

OFFSHORING AND TECHNOLOGICAL CHANGE AS DETERMINANTS OF INNOVATION

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To my parents

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Overview of papers and co-authorship

This thesis includes the following three self-contained articles:

Fritsch, Ursula, “Is Offshoring Beneficial or Harmful to Innovation in Developed Countries?,” mimeo 2016.

Fritsch, Ursula and Holger Görg, “Outsourcing, Importing and Innovation: Evidence from Firm-level Data for Emerging Economies,” *Review of International Economics*, 2015, 23 (4), 687-714.

Fritsch, Ursula, “Information Technology and Innovation in Chinese Firms,” mimeo 2016.

Each co-author contributed significantly to the concept, design and content of the joint article.

For copyright reasons chapter 3 cannot be included in the electronic version of this dissertation. Please see the respective journal article which can be accessed via the link on page 54.

Chapter 1

Introduction

When economists analyze productivity growth and labor market inequalities, they frequently discuss two explanatory factors: offshoring and technological change (Feenstra and Hanson (1999)). Both factors have been subject to large developments in the past two decades. The integration of China and other emerging countries into global value chains and the growing technological readiness of firms and the interconnectedness of production processes are just the most obvious examples. My thesis on the determinants of innovation relates to both the labor market and productivity literature. Researchers have been concerned with pinning down productivity effects occurring due to offshoring and technological change. Offshoring is generally believed to have increased productivity (Görg et al. (2008)), but results for investments in information and communication technology (ICT) have been weaker in terms of positive effects (Black and Lynch (2001), Bresnahan et al. (2002)). Labor economists have identified that both phenomena relate to growing wage inequality (Autor and Dorn (2013), Michaels et al. (2014), Hummels et al. (2014)). The fact that offshoring and technological change are skill-biased and increase productivity naturally leads to the question how these two factors relate to innovation. Innovation could be a channel through which productivity and labor market effects occur.

This dissertation asks whether offshoring and technological change induce more innovation. It is important to investigate determinants of innovation as innovation strongly affects productivity growth (Griffith et al. (2004)). Innovation, as studied in this thesis, comprises both innovation inputs, for example spending on research and development (R&D), and innovation outputs, as introducing new products. Griffith et al. (2004) identify two channels which link innovation to productivity growth. First, radical innovation shifts out the world technological frontier. Second, innovation increases absorptive capacity by strengthening the ability of firms to adapt products or services to local markets or by using technology that is conducive to efficient production. Developed countries are

likely to profit from both innovation channels, but emerging countries mostly only aim at increasing absorptive capacity. Determinants of innovation have recently received more attention in economics. Görg and Hanley (2011) document that services offshoring positively impacts on innovation, while Karpaty and Tingvall (2015) present mixed results for developed countries. Imported intermediate inputs have been found to enhance innovation activities in Indian firms (Goldberg et al. (2010)). Technological change promotes innovation in a study on valve manufacturing (Bartel et al. (2007)).

This dissertation seeks to answer the following questions. How does offshoring relate to innovation in developed and emerging countries? Are offshoring effects homogenous or do they depend on the type of offshoring? How are these adjustments related to the institutional environment or market conditions in which firms operate? And lastly, what is the role of adopting superior technology - here I consider the use of enterprise software - in stimulating innovation in firms?

Most recent studies in the fields of trade and innovation use disaggregated and comprehensive data to better control for selection effects and to account more thoroughly for endogeneity. Therefore this dissertation relies to a large extent on establishment-level data. Detailed establishment-level data by the World Bank is used for two papers. For a third paper, rich data on imported intermediate inputs on the industry-level is deployed to look in a more comprehensive way at offshoring structures of developed countries.

The first paper responds to a large public debate in developed countries: does sourcing intermediate inputs from abroad result in the relocation of complex or research-intensive parts of the production process as well?

The answer is a controversial issue in the theoretical trade literature. Some studies stress the short-term productivity-enhancing effects of offshoring to lower-income countries which should induce higher growth rates of innovation (Glass and Saggi (2001)). Trade liberalization can also turn countries into production locations, as opposed to innovation locations. Arkolakis et al. (2013) present evidence that the average developed country suffers from a reduction in innovation after trade liberalization as innovation is reallocated towards countries that are particularly productive in innovation. It is therefore a priori unclear which innovation effects can be expected from offshoring.

I follow the approach advocated by Michaels et al. (2014) and analyze *aggregate* industry effects thereby accounting for spill-over effects as non-offshoring firms might be affected by offshoring through competition effects. As previous studies are exclusively on the firm-level and covered only highly developed countries, my analysis on 15 developed countries should be better suited to shed light on an average country-industry effect. I

deploy for this purpose the novel World Input-Output Database (WIOD), which provides unique and detailed data on trade flows in intermediate inputs at the industry-level. This allows me to study the effects of various forms of offshoring on innovation in my paper “*Is Offshoring Beneficial or Harmful to Innovation in Developed Countries?*”.

This paper investigates the effect of offshoring on innovation using instrumental variables and finds a negative overall effect. Offshoring of services relates positively to innovation, whereas offshoring of manufacturing affects innovation negatively. The latter effect shapes the overall effect. Solely offshoring of manufacturing to high-income countries is harmful for innovation, but not offshoring of manufacturing to low-income countries. This effect heterogeneity of offshoring is rationalized by cost-reduction, variety and adverse competition effects. Three mechanisms furthermore mitigate the negative effect of offshoring: skill endowment, distance to the technological frontier and the relative position in the production chain. I draw on an instrument developed by Hummels et al. (2014) on world export supply to address endogeneity concerns. The idea is that changing export supply to the world due to price and quality changes should impact country-industry pairs stronger if business relationships are well-established. The argument behind this is persistence in trading relationships. Further instruments include lagged values and lagged changes in offshoring and a lagged wage gap to sourcing destinations.

Policy makers can learn from this paper that offshoring of services entails large gains from trade. As service sectors are still heavily regulated, further trade liberalization in these sectors could hold large innovation gains for firms. A second contribution to the current debate on further trade liberalization among developed countries is related to the finding that trade in intermediates between developed countries leads to adverse effects on innovation. This suggests differential effects on short-term and medium-term productivity growth. Complementary labor market policies can additionally be effective in averting adverse innovation effects.

The following two papers deal with innovation activities of firms located in emerging countries.

The paper entitled “*Outsourcing, Importing and Innovation: Evidence from Firm-level Data for Emerging Economies*”, which is co-authored with Holger Görg, looks at a new channel through which the fragmentation of production impacts on firms’ innovation activities by considering outsourcing¹. We also acknowledge the importance

¹This paper is published in the *Review of International Economics*, 2015, 23 (4), 687-714. While Holger Görg developed the idea for the paper, I conducted the empirical analysis and largely wrote the paper. I also changed the focus of the paper at a later stage of analysis and developed the instrumental variables

of intermediate imports for innovation (Goldberg et al. (2010)). This paper relies on a broad sample of establishments in emerging countries, the BEEPS-dataset, which is provided by the World Bank. We carefully disentangle the effects of outsourcing from the effects of importing. Outsourcing, as defined in this paper, relates to the decision whether a product is best produced in-house versus at arm's length, whereas importing captures whether firms source from local markets only or also rely on foreign intermediate inputs. An instrumental variables approach is deployed to address endogeneity concerns. We argue that the prevalence of intermediate imports and outsourcing reported by other firms in the same country, industry and year should be related to a firm's own propensity to import or outsource. The answers of other firms should reflect general obstacles to trade or to transport. A firm's statement on the pressure, that the firm experiences, to reduce costs due to competition is used as an additional instrument for the two endogenous globalization measures.

A key contribution of the paper is that differentiated effects for outsourcing and importing can be established. These effects also depend on the innovation measure under consideration. Outsourcing increases the likelihood to spend on R&D and via this channel raises innovation output, whereas importing increases innovation output, but not R&D. Outsourcing therefore leads to restructuring of business activities towards more complex activities, such as R&D. A possible explanation is that outsourcing allows the firm to target its core competencies more successfully. Importing is associated with larger input varieties or higher quality inputs that apparently affect innovation output, for instance by offering a new product, but not R&D.

Results crucially depend on the institutional environment in the economy, e.g., property rights and intellectual property rights protection. Our results suggest that better institutions magnify the gains from importing, but not from outsourcing. This could be because outsourcing is mostly domestic outsourcing. EU countries also reap additional positive innovation effects from importing compared to non-EU countries. This finding likely reflects the benefits of generally sound institutions in the EU.

The last paper of this dissertation "*Information Technology and Innovation in Chinese Firms*" is a single-authored paper. This paper relies on a recent establishment-level survey conducted by the World Bank in China. I investigate the effect of using enterprise software on innovation, in addition to considering the effect of a standard measure of ICT. ICT generally allows the firm to gather information more systematically and to evaluate this information at lower costs. Enterprise software is used by a firm to manage its inventory and the production process efficiently and in real-time. The use

strategy.

of enterprise software also enables firms to gather detailed information about customers so that firms can gear their products promptly to customers' preferences. The latter point should be especially crucial for studying effects on innovation. This paper speaks to a growing interest in linking ICT and innovation (Bartel et al. (2007)) and the use of "big data" (Brynjolfsson et al. (2011)). It also circumvents several drawbacks of previous research by using much more nuanced information on ICT and innovation and by relying on a large sample of Chinese firms operating in the manufacturing sector. This paper furthermore extends the literature by looking, for the first time, at an emerging country. This is a relevant question for China as China seeks ways to technologically catch up and produce higher value-added parts of the production chain. I control for selection effects into ICT use by deploying various propensity score matching (PSM) techniques.

This analysis presents differentiated results with respect to different ICT and innovation measures. The degree of sophistication of the ICT measure as well as the degree of standardization of the innovation measure matter for the results. The general use of ICT and to a stronger extent the use of enterprise software have positive and economically meaningful effects on various types of innovation of firms. Adopting enterprise software increases the probability of introducing new products or services, for instance, by about 11 percentage points (or 23 percent). A measure on the general frequency of ICT use is however not associated with a higher probability of introducing new products or services but with an increased probability of upgrading. Another novel finding is that effects of ICT are stronger the more routinized or standardized innovation activities are, i.e., effects are more robust for upgrading than for R&D intensity. Highly robust and large effects are also found for process innovation as outcome variable.

The presented results are relevant given that an emerging economy is being studied for the first time. It is an important finding for managers in emerging countries that firms in these countries can innovate in various ways by adopting technology. As previous research documents that large productivity effects are expected in these countries (Commander et al. (2011)), investing in ICT could enable firms in emerging countries to engage in more complex parts of the production chain. Policy makers should therefore promote and stimulate measures that facilitate the adoption of new technology with a special focus on more advanced forms of ICT capital.

This dissertation contributes to both the trade and the innovation literature. The papers share a common interest in firm dynamics and means that the firm can exploit to promote innovation as a conduit for longer-term productivity growth. Against the backdrop of rapid economic development in many emerging countries, this dissertation

contributes to a better understanding how firms located in these countries can engage in technological upgrading. Both imported intermediate inputs and the use of ICT relate to more innovation. How can these results be rationalized with the adverse effects documented for developed countries? The answer is likely related to the type of innovation that is being studied. I analyze R&D spending in the case of developed countries which reflects radical innovation effort of firms (*Paper 1*). Only this type of innovation is negatively affected by offshoring, whereas more basic forms of innovation are positively influenced by trade in intermediates (*Paper 2*). I interpret this as suggesting that firms always engage in some form of technological upgrading when exposed to new foreign inputs, but the average firm might well reduce more radical innovation effort mostly likely due to adverse competition effects. All three papers furthermore present some evidence for effect heterogeneity stressing the role of sound institutions, skill endowment and the distance to the technological frontier.

Chapter 2

Is Offshoring Beneficial or Harmful to Innovation in Developed Countries?

by Ursula Fritsch^{1 2}

Abstract

This paper investigates the effect of offshoring on innovation in a sample of 15 developed countries using instrumental variables and finds a negative overall effect. Offshoring of services relates positively to innovation, whereas offshoring of manufacturing affects innovation negatively. Solely offshoring of manufacturing to high-income countries is harmful for innovation, but not offshoring of manufacturing to low-income countries. Findings are rationalized by cost-reduction, variety and adverse competition effects. Three mechanisms furthermore influence the negative effect of offshoring: skill endowment, distance to the technological frontier and the relative position in the production chain.

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1 Introduction

A key development in international trade in the past decades has been the spectacular rise of offshoring and the increase of trade in intermediate goods and services ((Feenstra and Hanson (1999), Hummels et al. (2001)). While the effect of offshoring on innovation is controversially discussed in the theoretical literature, it only receives scant attention in the empirical trade literature. As innovation is a key driver of productivity growth (Griffith et al. (2004)), it is important to gain insights into the role of trade in intermediates in stimulating or hampering innovation. Innovation is crucial for medium- and long-term productivity growth and studying innovation is therefore markedly different from a short-term analysis of productivity effects. This is particularly relevant against the background of ambiguous developments of R&D intensities in developed countries over the considered time period (1995 to 2007). Only about 60% of our industry observations depict positive growth of R&D intensities over this time period with a median growth rate of 14%. This paper asks if and how these changes are related to growing trade in intermediates.

The theoretical literature discusses conflicting effects of offshoring on innovation. One strand of the literature posits that positive productivity gains from offshoring to low-cost destinations can be reinvested in innovation at home (Glass and Saggi (2001)). Trade in intermediates additionally allows access to superior technology or a greater variety of inputs (Goldberg et al. (2010), Colantone and Crinò (2014)). Offshoring is also related to changing patterns of specialization. These can entail adverse specialization effects due to differences in Ricardian technology (Arkolakis et al. (2013)). One dimension of trade in intermediates is therefore increasing competition. Effects of competition on innovation are however ambiguously discussed in the literature (Aghion et al. (2004), Aghion et al. (2005), Hashmi (2013)) and therefore ultimately require an empirical investigation. The aforementioned three factors - cost-reducing, variety-seeking offshoring and competition effects - determine the overall effect of offshoring on innovation.

This paper weighs in the debate by arguing that a differentiation of offshoring allows to test for the aforementioned channels. Cost-reducing effects that induce innovation should be stronger for offshoring to low-income countries and weaker for offshoring to high-income countries. The opposite effect is expected when variety and quality effects of offshoring are considered. Lastly, competition effects are analyzed by distinguishing offshoring of services from offshoring of manufacturing. Only offshoring of manufacturing is assumed to exert competitive pressure on R&D spending in the manufacturing sector.

There is currently little international evidence on the link between offshoring and innovation. Görg and Hanley (2011) document that offshoring of services increases innovation. Karpaty and Tingvall (2015) present mixed results showing that the direction of the offshoring effect depends on offshoring destinations and the level of aggregation of the analysis. By considering Ireland and Sweden, these studies focus on highly developed countries. The present paper suggests that these results might not be representative for a broader set of developed countries.

In this paper, we hypothesize that offshoring effects on innovation are not uniform. If effects were uniform, they are expected to be present at different levels of disaggregation of the offshoring measure. This is however not the case. We rationalize our results by relying on predictions made in the theoretical literature which have however not been integrated into a uniform framework. The differentiation between high and low-income countries allows us to disentangle the differences in cost-cutting versus variety- or quality-seeking offshoring (Glass and Saggi (2001), Colantone and Crinò (2014)). Separating offshoring of manufacturing from offshoring of services allows an analysis along an additional margin by reflecting competition effects (Aghion et al. (2005), Arkolakis et al. (2013)). Also note that considering offshoring of services separately is interesting as offshoring of services is growing much more rapidly than offshoring of manufacturing (Amiti and Wei (2009)).

We exploit comparable industry-level data for 15 developed countries for the period 1995 to 2007. We rely in particular on the novel World Input-Output Database to analyze trade in intermediates on a country-industry level. This allows us to disentangle the aforementioned effects in an unprecedented way.

This paper is, to the best of our knowledge, the first to consider effects for a set of developed countries. We present international validation and - compared to firm-level studies - account for spill-over effects as non-offshoring firms might be affected by offshoring through competition effects. This is the first major contribution of this paper¹. The second contribution lies in providing more nuanced results depending on the offshoring measure under consideration. The average country-industry effect of offshoring on innovation turns out to be negative. We subsequently differentiate four modes of offshoring: offshoring of manufacturing vs. offshoring of services and offshoring to high-income countries vs. offshoring to low-income countries. This allows us to make predictions about three hypotheses formulated in the theoretical literature: productivity effects due to cost saving or variety- and quality-effects and adverse competition effects. The empirical analysis delivers three main results. First, offshoring to low-income countries and offshoring of services induce positive effects on innovation due to cost reduction and

variety effects (Glass and Saggi (2001), Colantone and Crinò (2014)). Second, offshoring of manufacturing, on the contrary, negatively relates to innovation which is likely due to an adverse competition effect². As offshoring of manufacturing to high-income countries is by far the largest part of offshoring, this drives the aggregate effect. This is in line with recent work by Arkolakis et al. (2013) who present evidence that the average developed country suffers from a reduction in innovation after trade liberalization. These results also resonate with potentially negative effects of competition on innovation (Aghion et al. (2005), Hashmi (2013)). Third, this paper stresses the importance of effect heterogeneity. Fully in line with Arkolakis et al. (2013), offshoring is more detrimental to innovation the larger the distance to the technological frontier. Higher skill endowment mitigates adverse effects of offshoring on innovation as well. A third mitigation factor is considered: the relative position in the production chain, a novel measure of upstreamness pioneered by Fally (2012) and Antràs and Chor (2013). Upstreamness of an industry also reduces the negative effect of offshoring on innovation.

Endogeneity concerns arise from ample evidence that importing firms are more likely to spend on R&D (Boler et al. (2015)) and are addressed by implementing an instrumental variables strategy. We draw on an instrument developed by Hummels et al. (2014) on world export supply. The idea is that changing export supply to the world due to price and quality effects should impact country-industry pairs stronger if business relationships are well established. The argument behind this is persistence in trading relationships. We further deploy lagged values and lagged changes in offshoring and wage gaps to the sourcing destinations as additional instruments. The results using instrumental variables corroborate results of OLS-estimations. Due to the lack of a compelling natural experiment, our results should be primarily seen as conditional correlations though. As instrumental variables analysis replicates OLS-findings this adds further credibility to our results.

The remainder of this paper is structured as follows. Section II discusses the related literature especially the link with the theoretical trade literature, section III presents the data and section IV the empirical analysis. Section V concludes.

2 Related literature

The theoretical trade literature makes controversial predictions about the link between offshoring and innovation. We consider first a set of models in which offshoring involves production relocation from a developed country to a developing country. These models depict a static innovation gain which arises from a productivity effect (e.g., Glass and

Saggi (2001), Rodríguez-Clare (2010), Acemoglu et al. (forthcoming)). The productivity effect occurs as a result of increasing offshoring opportunities. These arise either as the subset of intermediates that becomes offshorable to the low-income country expands or as the costs of offshoring fall. This allows producers in the developed country to exploit the wage differential between the developed and the developing country, and this induces a positive productivity effect. Empirical studies have recently also stressed the role of superior inputs in terms of variety and quality in stimulating domestic innovation (Goldberg et al. (2010) and Colantone and Crinò (2014)). We argue in this paper that cost-reducing offshoring and variety- and quality-seeking offshoring can be analyzed by looking at offshoring to different destinations, in particular offshoring to high-income countries versus offshoring to low-income countries. These effects are hypothesized to be unambiguously positive.

