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The Return to R&D and Seller-buyer Interactions: A Quantile Regression Approach

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Abstract: In this paper we analyze whether a firm's return to its R&D stock is affected by seller-buyer interactions. We suggest that firms that are in close contact with their customers will be relatively more sensitive to their customers' needs, and therefore adjust their R&D activities accordingly. This, in turn, will boost sales and increase the return to R&D. To the extent that seller-buyer interactions are costly, large and productive firms will have an advantage in overcoming such costs. We test these hypotheses using a fixed effects quantile regression framework. Results suggest that large firms active in industries characterized by frequent seller-buyer interactions have a higher return to R&D than other firms.

JEL-codes: O32, D22, D29, L25

Keywords: firm behavior, firm performance, production and organizations, firm size, diversification and scope

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1 Introduction

Investments in research and development (R&D) is a main driver behind technological progress and economic growth (cf Romer, 1994). As Audretsch et al. (2006) point out, innovative activities are usually seen as the result of systematic and purposeful efforts to create new knowledge by investing in R&D, followed by commercialization (cf Griliches, 1979; Chandler, 1990; Cohen and Levinthal, 1989; Warsch, 2006). However, investments in R&D have been found to be more uncertain than other types of investments (Hall et al., 2009; Cardoso and Teixeira, 2009). Even if firms benefit from innovation it is not clear whether their R&D activities induces them to grow (Geroski et al. 1997; Coad and Hölzl, 2010). In fact, a direct and stable relationship between R&D activity and firm performance has been notably difficult to find (Klomp and Leeuwen, 2001). As suggested by Hall et al. (2009) and Mairesse and Sassenou (1991), the wide range of estimates of the outcome of R&D can be attributed to differences in time, industry or country considered, or to the distinctive features of individual studies.

In this paper, we suggest that the variation in the return to R&D partly can be explained by the extent to which firms are in contact with their buyers. Firms who frequently meet and interact with their clients learn about costumer preferences (Tingvall and Poldahl, 2012). Due to the knowledge transfer that occurs through seller-buyer interactions, firms are better able to adjust their R&D investments according to consumer preferences. Product development in close accordance to buyer preferences can hence be expected to increase sales and thereby enabling greater returns to R&D. Consequently, we suggest that the intensity of seller-buyer interactions is important for the innovation process and may explain some of the variation in the estimated returns to R&D.

However, seller-buyer interactions are also associated with a cost as meeting clients and understanding their needs requires resources from the firm. For some firms these costs may exceed the gains from the knowledge transfers attributable to seller-buyer interactions. Large firms may be better equipped to handle seller-buyer interactions than small firms for two reasons. First, large firms are better able to spread the costs associated with seller-buyer interactions over large output quantities. Secondly, large firms tend to engage in incremental usability improvements (Baumol, 2004) which may depend more on the customer feedback we attribute to seller-buyer interactions. For these reasons, we suggest that large firms have an advantage in relationship-specificity (RS) intensive industries and expect greater returns to R&D the larger the firm and the higher the intensity of relationship-specificity.

We explore the impact of seller-buyer interactions to the return to R&D with respect to both productivity and firm size. Melitz (2003) suggests that due to fixed costs associated with export market entry, productive firms are more likely to export than are other firms. Similarly, firms with high productivity may to a greater extent than other firms be able to overcome a threshold cost associated with seller-buyer interactions. We therefore hypothesize that productive firms also have an advantage in RS-intensive industries.

To analyze these questions we depart from the modelling framework developed by Griliches (1979) and Griffith et al. (2004). Seller-buyer interactions are measured by the relationship-specificity index developed by Rauch (1999) and Nunn (2007). To capture the interdependence between R&D and seller-buyer interactions we interact the relationship-specificity index with the firm R&D stock. We thereby introduce a novel channel for analyzing the impact variation of the returns to R&D[1], while at the same time controlling for the traditional determinants of the return to R&D. Since we are interested in how the impact of relationship-specificity varies with size and the level of productivity, we analyze the return to R&D using both a productivity- and value added (firm size) based approach and perform the analysis in a fixed effects quantile regression framework (Canay, 2011). A quantile regression framework allow us, in detail, to analyze the interplay between seller-buyer interactions and the return to R&D to firm size and productivity respectively. The analysis is performed using a panel consisting of all Swedish manufacturing firms with at least of 50 employees observed during period 1997-2005.

Results suggest that more seller-buyer interactions increase the returns to R&D and that the magnitude increases with both firm size and productivity. To assess potential time effects of innovation activity, we experiment with different lag structures of the R&D stock. The positive slope of R&D with respect to relationship-specificity and size remains when lagged values of R&D stock are considered but the level of the effect shifts downward. In the productivity based model, results tend to be less stable over the lag structure which implies that the relationship between seller-buyer interactions, the return to R&D and productivity is less robust than that of firm size.

The role of seller-buyer interactions has so far received limited or no attention in the R&D related empirical literature. The present study adds to that literature in several ways. First, by explicitly focusing on the role of seller-buyer interactions, we analyze a new determinant to the

[1] In this paper we refer to the estimated return to R&D as the return to R&D stock. Hence, we measure R&D as the accumulated contribution of R&D investments with a related depreciation rate.

return to R&D. Secondly, we analyze to what extent firm size and productivity help firms to overcome costs associated with seller-buyer interactions. Finally, to our knowledge this is the first paper to analyze the return to R&D in a fixed effect quantile regression framework.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature on the returns to R&D and on relationship-specificity. In section 3 we present the econometric specification where we elaborate on two models. In section 4 we present data and variables. Section 5 tests the hypothesis empirically. Section 6 concludes with a discussion of the results.

2 Literature Review

2.1 The impact variation of R&D activities

Theoretically, R&D activities can increase productivity by improving production quality through process innovation, by reducing production costs of existing goods, or by introducing new goods or intermediate inputs (Hall et al., 2009). Despite the theoretical importance of R&D, a direct and stable relationship between R&D activity and firm performance has been notably difficult to find (Klomp and Leeuwen, 2001).

A commercially viable innovation is an outcome from a complex process and it is therefore difficult to predict the return to investment in R&D (Hall et al., 2009). As outlined by Mansfield et al. (1977), this uncertainty is present in all three stages of the innovation process. The first stage depends on the availability of sufficient and relevant technology. Given the necessary technology in the first stage, the product or process innovation must thereafter be successfully commercialized. Finally, given commercialization, the innovation must yield a return larger than the initial investment. Hence, it is not surprising that there is considerable variation in the estimated return (Hall et al., 2009). Nor is it surprising that the returns to R&D differ over time, across sectors and firms (Cardoso and Teixeira, 2009).

A number of studies have addressed the impact variation of R&D by literature surveys. Mairesse and Sassenou (1991) surveys econometric studies investigating the impact of R&D to firm performance and finds a substantial variation between studies. They emphasize that estimating the impact of R&D is associated with great complexity. Furthermore, their comparison of different studies reveals inconsistencies and problems of interpretation about which no firm conclusions can be drawn. A recent paper that addresses the variation in the estimated return to R&D is Hall et al. (2009). They find that in most cases, the rate of return to

R&D is positive and generally higher than the rate of return to physical capital. Cardoso and Teixeira (2009) present a survey on the magnitude and evaluation methodologies on the return to R&D at three levels of aggregation. At the macro level the estimated returns varied with a minimum of 6% and a maximum of 66% and an average of 24%. At the sector level the estimated return to R&D averaged at 37.1% with minimum and maximum values at 19% and 45.7% respectively. At the firm level, the estimated return to R&D scored the highest average of all three categories at 38%, with a minimum at 27% and a maximum at 49%. They conclude that methodological approaches and the level of analysis are important to explain the variation between the studies.

Some of the impact variation of R&D have been attributed to industrial differences and methodological concerns. Hall et al. (2009) argue that the estimated return to R&D tend to decrease and become less significant when industry dummies are included. They find that industry dummies are often included to correct for industry bias but may also be a source of distortion. The reason is that industry controls may reflect the return to R&D resulting from the technological opportunities that differ by sector. These differences are essential for explaining the greater tendency to carry out R&D in some industries. Between industries, the difference in the estimated return to R&D can be quite large. For instance, Link (1981) finds that the return to R&D within large firms ranges from 25% in chemicals and 160% in transportation equipment. Such large sector differences and the variance in the estimated return have induced many researchers to measure the return to R&D for single or comparable industries. One example is Coad and Rao (2008) who estimate the return to R&D and focus their study on industries characterized by high patenting and large R&D expenditure.

