Productive Offshoring: Evidence from Spain*

Ishan D. Ghosh[†]

July 30, 2019

Abstract

Fragmentation of production and global sourcing of intermediates, popularly referred to as offshoring, is typically associated with lost jobs and displaced workers. Often ignored however, is a dimension of productivity-enhancing, within-firm reorganization spurred by offshoring. This paper provides novel evidence that in response to offshoring, such reorganization can take place in the form of increased domestic expenditure on R&D and change in firm level employment composition in favor of high-skilled workers. Using firm level microdata from the manufacturing sector in Spain, we construct a plausibly exogenous measure of offshoring and show that, following the financial crisis of 2008, offshoring has a positive effect on R&D expenditures and high-skilled employment in Spain. These findings are consistent with a stylized heterogeneous firms model where reduction in trade costs augments the productivity of offshoring firms through the intensive margin of technology investments.

JEL classification numbers: L25,F14,F61

Keywords: Firm-level Data, Offshoring, R&D, Productivity, Firm Dynamics

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*I thank Philip Luck and School of Economics, Drexel University for providing financial support to purchase the data. I thank my readers André Kurmann and Vibhas Madan for their sound advice, constructive criticism and feedback during the writing process. I also want to thank Konstantinos Serfes and Philip Luck for their guidance at different stages of the project. This paper has benefited from valuable and insightful suggestions from Mian Dai, Yoto V. Yotov, Teresa Fort, Mykyta Vesselovsky, Jeffrey Bergstrand, participants at the MidWest Trade Conference (Spring 2017), XX Applied Economics (Valencia, 2017), Biennial Economics Conference (Washington, D.C., 2017), Eastern Economic Conference (Boston, 2018) and NBER Entrepreneurship Research Bootcamp (ERBC, 2016). I thank Isabella Sanchez from ESEE for facilitating access to Spanish firm level data. All errors are my own.

[†]3220 Market Street, LeBow College of Business, School of Economics, Drexel University. Philadelphia, PA 19104. *tel:* +1 7163648999, *email:* idg23@drexel.edu

1 Introduction

Understanding the impact of trade on firm productivity has been viewed as one of the major challenges in international economics. Both in terms of theoretical and empirical research, this literature has received significant attention. The underlying mechanisms at work, however, are still debated and has potential unanswered questions. Prior trade literature has focused on innovation as one of the primary drivers of within firm growth and productivity gain. In order to analyze the trade-innovation nexus, it is imperative to understand why firms innovate in the first place and what do we gain from understanding the factors that cause firms to engage in innovation.

Simple economic models of firm dynamics predict that firms innovate when the cost of innovation is lower than their expected present value of future profits from innovation. Accordingly, exports and innovation have shown a strong correlation with firms being able to increase revenue and thereby profits, by expanding market size Aw, Roberts and Xu (2011). Similarly, there is evidence of firms engaging in innovation in response to import competition from low-wage countries in order to survive and stay in the race Bloom, Draca and Van Reenen (2016). In this paper, I focus on trade in intermediates, popularly known as offshoring as a third separate channel which can incentivize innovation and thereby lead to increase in firm level productivity.

Offshoring, has been studied more in the context of employment and earnings. Both in an academic and political context, offshoring has been subject to a number of criticisms especially because of its strong impact on labor market dynamics like job destruction, wage inequality and polarization of jobs to name a few. In this paper I argue that analysis of offshoring often ignores a dimension of productivity-enhancing, within-firm reorganization. Unlike export market access or import competition, which incentivize innovation by increasing expected future revenues, offshoring can spur innovation by reducing marginal cost of production, thereby increasing the value added from innovation.

We use rich microdata from the manufacturing sector in Spain to construct a plausibly exogenous firm-level measure of offshoring and focus particularly on a *couple* of channels through which offshoring affects firm productivity via innovation. First, we show that offshoring leads to within firm reallocation of resources by reducing marginal costs and incentivizing firms' involvement in more productivity-enhancing investments like expenditure in R&D. The intuition is that sourcing cheaper intermediates reduces marginal costs of production and raises profits, thereby making it more profitable to undertake R&D expenditure. This in turn boosts firm productivity. The benefits of declining trade barriers on the expected future value of the firm is thus relatively higher for R&D undertaking firms Boler, Moxnes and Ulltveit-Moe (2015).

Second, we show that offshoring leads to a change in within-firm employment composition skewed in favor of skilled workers. Offshoring on average leads to a decline in temporary workers, the majority of which most likely belong to the lower end of the skill distribution and perform more routine jobs. On the contrary, offshoring has a positive and significant effect on the hiring of high-skilled workers.

Since Melitz (2003), the trade literature has focused on firm heterogeneity in the sense that the impact of trade on firm outcomes is not likely to be uniform across the productivity or size/age distribution. We find that firms who have had a prior history of innovation[1] are significantly more likely to engage in R&D in response to offshoring. We also find similar effects for bigger, more mature and more productive firms in terms of their R&D investments in response to offshoring.

A plausible concern with the offshoring driven innovation channel is the absence of credit constraints in the firms' decision to engage in R&D, especially when we focus on the intensive margin of innovation. This is particularly reasonable when it comes to firms in Spain, which was quite severely affected by the financial crisis of 2008. It is not quite clear as to why firms would wait for offshoring to increase R&D expenditure if R&D is productivity-enhancing for firms? Garicano and Steinwender (2016) shows that in Spain, firms faced lower credit availability and higher credit cost compared to pre-financial crisis levels and that, negative credit shocks impacted firms' long-term investments. We follow Garicano and Steinwender (2016) in constructing firm-level measures of long term and short term credit shocks and point to a novel heterogeneous effect across firms. We show that the effect of offshoring on R&D is particularly pronounced for firms who are long-term credit constrained but who have access to short-term credit. To that end, our results suggest that offshoring can have a credit ameliorating effect on firms that face strong financial market frictions and cheaper intermediates thus provide a channel to save resources and redirect them to domestic innovation.

Offshoring being a conscious firm decision poses the potential problem of endogenity. In order to make an inference on the causal effect of offshoring on technology adoption or employment, it is important that the marginal effect truly captures the decision of firms to fragment production across countries solely for the purpose of refocusing attention on domestic innovation. However, as argued by Bernard et al. (2018), firms' offshoring decision can be influenced by a number of factors which are at best conflicting in nature. On one hand, firms might offshore production to save resources and invest more in innovation and R&D, while on the other hand, firms might self-select into offshoring in response to import competition as a potential response to reduce costs so that they could survive and stay in the race.

To account for the potentially conflicting channels, which can introduce bias in the estimation of offshoring, we use an instrumental variables approach similar to Hummels et al.

[1] We use four measures of prior innovation - whether the firm engaged in **product innovation**, **process innovation**, had any **technical collaboration with universities and/or research organization** and whether the firm **received subsidy for innovation**.

(2014) and Autor, Dorn and Hanson (2013), thereby accounting for the firms' intensive margin of offshoring due to factors external to the firms and Spain in general. Explained further in section **??**, we exploit the productivity growth in Spain's major trading partners proxied by the increase in their intermediate exports to four countries[2] similar to Spain and apportion the industry-level growth in exports to firms based on their pre-period import shares from Spain's major trading partners. The underlying assumption of this strategy is that within-industry productivity growth in trading partners is due to increase in foreign productivity and are uncorrelated with Spanish firms' innovation or employment outcomes.

To provide a theoretical foundation to our empirical results, we borrow from Bas and Ledezma (2015), to analyze offshoring in a *Melitz* type heterogeneous firms model comprised of an additional stage of endogenous investment. Unlike a binary-choice technology adoption environment similar to the likes of Bustos (2011) and Yeaple (2005), Bas and Ledezma (2015) extend Melitz (2003) to include an investment stage so as to account for continuous investment choice of firms in augmenting their productivity. However unlike Bas and Ledezma (2015), we don't consider an export market to analyze the open economy version of the model. Instead we assume that firms source intermediates from a foreign market and sell their entire output in the domestic economy thereby gaining access to possibly higher(lower) quality and higher(lower) variety of intermediates beyond what is available domestically.

The model predicts that in response to a decline in trade costs, non-offshorers become less productive while offshorers on account of increased R&D investment are able to augment their productivity. The productivity augmenting effect of offshorers theoretically depends on the elasticity of revenue to investment, level of trade costs, elasticity of substitution between domestic and imported intermediates and the level of import gain. We structurally estimate the elasticity of substitution between domestic and foreign intermediates and a quality shifter associated with foreign intermediates, to show that offshorers almost unambiguously increase investment levels and productivity irrespective of the levels of trade costs and elasticity of revenue to investment.

This analysis bring together a few different strands of literature. First, it relates to a burgeoning literature on firms which studies the strong positive impact of foreign intermediate sourcing on firm productivity in different countries like Indonesia (Amiti and Konings (2007)), Chile (Kasahara and Rodrigue (2008)), Hungary (Halpern, Koren and Szeidl (2015)) and India (Topalova and Khandelwal (2011)). Amiti and Konings (2007) using Indonesian manufacturing plant-level data on imported inputs show that productivity gain from lowering input tariffs is twice as high as any gains resulting from the reduction of output tariffs. In the context of Chilean manufacturing firms, during the liberalization period of 1979-1986, Kasahara and Rodrigue (2008) find evidence that becoming an im-

[2] Czech Republic, Mexico, Slovenia and Argentina

porter of foreign intermediates has a significant impact on plant productivity. Halpern, Koren and Szeidl (2015) use a panel of Hungarian firms to examine two different mechanisms, a quality and a variety channel, through which imports can affect firm productivity and find that importing inputs increases firm productivity by 14%, of which about two thirds is attributed to an increase in the variety of intermediates used in production. In section 8 in the Appendix, we follow Zhang (2017) to estimate a similar model as Halpern, Koren and Szeidl (2015) to show that for firms in Spain, the quality channel does not exist. However, the variety effect is strong and we estimate the elasticity of substitution between domestic and foreign intermediates to be around 7 which is significantly higher than that estimated by Halpern, Koren and Szeidl (2015) using Hungarian data. Biesebroeck (2003) on the other hand, does not find evidence of productivity improvements through use of more advanced inputs for Colombian firms while Muender (2004) reports that foreign intermediates contribute very marginally to output for Brazilian firms. Using a framework similar to Amiti and Konings (2007), Yu (2015) explores how reductions in tariffs on imported inputs and final goods affect the productivity of large Chinese trading firms, with the special tariff treatment that processing firms receive on imported inputs. The paper found the impact of input tariff reductions on productivity improvement to be weaker than that of output tariff reductions with opposite results however, for non-processing firms.

More specifically, this paper is closely related to the interdependent role of offshoring and R&D on productivity. Boler, Moxnes and Ulltveit-Moe (2015) was the first paper to explore this joint complementarity of R&D and imported intermediates on firm productivity. Boler, Moxnes and Ulltveit-Moe (2015) studied the impact of an R&D cost shock on R&D investment, imported inputs and their joint impact on firm productivity in Norway. The key to their channel was the exogenous tax policy on R&D for a subset of firms which incentivized firms to undertake more R&D expenditure and consequently expand internationally by sourcing cheaper inputs. However to the best of my knowledge, our paper along with Bernard et al. (2018) validate a more general version of the channel which is more plausible and empirically tractable for other countries too. In other words, Boler, Moxnes and Ulltveit-Moe (2015) required the exogenous R&D cost shock whereas in this paper we focus on trade openness which has been a more regular global phenomenon owing to stronger economic integration of the world economy as a whole. The challenge however lies in exploiting exogenous change in the firm level import of intermediates as opposed to an exogenous policy shock naturally facilitating the creation of a treatment and control group of firms.

Third, this paper is related to the more recent literature on trade and innovation as country-specific empirical studies do not consider the role of investment in knowledge capital as a result of which they are not able to disentangle the indirect effect of trade openness on firm productivity. Bloom, Draca and Van Reenen (2016) studies the effect of imports from developing countries on technology upgrading, innovation and productivity in OECD countries and show that import competition from China led to increase in R&D, patenting and TFP within firms. Steinwender (2015) , conducts a "horse race" between export opportunities and import competition and finds that in Spain, it is access to export markets that leads to productivity increases while the effect of import competition is weaker. Autor et al. (2016) investigate how U.S. manufacturing firms have responded to the threat of import competition from China by undertaking innovation. However unlike Bloom, Draca and Van Reenen (2016), they find no evidence that U.S. firms innovate or change their main line of business to escape the escalating threat of import competition. On the export side, Aw, Roberts and Xu (2011) use plant-level data from the Taiwanese electronics industry to find a positive effect of both investing in R&D and export on the plant's future productivity. Aghion et al. (2018) shows that with access to export markets, more productive firms are able to increase innovation as the accompanying rents increase with a firm's market size (market size effect) which dominate the increase in competition.

Finally, this paper relates to the broader literature on trade and firm reorganization along the lines of Caliendo and Rossi-Hansberg (2012) and Bernard et al. (2018) to name a few. Using firm level data from Denmark, Bernard et al. (2018) provides evidence of a channel which is very closely related to ours. However their paper also systematically differs from ours in a number of ways. Bernard et al. (2018) study the reorganization of labor as a result of offshoring which they define as imports of firms specifically in the products that they themselves produce in Denmark. Bernard et al. (2018) argue that instead of "hollowing" out domestic production, firms source lower quality imports and adjust within-firm skill composition by relocating labor from production work to technology and innovation-related occupations. While we also look at within-firm skill composition along with levels of R&D expenditure, our channel is not driven by quality differential of imports but rather by a broader shift in domestic innovation in response to falling trade costs and cheaper imports.

