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Spillover Asymmetry and Why It Matters

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Although spillovers are a crucial factor in determining the optimal environment for innovation, there is no consensus regarding their impact on firm behavior. One reason for this may be that models differ in their assumptions for the functional form of the spillover pool. In industrial organization and economic geography, for example, the predominant convention is that all innovation within an industry/region contributes to a spillover pool that has a common value for all firms. An alternative convention prevalent in endogenous growth and evolutionary economics is that spillovers have directionality—the size of the relevant pool differs across firms.

Knowing the correct functional form may facilitate theoretical consensus, either analytically (by modifying models' assumptions) or empirically (by supporting a critical test of competing theories). We characterize and test the functional form of spillover pools for efficiency-enhancing innovation across 50 markets in the banking industry. Our results in that setting are consistent with expectations for asymmetric spillovers but inconsistent with expectations for pooled spillovers.

Key words: spillovers; innovation; banking
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1. Introduction

Spillovers (the leakage of knowledge across firms) are one of the central constructs in the economics of innovation. Romer (1986) relies on spillovers to explain increasing economywide returns to innovation in the presence of decreasing firm-specific returns to innovation. Spillovers have two effects on aggregate innovation (Spence 1984): an *efficiency* effect and an *incentive* effect. The efficiency effect is that spillovers reduce the expenditures necessary for firms to achieve a given level of innovation. The incentive effect is that imitation by rivals reduces the potential returns to innovation and therefore the incentives to innovate. Accordingly, spillovers are a crucial factor in determining the optimal environment for innovation.

Two conventions have developed around the directionality of spillovers. One convention, prevalent in industrial organization (Griliches 1979; Levin and Reiss 1984, 1988; Spence 1984; Jaffe 1988; Adams and Jaffe 1996) and economic geography (Ellison and Glaeser 1997, Black and Henderson 1999) is that spillovers are nondirectional (pooled). All innovation in an industry/region contributes to a spillover pool that has a common value for all firms. Firms may differ in their access to the pool (if, for example, they are geographically distant) or in the relevance of the pool (if, for example, they use chemistry as their basic science but other firms use biology) to them. However, if the pool is proximate and relevant to all firms, then they draw equal benefit from the contributions of all other firms. In other words, there is no sense of a leader/follower relationship for spillovers, as there is for the flow of knowledge in the diffusion and imitation literatures.

An alternative convention prevalent in the endogenous growth literature (Jovanovic and Rob 1989, Jovanovic and MacDonald 1994, Eeckhout and Jovanovic 2002) is that spillovers have directionality. This view preserves the notion of an innovator and an imitator inherent in the diffusion literature (Mansfield 1968), the evolutionary economics literature (Nelson and Winter 1982, Klepper 1996), and the international trade literature (Krugman 1979, Abramovitz 1986, Baumol et al. 1989, Grossman and Helpman 1992). Under this view, some firms have superior knowledge relative to other firms, and knowledge flows exclusively from those with superior knowledge to those with inferior knowledge.

Thus, despite the fact that spillovers are central to models of innovation/growth across all these literatures, there is no consensus on their functional form. Correspondingly, there is no consensus regarding their impact on firms' innovative behavior. Predictions are that they increase (Ellison and Glaeser 1997, Black and Henderson 1999, Jovanovic and Rob 1989, Grossman and Helpman 1992), decrease (Spence 1984, Levin and Reiss 1988, Eeckhout and Jovanovic 2002), decrease then increase (Nelson and Winter 1982), and increase then decrease (Aghion et al. 2001) innovation/growth.

In principle it is possible to resolve the controversy via empiricism, but the empirical record is similarly equivocal. Studies of spillovers consistently indicate that R&D intensity and outcomes increase with the size of the spillover pool (Jaffe 1986, 1988). However, the studies exhibit an apparent anomaly where the output elasticity of spillovers is comparable to and sometimes greater than that for firms' own R&D (Jaffe 1986, Adams and Jaffe 1996). Given that the spillover pool in these studies is on average $n-1$ times the firm's own R&D, where n is the number of firms in the industry, the implied economic contribution of spillovers is sometimes orders of magnitude greater than that from the firm's own R&D spending. If this were true, few firms could justify R&D investment.

One explanation for the empirical anomaly may be that spillovers are capturing market-size effects, as suggested by Levin (1988). An alternative explanation is that the large coefficients on spillovers reflect estimation bias from using a pooled spillover specification when in fact spillovers are asymmetric (see derivation in §EC.1 of the e-companion).[1] Accordingly, knowing the correct functional form for spillovers has the potential to resolve empirical anomalies and thereby illuminate theory regarding their behavioral impact. The goal of this paper is to facilitate consensus in innovation theory by clarifying and testing the functional form of spillovers.

2. Background on Spillovers

Arrow (1962) discussed the problems of appropriability and innovation and the tension between incentives to innovate and the diffusion of the benefits. The central concern is that because knowledge is a public good (nonrival and nonexcludable), the best means to appropriate the returns from innovation is for a monopolist to keep the knowledge in house. However this is inefficient from a social standpoint, because the knowledge isn't fully exploited. It also may be privately inefficient, because a firm other than the inventing firm may be able to use the knowledge more effectively.

There are four operative uses of the term spillovers in the literature: the general phenomenon of leakage, the amount of knowledge available to rival firms (the pool), the percentage that leaks, and the elasticity of rival knowledge to own output. We clarify these distinctions using the Levin and Reiss (1988) expression for the contribution of rival R&D to focal firm innovative output, Y_i:

$$Y_i = r_i^{\alpha}(\omega S_i)^{\gamma}, \tag{1}$$

where r_i is focal firm R&D, α is the elasticity of own R&D to output, S_i is the pool of rival knowledge the focal firm draws on, ω is the extent of knowledge leakage between rivals, and γ is the elasticity of rival knowledge to output.

In this paper, we use the term *spillovers* to refer to the general phenomenon, the term *spillover pool* for the expression S_i, the term *leakage rate* for the expression ω, and the term *expropriability* for the expression γ. Thus, the value of spillovers may differ across firms through differences in their relevant spillover pool, S_i, differences in the ease of gaining access to the pool, ω, or differential effectiveness in utilizing the knowledge that has been accessed, γ. This paper deals exclusively with asymmetry in the functional form of the spillover pool, S_i.

Equation (1) illustrates one source of confusion regarding the phrase *spillovers*. In addition to this theoretical confusion is some empirical confusion, in that spillovers are often defined by how they are measured empirically. This is problematic given our goals. Much of the empirical treatment of spillovers inherently assumes directionality, in that it examines particular transfers of knowledge. For example, studies using patent citations to study spillovers trace the source and destination of knowledge (e.g., Thompson 2006). Studies examining the actual mechanisms of transfer such as alliances and labor mobility often refer to the transfer as spillovers (e.g., Rosenkopf and Almeida 2003). This empirical approach is attractive because it allows researchers to demonstrate that particular innovations have indeed transferred.

There are two concerns with the approach, however. First, these point-to-point transfers of knowledge are only subsets of the theoretical definition of spillovers. As Equation (1) illustrates, the theoretical concept is much broader. Spence (1984), for example, examines simultaneous R&D by all industry firms whose cost is reduced by the total spillovers being generated by the set of firms engaged in R&D. Thus there is no "innovation" that gets transferred. Second, the ability to identify a source and destination presupposes directionality, although our goal is to determine whether spillovers are better characterized as being directional or symmetric.

Because we want to determine which theories correctly model spillovers, we adopt the broad definition

[1] An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

of spillovers implied by Equation (1): knowledge generated outside the firm exploited to increase firm efficiency. Thus, our definition includes point-to-point transfers and imitation but is not restricted to them. Rather, we test where a firm's extramural knowledge appears to originate (from the set of all firms in the market versus the subset of firms with superior knowledge).

2.1. What Do We Mean by Spillover Pools?

There are two basic conventions in modeling the spillover pool, S_i. The first convention, shared by industrial organization and economic geography, is to treat all economic activity as contributing to a pool that is equally accessible/valuable to all firms. We refer to this convention as *pooled spillovers*. The second convention assumes that economic actors differ in their level of knowledge and that knowledge flows exclusively from those with superior knowledge to those with inferior knowledge. This convention is shared by evolutionary economics, endogenous growth, and trade theories.

The lack of consensus may reflect fundamental differences in beliefs; however, it is possible that it reflects simple measurement problems—researchers cannot identify knowledge sets. If researchers could actually identify a firm's knowledge set, then the spillover pool could be defined as the complement of its knowledge within the current frontier (the union of all knowledge sets). Unfortunately, we cannot characterize the knowledge set for each firm. Even if we could, the computational task of pairwise comparison of all knowledge sets in an industry would be overwhelming. The practical problem of spillover pools, then, is one of choosing the best simplifying assumption. Are we as researchers better off ignoring redundant knowledge (the bias inherent in the pooling assumption), or are we better off ignoring the superior knowledge of a firm that in general has less knowledge (the bias in the asymmetry assumption)?