Attention has also been devoted to the role of firm size to estimates of the return to R&D. One reason for a link between firm size and the return to R&D is that small and large firms often engage in different kinds of innovation. Large firms tend to engage in more process and incremental innovations relative to product R&D. Small firms, on the other hand, are associated with drastic innovations that are expected to generate rapid growth (Cohen and Klepper, 1996; Nightingale and Coad, 2014). According to Baumol (2004), engaging either in breakthrough product innovation or incremental and process innovation is seen as specialization. Small firms provide breakthrough inventions whereas large firms enhance these breakthroughs by improving their usefulness.[2]

It is often argued that there is a large firm advantage in R&D since many R&D projects involve substantial fixed set up costs (Geroski, 1995). However, empirical works show that the scale advantages to R&D are offset by lowered productivity in terms of product innovations. Even though larger firms devote proportionally more effort in R&D, they generate fewer innovations per dollar spent (Bound et al., 1984; Acs and Audretsch, 1991). This implies that there is no general advantage for large firms to realize their R&D expenses to commercial products. Moreover, Hall (2011) finds that the generally positive return to R&D is mainly due to product innovation whereas the impact of process innovation, that Baumol (2004) and Cohen and Klepper (1996) attributes to large firms, is more variable and often negative. Contrary to the evidence discussed above, Cohen and Klepper (1996) show that the return to R&D increase with firm size. This is explained by the fact that larger firms can spread costs over larger output quantities. In particular, the large firm advantage is more pronounced for process R&D relative product R&D (Cohen and Klepper, 1996; Baumol, 2004; Cohen, 2005). Hence, large and small firms complement each other by specializing in the innovative activity that yields the largest return for each type of firm. This joint contribution improves the innovation process beyond what either type of inventor may have been able to conceive alone (Baumol, 2004).

Finally, a number of recent studies have addressed that standard regression techniques may obfuscate the true importance of R&D and innovation. If the impact of R&D and innovation vary over the distribution of the dependent variable, standard regression techniques fail to capture the behavior of firms in the distribution tails (Coad and Rao, 2008). As a consequence, estimates of the return to R&D can result in misleading results. Among them, Coad and Rao (2008) address the highly skewed distribution of R&D expenditure. They measure innovation by both patent statistics and R&D expenditure to investigate its impact on sales growth by comparing estimation techniques based on average effects with quantile regression estimates. Hence, the idea is to explore the variance of the estimated return to R&D for different growth rates of sales. Their results imply that innovation is of great importance to sales growth for the fastest growing firms whereas estimates based on the mean effect of innovation tend to be

[2] Data collected by Acs and Audretsch (1990) shows that in 1982, the 85% of the identified innovations in an American sample of firms were improvements of existing products.

modest and often insignificant. Another recent paper that studies the effect of different aspects of R&D on firm performance in a quantile regression setting is Ebersberger et al. (2010). Analyzing the impact of R&D intensity on the share of innovative sales they find a positive effect of R&D intensity in the mid-section of the conditional distribution of innovative sales whereas R&D was subjected to decreasing returns in the distribution tails. Li and Hwang (2011) finds a significant and positive relationship between R&D expenditures and firm earnings among the companies with above average earnings. Falk (2012) studies the relationship between R&D intensity and firm growth and finds that the impact of R&D decreases with time. Furthermore, he finds that shrinking firms in the lower end of the distribution of firm growth do not benefit from investments in R&D whereas growing firms in the mid- and upper end of the growth distribution is positively affected by R&D intensity.[3]

Despite several attempts to better understand the drivers behind the variation in the return to R&D there is to our knowledge no study that has focused on the role of seller-buyer interactions. We therefore proceed to discuss and review existing literature on the role of seller-buyer interactions and its measures.

2.2 Relationship-specificity

In order to successfully turn R&D projects into commercial products, firms need awareness of technological possibilities and knowledge of the corresponding user needs. In this paper we assume that knowledge of consumer needs are transferred by seller-buyer interactions. A firm in a market characterized by frequent interactions between buyers and sellers will gain knowledge of buyer preferences and can manage its R&D activities according to its buyer's needs. Hence, we can expect a higher return to R&D for firms that frequently meet with its buyers.

Rauch (1999) analyzes trade in markets distinguished by high relationship-specificity defined by whether an input is sold on an organized exchange or not. If an input is sold on an exchange then the market for that input has many alternative buyers and sellers and does not require relationship-specific interactions. If a good is not sold on an exchange it may be reference priced in trade publications which indicates an intermediate level of market thickness. With the additional indicator of reference prices Nunn (2007) constructs an index so that for each final good, the index consists of the proportion of intermediate inputs that are relationship-specific.

[3] Other recent examples are Bartelsman et al. (2013); Bulut and Moschini (2009) and Coad and Rao (2006)

Thus, the index quantifies the seller need for personal interactions within each industry which enables us to employ the relationship-specificity index to analyze the importance of seller-buyer interactions to the return to R&D.

The relationship-specificity index (rs_j) can be expressed $rs_j = \sum_q \theta_{jq} I_q^{neither}$ where $\theta \equiv \frac{u_{jq}}{u_j}$ is the cost share and u_{jq} is the value of input q used in industry j; u_j is the total value of all inputs used in industry j. Hence, θ_{jq} is the cost-weighted production of input q in industry j. $I_q^{neither}$ is the proportion of input q that is neither sold on an organized exchange, nor reference priced. Hence, an input is relationship-specific if it is neither sold on an organized exchange market, nor reference priced. One can think of inputs sold on organized exchange markets as standardized products whose prices are defined by market value. A reference priced input is not sold on organized exchange market but associated with a standardized price. Thus, products with a reference price or prices established by organized exchange imply standardized products with many buyers. This means that the need for personal interactions is low, which in turn indicates low relationship-specificity. High relationship specificity is meanwhile present in industries characterized by highly differentiated products. In such markets there is a greater need for producers and consumers to customize products, and consequently a greater need for seller-buyer interactions (Nunn, 2007).[4]

Several recent studies employ the relationship-specificity index for a variety of uses. Altomonte and Bekes (2009) studies the impact of trade complexity, measured by the relationship-specificity index, on productivity; Kukenova and Strieborny (2009) interacts the index with banking development to quantify the importance of banking development for industries dependent on relationship-specific investments. Casaburi and Gattai (2009) and Ferguson and Formai (2011) use the index as a measure of contractual institutions. Tingvall and Poldahl (2012) analyze how relationship-specificity affects technology spillovers transferred by trade. They find that a firm enhances technological transfers if it is engaged in markets characterized by a high degree of seller-buyer interactions.

We suggest that large firms have an advantage in seller-buyer intensive industries driven by the capacity advantage spread the costs of seller-buyer interactions over a large output quantity. Furthermore, large firms tend to engage in incremental and usability innovation (Baumol, 2004)

[4] An example of a product in an industry where the RS-index scores low is fuel. An example of a high scoring industry classification is motor vehicles that often, as opposed to fuel, requires tailoring and client meetings.

in where we assume the knowledge gain of seller-buyer interactions to be more important than other types of innovation activities. It is also plausible that productive firms exhibit a relatively high return to R&D in markets distinguished by intense seller-buyer interactions. Melitz (2003) finds that only the most productive firms are able to overcome costs associated with export market entry. Moreover, he finds that further exposure to trade induces a reallocation of market shares to the most productive firms. Similarly, we anticipate a potential productivity threshold necessary to overcome the administrative costs of seller-buyer interactions and to successfully manage the attributed knowledge transfers. Hence, we argue that large and productive firms are more successful in their R&D ventures with respect to the degree of seller-buyer interactions. Small and low productive firms are to a lesser extent able to manage seller-buyer interactions as the related cost may exceed the knowledge gain attributed to frequent meetings with clients. This suggests a disadvantage of low productive and small firms relative large and productive firms in industries characterized by a high degree of seller-buyer interactions.

