&D intensity as a proxy for inputs to innovation, and citations received per patent as a proxy for its output. The spillover pool that is available to the firm, i.e., SP_{it} is calculated by aggregating measures of knowledge indicators for a set of external firms, which will be discussed in section 2.3. To explore whether higher mobility rates are more conducive to generating spillovers, I include a spillover-mobility interaction term, as well as the mobility rate separately to see the impact of labor mobility above and beyond that through incoming spillovers.

The main equation to be estimated is therefore

$$\log\left(\frac{V_{it}}{A_{it}}\right) \equiv \log q_t + \gamma_R \widetilde{R}_{it} + \gamma_C \widetilde{C}_{it} + \gamma_S SP_{it} + \gamma_{MS} M_{ht}\cdot SP_{it} + \gamma_M M_{ht} + \mathbf{x}'_{it}\psi_K \tag{3}$$

where $\widetilde{R}_{it} = R_{it}/A_{it}$ is R&D stock divided by ordinary assets, $\widetilde{C}_{it} = C_{it}/P_{it}$ is citation stock divided by patent stock, and SP_{it} is the logarithm of the spillover pool available to firm i at year t. M_{ht} denotes the logarithm of the mobility rate of scientists and engineers in industry sector h

[5] This approximation is suitable only if the K^*/A ratio is small. Hall (2000) reports that among the various functional forms used to estimate the market value equation, the nonlinear form gives the best fit to data, with the linearized form coming second. Hall and Oriani (2005) compare the performances of the two models using semi-parametric Kernel regressions having R&D as the only explanatory variable, and report that Eq. (2) performs somewhat better for K/A values above .01.

[6] To improve the efficiency of the estimators when the use of the linear model is called for, a potential remedy is to approximate the logarithmic term above by the first few terms of its Taylor series expansion. This method is not feasible here since the Taylor expansion includes too many terms unless most controls are parametrized into the intercept. Nevertheless, I experimented with linear regressions that include some higher order terms along with cross-products of regressors (terms that are part of the Taylor expansion). These trials do not change the main results, nor affect parameters of interest considerably, thus the simple first order approximation is maintained for the rest of the paper.

and year t. I use the logarithm of the mobility measure because it gives a better fit to data. The time-specific intercept $\log q_t$ is modelled through a full set of year dummies, and $\mathbf{x}_{it}$ is a vector of additional controls for firm i that will be discussed below[7].

2.2 Spillover Pools: Indicators of R&D Output

As discussed in the introduction, we would clearly like to use measures of the output of a firm's R&D efforts, instead of R&D dollars themselves, which measure inputs to the firm's R&D program. Coming up with such measures, though, is not straightforward, and there is no clear guidance on how to measure R&D outputs is a satisfactory way. One goal of the current work is to use measures based on the number of citations received by the firm's patents. On the other hand, in the face of such uncertainty, it is definitely preferable to work with a variety of measures instead of a single one, and see how results from different approaches measure up against each other. To this end, I will start by employing various measures of R&D success to construct spillover pools. External R&D stocks will be employed as well, along with measures based on citations. The rest of this subsection introduces additional output measures employed in the current paper.

2.2.1 Citations

Available evidence suggests that the number of citations received by a given patent is indicative of its value, thus citation counts (or stocks) are better measures of the output of innovative activity compared to R&D expenditures or patents. The seminal argument is due to Trajtenberg (1990), who tracks down a family of patents related to the computer tomography (CT) technology and the resulting improvements in the ensuing products. He estimates the consumer surplus from a discrete-choice demand model for CT scanners, and finds that the estimated surplus is highly correlated with the number of citations received by the corresponding patent, while no such correlation exists between consumer surplus and simple patent counts. Harhoff et al. (1999) carried out a survey among German patentholders, asking them to report a price for which they would be willing to sell the patent rights three years after application. They find that the eventual

[7]In terms of firm's own knowledge assets, a major difference between the equation used here and that of Hall et al (2005) is that I exclude the firm's propensity to patent (Patents/R&D). 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.

citations received by these patents are highly correlated with reported valuations, and that a single citation carries a value of about \$1 million. Giummo (2003) reports similar results in his study of the royalties received by patentholders under the German Employee Compensation Act. Also, some work has been done to establish the private value within citations using a large sample of manufacturing firms (Hall, Jaffe and Trajtenberg (2005)).

Accordingly, a natural indicator of a firm's R&D success is the total stock of citations received by a firm's patent stock[8].

2.2.2 Citation Yields

It is important to note that the total citation stock of a firm depends on its patent stock, and thus its patenting behavior. Due to the problems discussed previously, a measure of output that is independent of the firm's patent stock may also be useful. One natural candidate is the average number of citations the firm's patent stock receives, i.e., the average "citation yield" of the firm's patent stock. To motivate this measure, see the following direct estimation of the market value equation. That is, I estimate

$$\log V_{it} = \sigma \log \left(A_{it} + \sum_{j=1,2,3} \gamma_j K_{it}^j \right) + u_{it}$$

using R&D, patent and citation stocks as indicators of K. Here, all three indicators have a positive and significant effect on market value when used individually (or with R&D in case of the latter two), but the coefficient of patent stock becomes negative when citation stock is included. That is, among two firms with identical citation stocks, the one with the *lower* patent stock enjoys higher value[9]. This suggests the use of citation yield for firm i at year t,

$$\left(\frac{C}{P} \right)_{it}$$

as a measure of firm i's R&D output during the year in question.

For the purposes of the current study, this latter measure has more validity than citation stocks as long as receiving an additional citation is difficult, and it is a sign of much increased patent value. Consider two firms (i and j), where firm i has one patent application at time t that is eventually granted and received 5 citations, whereas firm j has two patent applications

[8] Note that "output" and "success" are used synonymously here.

[9] Care must be taken in reading into this estimation because most of the identification comes from the presence of assets on the right hand side, and R^2 values are at the order of 0.9. It is also useful in estimating σ, which is consistently between 0.96 and 0.98, but is statistically lower than 1 at 5% significance.

at time t that are eventually granted and received 4 citations each. This measure deems firm i to be the more successful of the two if they also have similar Patent/R&D ratios. The extreme skewness of the observed distribution of received citations, as well as that of estimated patent values support this idea[10]. Admittedly, aggregating these terms comes with issues regarding how the spillover pools should be interpreted and how viable their currency is. Notwithstanding the inherent problems, a more precise measurement of patent quality is outside the scope of this paper, and simple output measures that make use of citation data are preferred for current purposes[11]. Finally, it isn't clear which of these measures of external knowledge indicators is most relevant for the measurement of spillovers[12]. There is also no clear way of obtaining external validation for the different measures used. These problems are set aside for further research.

2.3 Spillover Pools: Industrial and Technological Neighborhoods

Consider a given firm (i), and a given measure of knowledge (K), and focus on how these measures should be aggregated to construct spillover pools. In accordance with the aims of the current paper, we could add up the knowledge available to this firm in its immediate industrial neighborhood. Thus, to address spillovers within the firm's 4-digit SIC code, I use

$$SP_{it}^{I} = \sum_{j \in SIC4(i),\, j \neq i} K_{jt} \tag{4}$$

as the spillover pool available to firm i. The superscript I is used to denote that we are constructing the spillover pool in the firm's industrial neighborhood. That is, we are simply summing knowledge stocks of all firms in the same 4-digit industry class as firm i, excluding firm i itself.

