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Knowledge Spillovers in the Supply Chain: Evidence from the High Tech Sectors

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Abstract

In addition to R&D investment, accessing external knowledge is widely considered as an essential lever for innovative performance. This paper analyzes knowledge spillovers in supply chain networks. Specifically, we investigate how supplier innovation is impacted by buyer innovation. Supply chain relationship data is merged with financial accounting data and patent data to create a sample of 521 supplier observations in the high tech industries. Using econometric panel data techniques we show evidence that buyer innovation has a significant positive impact on supplier innovation. We find that the duration of the buyer-supplier relationship positively moderates this effect, but that the technological proximity between the two firms does not have a significant effect on spillovers.

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Abstract

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Keywords: knowledge spillovers, innovation, Supply chain relationships

1 Introduction

Innovation has long been regarded as playing a key role in the competitive advantage and survival of firms (Audretsch 1995; Cefis and Marsili 2006; Schumpeter 1942). To innovate, firms can invest in internal R&D or leverage external channels, such as rivals, partners and academic institutions. Previous research has shown a strong link between innovative performance and the search for knowledge and information outside the firm (Chesbrough 2003; Laursen and Salter 2006). This paper focuses on supply chain partners as an external source of knowledge. More precisely, it explores knowledge spillovers in the supply chain and empirically investigates how suppliers can leverage buyers as a source of learning for innovation, using the example of the high tech sectors.

The ongoing patent infringement lawsuits between Apple Inc. and Samsung Electronics Co., Ltd. well illustrate how knowledge spillovers between buyers and suppliers can lead to unwanted outcomes. In 2005, Apple needed large volumes of flash memories for its new iPod and iPhone products, and turned to Samsung as a supplier (Poornima et al., 2013). Initially the two firms jointly developed the processors, which helped Samsung to learn about Apple's operations and its prediction of the market size for these novel product categories. In 2010, Samsung launched the Galaxy S (closely resembling the iPhone) and has since become Apple's major competitor. Dell and Asus show a similar, process-related, story. For cost reasons, Dell increasingly outsourced parts of it value chain to Asus - first the motherboard, then assembly, then management of the supply chain and, finally, the design of the computer. In the end, Asus was able to produce a similar computer to Dell but at a lower cost.

The above examples show that knowledge spillovers - which are often said to have positive effects on the economy as a whole - can both add to and devalue the resources of individual firms. An accurate understanding of knowledge spillovers in the supply chain hence becomes strategically important. Often, knowledge spillovers are referred to as an informal, unintentional and uncompensated transfer of knowledge. However, the innovation literature also routinely speaks of voluntary, intentional knowledge spillovers (De Jong and von Hippel, 2009) and strategic spillovers (Harhoff, 1996). In this paper we do not attempt to distinguish between intentional and unintentional knowledge spillovers and adopt a broader definition encompassing the both.

Innovation in the context of buyer-supplier relationships has received attention in the literature, mainly looking at the buyer as the focal firm. We take the opposite perspective and explore how suppliers can use their buyers as a source of information for innovation. Although there is relatively little academic research on the topic, interest has been high among practitioners (e.g. Arrunada and V´azquez 2006; Khanna and Palepu 2006), and there are strong managerial implications. From a supply chain perspective, previous research has shown that the innovativeness of a single firm has a positive effect on the supply chain as a whole and that knowledge can help to create superior supply chain performance (Hult et al., 2006). It can hence be in the buyer's interest to support supplier innovation through different means such as knowledge sharing and research collaboration. For example, Toyota is well known for having achieved a competitive advantage through knowledge transfer routines in the supply chain. It has an operations management consulting division and has developed practices that facilitate knowledge transfer to suppliers.

Although buyers can benefit from knowledge sharing and by supporting supplier innovation, the Apple-Samsung example illustrates the potential need to protect strategically important knowledge. The awareness that learnings from a past transaction can be reused in the future is crucial for firms when deciding where to source and how to structure projects. If a contract or product is outsourced to a supplier, the focal firm might not be able to appropriate the knowledge. Even if it can, the supplier will henceforth also have acquired the know-how. From a supplier perspective, the choosing of buyers to collaborate and innovate with becomes an important decision and is likely to strongly influence the future innovativeness of the firm. As an executive that we interviewed expressed: “We typically don’t select which customers to do business with, but we do select customers to innovate with. We work with selected alpha-customers, or early adopters who support supplier innovation in return for a head start in the market”.

In this study, by drawing on a financial accounting regulation regarding customer disclosures we can link suppliers with their major customers. We merge this information with financial accounting data from Compustat and patent data from the Patstat database to construct a sample of 521 supplier observations, with at least one observed buying firm per supplier. Using this unique data set we present novel empirical evidence of knowledge spillovers from buyers to suppliers in the high tech sectors. We find that spillovers increase with the duration of the buyer-supplier relationship. Surprisingly, our analysis does not support the hypothesis that knowledge spillovers increase with technological proximity.