In this paper we stipulate a positive relationship between seller-buyer interactions and the return to R&D. This relationship is first explored with respect to firm size and secondly with respect to productivity.

3 Econometric Specification

To analyze the return to R&D we depart from the framework suggested by Griliches (1979). Using a production function based approach, sales or value added to employment is related to physical capital and knowledge capital (R&D). The knowledge augmented production function takes the following form,

$$Y = A(L, K, R) \tag{1}$$

where Y is value added, A is technical progress, L is labor, K is capital and R is knowledge capital. To analyze how the return to R&D varies with respect to the degree of seller-buyer interactions we augment (1) by including human capital, H_{ijt}, and introducing the variable of interest, the RS-index which is denoted RS_j. To capture the interaction between R&D and the RS-index we append the interaction term, $r_{ijt} \cdot RS_j$. Taking logarithms[5], the target equation can be formulated as:

[5] For brevity, we define logarithms as lower case letters.

$$va_{ijt} = \beta_1 r_{ijt} + \beta_2 r_{ijt} \cdot RS_j + \beta_3 l_{ijt} + \beta_4 k_{ijt} + \beta_5 H_{ijt} + \mu_i + \zeta_j + \delta_t + u_{ijt} \qquad (2)$$

where r_{ijt} is log of the R&D stock in firm *i*, industry *j* and year *t*, RS_j is the industry specific RS-index, $r_{ijt} \cdot RS_j$ is the variable of interest capturing the interaction between R&D and relationship specificity. A positive sign of the interaction variable implies that the returns to R&D become larger if the higher the relationship-specificity is higher. The variables l_{ijt} and k_{ijt} is the log of employment and the log of capital stock respectively. H_{ijt} is human capital intensity measured as the share of skilled employees and added as a control variable assuming higher skilled staff contributes to output. Finally, μ_i is the firm fixed effects and u_{ijt} is the residual error term. Following Hall et al. (2009) the log of technical progress (A) is assumed to be captured by the sum of industry-specific effects, ζ_j, and the time effect, δ_t.

Another modeling strategy to analyze the return to R&D is to depart from total factor productivity (TFP). As an extension to the value added based analysis, we will in a productivity analysis set-up analyze the return to R&D. Here we build on Griffith et al. (2004) who depart from the production technology and model firm productivity as a function of the relative size of the R&D stock and a set of shift factors capturing residual influence. Contrary to Griffith et al. (2004) who study productivity growth, we focus on how the return to R&D vary with respect to the degree of seller-buyer interactions. Hence, we also estimate the following productivity model:

$$a_{ijt} = \beta_1 r_{ijt} \cdot RS_j + \beta_2 r_{ijt} + \beta_3 H_{ijt} + \mu_i + \zeta_j + \delta_t + u_{ijt}, \qquad (3)$$

where a_{ijt} is the log of productivity captured by the Levinsohn and Petrin (2003) productivity index, r_{ijt} is the relative size of the R&D stock, and $r_{ijt} \cdot RS_j$ is the variable of interest capturing the interaction between R&D and relationship specificity.

To analyze this relationship, a quantile regression approach fits our needs well since it offers us a way to model the heterogeneous response from R&D. First, because it allows us to investigate the extreme values rather than relying on Gaussian statistics. Secondly, because it reveals differences in the relationship between exogenous variables and the dependent variable at different points in the conditional distribution of the dependent variable (Koenker and Bassett, 1978). Furthermore, the impact of R&D is likely to vary over the distribution of firm size and productivity.

Recent developments allow for estimation of quantile regression models and at the same time controlling for unobserved heterogeneity, labeled fixed effect quantile regression. As suggested by Canay (2011), the employment a simple two-step estimator enables both the inclusion of fixed effects and a varying slope along the dependent variables conditional probability distribution. This approach departs from a simple data transformation under the assumption that the fixed effects are constant across all quantiles. Following Canay (2011) we employ a fixed effects regression at the conditional mean and derive estimates of the individual fixed effects, $\hat{\mu}_i = \frac{\sum_{t-1}^{T}(Y_{it} - x'_{it}\hat{\beta}_{\mu})}{T}$, where $\hat{\mu}_i$ are the fixed effects, x_{it}, represents the explanatory variables, $\hat{\beta}_{\mu}$ are the estimated parameters from the conditional mean regression, and Y_{it} is the dependent variable. In the second step, the fixed effects are subtracted from the dependent variable, $\hat{Y}_{it} \equiv Y_{it} - \hat{\mu}_i$. Using the transformed dependent variable we then proceed to estimate our models.

Specifically, applying the fixed effect transformations, the dependent variable in equation (1) becomes $\widehat{va}_{ijt} \equiv va_{ijt} - \hat{\mu}_i$ and the dependent variable in (2) becomes $\hat{a}_{ijt} \equiv a_{ijt} - \hat{\mu}_i$ where $\hat{\mu}_i$ is the estimated firm level fixed effects derived from a fixed effect estimation of (1) and (2) respectively. Using the transformed dependent variable we then proceed to estimate our models using quantile regression techniques and analyze how the return to R&D vary with respect to the degree of seller-buyer interactions over firm size and productivity respectively. Along with the quantile regression setting we are able to explore systematic differences of firms with varying intensity of personal interactions with their clients.

Finally, we consider the time delay from R&D expenditure to innovation and corresponding commercialization. A common procedure to handle such dynamics is to use lagged values of R&D (Hall et al., 2009). As the R&D stock is constructed by assuming accumulation of knowledge over time, past levels of R&D are to an extent accounted for. However, since lagged values of R&D stock rather than the latest addition to the R&D stock may be more important to the estimated return, we also account for a lag analysis for all our specifications.

4 Data, variables and description

Data is acquired from *Statistics Sweden* and originates from a number of register based data sets. The financial statistics (FS) includes firm level information for all Swedish firms, data on R&D expenditures is restricted to include firms with 50 employees or more in the manufacturing sector.[6] In total, there are 3,082 firms and 16,874 observations for the period 1997-2005.

The data is cleansed for influential outliers following data cleansing procedures presented in the literature on firm level analysis of R&D. Following Hall and Mairesse (1995) we drop some of the observations that are likely due to merger and acquisitions, i.e firms with employment growth, capital growth and R&D capital growth in excess of 200% or below -50%. This removed 480 observations. Moreover, we drop observations with a value added growth or sales growth above 300% or below -90%. In total this removed 219 observations. Furthermore, we analyze firms with sustained R&D expenditures. We follow Aldieri et al. (2008) and Kalayci (2013) who drop firms with a R&D intensity (R&D expenditure to sales ratio) of less than 0.2 % and above 50%. This removed an additional 65 observations. Finally, 101 negative observations of value added was removed. In total 865 (5 percent) observations were removed. The remaining data set is an unbalanced panel of 16,009 observations for 3,046 firms in the manufacturing sector. Since we restrict our attention to only firms with R&D expenditures, this reduces the number of observations to 7,892. Table 1 shows the variable description of R&D active firms after cleansing.

Table 1: Descriptive Statistics for R&D Performing Firms

VAR	Mean	Obs	Min	Max
va_{it}	11.46	7,891	7.64	17.07
	(1.20)			
a_{it}	7.32	7,790	1.69	13.42
	(.80)			
r_{it}	9.67	7,927	5.28	18.32
	(2.10)			
H_{it}	.06	7,892	0	.72
	(.07)			
k_{it}	10.65	7,867	4.03	16.61
	(1.60)			
l_{it}	5.23	7,892	3.91	9.89
	(1.03)			

Note: Only firms with positive R&D expenses are included. Lower case letters denote logarithm form. Standard errors in parenthesis.

[6] This data restriction does not change the fact that small firm innovative activity is difficult to measure in terms of R&D expenditures. Cardoso and Teixeira (2009) argues that small firms tend to carry out R&D activities in a less organized way meaning that the innovative activity in small firms may not be reported separate from other expenditures.