Another literature argues that the effect of offshoring on innovation might be negative. Arkolakis et al. (2013) is closely related to this study building a model of multinational production. Countries can specialize in innovation or production activities. The equilibrium is determined by a country's productivity of innovation, by costs of offshoring and by costs associated with locating multinational production close to final consumers. Simulations suggest that almost all developed countries gain from trade liberalization in terms of welfare but that the average country becomes a "production location" and innovates less than under autarky. The paper therefore stresses large reallocation effects of worldwide innovation towards countries that are particularly productive in innovation. We argue that sourcing heavily from high-income countries captures such competitive pressure and might therefore reflect an adverse specialization effect³. This should only hold for offshoring of manufacturing though. This motivates a differentiation between offshoring according to sector: manufacturing vs. services. Offshoring of services is expected to have a positive effect on innovation stemming from cost-reducing and quality-seeking motives, i.e. effects occur irrespective of the sourcing destination. Offshoring of manufacturing to high-income countries might reflect negative competition as well as positive quality-seeking effects leaving the overall effect undetermined, whereas offshoring of manufacturing to low-income countries entails increased competition as well as positive cost reduction effects. Competition from low-income countries makes firms in developed countries upgrade their technology (Bloom et al. (forthcoming)); this suggests an overall positive effect. Concerning competition from high-income countries, effects are expected to be less clear. Many economists since Arrow (1962) have stressed that competition provides incentives for efficient organization of production by putting downward pressure on costs. This might be particularly linked to the idea of process innovation

and economies of scales in open markets (Dhingra (2013)). Other scholars claim that product market competition reduces monopoly rents that induce innovation. Aghion et al. (2004) and Aghion et al. (2005) model both effects and document that the effect of competition on firms’ or industries’ willingness to innovate depends on their level of efficiency. Competition is expected to spur innovation by firms close to the efficient frontier (those with highest efficiency) while it discourages innovation by firms that are far from the frontier. Dhingra (2013) also model ambiguous innovation outcomes which are related to cannibalization effects of within brand products due to trade liberalization. Other papers model explicitly negative effects of offshoring on innovation. Managers could base their decision on short-term cost reduction motives and opt for offshoring thereby neglecting dynamic effects of innovation which stem from reduced feedback with affiliates (Naghavi and Ottaviano (2009)). Offshoring then diminishes innovation effort, and this entails dynamic losses.

Arkolakis et al. (2013) furthermore suggest that initially highly innovative countries are shielded from adverse effects, similar to the “escape competition” effect in Aghion et al. (2005). We therefore consider distance to the technological frontier and high-skilled labor endowment to test for these mitigation channels and thus effect heterogeneity.

On the empirical side, Görg and Hanley (2011) find that offshoring of services increases innovation activities of Irish firms and that effects for offshoring of manufacturing are weaker and less robust. Breunig and Bakhtiari (2013) document that low-cost-oriented offshoring damages future innovation, whereas innovation-related offshoring promotes future innovation. Karpaty and Tingvall (2015) show that the average firm effect of offshoring is negative. If regressions are re-weighted with firm’s employment to analyze aggregate effects, the estimated effect turns positive. There is evidence on the importance of newly imported inputs through variety and quality channels for the introduction of new domestic products⁴. We acknowledge that distinguishing between offshoring of manufacturing and services is important. Amiti and Wei (2009) document that offshoring of services exerts stronger and more robust effects on productivity than offshoring of manufacturing. Görg and Hanley (2011) present similar evidence for innovation. Compared to these papers, we provide however more compelling reasons why offshoring of manufacturing depicts weaker and even negative effects. We argue that competition from offshoring to other high-income countries triggers these effects⁵.

Lastly, we link our paper to a growing literature on the relative position of an industry in production chains (Fally (2012) and Antràs and Chor (2013)). Fally (2012) argues that upstreamness, i.e., producing at early stages of the production process, strongly negatively correlates with industry specificity, i.e., how thin an industry’s market

is. It might be therefore easier to offshore products that are more upstream and therefore more mature without incurring negative innovation effects. This would be in line with a product cycle theory in which offshoring only occurs for mature products (Costinot et al. (2011)). This hypothesis is tested in an extension.

3 Data sources

This paper deploys data for 15 developed countries on the industry level for the period 1995 to 2007⁶. The main source for analyzing trade in intermediates on the country-industry level is the World Input-Output Database (WIOD) (Timmer et al. (2015))⁷. Offshoring is defined as imported intermediates divided by output⁸:

$$OS_{abt} = \frac{\sum_{ij} II_{ij,abt}}{OUTPUT_{abt}} \quad (1)$$

OS_{abt} denotes offshoring by country a in industry b at time t . This is calculated as a summation over all intermediate imports of materials and services II_{ij} - where i indexes country and j industry - that ab sources and standardized by output of ab in the respective time period (therefore by definition: $i \neq a$). This corresponds roughly to “broad” offshoring as suggested by Feenstra and Hanson (1999) and is used in related studies, see Görg and Hanley (2011) and Karpaty and Tingvall (2015).

Offshoring can be further split into offshoring of manufacturing and services; the numerator is replaced by all imported intermediates in manufacturing or services⁹. Offshoring can additionally be split according to countries of origin; we differentiate between sourcing from high-income countries and low-income countries (see Table B3).

EU-KLEMS data contains information on the total number of hours worked by skill group¹⁰. It also has capital stock data and reports on expenditures for information and communication technology. EU-KLEMS further allows to calculate total factor productivity from the data.

I match these datasets with the ANBERD which provides information on private research and development expenditures¹¹. Data on R&D expenditures in the service sector is scarce. We therefore discard the service sector. R&D expenditures are also largely concentrated in manufacturing industries, although the share of R&D expenditures in manufacturing in all R&D expenditures is declining over time. R&D expenditures in manufacturing account on average for 77% of a country’s R&D spending in 1995 in our sample; this number decreases slightly to 70% in 2007. The share varies substantially between countries though. Germany’s share is at 95% in 1995, whereas Australia’s share

is just 55%. In 2007 Taiwan has the highest share with 92% and Australia the lowest with 30%.

We set zero values for R&D equal to missing values which affects 2% of observations. Zero values are usually preceded and followed by substantial spending on R&D so that it is likely that zero values are missing observations as opposed to zero R&D spending. In a next step, we match R&D data, which is reported on the two-digit level in the ANBERD, with the WIOD, which uses two-digit level industries and aggregates of two-digit level industries. For instance, we aggregate industries C27 and C28 to one industry C27t28. Data is aggregated in the following way: we sum over the respective industries in the ANBERD to be consistent with the WIOD classification, and we set this aggregated value equal to missing if information on at least one of the two-digit industries in the ANBERD is missing. We report in Table B2 a classification of industries according to the WIOD¹².

4 Empirical analysis

4.1 Methodology

The empirical methodology follows Görg and Hanley (2011) and Karpaty and Tingvall (2015):

$$R\&D_{intensity_{ijt}} = \alpha + \beta * Offshoring_{ijt} + \gamma' * \mathbf{X}_{ijt} + \kappa_1 * D_{it} + \kappa_2 * D_{jt} + \varepsilon_{ijt} \quad (2)$$

where i indexes countries, j denotes industries and t stands for years. R&D intensity is defined as the share of R&D expenditures over output. Offshoring is similarly defined as the share of imported intermediate inputs over output (see equation 1). A vector of control variables \mathbf{X} is also included. \mathbf{X} contains the shares of high-skilled and medium-skilled labor. A measure of export intensity controls for the openness of the economy. This variable is included to not confound the estimated coefficient on the offshoring variable with other factors that are related to trade openness. There is also evidence that importing and exporting are concentrated in the same firms (Bernard et al. (2007)), which makes it important to disentangle these two effects. Lastly, we add a measure on capital intensity. The equation is estimated with country-time (D_{it}) and industry-time fixed-effects (D_{jt}). We thereby try to capture that countries implement country-wide or industry-wide policies that are conducive to both trade and innovation. This could introduce omitted variables bias if these effects were not controlled for. In subsequent specifications, we extend the baseline regression by including different offshoring measures differentiating between offshoring of manufacturing and services (Amiti and Wei

(2009)) and offshoring to high- and low-income countries (Karpaty and Tingvall (2015)) as well as a combination of both.

4.2 Baseline results

Turning to the empirical analysis, estimations of equation 2 are presented in Table 1¹³.

Offshoring is found to have a negative effect on R&D intensity. The estimated coefficient is rather small and highly statistically significant. The share of high-skilled labor positively relates to innovation, whereas the opposite is true for medium-skilled labor. Skill upgrading per se might not be sufficient for increasing domestic innovation. A larger export share is associated with higher innovation. This could be because firms that export learn from exporting (De Loecker (2013)). The capital stock measure positively relates to innovation as well.

In specifications (2)-(4) we split offshoring into different sub-components. Offshoring is divided into offshoring of manufacturing and offshoring of services to separate out competition effects that are related to adverse specialization. Note also that the estimated effect for overall offshoring can be understood as a composite effect of - the more prevalent - offshoring of manufacturing and - the much smaller - offshoring of services. This differentiation matters as offshoring of services exerts large and positive effects on R&D intensity, whereas the offshoring coefficient for manufacturing stays statistically significant and negative. Offshoring of manufacturing can be split into offshoring within the same industry and offshoring to other manufacturing industries in almost equal parts. Both effects are individually significantly negative in similar regressions, although the former is slightly larger. We argue that the former effect is a direct competition effect whereas the latter is an *additional* adverse competition effect which occurs if industries experience similar adjustment patterns, i.e., if they experience complementarities in either offshoring or in R&D. We estimate a large coefficient for offshoring of services, which is about five-times as large as the estimated coefficient for offshoring of manufacturing. This is at the lower end of previously estimated differences (Amiti and Wei (2009) and Görg and Hanley (2011)). The size of the services effect could be this large because offshoring of services is a relatively recent development in international trade, which might offer large gains in early stages. The largest part of sourced services are business services, but we cannot say to which extent particular business services play a role in driving the effect. However, results are the most robust for offshoring of business services and somewhat weaker for financial services and point to the unique role of business services for innovation¹⁴. The negative effect of trade in manufacturing goods is likely

related to adverse competition effects à la Arkolakis et al. (2013). These induce industries to specialize in less R&D-intensive parts of the global value chain. Hashmi (2013) find a mildly negative relationship between competition (albeit measured by the inverse of markups) and innovation. Aghion et al. (2005) suggest that the relation is inverted U-shaped. Subsequent regressions will demonstrate heterogeneity of the estimated effect. While the average industry suffers from lower R&D intensities, industries closer to the technological frontier experience reduced adverse effects (Aghion et al. (2005)).

By looking at offshoring to high- and low-income countries, variety effects associated with trade with high-income countries can be separated from cost-reduction effects related to trade with low-income countries. Results demonstrate that cost-reduction - probably through a productivity effect - stimulates innovation whereas variety effects are not strong enough to compensate for adverse competition effects when trade with high-income countries is considered. The last column corroborates these insights. Offshoring of manufacturing is significantly and positively estimated only for offshoring to low-income countries. This is in line with predictions of theoretical models that stress the productivity-enhancing role of offshoring (e.g., Glass and Saggi (2001), Rodríguez-Clare (2010), Arkolakis et al. (2013), Acemoglu et al. (forthcoming)). If competition played a role, it would likely be innovation-enhancing as demonstrated by Bloom et al. (forthcoming). In contrast, offshoring of manufacturing to high-income countries is not beneficial - in terms of innovation - for developed countries. Less productive countries/industries source from more advanced countries because this is productivity-enhancing, for instance because new varieties are imported, but this does not necessarily result in higher spending on R&D¹⁵. Arkolakis et al. (2013) argues that countries might get trapped in production stages of the production chain thereby harming domestic innovation. It could also document that industries that still source a large share of their intermediates from high-income countries are worse off than industries that source from low-income countries because sourcing from the latter country group entails larger productivity effects due to larger wage gaps. Karpaty and Tingvall (2015) find similar effects for offshoring to EU15-countries on the firm-level which however disappear in an aggregate analysis. When we turn to the results for offshoring of services, domestic innovation is positively related to offshoring to high- and low-income countries. This suggests that offshoring of services is beneficial to domestic innovation irrespective of the sourcing destination.

(Table 1 here)

We run a battery of robustness checks, in particular of columns (1) to (3) of Table 1. These are presented in Tables B4 to B12 in the supplementary material¹⁶.

4.3 Confounding factors

In this section, it is documented that the presented results are not to be confounded with other factors. The factors under consideration are productivity shocks, technological change and import competition.

Total factor productivity is considered first. It could be that offshoring simply increases total factor productivity which strongly correlates with R&D intensity. EU-KLEMS data allows to compute total factor productivity by backing out the dependent variable from the following calculation for each variety ij at time t :

$$\ln(TFP) = \ln(VA) - CC * \ln(CS) - HSC * \ln(HHS) - MSC * \ln(HMS) - LSC * \ln(HLS). \quad (3)$$

VA denotes value added, CC is capital compensation as a share of value added, CS refers to the capital stock, HSC (MSC , LSC) is the share of high-skilled (medium-skilled, low-skilled) labor compensation in value added, and HHS (HMS , HLS) is the number of hours worked by the high-skilled (medium-skilled, low-skilled). The dependent variable from this calculation is included as a further control in equation 2¹⁷. This allows to control for a) exogenous TFP shocks and b) productivity increases due to offshoring. If we nevertheless find effects of offshoring on innovation then offshoring has additional beneficial effects that are unrelated to TFP effects. Results turn out to be robust to the inclusion of total factor productivity (see Table 2). Productivity strongly positively relates to innovation as expected, but does not change our baseline results. In fact, the estimated coefficients depict very similar magnitudes as in the baseline estimations. Productivity and innovation effects of offshoring are somewhat unrelated, for instance because firms channel cost savings immediately into innovation. This result corroborates previous and similar findings by Görg and Hanley (2011).

Technological change could be another driver of innovation. Information and communication technology (ICT) likely causes offshoring, but could also have a direct effect on innovation (Bartel et al. (2007)). We therefore include a measure of ICT in our baseline regression. ICT turns out to be an important determinant of R&D intensity. The estimated coefficient is large and highly significant. However, it does not change the estimated coefficients on the different offshoring variables, neither in significance nor in magnitude except for offshoring to low-income countries. The latter result seems to stem from the reduced sample though.

We lastly consider import competition of final manufacturing goods. Offshoring and import competition are likely triggered by the same events, such as falling transport and communication costs or tariff cuts. Hence these variables are expected to be highly

correlated. There is mixed evidence on the link between competition and innovation. Fernandes and Paunov (2013) argue that import competition induces Chilean firms to upgrade product quality. Bloom et al. (forthcoming) argue that import competition from China leads to more innovation in firms in developed countries. There is recent evidence that competition in general and innovation are slightly negatively related (Hashmi (2013)) although Aghion et al. (2005) present evidence for non-linear effects in a similar framework. Note that in the context of this paper offshoring is defined as trade in *intermediates* and import competition refers to trade of *final* goods. Import competition in country a and industry b at time t is then defined as follows:

$$IC_{abt} = \frac{\sum_i FI_{ib,at}}{VA_{abt}}. \quad (4)$$

The numerator sums over all final imports of industry b that country a sources from abroad, irrespective of the producing country i . This value is subsequently scaled by output of country a and industry b at time t . Import competition for Germany's textile industry is thus defined as the value of all final goods of the textile industry imported for final consumption by Germany, and this is then scaled by output of the German textile industry. Hence, import competition - by definition - never takes place in services.

Separate effects for offshoring and import competition are estimated¹⁸. Increasing import competition is found to be negatively related to R&D intensity. This corroborates recent findings by Hashmi (2013) and Dhingra (2013). A possible explanation is the prevalence of high competition environments in which laggard firms are - through increased competition - pushed further from the technological frontier (Hashmi (2013)). Dhingra (2013) stress cannibalization effects in brand portfolios due to increased competition. Most importantly though, the offshoring effects are very similar to previous effects. Offshoring of manufacturing to high-income countries likely triggers similar adjustment effects as import competition. Offshoring is in this paper more comprehensively defined as all manufacturing imports are considered whereas import competition only occurs within the same, narrow industry. This suggests that our offshoring measure captures more complex adjustment patterns which could be related to complementarities across industries that induce adverse spill-overs on other manufacturing sectors.

(Table 2 here)

4.4 Instrumental variables regressions

Potential endogeneity bias is a concern of this analysis. Ample evidence suggests that there are strong selection effects into offshoring and importing presumably due to sunk

costs associated with these activities, as suggested on the firm-level by Bernard et al. (2007) and Kasahara and Lapham (2013). Importing and offshoring firms are also more likely to perform R&D (Boler et al. (2015)). To identify the effect of offshoring on innovation, exogenous variation is exploited which drives the endogenous variable - offshoring - but not innovation except for the effect through offshoring. The instrument has to be relevant, i.e., sufficiently correlated with the endogenous variable, and valid, i.e., not correlated with the error term. We construct an instrument similar to Hummels et al. (2014) on world export supply. Further instrumental variables include lagged values of offshoring, lagged changes in offshoring and a lagged wage gap associated with offshoring. The choice of each instrument is now discussed in more detail.

Although our data is not as detailed as data by Hummels et al. (2014), we use a similar measure and argue that firm-level results should be broadly applicable to industry-level data. We argue that for some reason (e.g., trade barriers, quality, cost competitiveness) ab (country a and industry b) sources a particular input j from country i , and this sourcing structure depicts some persistence over time. Hummels et al. (2014) document evidence for persistence in business relationships in a large sample of Danish firms. The argument is admittedly harder to make in our more aggregated case, but we are confident that the general pattern still holds at the industry level. The idea behind their instrument is as follows. If competitiveness changes over time for a particular variety ij due to various reasons, then this should be reflected in changing export supply of variety ij to the world as a whole. As ab uses ij more intensively than the same industry in other countries, ab disproportionately profits from this development due to persistence in supplier relationships. The instrument is therefore defined as follows. World export supply $WES_{ij,at}$ are country i 's total intermediate exports of industry j to the world market minus its supply to country a at time t ¹⁹. WES measures comparative advantage of ij arising from changes in product price, quality or variety which lead to an expansion or contraction of respective exports. $s_{ij,ab}$ denotes the share of ij in total *intermediate* imports, that is imports of manufacturing as well as selected services imports, of country a and industry b in the year 1995. The latter term captures persistence in sourcing patterns. We then construct the instrument for ab as follows: $I_{abt} = \sum_{ij} s_{ij,ab} * WES_{ij,at}$. Hence, if ab uses ij more intensively than the same industry in other countries and ij becomes more attractive (i.e., cheaper or of better quality), the growing export supply of ij disproportionately benefits ab .

In a next step, the validity of the world export supply instrument is discussed. One concern is the aggregate level at which the effect is identified and for which a firm-level argument is deployed. We argue that the aggregate data that is used in this paper is

not too different from the firm-level data deployed by Hummels et al. (2014). They only focus on firms for which they observe changes in the intensity of offshoring which is due to the construction of their instrument. Their study likely looks at a sample of heavily globally engaged firms which import and export intensively. These firms should account for large trade and output shares (Bernard et al. (2007)) and hence also constitute a large part of the data that we rely on. Another concern is that country policies could influence both offshoring and innovation. Labor market policies are particularly likely to affect both if they change the skill composition or target wages within the country. Country-time fixed effects control for these policy changes. Industry-time fixed effects capture changes in trade agreements which could trigger similar adjustments. Both effects also take into account country- or industry-specific demand-side shocks that could be related to offshoring and innovation. We would additionally like to rule out that demand shocks from other countries explain the results. Controlling for export intensity should absorb these effects. Lastly, the inclusion of large countries could drive our results as these countries can strategically influence prices. Price changes can in turn affect offshoring and innovation. This should be less of a concern as the sample largely consists of small countries. We drop Germany, Japan and the US separately from the IV regressions and results stay the same²⁰.

