CROSS-FUNCTIONAL KNOWLEDGE INTEGRATION, PATENTING AND FIRM’S PERFORMANCE

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Cross-Functional Knowledge Integration, Patenting and Firm’s Performance

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Abstract

Internal knowledge integration and patenting are both reckoned to increase the productivity of human capital and the profitability of the firms implementing them. The combined effect of a joint use is in many ways ambiguous since those practices pursue different objectives in terms of managing the flow of knowledge and information within the firm’s boundaries. The presence of informational spillovers in situations of high technological rivalry could deteriorate the positive impact of knowledge integration. We investigate empirically different channels of interactions between patenting and knowledge integration and we find that they are substitutes in terms of economic profitability; consistently with our theory, the effect is exacerbated by high technological rivalry and scarce effectiveness of secrecy. Our empirical analysis is conducted using a cross-section database with detailed firm-level information on U.S. manufacturing firms.

Keywords: R&D, Performance, Knowledge Integration, Patents, Spillovers.

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1 Introduction

The ability of a firm to use and exploit its knowledge base within its boundaries is an important source of its competitive advantage, because knowledge represents a major input for innovation. This paper contributes the extensive literature about the management of innovation by focusing on the nature of the knowledge managed by the firm and its different appropriability strategies. We uncover complex interactions between three different key aspects: protection of intellectual property, intra-firm communication and product market competition. We use data on the performance of U.S. manufacturing firms to show that these three features are tightly linked by the nature of the knowledge assets owned by the firm and the exchange of information within and across the firm’s boundaries.

Information exchange is at the heart of a vast literature whose purpose is to identify and measure the impact of knowledge spillovers on various measures of R&D productivity. These works conclude that knowledge spillovers have a positive influence on the innovative performance, hence implying that greater circulation of information would be beneficial to the economy as a whole, i.e. firms and consumers. It is important to remark, however, that firms’ performance as evaluated by the stakeholders is not limited to a measure of innovation output, but rather, how this output translates into profits. The financial benefits of information spillovers are therefore filtered by the competitive structure of the market and its institutional setting, a dimension that has received scarce attention, especially in the management literature; this leaves widely open the question about whether within-firm internal knowledge flows and strategies of appropriation (that limit outgoing knowledge spillovers) serve as strategic complements or substitutes.

In particular, this paper focuses on the interactions between knowledge integration practices (or knowledge management, hereafter KM) aimed at diffusing information between R&D and other functions of the firm, and patenting. Increasing the volume of R&D information flows to other departments of the firm makes the R&D closer to the market and better aligned with consumers’ needs; at the same time, however, it increases the risk of leakage of valuable information
- complementary to knowledge disclosed and protected by patents - that could facilitate imitation by competitors. To the best of our knowledge, this is the first work that attempts to empirically measure the extent to which this spill-out is damaging firm’s performances via its negative impact on patenting.

To achieve this objective we use detailed cross-section data from the Carnegie-Mellon survey (CMS), described in detail in Cohen et al. (2000). This is a unique data source for many reasons: among others, it allows firm-level measures of the strategies used to appropriate innovation rents, as opposed to industry-level scores as measured in previous surveys. Also, it provides an extremely rich array of questions about the organization of the R&D function, including the adoption of organizational practices aimed at achieving greater cross-functional knowledge integration. We match the information of the CMS with S&P’s Compustat at the firm level to analyze the impact of patenting propensity and knowledge integration practices on commonly used measures of a firm’s performance, such as the Tobin’s $q$, which is defined as the market value of financial claims of a firm, divided by the replacement value of the firm’s assets. This is a particularly well-suited measure for a firm’s performance in our case, because it is a forward-looking variable and therefore it is able to capture the rents a firm expects to earn from its intangible assets. Consistent with the predictions of our theoretical framework, the empirical findings suggest that patenting and knowledge integration are substitutes in terms of a firm’s economic performance. This substitution effect tends to be exacerbated when technological rivalry is higher and when secrecy is not effective in preventing the spillovers of valuable R&D knowledge outside the firm.

The remainder of the article will be structured in the following way: section 2 will be devoted to the theoretical background and the development of the testable hypotheses. Section 3 will describe the empirical setting used to conduct the empirical analysis. Section 4 will describe in detail the database and the variables we use in the empirical section. In section 5 we present the description of the results and finally section 6 concludes.
2 Theoretical Framework

2.1 Knowledge and Integration

Intellectual capital is the critical asset that allows firms to achieve a competitive advantage in the knowledge economy. Understanding how it works, what is its role in the economy of the firm and which variables affect the dynamics of its evolution is an important concern for research in management science, economics of innovation and industrial organization alike. Since we focus on knowledge integration, this part of the theoretical framework will describe the different types of knowledge that are involved in the manufacturing process and why its analysis is decisive to understand firm’s performance.

The first difficulty of this task is represented by the identification and measurement of knowledge. In this work, we explicitly focus on the knowledge produced by the R&D unit of the firm: this is arguably the most valuable form of knowledge, which has long-term implications for the firm’s economic and financial performances. Even by focusing exclusively on knowledge managed within the firm boundaries, one realizes the existence of an extremely varied taxonomy of characteristics. Pavitt (1998), in describing how cognitive division of labour has contributed to the increased productivity of R&D, puts the accent on the existence of two distinct bodies of knowledge. He denotes them “body of understanding” and “body of practice” (see e.g. Nelson (2004)), which refer respectively to the competencies in given technological fields and the elements that belong to the design, development, production and sale of one particular product model. Further, this distinction allows the author to remark how competition among innovative firms is characterized by greater heterogeneity in the downstream body of practice, rather than in the base of technological knowledge.