The remainder of the paper is organized as follows. Section 2 describes the data as well as some stylized facts about R&D, imports, exports and firm characteristics. Section 3 outlines the theoretical framework and performs compartive static exercises to guide the empirical results. Section 4 describes the measure of offshoring and the instruments used to tackle the potential problem of endogeneity. Section 5 presents the empirical design while Section 6 outlines the reduced-form evidence and results respectively. Section 7 concludes.

2 Data Sources and Stylized Facts

2.1 Data

This paper uses panel data from a Spanish survey of manufacturing firms (ESEE; Encuesta Sobre Estrategias Empresariales)[3], collected by the Fundacion SEPI, a foundation affiliated with the Spanish Ministry of Finance and Public Administration.The survey is designed to cover a representative sample of Spanish Manufacturing firms and includes around 1,800 firms per year. Participation of firms with more than 200 employees is required, while firms with more than 10 but less than 200 employees are sampled via a stratified sampling approach. SEPI makes a great effort to replace non-responding and exiting firms to ensure the continuing representativeness of the sample, leading to a total number of around 3,000 observed firms between 2006 and 2014. The most distinctive feature of this data set is the very rich information it provides on several dimensions that are important for careful empirical investigation: Detailed capital stock and investment needed for TFP estimation; input and output price changes to construct firm level deflators instead of relying on aggregate industry level deflators; information on exits (distinct from non-response) and entry to deal with selection; R&D expenditure along with number of workers classified as R&D workers and temporary workers. In addition to the production data, this dataset provides information on trade related activities of the firm such as imports and exports and separately for intermediate products annually which plays a vital role in the construction of firm specific offshoring measure. The only major limitation in the data is the absence of source, destination and product specific trade data as it reports only aggregate values by firm and year. However it does report share of imports by country blocs[4] every four years which we later use to construct an instrument for offshoring and exports similar to Hummels et al. (2014).

The ESEE categorizes firms into 20 industries based on the two-digit Classification of Economic Activities in the European Community (NACE) classification. Summary statistics are given in Table 1, and variable definitions are included in the notes to the table.[5] Although we use data from 2006 through 2014, we particularly look at years following the financial crisis i.e. 2010 to 2014.

Total Factor Productivity: A particularly important variable in our analysis is the firm's total factor productivity (TFP). We estimate TFP as a firm-specific and time varying residual from industry-level production functions following a consistent three-step proce-

[3] http://www.fundacionsepi.es/indice.asp

[4] The country blocs are EU, OECD, Latin America and Rest of the World

[5] The 20 industries are: Meat related products; Food and tobacco; Beverage; Textiles and clothing; Leather, fur and footwear; Timber; Paper; Printing and publishing; Chemicals; Plastic and rubber products; Nonmetal mineral products; Basic metal products; Fabricated metal products; Machinery and Equipment; Computer products, electronics and optical; Electric materials and accessories; Vehicles and accessories; Other transportation materials; Furniture; Miscellaneous

dure proposed by Olley and Pakes (1996). In contrast to an alternative model proposed by Levinsohn and Petrin (2003), the model by Olley and Pakes (1996) takes into account the issue of sample selection due to firms entering and exiting the market. This is very important given the nature of economic turbulence that was observed in the given time period in consideration. The model tackles a potential endogeneity issue due to unobserved productivity shocks by using firm-specific capital investments as a proxy variable. The ESEE dataset provides both gross and net capital stock along with firm level depreciation and investment which allows a precise construction of capital stock using the Perpetual Inventory Method (PIM). Van Beveren (2012) points out in the estimation of TFP, it is necessary to control for output and input prices. The ESEE survey data provides a solution to the omitted price bias as it specifically asks firms to report by what percentage the sales prices of its products and the purchasing price of its inputs has changed compared to the previous year. The output price changes which are a weighted average across products and markets and input price changes which are a weighted average across intermediate inputs, energy consumption and purchased services are used to deflate output and intermediate inputs. Thus, instead of using industry-wide deflators, we use firm-level deflators which would facilitate a precise estimation of TFP at the firm level. For capital, we use industry level 2010 constant prices as deflator similar to Guadalupe, Kuzmina and Thomas (2012).

We plot the total factor productivity distribution of firms comparing offshorers to non-offshorers and innovators to non-innovators. Panels (a) and (b) of Figure 7 show that offshoring and innovating firms belong to the higher end of the productivity distribution as compared to non-offshoring and non-innovating firms respectively. This proves to be an important descriptive statistic as we control for both initial productivity and firm size in regressions estimating the impact of offshoring on R&D and composition of labor within the firm.

Exits: Unlike other dataset, we can distinguish exiting from non-responding firms which can be used to correct for the selection effect. This is important as strikingly different patterns emerge for continuing and exiting plants. Also, even among exiting firms, those that import, R&D or both have different trends over time which can have important policy implications.

Technology Adoption and Labor: To look into firm's technology choices, we use data on R&D expenditure and proxy high-tech workers using data on the number of R&D workers and engineers and scientists hired by the firm. To proxy for low-skilled and routine jobs, we use the number of temporary workers.

Industry Trade Flows: Finally in addition to the firm level data from the ESEE, we use industry-specific imports over time to account for import competition faced by Spanish industries. We merge the firm-level data with industry level trade data from the

COMTRADE using the NACECLIO industry classification of firms.[6]

2.2 Facts on R&D, Imports, Exports and Productivity

In this section, we document a few basic facts about R&D, and intermediate inputs at the firm level which is used as a motivation for the empirical analysis. These stylized facts are meant to guide the theory and the empirical model. There is strong evidence in the literature Steinwender (2015), Eppinger et al. (2015) regarding a surprisingly strong export performance of Spain in the aftermath of the great trade collapse which was dubbed by some as the "Spanish export miracle." However in this analysis, we show that the behavior of importers have not been too different from that of exporters and focusing on the exporters alone does not reveal the entire scenario. We also show that the share of R&D firms have witnessed a steady increase over the time period used for the analysis (2006-2014) while the share of importing and exporting firms have increased in an almost identical fashion. Figure 7 show that while the share of R&D firms increased from 30 percent to almost 36 percent, the share of importing and exporting firms increased from 61 percent to 70 percent and 61 percent to 72 percent respectively.

Fact 1: Extensive Margin *Only a subset of the firms invest in R&D. Among the firms that do, almost all them import and export.* This is illustrated in tables 2 and 3 where we see that only 35% of the firms invest in R&D and among those that do, around 94% of the firms import and export.

Fact 2: Intensive Margin *Firms investing in R&D import, are larger in size, have higher import and export intensity, have higher labor productivity and record higher sales.* Table 4 gives average numbers for R&D firms (firms with positive R&D investment) and non-R&D firms (firms are those that report zero R&D expenditures) while table 5 looks at importing and non-importing firms. R&D and importing firms are strikingly different from the others as they have more than seven times as many employees, have twice as much labor productivity and have significantly higher sales volume.

Fact 3: Complementary Margin *Firms that undertake both imports and R&D are more productive than firms who do not.* We categorize firms according to controls (firms that neither import nor engage in R&D), offshore (only imports but do not engage in R&D) and treated (firms that engage in both). Figure 7 clearly shows that the distribution of total factor productivity of treated firms significantly differs from both offshorers and control firms.

[6] The concordance between six digit HS codes and two digit NACECLIO codes are available upon request

Next, we run a set of simple regressions with log firm characteristics as left-hand-side characteristics and a dummy indicating whether a firm has positive or zero R&D investment as the right-hand-side variable, while controlling for industry fixed effects (2 digit NACECLIO). The results in column (1) through (4) in Table 6 show that the correlation between positive R&D investment and employment, import participation, import share and labor productivity holds within a given industry.

Then, we estimate a similar regression, this time with firm and year fixed effects, utilizing the entire sample from 2006 to 2014. The R&D and offshoring dummies' coefficients can be interpreted as the log point change in the dependent variable when a firm switches from zero R&D to positive R&D and zero offshoring to positive offshoring respectively. The results in column (1) through (4) in Table 8 show that switching is associated with increase in firm size, shift in firms' sourcing strategy both in terms of intensive and extensive margin. In Table 9, when firms start offshoring, they grow in size and start investing in technology adoption along both the intensive and extensive margins.

3 Theory

The aim of this section is to outline a mechanism which highlights adoption of foreign technology along the intensive margin in response to a decline in trade costs. It is supposed to motivate our empirical analysis which tries to understand how offshoring increases R&D investments at the firm level. In doing so, we build on Bas and Ledezma (2015) to additional stage of investment choice over a continuous support that determines final firm productivity. This is a departure from the binary-choice technology-adoption setting used in Bustos (2011), Yeaple (2005) and Bas and Berthou (2017) to name a few. The closed economy model is identical to Bas and Ledezma (2015) with the assumption that firms draw their productivity from a known Pareto distribution. However we differ from Bas and Ledezma (2015) in our treatment of the open economy. Instead of an export market (similar to Melitz (2003), we assume that firms sell all their produce in the domestic economy. The open economy adjustment takes place through purchase of intermediates as firms combine domestic and foreign intermediates in producing their output. Our focus relies on relative difference in production costs through differences in prices of intermediates associated with input trade liberalization.

3.1 The Closed Economy

Consumers Consumers derive utility from a continuum of differentiated varieties indexed by $\omega \in \Omega$. Preferences are characterized by a CES utility function $U = \left[\int_{\omega \in \Omega} q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega\right]^{\frac{\sigma}{\sigma-1}}$, where $\sigma > 1$ is the elasticity of substitution between two varieties. $p(\omega)$ is the price offered by each prodcuer and aggregate expenditure is $\int_{\omega\in\Omega} p(\omega)q(\omega)d\omega = R$ leading to standard CES demand $q(\omega) = Q\left[\frac{p(\omega)}{P}\right]^{-\sigma}$ and welfare based price index $P = \left[\int_{\omega\in\Omega} p(\omega)^{1-\sigma}d\omega\right]^{\frac{1}{1-\sigma}}$.

Producers and Timing Similar to Bas and Ledezma (2015), we consider a three-stage timing including entry, investment and production. Similar to the baseline Melitz (2003), at each stage an unbounded mass of prospective entrants decide whether to incur the sunk cost f_e and become active producers. Paying the sunk cost allows them to draw a level of "potential efficient" φ_0 from a know distribution. Here we simplify the analysis by assuming the known distribution to be Pareto with probability distribution $g(\varphi_0)$. The key difference here is that the level of "potential efficiency" (drawn productivity) is not the level of productivity with which firms undertake production. Firms on making this initial draw, decide on a technology investment $I > 0$ that will partially determine their final productivity level according to:

$$\varphi = \varphi_0 I^{\beta} \tag{1}$$

with $0 < \beta < 1$. The parameter β captures the responsiveness of firm productivity with technology investments (R&D) in the industry. Technology investments can be thought of as an endogenous sunk investment in a technology input produced with labor under constant returns to scale in a perfectly competitive sector with homogenous productivity γ. Labor which is inelastically supplied with wage rate w is the numeraire and hence $w = 1$. Hence the unit price of technology is $p_I = \frac{1}{\gamma}$.

Once investment is made upon entry, firms obtain productivity level $\varphi > 0$ before they begin production. In the Melitz (2003) framework, firm productivity entirely depends on what firms draw. In this case, Bas and Ledezma (2015) allow drawn productivity to only partially affect final productivity with endogenous technology investment (I) also playing a role.[7] Hence to summarize:

1. Drawn productivity: φ_0

2. Final productivity: φ according to equation 1

The production stage is standard where firms produce a horizontally differentiated variety and operate in a monopolistically competitive environment. The production of each variety of final good q involves a fixed production cost f in terms of labor with:

$$l(\varphi, q) = f + \frac{q}{\varphi}$$

Firms maximize profits which leads to well-known forms of price, revenue and profit

[7] I is assumed to be greater than unity

functions:

$$p(\varphi) = \frac{\sigma}{\sigma - 1}\frac{1}{\varphi}; r(\varphi) = \sigma D \varphi^{\sigma-1}; \pi(\varphi) = \frac{r(\varphi)}{\sigma} - f \tag{2}$$

where $D \equiv \frac{R}{\sigma}\left[\frac{\sigma}{\sigma-1}P\right]^{\sigma-1}$ is an index of residual demand.