This paper is structured as follows: In Section 2 we explore knowledge spillovers in the supply chain from a theoretical perspective and develop hypotheses. In Section 3 the research methodology and data are presented. The econometric results are presented in Section 4 and robustness checks in Section 5. The results and implications are discussed in Section 6.

2 Theoretical Background

2.1 Leveraging External Sources of Knowledge

Organizations can learn by leveraging both internal and external sources of information (Cohen and Levinthal 1990; Malerba 1992). It follows that innovation is not only an output of one’s own research efforts, but is also related to the pool of knowledge available to the firm and its ability to appropriate spillovers (Griliches, 1998a, p. 52-89). Knowledge spillovers have been documented at both national (Mansfield 1988; Rosenberg and Steinmueller 1988) and industry levels (Bresnahan 1988; Brock 1975).

At the organizational level, firms can learn by drawing on university research (Arora and Gambardella 1990; Griliches 1992; Mansfield 1991), by imitating competitors (March and Simon 1958, p. 34-47), and by cooperating with other firms (Cassiman and Veugelers, 2002).

The innovation literature discusses the different mechanisms through which knowledge spillovers are realized (Feldman, 1999). Spillovers can occur between firms that are not in direct contact, but they are even more likely to exist in a buyer-supplier relationship due to a facilitated transfer of tacit knowledge. Though firms rely on tacit knowledge to innovate (Cowan et al., 2000), it is inherently difficult to transfer and copy. Individuals can acquire tacit knowledge through training and experience, and the firm or organization forms an environment within which this individual learning occurs. A transfer between trading partners can hence occur when employees of the two firms interact (Brown and Duguid 2000). The inter-firm mobility of skilled labor has also been shown to result in a transfer of ideas (Almeida and Kogut, 1997). Though knowledge spillovers on the firm level primarily have been studied with respect to rivaling firms, these mechanism suggest that buyers and suppliers also must be considered as important sources for learning and innovation.

The flow of knowledge in networks has been thoroughly studied in the network literature. In a seminal paper, Granovetter (1973) introduces the concept of network ties and highlights the importance of weak ties as information links between different groups. Investigating innnovation in firm networks, Ahuja (2000) finds empirical evidence that both direct ties (direct trading partners) and indirect ties (trading partners not directly connected to the focal firm - e.g. the suppliers of a supplier) have a positive impact on innovation. This is supported by Inkpen and Tsang (2005) & Powell et al. (1996) who see interactive learning between network nodes as a source of network innovation.

The topics of supplier integration and supplier innovation have been widely studied in the field of operations management. Involving suppliers in new product development and selecting the right suppliers has been shown to have a positive effect on the innovative performance of the buyer (Appleyard 2003; Ellram and Choi 2000; Knudsen 2007; Petersen et al. 2003 & 2005; Primo and Amundson 2002). Additionally, the capabilities and culture of the supplier (Hartley et al. 1997; Petersen et al. 2005), as well as the relational dimension of social capital (Carey et al., 2011), have also been found to positively impact buyer innovation. More generally, having innovative suppliers will have a positive influence on firm performance (Azadegan and Dooley 2010; Stock and Tatikonda 2004). The impact of the buyer on the supplier has, relatively seen, gotten less attention - a gap that this paper aims to fill.

The literature, discussed above suggests that the innovative output of a firm should be positively influenced by the innovativeness of its supply chain partners. Therefore, viewing the supplier as the focal firm, we hypothesize:

Hypothesis 1. Supplier innovation is positively impacted by buyer innovation.

2.2 Relationship Duration

Transactions outside the firm require specific investments, coordination and governance efforts (Williamson, 1985). In this respect, the duration of a relationship likely has an important impact on the efficacy and efficiency of the exchanges between supply chain partners. This also relates to knowledge flows. For instance, firms may introduce explicit routines for knowledge sharing, resulting in a more efficient transmission of relevant knowledge between supply chain partners (Nelson and Winter 1982; Dyer and Singh 1998). These routines may consist of standardized knowledge codification procedures for tacit knowledge. As Cowan and Foray (1997) argue, such codification processes contain high initial fixed costs but subsequently allows knowledge transmissions at very low marginal costs. Over time, communication and trust may improve between exchange partners in the two firms, leading to more informal knowledge exchanges. It has been documented that even R&D employees of competing firms engage in knowledge exchanges, and trust or even friendship seem to be important determinants of information sharing (Levin and Cross 2004; Schrader 1991). Therefore, we expect that relationship duration positively moderates the impact of buyer innovation on supplier innovation.

Hypothesis 2. The impact of buyer innovation on supplier innovation is positively moderated by the duration of the relationship between the supplier and its buyers.