There is a rich literature that discusses the positive effects derived from combining and integrating the body of understanding and the body of practice. We want to distinguish these benefits in two different categories.

The first type of benefits coming from this integration relate to increased pro-
ductivity of the R&D function: in the management literature, Clark and Fujimoto (1991) highlighted the advantages of using an “integrated problem solving” approach; economists like Henderson and Cockburn (1994, 1996) stressed the importance to exploit economies of scope deriving from the heterogeneity in scientific elements within the firm’s knowledge base and how these elements fit into the more general organization of the R&D function. In the more recent economic empirical literature, Nesta and Saviotti (2005) show that coherence and scope of the knowledge base are crucial drivers of innovative performance in the U.S. pharmaceutical industry. The positive impact of knowledge integration on the R&D productivity is therefore the first effect that we want to measure.

The second type of advantages coming from integration is related to a more general view about the impact of knowledge integration. It has been shown that, by bringing the R&D unit closer to the market and the consumers, the firm is able to achieve smoother coordination in the development of its projects, reducing costs and time needed to embed ideas into products. This means that, on top of enhancing efficiency of the R&D unit, other functions unrelated to R&D will experience increased productivity and performances (Clark and Wheelwright, 1993). These practices allow the firm to generate “competencies” and organizational capabilities (Clark and Fujimoto, 1991; Malerba and Orsenigo, 2000; Cohendet and Meyer-Krahmer, 2001), that guarantee an important competitive advantage over its competitors. However, from a more applied perspective, very little has been done, so far, in terms of investigating the actual mechanism to achieve this integration.

To summarize, we formulate the following hypothesis:

Hypothesis 1: Knowledge integration contributes positively to the economic performance of the firm, both by increasing R&D productivity and by increasing the overall efficiency of the firm.
2.2 Knowledge Integration and Appropriability

In this subsection we examine the core argument of our theoretical framework, that is, the link between intra-firm information flows and appropriability. Supported by other recent works (Hellmann and Perotti, 2011; de Faria et al., 2012; Lee and Walsh, 2012), we highlight the existence of a fundamental tension between circulation of ideas inside the firm and the adoption of appropriability mechanisms; indeed, since both appropriability and knowledge integration strategies rely on knowledge and information flows, their joint use has a separate and potentially non-linear impact on firm’s performance. We briefly review the literature on appropriability and then proceed to extend our theoretical framework to account for the joint impact of knowledge integration and appropriability strategies.

Thanks to the pioneering work of Teece (1986), Levin et al. (1987) and Cockburn and Griliches (1988), we know that appropriating the returns over the intellectual assets of the firm has important implications for the stream of future profits. Many different strategies can be used to avoid essential knowledge to spill over from the firm’s boundaries to its competitors, ensuring a durable competitive advantage. The exercise of quantifying the market value of a firm’s knowledge assets has received considerable attention in the literature (e.g. Bloom and Van Reenen (2002); Hall et al. (2005)), but only recently, scholars have focused on how firms use patenting strategies and other institutional features of the Intellectual Property Right (IPR) system to ensure additional rents, for example by preemptive patenting over rivals’ technologies (Ceccagnoli, 2009). In general, the lower competitive pressure derived from appropriability mechanism critically relies on their capacity to prevent spillovers of valuable knowledge, which can undermine the competitive advantage of the firm (especially in rapidly evolving industries).

We focus in our work on one particular appropriation mechanism: patenting. Indeed, even though patenting does not directly influence the volume of information flows within the firm’s value chain, it matters for knowledge integration. To understand why, we argue that it is useful to rely on the concept of knowledge codification and the importance of tacit knowledge (Nelson and Winter, 1982). As
Cowan et al. (2000) also stress, tacitness is not a quality inherent in knowledge, but it is also the outcome of costs and incentives determined by the market structure and the institutional environment where the firm operates.

When a firm can effectively protect its inventions with patents, it necessarily discloses a certain amount of technological knowledge\(^1\). This constitutes a substantial fraction of the ex-ante costs of using patents, and plays a key role in the decision of whether to use patents or other appropriability mechanisms like secrecy (Arora et al., 2008; Horstmann et al., 1985). Once the invention has been patented, however, scholars have found very little and heterogeneous disclosure effects, which are associated to substantial rents for the patent holder. These gains do incorporate a strategic element\(^2\), but they also suggest that firms are able to retain and protect a stock of knowledge that is valuable, sticky, and complementary to the knowledge disclosed in the patent. This knowledge is decisive to rip the benefits from its R&D investment.

This stock of complementary knowledge features information about legal, marketing and even some technical aspects of the invention (Arora, 1997; Kline and Rosenberg, 1986; Saviotti, 1998) that are not disclosed in the patent. This knowledge represents a crucial building block of the competitive advantage of the firm, since it requires time, effort at all levels of the value chain and also a certain degree of risk to successfully implement an idea or a technology into a viable and profitable product to be sold on the market. Because of the imperfect nature of the protection offered by the patent system, the ability to retain this type of information within the boundaries of the firm (i.e. adopting secrecy) becomes essential and complementary to other appropriability strategies that involve disclosure of technological knowledge.