As mentioned in the introduction, the four subfields examining the impact of spillovers on innovation differ in their simplifying assumption about the spillover pool, S_i. However, the models also differ in which dimension of spillovers (leakage rate, ω, or elasticity, γ) drives innovation. Accordingly, the lack of consensus on the impact of spillovers is not surprising. Again as noted in the introduction, the models variously predict that spillovers increase, decrease, increase then decrease, and decrease then increase innovation and growth.

2.2. Empirical Record on Spillovers

The lack of theoretical consensus regarding spillovers is matched by an equivocal empirical record. Studies break down into two classes: those examining the impact of spillover pools on R&D and those examining survey-based measures of learning and imitation. The studies of spillover pools consistently indicate that R&D intensity and outcomes increase with the size of the spillover pool (Jaffe 1986, 1988). However, the spillover pool as constructed in these studies (sum of R&D spending by firms in the industry) is highly correlated with market size, and thus the spillover coefficient may be capturing market-size effects. Moreover, the empirical tests examine the impact of pool size, whereas propositions in the models pertain to the leakage and elasticity components of spillovers.

In contrast to the pool size studies, the survey-based studies examine the leakage and elasticity components of spillovers without regard to pool size. These dimensions are captured through questions regarding learning mechanisms and imitation lags. The learning measures are self-reports by R&D managers regarding the most effective mechanisms for learning about technology; the imitation lag measure is a self-report of the time it takes to imitate a patented major product invention. Levin et al. (1985) find that the imitation lag measure has no significant effect on R&D intensity. Looking at the learning mechanisms, Levin (1988) finds none of them to be significant in explaining R&D intensity. Using new survey data, Cohen et al. (2000) find that R&D intensity increases with the importance of ideas from rivals, but decreases with the importance of information from suppliers and market mediated information from rivals. Finally, Levin and Reiss (1988) identified three survey measures potentially related to the elasticity of spillovers (the importance of rivals to technological progress, the importance of government research to technological progress, and technological maturity). None of these explained variation in the elasticity of the spillover pool.

In summary, there is no empirical consensus on spillovers with which to illuminate the theoretical schism. One reason for this may be that the empirics capture spillovers as the sum of economic activity (pooled spillovers). Thus, the empirical measure differs from at least some of the theories (those that assume asymmetric spillovers). It also may differ from the actual functional form of spillovers. Accordingly, our empirical strategy is to test the functional form of the spillover pool.

3. Empirical Tests

We test the functional form of the spillover pool by examining firm innovation rates as a function of relative knowledge in a market. To do this, we begin by characterizing general functional forms in the literature and then specifying our empirical implementations of those forms.

3.1. Functional Forms of Spillovers

A general functional form for spillovers allows the knowledge for each rival firm j, k_j, to leak to focal firm i by a pairwise specific parameter ϕ_{ij}, such that the total spillovers available to firm i are characterized by

$$S_i = \sum_{j \neq i} \phi_j k_j, \tag{2}$$

Note that the general form in Equation (2) supports an infinite set of specific functional forms for spillovers. Rather than examine an exhaustive set of possibilities, we restrict attention to those forms currently employed in the innovation literature.

Pooled Spillovers. As noted previously, the predominant convention in industrial organization and economic geography (both theory and empiricism) treats $\phi_{ij} = 1$ for all i and j, as long as firms i and j are technically and geographically proximate:[2]

$$Sp_i = \sum_{j \neq i} k_j. \tag{3}$$

Asymmetric spillovers. A broad definition of asymmetric spillovers suggests all matrices in which ϕ_{ij} is not constrained to a single value. However, the theoretical presumption that knowledge flows from firms with more knowledge to those with less knowledge sets $\phi_{ij} = 0$ for all rivals whose knowledge is inferior to that of the focal firm:

$$Sa_i = \begin{cases} \sum_{j: k_j > k_i} \phi_{ij} k_j & \text{if } k_j > k_i \text{ for at least one } j, \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

3.2. Empirical Implementation of the Functional Forms

Within the general restriction for asymmetric spillovers in Equation (4), the theoretical literature has utilized two specific functional forms: *leader distance* from evolutionary economics and *superior density* from endogenous growth. Our empirical implementation of these forms follows theoretical convention (Spence 1984, Levin and Reiss 1984, Nelson and Winter 1982) in that we define relative knowledge in terms of firm cost. We employ a cost-efficiency measure that allows us to capture differences in cost for the same quality or differences in quality for the same cost. Following the same convention, we measure innovation as cost reduction. Our approach therefore preserves the primary theoretical foundations of spillovers.

The first empirical form, *leader distance*, matches the spillover construct in Nelson and Winter (1982), where firms have likelihood p of imitating the last period's best practice (lowest cost function across all rivals). Accordingly, we capture the *leader distance* spillover pool as the cost distance between the lowest cost firm and focal firm from the prior period:

$$Sldr_i = c_i - \min_j(c_j). \tag{5}$$

A companion measure, *laggard distance*, is the cost distance between the highest cost firm and the focal firm:

$$Slgd_i = \max_j(c_j) - c_i. \tag{6}$$

We test how a firm's innovation (cost reduction) is affected by both distance measures. If innovation is driven by spillovers and if spillovers are shared equally across firms (pooled), then we expect distance to be insignificant. If instead innovation is driven by mean reversion, we expect the coefficients on the two measures to be equal but of opposite signs. If, however, innovation is driven by imitating best practice, we expect the coefficient on *leader distance* to be positive and greater than the coefficient on *laggard distance*. Such a result implies that the laggards have more to gain from industry knowledge than do leaders and that the amount they gain increases with their distance from the leader.

The second empirical form, *superior density*, matches the spillover construct implicit in the endogenous growth models where firms randomly encounter rivals and the amount of knowledge they expropriate is a function of the rival's surfeit knowledge (Jovanovic and Rob 1989, Jovanovic and MacDonald 1994, Eeckhout and Jovanovic 2002). *Superior density* is the sum of the cost distances between focal firm i and rival firm j for all firms superior to the focal firm.[3] However, by its nature, density confounds two fundamentally separable constructs: average knowledge stock of superior rivals and the number of such firms. The number of superior rivals, n_s, captures the number of opportunities to encounter superior knowledge, and average stock captures the expected amount of knowledge gained per encounter. To isolate the effects of competition from those of spillovers we decompose *density* into these two constituent elements. Accordingly, we capture the *superior density* spillover pool with two variables: (a) *count superior*, the number of firms with lower costs than the focal firm, n_s, and (b) *average superior*, the average cost distance between focal firm i and rival j for all firms superior to the focal firm:

$$Sas_i = \begin{cases} \dfrac{1}{n_s} \sum_{j: c_j < c_i} (c_i - c_j) & \text{if } c_j < c_i \text{ for at least one } j, \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

[2] When firms are not proximate, then spillovers decay with geographic and/or technical distance (Jaffe 1986, 1988).

[3] From here on we use the term *superior* to refer to firms with lower cost than the focal firm; we use the term *inferior* to refer to firms with higher cost than the focal firm.

A companion measure for the n_i firms with higher costs than the focal firm, *average inferior* is the average cost distance between focal firm i and rival j for all firms inferior to the focal firm:

$$Sai_i = \begin{cases} \dfrac{1}{n_i} \sum\limits_{j: c_j > c_i} (c_j - c_i) & \text{if } c_j > c_i \text{ for at least one } j, \\ 0 & \text{otherwise.} \end{cases} \quad (8)$$

We are interested in testing the null hypothesis of nondirectional (pooled) spillovers using the density measure, just as we were using the distance measure. Although the distance test was principally one of directionality, the density test will be more compelling because it implicitly tests Equation (2), the functional form for pooled spillovers. Under this form, the entire density of firm knowledge contributes to the spillover pool, Sp_i. Because the entire spillover pool is the pool to the right of the focal firm plus that to the left, we can express pooled spillovers in terms of the average knowlege measures:

$$Sp_i = Sas_i + Sai_i. \quad (9)$$

Thus, to test the null hypothesis that spillovers are pooled, we compare the coefficients for *average superior* and *average inferior*. We accept the null hypothesis if the coefficients are of equal magnitude.

3.3. Industry

We conduct our tests in the banking industry following deregulation. This industry was chosen because it is fragmented with localized competition and has substantial innovation. Furthermore, because banking is regulated, we can obtain quarterly cost data for the full census of insured banks.

Fragmentation is important because it allows us to compare discrete markets within the same industry, where each market faces the same inverse demand function and shares the same technology. Thus, we can compare differences in spillover pools while controlling for other factors that affect cost improvement across distinct industries. We can also control for differences in level of demand through differences in economic conditions across markets.