2.3 Technological Proximity

As a further dimension, we examine the technological proximity between suppliers and buyers as a moderating factor of knowledge spillovers. To benefit from external knowledge, firms need to have an absorptive capacity to identify, assimilate, and transform external knowledge into their own technological outcomes (Cohen and Levinthal 1989, 1990 & 1994). When the scope of R&D is similar between buyers and suppliers, it should require less explicit efforts from the supplier to absorb the external knowledge. In addition to an increased absorptive capacity, the innovation activities of closely related buyers should be more relevant for the supplier, increasing the ”pool” of knowledge that can potentially be integrated. In line with these arguments, empirical studies suggest that technological proximity has positive impact on spillovers, indicating that firms benefit more from competitors with close technological portfolios (Jaffe 1986 & 1988; Los and Verspagen 2000; Orlando 2004). On the other hand, it can be argued that if firms are too similar with regard to their pool of technological knowledge, the learning opportunities are naturally limited (Gilsing et al. 2008; Rosenkopf and Almeida 2003). However, suppliers and buyers in the high-tech sectors are likely not working on the same technologies as otherwise there is little rationale to enter into a supply-chain relationship. Also, based on the empirical evidence on the positive effects of proximity, we hypothesize that the similarity effect is dominant in a supply-chain setting:

Hypothesis 3. The impact of buyer innovation on supplier innovation is positively moderated by the technological proximity between the supplier and its buyers.

3 Research Methodology and Data

3.1 Data

We test our hypothesis using a large-scale data set of U.S. firms created by merging information on buyer-supplier relations, financial accounting statements and patent data. We consider stock-market listed U.S. firms from the high technology sectors (biotechnology and pharmaceuticals, scientific and medical instruments, aircraft and aerospace, and chemicals). These industries are chosen using OECD's technology intensity definition, which is a classification of manufacturing industries based on overall R&D intensity (Hatzichronoglou, 1997). In light of our research question, these firms are an ideal setting because of their innovativeness, their dependence on continuous knowledge creation and the importance of formal intellectual property. Intellectual property is also important with respect to the empirical strategy that relies on patents as a measure of innovation. The industries included are listed in Table 1.

-- Insert Table 1 about here --

We match buyers and suppliers by drawing on a financial accounting standard regarding the disclosure of major customers. Paragraph 39 in financial accounting standard 131 stipulates that firms must report if revenues from a single customer exceed 10% of total sales (FAS, 1997). Although it is not mandatory to report the identity of the customer, most firms do so (and sometimes also if sales do not exceed 10% of total sales). Since the customers are filed by company name we use a matching algorithm that takes typos and abbreviations into account. For example, for General Motors one can find entries such as GM, General Motors Company, G. Motors and G. Mtrs, which must all be matched with a unique company identifier such as the CUSIP or ticker codes. In a second step, we manually review names with an imprecise or no match. For these firms, we extract yearly financial accounting data from Standard & Poor's Compustat.

This panel of firm-level data is combined with patent data from the Worldwide Patent Statistical database (Patstat) using name-based matching procedures. We consider patents with their application date to capture the period when the knowledge was created. The patent matching is done using a matching algorithm that queries the firm names in the applicant field of the Patstat database. Prior to the matching, an extensive cleaning and pre-testing of the firm names was carried out. After the matching, comprehensive manual checks were performed with a specific focus on firms with high patent/R&D ratios and problematic names (as detected in the pre-tests).

For the final sample, strong outliers, observations with economically insignificant values (e.g. negative sales) and firms with no R&D investment during the sample period2 are removed.[1] We also exclude dyads consisting of affiliated firms and subsidiaries. Our final data set contains complete information on 192 suppliers between the years 1990 and 2006. Our sample stops at 2006, since we use five years of forward citations as a control of patent quality, as outlined in Section 3.2. Table 2 shows descriptive statistics for the buyers and suppliers in our sample. We note that the suppliers in our sample are considerably smaller than the buyers. This is because of the accounting standard regarding the disclosure of major customers that is used for the data collection. These size differences will have important consequences for our econometric analysis and will be discussed further in Section 3.3.

-- Insert Table 2 about here --

3.2 Variables

Our aim is to study how, and to what extent, buyer innovation affects supplier innovation. For this purpose, we include several measures that capture the innovation activities of the buyers and suppliers, respectively. These include R&D investments, patents and scientific publications. We use patent productivity, *Log Buy Pat Prod* (number of patents, scaled by R&D expenditure to account for differences in input), as our core measure of innovation (Hall et al. 2005; Lanjouw and Schankerman 2004). Patents are a reliable way to capture the inventive output of firms. Besides patent productivity, we take into account that patents are highly skewed in their technological and economic value. In the innovation literature, patent forward citations are regarded as an informative quality measure (Jaffe et al. 2000; Nelson 2009; Trajtenberg 1997). We construct the variable *Log Forw Cit Int* by counting citations within a five year window starting from the priority date and scaling by patent count. We also include *Sci Pat* the number of science based patents scaled by total patents as a further proxy for patent quality (Chatterji and Fabrizio, 2012).[2] As an additional measure, innovative input is measured as R&D scaled by assets, *Log RD Int*. We take the natural logarithm of all the above variables to reduce the effect

[1] We exclude firms that did not invest in R&D at all during our sample period. However, it is still possible that a firm has no R&D investment in a given year. The rationale for excluding these firms is to avoid bias by firms with no innovation activities.