The previous discussion lays out a more complex theory of the relationship between knowledge integration and patenting than the simple productivity-increase

\(^1\)The literature on patent disclosure is a large one and a good and recent survey is offered by Hall and Harhoff (2012).

\(^2\)See for instance Ceccagnoli (2009).
At its core, there is the existence of a critical tradeoff between the benefits of knowledge integration and the costs derived from potential leakage of valuable knowledge to competitors. This leads us to formulate the following hypothesis:

Hypothesis 2: Knowledge integration and patenting will be substitutes through their joint negative impact on the returns to R&D.

2.3 The role of technological rivalry and secrecy

In this last part of our theoretical framework we ask under what conditions the magnitude of the trade-off summarized by Hypothesis 2 is likely to be exacerbated.

We focus on two factors. First, outgoing knowledge spillovers are typically more damaging for the innovating firm when its rivals can effectively evaluate and use the external knowledge flows (Cohen and Levinthal, 1989; Ceccagnoli, 2005). As such, we expect the spillovers of complementary knowledge from knowledge integration and patenting to be more damaging to the innovating firm when the number of technologically capable rivals is high.

Second, one may wonder what is the role played by secrecy, which is by far the most widespread appropriability mechanism (Cohen, 2010). According to Lee and Walsh (2012), intra-firm knowledge integration increases innovative performance, other things equal, and secrecy may dampen this positive effect by limiting knowledge circulation. While we are able to control for this, we emphasize the existence of a countervailing effect: in our framework, to the extent that secrecy is an effective appropriability mechanism, knowledge integration is less likely to generate potentially damaging outgoing flows of knowledge that is complementary to patents. Indeed, appropriability strategies based on secrecy have been shown to be an effective mechanism to protect know-how that is complementary to patenting (Arora, 1997; Hall et al., 2012). Therefore, we expect the tension between knowledge integration and patenting to be less severe when secrecy is effective. We summarize these ideas using the following testable hypotheses:
Hypothesis 3: The substitution effect between patenting and knowledge integration due to knowledge spillovers is exacerbated by:

a. close technical rivalry;

b. scarce effectiveness of secrecy.

3 Empirical Specification

To empirically test our hypotheses we follow the specification proposed by Griliches (1981), a widely adopted and well-established tool (Jaffe, 1986; Hall et al., 1993; Hall, 1993), and its extension proposed by (Ceccagnoli, 2009). The market valuation of a firm’s R&D is defined by:

\[
V = q(A + \gamma \bar{R})
\]

where \(V\) is the market value of the firm at the end of the year, \(A\) is the book value of the capital’s stock, \(\bar{R}\) is the value of the firm’s R&D capital and \(\gamma\) is the marginal contribution to the firm’s market value. \(q\) is the coefficient that reflects the firm’s differential risk and market power as determined by the firm’s total assets (Griliches, 1981). A more complete and detailed derivation of this equation as the outcome of the firm’s dynamic optimization problem of investment can be found in Hall et al. (1993). By dividing both sides by \(A\) and taking logs one obtains:

\[
\log \frac{V}{A} = \log q + \log \left(1 + \gamma \frac{\bar{R}}{A}\right)
\]

(1)

Following Griliches (1981) and Ceccagnoli (2009) we set:

\[
q = \exp(X\beta + \epsilon)
\]

where the vector \(X\) includes factors affecting firm’s market power: market share and the concentration ratio. \(\beta\) is a vector of estimated coefficients. We set

\[
\gamma = S\theta
\]

(2)
where $S$ is the vector of observed firm’s characteristics affecting the appropriability of returns to R&D, such as patent propensity. Consistent with our theory, we also add to this set a measure reflecting a firm’s knowledge management strategy. $\theta$ is the associated vector of estimated parameters. It is important to note that the variables included in (2) are interacted with the R&D intensity variable. Consistent with theory, we do not explicit the effect of the non-interacted patent propensity variable, since patenting should only affect a firm’s profitability only through its effect on the rate of return from R&D investments (a result that is supported by our unreported sensitivity analysis). However, we do include the standalone KM variable, since it may affect both the appropriability of R&D and the overall productivity of the firm.

In the next section we detail the procedure adopted in the construction of the variables used for the estimation.

## 4 Data and Variables

The data we use come from two datasets: the Carnegie Mellon Survey (Cohen et al., 2000), conducted at the R&D-unit level of the firm, and Compustat. We work with a resulting cross-sectional dataset of 314 observations related to the period 1991-1993 for which we have both information about R&D practices and financial information. In the following we describe in detail how we build the variables we are going to use in the empirical analysis, starting with the explanatory ones.

