Innovation, Productivity and the integration into Global Value Chain: Firm- level Evidence from China

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Abstract

This paper examines the effects of integration into global value chain on innovation and productivity with a firm-level panel dataset from China. Our results show that firms focusing on international collaboration in technology have a higher patenting activity than those focusing on national collaboration in technology. The innovation-enhancing effect of international collaboration in technology is higher for domestic firms having higher innovation capacity, having no prior experience in working with foreign customer and supplier, producing services, and pursuing high-quality patent. We also show firms with main supplier and customer abroad are more productive than those with main supplier and customer in China. The productivity-enhancing effect of having main supplier abroad is larger than that of having main customer abroad, and the productivity-enhancing effect of having main customer abroad applies to service firms only. Further, we find that international collaboration in technology indirectly foster productivity through a higher patenting activity. Consistent with the literature, we show that patenting activity and productivity associate with firm characteristics, industry characteristics and year fixed effects.

1. Introduction

Globalization generates massive trade flows of goods and services across the world. An interesting feature of this wave of globalization is that developing countries become more active in the global value chain in picking up production outsourcing generated by multinational firms and exporting goods to other countries. Particularly, in the last two decades, developing countries take up increasing proportions of trade flow and GDP in the global economy. For example, China's share in world trade has increased nearly tenfold over the past three decades to about 10%, while its share in world GDP has risen to 13% from less than 3%.[1]

Since the integration into global value chain allows firms in developing countries learning from their counterparts in developed countries, governments in developing countries use this opportunity to upgrade the structure of their economies to be more innovative and hence to sustain economic growth (Furman et al., 2002; Ulku, 2007). This issue not only important for policy makers in developing countries to formulate policy fostering their roles in the global economy, but also crucial for the global economy as developing countries play a pivotal role in supporting the global economic growth since the recession of global economy in year 2008.

However, there is no evidence on how the integration into global value chain affects innovation and productivity for firms in developing countries. Our paper fills this gap in the literature by studying innovation and productivity at firm-level using a unique dataset from China. Our data is a panel dataset covering firms in industrial and service industries located in Shanghai over the period 2008-2011. For each firm, we have information on the total asset, sales, employee, patent application, patent granted, patent stock, and the location of its main

[1] Purchasing-power-parity basis

technology partner, supplier and customer. We can thus examine whether innovation and productivity are associated with the location of its main technology partner, supplier and customer, which in turn identify whether agglomeration in local area or integration into global value chain provides a stronger support to innovation and productivity. Furthermore, we know firm age, firm size, the firm's ownership classification and the industry where the firm operates, which allows us to assess whether innovation and productivity of firms depending on their characteristics.

A modified version of Crepon et al. (1998) model, in which there are patent production function and productivity equation, is employed for our empirical analysis. Our results show that firms with main technology partner abroad have a higher patenting activity than those with main technology partner in China, conditional on a set of firm characteristics and year fixed effects. Consistent with the literature, we show that patenting activity associates with R&D expenditure, patent stock, age, size, ownership and industry characteristics.

We also find several channels through which international collaboration in technology fosters patenting of domestic firms. First. the innovation-enhancing effect is larger for firms with a higher innovative capacity. Particularly, firms with larger patent stock, younger in age and larger in size benefit more from engaging in international collaboration in technology. Second. the innovation-enhancing effect is larger for firms with no experience in working with foreign customer and supplier. Third, the innovation-enhancing effect is larger for firms in service industries than firms in manufacturing industries. Fourth, we find international collaboration in technology mainly encourages invention patenting instead of patenting in utility model and design. It suggests that international collaboration in technology fosters domestic firms learn advanced technology from abroad, and such effect is stronger for domestic firms with a higher innovative capacity and no prior experience in working with foreign customer and supplier..

We also show firms with main supplier and customer abroad are more productive than those with main supplier and customer in China. The productivity-enhancing effect of having main supplier abroad is stronger than that of having main customer abroad. Only the service firms enjoy a higher productivity from having main customer abroad. Further, we find that a higher number of patent application relates to a higher productivity, which indicates that international collaboration in technology indirectly fosters productivity through patenting. Finally, we show that productivity associates with age, size, ownership and industry characteristics.

Our paper contributes to the firm-level evidence of patenting in China. Hu and Jefferson (2009) report that patent application of large and medium manufacturing firms over the period 1995-2001 associate with R&D expenditures, industry FDI, ownership, year effects and industry characteristics.[2] Choi (2011) shows that publicly-listed Chinese firms (most of them belong to manufacturing industries with very few firms in communication industry) with shares owned by foreign investors and affiliated with a business group have more patent granted in year 2001. Our work differs from their works in several aspects. First, we exploit a more recent data set with a balanced sample in manufacturing and service industries. Second, our sample covers small and larger firms instead of large and medium firms or publicly-listed firms. The inclusion of small firms in our analysis is important because small firms are main drivers for innovation in the economy. Third, we distinguish the invention patenting from utility model and design patenting in our analysis. Fourth, we focus on examining whether firms integrating into global value chain have a higher propensity to patent or not.

[2] See Jefferson et al. (2003) for the details in their data.

Our paper also adds to the discussion on the effects of integration into global value chain on firm performance. First, recent studies show that firms linking to foreign invested enterprises (FIEs) and operating in industries with a higher fraction of FIEs are more innovative (Grima et al. 2008, 2009; Hu and Jefferson, 2009; Wang and Lin, 2013). Second, Chinese firms becomes more productive when they import more inputs from foreign market (Ge et al. 2011; Yu, 2013) and sell to foreign markets (Park et al. 2010; Sun and Hong, 2011; Dai and Yu, 2013). Our study unifies these three strands of literatures by showing how the spatial configuration of value chain (including technology partner, supplier and customer) affects innovation and productivity of domestic firms.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 explains the empirical strategy. Section 4 presents the empirical results. The last section concludes.

2. Data and Descriptive Statistics

We obtain a proprietary firm-level dataset from the Commission of Science and Technology of Shanghai municipality government in China (the Commission, hereafter). Shanghai has a population around 23 million and a GDP per capita more than 13 times the nationwide average, located in the south-east coastal area of China. Shanghai is also a leading province in patenting activity and innovation capacity (Cheung and Lin, 2004; Yang and Lin, 2012). The commission collects the data by requesting the firms to fill in an online survey since year 2008, and the surveys across years are consistent with each other. The commission collects data from firms locating in urban and rural regions across Shanghai, and uses the data to formulate science and technology policy.[3]

[3] More specifically, those firms locate in 18 regions in Shanghai, including 普陀区、崇明县、奉贤区、徐汇区、金山区、

For each observation, the data contain information on firm identifier, total assets, sales, number of employees, number of patent application, number of patent granted, number of invention patent application, number of invention patent granted, invention patent stock (i.e. number of invention patent owned),[4] firm age, the firm's ownership classification, and the industry sector where the firm operates. There are two unique features of our data. First, it contains the location of the firm's main technology partner, supplier and customer for analyzing the effect of spatial configuration of value chain on patenting and productivity. Second, it includes firms in industrial and service industries for comparative analysis.

Before reporting the descriptive statistics, we close this sub-section by discussing the differences between our dataset and the commonly used Chinese firm-level data set, i.e. the 1998-2007 Annual Survey of Industrial Firm (ASIF) conducted by the National Bureau of Statistics of China.[5] First, our dataset covers a more recent period over 2008-2011 than the ASIF. Second, our dataset covers service industries, which is absent in the ASIF. Third, our dataset contains the information on patenting activities, the main technological partner, the main supplier and the main customer, which is absent in the ASIF. Fourth, our dataset covers firms in Shanghai, a major trading Chinese city, instead of the whole China. Although the data set is less geographically representative, Shanghai fits into our objective in studying the effects of integration into global value chain on innovation and productivity of domestic firms because firms in inland provinces are less likely to engage in international collaboration and business. Finally, our dataset does not have the information on value-added and intermediates inputs, which leads us to use labor productivity instead of total factor

虹口区、松江区、闵行区、浦东新区、长宁区、杨浦区、静安区、闸北区、卢湾区、黄浦区、青浦区、嘉定区、宝山区.