[2] Patents that build on scientific publications as prior art. This variable indirectly reflects a basic research orientation.

of outliers.[3] We also investigate joint patents but find only eight cases where the buyer and supplier co-patent.

To test Hypothesis 2, we use the number of years that a buyer and supplier are linked in our data set as a measure of the Duration of the relationship. We acknowledge that this proxy has limitations as the dyad could have existed without being present in the data set. Technological proximity (*Tech Prox*) is measured by determining whether the two firms are in the same industry on different levels of SIC-code aggregation (using 2, 3 and 4 digit SIC-codes) (Orlando, 2004). Since not all firms in our sample patent, we cannot apply patent based proximity measures

In addition to the core measures, we include several control variables in order to take firm-heterogeneity into account. In particular the firm's financial performance (Czarnitzki and Hottenrott 2011; Greve 2003) and IT investments (Hall et al., 2000) can have an impact on the possibilities for engaging in inventive and knowledge management activities. This leads us to include return on assets (*ROA*) and capital expenditures scaled by assets (*CAPX Int*) in our regressions. To account for heterogeneities in firm size we also control for the sales of the buying and supplying firms (*Log Sales*).

3.3 Econometric Specification

Each supplier in our data set is observed over time. At the same time, a supplier can have several buyers in a given year, and vice versa. Both buyers and suppliers can enter and exit the panel. Unlike a standard two-dimensional panel we therefore potentially have unobserved heterogeneity on both the buyer and supplier dimensions.

In order not to bias our results by suppliers with many buyers (which would lead to multiple observations for a single supplier in a given year), we aggregate our data at the supplier dimension (McGahan and Silverman, 2006). For each supplier-year combination we calculate a weighted average for each observed buyer characteristic.[4] Our data set hence reduces to a standard two-dimensional panel with unique supplier-year observations. Table 3 shows the correlation between the variables described in Section 3.2 after aggregation.

-- Insert Table 3 about here --

[3] We make the transformation ln(1+variable) as suggested by Jaffe (1986).

[4] For example, aggregate buyer sales is the average sales of all buyers connected to the supplier i in year t, weighted by tie strength.

We estimate the following model:

$$Log\_Supp\_Pat\_Prod_{it} = \quad (1)$$

$$\beta_0 + \beta_1 Log\_Buy\_Pat\_Prod_{it-1} + \beta_2 Duration_{it} + \beta_3\ Tech\ Prox_{it} +$$

$$+ \beta_4 Duration_{it} \times Log\_Buy\_Pat\_Prod_{it-1} + \beta_5 Tech\_Prox_{it} \times Log\_Buy\_Pat\_Prod_{it-1} +$$

$$+ \sum_{j=1}^{k} \beta_j X_{it}^{j} + Fi + \mu_t + e_{it}$$

Where F_i denotes supplier fixed effects, μ_t year fixed effects, X_{it} the set of control variables described in Section 3.2 and e_{it} the error term. Similar to Bloom et al. (2013) we lag the main dependent variable, *Log Buy Pat Prod*, by one year to avoid simultaneity bias and to allow for a time delay in potential knowledge spillovers.

Due to the panel structure of our data we can control for supplier fixed effects by performing a within transformation (i.e. by using a fixed effects model). This means that we automatically control for all factors that stay fixed over time (e.g. location, firm culture, industry, as well as for all time-variant company characteristics preceding our data set). Unobserved time effects, μt, are accounted for by using time dummy variables. In Section 5 we also try specifications without aggregated data (three-way fixed effects where we can control for buyer, supplier and dyad level fixed effects) and find that our results remain robust.

As can be seen in Table 2, many of the suppliers in our sample do not have any patents. To take this left-censoring into account one could consider a panel-Tobit model. However, since the Tobit model with fixed effects is not consistent (Cameron and Trivedi 2005; Czarnitzki and Toole 2011) we use standard fixed effects in our main specification. In Section 5 we show that our results remain unchanged also when considering a random effects Tobit model.

Our study explores how buyer innovation impacts supplier innovation. Therefore, the possibility of reverse causality (or simultaneity) needs to be addressed. We must ensure that our results do not reflect knowledge spillovers going in the opposite direction - i.e. from the supplier to the buyers. Here, the size differences between the buyers and suppliers in our sample play a crucial role for identification. Since we are measuring innovative output by patent productivity, a change in the number of patents at the supplier should only have a negligible effect on the patent productivity of the buyers (because it is scaled by buyer R&D).[5] We acknowledge that a buying firm can learn from a smaller supplier, but argue that

[5] To exemplify, assume that 1 buyer patent leads to 1 supplier patent and vice versa. When using patent productivity as a measure of innovation, a 1:1 spillover effect should be 20 times larger in the buyer-to-supplier direction (since patents are scaled by R&D, which is, on average in our sample, almost 20 times higher for the buyers). The bias caused by reversed causality should hence be negligible.

the relative impact only should be minor thanks to our econometric set-up. Hence, we only expect a notable spillover effect in the hypothesized direction. In addition we consider a model where the independent variable of interest (buyer patent productivity) is lagged by one year.