[10] One might wonder why citation stock per R&D dollar (Citations/R&D) wouldn't do just as well, or even better, as a measure of success. In unreported regression results, I experimented with this latter measure and found that using citations per R&D gives comparable results itself when it's used in place of citations per patent, but it becomes insignificant in regressions in which both measures are controlled for. Finally, it is a tempting idea to use citation yields as weights in aggregations of external R&D stocks. That is, for firm i, we might propose using $\left(\frac{C}{P} \cdot R\right)_{it}$ as a proxy for the output of an R&D enterprise. This measure tends to be insignificant when used in spillover pools when measures based on $(C/P)_{it}$ are included.

[11] For a noteworthy attempt to quantify the quality of patents, see Lanjuow and Schankerman (2004). These authors estimate the common factor in four measures that are assumed to be positively related to patent quality: citations made *to* the patent, citations made *by* the patent, number of claims in patent application, and the number of countries the same application is patented in.

[12] Note that a measure that is more relevant for the measurement of firm's own assets may be different than the one that is best for the measurement of spillovers and related effects.

Another, and perhaps preferable option is to use a weighted sum of external knowledge, i.e.,

$$SP_{it}^{T} = \sum_{j \in \mathbf{I}_i,\, j \neq i} w_{ij} K_{jt} \tag{5}$$

where w_{ij} is a measure of the "distance" between firms i and j in the technological space. The set of firms $\mathbf{I}_i$ constrains the aggregation to a subset of the universal set of firms. Since the current work deals with scientific labor mobility within an industrial sector, the aggregation will be limited to the industry sector firm i belongs in, as this makes clearer the meaning of the interaction term in (3). The superscript T in this case is used to denote that this pool is constructed within the firm's technological neighborhood.

To construct each w_{ij}, I follow Jaffe (1986) and use the information contained in USPTO's technology classifications, in the following way. First, each firm (i) is assigned a vector T_i that contains in its k^{th} entry the number of patents it was granted and classified in technology class $k \in \{1, \ldots, C\}$, where C is the number of technology classes utilized. This will be called the "technological position vector" of firm i. Then, the technological distance between firms i and j is calculated simply as the uncentered correlation between vectors T_i and T_j. That is,

$$w_{ij} = \frac{T_i T_j'}{\left[(T_i T_j)\,(T_{ji})\right]^{1/2}} = \frac{\sum_k t_{ik} t_{jk}}{\left[\sum_k t_{ik}^2 \sum_k t_{jk}^2\right]^{1/2}} \tag{6}$$

Note that w_{ij} equals one if the distributions of patents across technology classes perfectly coincide for firms i and j , and it equals zero if the two firms never patent in the same USPTO technology class. For additional desirable properties of this distance measure, see Jaffe (1986).

To summarize, two different aggregation methods are used, along with three measures of knowledge to be aggregated. Table A1 summarizes all six variables that are used in this paper.

3 Data Sources and Discussion on Key Variables

3.1 Labor Mobility

The measure of labor mobility is constructed following Kim & Marschke (2005). The main data source is the Current Population Survey's Annual Demographic Files (March Supplement), which records, for each person in the sample, the number of employers worked for in the preceding year. The survey asks the respondent whether s/he had one of $(0, 1, 2, 3+)$ employers during the year in question. Thus, one cannot keep track of the exact distribution of the number of job changes, but can use the responses to come up with useful mobility measures. My measure of labor mobility is the the percentage of scientific and technical personnel[13] that changed employers during the year in question, aggregated at industry classes that (for the most part) coincide with the so called ARDSIC classification (Bound et al, 1984). It is desirable to get mobility measures at lower levels of aggregation, but the nature of the CPS data does not allow such a task. Even though a good match is available between the scientist and his/her 4-digit SIC class of employment, these classes are not sufficiently populated for the job categories we are interested in, thus prohibiting the construction of mobility at a finer aggregation. The classification used in this paper includes 15 industry classes, and the number of scientists I observe for each such industry class - year pair hovers around 50.

Up to 2002, CPS used an industry classification of its own (loosely following 3 and 4 digit SIC classes), and their classification system went through changes at various times, namely in 1983 and 1992. I match the CPS classification to other classifications of interest using the documentation files released by the US Census Bureau.

A few observations about the observed mobility rates are in order. Among the entire CPS sample of individuals, the average rate of mobility among the employed is 14.3%, while it is lower for the sample of scientists, at 11.5%. Mobility is clearly pro-cyclical, and the behavior of the mobility rate for scientists over time is similar to that of the entire sample. This is not surprising, but this cyclicality will require some additional robustness tests to ensure that the cyclical nature of the data is not driving the main results. Note that this observation is true for the aggregate rates, but sectoral mobility rates show much less correlation with business cycles.

3.2 Patents, Citations, and Firm Data

Patent and citation counts come from the NBER patent and citation database compiled by Hall, Jaffe and Trajtenberg (2001) as part of a large ongoing project undertaken with the NBER, 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 authors also managed to match the assignee names used by the USPTO to the cusip firm identifiers listed by Compustat for a total of over 700,000 patents. For further details, see Hall, Jaffe and Trajtenberg (2001) and Jaffe and

[13] Job classifications for scientists and engineers follow Kim & Marschke (2005) (SOC codes in paranthesis): 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).

Trajtenberg (2002).

The Compustat data file consists of all manufacturing firms (SIC between 2000 and 3999) between 1965 and 1995 that are publicly traded on the New York, American and regional stock markets, or on NASDAQ. A total of 4,864 firms appear on the data set, with approximately 1,700 firms each year.

3.3 Data Construction

R&D, patent and citation stocks are calculated as depreciated sums of their yearly counterparts. I follow most of the previous literature in assuming a 15% yearly depreciation rate for all three variables. There is little known about the true depreciation rate of knowledge, and this has been one of the longest lasting open questions in the literature. Notwithstanding the potential heterogeneity in the depreciation rates of different R&D dollars or patents, getting estimates for average depreciation rates has proven very difficult as well. 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%. She concludes that her efforts are inconclusive to a large extent, but are useful for future explorations. Accordingly, I stick to the conventional depreciation rates, but test robustness of my main results using various rates between 20-40% as well.

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 regressions is 1977. Thus, the effect of the missing initial condition is likely to be negligible. This approach is preferable since it also avoids the additional noise due to imposing aggregate growth rates for the variables in question on individual firms.