Cost Data. The Federal Deposit Insurance Corporation (FDIC) collects extensive data on bank inputs and outputs for all banks in its insurance program (more than 99% of all banks). We use the raw data on inputs and outputs to form a cost-efficiency measure that is comparable across firms. The use of cost as the measure of knowledge and change in cost as the measure of innovation preserves the conventions in Spence (1984), Nelson and Winter (1982), and Levin and Reiss (1984, 1988), where the goal of innovation is to reduce cost. A nice feature of the measure is that it is one dimensional. Knowledge of all types gets collapsed into a cost equivalent. Therefore, we can feasibly define a knowledge (cost) frontier and have a meaningful reference for direction and distance to that frontier. Such a measure is less feasible for multiproduct industries or for industries comprising diversified firms with consolidated reporting.

There are two discrete definitions of *market* that are appropriate for banking: the state, representing certificate/headquarters-level competition, or the municipality, representing branch-level competition. Following Morgan et al. (2004), our primary definition of a market is the state. However, as a robustness check, we replicate all tests defining metropolitan statistical area as the market.

3.3.1. Innovation and Spillovers in Banking. The intent of this section is threefold. First, we wish to reinforce the idea that banking has a high level of innovation, and thus is an appropriate setting for a study of spillovers. Second, we want to argue that banking is particularly appropriate for the study of spillovers because at any time there is a body of innovations at various stages of diffusion (spillover pool) as opposed to a single innovation that is innovated and then imitated. Finally, we want to identify (and ultimately control empirically) factors other than spillovers affecting firm innovation.

Level of Innovation. Because banking is not a science-based industry, it does not come to mind when we list innovative industries. However, banking has had tremendous innovation and productivity growth over the past 100 years (Batiz-Lazo and Wood 2002). Lerner (2002) documents 651 financial services innovations of sufficient quality to merit reporting in *The Wall Street Journal* and 922 patents awarded to financial services firms over the period 1990–2002. Indeed, the annual growth rate in this mature industry (6.6%) has outstripped gross domestic product growth over the past 20 years. By way of comparison, this growth rate places banking in the top third of the industries in the Carnegie Mellon Survey of R&D managers (Cohen et al. 2000).

Body of Innovation. Most studies of innovation in banking examine diffusion of innovations rather than invention (the noted exception is Lerner 2002). Theories of spillovers accommodate both invention and imitation (diffusion). Imitation is direct use of embodied knowledge, whereas invention combines knowledge underlying an existing invention with the firm's own R&D to create new inventions. Thus, imitation/diffusion is a subset of the innovative activity arising from spillovers. Although focusing on diffusion can be viewed as a limitation, it covers a substantial share of banks' innovation decisions as well as their performance improvement (there are approximately 10,000 potential adoptions for each invention).

In addition, the same basic model of firm profit maximization drives invention as well as adoption (with the exception that invention adds uncertainty as well as concerns with appropriability).

Studies of banking diffusion pertain primarily to three important innovations: automated teller machines (ATMs), small business scoring systems (SBSS), and transactional websites. There is little need to describe ATMs because they are ubiquitous. They were introduced by Chemical Bank in 1969; by 1979 they had been adopted by 12% of banks (Sharma 1992), and as of 2000 they were fully diffused throughout the industry. SBSS is a scoring system for assessing the credit risk of commercial loans; it was developed by Fair Isaac in 1993. This is the commercial equivalent of Fair Isaac's FICO system for evaluating consumer credit. As of 2000, 50% of large banks had adopted SBSS (Akhavein et al. 2005). The final innovation, Internet banking, was introduced in 1995 by Wells Fargo, initially as a means to allow customers access to their account information. Ultimately, websites began accommodating financial transactions. As of 2004, 75% of banks had websites, 80% of which were transactional (Sullivan and Wang 2005).

The histories of ATMs, SBSS, and Internet banking, together with the fact that these comprise only three of the 651 significant banking innovations, suggest an environment where numerous innovations are simultaneously being generated and adopted/diffused. Thus, in any given year there are innovations at each stage of a diffusion cycle and firms are making decisions as much (if not more) about *what* to adopt as *whether* to adopt. This is precisely the environment of diffuse innovative knowledge that spillovers seem to connote.

Other Factors Affecting Innovation. To understand factors other than spillovers that affect bank innovation, we turn to empirical studies of these three major innovations. Studies by Hannan and McDowell (1984) and Sharma (1992) of ATMs, by Sullivan and Wang (2005) of Internet banking, and by Akhavein et al. (2005) and Bofondi and Lotti (2006) of SBSS identify some general firm and market factors affecting the adoption of banking innovations.

Across these studies, the only market factor consistently associated with adoption is market concentration. Higher concentration (lower competition) increases the rate of adoption. This has been interpreted as support for the Schumpeterian market power hypothesis. Large market size (in the few studies where tested) tends to decrease adoption. This may mean that competition is suppressed in large markets. Factors that are significant in some studies but not others are wages, market growth, and urbanism.

Not surprisingly, firm effects have a greater influence on innovation than market effects do. Factors that consistently predict speed of adoption are firm scale, bank holding company membership, and years since the innovation's introduction. Their directions match expectations from adoption models. Adoption increases with firm scale, reflecting the large customer base over which to reap the marginal revenues or cost savings. Adoption also increases with holding company membership. Because this effect is above and beyond scale, it likely reflects benefits from centralized innovation. Time since introduction is a proxy for falling adoption costs.

Taken together, the results suggest that the adoption process reflects profit maximization logic and that there is greater heterogeneity within markets than across markets in the factors affecting profitability. Nevertheless, because our empirical strategy is to attribute cost reduction not otherwise accounted for to spillovers, we control for all these time-varying market and firm-level factors. In addition, we employ an Arellano-Bond specification that inherently controls for permanent differences across firms (and by extension markets) through first differencing.

3.3.2. Trends in Banking During the Period. A number of industry changes occurred during the period we examine. We want to understand the extent to which these, rather than spillovers, drove banks' cost improvement. The primary exogenous force affecting the industry was deregulation (gradual relaxation of branching restrictions) between 1979 and 1997. The intent of the regulatory changes was to offer U.S. banks scale economies to compete more effectively with foreign banks and nonbank intermediaries.

Deregulation had the intended effect of increasing the number of branches from 38,738 in 1980 to 64,079 in 2000. This heightened branch-level competition in turn fueled consolidation, reducing the number of banks from 14,500 to 8,300 over the same period. Early consolidation resulted from failures (1,352 through 1993), but ultimately consolidation continued through mergers. These mergers were initially motivated by cost savings. When banks acquired competitors, they consolidated back office operations and closed branches in overlapping territories. These efforts reduced costs in the target by about 20% and also reduced the number of competitors. Thus, scale economies are a competing explanation for cost improvement.

The banks also responded to competition by adopting a client-based approach to banking. The client-based approach (in conjunction with legislative changes from the Glass Steagel Act, allowing banks to underwrite securities) led banks into new areas (underwriting, derivatives, investment management, mutual funds, insurance, and annuities). The complementarities between the areas (the ability to cross-sell and leverage customer knowledge and monitoring from one area to another) yielded scope economies in relationship management. These scope economies provided additional rationale for acquisitions, because each acquired customer carried higher lifetime value.

Thus, a number of things were occurring in banking during the period we examine. The picture we want to paint is that these forces created the stimulus for innovation. When these factors act as a stimulus, they are not really a competing explanation to spillovers. Rather they are a complement—firms need a means to respond to the stimulus. Exploiting spillovers is one means for responding (own R&D is the other). However, to be conservative, we treat all these forces as controls. Thus, in addition to the market and firm controls identified in the diffusion studies, we add controls for competition, scale economies, and mergers.

3.4. Empirical Model

Analysis proceeds in two stages. In the first stage we model an industry cost frontier to collect measures of cost efficiency for each firm in each year. In the second stage, we model changes in a firm's efficiency (derived from stage 1) as a function of its spillover pool, where the spillover pool is alternatively defined as each of the three functional forms characterized in §3.1.

3.4.1. Stage 1—Firm Cost Efficiency. We follow convention in studies of bank efficiency by modeling a stochastic cost frontier using a translog cost function (Cebenoyan et al. 1992, Hermalin and Wallace 1994, Berger et al. 1993, Mester 1993).[4] Stochastic frontier analysis, developed by Aigner et al. (1977), is based on the econometric specification of a cost frontier (the minimum observed cost to produce a set of outputs). The model assumes that the log of firm i's cost in year t, c_{it}, differs from the cost frontier, $c^{\min}$, by an amount comprising two distinct components: a standard normally distributed error term e_{it} and a cost efficiency term modeled as a nonnegative random variable u_{it}, which we assume takes the form of a truncated normal distribution.[5]

Potential problems with observations that are far from the sample means have led some researchers to adopt nonparametric approaches to frontier analysis (Wheelock and Wilson 2008). The advantage of nonparametric approaches is that they do not impose a functional form on the distribution of the efficiency term (because all error is ascribed to efficiency). Although these recent nonparametric techniques solve the problem of outlier sensitivity through partial frontiers, they retain the problem of noise (Wheelock and Wilson 2008). Unfortunately, the work does not compare its estimates to those in prior studies, nor does it offer other approaches to validating the methodology. Given broader acceptance for efficiency measures derived from the translog cost function and given the ability of those measures to explain phenomena related to bank efficiency such as bank failure (Berger and Humphrey 1992, Wheelock and Wilson 1995) and problem loans (Berger and DeYoung 1997), we continue to employ them here. We address attendant concerns regarding outliers in our second stage analysis.