[4] There are three types of patents can be granted, namely invention, utility model and design. Invention patent must meet the requirements of "novelty, inventiveness and practical applicability", which is more innovative than the requirements of the other two patent types.

[5] The dataset has been used widely in previous research in economics; for example, Hsieh and Klenow (2009).

productivity (TFP) in empirical analysis.

2.1 Descriptive Statistics

Table 1 reports the industry distribution of invention patent applications, invention patents granted and invention patent stock, which shows there is a substantial variation in patenting activity across industries. First, the manufacturing industry (C) applies and is granted the largest portion of the patents, followed by the Scientific research, technical services and geological prospecting (M), and Information transmission, computer services and software industry (I). Second, the six industries of mining industry (B), Accommodation & catering industry (H), Finance (J), Real Estate (K), Resident services & other services (O) and Education (P) have zero or one patent application. Third, manufacturing and construction industries apply and are granted similar numbers of invention patents as service industries.

[Table 1 about here]

We apply several criteria to filter our working sample. First, we drop firms with missing information on age, ownership, industry, main technology partner, main supplier and main customer. Second, we eliminate observations of asset, sales or employment equal to zero and of sales per employee grow more than ten times over the sample years. Third, to make our results robust to outliers, we delete observations of the asset, sales, employment, patent application, patent granted, invention patent application, invention patent granted, or invention patent stock above the top 0.1% in the distribution. We also delete observations of the asset, sales, employment, below the bottom 0.1% in the distribution. Fourth, since our variable of interest is patent application and granted, we drop the industries with zero and too few patent application and granted. Specifically, we keep the observations from the industries with more than 1% of total invention patent applications in our sample: they include the Manufacturing (C), Construction (E), Wholesale & retail trade (G), Information transmission, computer services & software industry (I), Leasing & business services (L), and Scientific research, technical services & geological prospecting (M). The final dataset has 31,772 observations belonging to 12,765 firms.

Table 2 provides variable definitions (Panel A) and descriptive statistics (Panel B) for the firm characteristics. For all sample firms, the average total asset is 48.8 million RMB, the average total sales is 47.2 million RMB, the average firm size (i.e. number of employees) is 62.6 people and the average labor productivity (i.e. sales per employee) is 0.66 million RMB. On average, firm age is 7.76 years, among which about 70% are younger than 10 years.

[Table 2 about here]

According to the ownership, we categorize the firms into seven groups: state-owned firms (SOE), collective-owned firms (COE), firms with foreign assets (FOR), firms with assets from investors in Hong Kong, Macau and Taiwan (HKT), joint stock firms (STK) and privately-owned firms (PRI) and firms with other ownership types (OTH). Of the total 31,808 observations, 1.4% are belong to SOE, 0.8% to COE, 7.0% to FOR, 3.0% to HKT, 2.4% to STK, 6.3% to private firms and 79.1% to OTH.

Of the total 31,808 observations, 39.5%, 56.3% and 4.2% have their main technology partner in Shanghai, in China (excluding Shanghai) and abroad, respectively. Of all observation sampled, 33.1% have their main supplier in Shanghai, 62.6% in China (excluding Shanghai) and 4.4% abroad. On average, 29.5% of observations have their main customer in Shanghai, 66.4% in China (excluding Shanghai) and 4.1% abroad. The primary spatial configuration of firm's value chain is in Chinese provinces outside Shanghai, and only few firms integrate into global value chain.

[Figure 1 and 2 about here]

Figure 1 shows that firms with main technology partner abroad have higher patenting activities in invention, utility model and design than those with main technology partner in China. Figure 2 shows that firms with main supplier and customer abroad have a higher labor productivity than those with main supplier and customer in China. The productivity-enhancing effect of having the main supplier abroad is stronger than that of having the main customer abroad. Overall, these figures provide anecdotal evidences that firms integrating into global value chain are more innovative and productive than their local counterparts.

Table 3 presents the correlation between the invention patent variables, firm attributes and productivity. We find that invention patent application and granted positively correlate with invention patent stock, R&D expenditure per employee, firm age and firm size. Consistent with Figure 1 and 2, firms with main technological partner, supplier and customer further away from its locating region have higher invention patenting and labor productivity. Further, the spatial configurations of technology partner, supplier and customer are correlated with each other. Firms with main technological partner in Shanghai are more likely to have main suppliers and customers in Shanghai, whereas firms with main technological partner aboard are more likely to have main suppliers and customers abroad. This pattern is also consistent with evidence from other countries (such as Faria and Schmidt, 2007 for Germany; Avanitis and Bolli 2013, for Switzerland, Germany and Norway) that exporting firms are more likely to have international collaboration in innovation. Finally, invention patenting activity positively associates with labor productivity, but the economic and statistical significances are weak. Since most variables correlates with each other, thus it calls for multivariate analyses to further investigate on their independent effects on innovation.

[Table 3 about here]

3. Empirical Model and Estimation

We employ a two-stage model in the spirit of Crepon et al. (1998) to examine whether the integration into global value chain affects innovation and productivity. The first equation is a patent production function, which relates R&D input and other firm attributes to patent output.[6] Patents have long been considered, not without controversy, as a measure of innovation output (Grilliches, 1990; Furman et al., 2002). Although not all inventions are patented, the ones that are patented have to meet minimal standards of novelty, originality and potential use. Therefore, patents can be considered as a good proxy for economically significant technological innovation (Bottazi and Peri, 2003). The second equation associates productivity with patent output and other firm attributes. In our two-stage model, we include a set of variables that characterizes whether the firm integrates into global value chain or not. As a result, these specifications do not only allow the integration into global value chain directly affect innovation and productivity, but also allow an indirect effect of innovation on productivity.

3.1 Patent Production Function

We use the patent production function proposed by Pakes and Griliches (1980) and Hausman et al. (1984) to explore the determinants of patenting for our sample firms. This

[6] We observe the number of patent application instead of whether the firm files patent application or not. Therefore, we utilize the quantitative measure of patent output to extend the innovation equation of Crepon et al. (1998) from a discrete choice model to a count data model.

method is also applied by Hu and Jefferson (2009) to estimate the patent production function for large and medium sized Chinese firms over the period 1995-2001. The patent production function hypothesize that the expected number of patents applied for (Y_{it}) during the year is an exponential function of the firm's characteristics X_{it}:

$$E[Y_{it}|X_{it}] = \lambda_{it} = \exp(X_{it}\beta), \qquad (1)$$

We use the indices i and t to denote firm and year, respectively. The vector X includes R&D expenditure per employee, patent stock, along with other firm characteristics, such as age, size and ownership. We include year dummies to capture the overall trend of patenting and industry dummies to capture the inter-industry difference in patenting.

The variables of interest in this equation is the location of main technology partner, i.e. an indicator that the main technology partner is in other Chinese provinces and an indicator that the main technology partner is in abroad. There are debates on the role of geography in innovation. Following the idea of Porter (1990), Furman et al. (2002) show that, in addition to the resources devoted to innovation, local interaction in industrial clusters is decisive for knowledge exchange and innovation. Beaudry and Breschi (2003) show that Italian and British firms having a higher innovation performance if the firms belonging to a cluster of firms having high innovation capacity. On the other hand, recent studies find that firm connecting to outside the region are more innovative. Fitjar and Rodriguez-Pose (2011, 2013) show that Norwegian firms having international technology partner and technology partner outside their local area have a stronger innovation performance, respectively. Wu and Wei (2013) find that local and non-local knowledge are both useful for Chinese firms to innovate. The contrasting implication of agglomeration and globalization hypotheses can be tested with the effect of main technology partner locating outside the local region on innovation.