Observed citation counts are inherently truncated, since citations to a patent keep arriving over very long time intervals, and will continue to arrive after the final year we have citation data. Recent patents suffer to a larger degree from this problem, as they are at earlier stages in their life cycles, and have received a smaller percentage of their eventual citation totals. Hall, Jaffe and Trajtenberg (2001) explore various methods to correct citation counts for this truncation. In particular, they estimate the shape of the citation lag distribution (fraction of total citations that are received in each additional year after patent grant), under the assumptions that this distribution is stationary, and is independent of overall citation counts. After this distribution is estimated, the corrected citation count for a patent that has received citations for N observed years is found simply by dividing the observed citations by the fraction of lifetime citations received during the first N years of lifetime citations, as implied by the estimated lag distribution[14]. Since the citation lag distributions in different technology classes might differ (due to citation practices and the properties of the underlying technology), Hall, Jaffe and Trajtenberg (2001) estimate this distribution for each of the six main technology classes as defined by USPTO[15]. I correct all citation counts using the implied correction weights by this procedure, which are given in tables 6 through 8 in the same study.[16]

Note that this procedure gives noisier corrections as one approaches the final years in the citation data, and corrected citation counts for fairly recent years will be unreliable. For instance, a chemical patent for which we observe only one year of citations will have received 3.7% of its lifetime citations, and predicting total citations from such a small percentage of observed counts can be misleading. I leave a nine year window between the final year used in this study (application year 1993) and the final year there is citation data available (2002). On average, patents receive about half of their lifetime citations during the first nine years after application.

As mentioned before, spillover pools and all other variables that are related to "other" firms are constructed taking 4-digit SIC codes as the industry classification. The distinguisher "external" is used throughout the paper to mean that the variable is aggregated over all remaining firms in the same industry or the same technological neighborhood, excluding the firm in question, for the same year. All variable aggregations on the firm's industrial and technological neighborhoods are undertaken using the largest sample at hand for the specific variable.

Firms that have no patents at any point between 1976 and 1993 are removed from the sample, as well as industry sector-year pairs that have an underrepresented sample of scientists and engineers in the CPS data. 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 my main variables, 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

[14] Lifetime of a patent is taken as 30 years. Even though citations keep arriving at later dates, sometimes up to 50 years after patent grant, the noise due to this choice is likely to be insignificant.

[15] Main technology classes are (category codes in paranthesis): Chemical (1), Computers and communications (2), Drugs and medical (3), Electrical & electronics (4), Mechanical (5), and Others (6).

[16] Patent counts are inherently truncated as well due to the lag between application and grant dates, with a mean lag of about two years. I do not correct for this truncation because of the safe 9 year window between the final year in my dataset and the final year for which patent data is available. Thus, the effect of this truncation is negligible.

observations covering a total of 1280 firms, spanning a 17 year interval from 1977 to 1993. This sample is chosen so that an identical sample can be used for all reported regressions, while also keeping the sample size relatively large. The average number of years a firm appears in the data is 10, with a standard deviation of 5,2 years. Table 1 reports sample statistics for the main variables used. Sample correlations between key variables are shown in Tables 2 and 3. All current dollar values are deflated using the GNP deflator.

Finally, a last word of caution is necessary about the different industry classifications used in the paper. Note that "industry class", or "industry classification" refers to the 4-digit SIC classification. This is the level at which all industry level variables and spillover pools for industrial neighborhoods are aggregated, except mobility rates. Mobility rates are obtained at a higher level of aggregation, which are referred to as "industry sectors".[17] For spillover pools in the firm's technological neighborhood, weighted sums are confined to industry sectors the firm is located in, as discussed above.

4 Econometric Issues

The most important econometric issue in the estimation of (3) is the presence of permanent firm effects. In general, controlling for permanent effects proves to be a difficult task in estimating variants of these equations, and the literature often resorts to reporting results for OLS or NLLS regressions without any attempt to control for them.

There are numerous problems related to the presence of permanent firm effects, and methods that remove them. First, we have right hand side variables that are very persistent, by their nature and also by construction. Thus, any method that directly eliminates permanent effects usually removes too much variation. Second, R&D expenditures are prone to measurement error for various reasons (Grilliches and Hausman, 1986), a prominent 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[18]. Due to these reasons standard fixed effects

[17] See Table A1 for the industry sector classifications used.

[18] 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".

methods prove uninformative in the current study, as it has been in the previous literature at large. Standard GMM methods have also been reported unreliable for similar reasons (Mairesse and Hall, 1996). Due to the persistence of right hand side variables, usual instruments used in the equation in first differences have been reported to be weak (Blundell and Bond, 1998).

To determine whether these problems are present in the current dataset, I first check the degree of permanence in the right hand side variables, which is straightforward. There's also strong permanence in Tobin's q, which makes it difficult to include lagged dependent variables[19]. Finally, I estimate the linear equation in first differences and in orthogonal deviations (results unreported). Getting significantly different results from these two methods is considered evidence for the presence of measurement error (Arellano, 2003), which proves to be the case here[20].

I deal with the problem of permanent effects in a variety of ways. First, I estimate the linear and nonlinear models assuming random firm effects. However, it isn't reasonable to expect that firm effects are random, and we expect results based on random effects models to be biased. R&D expenditures result from the firm's optimization problem, and output measures such as citations are expected to be influenced by unobserved permanent effects such as managerial and scientific ability[21]. Indeed, random effects regressions give coefficients for firm's own variables that are quite unreasonable. On the other hand, it is important to note that the main results regarding external knowledge assets, spillovers and labor mobility hold in a random effects specification. A Hausman test rejects the random effects model against the fixed effects specification, hence these results are not reported.

Second, I estimate a linear version of the main equation using a GMM-IV estimator in the tradition of Arellano and Bover (1995) and Blundell and Bond (1998). 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 (mean stationarity) and makes use of the resulting additional moment conditions that allow the use of lagged differences as instruments for the equation in levels. Blundell and Bond (1998) argue these additional instruments to be particularly attractive under autoregressive errors, and report highly favorable Monte Carlo simulations, especially in cases where the standard first-

[19] Tobin's q shows plenty of short term variation, but is persistent in the long run. See Salinger (1984), who uses Tobin's q as a measure of long term monopoly power.

[20] For more on orthogonal deviations, see Arellano & Bover (1995).

[21] Although I control for various measures of innovative behaviour, it is obvious that many relevant factors remain unobserved. The ability and background of the firm's scientist pool is an important example.

differenced equation performs poorly[22]. Regression results in first-differences for the model at hand reveal a strong downward bias in estimates, which is consistent with the presence of highly autoregressive errors. This final point makes this estimator particularly suited for the current study[23]. It is important for this methodology that the serial correlation of the error term is explicitly accounted for. For this purpose, I study regressions that condition on a pre-sample value of the dependent variable, and those 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 R&D expenditures, as well as that of R&D output. It is easy to argue that R&D expenditures are 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. Citations and citation yields are less prone to such reverse causality since the proxied success of R&D activity 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.

I also undertake an extended system-GMM estimation that estimates a stacked system of equations that includes both the levels equations and the equations in first differences. In this case, lagged differences are used as instruments for the equations in levels, and lagged levels are used as instruments for the equations in differences. This latter method does not prove useful in the current context, particularly because no valid instruments for the R&D term can be found for the equation in first differences, as implied by the corresponding Sargan and Difference Sargan statistics. Nevertheless, the results are informative of the true error structure of the model.