### 4.1 R&D

We follow closely Ceccagnoli (2009), as we compute the stock of R&D ($\bar{R}$ in equation 1) using the cumulated stock of past deflated R&D expenditures, available from Compustat, using a 15% depreciation rate. To obtain the ratio $\bar{R}/A$ we divide the R&D stock by the book value of total assets, also available from Compustat. We denote the resulting explanatory variable R&D Intensity.
4.2 Appropriability

Following Ceccagnoli (2009), our main measure of the degree of appropriability is the *propensity to patent* (also denoted “Patent Prop.” or “PAT”), which is the share of product and process innovation for which a firm applied for patents in the period 1991-1993. As we have information about each type of invention, we weight product and process propensities using the percentage of R&D devoted to product and process innovations, as reported by the CMS respondent. Appropriability as measured by patenting propensity is a very fit and parsimonious measure, especially in our specification where interaction terms are critical to capture the non-linearities in profits; however, since patenting is not the only strategy that a firm could pursue in order to capture the returns of its own R&D and it could be subject to reverse causality, we rely on a set of instruments when estimating our main equation. We build variables that capture the perceived efficacy of different strategies from questions in the CMS; the respondent is asked to indicate the percentage of the product/process innovations for which *patent protection, secrecy, being first to enter the market* or *ownership of complementary assets*\(^3\) were perceived as effective in order to protect firm’s competitive advantage. Answers are provided on a Likert scale from 1 to 5 and are also weighted by the respondents’ focus on product and process innovation in the same way we weight patent propensity. We corroborate the complementary assets ownership efficacy variable with an additional dummy variable that takes value 1 when the R&D lab is located close to manufacturing (Arora and Ceccagnoli, 2006). In addition to these variables we have an additional instrument that captures *patent effectiveness at the industry level*, which is an average of the patent effectiveness in the primary business segment of the firm.

4.3 Knowledge Management and Information

Our “knowledge management” ("KM") variable represents the number of practices -from 0 to 4- that are put in place to favor the exchange of information between the R&D department and other functions of the firm; in particular, we exploit answers

\(^3\)In Table 1 these will be denoted “Patent eff.”, “Secrecy eff.”, “First to market eff.” and “Compl. assets eff.”
to the CMU survey questions on whether the following methods were used during the previous three years to facilitate interaction between R&D and other functions: 1) Rotation of personnel across functions; 2) Project team with cross-functional participation; 3) Interdepartmental committee; 4) Computer network with electronic mail, bulletin board or conferencing capabilities. It is important to remark how knowledge practices at this stage concern exclusively information flows that are internal to the firm’s boundaries. Also, we stress the fact that we neglect any qualitative differences between different types of knowledge management practices and we just focus on their number as an ordinal measure. Some of the techniques indicated as possible answers in the $K_M$ variable are costly to implement, this is why we believe that $K_M$ could suffer from an endogeneity problem just like patent propensity.

Analogously to our appropriability measures, also our knowledge management measure may be subject to reverse causality problems. We will therefore build a set of potential instruments for $K_M$ that rely on the organizational structure of the firm. As we outlined in the theory section, we believe the two are very closely related but organization cannot be changed in the short run because it relates with the physical and managerial structure of the firm. The first instrument is $R&D$ initiative, that is, the percentage of projects initiated by direct request of a department which is not R&D; such an instrument is consistent with Bloom et al. (2009), who find that implementation of (costly) communication techniques are substitute for delegation in decisions. Therefore, our first instrument is significantly and negatively correlated with our “$K_M$” variable. The second instrument is $R&D$ location, a binary variable that takes a value of 1 when the R&D laboratory is physically located far away from the other functions; this situation is associated with more intense knowledge management strategy as other communication channels are precluded by physical distance. The third instrument we adopt is who is making use of the R&D output generated by the lab (“R&D Usage” in the tables), and we build a dummy variable that takes a value of 1 when it is used by other R&D units of the firm; since our $K_M$ variable refers to practices used to move information over the value chain of the firm, when the R&D lab is more closely related to other research units these practices may become even more useful to
foster vertical (rather than horizontal) information flows.

4.4 Market Structure and Competition

Consistent with previous work (please refer to Hall (1999) for a review of the literature), we control for the market power of the firm by including two control variables, industry concentration (“C4W”) and market share (“MS”), both weighted using their 1991-1993 four-digit SIC sales distribution (available from Compustat). Market share is computed as the weighted average sales of the firm divided by the total industry sales, available from 1992 U.S. Census of Manufacturers. The concentration ratio is the percentage of total industry sales accounted for by the four leading firms in each business segment of the firm, also available from U.S. Census of Manufacturers. In all specifications we include a set of 18 dummies capturing industry fixed effects (denoted in the estimated equation by the vector “IFE”) in all specification, mostly defined at the two- and three-digit SIC level of the primary business segment of the firm.

4.5 Performance, Market Structure and Competition

Finally, we present our dependent variable. The Compustat files contain data to approximate Tobin’s $q$ (denoted “$Q$” in the estimated equation) as in Chung and Pruitt (1994), which is defined as the ratio of a firm’s market value to the book value of its total assets. The former is the sum of a firm equity value and the book value of long-term debt and net current liabilities. The dependent variable we use in the estimated equation will be the log of the 1991-1993 average of Tobin’s $q$.

4.6 Split-sample variables

We build two dummy variables that we will use to split our sample and test Hypothesis 3. From the CMS survey we identify the degree of technological rivalry from a question asking “how many firms are able to introduce competing innovations in time to effectively diminish your firm’s profit from your innovation”. We take into consideration the answer for the North America region, since it is the
region where our R&D labs are located and therefore it is more likely that the firm’s knowledge spillovers are captured by nearby competitors.