Investment Stage Once firms pay the sunk entry cost and gets to know their potential efficiency (φ_0), they make the investment decision. The present value of the investment is:

$$\nu(\varphi) = max\Big\{0, \sum_{t=0}^{\infty}[1-\delta]^t \pi_(\varphi) - \frac{1}{\gamma}I\Big\}$$

The elasticity of revenue to investment, $\varepsilon \equiv \frac{dr(\varphi)}{dI}\frac{I}{r(\varphi)} = \beta[\sigma - 1] > 0$ is of central importance in the optimal investment decision.[8] From the first-order condition and using the expression for ε, investment can be expressed as:

$$I(\varphi(\varphi_0)) = \left[\frac{\gamma\varepsilon}{\delta}\frac{r(\varphi_0)}{\sigma}\right]^{\frac{1}{1-\varepsilon}} \tag{3}$$

Substituting equation 3 in equation 1 gives us the endogenous productivity level φ as a function of "potential efficiency" φ_0:

$$\varphi(\varphi_0) = (\varphi_0)^{\frac{1}{1-\varepsilon}}\,\Delta \;; \Delta \equiv \left[\frac{\gamma\varepsilon}{\sigma\delta}D\right]^{\frac{\beta}{1-\varepsilon}} \tag{4}$$

From equation 4, it is clear that $\frac{\partial\varphi(\varphi 0)}{\partial D} = \frac{\beta}{1-\varepsilon} > 0$ implying that an exogenous decrease in price index (increase in competitiveness of the industry) will reduce profits and hence technology investments and productivity will decline.
Firm value after considering optimal investment is given by:

$$\nu(\varphi(\varphi_0)) = \frac{1}{\delta}\left\{[1-\varepsilon]\frac{r(\varphi(\varphi_0))}{\sigma} - f\right\} \tag{5}$$

Equilibrium We assume that firms draw their level of potential efficiency (φ_0) from a know Pareto distribution with:

$$G(\varphi_0) = 1 - \left(\frac{\varphi_{0min}}{\varphi_0}\right)^k$$

$$g(\varphi_0) = k\left(\frac{\varphi_{0min}^k}{\varphi_0^{k+1}}\right)$$

with $\varphi_{0min} > 0$ as the lower bound of the support of the productivity distribution and a shape parameter k. Firms calculate their present value of average profit flows before

[8] δ is the exogenous probability of survival similar to Melitz (2003).

entering the market and the cut-off level of potential efficiency below which entry is not profitable. This gives rise to the *Free Entry* and *Zero cut-off* conditions respectively as Melitz (2003). Using the Pareto distribution, equations 3 and 5 and optimal investment, we can characterize the Free Entry (FE) condition as:

$$\bar{\pi}(\varphi_0^*) = \frac{1}{1-\varepsilon}\left[\delta f_e \frac{\varphi_0^*}{\varphi_{0min}^k} + f\varepsilon\right] \tag{6}$$

Setting $\nu(\varphi(\varphi_0^*)) = 0$ and using equation 5, we can express the Zero-cutoff profit condition (ZCP) is:

$$\bar{\pi}(\varphi_0^*) = \frac{f}{1-\varepsilon}\left[\frac{k(1-\varepsilon)}{k(1-\varepsilon)-(\sigma-1)} - 1 + \varepsilon\right] \tag{7}$$

The condition for average variable profits to be finite is that $k(1-\varepsilon) > (\sigma-1)$. The intersection between the free-entry condition (6) and ZCP condition (7) gives the equilibrium cut-off level φ_0^* beyond which firms will enter and begin production:

$$\varphi_0^{*k} = \left[\frac{k(1-\varepsilon)}{k(1-\varepsilon)-(\sigma-1)} - 1\right]\frac{f}{\delta f_e}\varphi_{0min}^k \tag{8}$$

We can then solve for the equilibrium price index (P)[9], use the the macro equilibrium condition in the closed economy $(R = L)$ and the mapping given in equation 1 to solve for the endogenous productivity level described in equation 4:

$$\varphi(\varphi_0) = \varphi_0^{\frac{1}{1-\varepsilon}}\left[\frac{f\gamma\varepsilon}{\delta[1-\varepsilon]}\frac{1}{[\varphi_0^*]^{\frac{\sigma-1}{1-\varepsilon}}}\right]^{\beta} \tag{9}$$

3.2 The Open Economy

Unlike Melitz (2003), Bustos (2011) and Bas and Ledezma (2015) to name a few, our open economy version of the model ignores the export market.[10] We assume that firms sell all their produce in the domestic economy alone. However in order to undertake production, firms beyond a certain productivity threshold use both domestic(x_d) and foreign (x_m)intermediates. Final good producers are price-takers in intermediate input markets. However the price of imported intermediates takes into account the trade cost $\tau_m > 1$. Firms combine domestic and foreign intermediates according to a CES production function with elasticity of substitution θ.

$$q(\varphi) = \varphi(x_d^\alpha + B^\alpha x_m^\alpha)^{\frac{1}{\alpha}} \tag{10}$$

[9]Please refer to the Appendix section XX for the complete derivation

[10]This is an innocuous assumption to simplify the analysis. The main focus of this model is to understand how firms respond to offshoring in response to a decline in trade costs. We can easily extend this analysis by including an export market. However such an extension will not inform anything about the model unless we model interdependencies between the import and export market.

where $\theta = \frac{1}{1-\alpha}$. Domestic and foreign intermediates are imperfect substitutes and hence $1 \leq \theta \leq \infty$ and $0 < \alpha < 1$. The parameter B measures the quality advantage of the foreign input. We do not restrict $B > 1$, because we also want to allow foreign goods to have potentially lower quality than domestic goods. Gains from importing can arise due to a couple of factors. First, firms might be able to access higher quality intermediates ($B > 1$). Second, due to imperfect substitution, firms might get access to wider variety of intermediates outside of what is available domestically. The price of the domestic input equals the marginal cost of producing it: $p = w = 1$. Hence in the presence of trade costs, marginal costs in the open economy are:

$$c = \left[1 + (\frac{\tau_m}{B})^{\frac{\alpha}{\alpha-1}}\right]^{\frac{\alpha-1}{\alpha}} \tag{11}$$

Accordingly, we can think of prices as a constant markup over the marginal costs,

$$p_M = \frac{\sigma}{\sigma-1}\frac{\left[1 + (\frac{\tau_m}{B})^{\frac{\alpha}{\alpha-1}}\right]^{\frac{\alpha-1}{\alpha}}}{\varphi} \tag{12}$$

In order to ensure selection of offshorers, we assume that offshorers are subject to a fixed cost (f_M) similar to the fixed cost of exporting in *Melitz type* models. Similar to the closed economy, revenue and profit of offshoring firms can be expressed as:

$$r_M(\varphi) = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1} \varphi^{\sigma-1} R P^{\sigma-1} \left\{ \left[1 + (\frac{\tau_m}{B})^{\frac{\alpha}{\alpha-1}}\right]^{\frac{\alpha-1}{\alpha}} \right\}^{1-\sigma} \tag{13}$$

$$\pi_M(\varphi) = \left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1} \varphi^{\sigma-1} \frac{R}{\sigma} P^{\sigma-1} \left\{ \left[1 + (\frac{\tau_m}{B})^{\frac{\alpha}{\alpha-1}}\right]^{\frac{\alpha-1}{\alpha}} \right\}^{1-\sigma} - f - f_M \tag{14}$$

Investment in the Open Economy The investment stage in the open economy takes into account expected profits from sourcing both domestic and imported intermediates. After entry, the present of a firm able to obtain *ex-post* productivity level φ is now:

$$\nu(\varphi) = max\left\{0, \sum_{t=0}^{\infty}[1-\delta]^t \pi_M(\varphi) - \frac{1}{\gamma} I\right\} \tag{15}$$

Once again, after taking first-order condition of investment and using equation 1, we get the mapping between drawn productivity (φ_0) and realized productivity (φ) in the open economy.

$$\varphi(\varphi_{0M}) = \varphi_{0M}^{\frac{1}{1-\varepsilon}} \left(\frac{\gamma\varepsilon D}{\delta}\right)^{\frac{\beta}{1-\varepsilon}} \left\{ \left[1 + (\frac{\tau_m}{B})^{\frac{\alpha}{\alpha-1}}\right]^{\frac{\alpha-1}{\alpha}} \right\}^{\frac{(1-\sigma)\beta}{1-\varepsilon}} \tag{16}$$

Similar to equation 4, we rewrite equation 16 as:

$$\varphi(\varphi_{0M}) = \varphi_{0M}^{\frac{1}{1-\varepsilon}} \Delta_M \tag{17}$$

Hence value of a firm in the open economy, after entry and having drawn potential efficient of φ_0 is:

$$\nu(\varphi(\varphi_{0M})) = \frac{1}{\delta}\left\{[1-\varepsilon]\frac{r(\varphi(\varphi_{0M}))}{\sigma} - f - f_M\right\} \tag{18}$$

In order to understand offshorers and technology investments, we need the cut-off level of productivity ($\varphi(\varphi^*_{0M})$) beyond which firms will find it profitable to source foreign intermediates subject to trade costs (τ_m) and fixed costs of offshoring(f_M). At $\varphi(\varphi^*_{0M})$, the value for the marginal offshorer from sourcing foreign intermediates will be equal to sourcing intermediates exclusively from domestic firms. Hence at $\varphi(\varphi^*_{0M})$, the value for the marginal offshorer is:

$$\nu_M(\varphi(\varphi^*_{0M})) = \nu_d(\varphi(\varphi^*_{0M})) \tag{19}$$

In terms of "potential efficiency", domestic and offshorer revenues are:

$$r_d(\varphi(\varphi^*_{0M})) = RP^{\sigma-1)}\left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1}(\varphi^*_{0M})^{\frac{\sigma-1}{1-\varepsilon}}\left(\frac{\gamma\varepsilon D}{\delta}\right)^{\frac{\varepsilon}{1-\varepsilon}} \tag{20}$$

And,

$$r_M(\varphi(\varphi^*_{0M})) = RP^{\sigma-1)}\left(\frac{\sigma-1}{\sigma}\right)^{\sigma-1}(\varphi^*_{0M})^{\frac{\sigma-1}{1-\varepsilon}}\left(\frac{\gamma\varepsilon D}{\delta}\right)^{\frac{\varepsilon}{1-\varepsilon}}\left\{\left[1+(\frac{\tau_m}{B})^{\frac{\alpha}{\alpha-1}}\right]^{\frac{\alpha-1}{\alpha}}\right\}^{\frac{1-\sigma}{1-\varepsilon}} \tag{21}$$

Now, using $\nu_d(\varphi(\varphi^*_{0d})) = 0$ and equation 19, we can solve for the cut-off level of productivity for the offshoring firm $\nu_M(\varphi(\varphi^*_{0M}))$ as an implicit function of the cut-off productivity level for the surviving firm(φ^*_{0d}):

$$\varphi^*_{0M} = \varphi^*_{0d}(\frac{f_M}{f})^{\frac{1-\varepsilon}{\sigma-1}}\left\{\frac{1}{\left\{\left[1+(\frac{\tau_m}{B})^{\frac{\alpha}{\alpha-1}}\right]^{\frac{\alpha-1}{\alpha}}\right\}^{\frac{1-\sigma}{1-\varepsilon}} - 1}\right\}^{\frac{1-\varepsilon}{\sigma-1}} \tag{22}$$

Equilibrium The Free Entry condition (FE) would remain the same as the closed economy since firms would still need to calculate their present value of average profit flows before entering the market. Hence similar to 6, the *Free Entry* condition in the open economy is:

$$[1-G(\varphi^*_{0d})]\nu(\varphi(\tilde{\varphi}_0)) - fe = 0 \tag{23}$$

And applying the Pareto distribution, we obtain:

$$\bar{\pi} = \frac{1}{1-\varepsilon}\left[\delta f_e \left(\frac{\varphi^*_{0d}}{\varphi_{0min}}\right)^k + f\varepsilon\right] \tag{24}$$

Similar to the benchmark Melitz (2003) model, Bas and Ledezma (2015) uses the export market to account for the open economy adjustment. In that particular setting, all firms earn domestic profits and a subset of more productive firms earn both domestic and export profits. We however assume that firms sell all their produce in the domestic economy and hence profits in the domestic market are shared between firms who source only domestic inputs and firms who source both domestic and foreign inputs. Accordingly the Zero Profit Condition (ZCP) in the open economy is:

$$\bar{\pi} = \rho_d\left[\frac{1}{1-\varepsilon}\left(\frac{\tilde{\varphi}_{0d}}{\varphi^*_{0d}}\right)^{\frac{\sigma-1}{1-\varepsilon}} - 1\right] f + \rho_M\left[\frac{f_M}{1-\varepsilon}\left(\frac{\tilde{\varphi}_{0M}}{\varphi^*_{0M}}\right)^{\frac{\sigma-1}{1-\varepsilon}} \frac{X^{1-\sigma}}{X^{1-\sigma}-1} - f - f_M\right] \tag{25}$$

where ρ_d and ρ_M are the probabilities of domestic and offshoring firms respectively. $\rho_M = \frac{1-G(\varphi^*_{0M})}{1-G(\varphi^*_{0d})}$, $\rho_d = 1 - \rho_M$ and $X \equiv \left\{\left[1 + (\frac{\tau_m}{B})^{\frac{\alpha}{\alpha-1}}\right]^{\frac{\alpha-1}{\alpha}}\right\}$.
Combining the FE and ZCP condition, we can solve for the cut-off productivity of the surviving firm in terms of exogenous parameters.

$$(\varphi^*_{0d})^k = \frac{(1-\varepsilon)(\sigma-1+k\varepsilon)\left[f + \left(\frac{(X^{1-\sigma}-1)}{\left(\frac{f_M}{f}\right)}\right)^{\frac{k(1-\varepsilon)}{\sigma-1}} f_M\right]}{(k(1-\varepsilon)-(\sigma-1))\delta f_e}\varphi^k_{0min} \tag{26}$$

Using equation 22, we can also solve for the cut-off level of productivity for the offshoring firm.
The two remaining terms would be the endogenous level of offshorer productivity (φ_M) and level of investment (I) in the open economy. Similar to the closed economy, once again imposing the macro equilibrium condition (R=L), $M = \frac{L}{\bar{r}}$, the mapping of drawn productivity to realized productivity given by equation equation 16 and price index, we obtain the endogenous level of productivity (φ_M):

$$\varphi_M(\varphi_{0M}) = (\varphi_{0M})^{\frac{1}{1-\varepsilon}}\left[\frac{f\gamma\varepsilon}{\delta[1-\varepsilon]}\frac{\left\{\left[1+(\frac{\tau_m}{B})^{\frac{\alpha}{\alpha-1}}\right]^{\frac{\alpha-1}{\alpha}}\right\}^{\frac{1-\sigma}{1-\varepsilon}}}{[\varphi^*_{0d}]^{\frac{\sigma-1}{1-\varepsilon}}}\right]^{\beta} \tag{27}$$

For for firms who source domestic inputs $\tau_m = 0$ and hence,

$$\varphi(\varphi_{0d}) = \varphi_{0d}^{\frac{1}{1-\varepsilon}} \left[\frac{f\gamma\varepsilon}{\delta[1-\varepsilon]} \frac{1}{[\varphi_{0d}^{*}]^{\frac{\sigma-1}{1-\varepsilon}}} \right]^{\beta} \tag{28}$$

3.3 Model Predictions

Proposition 1: The first proposition follows directly from Bas and Ledezma (2015). *In the closed economy setting, there exists a unique equilibrium threshold φ_{0d}^{*} above which firms can participate in the production stage.*

Proposition 2: *In the open economy, the unique equilibrium threshold φ_{0d}^{*} beyond which firms participate in the production stage unambiguously increases with decline in trade costs τ_m* (Proof in Appendix).

$$\frac{\partial\left(\varphi_{0d}^{*}\right)}{\partial \tau_m} < 0 \tag{29}$$

The baseline Melitz (2003) model shows that firm selection increases as trade costs fall. In our model, as trade costs fall, offshoring firms are able to source more foreign inputs, increase revenue and thereby increase market share. Additionally, investment in technology boosts firm productivity which further reinforces the selection effect and makes the market more competitive, forcing lesser productive firms to exit.