Further instruments include: changes in offshoring between $t - 2$ and $t - 3$ and lagged values of offshoring depending on the specification as we instrument regressions (1) to (3) of the baseline model. These instruments are highly correlated with contemporaneous offshoring and are also used by Görg and Hanley (2011) and Crinò (2012b).

Lastly, a novel instrument on the wage gap associated with offshoring is deployed. The measure is unique in its richness as wage gaps can be computed with respect to different countries and industries and are then weighted with respective trade shares. Similar reasoning is applied in two papers. Girma and Görg (2004) instrument offshoring with skilled- and unskilled-wages at the firm-level and argue that higher wages lead to more offshoring. Egger and Egger (2006) instrument offshoring with unit labor costs in European countries. This paper looks at an average lagged wage gap thereby combining both approaches. We construct the instrument by computing average hourly wages on the country-industry level (ij). Wages are then weighted with their respective cost shares of intermediate imports, $\omega_{ij,abt}$. The shares, $\omega_{ij,ab}$, sum up to 1 and only capture imported intermediates in manufacturing and selected services inputs that are sourced from ij by ab . The wage gap, WG_{abt} , is then defined as the difference between the average country-industry-specific wage of variety ab , W_{abt} , and an import-share weighted wage

and is lagged by one period.

$$WG_{abt} = W_{abt} - \sum_{ij} \omega_{ij,abt} * W_{ijt} \quad (5)$$

$$\omega_{ij,abt} = \frac{II_{ij,abt}}{\sum_{ij} II_{ij,abt}} \quad (6)$$

The idea behind the instrument is that developed countries mostly source from other high-income countries although trade with low-income countries is admittedly growing rapidly. As technology-sourcing is a key factor behind trade in intermediates, more expensive sourcing destinations should be more attractive. This implies that wage gaps are negatively related to offshoring as high-skilled wages in high-income countries should reflect higher productivity and therefore greater offshoring potential.

We now discuss results presented in Table 3. The effect of offshoring is similar in the IV estimation compared to baseline results (see Table 1). The estimated coefficients for offshoring of manufacturing and services are also in line with previous results. The same holds for the coefficients of the control variables. The only difference is the much larger coefficient of offshoring to high-income countries and the positive (albeit insignificant) effect of offshoring to low-income countries. F-tests are equal to 13 or much larger, indicating that instruments should be relevant. The Hansen J test suggests that the hypothesis that instruments are valid cannot be rejected. Table A4 presents first stage results. The lagged world export supply instrument strongly positively relates to offshoring in almost all specifications, capturing changes in competitiveness of sourced varieties²¹. Lagged values of offshoring and changes in offshoring are equally highly significant predictors. Results for the lagged wage gap are mixed. Sourcing “cheaper” varieties induces offshoring of services, maybe because cost reduction matters more for services than for manufacturing. Offshoring to high-income countries, on the contrary, is triggered by sourcing more “expensive” varieties as these are likely technologically more advanced.

The estimated effects are economically relevant. We calculate that a one standard deviation increase of offshoring reduces R&D intensity by 63%. This effect is reduced to -34% when considering offshoring of manufacturing and offshoring of services jointly²². Other studies have also documented that trade has pronounced effects on domestic innovation. Bloom et al. (forthcoming) argue that import competition from China accounts for 15% of European technology upgrading between 2000 and 2007. Crinò (2012a) finds that importers have a 12 to 16 percentage points higher probability of engaging in in-

novation. Note that in our study adverse spill-over effects of increased competition are also taken into account which might contribute to the large magnitude of the estimated effect.

(Table 3 here)

4.5 Extensions

Offshoring is believed to influence labor markets markedly, both in terms of employment and wage effects. Suggestive evidence reports that the skill-bias that is associated with offshoring also leads to higher innovation output (Crinò (2012a) and Breunig and Bakhtiari (2013)). We test a similar hypothesis namely to what extent the skill composition affects the link between offshoring and innovation. We do so by introducing an interaction term of offshoring with the share of high-skilled labor (Table 4). Column 1 reports the results for an interaction term of overall offshoring and the high-skilled share. The magnitude of the offshoring effect is somewhat stronger than before, and reassuringly we find that a higher share of the high-skilled mitigates the adverse effect of offshoring. This implies that the potentially adverse effects of offshoring on innovation can be reversed if the share of high-skilled labor is large enough²³. We then look at the effect in more detail and split offshoring again. This gives more insightful results. We find significant effects, as before in the baseline regressions, for both offshoring variables. The negative effects for offshoring of manufacturing and in the subsequent column for offshoring to high-income countries are again mitigated by a highly skilled workforce.

In the same table, further evidence for effect heterogeneity of offshoring is presented. Offshoring is now interacted with the distance to the technological frontier which is defined on an industry-year basis. Results support the effects of skill composition. First, it is documented that the negative effects of offshoring in all three specifications are slightly reduced in magnitude. This means that for industries that are technological leaders (distance = 0), the negative effects are reduced as compared to baseline results²⁴. The further a variety departs from the technological frontier, the more severe are detrimental adjustment patterns. Although the distance effect cannot fully absorb the negative effect triggered by offshoring, it can at least mitigate the effect. It is well possible that industries that combine technological leadership with a highly-skilled workforce do not suffer from any adverse effects of offshoring.

(Table 4 here)

Lastly, we test whether the position in the production chain matters for offshoring effects on innovation. We deploy a measure on upstreamness which has recently been

proposed by Fally (2012) and Antràs and Chor (2013). Upstreamness measures the average position of a variety in the production chain and can be defined for each individual variety ab at each point in time as follows:

$$US_{ab} = 1 + \sum_{ij=1}^N \frac{d_{ab,ij}Y_{ij}}{Y_{ab}}U_{ij}, \quad (7)$$

where $d_{ab,ij}Y_{ij}/Y_{ab}$ is the share of variety ab 's total output that is purchased by variety ij , where Y denotes output and $d_{ab,ij}$ denotes the dollar amount of variety ab 's output needed to produce one dollar worth of variety ij 's output²⁵. N denotes the total number of varieties, i.e., the total number of country-industry combinations. This system can be written compactly in matrix notation as $US = [I - \Delta]^{-1}\mathbf{1}$, where Δ is the matrix with $d_{ab,ij}Y_{ij}/Y_{ab}$ in entry (ab, ij) and $\mathbf{1}$ is a column vector of ones.

As documented by Fally (2012), upstreamness strongly negatively correlates with the specificity of a particular variety, i.e., whether it is sold on thin markets, and R&D intensity, albeit not statistically significantly with the latter measure. Our results are similar in that upstreamness is associated with lower R&D intensity (see Table 5). More interesting results emerge when upstreamness and interaction terms with different offshoring measures are considered to assess whether the position in the production chain influences offshoring effects. We find that this is indeed the case. Upstreamness reduces the adverse effects of offshoring on innovation. This is compatible with a product cycle theory. It is optimal for highly-complex products to remain integrated and to only off-shore if production has matured (Costinot et al. (2011)). Acemoglu et al. (2010) find that the R&D intensity of upstream industries negatively correlates with intra-firm trade. They consider intra- vs. inter-firm trade, whereas we analyze offshoring. But we argue that both measures - inter-firm trade and offshoring - broadly reflect fragmentation. Although their dependent variable is intra-firm trade and we are looking at the effect on R&D intensity, our results are similar in terms of the correlations found. We report that offshoring increasingly lowers R&D intensity in more downstream industries²⁶. In column 2, we find that the negative effect of offshoring of manufacturing is mitigated by a variety being more upstream. The position in the production chain does not matter for the effects of offshoring of services. The last column documents that mitigation equally occurs for offshoring to high-income countries.

(Table 5 here)

5 Conclusion

This paper empirically highlights that offshoring triggers adverse adjustment processes in developed countries that harm domestic innovation. This effect is limited to trade in manufacturing intermediates with high-income countries though. We document that offshoring of services entails large innovation gains. Findings are rationalized by arguing that competition effects trigger major reallocation of innovation. Competition is particularly likely to reduce innovation if competition is already high which is likely to be the case in open developed countries (Aghion et al. (2005), Hashmi (2013)).

This paper furthermore highlights that productivity effects and innovation effects are not the same. Policy makers should therefore take various factors, and not just short-term productivity considerations, into account when designing a regulatory framework for future trade liberalization. Findings highlight substantial gains associated with services trade. This is an interesting finding given that services trade is still fairly restricted, and this suggests that there are potentially large gains from further trade liberalization in this sector.

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Table 1: Baseline results - Offshoring and innovation

<i>Dep. var. R&D intensity</i>	(1)	(2)	(3)	(4)
Offshoring	-0.088*** (0.008)			
Offshoring manufacturing		-0.090*** (0.007)		
Offshoring services		0.523*** (0.048)		
Offshoring HI			-0.105*** (0.008)	
Offshoring LI			0.077** (0.034)	
Offsh. manu. HI				-0.108*** (0.008)
Offsh. manu. LI				0.097*** (0.033)
Offsh. services HI				0.387*** (0.084)
Offsh. services LI				1.873** (0.778)
High skilled share	0.048*** (0.007)	0.053*** (0.007)	0.050*** (0.006)	0.056*** (0.006)
Medium skilled share	-0.068*** (0.011)	-0.069*** (0.011)	-0.062*** (0.010)	-0.064*** (0.011)
Export share	0.011*** (0.002)	0.014*** (0.002)	0.012*** (0.002)	0.014*** (0.002)
Capital share	0.315*** (0.087)	0.237*** (0.071)	0.262*** (0.095)	0.169** (0.079)
Observations	2377.00	2377.00	2377.00	2377.00
R-squared	0.75	0.76	0.75	0.77

Reported coefficients are from OLS estimations. Clustered standard errors at the country-year level are in parentheses. Country-time and industry-time dummies included. * 10% significance, ** 5% significance, *** 1% significance. HI stands for high-income countries and LI for low-income countries.

Table 2: Robustness check - Confounding factors

<i>Dep. var. R&D intensity</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Offshoring	-0.082*** (0.008)			-0.086*** (0.009)			-0.086*** (0.007)		
Offshoring manu.		-0.085*** (0.007)			-0.095*** (0.009)			-0.089*** (0.007)	
Offshoring services		0.611*** (0.077)			0.632*** (0.072)			0.517*** (0.049)	
Offshoring HI			-0.100*** (0.008)			-0.097*** (0.009)			-0.103*** (0.008)
Offshoring LI			0.093*** (0.033)			0.050 (0.062)			0.085** (0.036)
High skilled share	0.050*** (0.006)	0.055*** (0.007)	0.052*** (0.006)	0.041*** (0.009)	0.052*** (0.009)	0.036*** (0.008)	0.046*** (0.006)	0.052*** (0.007)	0.048*** (0.006)
Medium skilled share	-0.062*** (0.011)	-0.061*** (0.011)	-0.056*** (0.010)	-0.066*** (0.017)	-0.059*** (0.017)	-0.075*** (0.018)	-0.070*** (0.011)	-0.070*** (0.011)	-0.064*** (0.011)
Export share	0.013*** (0.002)	0.014*** (0.002)	0.014*** (0.002)	0.014*** (0.003)	0.017*** (0.003)	0.014*** (0.003)	0.011*** (0.002)	0.014*** (0.002)	0.012*** (0.002)
Capital share	0.383*** (0.099)	0.327*** (0.086)	0.326*** (0.107)	0.503*** (0.127)	0.360*** (0.123)	0.493*** (0.128)	0.294*** (0.086)	0.227*** (0.070)	0.236** (0.093)
TFP	0.260*** (0.066)	0.215*** (0.065)	0.253*** (0.065)						
ICT				0.308*** (0.054)	0.334*** (0.053)	0.318*** (0.055)			
Import competition							-0.248** (0.123)	-0.132 (0.114)	-0.287** (0.124)
Observations	2331.00	2331.00	2331.00	1684.00	1684.00	1684.00	2377.00	2377.00	2377.00
R-squared	0.74	0.75	0.75	0.80	0.81	0.80	0.75	0.76	0.75

Reported coefficients are from OLS estimations. Clustered standard errors at the country-year level are in parentheses. Country-time and industry-time dummies included. * 10% significance, ** 5% significance, *** 1% significance. HI stands for high-income countries and LI for low-income countries.

Table 3: Instrumental variables

<i>Dep. var. R&D intensity</i>	(1)	(2)	(3)
Offshoring	-0.095** (0.042)		
Offshoring manufacturing		-0.092** (0.041)	
Offshoring services		0.501*** (0.064)	
Offshoring HI			-0.196** (0.078)
Offshoring LI			0.220 (0.138)
High skilled share	0.047*** (0.009)	0.053*** (0.008)	0.047*** (0.007)
Medium skilled share	-0.085*** (0.014)	-0.087*** (0.014)	-0.077*** (0.012)
Export share	0.013*** (0.004)	0.015*** (0.003)	0.018*** (0.005)
Capital share	0.319*** (0.088)	0.248*** (0.075)	0.161 (0.126)
F-test Offshoring	19.33		
F-test Offshoring manu.		12.96	
F-test Offshoring services		122.35	
Offshoring HI			43.38
Offshoring LI			210.08
Underidentification (p-value)	0.000	0.000	0.011
Hansen J test (p-value)	0.799	0.420	0.844
Observations	1852.00	1852.00	1852.00
R-squared	0.21	0.26	0.14

Reported coefficients are from 2SLS-estimations. Clustered standard errors at the country-year level are in parentheses. Country-time and industry-time dummies included. * 10% significance, ** 5% significance, *** 1% significance. HI stands for high-income countries and LI for low-income countries.

Table 4: Mitigation channels - Skill endowment and distance to the technological frontier

<i>Dep. var. R&D intensity</i>	(1)	(2)	(3)	(4)	(5)	(6)
Offshoring	-0.136*** (0.009)			-0.074*** (0.009)		
High skilled share	0.020*** (0.008)	0.034*** (0.008)	0.023*** (0.007)	0.047*** (0.007)	0.054*** (0.007)	0.051*** (0.006)
Offsh. * high-skilled	0.004*** (0.001)					
Offshoring manu.		-0.138*** (0.008)			-0.076*** (0.008)	
Offshoring services		0.749*** (0.169)			0.454*** (0.051)	
Offsh. manu. * high-skilled		0.004*** (0.001)				
Offsh. services * high-skilled		-0.014 (0.010)				
Offshoring HI			-0.145*** (0.013)			-0.086*** (0.010)
Offshoring LI			-0.010 (0.082)			0.020 (0.046)
Offsh. HI * high-skilled			0.004*** (0.001)			
Offsh. LI * high-skilled			0.004 (0.006)			
Distance				-0.255*** (0.064)	-0.218*** (0.068)	-0.287*** (0.058)
Offsh. * distance				-0.010*** (0.003)		
Offsh. manu. * distance					-0.009*** (0.003)	
Offsh. services * distance					0.085* (0.044)	
Offsh. HI * distance						-0.013** (0.005)
Offsh. LI * distance						0.038 (0.028)
Medium skilled share	-0.060*** (0.010)	-0.062*** (0.010)	-0.056*** (0.010)	-0.070*** (0.011)	-0.069*** (0.011)	-0.063*** (0.010)
Export share	0.010*** (0.002)	0.013*** (0.002)	0.011*** (0.002)	0.014*** (0.002)	0.015*** (0.002)	0.014*** (0.002)
Capital share	0.335*** (0.091)	0.259*** (0.075)	0.295*** (0.095)	0.371*** (0.090)	0.291*** (0.077)	0.306*** (0.098)
Observations	2377.00	2377.00	2377.00	2354.00	2354.00	2354.00
R-squared	0.76	0.77	0.76	0.76	0.77	0.76

Reported coefficients are from OLS estimations. Clustered standard errors at the country-year level are in parentheses. Country-time and industry-time dummies included. * 10% significance, ** 5% significance, *** 1% significance. HI stands for high-income countries and LI for low-income countries.

Table 5: Extension: Upstreamness

<i>Dep. var. R&D intensity</i>	(1)	(2)	(3)
Offshoring	-0.128*** (0.013)		
Upstreamness	-0.639*** (0.117)	-0.592*** (0.119)	-0.656*** (0.133)
Offshoring * Upstream.	0.016*** (0.005)		
Offshoring manu.		-0.137*** (0.014)	
Offshoring services		0.600*** (0.129)	
Offshoring manu. * Upstream.		0.020*** (0.006)	
Offshoring services * Upstream.		-0.046 (0.055)	
Offshoring HI			-0.159*** (0.014)
Offshoring LI			0.193** (0.078)
Offshoring HI * Upstream.			0.022*** (0.006)
Offshoring LI * Upstream.			-0.055 (0.040)
High skilled share	0.048*** (0.007)	0.055*** (0.007)	0.051*** (0.007)
Medium skilled share	-0.071*** (0.012)	-0.071*** (0.012)	-0.063*** (0.011)
Export share	0.014*** (0.002)	0.017*** (0.002)	0.015*** (0.002)
Capital share	0.266*** (0.074)	0.191*** (0.060)	0.216*** (0.081)
Observations	2331.00	2331.00	2331.00
R-squared	0.75	0.77	0.76

Reported coefficients are from OLS estimations. Clustered standard errors at the country-year level are in parentheses. Country-time and industry-time dummies included. * 10% significance, ** 5% significance, *** 1% significance. HI stands for high-income countries and LI for low-income countries.

Appendix

Table A1: Summary statistics

	Mean	Std. dev.	Min.	Max.	Obs.
Offshoring	12.7021	8.7065	0.1123	48.8748	2377
Offshoring manu.	12.0373	8.4653	0.1007	48.2829	2377
Offshoring services	0.6649	0.6641	0.0115	8.1193	2377
Offshoring HI	11.0752	8.0035	0.0885	44.5349	2377
Offshoring LI	1.627	1.371	0.0238	10.2543	2377
Offshoring manu. HI	10.458	7.7716	0.0733	44.14	2377
Offshoring manu. LI	1.5792	1.3567	0.0227	10.2518	2377
Offshoring services HI	0.6172	0.6146	0.0105	7.9736	2377
Offshoring services LI	0.0477	0.0811	0.0008	1.845	2377
RD intensity	1.3126	1.859	0.0025	13.126	2377
High skilled share	15.7768	7.7019	2.0025	45.916	2377
Medium skilled share	47.2115	17.842	8.2203	87.327	2377
Export share	40.3472	25.0469	0.478	111.7126	2377
Capital share	0.6111	0.3247	0.1123	6.0602	2377
TFP	2.6123	0.7697	-0.2392	4.3949	2331
ICT	1.0867	0.7369	0.0087	4.9957	1684
Import competition	0.2123	0.2905	0.0009	3.6148	2377
Distance	1.2522	1.2589	0	9.9328	2354
Upstreamness	2.2466	0.5091	1.2851	3.4473	2331
<i>Instruments</i>					
World export supply (lagged)	1.4677	2.2809	0.0231	20.8843	2172
Change offsh. (lagged twice)	0.1184	1.1635	-11.696	10.3063	1888
Offsh. services (lagged three times)	0.6524	0.641	0.0115	8.1193	1888
Change offsh. manu. (lagged twice)	0.113	1.1569	-11.6977	10.209	1888
Lagged wage gap	0.0882	11.2115	-35.0778	58.7998	2216
Change offsh. HI (lagged three times)	0.0085	1.0401	-10.9437	10.0425	1888
Offsh. LI (lagged three times)	1.4043	1.124	0.0238	8.3849	1888

Offshoring is defined as foreign intermediate inputs as a share of industry output excluding foreign primary inputs. Offshoring of manufacturing and offshoring of services adds to total offshoring. Offshoring to high-income countries (HI) and low-income (LI) countries adds to total offshoring. R&D intensity is defined as R&D-expenditures over output. Share of high-skilled (medium-skilled) labor is the share of hours worked by high-skilled (medium-skilled) persons engaged in total hours worked. High-skilled labor is defined as people with tertiary education. Medium-skilled labor is defined as people who completed at least upper secondary education but not tertiary education. Exports refer to exports of final and intermediates, and exports are scaled by output. All of the aforementioned variables are multiplied by 100 for better readability of estimated coefficients. Capital share is defined as the capital stock scaled by output. ICT refers to ICT expenditures scaled by output and multiplied by 100. Import competition is defined as goods imported for final consumption from other countries scaled by industry output. TFP refers to total factor productivity. Distance is the distance to the technological frontier (on an industry-year basis). Upstreamness proxies for the position in the production chain. World export supply follows Hummels et al. (2014) (see instrument section). Change in offshoring refers to percentage point changes. The wage gap refers to an import-weighted average wage gap (see instrument section).