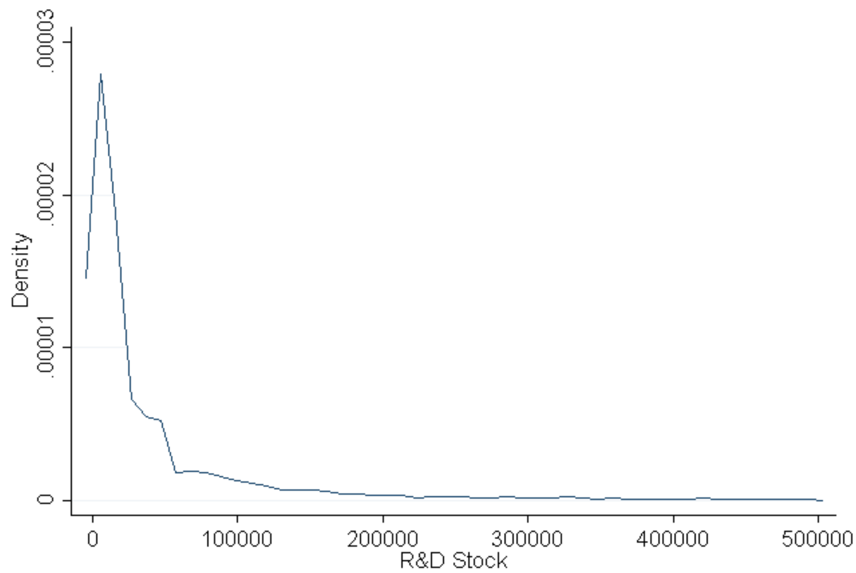
Descriptive statistics for the variables used in the empirical analysis are available in Table 1. va_{ijt} is the log of firm level value added and defined as gross output less purchased inputs, such as materials. a_{ijt} is the log of total factor productivity. It is estimated using a technique that builds on Levinsohn and Petrin (2003) which in turn builds on Olley and Pakes (1996). Levinsohn and Petrin's estimator utilizes intermediate inputs, such as energy and materials, to proxy the for the unobservable productivity term. Hence, the estimator accounts for the correlation between input levels and productivity which enables consistent estimates (Petrin and Poi, 2004). More specifically, TFP is calculated as the residual of a panel estimation of a standard production function at the industry level. The maximum value of productivity is almost eight times as high as the minimum value indicating relatively large differences between the least and most productive firms.

A common procedure to measure R&D activity within a firm by acknowledging that both past R&D and simultaneous R&D expenditure within a firm constitute a knowledge stock, commonly known as the R&D stock. We have chosen to construct the R&D stock using observations of R&D expenditure from the *Financial Statistics* (FS) over the years 1997-2002. To prolong the time period, FS is completed with the remaining years from a different data set, the R&D statistics (RS), which is collected on biannual basis and only include firms with R&D expenses of more than 5 million SEK. The year 2004 is linearly interpolated by the mean value of R&D expenditure between 2003 and 2005. We have to assume an initial stock value which we construct in line in accordance with the perpetual inventory method, defined by $r_{ij,1997} = \frac{R\&D_{ij0}}{\varepsilon+g_i}$ where g_i is the growth rate of the R&D stock measured by the average growth rate of R&D expenditures over the whole period, which is about 2 %. As the precise depreciation of R&D knowledge is unknown, we can only assume a depreciation rate, ε. Hall et al. (2009) argue that the depreciation rate falls within the range of 8% to 25% annually.[7] In this paper we have chosen to adapt the standard procedure which is to assume a depreciation rate of 15% (Hall et al., 2009). Subsequent values of the R&D stock is calculated by yearly accumulation of R&D expenditures and a related knowledge depreciation, $r_{ijt} = (1-\varepsilon)r_{ijt-1} + R\&D_{ijt}$, where $R\&D_{it}$ is expenditure, r_{it} is R&D stock.

[7] In all estimations in this paper the depreciation rate of R&D stock is set at 15%. Using depreciation rates of the R&D stock at 8%, 10%, 25% and 30% made little difference to the estimates.

As can be seen in Figure 1, the R&D stock is concentrated to a small number of firms[8]. The log of R&D stock, r_{it}, reports a relatively large standard deviation and differs dramatically between its minimum and maximum value. This variance is not unexpected keeping in mind that R&D activities can vary a great deal between industries and firms.

Figure 1: Kernel Distribution of R&D Stock



H_{ijt} is the firm share of skilled labour with an attributed mean at .06 which is low relative the maximum value at .72. Finally k_{ijt} and l_{ijt} are the logs of capital stock and labour respectively. Each of the variables capital, labour along with value added gives us an idea of the firm size distribution. From the reported values, the firm size distribution of R&D active firms appears relatively balanced in where the mean values appears not to lean heavily to either the maximum or minimum values.

The relationship-specificity index theoretically ranges from 0 to 1. Nunn (2007) base the index according to three digit ISIC[9] rev.2, accounting for a variation of twenty different types of industries. Ferguson and Formai (2011), followed by Tingvall and Poldahl (2012), translated the relationship specificity index into the Swedish industry classification system with two digits which corresponds to 22 different types of manufacturing industries.

[8] Approximately 75 percent of total R&D expenditures are concentrated to ten firms only.
[9] International Standard Industrial Classification of All Economic Activities

Table 2: Relationship-Specificity, Value Added and R&D stock

SNI2	Industry	RS
15	Food and beverage	0.71
16	Tobacco	0.32
17	Textiles	0.38
18	Leather	0.75
19	Tannery	0.65
20	Wood	0.52
21	Paper	0.35
22	Publishing	0.71
23	Mineral coal, Refined Petroleum and Nuclear fuel	0.06
24	Chemicals	0.24
25	Rubber and Plastic	0.41
26	Non-metallic and Minerals	0.38
27	Steel and Metal manufacturing	0.16
28	Metal products	0.76
29	Machinery and equipment	0.76
30	Computers and Office Machines	0.78
31	Electrical machinery	0.74
32	Radio, TV and comm. eq.	0.74
33	Precision, medical and optical instr.	0.78
34	Motor vehicles and Trailers	0.86
35	Other Transports	0.86
36	Furniture, other	0.55
Avg		0.57

Note: Each two-digit industry industry classification is reported with related index value of relationship-specificity.

As shown in Table 2, motor vehicles and other transports has the highest relationship-specificity, at .86, whereas mineral coal, refined petroleum and nuclear fuel category has the lowest, at .05. In order to accomplish a more detailed classification, we have also translated the index into four digit industry classification.[10]

[10] ISIC rev.2 is not directly correspondent to the Swedish industry classification system, so the data had to be translated in three steps. First, we re-categorized the ISIC rev.2 into ISIC rev.3, the latter consisting of several subgroups for each value of ISIC rev.2. As there were unique industry codes appearing in several subgroups we collapsed the data into means if that particular subgroup had different relationships specificity index values. Finally, ISIC rev.3 was translated into NACE which is directly correspondent of the four digit Swedish industry classification system.

5 Results

In this section we present results on the impact of seller-buyer interactions to the return to R&D using the two models presented above. Model 1 is derived from equation 2 in where we explore the impact of seller-buyer interactions to the return to R&D over firm size which we measure by point estimates of the conditional distribution of value added. Low and high points in the distribution defines small and large firms, respectively. Model 2 is estimated according to equation 3, where the Levinsohn and Petrin (2003) productivity index is the dependent variable. Hence, the coefficients can be interpreted as the change of the conditional quantile of the dependent variable with respect due to a marginal change in a particular regressor (Yasar et al., 2006).

5.1 Model 1: Value added, the return to R&D and relationship-specificity

Table 3 reports the results from estimating the return to R&D on firm's value added (Model 1), as suggested by Griliches (1979). The variable of interest is the interaction term between the R&D stock and the relationship-specificity index ($r_{ijt} \cdot RS_j$). The direct effects of the interaction terms are captured by the R&D stock and the industry dummies respectively. In Table 3 we analyze how the direct impact of R&D and the interaction effect between R&D and seller-buyer interactions vary as we move along the size distribution of firms (along the distribution of value added).

Results in Table 3 reveal a series of interesting observations. First, the interaction term goes from insignificant to positive and strongly significant as we move from small to large firms. This suggests a large firm advantage in RS-intensive industries. Specifically, the interaction term goes from -0.082 to 0.066 as we move from the 1st to the 99th percentile in the size distribution. Secondly, not only the interaction effect is increasing with firm size, so is the main effect of R&D. The corresponding increase for the direct effect of R&D goes from an insignificant value of -0.679 in the 1st percentile to a positive and significant values of 0.513 in the 99th percentile.