Another remedy sometimes used in this case is to use firm dummies. I shy away from this method because of the large number of firms in the dataset compared to the relatively short time horizon, hence the so called "incidental parameters problem" is expected to be elevated in such cases. For the rest of the paper, I assume that the error term in (3) exhibits properties of the usual one-way error component specification, with the error term written as $u_{it} = \eta_i + \varepsilon_{it}$. Here, ε_{it} is an i.i.d. error with zero mean, whereas η_i is the unobserved permanent effect for firm i.

[22] For recent applications of this methodology in a similar framework, see Blundell, Griffith and Van Reenen (1999), and O'Mahony and Vechhi (2009) for an application of the system GMM estimator. The latter deals with the measurement of spillover effects in a production function framework.

[23] Also see Hahn (1999) for a discussion on the efficiency gains resulting from this method.

In terms of reading into the regression results, a particularly acute problem is how one should interpret positive and significant coefficients for the spillover and mobility terms. After all, these conditional correlations can arise due to a variety of reasons. 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 (current or lagged), and when appropriate, interaction dummies for industry-year pairs (along with separate industry and time dummies). Note that these interaction dummies can only be used with the nonlinear specification. The former controls for demand effects, and partially for changes in various industrial conditions, while the interaction dummies are expected to pick up dynamics of technological opportunity within a given industry. Permanent industry effects are controlled by dummies for industry sectors. I also include the logarithm of firm's own sales to account for possible size effects.

Also, the coefficient of the interaction term in (3) may be positive if either labor mobility or spillover pools pick up the effects of aggregate or industrial economic conditions (Grilliches, 1992). This issue is particularly important since labor mobility is strongly pro-cyclical, and the sizes of spillover pools may well correlate with business cycles. In order to adress 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. In addition, 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.

A convincing case can be made for the presence of reverse causality from market value to mobility, thus the endogeneity of the mobility term in the above equations. 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 industry are doing collectively better, the average market 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 am seeking, I report additional results obtained by instrumenting the industrial mobility rate, in addition to the instrumentation described above. Following Kim and Marschke (2005), I use the logarithms of the fraction of male and white scientists, the average age of scientists, and the fraction of scientists that are married in the industry sector as instruments for the mobility rate. I also use the fraction of those that are married and do not live alone as an additional instrument. Instruments need to be both relevant (i.e., they are correlated with the variable being instrumented) and valid (i.e., they are orthogonal to the error term). That these instruments are correlated with the sectoral mobility rate is easy to demonstrate. An auxiliary regression of M_{ht} on the set of instruments reveal that they are significant individually and collectively ($F \simeq 333$), and jointly explain about 10% of the variation in sectoral labor mobility. A similar exercise is also undertaken using the original respondents as units, where "having changed employers" is a dichotomous binary variable. These analysis confirm the same result. The validity of instruments are demonstrated by the Sargan test of overidentifying restrictions.

An important restriction of the methodology I use is that coefficients of spillover terms will include the effects of positive spillovers as well as negative competitive effects. The coefficients of the spillover terms reflect the combination of both effects, and they will at best be *lower bounds* for their true values. Identifying the two effects while focusing on spillovers within the same industry is a difficult task that cannot be handled through additional controls alone, and any defense against this problem will be incomplete. Whenever a spillover pool other than $SP^{I}_{R\&D,i}$ or $SP^{T}_{R\&D,i}$ is used, I include external R&D stocks as a separate term, which tend to have consistently negative coefficients. Since investing in R&D is a competitive action, I conclude that this term picks up some of the negative competitive effects within the industry[24].

In some specifications I also include external patent yield to control for widespread patenting practices in the firm's industrial neighborhood. Note that this latter variable does not have an interpretation in terms of spillovers. An additional patent (per R&D dollar) represents an additional piece of externally created knowledge (an addition to the spillover pool), but patenting the innovation itself, to the extent it is protective, should hinder externalities (shrinks the spillover pool).

5 Estimation & Results

5.1 A "Horse Race" Regression of Knowledge Indicators

Table 4 presents OLS estimates of equation (3) that compare the performances of the different measures of external knowledge used in this paper. Columns 1 through 6 successively add external R&D, citations, and citation yields in the firm's industrial and technological neighborhoods as

[24] For an attempt to identify these two effects, see Bloom, Schankerman and Van Reenen (2008). Using a derivative of the "technological distances" of Jaffe (1986), the authors come up with a measure of product market closeness between any two firms, using average sales firms report in different SIC classifications..

additional controls. These results are also presented for comparison to previous studies, and to discuss some of the generic issues in estimation before delving into further details.

In this baseline specification, both measures of external R&D have negative coefficients when used alone, although the coefficient of $SP^I_{R\&D,it}$ is statistically insignificant at the 5% significance level (columns 1 and 2). This is consistent with the previous literature that used external measures of R&D to construct spillover pools (Jaffe, 1986). Industry citations ($SP^I_{CITE,it}$) also has a negative coefficient in all specifications, but it becomes statistically significant only when industrial citation yield ($SP^I_{CP,it}$) is included in regression. Citations in the firm's technological neighborhood ($SP^T_{CITE,it}$) consistently has a positive coefficient, but its coefficient reduces by several magnitudes and becomes insignificant when citation yield in the technological neighborhood ($SP^T_{CP,it}$) is controlled for (columns 3 through 6). Both citation yield measures have positive coefficients that remain robust to the inclusion of additional terms.

As will be seen, all of these measures produce positive coefficients when they are interacted with industrial mobility rates. At this stage, it isn't too clear what each of these measures tell us about various industrial and technological externalities. What is certain is that going beyond the use of R&D expenditures in the measurement of spillover effects opens up interesting possibilities, and that their use should be investigated further. A tempting interpretation is that external citation yields come closest to measuring positive knowledge externalities, while external R&D and citations pick up the previously discussed negative effects. Asserting such a claim would require additional work, and such issues are set aside for future research.

The coefficients and implied elasticities I find for the (own) R&D term are much smaller than previous estimates. This is mostly due to the additional firm and industry level controls I use. It is understood that the high explanatory power of the R&D term in previous studies is partially due to firm's optimization; that successful firms also choose to invest more in R&D. Thus, the coefficient and explanatory power of the R&D term is expected to diminish as more firm characteristics, or more group effects are controlled for. To this end, it is useful to note that the coefficient of the R&D term drops approximately by half with the inclusion of industry dummies (results with no industry dummies are not reported), and it further suffers at each step with the inclusion of industry sales, firm sales, external patenting propensity, and most importantly, when any attempt is made to control for permanent firm effects. These observations apply to all specifications used in this paper. The coefficients of firm and industry sales appear to be negative in all specifications. As expected, current (or lagged) industry growth has a positive and significant effect on Tobin's q.

5.2 Least Squares

Table 5 reports OLS estimates for the main specification including mobility-spillover interactions and a separate mobility term, without giving attention to firm effects. 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.