Table A2: Descriptive statistics

Country	Offsh.	Offsh.	Change	Offsh.	Offsh.	Change	Offsh.	Offsh.	Change	Offsh.	Offsh.	Change	RD	Change		
	1995	2007	Offsh.	manu.	manu.	Offsh.	manu.	2007	Offsh.	manu.	2007	HI	LI	1995	RD	
Australia	5.58	7.35	1.77	5.31	6.96	1.64	0.26	0.40	0.13	4.89	5.51	0.62	1.84	1.15	1.28	0.13
Austria	14.36	21.74	7.38	13.38	21.06	7.68	0.98	0.68	-0.30	13.17	18.49	5.32	3.25	2.06	1.79	2.35
Belgium	26.00	27.16	1.16	25.33	26.05	0.72	0.68	1.12	0.44	24.85	23.70	-1.15	3.46	2.31	1.85	1.90
Canada	16.45	16.06	-0.39	15.56	15.16	-0.40	0.89	0.90	0.01	15.50	13.55	-1.95	2.51	1.56	1.25	1.29
Germany	9.77	15.12	5.35	9.49	14.63	5.15	0.28	0.48	0.20	8.50	10.78	2.29	4.34	3.06	2.53	2.30
Spain	9.52	14.43	4.92	9.19	13.61	4.42	0.32	0.82	0.50	8.93	12.22	3.29	2.21	1.63	0.51	0.76
Finland	11.25	13.75	2.50	9.82	12.12	2.30	1.43	1.63	0.20	10.23	10.29	0.06	3.46	2.44	1.02	1.16
France	11.39	13.42	2.03	10.88	12.90	2.01	0.51	0.53	0.02	10.84	11.58	0.74	1.84	1.29	2.57	2.25
Great Britain	12.11	14.69	2.57	11.65	13.91	2.26	0.46	0.78	0.32	11.22	12.18	0.97	2.50	1.61	2.24	3.03
Italy	8.69	11.83	3.14	8.37	11.25	2.88	0.32	0.59	0.26	7.75	9.45	1.70	2.38	1.44	0.66	0.65
Japan	1.80	2.43	0.63	1.73	2.34	0.61	0.07	0.08	0.02	1.39	1.60	0.21	0.41	0.42	1.97	3.62
Netherl.	20.33	19.28	-1.04	18.08	16.90	-1.18	2.25	2.38	0.14	18.99	16.83	-2.16	2.45	1.12	1.54	1.34
Portugal	13.93	20.24	6.31	13.38	19.69	6.32	0.56	0.55	-0.01	13.37	18.21	4.85	2.03	1.47	0.12	0.44
Taiwan	14.55	20.69	6.14	14.02	19.97	5.95	0.53	0.72	0.19	12.96	16.78	3.82	3.91	2.32	1.06	1.55
USA	5.53	6.77	1.24	5.17	6.47	1.30	0.36	0.30	-0.06	4.61	4.39	-0.22	0.93	1.46	2.81	3.96

A list of countries can be found in Table B1. Change refers to percentage point changes between 1995 and 2007. Offshoring of manufacturing and offshoring of services sum to overall offshoring. Offshoring to HI (high-income countries) and LI (low-income countries) also sum to overall offshoring. Offshoring refers to trade in intermediates. All offshoring measures are standardized by output, i.e., offshoring reports the share of foreign inputs in output. All presented numbers are in percent. The first number in the upper left corner means that the share of foreign material and services inputs to industry output is 5.58 in 1995 for Australia. This share increased to 7.35 in 2007. Hence, offshoring changes by 1.77 percentage points between 1995 and 2007 in Australia. R&D int. stands for R&D intensity and is defined as R&D expenditures over output.

Table A3: TFP regressions

<i>Dep. var. TFP</i>	(1)	(2)	(3)	(4)
Offshoring	0.006** (0.003)			
Offshoring manu.		0.005** (0.003)		
Offshoring services		0.081*** (0.020)		
Offshoring HI			0.006** (0.003)	
Offshoring LI			0.005 (0.012)	
Offshoring HI manu.				0.005* (0.003)
Offshoring LI manu.				0.007 (0.012)
Offshoring HI services				0.043* (0.025)
Offshoring LI services				0.684** (0.318)
RD intensity	0.030*** (0.009)	0.027*** (0.009)	0.031*** (0.009)	0.024*** (0.009)
Export share	-0.006*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)
Observations	2331.00	2331.00	2331.00	2331.00
R-squared	0.69	0.69	0.69	0.69

Reported coefficients are from OLS estimations. Clustered standard errors at the country-year level are in parentheses. Country-time and industry-time dummies included. * 10% significance, ** 5% significance, *** 1% significance. TFP stands for total factor productivity. HI stands for high-income countries and LI for low-income countries.

Table A4: First stage regression results for excluded instruments

<i>Dep. var. 1st stage</i>	(1)	(2)	(3)	(4)	(5)
	Offshoring	Offshoring manufactur- ing	Offshoring services	Offshoring HI	Offshoring LI
World export supply lagged	0.279*** (0.068)	0.275*** (0.067)	0.000 (0.003)	0.157** (0.064)	0.031** (0.015)
Change offsh. (lagged twice)	0.578*** (0.139)				
Offshoring services (lagged three times)		-0.820***	1.038***		
Change offsh. manu. (lagged twice)		(0.185) 0.594***	(0.050) -0.010		
Lagged wage gap		(0.138) -0.021	(0.006) 0.001**	-0.031* (0.017)	0.000 (0.001)
Change offshoring HI (lagged three times)		(0.018)	(0.001)	0.469***	0.082***
Offshoring LI (lagged three times)				(0.139) 1.482***	(0.025) 0.975***
Observations	1852.00	1852.00	1852.00	1852.00	1852.00
R-squared	0.85	0.85	0.96	0.86	0.92

Clustered standard errors are in parentheses. Country-time and industry-time dummies included. * 10% significance, ** 5% significance, *** 1% significance. HI stands for high-income countries and LI for low-income countries.

Supplementary material

Table B1: Country coverage

Country	Number of obs.
Australia	182
Austria	98
Belgium	182
Canada	146
Germany	182
Spain	182
Finland	143
France	182
Great Britain	130
Italy	182
Japan	144
Netherlands	179
Portugal	155
Taiwan	140
USA	150
Total	2377

Table B2: Industry coverage

Industry	Industry (WIOD)	Number	Nace 2	Number of obs.
Food, Beverages and Tobacco	3		15t16	186
Textiles and Textile Products	4		17t18	143
Leather, Leather and Footwear	5		19	145
Wood and Products of Wood and Cork	6		20	169
Pulp, Paper, Printing and Publishing	7		21t22	169
Coke, Refined Petroleum and Nuclear Fuel	8		23	160
Chemicals and Chemical Products	9		24	186
Rubber and Plastics	10		25	173
Other Non-Metallic Mineral	11		26	178
Basic Metals and Fabricated Metal	12		27t28	179
Machinery, Nec	13		29	186
Electrical and Optical Equipment	14		30t33	153
Transport Equipment	15		34t35	172
Manufacturing, Nec; Recycling	16		36t37	178
Total				2377

Table B3: Country classification

Country	Classification
Australia	HIGH-INCOME
Austria	HIGH-INCOME
Belgium	HIGH-INCOME
Bulgaria	LOW-INCOME
Brazil	LOW-INCOME
Canada	HIGH-INCOME
China	LOW-INCOME
Cyprus	HIGH-INCOME
Czech Republic	LOW-INCOME
Germany	HIGH-INCOME
Denmark	HIGH-INCOME
Spain	HIGH-INCOME
Estonia	LOW-INCOME
Finland	HIGH-INCOME
France	HIGH-INCOME
Great Britain	HIGH-INCOME
Greece	HIGH-INCOME
Hungary	LOW-INCOME
Indonesia	LOW-INCOME
India	LOW-INCOME
Ireland	HIGH-INCOME
Italy	HIGH-INCOME
Japan	HIGH-INCOME
Korea	HIGH-INCOME
Lithuania	LOW-INCOME
Luxembourg	HIGH-INCOME
Latvia	LOW-INCOME
Mexico	LOW-INCOME
Malta	HIGH-INCOME
Netherlands	HIGH-INCOME
Poland	LOW-INCOME
Portugal	HIGH-INCOME
Romania	LOW-INCOME
Russia	LOW-INCOME
Slovak Republic	LOW-INCOME
Slovenia	HIGH-INCOME
Sweden	HIGH-INCOME
Turkey	LOW-INCOME
Taiwan	HIGH-INCOME
USA	HIGH-INCOME

Table B4: Excluding individual industries

<i>Excluded industry</i>	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Offshoring	-0.093*** (0.008)	-0.090*** (0.008)	-0.089*** (0.008)	-0.093*** (0.008)	-0.090*** (0.007)	-0.089*** (0.008)	-0.082*** (0.007)	-0.091*** (0.008)	-0.092*** (0.008)	-0.092*** (0.008)	-0.092*** (0.008)	-0.068*** (0.005)	-0.077*** (0.010)	-0.090*** (0.008)
High skilled share	0.037*** (0.007)	0.058*** (0.006)	0.055*** (0.006)	0.048*** (0.007)	0.055*** (0.007)	0.058*** (0.007)	0.058*** (0.007)	0.046*** (0.005)	0.051*** (0.005)	0.046*** (0.005)	0.045*** (0.005)	0.028*** (0.005)	0.046*** (0.005)	0.044*** (0.005)
Medium skilled share	-0.084*** (0.007)	-0.053*** (0.006)	-0.060*** (0.006)	-0.071*** (0.007)	-0.063*** (0.007)	-0.069*** (0.007)	-0.106*** (0.009)	-0.064*** (0.007)	-0.066*** (0.007)	-0.068*** (0.007)	-0.073*** (0.007)	-0.031*** (0.006)	-0.070*** (0.006)	-0.073*** (0.006)
Export share	0.012*** (0.013)	0.013*** (0.012)	0.013*** (0.011)	0.013*** (0.011)	0.013*** (0.011)	0.012*** (0.011)	0.003** (0.013)	0.011*** (0.011)	0.011*** (0.011)	0.012*** (0.012)	0.012*** (0.011)	0.012*** (0.007)	0.012*** (0.011)	0.012*** (0.011)
Capital share	0.334*** (0.002)	0.319*** (0.002)	0.227** (0.002)	0.255*** (0.002)	0.322*** (0.002)	0.492*** (0.002)	0.275*** (0.001)	0.320*** (0.002)	0.305*** (0.002)	0.310*** (0.002)	0.318*** (0.002)	0.303*** (0.002)	0.199** (0.002)	0.386*** (0.002)
Obs.	2191.00	2234.00	2232.00	2208.00	2208.00	2217.00	2191.00	2204.00	2199.00	2198.00	2191.00	2224.00	2205.00	2199.00
R-squared	0.74	0.75	0.76	0.74	0.75	0.75	0.77	0.75	0.75	0.75	0.75	0.70	0.76	0.75

Reported coefficients are from OLS estimations. Clustered standard errors at the country-year level are in parentheses. Country-time and industry-time dummies included. * 10% significance, ** 5% significance, *** 1% significance.

Table B5: Excluding individual industries

<i>Excluded industry</i>	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Offshoring manu.	-0.095*** (0.007)	-0.094*** (0.007)	-0.092*** (0.008)	-0.095*** (0.008)	-0.092*** (0.007)	-0.088*** (0.007)	-0.085*** (0.006)	-0.093*** (0.007)	-0.094*** (0.007)	-0.095*** (0.008)	-0.094*** (0.007)	-0.072*** (0.004)	-0.080*** (0.010)	-0.092*** (0.008)
Offshoring services	0.530*** (0.049)	0.542*** (0.049)	0.542*** (0.051)	0.520*** (0.048)	0.522*** (0.048)	0.523*** (0.049)	0.486*** (0.047)	0.524*** (0.048)	0.520*** (0.048)	0.530*** (0.048)	0.505*** (0.049)	0.702*** (0.083)	0.497*** (0.047)	0.531*** (0.051)
High skilled share	0.043*** (0.007)	0.065*** (0.006)	0.062*** (0.006)	0.052*** (0.007)	0.061*** (0.007)	0.065*** (0.008)	0.065*** (0.009)	0.052*** (0.007)	0.057*** (0.007)	0.052*** (0.007)	0.051*** (0.007)	0.031*** (0.007)	0.051*** (0.006)	0.050*** (0.006)
Medium skilled share	-0.084** (0.007)	-0.052*** (0.006)	-0.060*** (0.006)	-0.074*** (0.007)	-0.065*** (0.007)	-0.069*** (0.008)	-0.110*** (0.009)	-0.065*** (0.007)	-0.068*** (0.007)	-0.069*** (0.007)	-0.075*** (0.007)	-0.030*** (0.007)	-0.070*** (0.006)	-0.076*** (0.006)
Export share	0.013 (0.013)	0.015*** (0.012)	0.016*** (0.011)	0.015*** (0.012)	0.015*** (0.011)	0.013*** (0.011)	0.006*** (0.013)	0.013*** (0.012)	0.013*** (0.012)	0.015*** (0.012)	0.014*** (0.012)	0.014*** (0.008)	0.015*** (0.011)	0.016*** (0.012)
Capital share	0.258*** (0.002)	0.241*** (0.002)	0.044 (0.002)	0.185*** (0.002)	0.240*** (0.002)	0.405*** (0.002)	0.212*** (0.001)	0.239*** (0.002)	0.225*** (0.002)	0.232*** (0.002)	0.238*** (0.002)	0.263*** (0.002)	0.129* (0.002)	0.308*** (0.002)
Obs.	2191.00	2234.00	2232.00	2208.00	2208.00	2217.00	2191.00	2204.00	2199.00	2198.00	2191.00	2224.00	2205.00	2199.00
R-squared	0.76	0.76	0.77	0.76	0.76	0.77	0.79	0.77	0.76	0.76	0.76	0.71	0.77	0.76

Reported coefficients are from OLS estimations. Clustered standard errors at the country-year level are in parentheses. Country-time and industry-time dummies included. * 10% significance, ** 5% significance, *** 1% significance.

Table B6: Excluding individual industries

<i>Excluded industry</i>	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Offshoring	-0.112***	-0.108***	-0.108***	-0.111***	-0.107***	-0.108***	-0.099***	-0.108***	-0.110***	-0.107***	-0.109***	-0.080***	-0.087***	-0.107***
HI	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.006)	(0.012)	(0.008)
Offshoring	0.077**	0.108**	0.117***	0.084**	0.076**	0.082**	0.086***	0.078**	0.080**	0.065*	0.078**	0.041*	0.007	0.089**
LI	(0.035)	(0.049)	(0.037)	(0.037)	(0.036)	(0.035)	(0.030)	(0.034)	(0.035)	(0.037)	(0.035)	(0.023)	(0.036)	(0.035)
High skilled share	0.039***	0.057***	0.057***	0.051***	0.057***	0.060***	0.060***	0.049***	0.054***	0.048***	0.048***	0.029***	0.047***	0.048***
Medium skilled share	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.009)	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Export share	-0.078***	-0.052***	-0.052***	-0.065***	-0.058***	-0.063***	-0.098***	-0.058***	-0.059***	-0.062***	-0.066***	-0.027***	-0.067***	-0.066***
Capital share	(0.012)	(0.012)	(0.011)	(0.011)	(0.010)	(0.010)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.007)	(0.011)	(0.011)
Obs.	0.013***	0.014***	0.014***	0.014***	0.014***	0.013***	0.003**	0.011***	0.012***	0.013***	0.012***	0.012***	0.013***	0.013***
R-squared	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	0.281***	0.243**	0.194*	0.203**	0.263**	0.447***	0.220**	0.262***	0.252**	0.256***	0.253**	0.269***	0.174**	0.330***
	(0.098)	(0.098)	(0.104)	(0.095)	(0.102)	(0.129)	(0.091)	(0.101)	(0.097)	(0.094)	(0.098)	(0.085)	(0.083)	(0.113)
	2191.00	2234.00	2232.00	2208.00	2208.00	2217.00	2191.00	2204.00	2199.00	2198.00	2191.00	2224.00	2205.00	2199.00
	0.75	0.75	0.76	0.75	0.75	0.76	0.78	0.75	0.75	0.75	0.75	0.70	0.76	0.75

Reported coefficients are from OLS estimations. Clustered standard errors at the country-year level are in parentheses. Country-time and industry-time dummies included. * 10% significance, ** 5% significance, *** 1% significance. HI stands for high-income countries and LI for low-income countries.

Table B7: Excluding individual countries

<i>Excluded Country</i>	AUS	AUT	BEL	CAN	DEU	ESP	FIN	FRA	GBR	ITA	JPN	NLD
Offshoring	-0.088*** (0.008)	-0.093*** (0.008)	-0.089*** (0.008)	-0.100*** (0.007)	-0.083*** (0.008)	-0.084*** (0.008)	-0.094*** (0.008)	-0.089*** (0.008)	-0.082*** (0.007)	-0.092*** (0.008)	-0.088*** (0.009)	-0.095*** (0.008)
High skilled share	0.043*** (0.007)	0.047*** (0.007)	0.051*** (0.007)	0.051*** (0.006)	0.050*** (0.007)	0.047*** (0.007)	0.049*** (0.007)	0.049*** (0.007)	0.055*** (0.006)	0.044*** (0.006)	0.049*** (0.008)	0.048*** (0.007)
Medium skilled share	-0.069*** (0.011)	-0.070*** (0.011)	-0.070*** (0.011)	-0.072*** (0.012)	-0.065*** (0.011)	-0.063*** (0.011)	-0.069*** (0.011)	-0.074*** (0.011)	-0.072*** (0.011)	-0.065*** (0.011)	-0.063*** (0.011)	-0.072*** (0.011)
Export share	0.010*** (0.002)	0.011*** (0.002)	0.011*** (0.002)	0.010*** (0.002)	0.010*** (0.002)	0.012*** (0.002)	0.014*** (0.002)	0.013*** (0.002)	0.008*** (0.002)	0.011*** (0.002)	0.011*** (0.002)	0.015*** (0.002)
Capital share	0.543*** (0.125)	0.314*** (0.091)	0.314*** (0.085)	0.389*** (0.097)	0.283*** (0.088)	0.333*** (0.091)	0.288*** (0.081)	0.270*** (0.084)	0.210*** (0.074)	0.328*** (0.092)	0.339*** (0.096)	0.291*** (0.079)
Observations	2195.00	2279.00	2195.00	2231.00	2195.00	2195.00	2234.00	2195.00	2247.00	2195.00	2233.00	2198.00
R-squared	0.74	0.74	0.74	0.76	0.74	0.76	0.75	0.74	0.77	0.76	0.74	0.74

Reported coefficients are from OLS estimations. Clustered standard errors at the country-year level are in parentheses. Country-time and industry-time dummies included. * 10% significance, ** 5% significance, *** 1% significance.