One particularly nice feature of the translog cost function is its ability to accommodate the complex array of bank inputs and outputs. In addition, the translog form accommodates trade-offs in both market strategies (product mixes and prices) and operational strategies (input mixes). The basic translog cost function models a cost minimizing firm i in year t operating with (in log form) outputs y_{it} and input prices w_{it}:

$$c_{it}=\beta_0+\sum_j\beta_{1j}y_{it}^j+\sum_k\beta_{2k}w_{it}^k+\tfrac{1}{2}\sum_j\sum_j\beta_{3jj}y_{it}^jy_{it}^j + \tfrac{1}{2}\sum_k\sum_k\beta_{4kk}w_{it}^kw_{it}^k+\sum_j\sum_k\beta_{5jk}y_{it}^jw_{it}^k+u_{it}+e_{it}, \quad (10)$$

where

- c_{it}: log observed firm cost
- y_{it}^j: Vector of log output levels, j indexes output elements
- w_{it}^k: Vector of log input prices, k indexes input elements
- u_{it}: Cost efficiency with truncated normal distribution
- e_{it}: Error term with normal distribution.

We pool data for all firms over 14 years using the model to capture firm-year measures of cost efficiency relative to a global and permanent cost frontier. We collect the estimates of the expected value of firm-year cost efficiency in stage 1, $\mathrm{E}(u_{it} \mid e_{it})$, which for convenience we continue to label as u_{it}. We then use these estimates as the dependent variable in stage 2 to test the functional form of the spillover pool.

3.4.2. Stage 2—Test of Spillover Pool. We model innovation (reduction in firm cost)[6] as a function of three specifications for the firm's spillover pool. Equation (11) tests for spillover symmetry while controlling for time varying firm and market characteristics:

$$u_{i,\,t+1}=\beta_0+\beta_1S_{it}+\beta_2F_{it}+\beta_3M_{jt} + \sum_{n=0}^{\rho}(\beta_nu_{i,\,t-n}), \quad (11)$$

[4] Stage 1 analysis was originally conducted in Knott and Posen (2005). Our discussion closely follows that paper.

[5] All results are robust to half-normal and exponential distributions.

[6] For expositional simplicity, from this point forward *firm cost* refers to the cost-efficiency measure derived from stage 1. Accordingly it is not total cost (the dependent variable in stage 1); it is cost relative to lowest potential cost for a given scale, product mix and input mix.

where

u_{it}: Firm cost efficiency
S_{it}: Spillover pool for firm i under the various functional forms
F_{it}: Vector of time-varying firm characteristics
M_{jt}: Vector of time-varying market characteristics.

Equation (11) is a time series model that captures innovation as current period cost (on the left-hand side) relative to cost in the prior periods (on the right-hand side). The lagged dependent variables serve to capture the significant persistence in the data-generating process—in that firm cost changes only slowly over time. In addition to the persistence of the dependent variable, our key independent variables (spillover pools) are constructed from a lag of the dependent variable. As such, our model is inherently dynamic. The use of lagged dependent variables in a fixed-effects estimation leads to biased estimates (Nickell 1981). To account for this, Holtz-Eakin et al. (1988) and Arellano and Bond (1991) develop a generalized method of moments estimator (Arellano-Bond estimator), which has since become a standard procedure in estimating dynamic models with panel data. The Arellano-Bond model controls for endogeneity by estimating a first-difference model using lagged values of the dependent variable as instruments for the lagged difference. To deal with endogeneity of the spillover variables we also instrument the differences in the spillover variables with further lags of their levels. Our primary model uses two lags to capture the dynamics of the cost adjustment process, although the results are robust to a variety of alternative lag structures.

3.5. Data and Measures

The data for the study come from the FDIC Research Database of quarterly financial data for all commercial banks filing the "Report of Condition and Income" (Call Report). On entry into the market, each bank is allocated a unique certificate number by the FDIC—and we take the bank (certificate number) as our fundamental unit of analysis. We examine all banks in each of the 50 states plus the District of Columbia for the period 1984–1997. This initial data set contains 694,587 firm-quarter observations. Following convention in the banking literature, we aggregate to annual data by averaging the quarterly data (Mester 1993). The final first-stage data set comprises 170,859 firm-year observations.

There is considerable debate as to the choice of inputs and outputs in the banking sector, but a review of the literature suggests some convergence around a model that sees capital and labor as inputs to the production process and various forms of loans as outputs (Wheelock and Wilson 1995). We collect data to construct seven variables related to banking efficiency in log thousands of constant 1996 dollars. The dependent variable is *total cost*, total interest and noninterest expenses. The six independent variables are divided between input prices and output quantities. Input prices are (a) *labor price*, salary divided by the number of full-time-equivalent employees; (b) *physical capital price*, occupancy and other noninterest expenses divided by the value of physical premises and equipment; and (c) *capital price*, total interest expense divided by the sum of total deposits, other borrowed funds, subordinated notes, and other liabilities. Output quantities are stocks ($1,000) of (d) *mortgage loans*, (e) *nonmortgage loans*, and (f) *investment securities*.

To test the hypotheses in the second stage model, we create year-specific spillover pools for each firm in accordance with Equations (5)–(9). To test the leader distance spillover specification, we calculate *leader distance* as the cost of the focal firm less that of the leader. *Laggard distance* is calculated in an analogous manner.

To test the superior density specification, we disaggregate density into its constituent parts: *count* of competitors and *average* knowledge stock of competitors. *Count* captures the number of opportunities to encounter rivals; *average* captures the expected value of knowledge from any encounter. To disentangle pooled from asymmetric spillovers, we disaggregate *count* into *count_superior*, the number of firms with lower cost than the focal firm, and *count_inferior*, the number of firms with higher cost than the focal firm. We also disaggregate *average* into *average_superior*, the average cost distance between the focal firm and each lower cost rival, and *average_inferior* (calculated in an analogous manner).

We add to the spillover pool variables a number of firm-level and market-level controls. At the firm level, we control for bank scale with seven measures: (a) *assets*, in log thousands of constant 1996 dollars; (b) *branch_count*, number of branches operated by the bank; and (c) *market_share*, as the share of the total market size based on loan volume. In addition, because approximately one-third of banks are owned by a bank holding company that controls more than one bank (certificate), we include (d) *holding_company*, as a dummy variable for holding company ownership, as well as a number of measures of the size of the holding company; (e) *hc_certificates*, the number of additional banks (certificates) held by the holding company; (f) *hc_branches*, the number of additional branches in the bank holding company beyond those in the observation certificate; and (g) *hc_states*, the number of additional states in which the holding company operates banks. All count variables are logged, but all results are robust to the use of levels.[7]

[7] All variables are in log form except those that inherently take on values between zero and one. Where there is the potential to log a zero measure, one is added to the variable prior to logging.

At the market level we control for demand and supply-side factors affecting firms' incentives to innovate. Controls for demand include (a) *population*, log of market population; (b) *permits*, logged number of building permits (capturing growth); and (c) *market size*, logged total market value of loans. Controls for supply side include (d) *count_firms*, logged number of firms in market; (e) *Herfindahl*, market concentration; (f) *entered*, logged number of banks entering the market; (g) *failed*, logged number of failing banks; and (h) *merged*, logged number of bank mergers. In addition to these time-varying controls, Arellano-Bond estimation inherently controls for permanent characteristics of firms and markets via first differencing.

4. Results

Because stage 1 analysis is identical to the analysis in Knott and Posen (2005), we do not replicate the results here. They are, however, available in §EC.2 of the e-companion. Table 1 summarizes the data for approximately 122,000 bank-year observations used in the stage 2 analysis. Results for tests of spillover form (Equation (11)), estimated using our primary specification, are presented in Table 2.