In all regressions, key variables of interest 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 columns. This is consistent with the discussion in introduction on the effects of labor mobility on firm performance, as well as with previous results and the body of anecdotal evidence. The previously discussed trade-offs can be observed in the regression results. The 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 there is an adverse effect of mobility to firms that lack large external spillover pools. Note that this is true holding key industry characteristics constant, and with the presence of time, industry and interacted time-industry dummies[25]. Moreover, the coefficients of either mobility term do not change considerably when industry characteristics and industry dummies are controlled for, indicating that these coefficients are not affected by industry and year effects. It is important to note, however, that further controlling for dummies for each industry-year pair reduces the (negative) coefficient of the separate mobility term, while not affecting the interaction term significantly.

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

$$\frac{\partial \log q_{it}}{\partial M_{ht}} = \underbrace{\widehat{\gamma}_{MS} SP_{it}}_{+} + \underbrace{\widehat{\gamma}_{M}}_{-} \tag{7}$$

which is used to calculate marginal effects of the mobility rate for different values of S_{it}.

It is instructive to look at the composition of (7) into its positive (from the interaction term) and negative (from the separate mobility term) components. The former represents the increase in market value due to the spillovers that occur through labor mobility, while the latter represents the losses endured due to increased mobility. Evaluated at the mean spillover pool, the former ranges from 0.112 (column 1) to 0.261 (column 5). These are the contributions of the interaction term alone on the elasticity described above. The contribution of the standalone mobility term on (7) ranges from -0.093 (column 1) to -0.224 (column 5). To put more substance into these numbers, note that the mean and median mobility rates over the entire sample are 0.101 and

[25] Interaction dummies are used only in the nonlinear specification, the output of which are not reported.

0.10. 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 $(0.101)^{-1}$ to get the aforementioned value at the mean mobility rate. This implies that the positive impact of a percentage point increase in the mobility rate on market value ranges from 1.11% to 2.61%, with the corresponding negative impacts having magnitudes −0.92% and −2.22%. These two columns also correspond to the smallest and largest estimates for the "net" effect of mobility, which are 0.18% and 0.38%, respectively. 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 positive but small, if not negligible.

A summary of marginal effects is provided in Table 8, including those from estimates that will be discussed in the next subsection.

5.3 GMM

Tables 6 and 7 report results from GMM estimations that instrument firm level variables with appropriate lags of either levels or differences of regressors. In particular, columns 3 through 8 in Table 6 and all columns in Table 7 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. Firm's own R&D intensity and citation yield is treated as endogenous in all columns. Columns 1 through 3 in Table 6 treat the mobility rate as exogenous, while columns 4 through 8 treat it as an endogenous variable. Mobility is assumed to be endogenous in all columns in Table 7. All estimates are from two-step GMM methods.

It is important to note that this procedure mostly affects the coefficient of the R&D term. It is previously argued that unobserved effects mostly play into the coefficient of the R&D term, and the experience here conforms to this view, as well as the endogeneity of R&D which was not accounted for in the previous regressions.

Table 6 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, and their effect on model parameters. All regressions here use $SP^{T}_{CITE,it}$ as a measure for the spillover pool, but the progression of estimates is similar for the remaining five measures.

Column 1 uses lagged levels dated $t-2$ through $t-8$ of firm level variables as instruments for the levels equation. A striking feature of these estimates is that the coefficient of the R&D term is reduced by an order of multiple magnitudes compared to OLS estimates. There is a similar effect on the coefficient of citation yield. However, the Sargan test statistic strongly rejects the validity of these instruments ($\chi^2_{(165)} = 231.88$, $p - value = 0.00$). In particular, no subset of lagged levels is 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 previous estimates.

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 ($\chi^2_{(292)} = 389.98$, $p - value = 0.00$). 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. 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 these instruments, Arellano and Bover (1995) make the stationarity assumption

$$E\left(x_{it}\eta_i\right) = w_i \neq 0 \quad \text{for} \quad t = 1, 2, ..., T \tag{8}$$

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, (8) implies the set of moment conditions

$$E\left[\Delta x_{it}\eta_i\right] = w_i - w_i = 0 \tag{9}$$

which suggests the instrumentation discussed above. Note that (8) 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 ($\chi^2_{(166)} = 154.97$, $p - value = 0.418$). 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 here 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, as discussed in section 4. 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 ($\chi^2_{(154)} = 165.60$, $p - value = 0.247$)[26] [27]. 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. The implied impact of mobility through spillovers is such that a percentage point increase in the mobility rate increases market value by approximately 4.05% for a firm facing the mean spillover pool, an impact that is largely offset by the counteracting negative effect (-3.54%). The net effect of the aforementioned increase in labor mobility is 0.51% for a firm, again, that is facing the mean spillover pool.

The estimates so far have dealt with instrument validity. 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[28].

To control 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

[26] Relevance of these instruments was established in Section 4.

[27] Including lagged mobility results in the set of instruments to be rejected at the 5% significance level, hence this variable is not included in the set of instruments.

[28] This can also indicate the presence of an idiosyncratic trend in errors, i.e., $u_{it} = \eta_i + t\mu_i + \varepsilon_{it}$.

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 ($\chi^2_{(179)} = 199.31$, $p - value = 0.142$), 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 $\log q_{i,t-1}$, except when industrial citation yield is used as a measure of the spillover pool.

As discussed previously, 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 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 6 is used in regressions for all six spillover measures. These results are presented in Table 7. Controlling for GDP growth renders the coefficient of industrial citation yield insignificant at the 5% level, while the remaining spillover pool coefficients are robust to the inclusion of it, with somewhat smaller magnitudes compared to when GDP growth is excluded (i.e., estimates in column 6 of Table 7).

The marginal effects of labor mobility (the percentage increase in market value due to a one percentage point increase in the scientific mobility rate) from OLS and GMM regressions, and using all spillover pool measures are reported in Table 8. The positive effect due to spillovers ranges from 1% (column 1, $SP = SP^I_{R\&D,it}$), to 3.1% (column 6, $SP = SP^T_{CP,it}$) of market value. The effects implied by GMM estimates are larger than their OLS counterparts for spillover pools that aggregate knowledge in a firm's technological neighborhood, while such differences are small for spillover pools aggregated in a firm's industrial neighborhood. On the other hand, OLS estimates give larger net effects, ranging from 0.18% (column 1, $SP = SP^I_{R\&D,it}$) to 0.38%

(column 4, $SP = SP^T_{CITE,it}$). Net effects from GMM estimates are in between -0.17% (column 1, $SP = SP^I_{R\&D,it}$) and 0.16% (column 5, $SP = SP^T_{CITE,it}$). Again, the net effects of labor mobility remain small when calculated at the mean spillover pools.

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 quirtile enjoys net returns as high as 0.75% of firm's market value, due to the aforementioned increase in labor mobility. At the 90^{th} quintile of the spillover pool, net effects measure as high as 1.16%, with the corresponding positive and negative effects at 4.22% and -3.07%. The largest net effects are usually given by the variables $SP^T_{CITE,it}$ and $SP^T_{CP,it}$.