A second concern is that our results could be driven by a selection bias - i.e. that we find evidence of knowledge spillovers from buyers to suppliers, merely because innovative buyers tend to work with innovative suppliers. Such a bias can be strongly mitigated by taking the innovativeness and the innovative input of the supplier into consideration. By observing the dyads over time and using a fixed effects panel data model (as described in Section 3.3), we account for the degree of innovativeness of the supplier before it enters our sample (and hence also when the selection decision is made). Further, by including R&D intensity we control for the innovative input in each observed year. Therefore, the idea that firms select supply chain partners based on their level of innovativeness should not be driving our results.

4 Results

The results of our econometric analysis can be found in Table 4. Overall, we find strong evidence of knowledge spillovers from buyers to suppliers. Our first interest concerns the main effect, *Log Buy Pat Prod*$_{t-1}$, which has a positive and significant impact across all baseline model specifications (1-3).

-- Insert Table 4 about here --

Starting with an OLS model and a reduced set of control variables (1), a 1% increase in patent productivity at the buyers, on average, leads to a 0.13% increase for the supplier. Taking firm-fixed effects into account (2), the magnitude increases to 0.28%. After including a full set of firm-level controls (3), the magnitude remains unchanged, suggesting that the effect is rather robust. Consequently, we find strong and robust support for Hypothesis 1. Concerning the R&D investment intensity of the buyer, we do not detect any robust effects across model specifications. However, this is not surprising, since these R&D reflects the same, or very similar, knowledge as our main independent variable (as can be seen in the bivariate correlations in Table 3).

In a further step, we examine the moderating factors as indicated in Hypotheses 2 and 3, namely Duration, and Technological Proximity. In models (4) and (5) we introduce the corresponding interaction terms separately, before presenting the full models that estimate the supplier's patent productivity (6). The regression results suggest that the relationship duration does indeed have an important moderating role.

First, we find a strong positive impact of duration on spillovers from buyers to suppliers. After the introduction of the interaction effect, the main effect even disappears, which suggests that establishing a long-term relationship is a crucial antecedent for a supplier to learn from its buyers. As discussed for Hypothesis 2, a longer relationship should increase trust between supply chain partners leading to a decrease in communication and coordination costs. The marginal effects for varying average relationship durations are reported in Table 5. In the first years, buyer innovation has little or no positive impact on the supplier's innovative outcomes, but the magnitude increases over time.

-- Insert Table 5 about here --

Second, we examine Hypothesis 3, the moderating effect of the technological proximity between the supplier and its buyers and do not find a robust significant effect. Here, one has to consider that the buyers and suppliers in our sample are already probably relatively similar in terms of technology, as otherwise the supply chain relationship would not have been formed in the first place. Beyond this explanation, a certain heterogeneity in terms of knowledge overlap might also have positive consequences since the complementarities potentially increase.

Overall, we find strong support for the impact of buyer innovation on the supplier's innovation outcomes and document the importance of relationship duration as a moderating factor.

5 Robustness Checks

Our main result - that buyer innovation positively influences supplier innovation - also remains stable across numerous alternative specifications (see Table 6). Models 1-3 show fixed effects, random effects and OLS regressions with similar outcomes. To investigate whether suppliers with no patents in a given year might bias our results we run a Tobit panel regression (model 4). The results remain very similar to other specifications indicating that left-censoring is not masking the true effect.

-- Insert Table 6 about here --

We also try different specifications using different levels of lag in the independent variables. We find that buyer innovation in year t also significantly impacts supplier innovation in year t (model 5). This indicates that buyer innovation generates spillovers without notable time lags. Implicitly, this immediate effect also suggests that personal interaction is an important spillover channel, compared with codified documents like patents (where the disclosure takes place 18 months after application, at the earliest). Model (6) shows a non-significant effect when using two years of lag. In model (7) the control variables are lagged by 1 year showing similar results to model (1). It could be argued that an exogenous shock to a specific industry could lead to an increase in patenting for both the buyer and supplier. As an additional test we therefore include dummy variables for each industry-year combination. When doing so we find a coefficient of 0.18 ($p < 0.05$). By scaling patent count by R&D we implicitly assume a linear relationship between the two variables. However, we find that patent productivity tends to decrease with firm size. Since we control for both buyer and supplier sales this non-linearity should not be driving our results but we nevertheless try alternative specifications. We split our sample in two groups based on the average size difference between the supplier and its buyers. We find a spillover effect for the group with smaller size differences but no significant effect in the group with large size differences (see models 9 & 10). Although our identification strategy hinges on the use of a productivity measure that scales patents by R&D, we also estimate two count models (11 & 12) as robustness checks. Both the negative binomial and the Poisson panel regressions yield significant and positive coefficients. In our data set we can observe some suppliers (buyers) several times per year, if they are linked to more than one buyer (supplier). As explained in Section 3.3, in order not to give more weight to suppliers with many buyers, we aggregate the buyer data and only control for supplier fixed effects. To explore the influence of buyer and dyad level fixed effects, we group our original data set on the buyer- supplier level and run a three-way error-component model (Andrews et al., 2006). This does not significantly change our results, but we note a slightly higher spillover effect (0.31, $p < 0.05$, see model 13).