Table B8: Excluding individual countries

<i>Excluded Country</i>	PRT	TWN	USA	AUS	AUT	BEL	CAN	DEU	ESP	FIN	FRA	GBR
Offshoring	-0.070*** (0.007)	-0.090*** (0.008)	-0.078*** (0.007)	-0.091***	-0.096***	-0.092***	-0.102***	-0.086***	-0.087***	-0.096***	-0.092***	-0.084***
Offshoring manu.												
Offshoring services												
High skilled share	0.045*** (0.007)	0.050*** (0.008)	0.029*** (0.009)	0.051***	0.053***	0.057***	0.047	0.050	0.051	0.047	0.052	0.049
Medium skilled share	-0.061*** (0.011)	-0.061*** (0.013)	-0.065*** (0.016)	-0.070***	-0.071***	-0.070***	-0.074***	-0.066***	-0.064***	-0.069***	-0.076***	-0.073***
Export share	0.011*** (0.002)	0.012*** (0.002)	0.012*** (0.002)	0.013***	0.014***	0.014***	0.013***	0.013***	0.014***	0.011	0.011	0.011
Capital share	0.388*** (0.104)	0.189*** (0.061)	0.361*** (0.099)	0.372***	0.234***	0.229***	0.304***	0.212***	0.257***	0.214***	0.183***	0.138**
Observations	2222.00	2237.00	2227.00	2195.00	2279.00	2195.00	2231.00	2195.00	2195.00	2234.00	2195.00	2247.00
R-squared	0.77	0.76	0.72	0.76	0.76	0.75	0.78	0.75	0.78	0.76	0.75	0.79

Reported coefficients are from OLS estimations. Clustered standard errors at the country-year level are in parentheses. Country-time and industry-time dummies included. * 10% significance, ** 5% significance, *** 1% significance.

Table B9: Excluding individual countries

<i>Excluded Country</i>	ITA	JPN	NLD	PRT	TWN	USA	AUS	AUT	BEL	CAN	DEU	ESP
Offshoring manu.	-0.095*** (0.008)	-0.090*** (0.008)	-0.095*** (0.008)	-0.075*** (0.007)	-0.092*** (0.008)	-0.080*** (0.007)						
Offshoring services	0.473*** (0.049)	0.543*** (0.049)	0.791*** (0.135)	0.477*** (0.049)	0.509*** (0.049)	0.575*** (0.046)						
Offshoring HI							-0.108***	-0.109***	-0.113***	-0.112***	-0.100***	-0.104***
Offshoring LI	0.050*** (0.006)	0.054*** (0.008)	0.052*** (0.007)	0.050*** (0.007)	0.060*** (0.008)	0.035*** (0.009)	0.045*** (0.008)	0.049*** (0.008)	0.054*** (0.009)	0.051*** (0.008)	0.052*** (0.009)	0.049*** (0.009)
High skilled share	-0.067*** (0.011)	-0.066*** (0.012)	-0.071*** (0.011)	-0.063*** (0.011)	-0.058*** (0.013)	-0.068*** (0.016)	-0.062*** (0.011)	-0.064*** (0.011)	-0.062*** (0.010)	-0.070*** (0.011)	-0.060*** (0.010)	-0.056*** (0.010)
Medium skilled share	0.257*** (0.013)	0.262*** (0.014)	0.246*** (0.016)	0.311*** (0.013)	0.131** (0.015)	0.275*** (0.014)	0.537*** (0.010)	0.262*** (0.012)	0.256*** (0.012)	0.352*** (0.002)	0.225** (0.002)	0.275*** (0.002)
Capital share	0.077 (0.077)	0.078 (0.078)	0.070 (0.070)	0.086 (0.086)	0.058 (0.058)	0.081 (0.081)	0.126 (0.126)	0.098 (0.098)	0.097 (0.097)	0.104 (0.104)	0.095 (0.095)	0.099 (0.099)
Observations	2195.00	2233.00	2198.00	2222.00	2237.00	2227.00	2195.00	2279.00	2195.00	2231.00	2195.00	2195.00
R-squared	0.77	0.76	0.75	0.78	0.78	0.74	0.75	0.74	0.74	0.76	0.74	0.77

Reported coefficients are from OLS estimations. Clustered standard errors at the country-year level are in parentheses. Country-time and industry-time dummies included. * 10% significance, ** 5% significance, *** 1% significance. HI stands for high-income countries and LI for low-income countries.

Table B10: Excluding individual countries

<i>Excluded Country</i>	FIN	FRA	GBR	ITA	JPN	NLD	PRT	TWN	USA
Offshoring	-0.112***	-0.105***	-0.101***	-0.107***	-0.107***	-0.112***	-0.081***	-0.107***	-0.091***
HI	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.007)	(0.009)	(0.008)
Offshoring	0.076**	0.060*	0.104***	0.056*	0.095***	0.074**	0.022	0.094**	0.052
LI	(0.035)	(0.035)	(0.033)	(0.033)	(0.033)	(0.037)	(0.033)	(0.039)	(0.036)
High skilled share	0.051***	0.051***	0.058***	0.046***	0.053***	0.051***	0.046***	0.049***	0.031***
Medium skilled share	(0.006)	(0.007)	(0.006)	(0.006)	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)
	-0.063***	-0.068***	-0.065***	-0.060***	-0.056***	-0.065***	-0.058***	-0.061***	-0.056***
Export share	(0.011)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)	(0.012)	(0.015)
	0.015***	0.013***	0.009***	0.011***	0.012***	0.015***	0.011***	0.013***	0.012***
Capital share	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	0.230**	0.225**	0.149*	0.283***	0.276***	0.230***	0.355***	0.107	0.319***
	(0.089)	(0.092)	(0.083)	(0.099)	(0.105)	(0.086)	(0.107)	(0.068)	(0.104)
Observations	2234.00	2195.00	2247.00	2195.00	2233.00	2198.00	2222.00	2237.00	2227.00
R-squared	0.75	0.74	0.78	0.76	0.74	0.75	0.77	0.76	0.72

Reported coefficients are from OLS estimations. Clustered standard errors at the country-year level are in parentheses. Country-time and industry-time dummies included. * 10% significance, ** 5% significance, *** 1% significance. HI stands for high-income countries and LI for low-income countries.

Table B11: Robustness in different samples

<i>Specification</i>	Austria and Taiwan excl.	Countries with missing industries dropped	(2)	Austria and Taiwan excl.	Countries with missing industries dropped	(5)	Top and bot- tom 1% of re- spect. offsh. dropped	(6)	Austria and Taiwan excl.	Countries with missing industries dropped	(8)	Top and bot- tom 1% of re- spect. offsh. dropped	(9)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Offshoring	-0.095*** (0.008)	-0.050*** (0.008)	-0.071*** (0.008)	-0.098***	-0.054***	-0.071***							
Offshoring manu.				(0.008)	(0.007)	(0.009)							
Offshoring ser- vices				0.527***	0.509***	0.651***							
Offshoring HI				(0.049)	(0.050)	(0.095)							
Offshoring LI							-0.112*** (0.009)						
High skilled share	0.050*** (0.008)	0.026** (0.012)	0.057*** (0.007)	0.060*** (0.008)	0.030** (0.012)	0.069*** (0.008)	0.048*** (0.041)						
Medium skilled share	-0.062*** (0.013)	-0.057*** (0.017)	-0.064*** (0.011)	-0.059*** (0.013)	-0.060*** (0.012)	-0.059*** (0.008)	-0.063*** (0.008)						
Export share	0.012*** (0.002)	0.010*** (0.002)	0.011*** (0.002)	0.015*** (0.002)	0.012*** (0.002)	0.014*** (0.002)	0.013*** (0.002)						
Capital share	0.203*** (0.066)	0.361*** (0.117)	0.349*** (0.097)	0.144** (0.060)	0.288*** (0.097)	0.247*** (0.075)	0.121 (0.074)						
Observations	2139.00	1655.00	2331.00	2139.00	1655.00	2245.00	2139.00						
R-squared	0.75	0.77	0.76	0.77	0.79	0.76	0.76						

Reported coefficients are from OLS estimations. Clustered standard errors at the country-year level are in parentheses. Country-time and industry-time dummies included. * 10% significance, ** 5% significance, *** 1% significance. HI stands for high-income countries and LI for low-income countries.

Table B12: Robustness in different samples - lagged values

<i>Specification</i>	Lagged values	Lagged values	Lagged values
	(1)	(2)	(3)
Offshoring (lagged)	-0.087*** (0.008)		
Offshoring manu. (lagged)		-0.089*** (0.007)	
Offshoring services (lagged)		0.532*** (0.049)	
Offshoring HI (lagged)			-0.104*** (0.009)
Offshoring LI (lagged)			0.089** (0.037)
High skilled share	0.048*** (0.007)	0.054*** (0.007)	0.050*** (0.006)
Medium skilled share	-0.072*** (0.011)	-0.073*** (0.012)	-0.066*** (0.011)
Export share	0.011*** (0.002)	0.014*** (0.002)	0.012*** (0.002)
Capital share	0.324*** (0.090)	0.241*** (0.073)	0.265*** (0.099)
Observations	2216.00	2216.00	2216.00
R-squared	0.75	0.76	0.75

Reported coefficients are from OLS estimations. Clustered standard errors at the country-year level are in parentheses. Country-time and industry-time dummies included. * 10% significance, ** 5% significance, *** 1% significance. HI stands for high-income countries and LI for low-income countries.

Notes

¹By providing an aggregate analysis, we follow several recent papers that stress the importance of cross-country comparability (e.g., Michaels et al. (2014), Acharya (2015)).

²Note that this could either imply that offshoring firms scale back R&D spending or that non-offshoring firms are forced to conduct less R&D due to increased competition (Aghion et al. (2005)). The second effect is generally neglected in firm-level studies on offshoring and innovation.

³Arkolakis et al. (2013) argue that countries with small outward multinational production (MP) flows relative to their inward MP flows become production locations. We argue that these production countries rely comparatively more on sourced technology from other high-income countries.

⁴See Colantone and Crinò (2014) for European countries. Goldberg et al. (2010), Bustos (2011) and Crinò (2012a) study imported intermediates and innovation in emerging countries and find positive effects. They consider innovation outcome variables as opposed to looking at R&D as we do in this study. R&D is however more interesting to look at in developed countries because radical innovation as opposed to incremental innovation is the subject of interest.

⁵There is ample evidence that offshoring tends to increase wages of high-skilled workers, whereas it decreases wages of low-skilled workers in developed countries (e.g., Feenstra and Hanson (1999), Grossman and Helpman (2005), Grossman et al. (2006), Grossman and Rossi-Hansberg (2008), Hummels et al. (2014)). This supports the idea that countries specialize in higher value-added parts of the production chain (see Crinò (2012a) for suggestive evidence).

⁶We classify countries as developed countries if they are considered to be high-income countries by the World Bank for all years that the sample spans. A list of covered countries and industries can be found in the supplementary material (see Tables B1 and B2).

⁷See <http://www.wiod.org>.

⁸Trade in primary products is not included in our offshoring measure, as is standard in the literature.

⁹We follow Amiti and Wei (2009) in defining trade in services by including the following industries: post and telecommunications, financial intermediation, renting of machinery and equipment and other business services.

¹⁰We use EU-KLEMS version ISIC Rev. 3 because of its large country coverage. See <http://www.euklems.net/>. We deflate and convert all data, if necessary, into millions of US dollars with exchange rates given by EU-KLEMS.

¹¹We use ANBERD version ISIC Rev. 3 because of its large country coverage. See <http://www.oecd.org/innovation/inno/anberdanalyticalbusinessenterpriseresearchanddevelopmentdatabase.htm>. Cyprus, Denmark, Luxembourg, Malta and Sweden do not report on R&D spending. We additionally drop Ireland from our analysis as the prevalence of transfer pricing - due to Ireland being a low tax jurisdiction - distorts output and therefore R&D intensity figures (Barry (2005)). Firms report either R&D spending in their main activity - the methodology used by most countries in the sample - or firms report on product fields. We prefer this richer information and use, therefore, data on the product field if available and resort to data reported for the main activity of the firm if this is the only data available.

¹²We provide summary statistics, definitions of variables and descriptive statistics on offshoring and R&D intensities (Tables A1 and A2). R&D-intensities are only available for 1998 and from 2002-2007 for Austria and from 1998-2007 for Taiwan. The following industries are missing for these countries: Finland 8, 14, 15; Great-Britain 4, 5, 6, 7; Japan 4, 5, 14; Portugal 8, 10, and the US 4 and 5.

¹³Our results on the effects of offshoring on innovation are unlikely to be driven by concerns about data quality (Table A3). We report effects of offshoring on TFP to document that we can replicate general findings of the literature (e.g., Egger and Egger (2006), Amiti and Wei (2009), Moser et al. (2015)). TFP is calculated according to equation 3. TFP is then regressed on offshoring, R&D intensity and the export share, as defined above. Overall offshoring relates positively to TFP. There is also a positive link with offshoring of services and manufacturing with the former having a more pronounced effect (Amiti and Wei (2009)). We further report positive effects from offshoring manufacturing to high-income countries. All individual offshoring measures except one depict positive and significant coefficients.

¹⁴Results are not reported here to save space, but are available from the author upon request.

¹⁵Colantone and Crinò (2014) document for a sample of European countries that trade in newly imported inputs increases product variety in developed countries. They do not document, however, that this also leads to increases in R&D spending.

¹⁶In a first step, we try to rule out that sample selection is a problem. We drop each industry subsequently and analyze whether a particular industry drives our results. This is not the case. We then drop countries individually which does not change our main results either. In some specifications, offshoring to low-income countries turns insignificant though. We then move on and drop Austria and Taiwan as observations are only available for particular time periods for these countries. The results are robust to the exclusion of these countries. All countries for which particular industries are missing (Finland, Great Britain, Japan, Portugal, and the US) are deleted. Baseline results hardly change. Then, the top and bottom 1% of the respective offshoring measures are dropped. This does not influence the results either except for offshoring to low-income countries. Lastly, lagged values for offshoring are tested which again does not change results.

¹⁷We drop top and bottom 1% of observations of TFP to minimize measurement error which is expected to be large in TFP calculations. The same cleaning is applied to a measure of distance to the technological frontier introduced later.

¹⁸If offshoring is dropped from the regression import competition turns highly statistically significant and doubles in size pointing to multicollinearity between offshoring and import competition.

¹⁹We only consider *WES* of industries that are also used for offshoring, i.e., manufacturing and selected services industries. Furthermore only intermediate exports to high-income countries are considered as we seek to understand the sourcing patterns of these countries and suspect the sourcing patterns of low-income countries to be different.

²⁰The results are available from the author upon request.

²¹Top and bottom 1% of observations of WES are excluded to eliminate outliers.

²²We multiply the estimated coefficient for offshoring -0.095 with a one standard deviation change in offshoring 8.707 and then divide by mean R&D intensity 1.313 to compute the first effect. The latter effect is calculated as $(-0.092*8.465+0.501*0.664)/1.313=-0.34$.

²³We ask which share of high-skilled labor offsets the negative effect of offshoring. The following equation is solved for the share of high-skilled labor x : $-0.136*Offsh.+0.004*Offsh.*x = 0$. x equals 33.95 . Although no country has an average high-skilled share of 34% , several countries are close to this value in 2007 (e.g., Korea 33% , Finland 30% , and the US 28%) and might easily pass the threshold in particular industries.

²⁴We calculate that a one standard deviation change in offshoring and the distance measure leads to a reduction by 57% of R&D intensity, see $(-0.074*8.706-0.010*8.706*1.259)/1.313=0.569$.

²⁵Upstreamness is therefore 1 if production is equal to final demand and larger the more upstream the

respective variety is ranked. We drop top and bottom 1% of observations of upstreamness to exclude outliers.

²⁶Upstreamness reduces the negative offshoring effect only slightly. A one standard deviation increase of offshoring has a negative effect of -1.114 ($=-0.128*8.707$) on the level of R&D intensity. When taking into account a one standard deviation increase of upstreamness, we obtain a value of -1.043 for the joint effect. This is computed as $-0.128*8.707+0.016*8.707*0.5091=-1.043$.

Chapter 3

Outsourcing, Importing and Innovation: Evidence from Firm-level Data for Emerging Economies

by Ursula Fritsch¹ and Holger Görg^{2 3}

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Abstract

This paper investigates two sourcing strategies of firms, outsourcing and importing, and links these to innovation activities. We investigate this empirically using firm-level data for 28 emerging market economies. We find robust evidence that outsourcing increases the likelihood to spend on R&D and via this channel raises innovation output, whereas importing increases innovation output, but not R&D. The results hold when implementing an instrumental variables approach. We also find that results crucially depend on the institutional environment in the economy, e.g., property rights and intellectual property rights protection. Our results suggest that better institutions magnify the gains from importing, but not from outsourcing. EU-countries also reap additional positive innovation effects from importing compared to non-EU countries.

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Chapter 4

Information Technology and Innovation in Chinese Firms

by Ursula Fritsch^{1 2}

Abstract

This paper analyzes the link between information and communication technology (ICT) and innovation in a sample of Chinese manufacturing firms. The use of ICT, in particular the use of enterprise software, positively relates to several types of innovation by domestic firms. Adopting enterprise software corresponds to an increase in the probability of introducing a new product or service, for instance, of 11 percentage points. Effects of ICT are stronger the more routinized or standardized innovation activities are. ICT is additionally strongly related to a firm's propensity to engage in process innovation. All findings are robust to various propensity score matching techniques.

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1 Introduction

Information and communication technology (ICT) has recently received more attention as being a driver of innovation because ICT allows the firm to gather information more systematically and to evaluate this information at lower costs (Bartel et al. (2007)). Innovation is furthermore a key driver of productivity growth (Griffith et al. (2004)). It is therefore important to identify factors, such as ICT, that potentially promote innovation of firms¹. Studies thus far have however suffered from a lack of comprehensive firm-level data that offers more detailed information on different forms of ICT. This paper exploits a rich firm-level dataset to differentiate between effects of different types of ICT focusing on the use of enterprise software alongside standard measures of ICT use. Enterprise resource planning systems, supply chain management software and customer relationship management software are prominent examples of enterprise software. The former two are software tools that allow the firm to manage inventory and production processes efficiently and in real-time. The latter tool refers to the gathering of detailed information about customers so that firms can gear their products successfully and promptly to customers' needs. The use of enterprise software therefore involves direct efficiency improvements and increased availability of information, and both channels are expected to stimulate innovation.

This paper extends the existing literature on ICT and innovation along other lines. First, I make use of detailed information on ICT and innovation in a large sample of Chinese firms. This analysis presents differentiated results with respect to different ICT and innovation measures. The degree of sophistication of ICT as well as the degree of standardization of types of innovation matter for the results. Second, this paper is the first on this topic to control for selection into ICT use by deploying different propensity score matching (PSM) techniques among them a reweighting estimator (Hirano et al. (2003), Guadalupe et al. (2012)). Third, this is the first study, to the best of my knowledge, on this topic that considers an emerging country as opposed to several studies on developed countries². The role of ICT is interesting in the context of emerging countries as the use of ICT might enable firms in these countries to adopt foreign innovation to their market and to upgrade their technology. This is important as countries like China seek ways to technologically catch up and produce higher value-added parts of the production chain. These higher value-added parts of the production chain are generally associated with a focus on innovation. The magnitude and robustness of the effect is of special interest given that Commander et al. (2011) present large and robust effects of ICT on productivity in emerging countries. They also argue that these effects are larger

than effects found for developed countries.