6 Conclusion

This paper attempted to produce empirical evidence on two basic, and largely open questions related to industrial innovation and spillovers. The first is the extent to which knowledge spillovers are facilitated by the movement of scientific personnel among firms. The evidence produced here verifies that knowledge transfers are facilitated by the movement of scientists. The private value of spillovers that occur through this channel is significant, statistically and economically. According to my estimates, private gains from one job movement per 100 scientists are between 1% and 3.1% of the firm's market value. The second 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, thus facilitating the transfer of their scientific labor force to competitors[29]. My estimates show that positive and negative effects of increased labor mobility coexist, and make the aforementioned trade-offs (as discussed the introduction) faced by an R&D-active firm transparent. Results suggest that on average, firms tend to "break even" if the labor market they hire from becomes more mobile for some exogenous reason. In terms of its policy implications, the evidence is supportive of legal remedies that facilitate the mobility of employees, as previous anecdotal evidence has repeatedly suggested.

I have taken great 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 labor mobility rate is instrumented. This suggests that estimated coefficients and elasticities are, to a large extent, due to the mobility

[29] See Footnote 2 and the preceding discussion.

of engineers and scientists in the firm's immediate industrial environment, rather than being artifacts of external economic conditions, such as recessions and booms, or industrial expansion and decline.

The methodology used here relies on an aggregate measure of the scientific labor mobility within an industry sector, as indicated by the fraction of scientists that change employers during a given year. Estimates would be more accurate, the smaller the industry class at which we can obtain mobility data. At the limit, we would like to observe labor turnover rates for each firm, or be able to track the movements of key individuals. The unavailability of such data is restrictive in this regard, although promising avenues of research exist. It is in the nature of this field that the possibility of further and more detailed inquiry on the relationship between R&D, spillovers and scientific labor mobility will rest on data availability.

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 hypothesis require more detailed data on scientist turnover, and are exciting avenues of research in this area.

I have dealt with one channel of interfirm spillovers, those that occur through the movement of engineers and scientists. Transfer of knowledge through a company's scientific labor force does not necessitate the movement of an engineer to another, perhaps rival firm, although this is probably the most effective. Spillovers that occur through formal or informal networks of scientists and engineers is another means by which knowledge can dissipate. As stressed before, this line of inquiry also suggests the importance of personal contact in the dissipation of knowledge. Empirical validation of such network effects is difficult, but must be explored as sources of data become less scarce. The recently released NBER-Rennsellear scientific papers dataset (Adams and Clemmons, 2008) contains a wealth of information on research partnerships, thus it opens up promising areas for research on these topics. As an informal support for the importance of such mechanisms, anyone who has a Ph.D. would testify that learning from the papers of an academician, and learning directly from the academician can often be two very different things.

The measurement of spillover effects using external R&D expenditures has proved difficult in the past. In this paper I have demonstrated that weighted external R&D stocks tend to have a negative impact on market value, while external citations and citation yields tend to have a positive impact. This is a first indication that citation based measures of knowledge can be promising for a better and more detailed treatment of spillover effects. My use of these measures in this paper have been limited since the primary focus here is on scientific labor mobility. However, results suggest that these additional effects, and their implications for spillovers need to be explored in further detail in the future.

7 Appendix

- Tables A1, A2 and A3 here -.

8 References

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Table 1
Sample Statistics

		Mean	Median	Standard Deviation	Minimum	Maximum
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
Citations/Patents		11.716	9.484	11.115	0	174.4
Mobility		0.101	0.102	0.041	0.021	0.381
Spillover Pools (in logs)						
Industrial Neighborhood	*R&D*	5.705	6.008	2.298	-5.673	10.925
	Citations	7.719	7.977	2.133	-2.157	12.303
	Citations/Patents	4.306	4.312	1.047	-0.004	6.532
Technological Neighborhood	*R&D*	7.011	7.397	2.022	-1.614	10.789
	Citations	8.842	9.062	1.846	1.373	12.685
	Citations/Patents	4.391	4.425	1.312	-3.073	7.09
Sales		1749.82	220.37	6893.08	0.33	164933.14
log (Sales)		5.592	5.395	1.863	-1.097	12.013
Industry Sales		21457.75	4868.13	71771.53	50.49	752738.16
log (Industry Sales)		8.607	8.49	1.534	3.922	13.531
Industry Patents/R&D		33.82	7.75	94.79	0.0007	2304.8
log (Industry Patents/R&D)		2.088	2.048	1.613	-7.317	7.743
Industry Growth		0.03	0.028	0.209	-0.839	8.627
d(R&D=0)		0.204	0	0.403	0	1
Instruments						
	age	38.69	38.39	2.1	33.73	48.46
	male	0.85	0.86	0.1	0.43	1
	white	0.92	0.92	0.04	0.77	1
	married	0.75	0.74	0.07	0.53	0.94
	not alone	0.74	0.73	0.07	0.53	0.94
Mobility and instruments						
individual data, sample of scientists and engineers						
	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
	mobile	0.11	0	0.32	0	1
	mobile within industry sector	0.1	0	0.29	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. Sample period: 1977-1993.

Table 2
Sample correlations between key variables

Variables	log (q)	R&D/ Assets	Citations/ Patents	Spillover Pool: Industry R&D	log (Sales)	log (Industry Sales)	Industry Growth	log (Mobility)
log (q)	.	0.272	0.287	0.112	-0.153	-0.085	0.114	0.043
R&D/Assets		.	0.259	0.175	-0.204	-0.055	0.065	0.044
Citations/Patents			.	0.11	-0.073	-0.066	0.08	0.038
Spillover Pool: Industry R&D				.	0.13	0.737	0.023	-0.034
log (Sales)					.	0.475	-0.043	-0.073
log (Industry Sales)						.	*-0.008*	-0.087
Industry Growth							.	0.038
log (Mobility)								.

NOTES: Only one spillover pool measure in included, R&D in a firm's industrial neighborhood.

Table 3
Sample correlations between measures for the spillover pool

	Industrial Neighborhoods			**Technological Neighborhoods**		
	R&D	Citations	Citations/Patents	R&D	Citations	Citations/Patents
Industrial Neighborhoods						
R&D	.	0.910	0.652	0.558	0.536	0.289
Citations		.	0.708	0.534	0.538	0.295
Citations/Patents			.	0.459	0.473	0.408
Technological Neighborhoods						
R&D				.	0.975	0.759
Citations					.	0.817
Citations/Patents						.