We use R&D expenditure per employee and invention patent stock as proxies for innovation input (Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992). Previous studies use distributed lags of R&D expenditures to examine the effect of innovation input on patent production. However, a practical concern for us is that our sample is extremely unbalanced, thus it leads to a larger reduction in sample size when we include a comprehensive lag structure. Therefore, we use invention patent stock to proxy the cumulative effort made by the firm to innovate. Moreover, we use an indicator whether the firm has positive invention patent stock to examine whether there is a higher hurdle for new innovator to patent. We use the square of R&D expenditure per employee to capture the potential non-linear effect of R&D input on patent production.

Age is shown to be important for innovation. On one hand, older firms are more experienced in preparing patent application (Sorensen and Stuart, 2000). On the other hand, young firms are more likely to innovate in order to entering into an industry (Huergo and Jaumandreu, 2004). Large firms may have scale economies in patenting due to the fixed cost in innovation, thus firm size is expected to be positively related to patenting (Hall and Ziedonis, 2001). Ownership is shown to be an important determinant for patenting in China, in particular state-owned firms have lower propensity to patent (Hu and Jefferson, 2009).

The Poisson estimator assumes that the conditional mean $E(Y_{it}|X_{it})$ is equal to the conditional variance $Var(Y_{it}|X_{it})$. However, this assumption is violated in most empirical applications, the conditional variance is often larger than the conditional mean, leading to over-dispersion. A consequence of this violation of assumption is that the standard errors are underestimated, even though the Poisson estimates are still be asymptotically consistent. Therefore, we follow Hall and Ziedonis (2001) and Hu and Jefferson (2009) to report robust standard errors for the model.

Moreover, there is a large number of observations with zero invention patent application, thus we employ the Zero Inflated Poisson (ZIP) model proposed by Lambert (1992) to estimate the patent production function. The ZIP model assumes that firms fall into two categories, the innovators and the non-innovators. Let the probability of a firm being a non-innovator be p; the probability of a firm being an innovator is 1-p. With probability p, a firm's patent application is zero; with probability 1-p, the patent application is subject to the Poisson process in Equation (1). The full model is specified as follows:

$$\Pr(Y_{it}=y_{it})=\begin{cases} p_{it}+(1-p_{it})e^{-\lambda_{it}} & for \quad y_{it}=0 \\ (1-p_{it})e^{-\lambda_{it}}\lambda_{it}^{n}/y_{it}! & for \quad y_{it}=1,2,... \end{cases} \quad where \quad p_{it}=\frac{1}{1-e^{-Z\gamma}}$$

The decision to innovate is determined by a logistic process, in which the set of variables Z are determinants for the decision to innovate or not. Finally, we estimate the ZIP model with maximum likelihood estimation (MLE), and use the likelihood ratio test proposed by Vuong (1989) to determine whether the regime splitting mechanism in the ZIP model is empirically important or not.

3.2 Productivity Equation

In the second stage of our model, we specify the following empirical model to examine the effect of integration into global value chain on firm's productivity:

$$\ln(Sale/L)_{it} = W_{it}\gamma + \alpha_1 \ln(K/L)_{it} + \alpha_2 PAT_{it} + \varepsilon_{it}, \tag{2}$$

We use the indices i and t to denote firm and year, respectively. The dependent variable is the logarithm of labor productivity. Patent application is included in the model as knowledge input. The inclusion of capital intensity (capital-to-labor ratio) is consistent with the framework of Cobb-Douglas production function with constant returns to scale, and with capital, labor and knowledge as inputs. The vector W includes firm characteristics, namely age and ownership, year dummies to capture the overall trend of productivity and industry dummies to capture the inter-industry difference in productivity.

The variables of interest in this equation is the locations of main supplier and main customer, i.e. an indicator that the main supplier (customer) is in other Chinese provinces and an indicator that the main supplier (customer) is in abroad. The effects of having main supplier and customer is less debatable than that of having main technology partner abroad. Recent studies show that Chinese firms becomes more productive when they import more inputs from foreign market because foreign inputs are often with higher-quality (Ge et al. 2011; Yu, 2013). Chinese firms also learn from exporting to foreign markets in order to raise their productivity (Park et al. 2010; Sun and Hong, 2011; Dai and Yu, 2013). An interesting feature of our model is that the indicators of having main supplier and customer in other Chinese provinces allow us to infer that whether there is a positive (but potentially smaller) effect on productivity from engaging with main supplier and customer from the other parts of same country. It is because firms arrange their supply chain optimally, thus productivity increases as they have wider choice sets for suppliers and customers.

Finally, we follow Hall et al. (2009) to replace observed patent application by predicted patent application from the ZIP model. This approach addresses the potential endogeneity and measure error issues of knowledge input in productivity equation. We then estimate this model with ordinary least square (OLS) with robust standard errors.

4. Empirical Results

We start discussing the results on the determinants of patenting in Table 4, and then discussing the channels through which international technology collaboration fosters patenting of domestic firms. Finally, we report the results on labor productivity in Table 7. Since Hu and Jefferson (2009) provides a detailed discussion on the effects of R&D expenditure, ownership, year and industry on patenting, we will be brief in discussing those variables as our results on those variables are consistent with those reported in Hu and Jefferson (2009).

4.1 Invention Patenting

Table 4 reports that the Vuong test statistics in all columns indicate that the normal Poisson model is rejected in favor of the ZIP model, which supports the regime splitting mechanism specified in the ZIP model in our context.

Column 1 of Table 4 reports the results for a specification with the logarithm of R&D expenditure, industry dummies and year dummies only. This specification is close to that used in Hall and Ziedonis (2001), which allows to compare the innovation efficiency estimated from our sample to those reported in the literature. The patents-R&D elasticity for our sample is about 0.31. This estimate is close to that (0.06-0.3 for the period 1995-2001) reported in Hu and Jefferson (2009), but this estimate of patents-R&D elasticity is much smaller than those for the U.S. and European firms. For example, for U.S. firms, Hausman, Hall and Griliches (1984), Pakes and Griliches (1984) and Hall and Ziedonis (2001) report estimates of 0.87, 0.61 and 0.99, respectively. Crepon and Duguet (1997) and Licht and Zoz (2000) reports patents-R&D elasticities of 0.8 and 0.9 for French manufacturing and German firms, respectively. Hu and Jefferson (2009) argues that, relative to their OECD counterparts, the smaller elasticity associates with either low productivity of R&D in Chinese firms or the fact that Chinese firms patent a much smaller fraction of new knowledge generated by R&D. Our results indicates that the patents-R&D elasticity remains at a relatively low level for a economically-developed city in a recent period.

Starting from Column 2, we add a set of covariates and replace R&D expenditure by R&D expenditure per employee. We find that there is a marginal decreasing return in R&D expenditure per employee in producing patent. Firms with a higher patent stock and previous patenting experience have a higher propensity to patent. Young firms are more innovative than old firms, where the age semi-elasticity is about 0.02. Further, there is a positive scale effect, represented by Size, on patenting. The scale elasticity is around 0.35, which is close to the patents-R&D elasticity reported in Column 1. It indicates the scale effect of R&D expenditure is picked up by Size. Large firms apply more patents because there are potential scale economies in preparing patent applications and conducting R&D.