6 Discussion and Conclusion

This study provides novel evidence on knowledge spillovers in supply chains. We analyze knowledge spillovers between buyers and suppliers, and which factors that govern this phenomenon. We find both statistically and economically significant evidence that buyer innovation positively influences supplier innovation. We also show that knowledge spillovers from buyers to suppliers are positively moderated by the duration of the relationship between the two firms. To our surprise, our results do not support the hypothesis that knowledge spillovers increase the more similar a supplier is to its buyers in terms of technology.

With regard to external knowledge, academia, competitors and end users have been identified as important sources of information for innovation (e.g. Laursen and Salter 2006). Learning from supply chain partners has, relatively speaking, received much less attention. To our knowledge, this is the first empirical evidence of knowledge spillovers between buyers and suppliers. The magnitude of the estimated effect highlights the importance of downstream supply chain partners for innovation. The risk that the supplier might use uses the knowledge in a competitive manner also has implications for the literature on knowledge appropriation and supply chain contracts.

It has been suggested that technological proximity facilitates the integration of external knowledge (Cohen and Levinthal 1989 & 1990). Our results, however, do not confirm this argument. A possible explanation, in the context of our study, is that the formation of a buyer-supplier relationship already implies high technological proximity. In addition, if the knowledge overlap between the two firms is high, the learning potential might be reduced.

The operations management literature has investigated the supplier as a source of learning and innovation (Azadegan et al. 2008; Azadegan and Dooley 2010). This study takes a complementary view and shows that buyers also represent an important source of external knowledge. We accentuate that these spillovers can have both positive and negative consequences for the firm with potential implications for firm boundaries. In doing so, we add to the recent discussion on the potential "dark side" of buyer-supplier relationships and opportunistic behavior on the part of the supplier (Li and Choi 2009; Villena et al. 2011). In addition, our study also highlights knowledge spillovers as a potentially important dimension for future research on supplier selection practices (Choi and Hartley, 1996).

We find that relationship duration positively moderates spillovers from buyers to suppliers. Panel A in Table 5 indicates that the effect steadily increases and is actually not significant in the first two years. This supports the idea that relation-specific investments (Dyer and Singh 1998; Williamson 1985) and an increase in trust (Levin and Cross 2004; Schrader 1991) will facilitate knowledge transfer.

Our results also have important implications for managers. We provide evidence of knowledge spillovers from buyers to suppliers in sectors that are strongly influenced by outsourcing, and in which competition from suppliers is a real threat. This suggests that - in addition to factors such as price, quality and service - firms should also consider knowledge spillovers in their transactions with buyers and suppliers. If the potential for knowledge spillovers is present, it becomes important to understand how they can be accrued or avoided. From a buyer perspective, it is necessary to consider both the positive and negative effects of spillovers. On the one hand, spillovers to the supplier can improve the performance of the supply chain as a whole. On the other hand, they can be harmful if used in a competitive manner. As the Samsung/Apple and Dell/Asus examples show, a supplier can turn into a direct competitor. Another risk is that the supplier diffuses the knowledge to other buyers in the same industry. These prospects makes it crucial for firms to consider knowledge spillovers when making sourcing decisions. If products or processes are outsourced, employee awareness and well-designed supply chain contracts can, to a certain extent, be used to regulate spillovers. If the knowledge in question is critical for the buyer, vertical integration could be a favorable strategy.

From a supplier perspective, we show that buyers are important sources of information for innovation. Having innovative buyers is therefore likely to heavily influence the future innovative output of the firm. In Section 2, we argue that the interaction between employees of the two firms is an important channel of knowledge transfers. Since tacit knowledge is inherently difficult to imitate or copy, a successful transfer between the supplier and its buyers should lead to a sustainable competitive advantage.

In general terms, our results support the hypothesis that suppliers will learn more from their buyers over time and we argue that this is because of increase in trust and improved communication (it is logical also to conjecture that there will be a similar effect from suppliers to buyers). Consequently, innovation also represents an important motive for establishing long-term relationships with supply chain partners.