Proposition 3: The unique productivity threshold φ_{0M}^{*} beyond which firms find it profitable to source foreign inputs, decreases with decline in trade costs (Proof in Appendix).

$$\frac{d\left(\varphi_{0M}^{*}\right)}{d\tau_m} > 0 \tag{30}$$

Similar to Melitz (2003), input trade liberalization induces selection in domestic markets as a result of which we find in Proposition 2, least productive firms exit. However with decline in trade costs, the set of offshoring firms will increase as more firms will find it profitable to source foreign inputs and possibly overcome the fixed cost of offshoring(f_M). Although this is not the main focus of our empirical exercises, our model in the presence of technology investments preserves the salient features of the Melitz (2003) model in terms of the extensive margin of firms in response to decline in trade costs.[11]

The response of the cut-off productivity levels (for both the domestic and offshoring firm) is important for analyzing the dynamics of endogenous firm productivity and investment dynamics in response to trade costs.

[11] In the Appendix, we show that $\frac{d(\varphi_{0M}^{*})}{d\tau_m} > 0$ is not unambiguously true. If we shut down the investment channel, the only condition for this to be true is simply $f > 0$. However in the presence of ε, we show numerically that for all possibly reasonable parameter values, $\frac{d(\varphi_{0M}^{*})}{d\tau_m} > 0$.

Proposition 4: Firms who source inputs only from domestic suppliers suffer reductions in productivity in response to decline in trade costs.

$$\frac{\partial \varphi_d(\varphi_{0d})}{\partial \tau_m} > 0 \tag{31}$$

Endogenous productivity for firms who source inputs only from domestic suppliers is given by equation 28. Note than trade cost (τ_m) does not feature directly as one of the parameters in equation 28. However trade costs do affect the cut-off level of survival productivity φ^*_{0d} as noted in 29. Bas and Ledezma (2015) interpret this variation in trade costs as *unrelated to technical progress (UTP)*[12] to which firms will react by smaller technology investments thereby becoming less productive. This negative response of domestic firms to reduction in trade costs stems from the fact that increase in φ^*_{0d} would increase firm selection and unambiguously reduce incentives to invest in R&D.

Proposition 5: For offshoring firms, reduction in trade costs lead to increase in endogenous productivity and investment subject to elasticity of domestic market selection in response to trade costs.

$$\frac{\partial \varphi_M(\varphi_{0M})}{\partial \tau_m} < 0 \tag{32}$$

If the following condition holds[13]

$$-\left[\frac{\partial \varphi^*_{0d}}{\partial \tau_m}\frac{\tau_m}{\varphi^*_{0d}}\right] < \frac{\left(\frac{\tau_m}{B}\right)^{\frac{\alpha}{\alpha-1}}}{1+\left(\frac{\tau_m}{B}\right)^{\frac{\alpha}{\alpha-1}}} \tag{33}$$

And,

$$\frac{\partial I_M(\varphi_{0M})}{\partial \tau_m} < 0 \tag{34}$$

If

$$-\beta\left[\frac{\partial \varphi^*_{0d}}{\partial \tau_m}\frac{\tau_m}{\varphi^*_{0d}}\right] < \frac{\left(\frac{\tau_m}{B}\right)^{\frac{\alpha}{\alpha-1}}}{1+\left(\frac{\tau_m}{B}\right)^{\frac{\alpha}{\alpha-1}}} \tag{35}$$

Similar to Bas and Ledezma (2015), equation 33 shows that the productivity of offshoring firms will increase in response to a decline in trade costs if the domestic market selection

[12] According to Bas and Ledezma (2015), if parameter does not participate as a determinant of productivity, firm productivity will be lower. Exogenous reduction of the sunk entry cost f_e can be interpreted as UTP for firms who sell only in the domestic market.

[13] This is very similar to what Bas and Ledezma (2015) find: $\frac{\partial \varphi^*_{0d}}{\partial \tau}\frac{\tau}{\varphi^*_{0d}} < \frac{n\tau^{1-\sigma}}{n\tau^{1-\sigma}+1}$. However the contribution of this model is to a) Show that we get a similar condition when trade costs affect firms in terms of their input choices instead of export markets b) Estimate the parameters to show that the inequality actually holds for Spanish firms.

(with respect to trade costs) is highly inelastic. The contribution of this model is to estimate the unknown parameters and assuming firm productivity is drawn from a Pareto distribution, this model shows that 32 is very likely to hold for firms in the Spanish data.

A key feature of this model which makes it different from Bas and Ledezma (2015) is that unlike exports, importing intermediates gives rise to two potential channels for gains from trade. First, firms can benefit by importing higher quality intermediates (higher B).[14] Second, firms get access to a higher variety of intermediates proxied by the elasticity of substitution θ.[15] For some parameters $(f_m, f, \beta, \delta, \sigma, \tau_m)$ and the shape parameter of the Pareto distribution, we can borrow estimates from the literature. However using the firm level data, I estimate the two key import parameters B and θ to accurately understand the ranges of trade costs for which the condition in equation 33 might or might not hold. We experiment with two values of ε to highlight cases of "high" ($\varepsilon = 0.6$) and "low" ($\varepsilon = 0.3$) technology intensity.[16]

We use estimates from Bas and Ledezma (2015) for the set of parameters in $\Lambda = (f_m, f, \beta, \delta, \sigma, \tau_m)$ and k which is the shape parameter of the Pareto distribution.[17] Following Bas and Ledezma (2015), we express equation 33 as:

$$\frac{k-b}{b\left[\rho^{\alpha-b}-1\right]} < \frac{1}{\varepsilon} \tag{36}$$

where $b = \frac{\sigma-1}{1-\varepsilon}$ and $\rho = (\frac{f_M}{f})^{\frac{1-\varepsilon}{\sigma-1}} \left\{ \frac{1}{\left\{ \left[1+(\frac{\tau_m}{B})^{\frac{\alpha}{\alpha-1}}\right]^{\frac{\alpha-1}{\alpha}} \right\}^{\frac{1-\sigma}{1-\varepsilon}} - 1} \right\}^{\frac{1-\varepsilon}{\sigma-1}}$.[18] From equation 34, it can be noted that ρ cannot be calculated without B and α which is different from having an export market as in Bas & Ledezma (2015). We estimate B and θ and hence α using a production function approach where firms combine capital, labor and a combination of domestic and foreign intermediates to produce a given amount of output.[19] We estimate the firms' production function following Zhang (2017) in the spirit of Olley and Pakes (1996) and Halpern, Koren and Szeidl (2015). Section 8 in the Appendix provides extensive details on the estimation procedure.

Using the entire firm sample, we estimate $B = 0.85$ and $\theta \approx 7 \Rightarrow \alpha = 1 - \frac{1}{\theta} = \frac{6}{7}$. Our estimate of θ is comparable in size to other papers in the literature which confirms the variety effect associated with importing intermediates. Another interesting finding is

[14]For firms to have higher quality intermediates, B should be larger and statistically different from 1 (Halpern et al. (2015)). However we do not restrict B to be higher than 1. If the quality of intermediates sourced by Spanish firms are cheaper then it might be that B is less than 1.

[15]Note, that θ does not appear explicitly in equation 10. However $\theta = \frac{1}{1-\alpha}$.

[16]Intuitively the two values of ε can be interpreted as two industries with differing technology intensities.

[17]We use the following values for the parameters in Λ. $f_m = 1.1, f = 1, k = 10.5, \sigma = 5, \tau_m = 1.2 - 2$.

[18]$\varphi^*_{0M} = \rho\varphi^*_{0d}$.

[19]In most datasets, output is not observed. Hence we proxy output with total revenue.

that $B < 1$. However we should be cautious about interpreting this result as the estimated quality parameter, since (B) contains both the real input quality effect and the price difference between domestic and imported inputs.[20]

Armed with these estimates, we plot the inequality in equation 34 to identify ranges of trade costs for which the inequality holds for both high and low technology intensities.

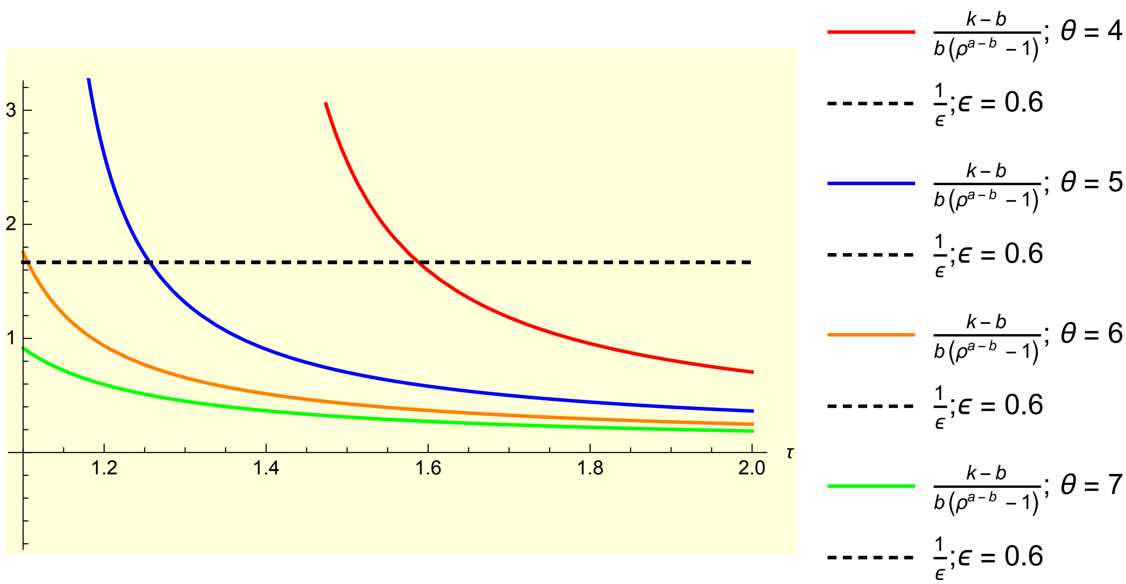

Figure 1: High technology intensity ε

First we plot the inequality in equation 34 for high technology intensity industries ($\varepsilon = 0.6$). With our estimated parameters of $\theta = 7$ and $B = 0.85$, we can see that in Figure 3.3, the inequality holds unambiguously for all possible values of trade costs greater or equal to 1 (refer to the Green line). However an interesting finding is that if we lower the elasticity of substitution θ from 7 to 5 (Blue line), we are able to identify a small range of trade costs (1.0-1.3), for which the inequality does not hold. That range further increases (1.0-1.6) if we lower the value of θ to 4 (Red line). This implies that when θ is low, for lower trade costs, productivity of offshorers decline with decline in trade costs. With the degree of substitutability between inputs (θ) being low, firms cannot take advantage of the low trade costs by sourcing all inputs from abroad. However when domestic and foreign inputs are highly substitutable (Green and Orange lines), offshorers can respond to lower trade costs by reducing domestic sourcing and increasing foreign sourcing of inputs.

For low technology intensity industries ($\varepsilon = 0.3$), we observe a similar pattern, with slight differences in the range of trade costs. Similar to Bas and Ledezma (2015), the

[20] The ESEE data provides changes in intermediate prices at the firm level. In Figure 8 we show that there does not exists significant differences in the distribution of the price index between offshoring and non-offshoring firms. This implies that offshoring firms on average do not pay significantly less for their inputs as compared to non-offshoring firms. In that case the estimated quality parameter B can be interpreted as lower quality of foreign intermediates.