Column 2 also reports that the coefficients on TPartner-N and TPartner-F are positive and significant. Firms with the main technology partner located outside the local market and abroad have a higher propensity to patent. Particularly, the innovation-enhancing effect of having the main technology partner abroad is stronger than that of having the main technology partner in other Chinese provinces. It suggests that firms with international collaboration tends to be more innovative as they may have technologically high-qualified partners. These results are also consistent with Arvanitis and Bolli (2013) that European firms with international collaboration in technology is more innovative than those with national collaboration.

4.2 Channels

4.2.1 Innovativeness

The benefit of having international technology collaboration differs across firms because firms with a higher innovation capacity are more capable in realizing the potential gain from international collaboration in technology. There is a vast literature in showing that adsorption capacity promotes learning from foreign technology. Recent studies show that R&D experience and skilled labor are useful in promoting the positive spillover effect on patenting from foreign direct investment (see Liu and Buck 2007; Cheung 2010 for industry evidence; and Fu 2008; Yang and Lin 2012 for provincial evidence). Based on a firm-level data, Grima et al. (2008, 2009) also find that industry FDI promotes new product sales of domestic firms if they engage in R&D. From the baseline model, we find that firms with a larger patent stock, more R&D employees and more employees with master and doctoral degrees are more innovative, thus we classify those firms to have higher absorption capacity and investigate whether they enjoy a larger benefit from having international technology collaboration.

In our first test, we separate the firms according to their patent stock. We label firms own more than two patents as innovators, and the remaining firms as typical firms. In our second test, we separate the firms according to their number of R&D employees. We label firms own more than 10 R&D employees as innovators, and the remaining firms as typical firms. In our third test, we separate the firms according to their number of employees with master and doctoral degrees. We label firms own positive number of employees with master and doctoral degrees as innovators, and the remaining firms as typical firms. Table 5 shows that, regardless the measures used for defining innovator, the innovation-enhancing effect of international technology partner is higher for innovators, whereas there is only weak evidence (from Column 2 of Table 5) for the typical firms to increase their patenting through national technology partnership.

4.2.2 Firm Attributes

We investigate whether the patenting effect of international technology collaboration for young firms, which are more innovative, is stronger. We focus on the sub-sample of firms that are younger than seven years, which is the mean age of our sample firms. In Columns 1 and 2 of Table 5b, we show that the innovation-enhancing effect of international technology collaboration is stronger for young firms than mature firms.

We then investigate whether the patenting effect of international technology collaboration for large firms, which are more innovative, is stronger. We focus on the sub-sample of firms that have sales above five million yuan in current year, which is the threshold sales value to define large firms in China. In Columns 3 and 4 of Table 5b, we show that the innovation-enhancing effect of international technology partner is stronger for large firms than small firms.

4.2.2 Supply Chain

Firms with the main customer and the main supplier from foreign countries have more opportunities to learn and acquire advanced technology, thus the benefit of having international technology collaboration can be smaller for firms have their supply chain extended to foreign countries. On the other hand, firms may raise their absorption capacity for advanced technology through interacting with customer and supplier from foreign countries, thus the benefit of having international technology collaboration can be larger for firms have their supply chain extended to foreign countries. In this sub-section, we investigate whether having extended supply chain abroad fosters the innovation-enhancing effect of international collaboration in technology or not.

In our first test, we separate the firms according to their location of main customer. We classify firms having their customer abroad if they report their main customer is located abroad for at least one year. We classify firms having their customer in other Chinese provinces if they report their main customer is located in other Chinese provinces for at least one year and do not ever report their main customer is located abroad. We classify firms having their customer in local market if they do not belong to the previous two groups. In Columns 1-3 of Table 6, we show that the innovation-enhancing effect of international technology partner is larger for firms having the main customer in other Chinese provinces.

Our second test relies on the location of main supplier. We use the same criteria as in the case of customer to classify firms whether they have the main supplier abroad, in other Chinese province and in local market. In Columns 4-6 of Table 6, we show that the innovation-enhancing effect of international technology partner is larger for firms having the main customer in local market. These results suggest that domestic firms do not extend their supply chain abroad enjoying a larger benefit from having international collaboration in technology.

4.2.3 Industry Differences

The benefit of having international technology collaboration differs across sectors because domestic firms in industry with advanced technology are more likely to be benefited from foreign partners. We estimate the patent production function for each sector to examine the industry differences in benefiting from international technology collaboration. Table 7 reports that international collaboration in technology fosters innovation for service firms in scientific research, technical services & geological prospecting sector. It suggests that domestic service firms need technologically high-qualified partner to advance their innovation capacity.

4.2.4 Quality of Innovation

Our results indicate that firms engaging with international technology partner file more invention patent, which is the patent with the highest quality. In this sub-section, we test whether international technology collaboration also fosters patenting in utility model and design, which requires lower technology content. The last three columns of Table 5 report the results for patent production function with utility model and design patent as dependent variable. Column 4 reports the patents-R&D elasticity for our sample is about 0.17, which is about half of that for invention patent. Column 5 also shows that patenting in utility model and design weakly relates to patent stock and do not correlate with R&D expenditure per employee. It suggests that applying a patent in utility model and design involves less R&D inputs than an invention patent, and relies less on previous patenting experience. Consistent with the case for invention patent, young and large firms are more innovative in utility model and design than their old and small counterparts. Finally, the location of main technology partner does not show significant effect on the patenting activity in utility model and design.

4.3 Labor Productivity

Table 8 reports that the empirical results for Equation (2) with predicted invention patent application from Equation (1) as the proxy variable for PAT. Firms with a higher capital intensity have a higher labor productivity, which is consistent with the implication of Cobb-Douglas production function with capital, labor and knowledge as inputs. Older firms are more productive than young firms in several service industries, but such pattern does not appear for firms in manufacturing industries. It suggests that learning-by-doing is an important channel to raise productivity for service firms because producing services involves more intangible skills than producing goods in manufacturing and construction industries. Patent application enhances productivity, in particular an invention patent application raise labor productivity by 18%. Further, the labor productivity of firms in service industries are more responsive to patenting activity because higher quality product and product differentiation are more essential for service firms to success.

Table 8 reports that the coefficient on SPartner-F are positive and significant for both manufacturing and several service industries. Firms importing input from abroad are more productive than firms sourcing their main input locally. Input from foreign countries are often with higher quality, which allows firms to produce higher quality product and hence achieve a higher sales. This result is consistent with Ge et al. (2011) and Yu (2013) that Chinese firms with higher quality and more variety of imported inputs are more productive. Our results also suggest that although there is a positive effect (about 5%) for productivity from sourcing input from other Chinese provinces but such effect is smaller than that (about 29%) from sourcing input from abroad. Further, Table 8 reports that the productivity-enhancing effect from sourcing input from other Chinese provinces (i.e. the coefficient on SPartner-N) is only significant for manufacturing industries, which suggests that service firms rely more on high-quality input from abroad than manufacturing firms. Reducing transportation cost within China in order to allow firm to procure input from other provinces can increase productivity for manufacturing firms.

The coefficients on CPartner-F are positive and significant for several service industries, whereas the coefficients on CPartner-N are insignificant for all industries. Service firms mainly selling product to abroad are more productive (about 18-54%) than service firms mainly selling their product locally, but such pattern does not show up for manufacturing and construction firms. It suggests that manufacturing and construction firms locate in the low-end of global value chain, which has a low value-added in the production process. On the other hand, service firms in China provides a higher value-added to the production process. This result is also consistent with Yu et al. (2013) that only Chinese firms producing differentiated product benefits from engaging in international trade.