4.1. Control Variables

Before reviewing the main test we examine the control variables in isolation. These variables behave as anticipated. Looking first at the lagged dependent variables (model 1), both were significant. The first lag was positive and significant. The second lag was negative and significant but an order of magnitude smaller than the first lag. We examined further lags but found them to be nonsignificant. This suggests the adjustment period for shocks to cost is approximately two years. Also of note in this model are the tests for autocorrelation in first differenced error terms. For the moment conditions of Arellano-Bond estimation to be valid, second-order autocorrelation must be nonsignificant. In our estimation models, although first-order autocorrelation was significant (see z-statistics), second-order correlation was not, suggesting the moment conditions hold. This remained true for all models in Tables 2 and 3.

Looking next at firm controls (model 2), the number of branches was negative and significant (reflecting cost reduction); assets were nonsignificant. The negative sign on branches suggests innovation is increasing in the size of the bank. (The lack of significance for assets is largely expected, as assets and branches are correlated at 0.79.) The coefficient on holding company is significant above and beyond the number of branches. Both results match studies of banking innovation discussed in §3.3.1 (as well as innovation theory, where the returns to innovation are defined as unit margin increase times output scale).

Table 1 **Data Summary for Stage 2 Test**

Variable	Mean	SD	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(1) *Inefficiency*	0.17	0.13	0.02	2.81	1.00																					
(2) ln_*count_superior*	4.99	1.25	0.69	7.59	0.41	1.00																				
(3) ln_*count_inferior*	5.05	1.22	0.69	7.59	−0.53	0.09	1.00																			
(4) *avarage_superior*	0.06	0.09	0.00	2.48	0.97	0.35	−0.54	1.00																		
(5) *average_inferior*	0.13	0.09	0.00	3.26	0.61	0.15	−0.30	0.58	1.00																	
(6) *leader_distance*	0.13	0.13	0.00	2.76	0.99	0.43	−0.50	0.97	0.61	1.00																
(7) *laggard_distance*	1.38	0.79	0.00	4.55	−0.00	0.17	0.34	−0.03	0.32	0.01	1.00															
(8) ln_*asset*	11.05	1.23	7.19	19.25	0.03	−0.09	−0.15	0.02	0.08	0.04	0.01	1.00														
(9) ln_*branch_counts*	1.24	0.73	0.00	7.58	0.05	−0.12	−0.30	0.04	0.04	0.05	−0.09	0.79	1.00													
(10) *market_share*	0.00	0.02	0.00	0.72	−0.00	−0.19	−0.15	0.00	0.03	−0.01	−0.07	0.48	0.50	1.00												
(11) *holding_company*	0.31	0.46	0.00	1.00	0.01	0.06	−0.03	0.02	0.01	0.02	0.04	0.31	0.26	0.17	1.00											
(12) ln_*hc_certificates*	0.65	1.13	0.00	4.55	0.06	0.08	−0.04	0.06	0.04	0.06	0.07	0.35	0.27	0.17	0.87	1.00										
(13) ln_*hc_branches*	1.04	1.81	0.00	7.96	0.04	0.01	−0.10	0.05	0.04	0.04	0.04	0.47	0.43	0.29	0.86	0.95	1.00									
(14) ln_*hc_states*	0.30	0.52	0.00	2.77	0.04	0.01	−0.09	0.05	0.03	0.04	0.02	0.41	0.37	0.29	0.86	0.90	0.93	1.00								
(15) ln_*population*	15.51	0.89	13.03	17.28	0.18	0.36	0.38	0.14	0.23	0.22	0.37	0.17	0.08	−0.12	−0.01	0.01	0.01	−0.02	1.00							
(16) ln_*permit*	10.06	1.10	3.56	12.66	0.15	0.28	0.30	0.12	0.23	0.19	0.37	0.16	0.10	−0.09	0.01	0.03	0.04	0.01	0.90	1.00						
(17) ln_*market_size*	17.52	0.98	14.59	19.53	0.13	0.34	0.36	0.11	0.21	0.18	0.33	0.19	0.09	−0.11	0.01	0.02	0.03	0.00	0.95	0.87	1.00					
(18) ln_*count_firms*	5.99	0.86	1.95	7.59	0.04	0.67	0.69	0.03	−0.00	0.07	0.35	−0.20	−0.33	−0.24	0.01	0.02	−0.06	−0.06	0.54	0.42	0.51	1.00				
(19) *Herfindahl*	0.06	0.06	0.01	0.52	0.08	−0.30	−0.31	0.06	0.12	0.07	−0.17	0.12	0.18	0.15	−0.06	−0.07	−0.02	−0.01	−0.01	0.08	0.09	−0.45	1.00			
(20) ln_*entered*	1.43	0.98	0.00	4.62	0.12	0.31	0.34	0.09	0.26	0.15	0.44	0.01	−0.09	−0.08	0.04	0.07	0.02	−0.00	0.50	0.55	0.52	0.47	−0.14	1.00		
(21) ln_*failed*	0.99	1.24	0.00	4.97	0.24	0.33	0.36	0.17	0.28	0.24	0.22	−0.08	−0.19	−0.07	−0.05	−0.02	−0.08	−0.08	0.33	0.20	0.28	0.50	−0.20	0.44	1.00	
(22) ln_*merged*	2.53	1.06	0.00	5.29	0.06	0.43	0.46	0.05	0.07	0.09	0.29	−0.07	−0.15	−0.14	0.04	0.04	−0.00	0.00	0.51	0.42	0.48	0.65	−0.22	0.28	0.23	1.00

Table 2 Stage 2 Test of Functional Form Using Arellano-Bond

Variable	1	2	3	4	5	6	7	8
ln_count_superior					−5.752e−03		−1.211e−02	
					(2.674e−03)*		(3.178e−03)***	
ln_count_inferior					−4.055e−02		−4.397e−02	
					(5.641e−03)***		(5.023e−03)***	
average_superior						−9.606e−01	−8.961e−01	
						(1.785e−01)***	(1.617e−01)***	
average_inferior						9.234e−02	1.206e−02	
						(2.793e−02)***	(2.354e−02)	
leader_distance								−3.299e−01
								(7.609e−02)***
laggard_distance								−8.637e−04
								(1.023e−03)
ln_asset		−9.993e−04	−2.124e−03	−2.523e−03	2.014e−03	2.165e−03	3.083e−03	2.076e−03
		(7.212e−03)	(7.237e−03)	(7.222e−03)	(5.393e−03)	(3.549e−03)	(3.360e−03)	(6.363e−03)
ln_branch_counts		−1.585e−02	−1.587e−02	−1.563e−02	−2.249e−02	−1.919e−02	−2.232e−02	−1.838e−02
		(5.626e−03)**	(5.274e−03)**	(5.259e−03)**	(4.789e−03)***	(3.151e−03)***	(3.051e−03)***	(5.167e−03)***
market_share		3.834e−01	4.488e−01	4.488e−01	4.379e−01	4.047e−01	4.079e−01	4.462e−01
		(1.112e−01)***	(1.088e−01)***	(1.071e−01)***	(1.123e−01)***	(1.053e−01)***	(1.169e−01)***	(1.042e−01)***
holding_company		−1.026e−02	−1.025e−02	−1.044e−02	−1.067e−02	−1.258e−02	−1.289e−02	−1.157e−02
		(3.419e−03)**	(3.423e−03)**	(3.413e−03)**	(3.482e−03)**	(2.951e−03)***	(3.016e−03)***	(3.466e−03)***
ln_hc_certificates		−1.311e−02	−1.235e−02	−1.237e−02	−1.220e−02	−1.171e−02	−1.182e−02	−1.080e−02
		(3.332e−03)***	(3.322e−03)***	(3.312e−03)***	(3.315e−03)***	(2.838e−03)***	(2.911e−03)***	(3.344e−03)**
ln_hc_branches		5.600e−03	5.357e−03	5.177e−03	4.592e−03	4.247e−03	3.836e−03	4.966e−03
		(2.370e−03)*	(2.372e−03)*	(2.362e−03)*	(2.364e−03)+	(1.929e−03)*	(1.958e−03)+	(2.399e−03)*
ln_hc_states		1.343e−02	1.344e−02	1.417e−02	1.460e−02	1.863e−02	1.920e−02	1.352e−02
		(4.216e−03)**	(4.237e−03)**	(4.226e−03)***	(4.251e−03)***	(3.829e−03)***	(3.848e−03)***	(4.277e−03)**
ln_population			5.896e−02	6.207e−02	9.147e−02	6.512e−02	8.215e−02	8.932e−02
			(2.914e−02)*	(2.722e−02)*	(2.709e−02)***	(1.641e−02)***	(1.602e−02)***	(2.529e−02)***
ln_permit			−2.003e−02	−1.638e−02	−2.241e−02	−1.684e−02	−2.375e−02	−1.749e−02
			(1.942e−03)***	(2.057e−03)***	(2.156e−03)***	(1.942e−03)***	(2.017e−03)***	(1.959e−03)***
ln_market_size			−4.963e−03	−7.510e−03	−8.439e−03	1.101e−02	8.698e−03	−2.477e−03
			(4.656e−03)	(5.625e−03)	(5.646e−03)	(4.900e−03)*	(5.376e−03)	(5.643e−03)
ln_count_firms				−6.252e−03		−2.530e−02		−1.961e−02
				(9.715e−03)		(9.252e−03)**		(1.011e−02)+
Herfindahl				−1.772e−02	−4.663e−02	−5.238e−02	−6.960e−02	−4.239e−02
				(2.288e−02)	(2.757e−02)+	(2.018e−02)**	(2.239e−02)**	(2.149e−02)*
ln_entered				−3.467e−05	5.713e−04	−1.944e−03	−3.764e−04	−1.543e−04
				(4.101e−04)	(4.624e−04)	(4.748e−04)***	(4.777e−04)	(5.058e−04)
ln_failed				3.475e−03	4.614e−03	2.830e−03	4.343e−03	3.532e−03
				(5.295e−04)***	(5.807e−04)***	(4.715e−04)***	(4.776e−04)***	(5.011e−04)***
ln_merged				2.618e−04	2.016e−03	1.895e−04	1.732e−03	2.711e−04
				(4.400e−04)	(4.747e−04)***	(4.036e−04)	(4.204e−04)***	(4.480e−04)
Inefficiency (t)	7.780e−01	7.832e−01	7.839e−01	7.797e−01	5.910e−01	1.416e+00	1.171e+00	1.139e+00
	(3.163e−02)***	(3.193e−02)***	(3.180e−02)***	(3.116e−02)***	(4.265e−02)***	(1.233e−01)***	(1.101e−01)***	(7.456e−02)***
Inefficiency ($t-1$)	−9.120e−02	−9.441e−02	−1.013e−01	−1.009e−01	−8.285e−02	−7.122e−02	−7.207e−02	−8.049e−02
	(1.785e−02)***	(1.800e−02)***	(1.799e−02)***	(1.795e−02)***	(9.020e−03)***	(5.930e−03)***	(5.738e−03)***	(6.786e−03)***
Constant	5.342e−02	8.624e−02	−5.253e−01	−5.254e−01	−7.392e−01	−8.922e−01	−8.820e−01	−1.014e+00
	(5.270e−03)***	(7.990e−02)	(4.173e−01)	(3.912e−01)	(3.761e−01)*	(2.503e−01)***	(2.426e−01)***	(3.568e−01)**
Year indicators	Sig.	Sig.	Sig.	Sig.	Sig.	Sig.	Sig.	Sig.
N	122,065	122,065	122,060	122,060	122,060	120,874	120,874	122,060
χ^2	6,459.25	6,912.638	7,503.225	7,792.932	8,262.022	7,328.907	8,020.242	8,409.555
χ^2_p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Abond 1st order (z)	−16.38423	−16.41497	−16.62482	−16.77283	−17.57868	−17.57031	−18.28165	−17.51801
Abond 2st order (z)	0.6750371	0.8858542	1.148406	1.137191	0.2802147	−1.039963	−0.8953027	0.060151