My analysis rests on a sample of more than 1300 Chinese firms operating in the manufacturing sector. The survey refers mainly to the year 2010. The distinct advantage of the data is its uniqueness with respect to various ICT and innovation measures as well as the availability of rich firm characteristics. The survey covers information on the use of enterprise software and the frequency of ICT use. The survey also contains R&D expenditures, information on the introduction of products or services, and information on upgrading, as different types of innovation. I implement several propensity score matching techniques to control for selection into ICT use³. Two treatments are considered in this paper: a) the use of enterprise software - as a *sophisticated* form of ICT use - and b) whether the firm uses ICT frequently or rarely - as a general proxy for ICT prevalence within a firm.

This paper finds robust evidence that ICT is associated with innovation of firms. These results hold after accounting for selection effects into ICT use by deploying PSM. The data allow more nuanced investigations than previous research. Effects for the use of enterprise software are more robust than effects for general use of ICT, i.e., a more advanced form of ICT has more robust effects. I find interesting heterogeneity of effects with respect to different innovation measures as well. These are independent of the measure of ICT. Effects of ICT are stronger the more routinized or standardized innovation activities are. Effects are, in particular, more robust for upgrading than for R&D intensity. I also investigate the link with process innovation in an extension which is found to be highly robust and large in terms of magnitude. The estimated coefficients of ICT on innovation are economically meaningful. Implementing enterprise software is associated with an increase in the probability of introducing a new product or service by about 23 percent and an increase in the probability of upgrading by 31 percent. This paper therefore finds that ICT goes beyond productivity effects established for emerging countries (Commander et al. (2011)) and also entails substantial positive effects on innovation even if productivity is controlled for.

The remainder of this paper is structured as follows. Section 2 discusses the related literature, section 3 the data, section 4 the methodology, and section 5 presents the results. Section 6 concludes.

2 Related literature

The link between ICT and innovation has received increased attention by researchers in the past. Previous research suggests that ICT is a vital factor for stimulating in-

novation⁴. Firms can collect data in real-time and at lower costs on various business processes (Zand and van Beers (2010), Brynjolfsson et al. (2011), Engelstätter (2012)). ICT facilitates better control of the firm by improving monitoring and reviewing of performance targets. It also enables the firm to analyze the behavior of business partners, such as customers and suppliers, more closely and to exchange information with them in a structured way. Specific software can additionally act as a knowledge management tool that enables firms to document and share ideas and strategies (Cantner et al. (2011)). This could be useful to coordinate joint R&D efforts of firms. The aforementioned arguments highlight that some of these applications entail efficiency effects, whereas others alter the way in which innovation is conducted and information can be exploited. The evidence on the link between ICT and innovation thus far is nevertheless scarce due to data availability problems. Past research has therefore either focused on a particular industry or small-scale datasets in which endogeneity concerns could be addressed or has presented evidence from larger samples without accounting for selection bias.

There is strong suggestive evidence that ICT allows the firm to offer greater product variety and to increase product turnover (Gao and Hitt (2012)). Bartel et al. (2007) similarly document that the use of ICT-enhanced equipment in valve manufacturing leads to more customized valve products. They also investigate a potential mechanism and argue that ICT makes it less costly to switch production from one product to another. Increasing use of ICT is, furthermore, related to better product quality implying that ICT is an effective tool for monitoring quality (Licht and Moch (1999)). ICT is also strongly believed to increase production flexibility and, through this channel, enhance innovation (Hempell and Zwick (2008)).

Few studies have looked at specific forms of ICT investments, such as the use of enterprise software. Enterprise resource planning (ERP) systems, supply chain management (SCM) software, and customer relationship management (CRM) software are most common. The former two are software tools that allow the firm to manage inventory and production processes efficiently and in real-time. CRM could be particularly important for innovation as it tracks customers' preferences and changing consumer behavior.

The implementation of enterprise software relates positively and strongly to innovation activities (e.g., Zand and van Beers (2010), Engelstätter (2012)). Zand and van Beers (2010) further document that positively estimated productivity effects vanish once innovation effects are taken into account in productivity regressions. Hence, innovation acts as a channel through which ICT impacts on productivity. Brynjolfsson et al. (2011), on the contrary, document that data-driven decision making *does* have positive direct effects on productivity.

These findings point to strong complementarities between ICT and innovation (Bresnahan et al. (2002)). None of the aforementioned studies has however considered effect heterogeneity with respect to a) different types of innovation and b) different ICT measures.

This paper also relates to a broad literature on the productivity effects of ICT. Commander et al. (2011) present the first large-scale study on ICT in *emerging* countries⁵. They find large positive effects of ICT use on productivity for firms in Brazil and India and highlight that the estimated effects are larger than effects found in developed countries. If ICT is effective in enhancing productivity of firms in emerging countries, it is relevant to understand whether ICT plays an additional role in boosting innovation.

Lastly, this paper considers a more immediate effect of ICT by analyzing the link between ICT and process innovation. Process innovation should be related to the efficiency-enhancing role of ICT (Commander et al. (2011)). The choice of looking at process innovation is also motivated by recent evidence for the US that better management strongly correlates with ICT intensity (Bloom et al. (2014)). Bloom et al. (2013) further demonstrate that better management is highly effective in emerging countries in stimulating productivity, partly through a reduction in defects of products. I link this paper to this literature by analyzing whether ICT use - as a tool for better management - is related to the implementation of quality control.

3 Data and descriptives

This paper draws on detailed establishment-level information on ICT and innovation for about 1700 Chinese firms that belong to the manufacturing sector⁶. The survey was conducted by the World Bank in 2012, and questions refer to the year 2010 unless otherwise indicated⁷.

The dataset differentiates between the following innovation measures. *R&D intensity* is defined as R&D expenditures divided by the number of employees plus one and is then logarithmized⁸. This is the preferred dependent variable because it captures that the firm makes an effort to develop or improve a product as opposed to buying, for instance, superior inputs that improve/upgrade a product without any own effort of the firm. It is generally likely that firms in China are still far from the technological frontier and unlikely that these firms engage in innovation that is new to the world market. It is rather important for these firms to be able to adopt technology and adjust products, for instance to the Chinese market. This should be captured by looking at R&D intensity. I also deploy questions on *new products or services* (“In the last three years,

has this establishment introduced any new products or services?") and *upgrading* ("Over the last three years, what type of innovation activities has this establishment engaged in? ... Add new features to existing products and services"). I thereby account for the fact that innovation activities can be incremental or radical. I look at R&D intensity as an input factor of innovation and also consider the two other outcomes as outputs of the innovation process⁹. The survey asks for the introduction or upgrading and not the development of products and services. As I seek to capture own innovation effort, R&D intensity is therefore the preferred innovation measure. Several other studies also consider determinants of the aforementioned types of innovation and study these effects relying on similar survey instruments of the World Bank (e.g., Gorodnichenko et al. (2010) and Crinò (2012)). In this paper, I argue that ICT could, in particular, through standardization lead to minor product improvements within firms but not to fundamental increases in research activities. It could, however, also be the case that information on consumer behavior is so rich that increasing ICT use leads to entirely new products.

The data also allow to differentiate between two different ICT measures: 1) *use of enterprise software* and 2) *frequency of ICT use*¹⁰. The firm is asked for 1) whether the firm uses "software, such as enterprise resource planning (ERP) systems, supply chain management (SCM) systems, and customer relationship management (CRM) systems for inter-organizational relationships and transactions". This variable is supposed to capture a *sophisticated* form of ICT. Next, I construct a measure of the frequency with which ICT is used to support key business activities in different business processes¹¹. Firms can mark the following answers for these different business processes: "never", "rarely (once in a while)", "sometime (few times a month)", "frequently (few times a week)" and "all the time (daily)". I z-standardize sub-questions for different business processes by subtracting the respective mean of each sub-question and by dividing through the standard deviation of each sub-question. This is to ensure comparability between sub-questions. Subsequently, an average over these standardized sub-questions is computed. This paper is one of the first to exploit various information on the use of ICT (see also Commander et al. (2011) and Moshiri and Simpson (2011)). Previous authors have discussed the importance of enterprise software as a specific tool for gathering and evaluating information (Engelstätter (2012)). The frequency of ICT use measures how prevalent the use of ICT is in daily business operations, i.e., the breadth of ICT use.

Table 1 documents pronounced differences in innovation activities conditional on ICT use of firms (see Table A1 for summary statistics). Panel A looks at firms that use enterprise software vs. firms that do not. I also split the sample at the median between firms that make often vs. rarely use of ICT (Panel B). There are marked and

statistically significant differences in innovation between firms that have implemented enterprise software as opposed to firms that did not adopt this technology and firms with high and low frequency of ICT use. It is twice as likely that a firm that uses enterprise software engages in innovation (such as spending on R&D, introducing new products, and upgrading) than a firm that does not use this technology. Similar results are found for firms that use ICT often vs. firms that use ICT rarely. This table suggests that there is a strong positive correlation between ICT and innovation. I test in the subsequent analysis whether this relation is robust to the inclusion of control variables and selection effects.

(Table 1 here)

4 Methodology

In order to disentangle the relationship between ICT and innovation in more detail, I start with a simple OLS specification in which I regress different innovation measures on the aforementioned ICT variables.

$$INNO = \alpha + \beta * ICT + \gamma' * \mathbf{X} + \phi' * \mathbf{IND} + \pi' * \mathbf{REG} + \varepsilon \quad (1)$$

INNO stands either for *R&D intensity*, the *introduction of new products or services*, or *upgrading*. *ICT* captures the *use of enterprise software* or the *frequency with which ICT is used in different business processes*. I also add a vector of control variables \mathbf{X} , a vector of industry dummies (\mathbf{IND}), and a vector of regional dummies (\mathbf{REG}). I will use the same set of control variables that is deployed for propensity score matching. These variables will be discussed in more detail in the following paragraph on PSM.

In a second step, selection into ICT use is addressed by PSM. I methodologically follow work by Crinò (2012) who applies propensity score matching to a similar dataset by the World Bank and extend his approach by deploying a reweighting estimator. As I am not aware of natural experiments in which the use of ICT is randomly assigned to firms, instrumental variables use is hard to justify in this context unless an experimental setup within a narrow industry is studied (Bartel et al. (2007)). I am interested in the effect of ICT on innovation. Two endogeneous variables are considered as binary *treatments*: a dummy on whether the firm uses enterprise software and a dummy variable which captures frequent versus rare use of ICT¹². Different innovation measures, as outlined in the previous section, are used as *outcome* variables. The challenge is now to find an unbiased estimate for the average treatment effect on the treated (ATT). This is the

difference between the innovation outcome observed at treated firms - i.e., at firms that use ICT (intensively) - and compare it to the innovation outcome that would have been observed had these firms not been treated - i.e., not have used ICT (used ICT rarely).

$$ATT = E((Y_1 - Y_0)|T = 1) = E(Y_1|T = 1) - E(Y_0|T = 1) \quad (2)$$

The last term in equation 2 is unobservable and is obtained from constructing a meaningful counterfactual. This counterfactual can be estimated using the outcomes of a selected sub-sample of non-treated firms under the “strong ignorability assumption” (Rosenbaum and Rubin (1983)). First, the conditional independence assumption (CIA) has to hold: $Y_0 \perp T|X$. The counterfactual outcome, Y_0 , is thereby independent of the treatment T conditional on a set of observable control variables \mathbf{X} . If the treatment and the outcome are jointly determined by unobservable characteristics, then the estimated coefficient would be biased. As the dataset at hand is rich in the provision of control variables, I am able to exhaust this external variation to a large extent. This should substantially reduce endogeneity concerns. I also impose the common support assumption (CSA): $0 < Pr(T = 1|X) < 1$. Propensity scores observed in the treatment group also have to be observable in the control group so that a meaningful counterfactual can be computed. I then estimate propensity scores with Logit models in the first stage and use kernel matching with replacement in the second stage to pair each treated firm to a weighted average of all untreated firms, with weights depending on the distance between the propensity scores of the two groups. Kernel matching is the preferred specification as this approach lowers the variance of the estimator. At the same time, kernel matching does not introduce systematic bias in the estimates when comparing estimates from different PSM techniques.

Several robustness checks using different matching techniques are subsequently implemented. I start with radius matching. Radius matching matches on all observations within a given maximum radius (here: 0.03). Nearest-neighbor matching (NNM) is also considered, and the closest five observations are used. I compare my initial estimates to NNM estimates as the latter estimates are expected to be the least biased. All estimations use replacement due to the size of the sample and the fact that the distributions of treated and untreated firms only partly overlap. Replacements in the group of untreated firms ensure that a counterfactual can be constructed for many observations. I evaluate matching quality by reporting pseudo- R^2 and the standardized bias. If matching quality is good, these statistics should be small.

Lastly, a propensity score reweighting estimator is used (Hirano et al. (2003)),

which has been recently applied by Guadalupe et al. (2012) and Girma et al. (2015). Busso et al. (2014) document that this estimator outperforms standard PSM estimators if overlap is good. They also note, however, that standard PSM usually performs better if researchers are concerned with overlap and suggest in general to present different approaches because the performance of estimators hinges strongly on the features of the data-generating process. I carefully follow their suggestion. I estimate equation 1 weighting observations with a weight of one if the firm received treatment and with $PS_0/(1 - PS_0)$ if the firm did not receive treatment. PS_0 is the propensity score of the untreated observations. Untreated observations are therefore given greater weight the higher their propensity score is.

I now discuss which control variables are included in the vector \mathbf{X} to control for selection into the use of enterprise software and for selection into frequent use of ICT. These controls are also used for the initial OLS-estimations. Size should be related to more intensive use of ICT as monitoring and coordination problems likely increase with firm size (Gallego et al. (2014)). The variable captures three different groups of firms: small, medium, and large firms¹³. Productivity has been found to influence the decision to adopt ICT (Vries and Koetter (2011)). I consider labor productivity which has been documented to proxy well for total factor productivity in Chinese firms (Girma and Gong (2008)). I also control for the age of the firm as younger firms are more likely to implement ICT (Haller and Siedschlag (2011)). Furthermore, ownership of the firm is considered as foreign firms are more technologically aware, whereas state-owned firms are expected to lag behind in the use of state-of-the-art technology (Correa et al. (2010)). If the share of high-skilled workers is low in a firm, this could prevent the firm from investing in ICT as skill-complementary has been widely documented (Bresnahan et al. (2002), Gallego et al. (2014)). I additionally control for whether the firm reports that an "inadequately educated workforce is a major problem to the operations of the firm". This acts as a proxy for skill-shortage that a firm experiences. Firms that operate in global markets are exposed to stronger competitive pressure which makes them implement superior technology (Haller and Siedschlag (2011), Bloom et al. (forthcoming)). I control for both exporting and importing because many exporting firms in China are heavily subsidized, and "true" engagement in global markets might be better captured by importing. Financial constraints may prevent firms from investing in new technology, especially if this technology is not widespread, and firms experience uncertainty with respect to the returns of this technology (Correa et al. (2010)). This is a firm's answer to the question: "What percentage, as a proportion of the value of total annual purchases of material inputs or services were paid for after delivery?". This

should reflect whether the firm is considered to be credit-worthy by its business partners. Lastly, I control for the fact that the firm might simply use the internet to increase performance (Paunov and Rollo (2015)). R&D intensity is added in all regressions that have an innovation outcome variable as dependent variable in order to disentangle effects of inputs into innovation and outputs of innovation (Gallego et al. (2014)). Innovation effects that occur through increases in R&D are therefore controlled for in regressions considering innovation outputs. These effects are therefore *direct* effects on innovation outputs that do not involve own research effort of the firm. These direct effects might reflect direct learning or knowledge spill-overs from customers.

5 Results

5.1 Baseline regressions

Table 2 presents regression results of equation 1 using OLS and Probit estimations. I find evidence that the use of enterprise software and the frequent use of ICT both positively relate to various innovation measures. ICT use is a continuous variable in these specifications and not a dummy as in PSM. The estimated coefficients are large in terms of economic magnitude. Introducing enterprise software is associated with an increase of almost 12 percentage points in the probability of introducing a new product or service, and this effect is even stronger for upgrading. Increasing ICT use also depicts economically meaningful effects on innovation. Firms that increase their ICT use by one standard deviation have a 9 percentage points higher probability of introducing new products or services and a 13 percentage points higher probability of upgrading. These effects are robust to the inclusion of a broad set of control variables. R&D intensity is unsurprisingly strongly related to all innovation output measures as is the size of the firm. Productivity positively relates to R&D intensity but not to the other innovation measures. I suppose that this is because R&D intensity captures productivity effects in the regressions on innovation outputs. Younger firms tend to spend more on R&D, but are not more successful in terms of innovation output. Foreign ownership is not related to more innovation, but state ownership is significantly negatively related to all innovation measures. The share of high-skilled workers is positively associated with more innovation and so is a firm's perception that the workforce is inadequately educated. Innovating firms most likely face stronger skill shortages. There is some evidence that globally active firms are more likely to innovate and that financially constrained firms are not.

(Table 2 here)

Both ICT measures are jointly included in the following specification (see Table 3). I thereby test which ICT measure matters most for innovation activities. I hypothesize that the use of enterprise software is a comparatively advanced form of ICT that allows firms to gather systematically large amounts of information. This could imply that firms collect detailed information on customers which allows them to adjust/design their products along the preferences of their customers. ICT use broadly reflects the prevalence of ICT within a firm and how structured business operations of the firm are. The results show that both ICT measures individually explain some part of innovation (similar to findings by Commander et al. (2011)). Both variables are highly significant predictors of all three types of innovation. The estimated coefficients on the frequency of ICT use are only slightly reduced, whereas coefficients for the use of software are reduced by about 30% in all three specifications. This is unsurprising as software is just one part of the overall ICT stock, and ICT measures are expected to be correlated. Hence, controlling for ICT use is expected to lower the coefficient of enterprise software. I will control for the other variable respectively in all PSM estimations as Table 3 shows that both variables are important predictors for innovation activities of firms¹⁴.

(Table 3 here)

5.2 Propensity score matching

Propensity score matching results are presented in this section. PSM allows to control for selection into ICT use and should address endogeneity concerns given that the conditional independence assumption holds. The common support assumption is imposed. I first estimate the propensity score, assess matching quality, and then compare estimates of the ATT to the results presented in the baseline regressions. Quality control is considered as an outcome in an extension. Two endogenous variables are considered in the PSM estimations: the use of enterprise software - as a *sophisticated* form of ICT - and a more general measure on ICT use, namely whether the firm uses ICT frequently or rarely.

Table 4 presents estimations of the propensity score for both treatment variables¹⁵. The coefficients have generally the expected sign, as discussed in section 4. First of all, other ICT measures are strongly and highly significantly related to treatments. The probability of adopting enterprise software increases with R&D intensity, firm size and globalization proxies, such as foreign ownership and importing. Firms facing less financial constraints are also more likely to use enterprise software. The probability is instead lower for firms that are state-owned and for firms that report that skill-shortage is an obstacle. Similar results are obtained for the probability of being in the group of firms

that use ICT frequently. Different first stage results than for the software treatment are reported for export status and the share of high-skilled workers. Both increase the probability of being a firm that intensively uses ICT.