Table 4
Spillover pools, OLS regressions. Dependent variable: log (*q*)

	(1)	(2)	(3)	(4)	(5)	(6)
R&D / Assets	0.10482	0.11559	0.114601	0.111161	0.114769	0.112256
	(6.00)	(6.57)	(6.59)	(6.4)	(6.69)	(6.55)
Citations / Patents	0.00837	0.00838	0.007896	0.007438	0.0072	0.006924
	(11.41)	(11.49)	(10.61)	(9.87)	(9.65)	(9.18)
Spillover Pools (in logs)						
Industry R&D	-0.00494	-0.00279	0.00614	0.00008	0.006607	0.002165
	(-0.76)	(-0.43)	(0.78)	(0.01)	(0.85)	(0.28)
Industry Citations			-0.01422	-0.02254	-0.01427	**-0.02032**
			(-1.86)	(-2.92)	(-1.88)	**(-2.64)**
Industry Citations/Patents				0.050505		**0.036698**
				(4.78)		**(3.43)**
Tech. R&D		-0.04213	-0.17495	-0.16777	-0.14551	**-0.14273**
		(-6.07)	(-8.08)	(-7.78)	(-6.84)	**(-6.71)**
Tech. Citations			0.15071	0.142463	0.02932	0.033347
			(6.21)	(5.9)	(1.1)	(1.24)
Tech. Citations/Patents					0.108049	**0.099128**
					(7.56)	**(6.81)**
log (External Patents/R&D)	-0.00466	-0.00583	-0.00523	-0.01491	-0.00723	-0.01409
	(-1.15)	(-1.45)	(-1.19)	(-2.99)	(-1.64)	(-2.82)
log (Sales)	-0.02082	-0.00985	-0.01179	-0.01001	-0.01263	-0.01127
	(-4.94)	(-2.21)	(-2.63)	(-2.23)	(-2.83)	(-2.52)
log (Industry Sales)	-0.01481	-0.01326	-0.00993	-0.00858	-0.00743	-0.00665
	(-1.41)	(-1.26)	(-0.92)	(-0.8)	(-0.69)	(-0.62)
Industry Sales Growth	0.23688	0.23799	0.23493	0.23111	0.230764	0.228326
	(3.97)	(4.00)	(4.00)	(4.07)	(4.00)	(4.05)
D (Year: 1977-1993)	YES	YES	YES	YES	YES	YES
D(Industry Sector: 1-14)	YES	YES	YES	YES	YES	YES
Adj. R square	0.2628	0.2659	0.2684	0.2698	0.2723	0.273
Sample size	12802	12802	12802	12802	12802	12802

NOTES: All equations include a complete set of year dummies. Standard errors are robust to arbitrary form of heteroscedasticity. *t*-statistics are reported in parenthesis.

Table 5
OLS regressions
Dependent variable: log (*q*)

	INDUSTRIAL NEIGHBORHOODS			TECHNOLOGICAL NEIGHBORHOODS		
	(1)	(2)	(3)	(4)	(5)	(6)
	SP = $SP^{I}_{R\&D,it}$	SP = $SP^{I}_{CITES,it}$	SP = $SP^{I}_{CP,it}$	SP = $SP^{T}_{R\&D,it}$	SP = $SP^{T}_{CITES,it}$	SP = $SP^{T}_{CP,it}$
R&D / Assets	0.10452 (5.98)	0.10467 (5.98)	0.10017 (5.72)	0.11569 (6.56)	0.11287 (6.36)	0.10449 (5.93)
Citations / Patents	0.00837 (11.41)	0.00839 (11.32)	0.00785 (10.51)	0.00841 (11.63)	0.00852 (11.69)	0.00834 (11.29)
Spillover Pool	0.04317 (2.70)	0.05143 (3.18)	0.1254 (3.91)	0.01402 (0.84)	0.03791 (1.96)	0.06793 (2.53)
Mobility × Spillover Pool	**0.01963** **(3.64)**	**0.02307** **(4.11)**	**0.03536** **(2.86)**	**0.02362** **(3.77)**	**0.02949** **(4.03)**	**0.02771** **(2.64)**
Mobility	**-0.09338** **(-2.91)**	**-0.15719** **(-3.63)**	**-0.13234** **(-2.59)**	**-0.13670** **(-3.24)**	**-0.22494** **(-3.69)**	**-0.09697** **(-2.22)**
log (External Patents/R&D)	-0.00415 (-1.030	-0.0027 (-0.64)	-0.01145 (-2.41)	-0.00526 (-1.31)	-0.00428 (-1.06)	-0.00428 (-1.06)
log (Sales)	-0.02068 (-4.91)	-0.0206 (-5.02)	-0.01614 (-4.04)	-0.00912 (-2.2)	-0.01219 (-2.91)	-0.02001 (-4.82)
log (Industry Sales)	-0.0166 (-1.57)	-0.01798 (-1.95)	-0.03477 (-5.48)	-0.01728 (-3.13)	-0.01863 (-3.37)	-0.02164 (-3.94)
Industry Sales Growth	0.23351 (3.94)	0.23466 (3.94)	0.23630 (4.07)	0.23873 (4.04)	0.238839 (4.03)	0.23785 (4.01)
D (R&D = 0)	-0.04002 (-2.6)	-0.04004 (-2.61)	-0.03564 (-2.31)	-0.05651 (-3.61)	-0.05197 (-3.32)	-0.03865 (-2.45)
D (Year: 1977-1993)	YES	YES	YES	YES	YES	YES
D(Industry Sector: 1-14)	YES	YES	YES	YES	YES	YES
Adj. R square	0.264	0.2637	0.2644	0.2667	0.2653	0.2631
Sample size	12802	12802	12802	12802	12802	12802

NOTES: All equations include a complete set of year dummies. Standard errors are robust to arbitrary form of heteroscedasticity. *t*-statistics are reported in parenthesis.

Table 6
GMM Regressions
Dependent variable: log (*q*). Spillover pool: $SP^{T}_{CITES,it}$

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

Table 7
GMM regressions
Dependent variable: log (*q*)

	INDUSTRIAL NEIGHBORHOODS			TECHNOLOGICAL NEIGHBORHOODS		
	(1)	(2)	(3)	(4)	(5)	(6)
	SP = $SP^{I}_{R\&D,it}$	SP = $SP^{I}_{CITES,it}$	SP = $SP^{I}_{CP,it}$	SP = $SP^{T}_{R\&D,it}$	SP = $SP^{T}_{CITES,it}$	SP = $SP^{T}_{CP,it}$
R&D / Assets	0.03682 (8.92)	0.03696 (8.97)	0.03778 (9.33)	0.04040 (9.83)	0.04016 (9.80)	0.04059 (9.97)
Citations / Patents	-0.00172 (-2.41)	-0.00175 (-2.50)	-0.00142 (-2.03)	-0.00161 (-2.26)	-0.00153 (-2.16)	-0.00157 (-2.18)
Spillover Pool	0.04177 (2.15)	0.05340 (2.24)	0.09739 (1.52)	0.06068 (2.94)	0.07903 (3.11)	0.17275 (3.83)
Mobility × Spillover Pool	**0.01768** **(2.25)**	**0.02000** **(2.06)**	**0.04075** **(1.53)**	**0.02849** **(3.32)**	**0.03428** **(3.26)**	**0.07154** **(3.85)**
Mobility	**-0.11757** **(-2.24)**	**-0.16110** **(-2.05)**	**-0.17485** **(-1.52)**	**-0.19580** **(-3.27)**	**-0.28686** **(-3.24)**	**-0.30977** **(-3.85)**
log (Sales)	-0.00342 (-1.75)	-0.00227 (-1.15)	-0.00326 (-1.67)	-0.00171 (-0.83)	-0.00281 (-1.37)	-0.00351 (-1.74)
log (Industry Sales)	-0.00710 (-1.62)	-0.01455 (-3.60)	-0.00769 (-2.59)	-0.00744 (-3.06)	-0.00790 (-3.26)	-0.00823 (-3.39)
Industry Sales Growth	0.06794 (3.91)	0.06906 (3.97)	0.06792 (3.90)	0.07370 (4.24)	0.07183 (4.18)	0.07069 (4.11)
log (q) | t - 1	0.85370 (66.2)	0.85530 (65.8)	0.85606 (67.1)	0.84676 (65.4)	0.84870 (65.3)	0.85045 (64.9)
GDP Growth	-0.01145 (-0.23)	-0.04457 (-0.61)	-0.06105 (-0.58)	-0.05984 (-1.10)	-0.14815 (-1.84)	-0.16383 (-2.35)
Sargan	187.71 (165) (p = 0.109)	188.55 (165) (p = 0.101)	190.10 (165) (P = 0.088)	185.01 (165) (p = 0.136)	186.17 (165) (p = 0.124)	181.94 (165) (p = 0.174)
Arellano-Bond (m_1)	-2.58 (p = 0.010)	-2.58 (p = 0.010)	-2.68 (p = 0.007)	-2.38 (p = 0.018)	-2.46 (p = 0.010)	-2.55 (p = 0.011)
Arellano-Bond (m_2)	-1.11 (p = 0.266)	-1.19 (p = 0.234)	-1.30 (p = 0.193)	-0.079 (p = 0.484)	-0.80 (p = 0.424)	-0.801 (p = 0.423)
Sample size	12802	12802	12802	12802	12802	12802