Our study comes with several limitations that future research could try to address. First, as mentioned in Section 3.3, we acknowledge that our results could partly be driven by the fact that innovative buyers select innovative suppliers. However, we try to minimize this bias by controlling for the level of innovativeness of the supplier, at the time of the selection. In addition, we also take the innovative input (R&D) of both the buyer and supplier into account.

Second, since patents only capture those inventions that firms choose to patent (or are able to patent), patent counts might underestimate the true amount of innovative activity (Acs and Audretsch 1989; Griliches 1998b). Still, since we focus on firms in the high tech sectors, which are known to be patent intensive, we consider patents a reliable measure of innovation.

Third, we do not observe the full set of buyers connected to the suppliers in our sample. An assumption in our model is therefore that the observed buyers are representative of the whole set. If this assumption does not hold, the subsequent measurement error, if random, should have an attenuating effect on our results. Since we do not have reason to suspect a systematic difference between observed and non-observed buyers, this limitation should not affect our findings.

Fourth, by using a within transformation we control for the geographical proximity between the supplier and its buyers. Previous studies have shown that geographical distance is an important determinant for both spillovers and supplier selection. Therefore, it would be desirable to investigate the role of geography more explicitly.

Finally, we cannot determine whether a knowledge spillover is intentional or not. Although this was not the objective of our study, future research could investigate the underlying mechanisms by which knowledge spillovers occur. It would be interesting to measure the relative importance of tacit and codified knowledge transfers. Admittedly, this is a challenging endeavour, but detailed surveys and case studies could provide additional insights. Such complementary efforts would deepen our understanding of the actions that firms can take to actively regulate knowledge spillovers as a means to gain competitive advantage.

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Table 1: Sample composition

SIC CODE	Industry	Suppliers
2810	Industrial Inorganic Chemicals	2
2821	Plastic Materials, Synth Resins & Nonvulcan Elastomers	3
2833	Medicinal Chemicals & Botanical Products	2
2834	Pharmaceutical Preparations	27
2835	In Vitro & In Vivo Diagnostic Substances	11
2836	Biological Products, (No Diagnostic Substances)	31
3570	Computer & Office Equipment	1
3661	Telephone & Telegraph Apparatus	13
3663	Radio & TV Broadcasting & Communications Equipment	9
3669	Communications Equipment, NEC	3
3670	Electronic Components & Accessories	1
3672	Printed Circuit Boards	5
3674	Semiconductors & Related Devices	25
3678	Electronic Connectors	1
3679	Electronic Components, NEC	6
3728	Aircraft Parts & Auxiliary Equipment, NEC	5
3812	Search, Detection, Navigation, Guidance, Aeronautical Sys.	3
3823	Industrial Instruments for Measurement, Display, and Control	1
3825	Instruments for Meas. & Testing of Electricity & Elec Signals	19
3826	Laboratory Analytical Instruments	1
3829	Measuring & Controlling Devices, NEC	1
3841	Surgical & Medical Instruments & Apparatus	6
3842	Orthopedic, Prosthetic & Surgical Appliances & Supplies	4
3845	Electromedical & Electrotherapeutic Apparatus	9
4813	Telephone Communications (No Radiotelephone)	3

Table 2: Buyer and Supplier Characteristics

	Mean	Median	S.D.	Min	Max
Buyers					
Patents	179.2	56	338.7	1	2448
Forward citations	1,266.2	302	2,568.6	0	20,606
R&D (USD million)	979.6	327.7	1,453.6	0.32	12,942.1
Sales (USD million)	11,375.4	4,095.3	16,414.2	1.2	97,557.6
Suppliers					
Patents	8.6	1	37.0	0	669
Forward citations	55.5	3	271.0	0	6,364
R&D (USD million)	50.3	11.0	217.6	0.03	3,439.8
Sales (USD million)	762.8	31.4	3244.1	0.02	39220.3
Tie Strength	25%	16%	23%	0.001%	100%

Table 3: Descriptive statistics and correlations

	Mean	S.D.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(81)	(9)	(10)	(11)	(12)
(1) Log Supp Pat Prod	0.19	0.30	1											
(2) Log Buy Pat Prod$t-1$	0.19	0.20	0.056	1										
(3) Duration	3.34	1.74	0.064	-0.070	1									
(4) Tech Prox	0.29	0.45	0.094*	0.052	-0.045	1								
(5) Log Buy Frwd Cit Int	1.92	0.52	-0.16***	0.27***	-0.090*	-0.021	1							
(6) Sci Pat	0.47	0.24	-0.049	-0.26***	-0.095*	0.14**	-0.34***	1						
(7) Log Supp R&D Int	0.15	0.13	-0.13**	-0.081	-0.20***	0.096*	-0.22***	0.38***	1					
(8) Log Buy R&D Int	0.08	0.04	0.033	-0.035	-0.16***	0.28***	-0.057	0.29***	0.21***	1				
(9) Supp ROA	-0.10	0.27	0.043	0.081	0.11*	-0.12**	0.18***	-0.27***	-0.60***	-0.27***	1			
(10) Log Supp Sales	4.09	2.15	0.037	-0.019	0.22***	0.00036	0.20***	-0.27***	-0.51***	-0.22***	0.40***	1		
(11) Log Buy Sales	9.10	1.55	-0.12**	-0.28***	0.094*	-0.22***	0.051	-0.14**	-0.18***	-0.37***	0.24***	0.33***	1	
(12) Supp CAPX Int	0.06	0.05	0.025	0.15***	-0.0037	0.14***	0.20***	-0.061	-0.12**	0.069	0.12**	0.19***	-0.10*	1