The second split sample dummy equals 1 when the firm reports a level of perceived efficacy of “secrecy” (as described before) which is below the sample median and mean.

5 Empirical Estimation

We start our empirical investigation by providing some descriptive statistics about our variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Tobin’s q (log Q)</td>
<td>314</td>
<td>0.270</td>
<td>0.616</td>
<td>-2.010</td>
<td>2.147</td>
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<tr>
<td>R&amp;D Intensity (R/A)</td>
<td>314</td>
<td>0.287</td>
<td>0.433</td>
<td>0.005</td>
<td>4.541</td>
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<tr>
<td>Patent Prop. (PAT)</td>
<td>314</td>
<td>0.337</td>
<td>0.275</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Knowledge Integration (KM)</td>
<td>314</td>
<td>2.856</td>
<td>1.007</td>
<td>0.000</td>
<td>4.000</td>
</tr>
<tr>
<td>Market Share (MS)</td>
<td>314</td>
<td>0.117</td>
<td>0.175</td>
<td>0.000</td>
<td>0.966</td>
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<tr>
<td>Market Concentration (C4W)</td>
<td>314</td>
<td>0.289</td>
<td>0.178</td>
<td>0.004</td>
<td>0.840</td>
</tr>
<tr>
<td>KM Instruments</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R&amp;D Initiative</td>
<td>299</td>
<td>0.756</td>
<td>0.202</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>R&amp;D usage</td>
<td>313</td>
<td>0.198</td>
<td>0.399</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>R&amp;D location</td>
<td>313</td>
<td>0.230</td>
<td>0.422</td>
<td>0.000</td>
<td>1.000</td>
</tr>
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<td>R&amp;D manuf. Proximity</td>
<td>313</td>
<td>0.406</td>
<td>0.492</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>PAT Instruments</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Patent eff. (firm)</td>
<td>314</td>
<td>0.395</td>
<td>0.294</td>
<td>0.050</td>
<td>0.950</td>
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<tr>
<td>Patent eff. (industry)</td>
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<td>0.343</td>
<td>0.102</td>
<td>0.138</td>
<td>0.614</td>
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<tr>
<td>Secrecy eff.</td>
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<td>0.493</td>
<td>0.295</td>
<td>0.050</td>
<td>0.950</td>
</tr>
<tr>
<td>First to market eff.</td>
<td>314</td>
<td>0.466</td>
<td>0.288</td>
<td>0.050</td>
<td>0.950</td>
</tr>
<tr>
<td>Compl. assets eff.</td>
<td>314</td>
<td>0.383</td>
<td>0.274</td>
<td>0.050</td>
<td>0.950</td>
</tr>
</tbody>
</table>

Table 1: Descriptive statistics
## Table 2: Correlation Matrix

* indicate correlations significant at the 5% level.

<table>
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<tbody>
<tr>
<td>1.000</td>
<td>0.2340*</td>
<td>0.1475*</td>
<td>-0.034 -0.2445* -0.2067*</td>
<td>0.059 0.1886* 0.2544* -0.2351* 1.000</td>
<td>-0.100 0.2226* 0.2140* -0.1999* 0.1855* 1.000</td>
<td>-0.091 0.058 0.1926* -0.2248* 0.1630* 0.2566* 1.000</td>
<td>-0.1900* -0.081 0.1614* -0.005 0.049 0.076 0.2613* 1.000</td>
<td>0.2826* 0.6043* 0.056 -0.1548* 0.1358* -0.004 -0.021 -0.107 1.000</td>
<td>0.3923* 0.406* 0.048 -0.078 -0.001 0.004 -0.1889* -0.2016* 0.3684* 1.000</td>
<td>0.097 0.043 0.075 -0.009 0.009 -0.090 -0.018 0.019 0.1346* 0.000 1.000</td>
<td>0.025 0.037 0.052 -0.009 -0.075 -0.1639* -0.034 0.025 0.1460* 0.1131* 0.3239* 1.000</td>
<td>-0.0038 -0.0306 0.0319 0.0596 0.0292 -0.1272* -0.1310* -0.1102 0.0568 -0.0071 0.1268* 0.4658* 1.000</td>
<td>0.1192* 0.0942 -0.0733 0.0361 -0.0553 -0.1570* -0.1711* -0.0409 0.1511* 0.1210* 0.0099 0.0111 0.0295</td>
<td>-0.1031 -0.1786* -0.2248* 0.1714* -0.1352* -0.4053* -0.1666* -0.0893 -0.0976 -0.1130* -0.0035 0.0713 0.0649 0.1253*</td>
<td></td>
</tr>
</tbody>
</table>
Our main variable of interest, $KM$, shows an average of 2.856 and standard deviation of 1.007. The median firm in the sample implements at least 3 out of 4 knowledge integration practices, with 25% of firms implementing the 4 of them and only 1% none. Indeed, looking at table 3, we remark the high degree of correlation between the four of them. Still, the variable provides enough variation to examine it as a continuous explanatory variable.