Notes. Dependent variable = cost efficiency [$u\_tn\_pl(t+1)$]. Absolute value of t-statistics in parentheses. $^{+}$Significant at 10%; *significant at 5%; **significant at 1%; ***significant at 0.1%.

Table 3 Robustness Tests

	Drop largest states		Drop 5% tails		MSA level analysis		Firm fixed effect	
Variable	1	2	3	4	5	6	7	8
ln_*count_superior*	−2.965e−04		−8.658e−03		2.190e−03		−2.220e−04	
	(5.245e−03)		(3.423e−03)*		(5.703e−03)		(4.600e−04)	
ln_*count_inferior*	−2.210e−02		−4.844e−02		−4.231e−03		4.188e−03	
	(7.082e−03)**		(6.028e−03)***		(7.194e−03)		(6.331e−04)***	
average_superior	−7.007e−01		−1.334e+00		−5.004e−01		−3.340e−01	
	(2.399e−01)**		(1.587e−01)***		(1.801e−01)**		(1.835e−02)***	
average_inferior	3.339e−02		−1.428e−01		6.059e−02		2.618e−02	
	(2.385e−02)		(2.718e−02)***		(2.217e−02)**		(3.171e−03)***	
leader_distance		−1.315e−01		−2.699e−01		−1.929e−02		−6.758e−02
		(9.092e−02)		(7.113e−02)***		(1.073e−01)		(2.164e−02)**
laggard-distance		−1.674e−04		1.145e−03		1.678e−02		1.657e−03
		(1.067e−03)		(9.909e−04)		(3.445e−03)***		(3.614e−04)***
ln_*asset*	3.499e−03	2.282e−03	−8.830e−03	−1.855e−02	−1.623e−03	9.708e−03	−9.912e−03	−1.263e−02
	(3.849e−03)	(7.929e−03)	(2.590e−03)***	(2.564e−03)***	(4.878e−03)	(8.394e−03)	(9.527e−04)***	(9.709e−04)***
ln_*branch_counts*	−2.212e−02	−1.771e−02	−4.166e−03	1.091e−02	−8.852e−03	−1.503e−02	9.913e−03	1.110e−02
	(3.462e−03)***	(6.479e−03)**	(2.469e−03)+	(2.208e−03)***	(4.392e−03)*	(7.975e−03)+	(1.135e−03)***	(1.151e−03)***
market_share	4.128e−01	4.495e−01	1.832e−01	7.431e−02	5.825e−02	5.741e−02	−1.692e−01	−1.963e−01
	(1.117e−01)***	(1.066e−01)***	(9.119e−02)*	(8.704e−02)	(2.648e−02)*	(2.695e−02)*	(3.313e−02)***	(3.162e−02)***
holding_company	−1.331e−02	−1.125e−02	−1.488e−02	−1.455e−02	−1.580e−02	−1.147e−02	−1.614e−02	−1.669e−02
	(3.238e−03)***	(4.004e−03)**	(2.353e−03)***	(2.275e−03)***	(4.388e−03)***	(5.572e−03)*	(1.394e−03)***	(1.443e−03)***
ln_*hc_certificates*	−1.097e−02	−1.019e−02	−9.869e−03	−8.864e−03	−1.374e−02	−1.311e−02	−5.313e−03	−5.010e−03
	(2.923e−03)***	(3.400e−03)**	(2.358e−03)***	(2.282e−03)***	(4.077e−03)***	(4.366e−03)**	(1.126e−03)***	(1.161e−03)***
ln_*hc_branches*	3.909e−03	4.537e−03	2.893e−03	4.295e−03	3.859e−03	5.252e−03	2.942e−03	3.183e−03
	(2.076e−03)+	(2.633e−03)+	(1.566e−03)+	(1.524e−03)**	(2.851e−03)	(3.376e−03)	(7.599e−04)***	(7.843e−04)***
ln_*hc_states*	1.634e−02	1.152e−02	2.199e−02	1.699e−02	2.440e−02	1.362e−02	1.862e−02	1.740e−02
	(3.820e−03)***	(4.390e−03)**	(3.043e−03)***	(3.024e−03)***	(5.522e−03)***	(6.162e−03)*	(1.576e−03)***	(1.630e−03)***
ln_*population*	3.836e−02	2.760e−02	1.841e−01	2.067e−01			6.556e−03	1.865e−02
	(1.696e−02)*	(2.899e−02)	(2.068e−02)***	(2.058e−02)***			(5.080e−03)	(5.250e−03)***
ln_*permit*	−1.508e−02	−1.083e−02	−3.319e−02	−3.186e−02			−1.303e−02	−1.641e−02
	(2.387e−03)***	(2.354e−03)***	(1.749e−03)***	(1.613e−03)***			(8.284e−04)***	(8.943e−04)***
ln_*market_size*	1.226e−02	7.860e−03	−3.883e−02	−4.402e−02	1.808e−03	8.422e−03	−1.156e−03	−1.095e−04
	(5.718e−03)*	(7.365e−03)	(5.001e−03)***	(3.454e−03)***	(5.585e−03)	(4.037e−03)*	(1.616e−03)	(1.948e−03)
ln_*count_firms*		1.684e−02		−7.433e−02		−2.383e−02		−2.103e−02
		(1.069e−02)		(8.270e−03)***		(8.750e−03)**		(3.147e−03)***
Herfindahl	−4.939e−02	−2.716e−02	9.170e−02	6.689e−02	5.508e−03	−3.294e−02	7.614e−03	−1.694e−02
	(2.578e−02)+	(2.517e−02)	(1.913e−02)***	(1.675e−02)***	(1.416e−02)	(1.401e−02)*	(8.757e−03)	(9.943e−03)+
ln_*entered*	−1.634e−05	4.670e−04	3.029e−04	−1.308e−03	−5.464e−03	−7.950e−03	−1.812e−03	−2.088e−03
	(5.732e−04)	(5.877e−04)	(3.998e−04)	(3.546e−04)***	(1.377e−03)***	(1.345e−03)***	(2.940e−04)***	(3.192e−04)***
ln_*failed*	3.421e−03	3.065e−03	3.214e−03	2.875e−03	6.185e−03	5.870e−03	4.610e−03	5.342e−03
	(6.347e−04)***	(5.878e−04)***	(3.634e−04)***	(3.794e−04)***	(1.324e−03)***	(1.356e−03)***	(2.825e−04)***	(2.945e−04)***
ln_*merged*	1.672e−04	−9.271e−04	2.860e−03	2.408e−03	2.444e−03	3.861e−03	4.298e−04	1.132e−03
	(4.401e−04)	(4.642e−04)*	(3.571e−04)***	(3.285e−04)***	(8.182e−04)**	(8.170e−04)***	(2.673e−04)	(2.856e−04)***
Inefficiency (t)	1.073e+00	9.097e−01	1.082e+00	5.742e−01	9.237e−01	8.315e−01	9.894e−01	7.801e−01
	(1.665e−01)***	(9.484e−02)***	(1.107e−01)***	(7.407e−02)***	(1.369e−01)***	(1.026e−01)***	(1.530e−02)***	(2.170e−02)***
Inefficiency ($t-1$)	−6.736e−02	−7.712e−02	−4.270e−02	−5.813e−02	−6.267e−02	−7.675e−02	−1.061e−01	−9.918e−02
	(6.316e−03)***	(7.869e−03)***	(4.249e−03)***	(4.197e−03)***	(7.748e−03)***	(7.541e−03)***	(1.981e−03)***	(2.001e−03)***
Constant	−5.199e−01	−5.078e−01	−1.376e+00	−1.386e+00	7.355e−02	−9.031e−02	1.660e−01	1.820e−01
	(2.468e−01)*	(3.677e−01)	(3.121e−01)***	(3.041e−01)***	(9.871e−02)	(9.723e−02)	(7.628e−02)*	(7.822e−02)*
Year indicators	Sig.	Sig.	Sig.	Sig.	Sig.	Sig.	Sig.	Sig.
N	90,423	91,542	110,956	111,256	47,150	54,785	136,677	137,585
R-squared							0.4279017	0.4440443
χ^2	5,180.165	5,417.446	7,415.871	6,468.201	3,567.163	5,004.73		
χ^2_p	0.000	0.000	0.000	0.000	0.000	0.000		
Abond 1st order (z)	−15.63965	−13.58011	−19.6962	−11.85359	−12.17879	−13.91105		
Abond 2st order (z)	−0.5318587	0.1193353	−0.9856812	3.029354	0.5838731	0.8769129		