NOTES:

(1) All columns include year dummies, dummies for industry sectors, and a dummy for having zero R&D expenditures that year (coefficients not reported). Standard errors are robust to arbitrary forms of heteroscedasticity, *t*-statistics are in parenthesis.
(2) Instruments used for firm-level variables are, combinations of lagged differences dated $t - 3$ through $t - 10$;
(3) 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.
(4) Instruments for $\log q_{i,t-1}$ (in all columns) 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.

Table 8

Labor mobility, summary of marginal effects at the mean spillover pool

(percentage change in market value as a result of a percentage point increase in the mobility rate)

GMM Estimates	**INDUSTRIAL NEIGHBORHOODS**			**TECHNOLOGICAL NEIGHBORHOODS**		
	(1)	(2)	(3)	(4)	(5)	(6)
	SP = $SP^{I}_{R\&D,it}$	SP = $SP^{I}_{CITES,it}$	SP = $SP^{I}_{CP,it}$	SP = $SP^{T}_{R\&D,it}$	SP = $SP^{T}_{CITES,it}$	SP = $SP^{T}_{CP,it}$
Mobility × Spillover Pool	0.01768	0.02000	0.04075	0.02849	0.03428	0.07154
	(2.25)	(2.06)	(1.53)	(3.32)	(3.26)	(3.85)
Mobility	-0.11757	-0.16110	-0.17485	-0.19580	-0.28686	-0.30977
	(-2.24)	(-2.05)	(-1.52)	(-3.27)	(-3.24)	(-3.85)
Positive effect (interaction term)	0.999 %	1.529 %	1.737 %	1.978 %	3.001 %	3.110 %
Negative effect (mobility term)	-1.164 %	-1.595 %	-1.731 %	-1.939 %	-2.840 %	-3.067 %
Net effect	-0.165 %	-0.067 %	0.006 %	0.039 %	0.161 %	0.043 %
OLS Estimates	**INDUSTRIAL NEIGHBORHOODS**			**TECHNOLOGICAL NEIGHBORHOODS**		
Mobility × Spillover Pool	0.01963	0.02307	0.03536	0.02362	0.02949	0.02771
	(3.64)	(4.11)	(2.86)	(3.77)	(4.03)	(2.64)
Mobility	-0.09338	-0.15719	-0.13234	-0.13670	-0.22494	-0.09697
	(-2.91)	(-3.63)	(-2.59)	(-3.24)	(-3.69)	(-2.22)
Positive effect (interaction term)	1.109 %	1.780 %	1.522 %	1.656 %	2.608 %	1.217 %
Negative effect (mobility term)	-0.925 %	-1.556 %	-1.310 %	-1.353 %	-2.227 %	-0.960 %
Net effect	0.184 %	0.224 %	0.212 %	0.302 %	0.380 %	0.257 %

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

TABLE A1 **Summary of Spillover Measures Used**

Spillover Pools	Industrial Neighborhoods	Technological Neighborhoods
R&D	$SP^{I}_{R\&D,it} = \sum_{j \in SIC4(i), j \neq i} R_{jt}$	$SP^{T}_{R\&D,it} = \sum_{j \in \mathbf{I}, j \neq i} w_{ij} R_{jt}$
Citations	$SP^{I}_{CITE,it} = \sum_{j \in SIC4(i), j \neq i} C_{jt}$	$SP^{T}_{CITE,it} = \sum_{j \in \mathbf{I}, j \neq i} w_{ij} C_{jt}$
Citation Yields	$SP^{I}_{CP,it} = \sum_{j \in SIC4(i), j \neq i} \left(\frac{C}{P}\right)_{jt}$	$SP^{T}_{CP,it} = \sum_{j \in \mathbf{I}, j \neq i} w_{ij} \left(\frac{C}{P}\right)_{jt}$

TABLE A2 **Variable Definitions**

V_{it}	Market value (of firm i at year t)
A_{it}	Ordinary physical assets
q_{it}	Tobin's Q
R_{it}	R&D stock
P_{it}	Patent stock
C_{it}	Citation stock (corrected)
SP_{it}	Spillover pool available to firm i at year t
$SP^{I}_{R\&D,it}$	External R&D stock, aggregated in firm's industrial neighborhood
$SP^{I}_{CITE,it}$	External citation stock, aggregated in firm's industrial neighborhood
$SP^{I}_{CP,it}$	External citation yield, aggregated in firm's industrial neighborhood
$SP^{T}_{R\&D,it}$	External R&D stock, aggregated in firm's technological neighborhood
$SP^{T}_{CITE,it}$	External citation stock, aggregated in firm's technological neighborhood
$SP^{T}_{CP,it}$	External citation yield, aggregated in firm's technological neighborhood
M_{ht}	Logarithm of the scientific mobility rate in industry class h at year t
Generic Notation:	
K_{it}	Knowledge assets
K_{-it}	External knowledge assets
K^{*}_{it}	Effective knowledge assets (= K_{it}+αSP_{it})
σ	Returns to assets
γ	Shadow value of knowledge assets relative to ordinary assets

TABLE A3	**Industry Sectors for the Mobility Variable**
Industry 1	Paper & Printing
Industry 2	Chemicals (excluding Drugs)
Industry 3	Rubber
Industry 4	Wood & Miscellaneous Manufacturing
Industry 5	Primary Metal
Industry 6	Fabricated Metal
Industry 7	Machinery
Industry 8	Electrical Machinery
Industry 9	Autos
Industry 10	Air & Boat
Industry 11	Textiles & Leather
Industry 12	Drugs
Industry 13	Food
Industry 14	Computers & Instr.
Industry 15	Oil