Our empirical strategy consists in estimating

$$
\log Q = \beta_0 + \log \left( 1 + \theta_1 \times \frac{\bar{R}}{A} + \theta_2 \times PAT \times \frac{\bar{R}}{A} + \theta_3 \times KM \times \frac{\bar{R}}{A} + \theta_4 \times KM \times PAT \times \frac{\bar{R}}{A} \right) \\
+ \theta_5 \times KM + \beta_1 \times CW + \beta_2 \times MS + IFE \times \Gamma + \xi
$$

where $\xi$ is the unobserved error term and $\beta_0$ is the constant. We remark that the use of both the interacted ($KM \times \frac{\bar{R}}{A}$) and the non-interacted ($KM$) knowledge integration variable allows to structurally identify the potential benefits obtained via, respectively, an improved performance of the R&D or the creation of firm-level competencies.

It is useful at this point, before presenting the estimation results, to provide the reader an overview of the sign predictions for our estimated coefficients, as derived from our theoretical framework.

Hypothesis 1 states that $KM$ has a double positive impact, both on the R&D
productivity and on the overall efficiency of the firm. These effects should imply a *positive* sign for the estimated coefficients $\theta_3$ and $\theta_5$. Motivated by the existence of informational spillovers of complementary knowledge, Hypothesis 2 argues that $\theta_4$ should have *negative* sign. Eventually, we expect the absolute value of $\theta_4$ to *increase* in the technological rivalry and to *decrease* in the effectiveness of secrecy, as Hypothesis 3 points to.

- **HP1**: $\theta_3, \theta_5 > 0$
- **HP2**: $\theta_4 < 0$
- **HP3**: $\frac{\partial \theta_4}{\partial x_1} > 0$, $\frac{\partial \theta_4}{\partial x_2} < 0$, where $x_1 =$ technological rivalry and $x_2 =$ secrecy effectiveness.

In a first step, we assume that there is no unobserved heterogeneity that could explain the choice to adopt either $KM$ or $PAT$ and we estimate our model via the Nonlinear Least Square (NLS) method. This first estimation methodology allows us to compare our estimates with what has been found in the literature (Ceccagnoli, 2009). In a second step, we address the endogeneity concern by re-estimating our main equation using the Generalized Method of Moments (GMM).

The full sample estimates using NLS, which corresponds to the first column of Table 4, provides some support for both hypotheses 1 and 2. Indeed, for Hypotheses 1, we do find a statistically positive effect (at 10%) level for the non-interacted $KM$, hinting at a possible contribution of $KM$ as a cost-reduction practice, rather than just a R&D-productivity enhancing tool. In our interpretation, because $KM$ is related to the firm’s organization and its boundaries, this result confirms that important benefits from $KM$ come from the creation of organizational capabilities that increase the efficiency of its non-intellectual assets (Malerba and Orsenigo, 2000; Cohendet and Meyer-Krahmer, 2001). The interacted term $KM \times \bar{R}/A$ is negative, but not statistically significant, while the estimated coefficient for $PAT \times \bar{R}/A$ is positive, significant and higher in magnitude with respect to Ceccagnoli (2009). The triple interaction term $PAT \times KM \times \bar{R}/A$ is negative and statistically significant, providing solid ground for our theory about the possibility of
### Table 4: Summary of Empirical Results; method: NLS; dependent variables: log of Tobin’s q.

Significance levels ***=0.01 **=0.05 *=0.10. Standard errors are reported in parenthesis below the estimated coefficient. The last row reports the value of the 2-sided t-test for $H_0$. 

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>Technological Rivarly</th>
<th>Secrecy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>LOW</td>
<td>HIGH</td>
</tr>
<tr>
<td>R&amp;D Intensity</td>
<td>0.085</td>
<td>-0.104</td>
<td>-0.689</td>
</tr>
<tr>
<td>(0.189)</td>
<td>(0.613)</td>
<td>(0.482)</td>
<td>(0.675)</td>
</tr>
<tr>
<td>$PAT \times \bar{R}/A$</td>
<td>3.100 ***</td>
<td>2.449 *</td>
<td>2.993 **</td>
</tr>
<tr>
<td>(0.843)</td>
<td>(1.388)</td>
<td>(1.294)</td>
<td>(1.792)</td>
</tr>
<tr>
<td>$KM \times \bar{R}/A$</td>
<td>-0.053</td>
<td>-0.121</td>
<td>0.252</td>
</tr>
<tr>
<td>(0.093)</td>
<td>(0.223)</td>
<td>(0.241)</td>
<td>(0.336)</td>
</tr>
<tr>
<td>$PAT \times KM \times \bar{R}/A$</td>
<td>-0.768 ***</td>
<td>-0.456</td>
<td>-0.708</td>
</tr>
<tr>
<td>(0.281)</td>
<td>(0.525)</td>
<td>(0.443)</td>
<td>(0.613)</td>
</tr>
<tr>
<td>$KM$</td>
<td>0.056 *</td>
<td>0.044</td>
<td>0.003</td>
</tr>
<tr>
<td>(0.033)</td>
<td>(0.046)</td>
<td>(0.067)</td>
<td>(0.072)</td>
</tr>
<tr>
<td>MS</td>
<td>0.070</td>
<td>0.305</td>
<td>0.015</td>
</tr>
<tr>
<td>(0.177)</td>
<td>(0.274)</td>
<td>(0.265)</td>
<td>(0.304)</td>
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<tr>
<td>C4W</td>
<td>-0.325</td>
<td>-0.690 **</td>
<td>-0.042</td>
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<td>(0.198)</td>
<td>(0.292)</td>
<td>(0.298)</td>
<td>(0.322)</td>
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<td>(0.152)</td>
<td>(0.226)</td>
<td>(0.251)</td>
<td>(0.270)</td>
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</table>