Hence, the quantile regression approach show that the impact of the R&D coefficients are larger in large firms (at higher quantiles of value added). As a reference point we also show a fixed effect estimation in the far right column reporting the effect for the average firm at a single point in the size distribution. As can be seen the values of both the direct effect and the interaction term are insignificant and small. Hence, evaluated at the average sized firm, the impact of seller-buyer interactions to the return to R&D appears to have a small effect.

As for the controls, the variables l_{ijt} and k_{ijt} come with expected signs at all points along the distribution. The sign of firm skill intensity, H_{ijt}, is with the exception of the 99th percentile, significant and negative which means that an increase in the share of skilled labour is associated with a negative impact to value added. One reason for this perhaps surprising outcome, may be the fundamental difference between large and small firms in how R&D is practiced. Established and organized R&D activities within a firm are more likely to be attributed to large firms. In such settings, a large share of high skilled workers will generate more value to the firm. In a small firm R&D activities are often less formal (Baumol, 2004), where the cost of high skilled labour may exceed its benefits.

Table 3: Model 1, Value Added

	Value Added Quantiles					
VAR	0.01	0.25	0.5	0.75	0.99	FE
$r_{ijt} \cdot RS_j$	-0.082	-0.007	0.012**	0.015**	0.066***	0.009
	(-0.056)	(-0.007)	(-0.005)	(-0.006)	(-0.020)	(-0.031)
r_{ijt}	-0.679	-0.048	0.091**	0.121**	0.513***	0.064
	(-0.441)	(-0.058)	(-0.039)	(-0.05)	(-0.159)	(-0.245)
H_{ijt}	-3.164***	-0.155***	-0.357***	-0.147*	0.983***	-0.396
	(-0.318)	(-0.047)	(-0.036)	(-0.078)	(-0.219)	(-0.322)
l_{ijt}	0.855***	0.825***	0.821***	0.810***	0.835***	0.824***
	(-0.045)	(-0.006)	(-0.004)	(-0.005)	(-0.019)	(-0.039)
k_{ijt}	0.0275	0.0133***	0.0384***	0.0438***	0.0418***	0.0381**
	(-0.027)	(-0.003)	(-0.002)	(-0.003)	(-0.01)	(-0.017)
Obs	7,867	7,867	7,867	7,867	7,867	7,867

Note: Estimates are calculated according to equation 2, using fixed effect quantile regression. Dependent variable is $\widehat{va}_{ijt}$, control variables not included in this table are time- and industry dummies. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

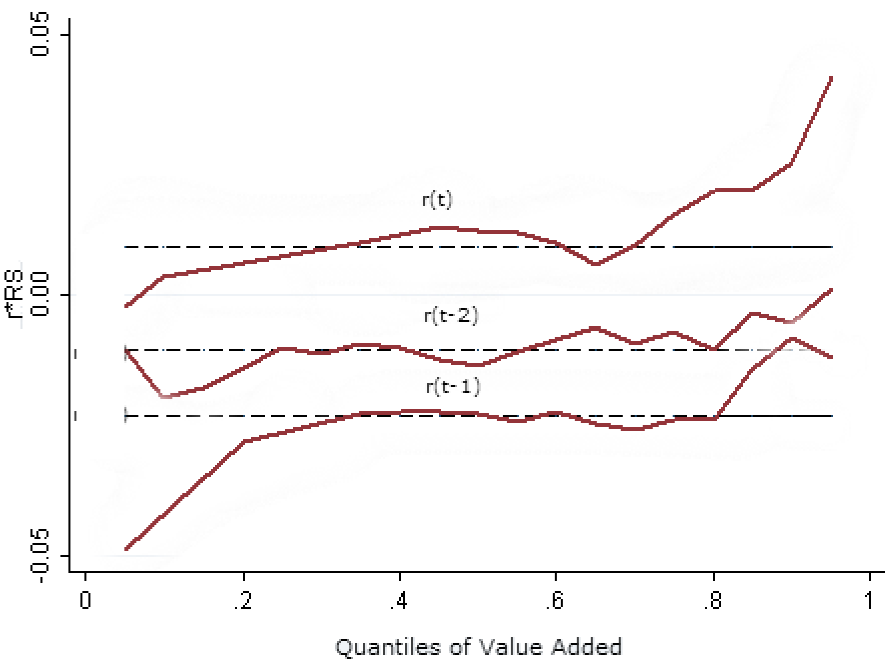
Investments in R&D may come with time lags before successfully incorporated into a commercialized innovation. As previously discussed, r_{ijt} is the R&D stock which by construction contains information of past levels of expenditure. However, without employing lags we may over emphasize the importance of the latest addition of R&D expenditure. In Table 4 we proceed to analyze the stability of the results in Table 3 by using one and two year lagged values of the R&D stock. Using one or two year lagged values of R&D stock does not upset the main findings in Table 3. As seen in Table 4, the positive relation between the interaction term and firm size is maintained. Both the direct effect of R&D and the interaction effect between R&D stock and relationship-specificity increase with firm size. However, the absolute value of the direct effect of R&D as well as the interaction term, are shifted downward.

Table 4: Lag analysis of Model 1, Value Added

	Value Added Quantiles					
VAR	0.01	0.25	0.5	0.75	0.99	FE
$r_{ijt-1} \cdot RS_j$	-0.07	-0.023***	-0.023***	-0.024***	0.036*	-0.022
	(-0.046)	(-0.007)	(-0.005)	(-0.007)	(-0.02)	(-0.031)
r_{ijt-1}	-0.588*	-0.187***	-0.179***	-0.179***	0.285*	-0.172
	(-0.357)	(-0.054)	(-0.037)	(-0.052)	(-0.151)	(-0.24)
Obs	6,316	6,316	6,316	6,316	6,316	6,316
$r_{ijt-2} \cdot RS_j$	-0.092*	-0.01	-0.014***	-0.007	0.062***	-0.01
	(-0.055)	(-0.007)	(-0.005)	(-0.006)	(-0.022)	(-0.046)
r_{ijt-2}	-0.739*	-0.075	-0.095**	-0.037	0.502***	-0.073
	(-0.43)	(-0.058)	(-0.037)	(-0.0507)	(-0.173)	(-0.362)
Obs	5,195	5,195	5,195	5,195	5,195	5,195

Note: Estimates are calculated according to equation 2, using fixed effect quantile regression. R&D stock is lagged one year in the upper block and lagged two years in the lower block. Dependent variable is $\widehat{va}_{ijt}$, control variables not shown are k_{ijt}, l_{ijt}, H_{ijt} , time- and industry dummies. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Figure 2: Quantile Plots of Model 1, Value Add



Note: The estimated coefficient $r_{ijt} \cdot RS_j$ is shown along the y-axis. The x-axis represents the conditional quantiles of the left hand side variable $\widehat{va}_{ijt}$. Results for three different lag lengths of r_{ijt-n} denoted r(t-n). Horizontal dashed lines represents the OLS estimate for each lag length.

To illustrate how the interaction between R&D stock and relationship-specificity vary across the size distribution of firms (value added) Figure 2 depicts the pattern found in Tables 3 and 4. Figure 2 depicts the variation of the impact of the interaction variable over firm size measured by the conditional distribution of value added. Hence, low points in the distribution of value added defines small firms whereas the corresponding high points define large firms. Figure 2 clearly illustrates the downward shift caused by employing lags, and that the positive relation with respect to relationship-specificity and firm size is maintained, throughout all lag specifications.

A plausible interpretation of the downward shift when introducing lagged R&D stocks in our estimations is found in Hall and Mairesse (1995). They find an upward bias for contemporaneous values of R&D intensity arising from a potential simultaneity between output level and unobservable information. For the lagged values of R&D stock in Figure 2 the impact of relationship-specificity to the estimated return appears negative at some points in the distribution, but increases with firm size. The negative returns to R&D might seem counterintuitive at first. However, as pointed out by Coad and Rao (2008), R&D activities are associated with high risk and may therefore fail to generate returns to the firm if their innovation efforts fail. A firm that invests in R&D but fails to develop a commercially viable innovation will be worse off than a comparable firm without R&D expenditures.