Table 4: Regression outputs

Log Supp Pat Prod	(1)	(2)	(3)	(4)	(5)	(6)
Log Buy Pat Prod$t-1$	0.129*	0.276***	0.276***	-0.049	0.326***	-0.008
	(0.072)	(0.104)	(0.105)	(0.158)	(0.124)	(0.175)
Log Buy Pat Prod$t-1$ x Duration				0.102***		0.100***
				(0.037)		(0.038)
Log Buy Pat Prod$t-1$ x Tech Prox					-0.176	-0.125
					(0.231)	(0.230)
Duration	-0.0003	0.0003	0.001	-0.015	0.0002	-0.015
	(0.008)	(0.012)	(0.013)	(0.014)	(0.013)	(0.014)
Tech Prox	0.069**	0.026	0.015	0.027	0.060	0.059
	(0.030)	(0.091)	(0.095)	(0.093)	(0.112)	(0.111)
Log Buy Frwd Cit Int	-0.133***	0.029	0.030	0.030	0.028	0.029
	(0.028)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Sci Pat (Buy)	-0.056	0.006	0.008	0.011	0.006	0.009
	(0.064)	(0.066)	(0.066)	(0.065)	(0.066)	(0.065)
Log Supp R&D Int	-0.445***	-0.439***	-0.637***	-0.552***	-0.631***	-0.549***
	(0.116)	(0.169)	(0.199)	(0.199)	(0.199)	(0.200)
Log Buy R&D Int	0.300	-0.270	-0.380	-0.487	-0.342	-0.458
	(0.327)	(0.472)	(0.492)	(0.488)	(0.494)	(0.492)
Supp ROA			-0.114	-0.104	-0.109	-0.101
			(0.069)	(0.069)	(0.070)	(0.069)
Log Supp Sales			-0.0207	-0.0163	-0.0209	-0.0166
			(0.0298)	(0.0296)	(0.0298)	(0.0296)
Log Buy Sales			-0.011	-0.013	-0.009	-0.011
			(0.026)	(0.026)	(0.027)	(0.027)
Supp CAPX Int			-0.013	-0.033	0.015	-0.012
			(0.303)	(0.300)	(0.306)	(0.303)
Fixed Effect Included	No	Yes	Yes	Yes	Yes	Yes
Year Effects Included	Yes	Yes	Yes	Yes	Yes	Yes
Observations	521	521	521	521	521	521
Suppliers	192	192	192	192	192	192
Within R-Square		0.110	0.121	0.142	0.123	0.143
Between R-Square		0.028	0.038	0.028	0.040	0.029
Overall R-Square		0.022	0.027	0.027	0.028	0.028

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

(1) Baseline OLS regression. (2) Baseline fixed effects regression. (3) Including remaining controls. (4) Interaction between patent productivity and duration. (5) Interaction between patent productivity and technological proximity. (6) Full model.

Table 5: Marginal effects of relationship duration over time

Relationship duration (years)	**Log Buy Pat Prod**$t-1$
1	0.0557
2	0.156
3	0.256**
4	0.356***
5	0.456***
6	0.556***
7	0.656***
8	0.756***

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The table shows the impact (elasticity) of Log Buy Pat Prodt_{-1} on Log Supp Pat Prod for buyer-supplier relationship durations ranging from 1 to 8 years.

Table 6: Main coefficients of robustness test regressions

Specification	**Description of Robustness Test**	**Main effect**	**S.E.**	**N**
(1)	Fixed effects	0.276***	0.105	521
(2)	Random effects	0.227***	0.082	521
(3)	OLS	0.067	0.101	521
(4)	Panel-Tobit random effects	0.382***	0.138	521
(5)	Without lag	0.227***	0.078	969
(6)	With 2 lags	0.100	0.142	344
(7)	With lagged control variables	0.269**	0.108	521
(8)	With time-x-industry dummies	0.181**	0.085	521
(9)	Subsample: dyads with large size differences	0.343	0.229	249
(10)	Subsample: dyads with small size differences	0.273**	0.136	273
(11)	NB fixed effects count model	0.0009***	0.0003	323
(12)	Poisson fixed effects count model	0.0006**	0.0002	323
(13)	Without aggregating data on the buyer dimension	0.305**	0.131	551

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$