<table>
<thead>
<tr>
<th>Industry Fixed Effects</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
<th>Yes</th>
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<tr>
<td>N</td>
<td>313</td>
<td>141</td>
<td>172</td>
<td>143</td>
<td>170</td>
</tr>
</tbody>
</table>

$H_0 : \theta_4(LOW) = \theta_4(HIGH)$ - 4.611 13.598

The subsample estimations implemented to test hypothesis 3 are reported in the second and third column of the table. They show that the triple interaction term is significantly different - the t-statistic in both subsample being above the threshold of 3.291 - and it moves in the right direction in terms of magnitude.

In the following we compare and discuss the results obtained by estimating our equation using the GMM and the instrumental variables for $PAT$ and $KM$ discussed in section 4. The advantage of GMM is that it allows to retrieve robust standard errors even in presence of residual heteroskedasticity of the residuals, in addition to providing tests for our over-identifying restrictions. We implement a standard two-steps estimation consistent with the Feasible Efficient GMM Estimation (Cragg, 1983). The results are summarized in table 5.
We proceed by examining the implication of the estimated coefficients for our testable hypotheses. As before, the first column of Table 5 reports the estimated coefficients for the full sample, and columns two and three refer to, respectively, the “technological rivalry” and “secrecy” subsamples. We start by focusing on the results related to the entire sample of firms in our database, which decreases to 299 observations due to few missing values in the instrumental variables. \( \theta_2 \) (patent propensity) still keeps a strong positive and statistical significance. The significant effect of \( KM \) relates once again only to the standalone variable and not to its interaction with the R&D intensity, which now is positive and significantly different from zero. The fact that the coefficient associated to \( KM \times \bar{R}/A \) is not significant should not be entirely surprising: the R&D-enhancing effect that we mentioned in our theoretical framework (Henderson and Cockburn, 1994; Nesta and Saviotti, 2005) might be captured by the increase in the estimated coefficient.
of $\theta_4^4$. The third significant estimated coefficient in our regression is again that related to the interaction term between $PAT$ and $KM$. This reflects the tension that we discussed in Section 3.2 concerning the possibility of spillovers of valuable knowledge that is complementary to the one disclosed by the firm’s patent, supporting Hypothesis 2.

To provide additional information on our identification strategy, we perform additional regressions (reported in the Appendix) where we project our endogenous variables on the whole set of instruments and the exogenous variables employed in the main regression. Given the value of the F-statistic, we can reject the null hypothesis that the instruments have no effect at conventional significance levels. Moreover, the $p$-value of Hansen’s J test tells us that we cannot reject the null hypothesis of exogeneity of our set of instruments at the 10% level of significance.

Next we turn to examine our third and last hypothesis. To empirically test it we run the same baseline regression on split samples of the initial population identified by the technological rivalry and the secrecy dummies, as described in the previous section. The results are reported, as before, in the second and third columns of Table 5. The reader can immediately notice that a greater significance of the estimated coefficient with respect to the NLS case. Moreover, the sign and changes of the estimated coefficients are consistent with our second hypothesis: when technology rivalry is high, the contribution of patenting - captured by $\theta_2$ - to value creation increases, as the magnitude of the estimated coefficient. Analogously, the tradeoff between patenting and $KM$ is exacerbated, as it is shown by the increase in absolute value of the estimated (negative) coefficient of the triple interaction term, $\theta_4$; in fact, in situations with a high number of technological rivals, we expect a stronger dissipation of rents following the spillovers of complementary knowledge associated with $KM$ and patenting$^5$.

$^4$Moreover, that would be consistent with what Lee and Walsh (2012) suggest, since those benefits are reaped according to the appropriability strategy adopted.

$^5$Notice that, analogously to the NLS estimates, the positive contribution of the $KM$ term is not significant anymore. This captures a quite different information from the triple interaction term: it suggests that on average, in the context of strong technological competition, the main channel of value creation is the protection of intellectual assets and not the creation of capabilities. This is consistent with a model of vertical differentiation between competing products, where
Finally, we turn our focus on secrecy. When the effectiveness of secrecy is low (spillovers are high), the estimated values of $\theta_2$ and $\theta_4$ change in a way coherent with the subsample of high technological rivalry, supporting Hypothesis 3$^6$.

6 Conclusions

This paper contributes to our understanding of the tradeoffs between intra-firm knowledge integration and protection of intellectual assets in a competitive economy. One part of the literature has shown that knowledge integration increases the productivity of the R&D department (Clark and Wheelwright, 1993; Henderson and Cockburn, 1994; Nesta and Saviotti, 2005). Another strand of the literature has focused on more organization-wide benefits that go under the definition of competencies or organizational capabilities (Malerba and Orsenigo, 2000; Cohen-det and Meyer-Krahmer, 2001). We show the existence of a non-trivial tradeoff between these two benefits and the strategy of appropriation of returns from R&D adopted by the firm. The main ingredients of this tradeoff are essentially the type of knowledge managed, the disclosure mechanism associated with patents, spillovers and the competitive structure of the market. We combine these ingredients formulating three testable hypotheses regarding the positive contribution to market value of knowledge integration (Hypothesis 1), the existence of a trade-off between appropriability and knowledge integration (Hypothesis 2) and the conditions under which this trade-off is exacerbated (Hypothesis 3).