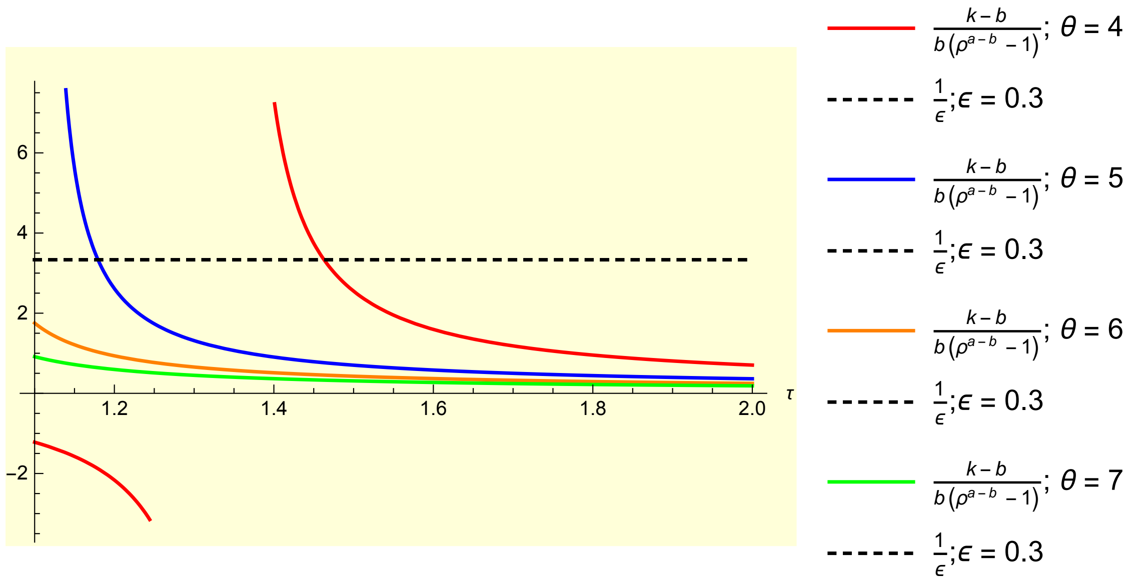

Figure 2: Low technology intensity ε

inequality is more likely to hold in low technology industries as we observe that for $\theta = (6, 7)$, the inequality holds unambiguously. For lower values of θ (say $\theta = 4$), the inequality holds for $\tau > 1.5$, which is slightly less than the cutoff for high technology intensity industries.

The model shows that when trade affects intermediates in production, the results are driven largely by the elasticity of substitution. Instead of relying on the literature for relevant estimates of the θ and B parameter, we estimate them in a structural model and show that when the elasticity of substitution is high enough, offshorers unambiguously augment their productivity in response to a decline in trade costs. We use the model framework of Bas and Ledezma (2015) and outline cases for which our numerical results could significantly differ from their results in the analysis of trade liberalization episodes.[21]

The following sections use microdata from Spain to validate the salient features of the stylized model in a reduced form setting using plausibly exogenous measures of intermediate sourcing at the firm level.

4 Back to the Data: Measuring Offshoring

In this section, we describe the construction of the firm level measure of offshoring and exploit plausibly exogenous variation using export supply shocks, to establish a causal relationship between offshoring, and technology adoption. The two main questions associated with this empirical analysis are a) how offshoring choices impact firms' decision to conduct

[21] The response of endogenous investment is exactly the same and hence plots are available upon request.

R&D and b) what is its impact on employment composition of the firm. This automatically raises the question whether the observed firm-level imports are final goods or inputs into production and if these inputs are potential substitutes of labor within the offshoring plants. Hummels et al. (2014) defined "broad offshoring" as the total value of imports by a given manufacturing firm in a given year. To particularly focus on inputs which could substitute labor within the firm, Hummels et al. (2014) defined "narrow offshoring" as a firm-level variation of Feenstra and Hanson (1999) industry level measure of offshoring. Since Hummels et al. (2014) observed detailed product level trade data, the restriction of including imports in the same HS4 category as goods sold by the firm, could be applied. In the ESEE data however, we only observe aggregate firm level imports in a given year. However the ESEE data does provide information specifically on the intermediate imports by firms from foreign firms in the same group which enables us to construct a similar measure of "narrow offshoring" at the firm level. The "narrow offshoring" measure would thus reflect relocation of the firm's production processes which could very well be performed within the firm but is moved abroad owing to a cost advantage.

The major identification challenge here is that unobserved firm-level shocks to demand will affect both trade, technology choice and TFP. To address the potential endogeneity problem, we construct an instrument that is correlated with the firm's offshoring level but is uncorrelated with its decision to conduct R&D. The IV strategy is designed to identify firms' offshoring levels due to factors which are uncorrelated with its decision making and are also external to Spain. More specifically, we construct industry level measures exploiting supply shocks within destinations, weighted by firms' pre-sample period purchase share of total material imports by country blocs. The ESEE reports share of firms' imports from four different country blocs every four years which I use to attribute changes in world trade costs to firms in a way similar to Hummels et al. (2014). Ideally, detailed imports by country and more disaggregate industry classifications are required for a strong first stage.

We attempt to get around this problem by selecting the top two trade partners of Spain within those country blocs to exploit variation in trade costs instead of considering all major trade partners. This is plausible as a very high percentage of Spain's imports within EU (this is by far the most relevant trading bloc) are Germany and France. Similarly for the OECD countries that are not part of EU, Spain's largest trading partner is the US, while Brazil and China dominate trade in the Latin American and Rest of the World category respectively. Using data from COMTRADE on those countries' intermediate exports[22] to three countries which are similar to Spain in terms of standard of living, GDP per capita and trade openness[23], I attribute these trade flows to firms based on their 2006 or 2010[24] import shares from these country blocs. The underlying assumption is that controlling for industry

[22] I use the HS6 to end-use classifications to generate intermediate exports

[23] The three countries are Slovenia, Czech Republic and Mexico

[24] Year 2010 import shares are used for firms who enter post 2006

and time fixed effects, demand shocks are assumed to be uncorrelated between Spain and the other similar countries. Additionally in the spirit of Feenstra and Hanson (1999), I use an input-output table for Spain's imports to apportion an industry's intermediate imports to other industries according to the pre-period purchase share specified in the I-O table [25]. Hence for firm i in industry j at time t, the instrument for offshoring O_{ijt} is defined as:

$$O_{ijt} = \sum_{c} s_{ijc,base} * EX_{cjt} \tag{37}$$

where $s_{ijc,base}$ is the year 2006 or 2010 import share of firm i in industry j from country bloc c and EX_{cjt} is the intermediate exports of the county bloc c in industry j at time t to the three similar countries multiplied by the purchase share obtained from the Spain's IO table.

Our instrument strategy following Hummels et al. (2014) relies on comparative advantage for the exporting country which can be attributed to costs of production, variety or quality. As with any instrument, there still exists threats to identification which can potentially invalidate the exclusion restriction and produce biased estimates. We now discuss such potential threats to identification and how we counter them.

Bustos (2011) and Aghion et al. (2018) provide evidence that trade shocks in foreign markets incentivize firms to upgrade their technology. Additionally as argued by Hummels et al. (2014), rise in world export supply of a particular product,[26] can be due to both supply and demand shocks around the world and in Spain. In that case, the firm producing the concerned product might engage in increased R&D in response to increased demand. Hence in light of prior work and intent to control for time-varying demand shocks outside of Spain, we control for firm exports to correctly estimate the offshoring channel. Bernard et al. (2018) points out that, for the exclusion restriction to be valid, growth in foreign productivity should affect firms' innovation decision only through offshoring. However as shown by Bloom, Draca and Van Reenen (2016), Steinwender (2015) and others, import competition (i.e. via supply shocks) have a direct impact on technology adoption of firms. we use a long difference framework for our estimation, usage of aggregate industry fixed effects allows us to identify within-industry changes thereby controlling for industry level import competition.

5 Empirical Strategy

The goal of the empirical analysis is to study the impact of offshoring on within-firm R&D expenditure and employment composition by skill type. Estimating the causal impact

[25] I use year 2006 Spanish I-O table for Imports

[26] Here product refers to an aggregate 2 digit NACE industry

of offshoring involves exploiting variations in offshoring uncorrelated with firm specific decisions to undertake technology adoption or reorganize the skill composition. To that end, I use an IV strategy described in section ?? exploiting factors which are external to the firm and Spain in general to efficiently and consistently estimate the marginal effect of offshoring on firm level outcomes. We use data from 2010 through 2014 in a long difference framework to understand the evolution of R&D expenditures over time in response to firm-level offshoring. We focus on the years following following the financial crisis for a few reasons. First, attributing firm specific decisions to any particular channel is tricky during the years of recession as business cycle effects might be hard to disentangle simply by using industry and firm fixed effects. Second, even though we implement the full set of firm and industry fixed effects, it is quite reasonable to question the validity of the instrument used for the trade shocks as demand shocks might be highly correlated across countries during the recession. Finally, firms that offshore more may be exposed to other economic shocks that are correlated with global trade and might introduce bias in the estimation. I instead use data from 2006 to 2010 to control for important firm level pre-trends and perform exhaustive robustness checks.

Boler, Moxnes and Ulltveit-Moe (2015) found the scale effect through increased profitability to be the primary driver of R&D on sourcing foreign intermediates. We address the scale-effect by controlling for the contemporaneous change in sales capital stock which might also facilitate adoption of advanced technology. The ESEE dataset is unusually informative in terms of its information on firm level investments in capital and industrial machinery, both of which can be strongly correlated with R&D expenditure. In section ??, we show the initial productivity of firms matter when it comes to investments in technology in an effort to augment productivity. Similar to Steinwender (2015), I test heterogeneous response of firms in terms of their initial productivity, age, size and innovation history by interacting the firm level offshoring measure by their initial period covariates.[27] A possible concern with the trade driven innovation channel is the absence of credit constraints in the firms' decision to engage in R&D. In other words, why do firms wait for offshoring to do more R&D? If R&D is known to boost firm productivity, what is it that prevents firms from borrowing and undertaking R&D expenditure. Spain was one of the countries worst hit by the financial crisis and Garicano and Steinwender (2016) shows that firms faced lower credit availability and higher credit cost compared to pre-financial crisis levels. Garicano and Steinwender (2016) also shows that negative credit shocks impacted firms' long-term relative to short-term investment.[28] We follow Garicano and Steinwender (2016) in constructing firm-level measures of long term and short term credit shocks and show that the trade and innovation nexus is particularly pronounced for firms who are long-term

[27] I consider year 2010 as the base period here

[28] In Garicano and Steinwender (2016), R&D is considered as a long-term investment.

credit constrained but have access to short-term credit.[29] To that end, offshoring can have a credit ameliorating effect on firms that face strong financial market frictions and cheaper intermediates provide a channel for them to save resources and redirect them to domestic innovation.

5.1 Identification

We now present our baseline specification to capture the impact of offshoring on R&D and skill composition of firms. Specifically we estimate:

$$\Delta y_{ij\tau} = \alpha + \beta_{off} \Delta Off_{i\tau} + \beta_X \Delta X_{i\tau} + \theta_j + \varepsilon_{ij\tau} \tag{38}$$

where for firm i in industry j and time period τ, $\Delta y_{ij\tau}$ represents the change in firm outcome from 2010 to 2014 which includes changes in firm level R&D expenditure, temporary employment and R&D employment. β_{off} is the main variable of interest and captures the effect of offshoring on the concerned firm-level outcomes. $\mathbf{X}_{ij\tau}$ contains the set of firm controls which include firm size (proxied by sales), firms' investment in capital goods and exports which could drive firms' investment in R&D. In addition to contemporaneous controls, the vector $\mathbf{Z}_{i,2010}$ includes the firm's size and level of sales in 2010 to control for initial propensity of firms to potentially engage in R&D. θ_j is a sector fixed effect where sectors are defined as 2-digit NACECLIO industries.

As described in **??**, firm's decision and level of offshoring is endogenous and is subject to potential bias. As argued by Bernard et al. (2018), the presence of negative productivity/demand shocks will induce downward bias on the OLS coefficient. Alternatively, in the presence of positive demand shocks, the OLS coefficient will bias upward the marginal effect of offshoring, as it will incorrectly capture the firm's overall strategy to innovate in response to increased productivity or demand which may or may not be related to offshoring. In order to tackle the problem of endogeneity, we use an instrumental variable (IV) to identify changes in the firms' level of offshoring due to factors beyond the control of the firm and the domestic economy of Spain as a whole. Hence following Hummels et al. (2014) and Autor, Dorn and Hanson (2013), we apportion changes in world trade costs to firms based on their base period import share from countries according to equation 37.

Heterogeneous responses: Firms' response to decline in trade costs (and hence more offshoring) might be non-linear with respect to initial productivity, age and size. In order to test and identify these heterogeneous responses, I interact the firm-level offshoring measure with categorical variables indicating the firms' position in different quartiles of baseline

[29] Similar to firm age, size and other baseline covariates, we interact the offshoring measure with a categorical variable which denotes the firms' position on the credit (long term or short term) distribution at the start of the period, i.e. in year 2010.

covariates' distribution. Similar to Steinwender (2015), I experiment with different cutoffs in the distribution like median, 25th and 75th percentiles. Specifically I estimate:

$$\Delta y_{ij\tau} = \alpha + \sum_{q=1}^{q=4} \beta_q \Delta Off_{i\tau} \times \mathbf{1}\{q = Quartiles_{base}\} + \beta_X \Delta \mathbf{X}_{i\tau} + \gamma \mathbf{Z}_{i,base} + \theta_j + \varepsilon_{ij\tau} \quad (39)$$

where I consider the same dependent variables as in 38, and pool all trade and non-trade contemporaneous controls in the vector $\mathbf{X}_{ij\tau}$. In 39, I interact the offshoring measure $\Delta Off_{ij\tau}$ with a categorical variable $Qaurtile_{base}$ which accounts for a firm's position in the base period productivity, age or size distribution. For example, considering q = 75, I construct an indicator variable which is 1 if the firm's age in 2010 is higher than the 75th percentile age across all firms. Then I interact the indicator variable with the offshoring measure to test marginal effect of offshoring β_{off} in 38 for firms belonging to a certain age/size/productivity category.

Innovation History: The response of firms' R&D might also be non-linear according to prior record of innovation. It is quite reasonable to believe that firms who have undertaken R&D, process or product innovations in the past, have had technical collaborations with research organizations or have been the recipient of innovation subsidies to have a stronger impact on technology adoption due to trade, as compared to other firms. Accordingly I estimate:

$$\Delta y_{ij\tau} = \alpha_0 + \sum_{Innovation} \beta_I \Delta Off_{i\tau} \times \mathbf{1}\{i_{base}\} + \beta_X \Delta \mathbf{X}_{i\tau} + \gamma \mathbf{Z}_{i,base} + \theta_j + \varepsilon_{i\tau} \quad (40)$$

where I is an indicator variable which is equal to 1 if the firm i has engaged in innovation activity in the past. Once again, I consider year 2010 as the base period for both 39 and 40 to avoid problems of endogeneity.