5. Conclusion and Policy Implications

Our work provides policy implications for China, which in search for strategy in sustaining the economic growth. There have been debates on how Chinese economy can be transformed from low-cost, polluting and resource-exhausting mode of growth to high valued-added and innovative mode of growth. Moreover, since the entry of World Trade Organization, export has been contributing to the economic growth of China. However, there is evidence showing that the cost advantage of Chinese product declines in recent years due to the rising labor cost. Thus, it is essential for exporting firms to upgrade their products in order to maintain their competitiveness. Our results have policy implications that government should promote firms' incentive in joining the national value chain outside the local market and the global value chain in order to increase their innovation and productivity.

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Figure 1: Patent Application and the Location of Main Technology Partner (Unit: 1)

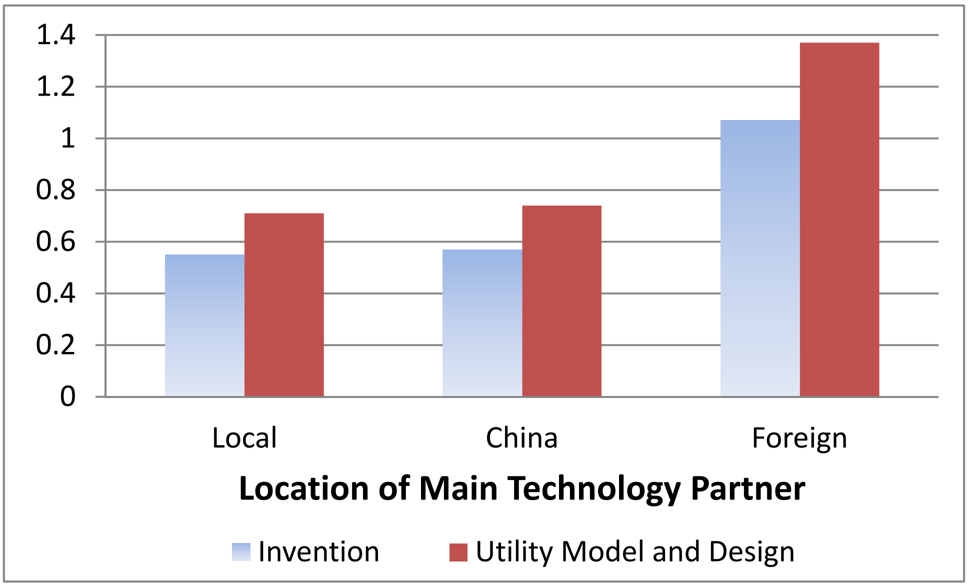

Figure 2: Labor Productivity and the Location of Main Supplier and Customer

(Unit: 1 Million RMB)

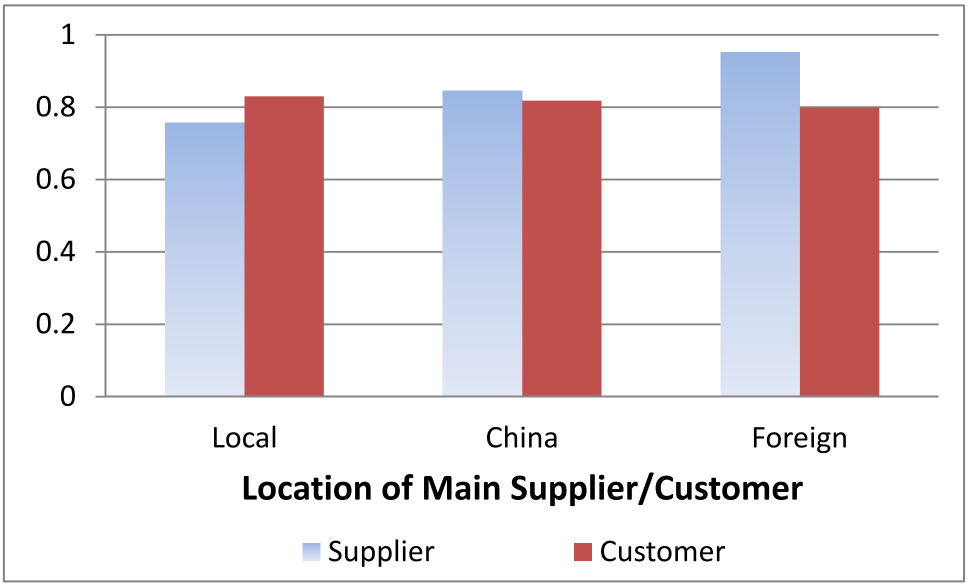

Table 1
This table presents the industry distribution of the firms. Percentage refers to the percentage share of occurrence to that sector of total occurrence.

CSIC Code	Sector	Number of Observation	%	Patent Application	%	Patent Granted	%	Patent Stock	%
A	Agriculture, forestry, animal husbandry, fishery	57	0.17%	36	0.18%	3	0.05%	16	0.06%
B	Mining industry	0	0.00%	0	0.00%	0	0.00%	0	0.00%
C	Manufacturing	8,218	24.17%	8,027	40.44%	2,551	38.56%	11,356	44.70%
D	Electricity, gas & water production & supply	26	0.08%	110	0.55%	12	0.18%	165	0.65%
E	Construction	908	2.67%	529	2.66%	189	2.86%	705	2.77%
F	Transportation, storage & postal services	200	0.59%	39	0.20%	17	0.26%	63	0.25%
G	Wholesale & retail trade	4,395	12.93%	1403	7.07%	530	8.01%	1,880	7.40%
H	Accommodation & catering industry	5	0.01%	0	0.00%	0	0.00%	0	0.00%
I	Information transmission, computer services & software industry	4,200	12.35%	1,984	9.99%	598	9.04%	2,150	8.46%
J	Finance	31	0.09%	0	0.00%	0	0.00%	0	0.00%
K	Real Estate	150	0.44%	1	0.01%	0	0.00%	0	0.00%
L	Leasing & Business Services	2,316	6.81%	1,182	5.95%	481	7.27%	1,810	7.12%
M	Scientific research, technical services & geological prospecting	13,213	38.86%	6,489	32.69%	2,219	33.54%	7,230	28.46%
N	Water, environment & public facilities management industry	94	0.28%	11	0.06%	1	0.02%	2	0.01%
O	Resident services & other services	107	0.31%	0	0.00%	0	0.00%	0	0.00%
P	Education	7	0.02%	0	0.00%	0	0.00%	0	0.00%
Q	Health, social security & social welfare	20	0.06%	10	0.05%	3	0.05%	12	0.05%
R	Culture, Sports & Entertainment	51	0.15%	29	0.15%	11	0.17%	18	0.07%
	Total	33,998	100.00%	19,850	100.00%	6,615	100.00%	25,407	100.00%

Table 2

Panel A: Variable definitions.

	Definition
Performance variables	
Asset	Total assets in RMB 1,000
Sales	Total sales in RMB 1,000
Labor Productivity	Sales per employee in RMB 1,000
Innovation variables	
PATA	Number of invention patent application
PATG	Number of invention patent granted
PS	Number of invention patent owned
Inference variables	
LT (/LS/LP)	Dummy variable equal to one if the main technology partner (/supplier/customer) of the firm locates in Shanghai
NT (/NS/NP)	Dummy variable equal to one if the main technology partner (/supplier/customer) of the firm locates in China but outside Shanghai
FT (/FS/FP)	Dummy variable equal to one if the main technology partner (/supplier/customer) of the firm locates abroad
Control variables	
RD/L	R&D expenditure per employee in RMB 1,000
Age	Firm age
Size	Number of employees in person
GOVF/L	Government subsidy on R&D per employee in RMB 1,000
SOE	Dummy variable equal to one if the firm is a state-owned firm
COE	Dummy variable equal to one if the firm is a collective-owned firm
FOR	Dummy variable equal to one if the firm includes foreign-owned assets
HKT	Dummy variable equal to one if the firm includes assets from investors in Hong Kong, Macau or Taiwan
STK	Dummy variable equal to one if the firm is a shareholding or joint-stock firm
PRI	Dummy variable equal to one if the firm is a privately-owned firm
OTH	Dummy variable equal to one if the firm belong to other types of ownerships

Table 2 (Continued)

Panel B: Summary statistics. The number of observations corresponds to the number of firm and is equal to 19,040 after extracting a sub-sample of data based on certain filtering criteria described in the data section.