(Table 4 here)

I start by discussing the results for the treatment: *use of enterprise software*. I follow the standard approach in the literature and estimate PSM with replacement. Table 5 reports that less than 6 percent of all observations are off-support and provides further evidence on matching quality. Matching markedly reduces the median standardized bias by about 90 percent. The remaining bias is also small. The pseudo- R^2 is reassuringly very small in all specifications. This means that the covariates have no explanatory power for predicting the use of enterprise software in the matched sample. Differences in statistical significance of covariates between the unmatched and the matched sample are presented in Tables A3 and A4¹⁶. Tables A3 and A4 document pronounced and statistically significant differences for all control variables except age between firms that use enterprise software and firms that do not in the unmatched sample. It is therefore important to control for a wide range of observables when estimating the propensity score. This is also evident from the literature discussed in section 4. The tables also document that these differences vanish after matching. This can be seen from the p-value in the last column. Overall, this evidence reassures that PSM is successful at balancing the distribution of covariates between firms that use enterprise software and firms that do not use software¹⁷.

Table 5 reports the ATT for PSM based on a kernel distribution. Standard errors are computed via bootstrapping based on 100 replications. The estimated magnitude of the coefficients is similar to OLS-estimates (compare to Table 2) but is somewhat weaker in terms of statistical significance. When compared to the specification which includes both ICT variables (Table 3), PSM-estimates are slightly larger than OLS-estimates. The implementation of enterprise software is associated with a substantial increase in innovation, both in terms of innovation input, i.e., R&D spending, and innovation output. Using enterprise software corresponds to an increase in the probability of introducing a new product or service of 11 percentage points and to an increase in the probability of upgrading of 15 percentage points. The estimated effects are also economically meaningful. Adopting enterprise software leads to an increase in the probability of introducing a new product or service of 23 percent and to an increase in the probability of upgrading of 31 percent¹⁸. The effect is the most robust for upgrading and the weakest (although still statistically significant) for new products or services. This effect heterogeneity is unsurprising as technology might complement more structured processes, as upgrading, more

effectively than more complex processes, as developing new products. It is nevertheless an interesting result that software use is related to all three types of innovation. This is an important finding as it suggests that a) enterprise software makes the firm increase own research effort and b) enterprise software is associated with incremental and radical changes in innovation activities. This finding is novel and extends the previous literature which has only considered product innovation (Engelstätter (2012)). It is unlikely that the majority of firms covered in the sample are technologically leading firms in the world, but they are rather firms catching up with the technological frontier. The finding that firms spend more on R&D as a response to ICT adoption is reassuring as this is a first step towards technology upgrading. The fact that the use of enterprise software is associated with more radical innovation, proxied as the introduction of new products or services, is likely related to the idea that software allows to collect broader amounts of data which track the behavior of customers more quickly and more accurately.

(Table 5 here)

The *frequency of ICT use* - the second treatment - is considered next (Table 6). Overlap is slightly better for these estimations than for the first treatment, see the number of treated observations outside common support. Statistics on the median standardized bias and the Pseudo- R^2 point again to the fact that matching was successful. The estimated coefficients are only highly significant for upgrading and significant at 10 percent for R&D intensity. No longer are statistically significant effects found for the introduction of new products or services (compare to Table 3). Firms that use ICT frequently increase their R&D intensity by 0.75 (or 21 percent) and have a higher probability of 12 percentage points (or 24 percent) of engaging in upgrading.

(Table 6 here)

I will next discuss robustness checks with respect to different PSM estimators and the treatment *use of enterprise software* (Table 7). Results are reported for radius matching, nearest-neighbor matching (with the five closest neighbors) and inverse probability weighted regressions. The median standardized bias is substantially reduced in all specifications after matching and the Pseudo- R^2 drops to zero. Hence, these alternative estimators depict good matching quality as well. The estimated effects for the ATT are similar in terms of statistical significance and remain close to the ATT estimated under kernel matching. Inverse probability weighted regressions yield more robust estimates with smaller standard errors. As I do not want to overstate the estimated effects, I rely for the interpretation of the effect on the more conservative estimates presented in Table 5.

(Table 7 here)

Table 8 replicates the estimation strategies of Table 7 for the second treatment. The estimated coefficients stay the same in terms of magnitude with the exception of R&D intensity as outcome variable. Coefficients are additionally not entirely stable in terms of statistical significance for estimations on R&D intensity and the introduction of new products or services. Estimated effects on upgrading stay significantly positive and stable. As documented before, reweighting regressions improves efficiency and leads to more precisely estimated coefficients.

I now briefly discuss the findings thus far. As documented effects between the baseline regressions and PSM differ in terms of statistical significance and to a smaller extent in terms of magnitude, it turns out to be important to control for selection effects. Generally, the use of ICT relates to more innovation within firms. The results are therefore in line with previous findings (e.g., Bartel et al. (2007), Zand and van Beers (2010), Engelstätter (2012)) and extend those results along three lines. First, I document effect heterogeneity for different innovation measures irrespective of the ICT measure under consideration. Results are the strongest for upgrading and weaker (or insignificant) for more radical forms of innovation. This likely relates to the fact that these processes are differently complex and have different propensities of standardization. It is particularly interesting that ICT relates to own innovation effort of firms, captured by R&D spending, as this suggests that firms alter or develop products or services themselves, as opposed to buying superior inputs, for instance, and then offering “new” products. Second, a more sophisticated form of ICT use, namely enterprise software, has more robust effects on innovation than a general measure on the frequency of ICT use. This points to the unique role of enterprise software in gathering and evaluating information (Cantner et al. (2011)). Third, these results hold for an emerging economy. As China seeks ways to catch up with developed countries, ICT use is found to be an effective tool to engage in innovation which could promote productivity growth.

(Table 8 here)

I carry out several other robustness checks. First, the sensitivity of the estimated coefficients with respect to the set of covariates used for matching is checked (Table A5). I construct a new set of covariates in which I drop age because age is never statistically significant in the first stage of the PSM estimation (Table 4)¹⁹. The ICT-related variables are also dropped and replaced by the share of workers that regularly used computers three years ago. Finally, the exporter dummy is replaced by the number of years that the firm has been exporting. The estimated coefficients are similar for the estimates of software use but substantially larger for ICT use as treatment. If only the most technologically-advanced firms use enterprise software, then this effect

is not captured in the estimation for the latter treatment, and the estimation leads to overly large coefficients. This highlights that it is legitimate and in fact necessary to control for ICT in the first stage. One additional concern might be that results presented thus far are driven by firms with particular characteristics. Foreign-owned firms are very prone to using superior technology in their business networks and to also innovate more. Foreign-owned firms are therefore dropped which does not change any of the results²⁰. As Stiroh (2002) suggest that ICT-producing and ICT-using industries experience different dynamics between ICT and productivity, ICT-producing industries (“Machinery and equipment” and “Electronics”) are dropped. This eliminates about 15% of all observations and leaves results unaltered²¹.

In the last section, I explore ICT and a more immediate innovation outcome, namely process innovation (see Table 9). I make use of a question on whether “the firm introduced quality control over the last three years”. The use of this variable is also motivated by a recent literature on management practices. Bloom et al. (2014) hypothesize that ICT is related to “better” management in firms as ICT facilitates monitoring and the evaluation of business processes and performance targets of firms. Bloom et al. (2013) furthermore argue that firms that introduce tougher management practices improve their product quality, measured as a reduction in the number of product defects, in a sample of Indian firms. Therefore, a direct and very robust link between ICT and quality control is expected. Table 9 reports the results for quality control as outcome and both treatments. The estimated coefficients on both treatments are highly statistically significant and depict large coefficients in terms of economic magnitude²². They are, in particular, more than double the size of the ATT found for the introduction of new products or services. Hence, ICT is most strongly related to innovation activities which are standardized or routinized. This effect is present for both process innovation, such as quality control, and product innovation, such as upgrading. More importantly though, I have documented a robust link between different ICT measures and R&D intensity and the introduction of new products or services. ICT therefore also induces firms to engage in more radical research activities. The role of ICT is therefore not just in standardizing processes, but also in complementing research conducted by workers (Bresnahan et al. (2002)). This is in line with a broad literature which documents skill-biased technical change (Boothby et al. (2010), Goos et al. (2014), Michaels et al. (2014)). This literature has also stressed that high-skilled workers that perform non-routine activities benefit the most from technical change in terms of higher wages and increased labor demand. This matches results presented for innovation activities, i.e., non-routine tasks, in this paper.

(Table 9 here)

6 Conclusion

This paper is concerned with the relationship between ICT use and innovation in a sample of Chinese firms. It thereby contributes to the existing literature (e.g., Bartel et al. (2007), Zand and van Beers (2010), Gao and Hitt (2012), Engelstätter (2012)) by looking at large-sample evidence and by addressing endogeneity concerns.

The results suggest that ICT is a robust and economically relevant driver of different types of innovation. The paper presents two novel findings. First, the effects of ICT are stronger the more routinized or standardized the type of innovation is, i.e., effects are more robust for upgrading than for R&D intensity. Highly robust and large effects are also found for process innovation as outcome which further corroborates the hypothesis that the degree of standardization matters for the innovation effect. Second, this study exploits information on different types of ICT. Stronger effects are found for more sophisticated forms of technology adoption. This highlights that ICT is not a homogenous input into the innovation process, a point largely neglected in the existing literature. A crucial contribution of the paper is that the results are robust to various propensity score matching techniques and are therefore less likely to suffer from endogeneity bias. A similar strategy is applied by Cantner et al. (2011) in a study on the effect of knowledge management on innovation of German firms. It would be preferable to exploit exogenous variation that randomly induces firms to engage in ICT adoption, but I am not aware of any such experiment.

One interesting field to be explored in the future could be the consequences of the use of “big data” (Brynjolfsson et al. (2011)). Little is known about if and how “big data” stimulates productivity growth. Exploring potential mechanisms, such as improving lean management and improved information about customers, seems to be a worthwhile exercise against the background of this paper.

The presented results are also relevant given that an emerging economy is being studied, and there is no previous research in this field on firms in emerging countries. It is an important finding for managers in emerging countries that firms in these countries can innovate in various ways by adopting technology. The use of ICT can therefore be seen as a modern management strategy (Bloom et al. (2013)). As ICT is comparatively easy to adopt for firms and previous research documents that large productivity effects are expected in these countries (Commander et al. (2011)), this could enable firms in emerging countries to engage in more complex parts of the global value chain. Policy makers should therefore promote and stimulate measures that facilitate the adoption of new technology with a special focus on more advanced forms of ICT capital. They

should also keep in mind the highly complementary effects between ICT and further training of employees when designing technology policy (Boothby et al. (2010)).

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Table 1: Descriptives - ICT and innovation

Enterprise software use (A)	R&D intensity	New product	Upgrading
No			
Mean	2.41	0.32	0.33
Std. Dev.	4.02	0.47	0.47
Yes			
Mean	4.88***	0.61***	0.68***
Std. Dev.	4.66	0.49	0.47
ICT use (dummy) (B)	R&D intensity	New product	Upgrading
Low ICT use			
Mean	2.48	0.31	0.34
Std. Dev.	4.09	0.46	0.47
High ICT use			
Mean	4.79***	0.62***	0.68***
Std. Dev.	4.64	0.49	0.47

ICT use stands for the frequency of ICT use. * 10% significance, ** 5% significance, *** 1% significance. Statistical significance refers to differences between firms that use enterprise software vs. firms that do not use software (A) and firms that use ICT frequently vs. firms that use ICT rarely (B).

Table 2: Baseline 1 - Enterprise software, ICT use and innovation

<i>Depend. var.</i>	R&D inten- sity	R&D inten- sity	New product	New product	Upgrading	Upgrading
<i>ICT</i>						
Software	1.110*** (0.254)		0.116*** (0.025)		0.187*** (0.026)	
ICT use		0.760*** (0.131)		0.089*** (0.013)		0.131*** (0.014)
<i>Controls</i>						
R&D intensity			0.030*** (0.002)	0.029*** (0.002)	0.031*** (0.003)	0.030*** (0.003)
Workforce	0.414*** (0.088)	0.423*** (0.089)	0.022** (0.009)	0.023** (0.009)	0.016 (0.010)	0.017* (0.010)
Productivity	0.380*** (0.103)	0.386*** (0.103)	-0.008 (0.011)	-0.010 (0.011)	-0.016 (0.012)	-0.016 (0.012)
Age	-0.029** (0.012)	-0.032** (0.013)	-0.002 (0.002)	-0.002* (0.001)	-0.000 (0.001)	-0.001 (0.001)
Foreign owned	-0.655 (0.553)	-0.747 (0.567)	-0.072 (0.050)	-0.078 (0.050)	0.031 (0.054)	0.019 (0.052)
State owned	-1.154*** (0.366)	-0.586 (0.376)	-0.271*** (0.074)	-0.207*** (0.075)	-0.278*** (0.070)	-0.166** (0.070)
High-skilled	0.016*** (0.004)	0.014*** (0.004)	0.001* (0.000)	0.001* (0.000)	-0.000 (0.000)	-0.000 (0.000)
Problem educa- tion	0.802*** (0.157)	0.683*** (0.155)	0.025* (0.014)	0.011 (0.015)	0.038** (0.015)	0.014 (0.016)
Exporter	1.052*** (0.259)	0.956*** (0.264)	0.002 (0.026)	-0.002 (0.027)	0.033 (0.027)	0.026 (0.027)
Importer	0.719* (0.379)	0.881** (0.388)	0.077** (0.038)	0.088** (0.039)	-0.028 (0.040)	-0.011 (0.040)
Financials	-0.008* (0.004)	-0.008* (0.004)	-0.001 (0.000)	-0.001 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Internet R&D	1.894*** (0.240)	1.752*** (0.245)	0.059** (0.025)	0.058** (0.025)	0.093*** (0.026)	0.074*** (0.026)
Region dummies	✓	✓	✓	✓	✓	✓
Industry dum- mies	✓	✓	✓	✓	✓	✓
Observations	1339.00	1308.00	1337.00	1307.00	1333.00	1303.00
R^2	0.37	0.38				

Robust standard errors are in parentheses. * 10% significance, ** 5% significance, *** 1% significance. Regressions for R&D intensity are standard OLS estimations. Regressions for New product and Upgrading report marginal effects from a Probit model. ICT use stands for the frequency of ICT use.

Table 3: Baseline 2 - Joint estimations of both ICT measures and innovation

<i>Depend. var.</i>	R&D intensity	New product	Upgrading
<i>ICT</i>			
Software	0.732*** (0.283)	0.075*** (0.026)	0.129*** (0.026)
ICT use	0.636*** (0.142)	0.079*** (0.014)	0.112*** (0.015)
<i>Controls</i>			
R&D intensity		0.028*** (0.002)	0.029*** (0.003)
Workforce	0.380*** (0.089)	0.019** (0.009)	0.009 (0.010)
Productivity	0.366*** (0.103)	-0.012 (0.011)	-0.019 (0.012)
Age	-0.031** (0.013)	-0.002 (0.001)	-0.001 (0.001)
Foreign owned	-0.791 (0.557)	-0.086* (0.049)	0.010 (0.051)
State owned	-0.584 (0.370)	-0.205*** (0.073)	-0.157** (0.069)
High-skilled	0.015*** (0.004)	0.001* (0.000)	-0.000 (0.000)
Problem education	0.715*** (0.155)	0.015 (0.015)	0.019 (0.016)
Exporter	0.944*** (0.263)	-0.001 (0.027)	0.034 (0.027)
Importer	0.799** (0.387)	0.082** (0.039)	-0.028 (0.039)
Financials	-0.009** (0.004)	-0.001* (0.000)	-0.001 (0.000)
Internet R&D	1.687*** (0.245)	0.048* (0.025)	0.064** (0.026)
Observations	1305.00	1304.00	1300.00
R^2	0.38		

Robust standard errors are in parentheses. * 10% significance, ** 5% significance, *** 1% significance. Regressions for R&D intensity are standard OLS estimations. Regressions for New product and Upgrading report marginal effects from a Probit model. Region and industry dummies are included in all specifications. ICT use stands for the frequency of ICT use.

Table 4: Propensity score matching 1 - First-stage Logit model

<i>Depend. var.</i>	Software	Software	ICT use dummy	ICT use dummy
<i>ICT</i>				
ICT use	0.230*** (0.021)	0.227*** (0.021)		
Software			0.261*** (0.024)	0.260*** (0.024)
<i>Controls</i>				
R&D intensity		0.011*** (0.003)		0.011*** (0.003)
Size	0.077*** (0.014)	0.078*** (0.014)	0.014 (0.016)	0.006 (0.016)
Productivity	0.016 (0.010)	0.014 (0.010)	-0.003 (0.011)	-0.006 (0.011)
Age	-0.000 (0.001)	-0.000 (0.001)	0.001 (0.001)	0.002 (0.001)
Foreign owned	0.097* (0.053)	0.093* (0.051)	0.009 (0.051)	0.016 (0.051)
State owned	-0.178*** (0.068)	-0.110* (0.062)	-0.287*** (0.072)	-0.338*** (0.079)
High-skilled	-0.000 (0.000)	-0.000 (0.000)	0.001* (0.000)	0.000 (0.000)
Problem education	-0.020 (0.013)	-0.033** (0.014)	0.059*** (0.015)	0.052*** (0.015)
Exporter	-0.006 (0.026)	-0.019 (0.026)	0.051* (0.026)	0.050* (0.027)
Importer	0.132*** (0.035)	0.116*** (0.036)	0.014 (0.038)	0.002 (0.040)
Financials	0.001*** (0.000)	0.001*** (0.000)	0.001 (0.000)	0.001 (0.000)
Internet R&D	0.091*** (0.023)	0.065*** (0.024)	0.129*** (0.024)	0.099*** (0.026)
Observations	1370.00	1305.00	1370.00	1305.00

Robust standard errors are in parentheses. * 10% significance, ** 5% significance, *** 1% significance. Reported coefficients are marginal effects from a Logit-model. Columns (1) and (3) refer to R&D intensity as outcome. Columns (2) and (4) refer to the introduction of new products/services (upgrading) as outcomes. Region and industry dummies are included in all specifications. ICT use stands for the frequency of ICT use.

Table 5: Propensity score matching 2 - Enterprise software and innovation

<i>Depend. var.</i>	R&D intensity	New product	Upgrading
<i>Treatment</i>		Enterprise software	
<i>(a) Covariate balancing tests</i>			
Treated	498	485	484
Controls	745	745	742
Total	1,305	1,304	1,300
Treated observations outside common support			
Number	62	74	74
Median standardized bias			
Before matching	27.180	29.909	29.990
After matching	1.640	3.080	3.029
Pseudo R^2			
Before matching	0.225	0.239	0.239
After matching	0.001	0.004	0.004
<i>(b) ATT</i>			
Coefficient	1.177	0.105	0.154
Std. error	0.484	0.057	0.047
P-value	0.015	0.064	0.001

Propensity score matching estimates with kernel matching using common support. Standard errors are bootstrapped (based on 100 replications).

Table 6: Propensity score matching 3 - Frequency of ICT use and innovation

<i>Depend. var.</i>	R&D intensity	New product	Upgrading
<i>Treatment</i>		ICT use (dummy)	
<i>(a) Covariate balancing tests</i>			
Treated	580	571	571
Controls	687	687	683
Total	1,305	1,304	1,300
Treated observations outside common support			
Number	38	46	46
Median standardized bias			
Before matching	21.194	22.685	22.409
After matching	4.022	3.644	3.606
Pseudo R^2			
Before matching	0.195	0.198	0.198
After matching	0.004	0.005	0.005
<i>(b) ATT</i>			
Coefficient	0.749	0.064	0.121
Std. error	0.422	0.044	0.039
P-value	0.076	0.148	0.002

Propensity score matching estimates with kernel matching using common support. Standard errors are bootstrapped (based on 100 replications).