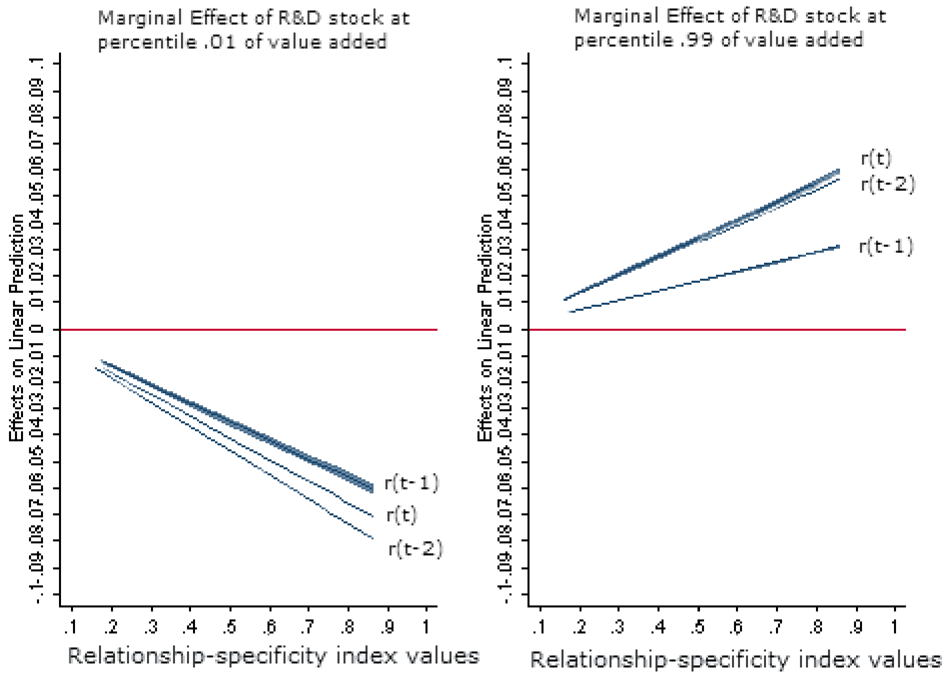
Nevertheless, results imply that larger firm size imparts a relative advantage to the return to R&D. To illustrate how the marginal effect of R&D varies with the degree of relationship-specificity and firm size we in Figure 3 depict this relation for three different lag structures with respect to the smallest (1st percentile) and largest firms (99th percentile) in the distribution. As can be seen, the impact of relationship-specificity on the return to R&D is significantly different when comparing the largest of firms with the smallest ones. The return to R&D in small firms are negatively affected for increasing relationship-specificity index values whereas large firms R&D outcomes are larger the higher the index value.[11]

Hence, large firm R&D activities are enhanced by the increased knowledge of consumer preferences enabled by seller-buyer interactions. We find two interpretations of the apparent large firm superiority in managing seller-buyer interactions into increased return to R&D. First, large firms are generally involved in incremental innovation (Cohen and Klepper, 1996; Cohen, 1995) and tend to engage in improvements of existing products rather than inventing new and

[11] Apart from the tails of the distribution, we also calculated the marginal effect of R&D over relationship-specificity at other points in the distribution. Here, the impact of relationship-specificity was less clear and often produce mixed results for different lag lengths of R&D stock.

game-changing innovations (Baumol, 2004). It is likely that knowledge of buyer needs is more important to the innovation process of improving products in where large firms tend to be overrepresented. For instance, innovative efforts to improve the usability of a product requires firms to understand what type of improvements that consumers will appreciate. Frequent seller-buyer interactions induces firms to learn about their buyers and can allocate their innovation strategies according to this knowledge. Secondly, large firms are able to manage the costs of managing client interactions by the capacity to spread costs over quantity. Small firms are disadvantaged by seller-buyer interactions for the same reasons. First, small firms engage in less formal R&D environments and are overrepresented in the development of new products. Secondly, small firms less able to spread costs over quantity. Hence, for small firms the cost of seller-buyer interactions may often exceed the knowledge advantage related to firm interactions with buyers.

Figure 3: Marginal Effect of R&D stock on value added over Relationship-Specificity



Note: This figure illustrates the marginal effect of R&D on the left hand side variable $\widehat{va}_{ijt}$ from the regressions in Table 3 and 4. The x-axis represent the index value of relationship-specificity and the y-axis is the marginal effect of R&D. I calculate the marginal effect of R&D stock for three lag lengths denoted r(t-n). The left panel displays the marginal effect of percentile .01 and the right panel shows corresponding effect for percentile .99.

5.2 Model 2: Productivity, the Return to R&D and Relationship-specificity

In this section we use firm productivity as dependent variable to explore the impact of relationship-specificity on the returns to R&D at different levels of productivity. According to the heterogeneous firm model (Melitz, 2003) productive firms are better equipped than low productive firms to handle costs associated with export entry. Similar to export entry, handling seller-buyer interactions is costly to the firm, it can therefore be assumed that highly productive firms have an edge over low productive firms in RS-intensive industries. Since seller-buyer interactions allow the seller to adjust the R&D and product development according to the preferences of the buyers this suggests a positive relation between the return to R&D with respect to productivity and the RS-index. We begin by estimating equation 3 in Table 5 where contemporaneous values of R&D stock is used.

Table 5: Model 2, Productivity

	Total Factor Productivity Quantiles					
VAR	0.01	0.25	0.5	0.75	0.99	FE
$r_{ijt} \cdot RS_j$	-0,0216	0.0500***	0.0536***	0.0492***	0.130***	0.0498
	(-0.038)	(-0.007)	(-0.005)	(-0.007)	(-0.023)	(-0.049)
r_{ijt}	-0.189	0.389***	0.420***	0.387***	1.044***	0.39
	(-0.303)	(-0.054)	(-0.043)	(-0.055)	(-0.178)	(-0.381)
H_{ijt}	-3.312***	-0.643***	-0.464***	-0.135**	0.292	-0.51
	(-0.474)	(-0.073)	(-0.045)	(-0.058)	(-0.224)	(-0.388)
Obs	7,790	7,790	7,790	7,790	7,790	7,790

Note: Estimates are calculated according to equation 3, using fixed effect quantile regression. Dependent variable is $\hat{a}_{ijt}$, control variables not shown are time- and industry dummies. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Using productivity as the dependent variable the results in Table 5 suggests that high productivity firms both have a higher direct return to R&D and a larger indirect effect stemming from the degree of relationship-specificity. Hence, we find that the direct effect of R&D and the interaction effect both are increasing with productivity, suggesting a non-uniform advantage for highly productive firms. From the 25^{th} to the 99^{th} percentile both the interaction effect and the direct effect more than doubles. This implies that seller-buyer interactions have a positive impact to the estimated return to R&D for firms with high levels of productivity.

The fixed effects estimation in the far right column of Table 5 represents the least square results with within transformation firm effect. As can be seen, on average the impact of seller-buyer interactions to the return to R&D produce modest results. Comparing with the quantile regression estimates the results indicates that the impact of seller-buyer interactions has an asymmetric effect on the return to R&D in terms of productivity which is not captured by estimates based on plain averages.

Similar to the results from model 1, the share of skilled workers (H_{ijt}) comes with a negative sign but is increasingly less negative along the distribution of productivity. One plausible interpretation is that a large share of high skilled workers is of little use in a firm associated with low productivity. For the most productive firms, at the 99th percentile, the cost of high skilled workers are less pronounced relative the skill gain of such workers.

Table 6 is a lag analysis of model 2 where we employ lagged levels of R&D stock intensity to analyze the stability of the results in Table 5. As can be seen, the positive three-way relationship between relationship-specificity, R&D and productivity is maintained when R&D stock intensity is lagged.