	Mean	Standard Deviation	Min	P(25)	Median	P(75)	Max
Performance variables							
Asset (RMB1,000)	57589	262495	5	1105	4396	22666	7263571
Sales (RMB1,000)	54192	231791	1	978	4702	23622	7687646
Labor Productivity (RMB1,000)	693.7	3286	0.05	94.22	244.3	587.2	183570
Innovation variables							
PATA	0.689	2.857	0	0	0	0	64
PATG	0.242	1.104	0	0	0	0	24
PS	0.975	4.539	0	0	0	0	111
Inference variables							
LT	0.380	0.485	0	0	0	1	1
NT	0.575	0.494	0	0	1	1	1
FT	0.044	0.206	0	0	0	0	1
LS	0.331	0.463	0	0	0	1	1
NS	0.643	0.479	0	0	1	1	1
FS	0.046	0.209	0	0	0	0	1
LP	0.275	0.447	0	0	0	1	1
NP	0.680	0.467	0	0	1	1	1
FP	0.045	0.208	0	0	0	0	1
Control variables							
RD/L (RMB1,000)	35.75	504.1	0	0	0	22.18	44901
Age	8.647	4.980	1	5	8	11	48
Size (Person)	69.44	173.6	1	8	17	54	3134
GOVF/L (RMB1,000)	2.087	33.24	0	0	0	0	3370
SOE	0.016	0.125	0	0	0	0	1
COE	0.009	0.094	0	0	0	0	1
FOR	0.075	0.263	0	0	0	0	1
HKT	0.031	0.174	0	0	0	0	1
STK	0.028	0.165	0	0	0	0	1
PRI	0.839	0.367	0	1	1	1	1
OTH	0.002	0.040	0	0	0	0	1

Table 3: Correlation Matrix

The number of observations is equal to 19,040

	PATA	PS	ln(RD/L)	Age	Size	ln(GOVF/L)	LT	NT	FT	LS	NS	FS	LP	NP	FP
PS	0.29	1.00													
ln(RD/L)	0.27	0.20	1.00												
Age	0.07	0.12	0.06	1.00											
Size	0.28	0.23	0.38	0.30	1.00										
ln(GOVF/L)	0.22	0.14	0.04	-0.00	0.19	1.00									
LT	-0.02	0.01	0.04	0.05	-0.05	0.04	1.00								
NT	0.00	-0.01	-0.09	-0.05	0.01	-0.04	-0.91	1.00							
FT	0.04	0.01	0.12	0.01	0.11	0.01	-0.17	-0.25	1.00						
LS	-0.06	-0.04	-0.02	0.02	-0.11	0.00	0.71	-0.67	-0.07	1.00					
NS	0.05	0.03	-0.02	-0.03	0.07	-0.01	-0.66	0.70	-0.13	-0.90	1.00				
FS	0.02	0.00	0.09	0.01	0.07	0.02	-0.08	-0.11	0.45	-0.15	-0.29	1.00			
LP	-0.08	-0.06	-0.10	0.01	-0.15	-0.05	0.69	-0.64	-0.10	0.72	-0.66	-0.08	1.00		
NP	0.05	0.04	0.03	-0.03	0.06	0.03	-0.63	0.67	-0.12	-0.67	0.66	-0.03	-0.90	1.00	
FP	0.07	0.05	0.14	0.02	0.18	0.04	-0.07	-0.13	0.48	-0.05	-0.06	0.25	-0.13	-0.32	1.00
ln(Sales/L)	0.11	0.09	0.21	0.13	0.28	0.08	-0.03	0.00	0.06	-0.09	0.05	0.09	-0.07	0.04	0.07

Table 4: ZIP Model for Patent Application - All Industries

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	INV	INV	INV	UMD	UMD	UMD
L.PS		0.0164***	0.0157***		0.00725***	0.00703***
		(0.00214)	(0.00216)		(0.00271)	(0.00271)
ln(RD/L)		0.735***	0.525***		0.191	0.177
		(0.0911)	(0.114)		(0.256)	(0.251)
(ln(RD/L))2		-0.0666***	-0.0500***		-0.0195	-0.0187
		(0.0127)	(0.0156)		(0.0327)	(0.0323)
L.ln(RD/L)			0.321***			0.0868
			(0.0857)			(0.0752)
L.(ln(RD/L))2			-0.0264*			-0.0101
			(0.0137)			(0.0135)
Age		-0.0162***	-0.0185***		-0.0196***	-0.0203***
		(0.00485)	(0.00495)		(0.00534)	(0.00549)
Size		0.346***	0.335***		0.352***	0.352***
		(0.0256)	(0.0248)		(0.0517)	(0.0504)
ln(GOVF/L)		0.115***	0.0982***		0.0207	0.0186
		(0.0227)	(0.0227)		(0.0260)	(0.0265)
COE		1.503***	1.436***		0.794**	0.794**
		(0.505)	(0.519)		(0.351)	(0.350)
FOR		0.714***	0.718***		0.167	0.168
		(0.177)	(0.175)		(0.141)	(0.142)
HKT		0.295	0.297		0.108	0.103
		(0.187)	(0.185)		(0.161)	(0.162)
STK		0.620***	0.614***		0.595***	0.595***
		(0.187)	(0.186)		(0.204)	(0.202)
PRI		0.496***	0.493***		0.256**	0.255*
		(0.163)	(0.161)		(0.130)	(0.130)
OTH		-0.284	-0.273		-2.319***	-2.292***
		(0.515)	(0.496)		(0.638)	(0.616)
TPartner-N		0.123**	0.141**		0.0240	0.0276
		(0.0570)	(0.0566)		(0.0689)	(0.0689)
TPartner-F		0.260*	0.253*		-0.0353	-0.0329
		(0.135)	(0.135)		(0.118)	(0.118)
lnRD	0.303***			0.169***		
	(0.0151)			(0.0624)		
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Vuong Test	18.75***	16.09***	16.24***	17.53***	14.89***	15.17***
Likelihood	-18568	-17898	-17680	-20660	-19948	-19932
Observations	19,040	19,040	19,040	19,040	19,040	19,040

Note: Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Innovator and Technology Partnership - All Industries (Invention)