Notes. Dependent variable = cost efficiency [$u\_tn\_pl(t+1)$]. Absolute value of t-statistics in parentheses. +Significant at 10%; *significant at 5%; **significant at 1%; ***significant at 0.1%.

We included additional controls for holding company scale (number of banks, number of states, and number of branches); however, because these variables are highly correlated (0.86 to 0.95), their coefficients should not be interpreted separately. Finally, market share was positive and significant, suggesting that market power inhibits innovation. This result conflicts with the interpretation from diffusion studies that the link between concentration and innovation reflects market power.

Finally we look at market controls (models 3 and 4). Of the two measures for market size, population is positive and significant, and industry size is negative but not significant. Because these variables are highly correlated, they are not separately interpretable. However, the joint effect of the two controls indicates that innovation decreases with market size. This matches results from the diffusion studies discussed in §3.3.1. Market growth, as captured by building permits, is negative and significant, indicating that growth increases innovation (decreases cost), which matches the Sharma (1992) and Hannan and McDowell (1984) results for adoption of ATM technology. The two competition variables—number of firms (*count*) and market concentration (*Herfindahl*)—are both negative, though not significant in this model (both become marginally significant in later models). Of the two measures, only concentration has been included in prior studies. In these studies, concentration has tended to increase innovation. This has been interpreted as evidence of the Schumpeterian market power hypothesis. The fact that market share decreases innovation in all our models argues against that interpretation.

4.2. Main Test

Models 5–7 test the superior density form of spillovers. Recall that density has two components—*count superior,* capturing the number of opportunities to encounter superior rivals, and *average superior*, capturing the expected cost distance of those rivals. We test each variable separately then jointly. In model 5, we disaggregate the number of firms into *count_superior* and *count_inferior*. Both were negative and significant, but the coefficient on *count_inferior* was an order of magnitude larger (more negative) than the coefficient on *count_superior*. A chi-squared test rejects the equality of the coefficients ($p < 0.0001$). This result suggests that the influence of the number of firms is asymmetric.

One interpretation of the result is that it is picking up effects from asymmetric spillovers (count is one of the components of superior density). However, the result is inconsistent with an asymmetric spillover story (unless one believes that less efficient firms somehow offer more useful knowledge than more efficient firms). The more likely explanation is that *count* captures competition. From that perspective the results suggest that firms respond more strongly to competition from inferior rivals than from superior rivals.

Model 6 presents the results of the *average_superior* and *average_inferior* elements of density using aggregate firm count rather than decomposed firm count. The coefficient on *average_superior* is negative and significant. In contrast, the coefficient on *average_inferior* is positive and significant—although an order of magnitude smaller than *average_superior*. These results are consistent with expectations for asymmetric spillovers—the knowledge from superior firms is more valuable than the knowledge from inferior firms.[8]

Model 7 includes both elements of density—*count* and *average*—in the same model. While *average_superior* remained negative and significant, *average_inferior* became nonsignificant. Accordingly, a chi-squared test confirms that the coefficient on *average_inferior* is significantly smaller than that of *average_superior* ($p < 0.0001$). The coefficients on *count-superior* and *count-inferior* are negative and significant as they were in model 5, but *count_inferior* remains significantly larger (factor of three) than *count_superior*. Thus again competition from inferior firms seems to provide greater stimulus to innovation than competition from superior firms. In sum, models 5–7 provide significant evidence for asymmetric spillovers of a superior density form.

Model 7 also allows us to test the null hypothesis that the entire rival pool (pooled spillovers) drives innovation. We do this by comparing the coefficients on *average_superior* and *average_inferior*. If the null hypothesis is correct, then the coefficients on *average_superior* and *average_inferior* should be of equal magnitude. Tests that the two coefficients are equal are rejected at the 0.001 level in both models 5 and 7. Thus, pooling all rival knowledge does not appear to be the correct functional form for spillovers.

To gauge the economic significance of the main variables, we examined their marginal effects from model 7. A 1% increase in *average_superior* leads to a 0.06% decrease in cost, and a 1% increase in *count_inferior* leads to a 0.04% decrease in cost. Of the significant control variables, only the marginal contribution of market share was larger (at 0.4%). Indeed, the marginal effect of *average_superior* was 14 times

[8] The reversal of effects for count versus average (the coefficient for *count* is higher for inferior firms, whereas the coefficient for *average* is higher for superior firms) raises the prospect that the competitive stimulus from inferior firms dominates the spillover effect from superior firms. Because density combines both components, we wanted to compare the two effects. Comparison of the marginal effects reveals that *average_superior* dominates *count_inferior*.

larger than that of concentration, 15 times larger than that of *holding_company membership*, and at least 32 times larger than the marginal effect of any of the entry and exit measures.

Finally in model 8, we present the results of the *leader_distance* spillover specification. The coefficient on *leader_distance* was negative and significant, and the coefficient on *laggard_distance* was nonsignificant. A chi-squared test of the difference between *leader_distance* and *laggard_distance* was highly significant ($p < 0.0001$), providing further evidence in support of asymmetric rather than pooled spillovers. The marginal effect of a 1% increase in leader distance was a 0.04% decrease in cost. Thus, the marginal contribution of *leader_distance* was similar to that of *average_superior*.

4.3. Robustness Models

We conducted two broad sets of robustness analyses (Table 3)—first to alternative constructions of the data sample and second to alternative estimation models. With regard to the sample, we examined three alternative constructions. First, to reduce the potential effects of outlier markets, we dropped the three largest states (models 1 and 2). The results for *average_superior* and *average_inferior* were largely unchanged. *Average_superior* remained negative and significant, and *average_inferior* remained insignificant. This continues to support the asymmetric spillover hypothesis. Moreover, a test that the two coefficients are equal was again rejected at the 0.001 level. Thus, we continue to reject the null hypothesis that spillovers are pooled. Of note, however, is that with this sample construction, *leader_distance* became nonsignificant.

Second, to reduce the potential effects of outlier firms (one of the concerns raised in §3.4 for frontier models), we dropped bank-year observations in the top and bottom 5% of the sample (models 3 and 4). The results were robust to this specification.