Credit Constraints: Prior literature based on the works of Aw, Roberts and Xu (2011) and Doraszelski and Jaumandreu (2013) have shown the decision of R&D to have a strong and robust relationship with future endogenous productivity. It is not quite clear as to why firms would engage in offshoring to do R&D instead of depending on external credit to fund their innovation undertaking. In order to alleviate this concern, we use Garicano and Steinwender (2016) to construct categories of long and short-term credit ratios[30] and similar to age and size effects, we interact the firms' offshoring measure with a categorical variable which denotes the firm's position in the baseline long(short) term credit ratio distribution. The intuition is that firms who are more credit constrained , are likely to have a stronger impact of offshoring on R&D expenditures as they are likely to use

[30] Credit ratio is defined as the amount of long(short) term credit as a share of its total credit in the base year 2010. Refer to Garicano and Steinwender (2016) for further details.

offshoring to cut down on production costs and divert costly resources towards funding domestic innovation. Accordingly I estimate:

$$\Delta y_{ij\tau} = \alpha + \sum_{q=1}^{q=4} \beta_c \Delta Off_{i\tau} \times \mathbf{1}\{c = Credit\ Quartile_{base}\} + \beta_X \Delta \mathbf{X}_{i\tau} + \gamma \mathbf{Z}_{i,base} + \theta_j + \varepsilon_{i\tau} \quad (41)$$

where $Credit2010_{pi}$ accounts for a firm's position in the long(short) credit ratio distribution. For example, considering p = 50, I construct an indicator variable which is 1 if the firm's long(short) credit ratio is higher than the median long(short)credit ratio across all firms in the year 2010.

6 Results

6.1 R&D Expenditures

We first estimate 38 using OLS in table 10. As expected, estimates show that change in firms' R&D investment is positively correlated with changes in levels of offshoring. We also observe from column (2) that controlling for the scale effect attenuates the marginal offshoring by more than half while both the scale effect and growth in capital investment are themselves positively and significantly (at the 1%) correlated with change in R&D.

As discussed in section 5.1, estimates presented in Table 10 may be biased since offshoring might capture unobserved positive or negative demand and productivity shocks faced by firms over the sample period. If the unobserved shock is positive, then the marginal effect of offshoring will be biased upward. Alternatively if firms face negative productivity/demand shocks, then offshoring will capture the effect of trade as well as the unobserved shock which is likely to be negatively correlated with R&D expenditures, thereby attenuating β_{off} towards zero.

Table 11 presents the results from estimating 38, while instrumenting for changes in firm's offshoring using export growth of similar countries in the same two digit NACE industry as that of the firm. A few important findings stand out. First, we observe that the IV estimates of offshoring are significantly larger than their OLS counterparts implying that OLS estimates are downward biased similar to Bernard et al. (2018). This is not unreasonable given that the sample period is characterized by firms recovering from the financial crisis and is likely to respond to negative demand and productivity shocks. Second, in column (2), similar to the OLS estimates, the scale effect is once again important and attenuates IV estimates by more than 30%. In column (4), after controlling for baseline covariates in labor and sales, contemporaneous changes in sales and capital investment, we observe that the effect of offshoring on R&D investment is strikingly robust and significant at the 1% level. Since we estimate the regression in log changes, the point estimate implies that a 10% increase in offshoring causes average R&D expenditure to increase by 3.4% over the course of four years (2010-2014).

Next, we follow the burgeoning literature on the impact of exports on productivity by explicitly controlling for exports in the vector of controls $X_{ij\tau}$ along with change in domestic sales and capital investment. Results presented in table 12 shows that in columns (1) through (3), controlling for exports renders the OLS estimates of offshoring insignificant, while the exports coefficient is itself positive and significant at 1%. For the IV estimates in columns (3), we see that although the coeffient of offshoring attenuates compared to column (1) in Table 11, it is still strongly positive and significant. In column (5), controlling for the contemporaneous scale effect reduces it further. Finally, in column (6), we present the most exhaustive specification where controlling for exports, domestic sales and investment in capital, the marginal effect of offshoring is significant only at the 10% level. Although it is significant only at the 10% level, it is encouraging to observe that the absolute value of the coefficient is still considerably large and economically significant.

The literature on firm heterogeneity following Melitz (2003) has shown that firm response to trade liberalization is not uniform across the productivity, size or age distribution. More specifically, in the absence of distortions, the Melitz (2003) shows that resources get reallocated towards the more productive firms who also happen to be mature and larger in size. To that end, I categorize firms according to their position in the distribution of baseline covariates like productivity, age, size and past innovation history. First, I interact the offshoring measure with an indicator variable which is equal to 1 if the firm's productivity in 2010 is higher than 25th percentile, median or 75th productivity across all firms.

The results are presented in 13 point to an interesting and slightly puzzling pattern. Column (1) estimates 38 controlling for sales and capital stock growth as a baseline specification.[31] In column (2), we interact the offshoring measure with indicator variables according to the firm's productivity quartile in year 2010 by essentially fixing the controls. We observe that firms in the second and third quartile of productivity have the largest effect of offshoring on R&D. While it is not surprising that the effect for the firms in the bottom quartile is indistinguishable from zero, it is striking that the most productive firms do not have a significant effect of offshoring on R&D. A plausible explanation for this could be that for the already most productive firms, we do not observe sufficient variation in their R&D expenditure as their initial productivity might be a result of intensive R&D in the years leading upto the sample.

Second, we test for heterogeneous responses according to firm age and size to test if firms belonging to a certain age or size distribution react differently to trade liberalization in terms of investment in R&D. Following the literature on firm age and size by Haltiwanger, Jarmin and Miranda (2013) and others, we interact the offshoring measure with discrete

[31] Column (1) in Table 13 is the same as column(4) in Table 11.

firm age and size categories[32] based on the initial (year 2010) age and size of firms. In both tables 14 and 15, we observe that the effect of firms' offshoring on R&D increases with baseline firm age and size respectively. However for the very old (61+) and very big firms (301+), the effect is less pronounced and is significant at the 10% level. For firm age, the results are not striking as very mature firms are not known to be big innovators. Moreover, the share of firms in the 61+ category happens to be around 7.5% which makes the effect less pronounced as opposed to the younger firm categories. With respect to firm size, we have about 13% firms in the 301+ size category and yet we observe that the effect of offshoring on R&D specifically for this category is more than half of that of the previous category (126-200). The only plausible explanation for this could be the same as that of the high tfp firms which are very large and offer less dynamics in their R&D undertaking.[33]

Third, we test if prior innovation history has any significant role in firm's R&D due to offshoring. Similar to tfp, age and size, we interact the offshoring variable with different measures of innovation undertaking in the past. More specifically we consider four types of innovation activity - product innovation, process innovation, technical collaboration with universities and availability of innovation subsidy. In table 16, we show that the strongest effect of offshoring on R&D appears to be present for firms who have had technical collaborations with universities and/or research organizations in the past and for firms who have received subsidies for the purpose of undertaking innovation activities.

Firms require credit to undertake innovation in the form of R&D expenditures. However owing to strong financial market frictions in Spain especially in the post-financial crisis period, firms experienced decline in availability of credit accompanied by rising borrowing costs.[34] Following Garicano and Steinwender (2016) we construct measures of long and short-term credit ratios to test if firms who are long-term credit constrained, find it more lucrative to use offshoring to cut down production costs and re-direct costly resources into domestic innovation. This highlights a novel margin of firm-specific heterogeneous effect linking credit constraints, sourcing of cheaper intermediates and innovation to study firm performance.

Results presented in Table 17 shows that for firms which belong to the top two quartiles of long-term credit ratio distribution, there exists no significant effect of offshoring on R&D expenditures. However firms who are at the bottom two quartiles of credit access (i.e., more than median credit constrained), there exists a positive and significant effect of offshoring on R&D implying that these credit-crunched firms find offshoring profitable to reduce

[32] Firm age categories are: 0-9,10-20,21-35,36-60 and 61+. Firm size categories are: 0-19,20-50,51-125,126-300,301+. The firm age and size bins are chosen in a way there we have a similar number of firms in each category.

[33] In figure 7, we show that initial size and productivity of firms is highly correlated. This provides explanation for the similarity of results in Table 13 and 15.

[34] Garicano and Steinwender (2016) shows that average credit ratio in the after-crisis period declined by 5.3% compared to pre-crisis levels.

marginal costs and refocus on innovation. Results in table 17 would have a completely different interpretation if firms with higher long-term credit ratios are firms that are heavily in debt and under perform in terms of sales and revenue. In that case, firms with lower long term credit ratios would instead be interpreted as credit access firms which have a strong effect of offshoring on R&D. To alleviate this concern, in Figure 7, we the levels of credit by sales bins and find that firms with higher credit ratios are the ones with higher sales, justifying our definition of credit crunched firms in table 17 results. The opposite is true for short-term credit as column (3) of Table 17 shows that firms that have more than median short-term credit access (belonging to the top two quartiles of the short-term credit ratio distribution), have a significantly stronger impact of offshoring on R&D compared to the short-term credit crunched firms. This provides descriptive evidence of a dimension of credit availability (by duration) affecting trade driven innovation expenditures at the firm level.

6.2 Skilled Employment

The second potential channel through which offshoring can affect firm productivity is via change in composition of employment. Offshoring is typically associated with loss of routine jobs thereby causing firms to lay off low skilled workers. Tasks associated with such routine jobs could be performed in a cost efficient way at cheaper production sites across the globe. Firms instead could focus on hiring more skilled workers, which can potentially change the skill composition of employment in a manner which is productivity enhancing. Using data on temporary, R&D and skilled workers,[35] we test if offshoring is associated with a skill-biased change in employment composition. We estimate equation 38 using R&D, temporary and skilled workers as dependent variables. The results are presented in Table 18.

Columns (1) and (2) in Table 18 show that the effect of offshoring on change in temporary employment is negative, although insignificant. In columns (3) and (4), offshoring is shown to have a significantly positive effect on R&D employment and an even stronger effect on the growth in firm level high-skilled employment. We proxy for high-skilled employment using the number of engineers and graduates employed by the firm. In Table 19, we perform a similar exercise as Table 13, where we interact the offshoring measure with baseline *tfp* covariates to identify the non-linear effects of offshoring on R&D and high-skilled employment by initial productivity of firms. Column (1) shows that firms belonging to the bottom most quartile of the productivity distribution in fact, have a significantly negative effect of offshoring on R&D and high-skilled employment, while initially more productive firms have a significantly positive effect of offshoring on high-skilled jobs. These

[35] We use engineers and graduates as proxies for skilled employment. Its refers to the variable **PIL** in the ESEE dataset.

results complement the Melitz (2003) type models where initial productivity of firms play a key role in benefiting from episodes of trade liberalization.

As a further sensitivity check, in Table 20, following the burgeoning literature on exports and R&D, we include firm exports in the vector of contemporaneous controls $\mathbf{X}_{ij\tau}$. In column (1), we find that although exports has a positive and significant effect on the growth of temporary employment, the effect of offshoring is negative, larger compared to Table 18 and is significant at the 5% level. This result highlights that while exports represent a demand shock by expanding potential market size and hence employment, offshoring acts as a negative demand shock for workers belonging to the lower end of the skill distribution. In column (2), we find that on separately controlling for exports, the effect of offshoring on R&D employment attenuates drastically to make the marginal effect insignificant while the effect of exports on R&D employment is positive and significant at the 1% level. While seemingly discouraging at first, we interpret these results as potentially interesting future research to disentangle exogenous variation in both exports and offshoring to potentially understand how both of them have a combined effect on employment by skill-type. Column (3) shows that for overall within firm high-skilled employment, the effect of offshoring is robust and remains significant at the 1% level even after separately controlling for the exports channel.

7 Conclusion

Trade liberalization affects firms across several dimensions. On one hand, access to foreign markets gives firms an added opportunity for growth and innovation while on the other hand, entry of foreign firms increases competition in the domestic market, thereby potentially encouraging innovation. Earlier work has focused on these two "faces" of globalization which could induce firms to upgrade technology and productivity. Bloom, Draca and Van Reenen (2016) looked at import competition while Steinwender (2015) using microdata from Spain argued that imports are highly correlated with exports. Avoiding the export channel could then lead to potential upward bias on the import competition coefficient. In this paper, we focus on offshoring, i.e., sourcing foreign intermediates as a potential mechanism through which firms reduce costs and redirect increased profits to domestic innovation in an attempt to augment productivity. We also show that the burden of offshoring falls on the lower-skilled workers as firms reorganize and respond to offshoring by changing within-firm employment composition in favor of skilled workers.

We develop a simple *Melitz* type model, where we allow firms to combine domestic and foreign intermediates in production governed by the price-adjusted quality of the imports and the elasticity of substitution between domestic and foreign intermediates. Then we follow Bas and Ledezma (2015) very closely to allow for an additional investment stage in which firms upgrade their productivity through an intensive margin of technology investment. The model highlights conditions under which productivity of offshoring firms increases in response to trade liberalization. However, we follow Zhang (2017) to estimate key parameters of the model and show that within our estimated parameter space, offshorers unambiguously increase productivity and investment when trade costs decline.

Following Hummels et al. (2014) and Autor, Dorn and Hanson (2013), we use microdata from Spain to construct a plausibly exogenous measure of offshoring to show that firms' growth in R&D expenditure and high-skilled employment is positively correlated with offshoring growth. We perform a series of sensitivity checks to posit that initial productivity, size, age, innovation history and long-term credit availability play key roles in determining firms' investment in R&D in response to offshoring.