VARIABLES	(1) Innovator	(2) Typical	(3) RDEMP>10	(4) RDEMP<=10	(5) M&D>0	(6) M&D==0
L.PS	0.0134***	0.137	0.0157***	0.104***	0.0160***	0.0303***
	(0.00251)	(0.0846)	(0.00220)	(0.0190)	(0.00217)	(0.00905)
ln(RD/L)	-0.295***	0.790***	-0.0315	0.535**	0.274*	1.237***
	(0.113)	(0.106)	(0.148)	(0.221)	(0.148)	(0.228)
(ln(RD/L))2	0.0540***	-0.0739***	0.0263	-0.0762**	-0.0119	-0.181***
	(0.0150)	(0.0159)	(0.0176)	(0.0357)	(0.0172)	(0.0490)
Age	-0.0160**	-0.0229***	-0.0142***	-0.0148	-0.0139***	-0.0191
	(0.00652)	(0.00765)	(0.00486)	(0.0167)	(0.00507)	(0.0138)
Size	0.270***	0.355***	0.287***	0.274***	0.311***	0.205***
	(0.0366)	(0.0335)	(0.0295)	(0.0744)	(0.0266)	(0.0694)
ln(GOVF/L)	0.0699**	0.136***	0.105***	0.0814	0.102***	0.140**
	(0.0296)	(0.0344)	(0.0240)	(0.0521)	(0.0233)	(0.0675)
TPartner-N	-0.0164	0.252***	0.117*	0.0843	0.152**	-0.0376
	(0.0808)	(0.0757)	(0.0637)	(0.127)	(0.0624)	(0.115)
TPartner-F	0.324*	0.190	0.289**	-0.0428	0.277*	0.306
	(0.182)	(0.184)	(0.142)	(0.345)	(0.145)	(0.308)
Ownership FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Likelihood	-5296	-11607	-12325	-4502	-14109	-3197
Observations	1,774	17,266	5,667	13,373	8,794	10,246

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 5: Innovator and Technology Partnership - All Industries (UMD)

VARIABLES	(1) Innovator	(2) Typical	(3) RDEMP>10	(4) RDEMP<=10	(5) M&D>0	(6) M&D==0
TPartner-N	0.0881	-0.0367	0.0184	-0.0187	0.00643	0.0352
	(0.106)	(0.0852)	(0.0711)	(0.211)	(0.0714)	(0.201)
TPartner-F	-0.0481	-0.0159	-0.0274	-0.475*	-0.0573	-0.0715
	(0.179)	(0.154)	(0.123)	(0.280)	(0.126)	(0.353)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
Ownership FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Likelihood	-5725	-13481	-139334	-4464	-14144	-4835
Observations	1,774	17,266	5,667	13,373	8,794	10,246

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 5b: Innovativeness and Technology Partnership - All Industries (Invention)

VARIABLES	(1) Young	(2) Mature	(3) Large	(4) Small
L.PS	0.0226***	0.0136***	0.0154***	0.0203***
	(0.00362)	(0.00244)	(0.00250)	(0.00354)
ln(RD/L)	0.291	0.940***	0.594***	0.864***
	(0.271)	(0.0960)	(0.120)	(0.252)
(ln(RD/L))2	-0.0132	-0.0912***	-0.0461***	-0.114***
	(0.0336)	(0.0146)	(0.0149)	(0.0420)
Age	-0.000168	-0.00959	-0.0153***	-0.00841
	(0.0224)	(0.00626)	(0.00506)	(0.0200)
Size	0.292***	0.386***	0.339***	0.347***
	(0.0398)	(0.0305)	(0.0275)	(0.130)
ln(GOVF/L)	0.0523	0.167***	0.116***	0.0796
	(0.0328)	(0.0285)	(0.0244)	(0.0590)
TPartner-N	0.147	0.0923	0.0968	0.192
	(0.103)	(0.0673)	(0.0612)	(0.139)
TPartner-F	0.408*	0.167	0.295**	-0.398
	(0.214)	(0.171)	(0.144)	(0.246)
Ownership FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Likelihood	-7465	-10107	-13684	-3778
Observations	8,809	10,231	9,334	9,706

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 5b: Innovativeness and Technology Partnership - All Industries (UMD)

VARIABLES	(1) Young	(2) Mature	(3) Large	(4) Small
TPartner-N	0.219**	-0.0493	-0.0158	0.596***
	(0.103)	(0.0824)	(0.0695)	(0.213)
TPartner-F	0.0844	-0.0725	-0.0760	0.600
	(0.179)	(0.148)	(0.120)	(0.476)
Additional controls	Yes	Yes	Yes	Yes
Ownership FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Likelihood	-6628	-12924	-16246	-2811
Observations	8,809	10,231	9,334	9,706

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 6: Supply Chain and Technology Partnership

VARIABLES	(1) Customer=L	(2) Customer =N	(3) Customer=I	(4) Supplier=L	(5) Supplier=N	(6) Supplier=I
L.PS	0.0298***	0.0150***	0.0262***	0.0135***	0.0167***	0.0344***
	(0.00722)	(0.00238)	(0.00585)	(0.00399)	(0.00223)	(0.00688)
ln(RD/L)	0.762***	0.811***	-0.191	0.644***	0.786***	0.773**
	(0.186)	(0.105)	(0.305)	(0.202)	(0.106)	(0.368)
(ln(RD/L))2	-0.0535**	-0.0797***	0.0572	-0.0423	-0.0761***	-0.0728
	(0.0222)	(0.0146)	(0.0463)	(0.0264)	(0.0149)	(0.0548)
Age	0.0291	-0.0186***	-0.00380	0.0424**	-0.0235***	-0.00820
	(0.0203)	(0.00537)	(0.0158)	(0.0190)	(0.00541)	(0.0160)
Size	0.289***	0.345***	0.322***	0.307***	0.310***	0.465***
	(0.107)	(0.0284)	(0.0695)	(0.0822)	(0.0303)	(0.0714)
ln(GOVF/L)	0.0685	0.108***	0.161*	0.174***	0.110***	0.0468
	(0.0609)	(0.0246)	(0.0890)	(0.0492)	(0.0260)	(0.0955)
TPartner-N	0.506	0.0866	0.00862	-0.239	0.0725	0.273
	(0.374)	(0.0674)	(0.181)	(0.300)	(0.0674)	(0.170)
TPartner-F	-0.0374	0.357**	0.0238	1.326***	0.0172	0.251
	(0.520)	(0.171)	(0.216)	(0.443)	(0.136)	(0.263)
Ownership FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Likelihood	-1359	-14066	-2158	-1877	-13804	-1917
Observations	3,094	14,623	1,323	3,394	14,135	1,511

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 6: Supply Chain and Technology Partnership (UMD)

VARIABLES	(1) C=L	(2) C=N	(3) C=I	(4) S=L	(5) S=N	(6) S=I
TPartner-N	1.293***	-0.00191	-0.232	0.947**	-0.0458	-0.0867
	(0.463)	(0.0783)	(0.183)	(0.446)	(0.0769)	(0.170)
TPartner-F	-0.173	0.0370	-0.270	0.856	-0.197	0.0752
	(0.332)	(0.172)	(0.197)	(0.543)	(0.147)	(0.195)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
Ownership FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Likelihood	-1117	-16079	-2349	-1612	-16128	-1692
Observations	3,097	14,626	1,323	3,397	14,138	1,511

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 7: Sector and Technology Partnership

VARIABLES	(1) Manu	(2) Construct	(3) W&R	(4) Info	(5) Business	(6) Scientific
L.PS	0.0167***	0.0534***	-0.0101	0.0216***	0.0133**	0.0198***
	(0.00365)	(0.0173)	(0.0123)	(0.00728)	(0.00532)	(0.00175)
ln(RD/L)	0.690***	1.650***	1.418***	0.747***	1.115***	0.556***
	(0.170)	(0.346)	(0.247)	(0.245)	(0.280)	(0.177)
(ln(RD/L))2	-0.0661***	-0.198**	-0.146***	-0.0560	-0.0865**	-0.0492**
	(0.0235)	(0.0830)	(0.0463)	(0.0380)	(0.0351)	(0.0224)
Age	-0.0132	-0.0932**	0.00543	-0.0559**	0.0144	-0.0230***
	(0.00810)	(0.0456)	(0.0131)	(0.0240)	(0.0155)	(0.00754)
Size	0.351***	0.232	0.320***	0.260***	0.532***	0.388***
	(0.0386)	(0.187)	(0.0855)	(0.0818)	(0.0869)	(0.0428)
ln(GOVF/L)	0.163***	0.335**	0.198*	0.103	0.0430	0.0573*
	(0.0373)	(0.145)	(0.109)	(0.0664)	(0.0892)	(0.0306)
TPartner-N	0.165*	0.172	0.279	0.0669	0.100	0.00507
	(0.0928)	(0.281)	(0.181)	(0.179)	(0.185)	(0.0983)
TPartner-F	0.241	0.340	0.0357	0.162	0.132	0.436**
	(0.209)	(0.563)	(0.342)	(0.443)	(0.352)	(0.208)
Ownership FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Likelihood	-6680	-370	-1303	-1859	-732	-6282
Observations	4,486	513	2,292	2,578	1,295	7,876