We test our hypotheses using cross-sectional data of U.S. manufacturing firms, using firm-level information from the match between two databases: the CMS and Compustat. Our results confirm the existence of such a trade-off, and through the this dimension of heterogeneity can be characterized by a discrete state variable of “having” vs. “not having” a given technology, rather than other dimensions of quality. A good example may be the impact of the introduction of radical innovations like the touch screen for smartphones.

$^6$It is interesting to remark that when spillovers are high, the positive contribution of $KM$ to firm’s value is captured by the R&D interaction: this is consistent with the absorptive capacity literature (Kamien and Zang, 2000) that has shown the importance of performing R&D activity in order to be able to source knowledge from the economic environment where the firm operates.
use of subsample regressions, we find positive evidence in support of our theory.

This work has a number of implications. First, our results shed light on the impact of intellectual property strategies on incentives for information disclosure at the firm level. We showed how firms should tend to minimize knowledge integration within their boundaries to reduce the flow of R&D knowledge that spills over to the market. Leakage of valuable knowledge may deteriorate the effect of patents in appropriating the returns from its intellectual assets, especially when competing with capable innovators and when secrecy is a relatively ineffective protection mechanism. Second, future research will need to explore further the role of information for the functioning of the firm by taking into account the incentives coming from market competition. Last, but not least, this work speaks to other recent findings about the impact that changes in the market structure, like competition or ability to protect intellectual property, have on firms’ organizational and strategic decisions. Our work indeed suggests that flatter hierarchical structures may be a solution adopted to integrate knowledge while avoiding knowledge spillovers. There is growing interest in trying to understand market- and firm-level transformation when exogenous shocks increase the level of competition, but so far very little work has taken into account knowledge and the legal tools that influence its circulation and its economic value: an aspect that is already at the heart of the knowledge economy we live in.

\footnote{See, among others, Caliendo and Rossi-Hansberg (2012) and Conconi et al. (2011).}
\footnote{notable exceptions include, among others, Garicano and Rossi-Hansberg (2012)}
References


### Additional Tables

<table>
<thead>
<tr>
<th>Explanatory variable</th>
<th>Dependent Variable</th>
<th>( PAT )</th>
<th>( KM )</th>
</tr>
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<tbody>
<tr>
<td>R&amp;D Intensity</td>
<td>0.098</td>
<td>-0.526</td>
<td></td>
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<tr>
<td>Market share MS</td>
<td>0.346</td>
<td>1.513</td>
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<tr>
<td>Market concentration C4W</td>
<td>0.096</td>
<td>0.896  **</td>
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<td>Patent eff. (firm)</td>
<td>0.086</td>
<td>0.364</td>
<td></td>
</tr>
<tr>
<td>Patent eff. (industry)</td>
<td>0.393 ***</td>
<td>0.038</td>
<td></td>
</tr>
<tr>
<td>Patent eff. (industry)</td>
<td>0.346</td>
<td>0.260</td>
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<td>Secrecy eff.</td>
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<td>0.118</td>
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<td>First to market eff.</td>
<td>-0.086</td>
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<td></td>
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<tr>
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<td>-0.120</td>
<td>0.836</td>
<td></td>
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<tr>
<td>R&amp;D's manufacturing prox.</td>
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<td>0.528</td>
<td></td>
</tr>
<tr>
<td>R&amp;D’s manufacturing prox. X ( R/A )</td>
<td>-0.120</td>
<td>0.242</td>
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<tr>
<td>Patent eff. (firm) x ( R/A )</td>
<td>0.187</td>
<td>-0.688</td>
<td></td>
</tr>
<tr>
<td>Patent eff. (industry) x ( R/A )</td>
<td>-0.144</td>
<td>2.541</td>
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<tr>
<td>First to market eff. X ( R/A )</td>
<td>0.248</td>
<td>1.504  **</td>
<td></td>
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<td>-0.071</td>
<td>0.425</td>
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<td>0.087</td>
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<td>-0.138</td>
<td>0.197</td>
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<tr>
<td>R&amp;D usage</td>
<td>0.023</td>
<td>0.406  **</td>
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<td>R&amp;D Initiative</td>
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<tr>
<td></td>
<td>0.128</td>
<td>0.684</td>
<td></td>
</tr>
</tbody>
</table>

| N       | 299   | 299   |
| R^2     | 0.540 | 0.544 |
| F-statistic | 13.70 | 5.00  |

Table 6: First stage regression for instruments used in GMM. Standard errors are reported below the estimated coefficient. Significance levels ** *=0.01 ** *=0.05 *=0.10
001 - Exploring europe’s r&d deficit relative to the us: differences in the rates of return to r&d of young leading r&d firms - Michele Cincera and Reinhilde Veugelers

002 - Governance typology of universities’ technology transfer processes - A. Schoen, B. van Pottelsberghe de la Potterie, J. Henkel.

003 - Academic Patenting in Belgium: Methodology and Evidence – M. Mejer.

004 - The impact of knowledge diversity on inventive performance at European universities – M. Mejer