This paper adds to a burgeoning literature analyzing the impact of trade on innovation pioneered by Bloom, Draca and Van Reenen (2016), Bernard et al. (2018) and Bustos (2011) among others. Perhaps the main caveat to our analysis is that we do not observe disaggregate firm-product trade and shipment data to compute the degree of closeness between firms' imports and their final shipments. With such granular data, an obvious path of future research is to study if firms perform more R&D when they import more similar products, highlighting a clear substitution from domestic to foreign resources. Additionally, we do not model the decision rule of R&D in this paper, but rather provide descriptive reduced-form evidence on the link between offshoring and R&D. Future research could involve modeling the dynamic decision of R&D in addition to estimating the production function along the lines of Aw, Roberts and Xu (2011). That would allow us to perform counterfactual exercises by simulating the decline of trade costs and studying the evolution of R&D.

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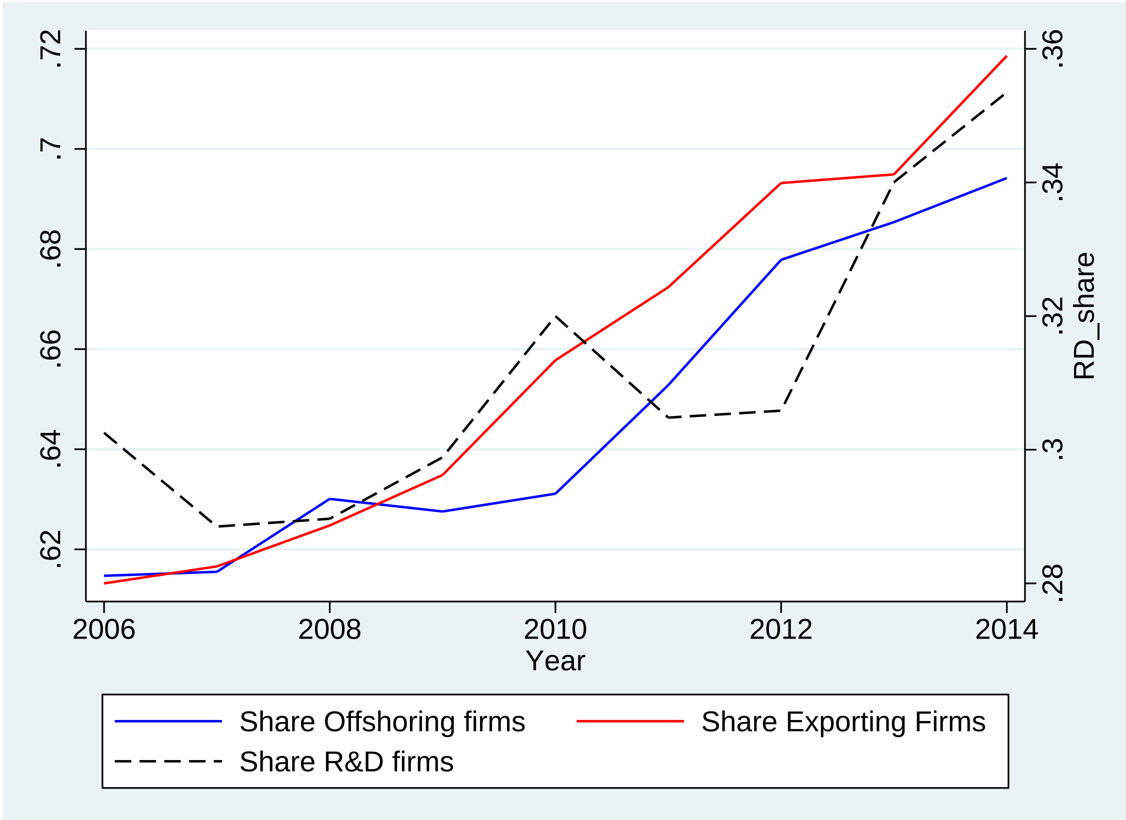


Figure 3: Share of Firms

Table 1: Summary Statistics

	Mean	SD	Min	Max
Log Sales	15.91	2.100	9.925	22.78
Log Labor Productivity	11.78	0.865	7.727	15.96
Log of R&D Expenses	4.454	6.178	0	20.03
Log Employment	4.157	1.513	0	9.556
Log Offshoring	6.419	7.248	0	22.02
Log Import Intensity	2.089	1.431	-2.303	5.788
Log Export Intensity	2.800	1.542	-2.303	4.605
Product Innovation	0.185	0.388	0	1
Process Innovation	0.312	0.463	0	1
R&D Dummy	0.350	0.477	0	1
N	12442			

Notes: The sample includes the observations from all firms in the ESEE (2006-2014). Log sales is the natural logarithm of the firm's real sales. Log labor productivity is the natural logarithm of real value added per worker (where value added is calculated by ESEE as the sum of sales plus change in inventory, less purchases and costs of goods sold). Log of R&D Expenses is the sum of internal and external R&D Expenses of the firm while Log Employment is the natural log of the total average employment of the firm. Log Offshoring is the natural log of the total amount of material inputs offshored by the firm while Log of Import (Export) Intensity is the ratio of the value of imports (exports) to the total sales of the firm. Process innovation and product innovation new methods of organizing production, and both are all defined in a similar way and reflect the stock of reported innovations of each type the firm has done during the sample period. R&D Dummy is a categorical variable which is 1 if the firm reports positie R&D expenditures and zero otherwise.

Table 2: R&D Investment and Import Participation, 2012

	R&D Investment		
Importing	No	Yes	Total
No	30.41	2.21	32.91
Yes	34.90	32.89	67.79
Total	64.91	35.09	100

Table 3: R&D Investment and Export Participation, 2012

	R&D Investment		
Exporting	No	Yes	Total
No	28.95	1.73	30.68
Yes	35.95	33.73	69.32
Total	64.91	35.09	100

Table 4: R&D versus non-R&D Firms

	R&D Firms	Non-R&D Firms
Employees	561	71
Import Intensity	0.18	0.08
Labor Productivity	64	37
Sales	210365	22720
Observations	366	677

Table 5: Importing versus non-importing Firms

	Importing Firms	Non-Importing Firms
Employees	340	40
R&D Expenses	2686	13
Labor Productivity	55	30
Sales	127678	6272
Observations	707	336

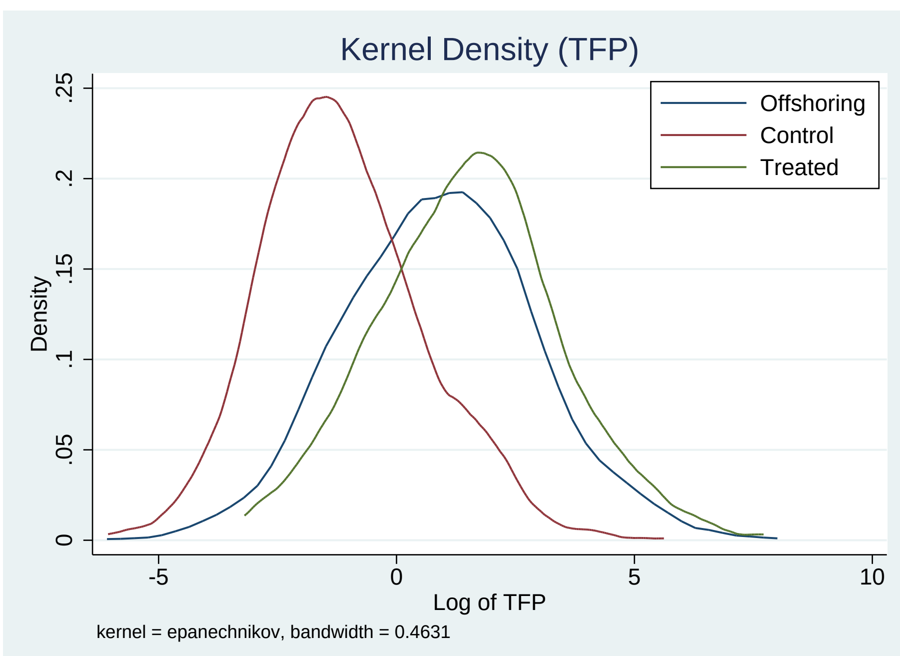


Figure 4: Complementary Margin

Table 6: R&D Premia

	Employees	Import Dummy	Import Share	Labor Productivity
R&D Dummy	1.716***	0.341***	0.470***	0.467***
	(0.1115)	(0.0537)	(0.1327)	(0.0639)
Year fixed effects	X	X	X	X
Industry fixed effects	✓	✓	✓	✓
Firm fixed effects	X	X	X	X
R^2	0.423	0.263	0.128	0.282
Observations	1043	1043	707	1022

Notes: The independent variable is an R&D dummy = 1 if R&D investment is positive. The regressions are run with industry fixed effects using the 2012 cross section. Standard errors are clustered by the two-digit industry. All firm characteristics except import dummy are in logs. Import share is defined as firm import value relative to operating costs.
* p<0.10, ** p<0.05, *** p<0.01

Table 7: Offshoring Premia

	Employees	R&D Dummy	Labor Productivity	R&D Exenditure
Offshoring Dummy	1.184***	0.299***	0.348***	3.860***
	(0.11)	(0.04)	(0.05)	(0.45)
Year fixed effects	X	X	X	X
Industry fixed effects	✓	✓	✓	✓
Firm fixed effects	X	X	X	X
R^2	0.313	0.233	0.253	0.257
Observations	1043	1043	1022	1039

Notes: The independent variable is an Offshoring dummy = 1 if level of offshoring is positive. industry fixed effects using the 2012 cross section. Standard errors are clustered by the two-digit industry. All firm characteristics except R&D dummy are in logs.
* p<0.10, ** p<0.05, *** p<0.01

Table 8: R&D Premia with Firm fixed effects

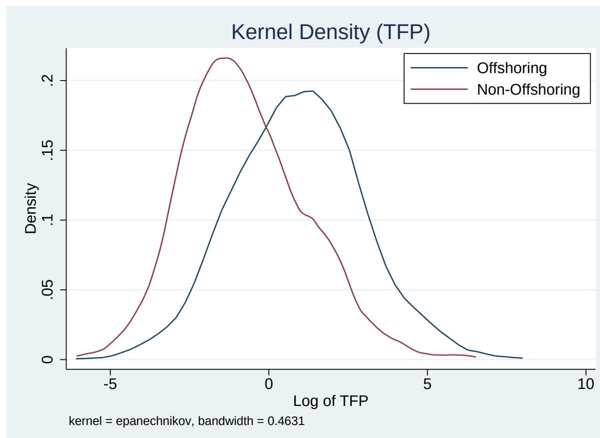
	Employees	Import Dummy	Import Value	Labor Productivity
R&D Dummy	0.096***	0.017*	0.225*	0.022
	(0.0112)	(0.0097)	(0.1149)	(0.0227)
Year fixed effects	✓	✓	✓	✓
Industry fixed effects	X	X	X	X
Firm fixed effects	✓	✓	✓	✓
R^2	0.982	0.805	0.879	0.666
Observations	11989	12316	12288	11874

Notes: The independent variable is an R&D dummy = 1 if R&D investment is positive. The regressions are run with firm fixed effects utilizing the whole sample from 2006 to 2014. Standard errors are clustered using industry by time clusters. All firm characteristics except import dummy are in logs. Import value is defined as firm import value in a given year.
* p<0.10, ** p<0.05, *** p<0.01

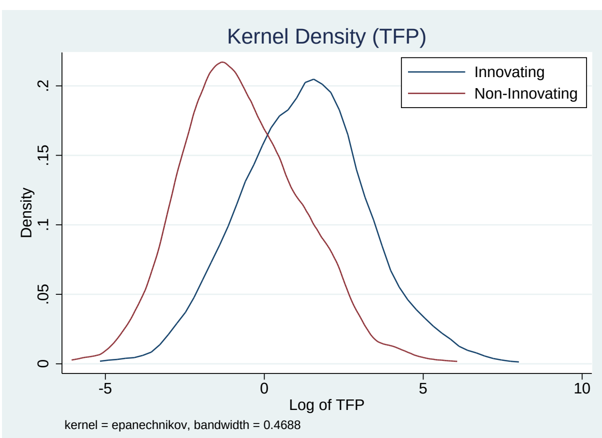
Table 9: Offshoring Premia with Firm fixed effects

	Employees	R&D Dummy	Labor Productivity	R&D Expenditure
Offshoring Dummy	0.035***	0.016*	0.025	0.227**
	(0.008)	(0.008)	(0.015)	(0.097)
Year fixed effects	✓	✓	✓	✓
Industry fixed effects	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓
R^2	0.982	0.797	0.667	0.843
Observations	11989	12316	11874	12292

Notes: The independent variable is an Offshoring dummy = 1 if level of offshoring is positive. The regressions are run with firm fixed effects utilizing the whole sample from 2006 to 2014. Standard errors are clustered using industry by time clusters. All firm characteristics except R&D dummy are in logs.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$



(a) Offshorers v/s Non-Offshorers



(b) Innovators v/s Non-Innovators

Figure 5: Distribution of TFP

Table 10: OLS Results - Offshoring & R&D

	Δ Log R&D Expenditure			
	(1)	(2)	(3)	(4)
Δ Offshoring	0.222***	0.104**	0.089**	0.087*
	(0.06)	(0.04)	(0.04)	(0.04)
Δ Sales		0.183***	0.132***	0.134***
		(0.04)	(0.03)	(0.03)
Δ Capital Investment			0.119***	0.118***
			(0.04)	(0.04)
Industry Fixed Effect	✓	✓	✓	✓
Estimation	OLS	OLS	OLS	OLS
Baseline Sales				✓
Baseline Size				✓
R^2	0.098	0.185	0.204	0.205
Observations	1970	1970	1970	1970