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 7: Sector and Technology Partnership (UMD)

VARIABLES	(1) Manu	(2) Construct	(3) W&R	(4) Info	(5) Business	(6) Scientific
TPartner-N	0.126	0.0357	0.0663	0.229	-0.326	-0.151
	(0.0870)	(0.290)	(0.180)	(0.183)	(0.261)	(0.143)
TPartner-F	0.0851	-1.442	0.989***	0.0408	-0.601	-0.292
	(0.139)	(0.992)	(0.368)	(0.289)	(0.384)	(0.282)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
Ownership FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Likelihood	-8900	-379	-1391	-1393	-1140	-5633
Observations	4,486	513	2,292	2,578	1,295	7,876

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 8: Logarithm of Labor Productivity

VARIABLES	(1) ALL	(2) Manu	(3) Construct	(4) W&R	(5) Info	(6) Business	(7) Scientific
PA-Inv	0.182***	0.165***	0.326***	0.188***	0.183***	0.319***	0.167***
	(0.0121)	(0.0191)	(0.0507)	(0.0498)	(0.0319)	(0.0668)	(0.0208)
ln(K/L)	0.689***	0.697***	0.568***	0.846***	0.620***	0.571***	0.698***
	(0.00839)	(0.0162)	(0.0627)	(0.0263)	(0.0251)	(0.0274)	(0.0127)
Age	0.00444**	-0.000458	0.0235**	-0.00961	0.0308***	-0.0219**	0.00872***
	(0.00179)	(0.00268)	(0.00917)	(0.00596)	(0.00612)	(0.0104)	(0.00289)
COE	-0.576***	-0.299	-1.294***	-0.500	-1.754***	-0.354	-0.707***
	(0.117)	(0.200)	(0.352)	(0.650)	(0.284)	(0.744)	(0.153)
FOR	0.264***	0.204*	-0.367	-0.141	0.219	0.541	0.114
	(0.0670)	(0.116)	(0.374)	(0.249)	(0.157)	(0.477)	(0.122)
HKT	0.223***	0.149	-0.620	0.210	0.370**	0.117	-0.0826
	(0.0734)	(0.118)	(0.521)	(0.279)	(0.186)	(0.499)	(0.150)
STK	-0.0198	0.0103	-0.694**	-0.263	-0.0704	0.275	-0.0816
	(0.0742)	(0.131)	(0.323)	(0.522)	(0.171)	(0.466)	(0.102)
PRI	0.162***	0.0221	-0.608**	-0.392*	0.266*	0.0496	0.245***
	(0.0624)	(0.115)	(0.308)	(0.220)	(0.144)	(0.464)	(0.0777)
OTH	0.258	0.0960	-2.392***			1.061**	0.244
	(0.188)	(0.217)	(0.332)			(0.516)	(0.282)
SPartner-N	0.0526**	0.132***	-0.0157	-0.00891	0.0170	-0.0683	0.0505
	(0.0238)	(0.0502)	(0.137)	(0.0798)	(0.0579)	(0.0971)	(0.0359)
SPartner-F	0.296***	0.233***	0.214	0.346***	0.218***	0.0954	0.405***
	(0.0387)	(0.0656)	(0.251)	(0.124)	(0.0838)	(0.203)	(0.0692)
CPartner-N	-0.0170	-0.0521	-0.0944	-0.0198	-0.0607	0.149	0.00387
	(0.0253)	(0.0577)	(0.142)	(0.0827)	(0.0632)	(0.101)	(0.0373)
CPartner-F	0.133***	0.0219	-0.412	0.302**	0.137	0.535***	0.179**
	(0.0382)	(0.0682)	(0.329)	(0.138)	(0.0851)	(0.205)	(0.0802)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.451	0.560	0.502	0.446	0.370	0.465	0.409
Observations	19,040	4,486	513	2,292	2,578	1,295	7,876

Note: Manu stands for Manufacturing; W&R stands for wholesale and retail. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 8b: ROA

VARIABLES	(1) ALL	(2) Manu	(3) Construct	(4) W&R	(5) Info	(6) Business	(7) Scientific
PA-Inv	0.0873	0.0256**	1.931	0.0637**	0.215	-0.164	0.0274***
	(0.0755)	(0.0109)	(2.112)	(0.0313)	(0.150)	(0.122)	(0.00806)
ln(K/L)	-0.0529	-0.121	-4.077	0.0963	0.170*	0.223**	0.0526**
	(0.144)	(0.131)	(4.812)	(0.0738)	(0.0868)	(0.111)	(0.0257)
Age	0.00870	0.0115	0.356	-0.000262	-0.0585	0.00562	0.00302
	(0.0126)	(0.0108)	(0.358)	(0.00284)	(0.0750)	(0.00506)	(0.00205)
COE	-0.121	-0.107	-4.506	0.0797	-0.376	-0.130	0.0170
	(0.174)	(0.108)	(6.302)	(0.111)	(0.281)	(0.118)	(0.0536)
FOR	-0.0967	0.153	5.126	-0.251	-0.800	0.0582	-0.165***
	(0.216)	(0.111)	(5.221)	(0.181)	(0.709)	(0.171)	(0.0633)
HKT	0.0680	-0.0126	9.642	-0.377*	-0.120	-0.282**	-0.117**
	(0.114)	(0.0395)	(10.09)	(0.206)	(0.333)	(0.139)	(0.0540)
STK	0.0305	0.0354	4.440	-0.0427	-0.257	-0.127	0.0285
	(0.0426)	(0.0410)	(4.757)	(0.151)	(0.365)	(0.111)	(0.0405)
PRI	0.0708	-0.0121	4.857	-0.188	-0.139	-0.0315	0.0255
	(0.0660)	(0.0466)	(4.650)	(0.158)	(0.327)	(0.141)	(0.0245)
OTH	-0.000471	0.0926	-3.410			-0.0608	-0.0186
	(0.0854)	(0.0711)	(5.667)			(0.204)	(0.0890)
SPartner-N	-0.00206	0.0922*	1.402	-0.0616	-0.553	0.206**	-0.0332
	(0.0909)	(0.0511)	(1.878)	(0.0647)	(0.563)	(0.0908)	(0.0227)
SPartner-F	0.225	0.551	2.389	-0.334	0.587	0.0872	-0.0302
	(0.173)	(0.486)	(3.324)	(0.311)	(0.576)	(0.201)	(0.0219)
CPartner-N	0.00823	-0.0936	0.128	-0.0359	0.236	-0.00801	0.0193
	(0.0345)	(0.0662)	(0.949)	(0.0423)	(0.287)	(0.130)	(0.0201)
CPartner-F	-0.233	0.160	-4.012	0.00327	-1.134	-0.0420	0.00638
	(0.309)	(0.244)	(5.071)	(0.0408)	(1.178)	(0.362)	(0.0267)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.002	0.011	0.058	0.007	0.011	0.034	0.005
Observations	19,040	4,486	513	2,292	2,578	1,295	7,876

Note: Manu stands for Manufacturing; W&R stands for wholesale and retail. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1