Third, we assumed in our main model that the market—and accordingly the market characteristics and spillover variables—were defined by state boundaries. In models 5 and 6, we reconstructed all market characteristics and spillover variables using metropolitan statistical area as the definition of market. The results for the superior density hypothesis are maintained. *Average_superior* is negative and significant; *average_inferior* is positive and significant. Thus, we continue to find support for asymmetric spillovers and continue to reject the null hypothesis that spillovers are pooled. *Leader_distance* again failed to hold, which further calls into question this spillover specification.

Our final set of robustness checks examines alternative specifications to Equation (11). In models 7 and 8, we replace Arellano-Bond with a simple bank fixed-effect specification. The results were robust for this alternative model specification.[9] The coefficients for *average_superior* and *leader_distance* are positive and significant, and the tests that *average_superior* is greater than *average_inferior* and *leader_distance* is greater than *laggard_distance* continue to be rejected at the 0.001 level.

In sum, the robustness analyses provide significant additional support for the asymmetry of spillovers. Although the *leader_distance* result is sensitive to sample specification, the coefficient estimates on *average_superior* are remarkably robust. In all specifications, *average_superior* was negative and significant and always significantly larger than *average_inferior*. Thus, across all tests our results reject the null hypothesis that spillovers are pooled in favor of a hypothesis that they are asymmetric and conform to a superior density functional form.

5. Discussion

Although spillovers are a crucial factor in determining the optimal environment for innovation and growth, there is no consensus regarding their impact on firms' innovative behavior. We suggested that one reason may be that models differ in their assumptions about the functional form of the spillover pool. Accordingly, knowing the correct functional form may facilitate consensus—either analytically (by modifying models' assumptions) or empirically (by facilitating a critical test of competing theories).

Toward that end, we characterized and tested alternative specifications for the spillover pool in the banking industry. We chose that industry because it has one of the highest innovation and growth rates in the economy and it comprises 50 markets that share a common demand curve and underlying technology. Thus, we could exploit variance in spillover pools while controlling implicitly for technology and explicitly for market factors affecting incentives to innovate. This is not possible for industries with a single market (most of the manufacturing industries engaged in R&D).

Our results in that setting indicate that knowledge does appear to have directionality. The rate at which firms reduce their cost is related to the amount of knowledge held by more efficient firms rather than the amount held by the entire set of firms. A test of the null hypothesis that spillovers are pooled is rejected in all models. These results are robust to an extensive set of alternative specifications.

[9] Results are also robust to a fixed-effect specification weighted by the number of banking certificates in the state.

One interesting result from the robustness checks is that the *leader distance* form of spillover pools is sensitive to sample construction. Thus, it appears firms benefit from the entire set of knowledge held by superior firms rather than their distance from the leader. This contrast is important for three reasons. First, it means the role of spillovers is more nuanced than merely imitating best practice. Second, it means our spillover variables are not merely picking up an "opportunity to improve" effect (firms are not merely improving based on how far they have to go). Third, the results suggest a model in which firms pay attention to the entire set of superior firms and synthesizie what they learn with what they know or do internally.

Our measures for spillover pools are novel as well as consistent with theory (and past empirical practice for pooled spillovers), yet there is a question of whether the measures and results really capture spillover-driven innovation. To verify this, we informally interviewed executives with experience across a number of banks. Those discussions revealed several things: (1) The primary source of new product/service and process ideas is indeed "other banks": "bankers are reluctant to pioneer, they are not very creative": (2) The initial innovations come from large banks. They can afford to innovate, because their scale increases the benefits to innovating, because they can absorb losses from mistakes, and because knowing all this, regulators are lenient with them. When small banks introduce new financial instruments "they get their hands slapped." (3) Banks learn about innovations through a number of mechanisms typically associated with spillovers: directly from other bankers (regular meetings between local CEOs and informal meetings of top loan officers; "they meet informally because no one wants to go out on a limb") and indirectly from from accountants (there are only three major accounting firms servicing the entire industry), at conventions, from rivals' marketing materials, from vendors, and from customers, (4) Once banks identify an innovation and an exemplar bank that has adopted it, they check its success by examining that bank's Call Report (the same publicly available data we use for this study). Thus, industry behavior seems to reinforce the results here: There are substantial spillovers in the industry; innovative behavior seems to rely on these spillovers; and there is directionality from large banks to small banks.

Our main interest was testing the functional form of spillovers, but our efforts to isolate the effects of spillovers allow us to say something about other factors affecting innovation. The most notable results pertain to competition. In a model without spillovers, neither market concentration nor the number of rivals is significant. Only when we introduce asymmetric spillover pools do the competition variables become marginally significant. Thus, competition seems to interact with spillovers. Our most interesting result regarding competition emerged when we decomposed the density form of spillovers into constituent elements (number of firms and knowledge per firm). We did this precisely to isolate all potential effects of competition from our spillover measures. Because we were looking at spillovers asymmetrically (treating superior and inferior firms separately), we were able to examine asymmetric effects of competition as well. Here we found that firms respond more to competition from inferior rivals than from superior rivals. This result fits with the intuition in the "escape competition" stimulus for innovation, where firms innovate to restore lost profits associated with laggards who have imitated them (Aghion et al. 2001).

We wish to offer some caveats for the results. Our explanation for differential innovation rates between superior and inferior firms is that inferior firms free-ride on superior firms' knowledge. An alternative explanation relies on aspiration theory (Cyert and March 1963, Bromiley 1991). In this view, inferior firms are more likely to innovate because their lower profits give them greater incentive to do so (Cockburn et al. 2000). The puzzle with the aspiration explanation is that the firms with the greatest incentive to innovate are by definition the ones with the fewest resources to do so. Accordingly, a theory of asymmetric spillovers is not an alternative to aspiration theory; it is the means (higher level of free inputs) by which aspirations can be realized (Acs et al. 1994). To demonstrate this, we ran a robustness check of Equation (11) that included lagged profits. Results revealed that lagged profits were negative and significant (increasing innovation). Moreover, the coefficient on *average_superior* remain unchanged. Thus, it appears profits and spillovers are substitute sources of innovative inputs: superior firms use profits to fund their own innovation, and inferior firms rely on spillovers.

A second caveat is that our test was conducted in a single setting—banking. What is appealing about this setting is that market structure is not endogenously determined by technology (at least not entirely). Accordingly, it inherently controls for many unobserved factors that plague cross-industry tests of innovative productivity. Despite the advantage, there are things unique to banking that may limit our ability to extend results to other settings. First, this is a setting where patents do not appear to be important. The major innovations discussed in the paper (ATM, SBSS, and Internet transactions) all diffuse rapidly. Accordingly, this is not a setting where profits are driven by patent-protected monopolies for new products. Because patents offer temporary monopolies on inventions in exchange for full disclosure of the knowledge underlying the invention, it is likely that spillovers behave quite differently in industries where patenting is important, e.g., pharmaceuticals and semiconductors.

A third caveat is that banking is an extremely dense industry—on average 10,000 banks with 60,000 branches over our sample period. Spillover patterns may differ in industries serving national or global markets, e.g., autos, communications, and petroleum.

Fourth, this is a setting where we do not observe R&D, so we cannot say anything concrete about the link between spillovers and own R&D. Our implicit assumption in the empirics is that R&D expenditures increase monotonically with firm size (matching the stylized fact in Cohen and Levin 1989). We have multiple measures for firm size, but the one that is consistently significant is branch counts. Innovation increases with the number of branches in all models. If branch counts is a proxy for R&D expenditures, then our spillover results hold in the presence of R&D expenditures. Having said that, lack of R&D expenditure data is a limitation, so in separate analyses, we examined R&D expenditures and spillover pools in 25 manufacturing industries. Results there are consistent with the results reported here.[10]

These results have a number of implications. First, for theory, models of innovative behavior that rely on identical firms with pooled spillovers conclude that innovation decreases with the potential for spillovers and the number of firms. Our results indicate instead that innovation increases with the amount of spillovers and with the number of firms (particularly less-efficient firms). Thus, changing the functional form of spillovers in such models may yield results that more closely match our observations.

Second, for the empirical anomaly of higher returns to spillovers than to focal firm R&D, the results here imply that the anomaly is an artifact of specification error—pooling spillovers when their correct functional form is asymmetric. Estimates of spillover elasticity using asymmetric spillovers indicate values that are closer to expectations, i.e., less than or equal to the productivity of own R&D (Knott and Posen 2008).

Finally, asymmetric spillovers offer a simple solution to the firm size and R&D puzzle—the empirical regularity that large firms spend proportionately more on R&D but that small firms have higher R&D productivity. Asymmetric spillovers imply that small firms (those most likely to be inferior) derive greater benefits from rival R&D than large firms do. Given that inputs from own R&D and spillovers both contribute to innovative outcomes, estimates of R&D productivity that consider only own R&D input (or equivalently consider own R&D plus a common spillover pool) will exhibit artificially high estimates of R&D productivity for small firms.

[10] Results available from the authors.

6. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

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