Table 6: Lag Analysis of Model 2, Productivity

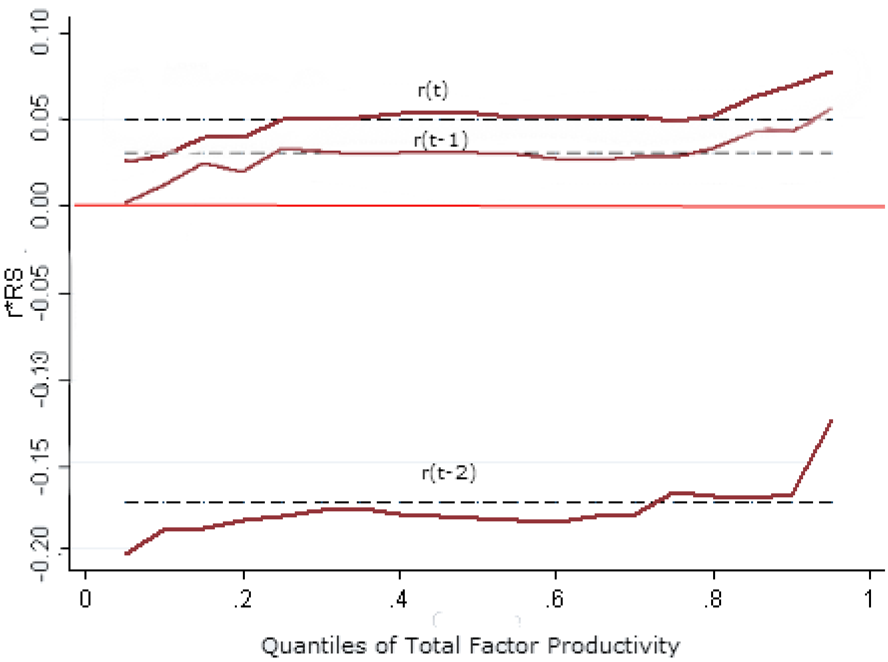
	Total Factor Productivity Quantiles					
VAR	0.01	0.25	0.5	0.75	0.99	FE
$r_{ijt-1} \cdot RS_j$	-0,0333	0.0332***	-0.170***	0.0284***	0.0879**	0,031
	-(0.071)	(-0.007)	(-0,028)	(-0,007)	(-0,037)	(-0,055)
r_{ijt-1}	-0.285	0.255***	-1.391***	0.223***	0.706**	0,241
	(-0.548)	(-0,054)	(-0,217)	(-0,054)	(-0,282)	(-0,428)
Obs	6,268	6,268	6,268	6,268	6,268	,6268
$r_{ijt-2} \cdot RS_j$	-0.219***	-0.181***	-0.182***	-0.167***	-0.058***	-0,032
	(-0.056)	(-0.009)	(-0.006)	(-0.007)	(-0.020)	(-0.049)
r_{ijt-2}	-1.719***	-1.412***	-1.418***	-1.298***	-0.436***	-0,239
	(-0.446)	(-0.069)	(-0.045)	(-0.058)	(-0.152)	(-0.384)
Obs	5,158	5,158	5,158	5,158	5,158	5,158

Note: Estimates are calculated according to equation 3, using fixed effect quantile regression. R&D stock is lagged one year in the upper block and lagged two years in the lower block. Dependent variable is $\hat{a}_{ijt}$, control variables not shown in this table are H_{ijt}, time- and industry dummies. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

As previously explained, the downward shift seen here can be explained by a simultaneity bias occurring for contemporaneous values of R&D stock resulting from choices within firms that we are unable to control for. However, our concern here is primarily the evolution of the impact of seller-buyer interactions as we move along the level of productivity.

Figure 4 depicts quantile plots of the impact variation of the interaction term stemming from the regression analysis in Tables 5 and 6. Figure 4 visualizes both the downward shift that occurs when we lag the R&D stock and the positive relation between the return to R&D, firm productivity and the RS-index. The average effect is visualized by dashed lines for each lag length. As can be seen, the middle range of the distribution resembles the average effect for contemporaneous values of R&D stock. However, applying lags to the R&D stock magnify the impact variance of the interaction term along the distribution of productivity.

Figure 4: Quantile Plots of the impact of the interaction between firmn R&D stock and the RS-index for different values of firm productivity

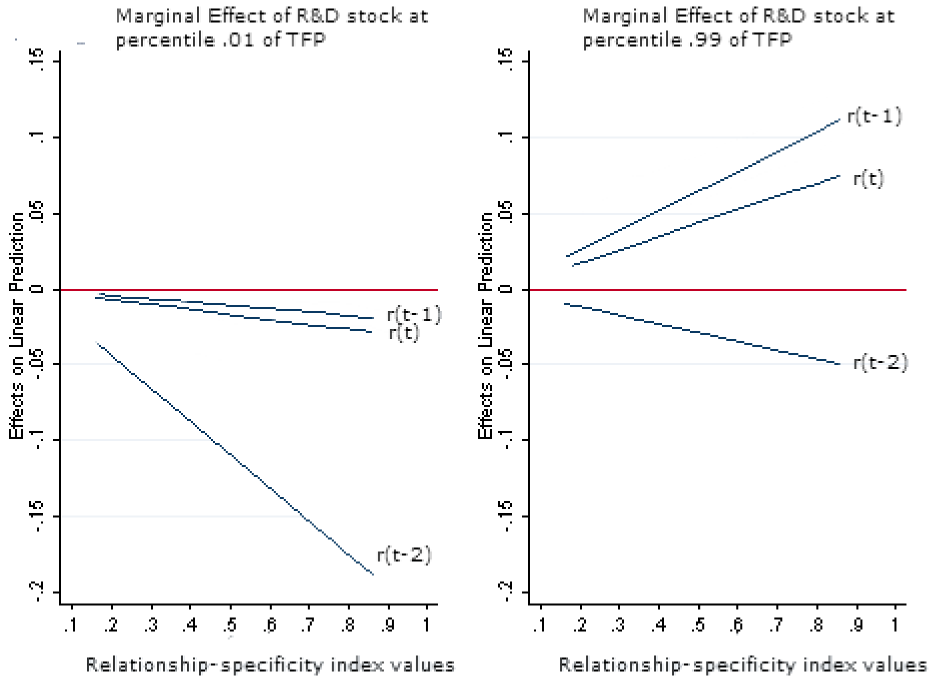


Note: The impact variation of the coefficient $r_{ijt} \cdot RS_j$ is shown along the y-axis. The x-axis represents the conditional quantiles of the left hand side variable $\hat{a}_{ijt}$. Results for three different lag lengths of are included and represented by r_{ijt-n}. Horizontal dashed lines represents the OLS estimate for each lag length.

Despite the sensibility to the employment of lags, Figure 4 visualizes a seemingly asymmetric effect in the higher end of the productivity distribution tails for all employed lag lengths. The impact variance along the middle range of the productivity distribution is less clear cut.

To furthermore investigate what this apparent productive firm advantage to seller-buyer interactions, we proceed to Figure 5 where we depict the marginal effect of R&D with respect to relationship-specificity and productivity in the distribution tails. As can be seen, higher index values of the relationship-specificity index implies a negative marginal effect of R&D for less productive firms whereas the marginal effect of R&D for highly productive firms are generally enhanced by higher index values. The exception is under the employment of a two year lag to the R&D stock where a negative marginal effect of R&D stock is apparent for both low and highly productive firms, although less negative for large firms.

Figure 5: Marginal Effect of R&D stock on Productivity for Different Values of the RS-index.



Note: This figure illustrates the marginal effect of R&D stock on the left hand side variable $\hat{a}_{ijt}$ from the regressions in Table 5 and 6. The x-axis represent the index value of relationship-specificity and the y-axis is the marginal effect of R&D stock. I calculate the marginal effect of R&D stock for three lag lengths denoted a) no lag, b) one year lag and c) two year lags. The left panel displays the marginal effect of percentile .01 and the right panel shows corresponding effect for percentile .99.

To sum up, we have found indications of a positive three-way relationship between the return to R&D, relationship-specificity and productivity.

5.3 Robustness

As a robustness check we employ the relationship-specificity index defined by four digit industry codes. This enables a finer detail to the RS-index than previous estimations. However, we lose some accuracy to the related relationship-specificity index attributed to some industries as we were forced to merge some industry classification codes that were not directly comparable.

Results reported in Table 7, applying the relationship-specificity index at this lower level of aggregation does not upset the previous results of model 1. That is, the return to R&D increases with respect to relationship-specificity, and for any level of relationship-specificity, large and productive firms tend to have a higher return to R&D.