Table 7: Robustness check 1 - Different propensity score matching techniques (treatment: use of enterprise software)

<i>Depend. var.</i>	R&D intensity			New product			Upgrading		
	Radius matching	Nearest-neighbor, 5 matches	Inverse prob. weighted LS	Radius matching	Nearest-neighbor, 5 matches	Inverse prob. weighted LS	Radius matching	Nearest-neighbor, 5 matches	Inverse prob. weighted LS
<i>(a) Covariate balancing tests</i>									
Treated	498	498		485	485		484	484	
Controls	745	745		745	745		742	742	
Total	1,305	1,305	1,305	1,304	1,304	1,304	1,300	1,300	1,300
Treated observations outside common support									
Number	62	62		74	74		74	74	
<i>(b) Median standardized bias</i>									
Before matching	27.180	27.180		29.909	29.909		29.990	29.990	
After matching	2.836	4.003		2.849	4.071		3.089	4.171	
<i>Pseudo R^2</i>									
Before matching	0.225	0.225		0.239	0.239		0.239	0.239	
After matching	0.003	0.005		0.005	0.005		0.004	0.005	
<i>(b) ATT</i>									
Coefficient	1.225	1.131	1.185	0.105	0.094	0.106	0.157	0.188	0.136
Std. error	0.560	0.550	0.346	0.059	0.054	0.029	0.053	0.051	0.028
P-value	0.029	0.040	0.001	0.076	0.079	0.000	0.003	0.000	0.000

Standard errors are bootstrapped (based on 100 replications) for radius matching and nearest-neighbor matching.

Table 8: Robustness check 2 - Different propensity score matching techniques (treatment: frequency of ICT use (dummy))

<i>Depend. var.</i>	R&D intensity			New product			Upgrading		
	Radius matching	Nearest-neighbor, 5 matches	Inverse prob. weighted LS	Radius matching	Nearest-neighbor, 5 matches	Inverse prob. weighted LS	Radius matching	Nearest-neighbor, 5 matches	Inverse prob. weighted LS
<i>(a) Covariate balancing tests</i>									
Treated	580	580		571	571		571	571	
Controls	687	687		687	687		683	683	
Total	1,305	1,305	1,305	1,304	1,304	1,304	1,300	1,300	1,300
Treated observations outside common support									
Number	38	38		46	46	46	46	46	
Median standardized bias									
Before matching	21.194	21.194		22.685	22.685		22.409	22,409	
After matching	3.724	3.518		4.229	4.754		4.192	4.531	
Pseudo R^2									
Before matching	0.195	0.195		0.198	0.198		0.198	0.198	
After matching	0.004	0.005		0.006	0.008		0.006	0.008	
<i>(b) ATT</i>									
Coefficient	0.780	0.571	0.940	0.060	0.078	0.065	0.121	0.130	0.134
Std. error	0.376	0.381	0.314	0.043	0.044	0.028	0.046	0.048	0.030
P-value	0.038	0.134	0.003	0.160	0.076	0.020	0.008	0.007	0.000

Standard errors are bootstrapped (based on 100 replications) for radius matching and nearest-neighbor matching.

Table 9: Propensity score matching 4 - Software and frequency of ICT use (dummy) and process innovation

<i>Depend. var.</i>	Quality control	Quality control
<i>Treatment</i>	Software	ICT use (dummy)
<i>(a) Covariate balancing tests</i>		
Treated	485	572
Controls	742	683
Total	1,301	1,301
Treated observations outside common support		
Number	74	46
Median standardized bias		
Before matching	30.004	22.518
After matching	2.957	3.600
Pseudo R^2		
Before matching	0.240	0.198
After matching	0.004	0.005
<i>(b) ATT</i>		
Coefficient	0.267	0.160
Std. error	0.051	0.036
P-value	0.000	0.000

Propensity score matching estimates with kernel matching using common support. Standard errors are bootstrapped (based on 100 replications).

Appendix

Table A1: Summary statistics

	Mean	Std. dev.	Observations
Software	0.474	0.499	1653
ICT use	-0.002	0.998	1612
ICT use (dummy)	0.501	0.5	1612
R&D intensity	3.53	4.49	1545
New product	0.457	0.498	1666
Upgrading	0.495	0.5	1658
Workforce	4.46	1.27	1633
Size	2.074	0.761	1672
Productivity	11.853	1.003	1508
Age	13.107	8.342	1631
Foreign owned	0.042	0.201	1668
State owned	0.04	0.195	1668
High-skilled	50.255	28.188	1641
Problem education	0.823	0.830	1669
Exporter	0.325	0.468	1671
Importer	0.125	0.331	1667
Financials	63.648	27.841	1644
Internet R&D	0.59	0.492	1643
ICT intensity	6.724	2.385	1444
Quality control	0.483	0.5	1661
Computer	22.004	18.713	1644
Export experience	2.697	4.828	1606

ICT use stands for the frequency of ICT use.

Table A2: Robustness check 3 - Joint estimations of three ICT measures and innovation

<i>Depend. var.</i>	R&D	inten-	New product	Upgrading
	sity			
<i>ICT</i>				
Software	0.806*** (0.301)		0.062** (0.028)	0.138*** (0.028)
ICT use	0.662*** (0.148)		0.074*** (0.015)	0.106*** (0.015)
ICT intensity	0.112* (0.064)		0.012* (0.006)	0.011* (0.006)
<i>Controls</i>				
R&D intensity			0.027*** (0.003)	0.028*** (0.003)
Workforce	0.427*** (0.095)		0.018* (0.010)	0.009 (0.011)
Productivity	0.310*** (0.113)		-0.011 (0.012)	-0.031*** (0.012)
Age	-0.028** (0.013)		-0.002 (0.002)	-0.000 (0.001)
Foreign owned	-0.712 (0.564)		-0.079 (0.049)	0.016 (0.052)
State owned	-0.380 (0.382)		-0.220*** (0.074)	-0.129** (0.065)
High-skilled	0.013*** (0.005)		0.001* (0.000)	-0.000 (0.000)
Problem education	0.763*** (0.164)		0.014 (0.015)	0.022 (0.016)
Exporter	0.909*** (0.273)		0.004 (0.028)	0.038 (0.027)
Importer	0.883** (0.393)		0.073* (0.039)	-0.022 (0.040)
Financials	-0.012*** (0.005)		-0.001 (0.000)	-0.000 (0.000)
Internet R&D	1.596*** (0.256)		0.048* (0.026)	0.051* (0.027)
Observations	1193.00		1192.00	1191.00
R^2	0.40			

Robust standard errors are in parentheses. * 10% significance, ** 5% significance, *** 1% significance. Regressions for R&D intensity are standard OLS estimations. Regressions for New product and Upgrading report marginal effects from a Probit model. Region and industry dummies are included in all specifications. ICT use stands for the frequency of ICT use.

Table A3: Matching quality in the first stage 1 - Pre- and post-estimation characteristics

<i>Depend. var.</i>		R&D intensity					
Variable	Sample	Treated	Control	%bias	%bias	t	p>t
ICT use	Unmatched	0.725	0.28456	98.0		17.52	0.000
	Matched	0.72892	0.73367	-1.1	98.9	-0.17	0.866
Size	Unmatched	2.2321	1.9168	42.4		7.56	0.000
	Matched	2.2229	2.2259	-0.4	99.1	-0.06	0.950
Productivity	Unmatched	11.962	11.791	16.6		2.99	0.003
	Matched	11.982	11.944	3.7	77.7	0.61	0.543
Age	Unmatched	13.221	12.855	4.5		0.81	0.419
	Matched	13.183	13.04	1.8	61.1	0.29	0.771
Foreign owned	Unmatched	0.06964	0.03087	17.8		3.27	0.001
	Matched	0.06627	0.06316	1.4	92.0	0.20	0.842
State owned	Unmatched	0.01071	0.06846	-29.9		-5.10	0.000
	Matched	0.01205	0.0071	2.6	91.4	0.80	0.423
High-skilled	Unmatched	52.966	46.107	24.4		4.39	0.000
	Matched	51.528	51.734	-0.7	97.0	-0.11	0.910
Problem education	Unmatched	0.75893	0.9047	-17.8		-3.17	0.002
	Matched	0.72892	0.76186	-4.0	77.4	-0.63	0.526
Exporter	Unmatched	0.40536	0.2604	31.1		5.61	0.000
	Matched	0.37149	0.37856	-1.5	95.1	-0.23	0.818
Importer	Unmatched	0.18571	0.06577	36.8		6.78	0.000
	Matched	0.17269	0.18103	-2.6	93.0	-0.34	0.731
Financials	Unmatched	66.655	60.404	23.0		4.10	0.000
	Matched	67.313	67.933	-2.3	90.1	-0.35	0.727
Internet R&D	Unmatched	0.73571	0.45235	60.2		10.68	0.000
	Matched	0.70482	0.70776	-0.6	99.0	-0.10	0.919

Matching results from column 1 of Table 5. Only firms that are on common support are considered.

Table A4: Matching quality in the first stage 2 - Pre- and post-estimation characteristics

<i>Depend. var.</i>	New product						
Variable	Sample	Treated	Control	%bias	%bias	t	p>t
ICT use	Unmatched	0.72451	0.28456	97.9		17.49	0.000
	Matched	0.72165	0.70948	2.7	97.2	0.42	0.675
R&D intensity	Unmatched	5.0274	2.4113	59.9		10.82	0.000
	Matched	4.5594	4.694	-3.1	94.9	-0.44	0.656
Size	Unmatched	2.2308	1.9168	42.2		7.52	0.000
	Matched	2.2165	2.2462	-4.0	90.5	-0.63	0.532
Productivity	Unmatched	11.964	11.791	16.8		3.01	0.003
	Matched	11.98	11.961	1.9	88.9	0.31	0.760
Age	Unmatched	13.229	12.855	4.6		0.82	0.410
	Matched	13.208	12.652	6.9	-48.8	1.13	0.257
Foreign owned	Unmatched	0.06977	0.03087	17.8		3.28	0.001
	Matched	0.06598	0.06667	-0.3	98.2	-0.04	0.966
State owned	Unmatched	0.01073	0.06846	-29.9		-5.09	0.000
	Matched	0.01237	0.00754	2.5	91.6	0.76	0.449
High-skilled	Unmatched	52.989	46.107	24.5		4.40	0.000
	Matched	51.623	49.723	6.8	72.4	1.03	0.304
Problem education	Unmatched	0.76029	0.9047	-17.6		-3.14	0.002
	Matched	0.73402	0.73896	-0.6	96.6	-0.09	0.926
Exporter	Unmatched	0.40429	0.2604	30.9		5.56	0.000
	Matched	0.3732	0.38995	-3.6	88.4	-0.54	0.592
Importer	Unmatched	0.18605	0.06577	36.8		6.79	0.000
	Matched	0.17526	0.19339	-5.6	84.9	-0.73	0.467
Financials	Unmatched	66.667	60.404	23.0		4.10	0.000
	Matched	67.262	69.488	-8.2	64.5	-1.27	0.205
Internet R&D	Unmatched	0.73524	0.45235	60.1		10.65	0.000
	Matched	0.69897	0.70919	-2.2	96.4	-0.35	0.728

Matching results from column 2 of Table 5. Only firms that are on common support are considered.

Table A5: Robustness check 4 - Matching on different covariates (treatment: software use and frequency of ICT use (dummy))

<i>Depend. var.</i>	R&D intensity	New product	Upgrading	R&D intensity	New product	Upgrading	Frequency of ICT use (dummy)		
							R&D intensity	New product	Upgrading
<i>Treatment</i>									
<i>(a) Covariate balancing tests</i>									
Treated	524	497	497	559	548	548			548
Controls	744	744	742	685	685	683			683
Total	1,325	1,323	1,321	1,294	1,293	1,291			1,291
Treated variations common support									
Number	57	82	82	50	60	60			60
Median standardized bias									
Before matching	24.495	27.546	27.374	17.015	20.235	20.237			20.237
After matching	4.268	4.585	5.395	2.089	1.847	2.008			2.008
Pseudo R^2									
Before matching	0.112	0.142	0.142	0.067	0.093	0.093			0.093
After matching	0.004	0.004	0.005	0.002	0.002	0.003			0.003
<i>(b) ATT</i>									
Coefficient	1.511	0.120	0.157	1.427	0.109	0.196			0.196
Std. error	0.383	0.038	0.042	0.354	0.039	0.037			0.037
P-value	0.000	0.002	0.000	0.000	0.005	0.000			0.000

Propensity score matching estimates with kernel matching using common support. Standard errors are bootstrapped (based on 100 replications).

Table A6: Variable definitions

Variable	Variable definition
Software	Currently, does this establishment use software, such as enterprise resource planning (ERP) systems, supply chain management (SCM) systems, and customer relationship management (CRM) systems for inter-organizational relationships and transactions?*
ICT use	To what extent are information and communication technologies (computers, internet, and software) used to support key business activities in each of the following business processes? a) Partner relations (suppliers, contractors, etc.), b) Product and service enhancement, c) Production and operations, d) Marketing and sales and e) Customer relations. Possible answers for different business processes: “never” (= 1), “rarely (once in a while)” (= 2), “sometime (few times a month)” (= 3), “frequently (few times a week)” (= 4) and “all the time (daily)” (= 5). I then standardize these sub-questions for different business processes by subtracting their respective mean and by then dividing through the standard deviation. I then compute an average over these standardized sub-questions.
ICT use dummy	ICT use is divided at the median into firms that intensively use ICT (= 1) and firm that do not (= 0)
R&D intensity	Log of (Expenditures on R&D performed within the establishment and contracted with other companies (three year average) divided by the average of the number of permanent employees in 2010 and 2008 (in Renminbi)+1)
New product	In the last three years, has this establishment introduced any new products or services?*
Upgrading	Over the last three years, did this establishment add new features to existing products or services?*
Workforce Size	Number of permanent and temporary employees (in full-term equivalents) Small (≥ 5 and ≤ 19 workers, coded as 1), medium (≥ 20 and ≤ 99 , coded as 2) and large (≥ 100 , coded as 3)
Productivity	(Sales - intermediate inputs) divided by workforce in 2010 (in Renminbi)
Age	Number of years in operation since establishment
Foreign owned	1 if the share of private foreign individuals, companies or organizations ownership is $\geq 50\%$, otherwise 0
State owned	1 if share of this firm owned by government or state is $\geq 50\%$, otherwise 0
High-skilled	Percentage of full time permanent workers who completed secondary school**
Problem education	To what degree is an inadequately educated workforce an obstacle to the current operations of this establishment? Possible answers: “No obstacle” (= 0), “Minor obstacle” (= 1), “Moderate obstacle” (= 2), “Major obstacle” (= 3), “Very severe obstacle” (= 4)
Exporter	Does this establishment export?*
Importer	Does this establishment import?*
Financials	In fiscal year 2010, what percentage, as a proportion of the value of total annual purchases of material inputs or services were paid for after delivery?***
Internet R&D	Is this establishment’s internet connection used to do research and develop ideas on new products and services?*
ICT intensity	Log of (Expenditures on computers and other information processing equipment (including printers, terminals, optical and magnetic reader, RFID, operating systems and software) (three year average) divided by the average of the number of permanent employees in 2010 and 2008 (in Renminbi)+1)
Quality control	Over the last three years, did this establishment introduce new quality control procedure in production or operations?*
Computer	Three years ago, what percent of this establishment’s workforce regularly used computers in their jobs?***
Export experience	Number of years since the firm exported directly or indirectly for the first time

Note: * 1 = yes and 0 = no; ** Defined between 0 and 100

Notes

¹Determinants of innovation on the firm-level are currently intensively studied. Other studies that also consider innovation outcomes and deploy similar data by the World Bank include Gorodnichenko et al. (2010) and Crinò (2012).

²See Zand and van Beers (2010), Brynjolfsson et al. (2011), Gao and Hitt (2012), Engelstätter (2012) for evidence on developed countries. Frank et al. (2016) study the implications of software use for innovation in Brazilian industries.

³See for examples with similar data Cantner et al. (2011) and Crinò (2012).

⁴A notable exception is Frank et al. (2016) who document that software adoption lowers innovation in a study on Brazilian industries.

⁵Several studies (e.g., Black and Lynch (2001), Bresnahan et al. (2002), Moshiri and Simpson (2011), Venturini (2015)) have documented the role of ICT in enhancing productivity in the context of developed countries.

⁶Information for more than 1300 firms is deployed for regression analysis.

⁷See <http://microdata.worldbank.org/index.php/catalog/1559> for further information on the questionnaire and methodology. The survey follows the standardized survey methodology developed by the World Bank for enterprise surveys. Stratification for this survey follows three criteria: sector of activity (11 manufacturing industries), firm size (3 groups) and geographic location (25 metropolitan areas). I drop all firms that belong to the service sector. These firms answer a different questionnaire which has less information on the variables of interest.

⁸A full description of variables can be found in the appendix (Table A6).

⁹Although R&D intensity is an input into the innovation process, it is regularly considered as a proxy for innovation activities of a firm (e.g., Crinò (2012), Bloom et al. (forthcoming)).

¹⁰ICT intensity is considered in a robustness check in the appendix.

¹¹These business processes are (a) partner relations, b) product and service enhancement, c) production and operations, d) marketing and sales and e) customer relations.

¹²The control group for the use of enterprise software includes firms that a) do not use ICT at all or b) use ICT but not enterprise software. The control group for the frequency of ICT use dummy includes firms that either use or do not use enterprise software. About 0.6% of the sampled firms state that they use enterprise software but never use ICT for key business activities. As this might be considered inconsistent, these firms are dropped in a robustness check which leaves all results unaltered. Results are available upon request.

¹³The log of the number of employees is instead used in baseline regressions.

¹⁴ICT intensity is considered as a proxy for ICT stock in a robustness check. As ICT is a rapidly depreciating asset, this measure of ICT intensity should be a sensible measure for ICT stock even though the measure relates to average ICT expenditures in the past three years. ICT intensity is included along the two other measures in joint estimations (see Table A2 in the appendix). ICT intensity seems to be the weakest predictor of innovation compared to the other two ICT measures. This is an interesting finding as ICT intensity is a frequently used proxy for overall ICT in empirical studies. I, however, find that the frequency of ICT use is more robustly related to innovation in firms.

¹⁵R&D intensity enters the propensity score estimations as a control variable for the following outcomes: introduction of new products or services and upgrading.

¹⁶Table A3 refers to Table 5 column 1 with R&D intensity being the outcome, and Table A4 refers to Table 5 column 2 with introduction of new products or services being the outcome.

¹⁷Similar results apply to the second treatment, the frequency of ICT use, and are not reported to save space but are available from the author upon request.

¹⁸The percentage change for developing a new product or service is computed as $(0.105*1)/0.457=0.230$ with 0.457 being the mean of the question on the introduction of new products or services.

¹⁹I also drop productivity in a specification not reported here. The results are available from the author upon request. Although productivity is never a statistically significant predictor of ICT use, estimated coefficients are much larger when productivity is not controlled for. Productivity also markedly differs between treated and untreated firms before matching (see Tables A3 and A4), which is not the case for firm's age. Hence, I keep productivity in the set of covariates.

²⁰I drop all firms from the sample with some positive foreign ownership (8% of firms). Results are available upon request.

²¹Results are available upon request.

²²I only report estimations using PSM based on kernel matching. The presented results are highly robust to the use of all other matching techniques which have been presented in this paper. They are available from the author upon request.

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Eidesstattliche Erklärung zum selbstständigen Verfassen der Arbeit

Ich erkläre hiermit, dass ich meine Doktorarbeit „Offshoring and Technological Change as Determinants of Innovation“ selbstständig und ohne fremde Hilfe angefertigt habe und dass ich als Koautor maßgeblich zu den weiteren Fachartikeln beigetragen habe. Alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen der aufgeführten Beiträge wurden besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert.

Kiel, den 28. September 2016

Ursula Fritsch