Table 7: Fixed effects quantile regressions, the RS-index identified at the four digit level. Dependent variable, firm value added

	Quantiles of Value Added					
VAR	0.01	0.25	0.5	0.75	0.99	FE
$r_{ijt} \cdot RS_j$	-0.034	0.005	0.035***	0.050***	0.127***	0.026
	(-0.028)	(-0.009)	(-0.008)	(-0.01)	(-0.017)	(-0.050)
r_{ijt}	-0.054***	-0.009***	-0.005***	-0.002	0.010***	-0.007
	(-0.01)	(-0.002)	(-0.002)	(-0.002)	(-0.004)	(-0.01)
Obs	7,725	7,725	7,725	7,725	7,725	7,725
$r_{ijt-1} \cdot RS_j$	-0.135***	-0.051***	-0.029***	-0.015	0.033	-0.034
	(-0.025)	(-0.011)	(-0.008)	(-0.011)	(-0.025)	(-0.062)
r_{ijt-1}	-0.029***	-0.004	0.003	0.008***	0.012**	0.0005
	(-0.007)	(-0.002)	(-0.002)	(-0.002)	(-0.005)	(-0.014)
Obs	6,194	6,194	6,194	6,194	6,194	6,194
$r_{ijt-2} \cdot RS_j$	-0.160***	-0.070***	-0.052***	-0.042***	0.013	-0.054
	(-0.023)	(-0.013)	(-0.008)	(-0.014)	(-0.024)	(-0.076)
r_{ijt-2}	-0.019***	0.010***	0.014***	0.020***	0.015***	0.012
	(-0.006)	(-0.002)	(-0.002)	(-0.002)	(-0.004)	(-0.014)
Obs	5,085	5,085	5,085	5,085	5,085	5,085

Note: In this table relationship-specificity is defined according to a four digit industry class. Estimates are calculated according to equation 2, using fixed effect quantile regression. In the upper block, contemporaneous values of R&D stock is used. In the lower blocks R&D stock is lagged with one and two years respectively. Dependent variable is $\widehat{va}_{ijt}$, control variables not shown in this table are k_{ijt}, l_{ijt}, H_{ijt} , time- and industry dummies. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

In Table 8 we proceed to estimate the productivity based model (model 2) using the alternate RS-index based on four digit industry classification. For contemporaneous values of R&D stock the interaction term goes from negative and insignificant at low points in the TFP distribution to positive and significant at the higher end of the TFP distribution.

The inclusion of lagged levels of R&D stock causes a downward shift in the R&D variables as before. The impact variation along the productivity distribution is maintained in direction in where the impact of seller-buyer interactions to the return to R&D is higher (or less negative) for more productive firms.

Table 8: Fixed effect quantile regressions, the RS-index identified at the four digit level. Dependent variable, firm productivity.

	Quantiles of Total Factor Productivity					
VAR	0.01	0.25	0.5	0.75	0.99	FE
$r_{ijt} \cdot RS_j$	-0,075	-0.030***	-0,001	0,008	0.119***	-0.006
	(-0.072)	(-0.009)	(-0.006)	(-0.009)	(-0.036)	(-0.068)
r_{ijt}	-0,015	0,001	0.004***	0.006***	0.028***	0.003
	(-0,018)	(-0,002)	(-0,001)	(-0.002)	(-0.007)	(-0.013)
Obs	7,650	7,650	7,650	7,650	7,650	7,650
$r_{ijt-1} \cdot RS_j$	-0.104*	-0.055***	0.055	-0.024**	0.042	-0.042
	(-0.056)	(-0.010)	(-0.038)	(-0.009)	(-0.034)	(-0.068)
r_{ijt-1}	-0.026	-0.001	-0.039***	0.005***	0.015*	0.002
	(-0,023)	(-0,002)	(-0,006)	(-0,002)	(-0,009)	(-0.014)
Obs	6,146	6,146	6,146	6,146	6,146	6,146
$r_{ijt-2} \cdot RS_j$	-0.474***	-0.390***	-0.359***	-0.339***	-0.271***	-0.075
	(-0,052)	(-0,013)	(-0,010)	(-0,012)	(-0,025)	(-0.058)
r_{ijt-2}	0,016	0.015***	0.019***	0.019***	0.027***	0.013
	(-0,017)	(-0,002)	(-0,002)	(-0,002)	(-0.008)	(-0.015)
Obs	5,048	5,048	5,048	5,048	5,048	5,048

Note: In this table relationship-specificity is defined according to a four digit industry class. Estimates are calculated according to equation 3, using fixed effect quantile regression. In the upper block, contemporaneous values of R&D stock is used. In the lower blocks R&D stock is lagged with one and two years respectively. Dependent variable is $\hat{a}_{ijt}$, control variables not shown in this table H_{ijt} , time- and industry dummies. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

The choice of RS-index at a two or four digit industry classification level reduces significance at several points in the distribution of TFP for some lag choices. Hence, although the positive relationship between the interaction variable and productivity is maintained using the RS-index at the four digit level, the relationship between seller-buyer interactions and the return to R&D over the distribution of productivity appear less clear than the value added based estimations.

6 Conclusions

R&D is a main driver of technological progress and an important contributor to economic growth. Despite the theoretical importance of firm level R&D the estimated return to R&D greatly varies between studies. The impact variation of R&D may be the result of a series of confounding factors such as industry level differences and empirical approach. However, little is known about the underlying mechanisms that drive the variation of the return to R&D. In this paper we have analyzed a previously unexplored aspect of the innovation process in where we hypothesize that the intensity of interactions between sellers and buyers is a relative advantage to some firms. We emphasize that this advantage stems from knowledge transfers of buyer preferences which are channeled by seller-buyer interactions and may therefore help to explain the impact variation of R&D between studies. Furthermore, we assume that large and productive firms are better able to manage the cost of seller-buyer interactions and have the capacity to take use of the attributed knowledge transfers. Thus, we hypothesize that seller-buyer interactions transfer knowledge of buyer needs which drives higher return to R&D and that this effect is greater for large and productive firms.

A novelty of this study is the employment of the previously unexplored interaction between relationship-specificity and R&D. We allow the estimated return to R&D to vary along the distribution of seller-buyer interaction intensity by an interaction of relationship-specificity and R&D stock. Furthermore, the impact of seller-buyer interactions to the return to R&D is analyzed using two alternate models in a fixed effect quantile regression setting. The first model explores the variance of the estimated return along the frequency of personal interactions and firm size. The second model explores the same relationship but along the distribution of total factor productivity.

In our first model, regression results imply that the effect of seller-buyer interactions diverges for small and large firms. For small firms the impact of seller-buyer interactions to the returns to R&D are inconclusive or negative. For larger firms, the effect is either less negative or positive. These results are in line with our hypothesis and implies a positive three-way relationship between seller-buyer interactions, R&D and firm size. Hence, we find scale advantages to R&D active firms characterized by frequent interactions with their clients. We present two plausible interpretations. First, large firms tend to engage in incremental development of existing technologies, in where high responsiveness to buyer preferences is more rewarding than other types of innovation activities. For this reason, seller-buyer interactions and the corresponding knowledge transfer of consumer preferences are more beneficial to that type of innovation process. Secondly, seller-buyer interactions also comes with a cost. Large firms are better able to spread these costs over quantity and can thus manage such interactions better than a small firm. For the same reasons, the cost of seller-buyer interactions can be high enough to offset the attributed knowledge gain for small firms.

In our second model we explore the impact of seller-buyer interactions to the returns to R&D along the distribution of productivity. We find some support for a positive impact of seller-buyer interactions for the most productive firms. However, this relationship is found to be more sensitive for alternate specifications. There is hence less consistent evidence for a positive relationship between the impact of seller-buyer interactions on the return to R&D and productivity.

Knowledge of consumer preferences is beneficial to innovation activities in where the opinions and preferences of the users of the corresponding product is important. However, the final users of a product do not always know beforehand how to appreciate an innovation until they have actually seen it in practice. In many cases, important and game-changing innovations have emerged without user feedback and formal R&D environments. For such revolutionary innovations, there is little to gain from knowledge transfers enabled by seller-buyer interactions. Little is known of the confounding factors that create breakthrough ideas without influences from user preferences or any recorded R&D investments. Hence, further research should be directed to firms engaged in environments where R&D activities are carried out in a less formal way.

7 References

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