Notes: The dependent variable is change in log **R&D expenditure** from 2010 to 2014. In column (4), we include year 2010 sales and size (employment) of firms. All variables are expressed as log changes. Standard errors are clustered at the two-digit NACE industry level. All regressions include a constant.
* p<0.10, ** p<0.05, *** p<0.01 **??**

Table 11: IV Results - Offshoring & R&D

	Δ Log R&D Expenditure			
	(1)	(2)	(3)	(4)
Δ Offshoring	0.547***	0.376***	0.347***	0.347***
	(0.10)	(0.11)	(0.11)	(0.11)
Δ Sales		0.091**	0.060*	0.061*
		(0.04)	(0.03)	(0.03)
Δ Capital Investment			0.084**	0.084**
			(0.04)	(0.04)
Industry Fixed Effect	✓	✓	✓	✓
Estimation	IV	IV	IV	IV
Baseline Sales				✓
Baseline Size				✓
First Stage F-Stat	87	45	40	37
R^2	.	0.088	0.118	0.119
Observations	1949	1949	1949	1949

Notes: The dependent variable is change in log **R&D expenditure** from 2010 to 2014. In column (4), we include year 2010 sales and size (employment) of firms. All variables are expressed as log changes. Standard errors are clustered at the two-digit NACE industry level. All regressions include a constant.
* p<0.10, ** p<0.05, *** p<0.01 **??**

Table 12: OLS and IV Results - Offshoring & R&D

	Δ Log R&D Expenditure					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Offshoring	0.074*	0.058	0.046	0.442***	0.304**	0.278*
	(0.04)	(0.04)	(0.04)	(0.14)	(0.14)	(0.14)
Δ Exports	0.267***	0.187***	0.173***	0.078	0.089	0.085
	(0.06)	(0.06)	(0.05)	(0.10)	(0.08)	(0.08)
Δ Domestic Sales		0.098***	0.057**		0.066***	0.037*
		(0.02)	(0.02)		(0.02)	(0.02)
Δ Capital Investment			0.110**			0.084*
			(0.04)			(0.04)
Industry Fixed Effect	✓	✓	✓	✓	✓	✓
Estimation	OLS	OLS	OLS	IV	IV	IV
First Stage F-Stat				26	15	15
R^2	0.196	0.214	0.230	0.028	0.145	0.170
Observations	1965	1947	1947	1944	1926	1926

Notes: The dependent variable is change in log **R&D expenditure** from 2010 to 2014. Columns (1) through (3) estimates equation 38 using OLS while columns (4) through (6) estimates equation 38 using IV. Standard errors are clustered at the two-digit NACE industry level. All regressions include a constant.
* p<0.10, ** p<0.05, *** p<0.01 **??**

Table 13: Offshoring & R&D (Firm TFP)

	Δ Log R&D Expenditure	
	(1)	(2)
Δ Offshoring	0.347***	
	(0.11)	
× **1**{Quartile 1: TFP}		-0.008
		(0.12)
× **1**{Quartile 2: TFP}		0.661***
		(0.15)
× **1**{Quartile 3: TFP}		0.461***
		(0.11)
× **1**{Quartile 4: TFP}		0.158
		(0.10)
Δ Sales	0.060*	0.066**
	(0.03)	(0.03)
Δ Capital Investment	0.084**	0.084**
	(0.04)	(0.04)
Industry Fixed Effect	✓	✓
Estimation	IV	IV
Discrete Interactions		baseline *tfp* Quartiles
TFP Category Fixed Effect		✓
First Stage F-Stat	40	
Observations	1949	1949

Notes: The dependent variable is change in log **R&D expenditure** from 2010 to 2014. All regressions also include dummies for different tfp quartiles. Coefficients on those dummies are suppressed for reasons of brevity. All variables are expressed as log changes. Standard errors are clustered at the two-digit industry level. All regressions include a constant.
* p<0.10, ** p<0.05, *** p<0.01 **??**

Table 14: **Offshoring & R&D (Firm Age)**

	Δ Log R&D Expenditure			
	(1)	(2)	(3)	(4)
Δ Offshoring	0.547***		0.347***	
	(0.10)		(0.11)	
$\times$ **1**{Age >= 0 & <= 9}		0.256		0.024
		(0.30)		(0.23)
$\times$ **1**{Age >= 10 & <= 20}		0.512**		0.277
		(0.20)		(0.23)
$\times$ **1**{Age >= 21 & <= 35}		0.585***		0.386**
		(0.13)		(0.15)
$\times$ **1**{Age >= 36 & <= 60}		0.620***		0.439***
		(0.14)		(0.12)
$\times$ **1**{Age >= 61}		0.460**		0.296*
		(0.19)		(0.18)
Δ Sales			0.060*	0.056*
			(0.03)	(0.03)
Δ Capital Investment			0.084**	0.090**
			(0.04)	(0.04)
Industry Fixed Effect	✓	✓	✓	✓
Estimation	IV	IV	IV	IV
Discrete Interactions		Firm Age		Firm Age
Age Category Fixed Effect		✓		✓
First Stage F-Stat	87		40	
R^2	.	.	0.118	0.106
Observations	1949	1949	1949	1949

Notes: The dependent variable is change in log **R&D expenditure** from 2010 to 2014. All regressions also include dummies for different age bins. Coefficients on those dummies are suppressed for reasons of brevity. All variables are expressed as log changes. Standard errors are clustered at the two-digit industry level. All regressions include a constant.
* p<0.10, ** p<0.05, *** p<0.01

Table 15: Offshoring & R&D (Firm Size)

	Δ Log R&D Expenditure			
	(1)	(2)	(3)	(4)
Δ Offshoring	0.547***		0.347***	
	(0.10)		(0.11)	
× **1**{Size >= 0 & <= 19}		0.283**		0.111
		(0.14)		(0.14)
× **1**{Size >= 20 & <= 50}		0.552***		0.363*
		(0.16)		(0.19)
× **1**{Size >= 51 & <= 125}		0.425***		0.281**
		(0.11)		(0.11)
× **1**{Size >= 126 & <= 300}		0.890***		0.719***
		(0.16)		(0.15)
× **1**{Size >= 301}		0.453***		0.313*
		(0.17)		(0.18)
Δ Sales			0.060*	0.052*
			(0.03)	(0.03)
Δ Capital Investment			0.084**	0.062
			(0.04)	(0.05)
Industry Fixed Effect	✓	✓	✓	✓
Estimation	IV	IV	IV	IV
Discrete Interactions		Firm Size		Firm Size
Size Category Fixed Effect		✓		✓
First Stage F-Stat	87		40	
R^2	.	.	0.118	0.048
Observations	1949	1949	1949	1949

Notes: The dependent variable is change in log **R&D expenditure** from 2010 to 2014. All regressions also include dummies for different age bins. Coefficients on those dummies are suppressed for reasons of brevity. All variables are expressed as log changes. Standard errors are clustered at the two-digit industry level. All regressions include a constant.
* p<0.10, ** p<0.05, *** p<0.01

Table 16: Offshoring & R&D (Past Innovation)

	Δ Log R&D Expenditure (2010-2014)			
	(1)	(2)	(3)	(4)
Δ Offshoring	0.230**	0.256**	0.142	0.229**
	(0.11)	(0.10)	(0.12)	(0.10)
$\times$ **1** {Product Innovation}	0.411**			
	(0.16)			
$\times$ **1** {Process Innovation}		0.406**		
		(0.18)		
$\times$ **1** {Tech Collaboration}			0.801***	
			(0.17)	
$\times$ **1** {Innovation Subsidy}				0.838***
				(0.24)
Δ Sales	0.050	0.050	0.055*	0.062**
	(0.03)	(0.03)	(0.03)	(0.03)
Δ Capital Investment	0.083*	0.076*	0.061	0.081**
	(0.04)	(0.05)	(0.05)	(0.04)
Industry Fixed Effect	✓	✓	✓	✓
R^2	0.127	0.066	0.031	0.144
Observations	1949	1949	1949	1949

Notes: The dependent variable is change in log **R&D expenditure** from 2010 to 2014. All regressions also include dummies for product and process innovations, technical collaborations and innovation subsidy. Coefficients on those dummies are suppressed for reasons of brevity. All variables are expressed as log changes. Standard errors are clustered at the two-digit industry level. All regressions include a constant.
* p<0.10, ** p<0.05, *** p<0.01

Table 17: OLS Results - Offshoring & R&D

	Δ Log R&D Expenditure		
	(1)	(2)	(3)
Δ Offshoring	0.347***		
	(0.11)		
× **1**{Quartile 1:Long Credit Ratio}		0.384*	
		(0.23)	
× **1**{Quartile 2:Long Credit Ratio}		0.586***	
		(0.13)	
× **1**{Quartile 3:Long Credit Ratio}		0.169	
		(0.17)	
× **1**{Quartile 4:Long Credit Ratio}		0.222	
		(0.15)	
× **1**{Quartile 1:Short Credit Ratio}			0.222
			(0.15)
× **1**{Quartile 2:Short Credit Ratio}			0.167
			(0.17)
× **1**{Quartile 3:Short Credit Ratio}			0.587***
			(0.13)
× **1**{Quartile 4:Short Credit Ratio}			0.384*
			(0.23)
Δ Sales	0.060*	0.057**	0.057**
	(0.03)	(0.03)	(0.03)
Δ Capital Investment	0.084**	0.085*	0.085*
	(0.04)	(0.05)	(0.05)
Industry Fixed Effect	✓	✓	✓
Estimation	IV	IV	IV
Discrete Interactions		Long Credit Ratio Quartiles	Short Credit Ratio Quartiles
Credit Category Fixed Effect		✓	✓
First Stage F-Stat	40		
Observations	1949	1949	1949

Notes: The dependent variable is change in log **R&D expenditure** from 2010 to 2014. All regressions also include dummies for different credit quartiles. Coefficients on those dummies are suppressed for reasons of brevity. All standard errors are clustered at the two-digit industry level. All regressions include a constant.
* p<0.10, ** p<0.05, *** p<0.01

Table 18: Offshoring & Employment

	Δ Temporary		Δ R&D		Δ High-Skilled	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Offshoring	-0.011	-0.023	0.049***	0.039**	0.112***	0.114***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Δ Sales	0.070***	0.056***	0.015**	0.007	0.017**	0.019**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Δ Capital Investment		0.038***		0.026**		-0.006
		(0.01)		(0.01)		(0.01)
Estimation	IV	IV	IV	IV	IV	IV
Industry Fixed Effect	✓	✓	✓	✓	✓	✓
First Stage F-Stat	45	40	47	37	42	38
Observations	1958	1958	1465	1465	1916	1916

Notes: The dependent variable is change in log **Employment Type** from 2010 to 2014. In columns (1) and (2), the dependent variable is change in log **Temporary Employment** while in columns (3)-(4) and (5)-(6), the dependent variable is log **R&D Employment** and **High Skilled Employment** respectively. High-skilled employment represents the engineers and graduates within the firm. All standard errors are clustered at the two-digit industry level. All regressions include a constant.

* p<0.10, ** p<0.05, *** p<0.01

Table 19: Offshoring & Employment

	Δ R&D	Δ High-Skilled
	(1)	(2)
Δ Offshoring		
× **1**{Quartile 1: TFP}	-0.021**	0.021
	(0.01)	(0.02)
× **1**{Quartile 2: TFP}	0.053**	0.062***
	(0.02)	(0.02)
× **1**{Quartile 3: TFP}	0.068***	0.125***
	(0.02)	(0.02)
× **1**{Quartile 4: TFP}	0.033	0.130***
	(0.03)	(0.04)
Δ Sales	0.008	0.028***
	(0.00)	(0.01)
Δ Capital Investment	0.021**	-0.011
	(0.01)	(0.01)
Industry Fixed Effect	✓	✓
Estimation	IV	IV
Discrete Interactions	baseline *tfp* Quartiles	baseline *tfp* Quartiles
TFP Category Fixed Effect	✓	✓
Observations	1465	1916

Notes: The dependent variable is change in log **Employment Type** from 2010 to 2014. In column (1), the dependent variable is change in log **R&D Employment** while in columns (2), the dependent variable is log **High Skilled Employment** respectively. High-skilled employment represents the engineers and graduates within the firm. All regressions also include dummies for different tfp quartiles. Coefficients on those dummies are suppressed for reasons of brevity. All standard errors are clustered at the two-digit industry level. All regressions include a constant.
* p<0.10, ** p<0.05, *** p<0.01

Table 20: Offshoring & Employment

	Δ Temporary	Δ R&D	Δ High-Skilled
	(1)	(2)	(3)
Δ Offshoring	-0.074**	0.003	0.083***
	(0.04)	(0.02)	(0.03)
Δ Exports	0.053***	0.039***	0.036*
	(0.02)	(0.01)	(0.02)
Δ Domestic Sales	0.044***	-0.002	0.012
	(0.01)	(0.00)	(0.01)
Δ Capital Investment	0.041***	0.025**	-0.009
	(0.01)	(0.01)	(0.01)
Estimation	IV	IV	IV
Industry Fixed Effect	✓	✓	✓
First Stage F-Stat	15	14	15
Observations	1935	1454	1894

Notes: The dependent variable is change in log **Employment Type** from 2010 to 2014. In column (1), the dependent variable is change in log **Temporary Employment** while in columns (2) and (3), the dependent variable is log **R&D Employment** and **High Skilled Employment** respectively. High-skilled employment represents the engineers and graduates within the firm. All standard errors are clustered at the two-digit industry level. All regressions include a constant.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

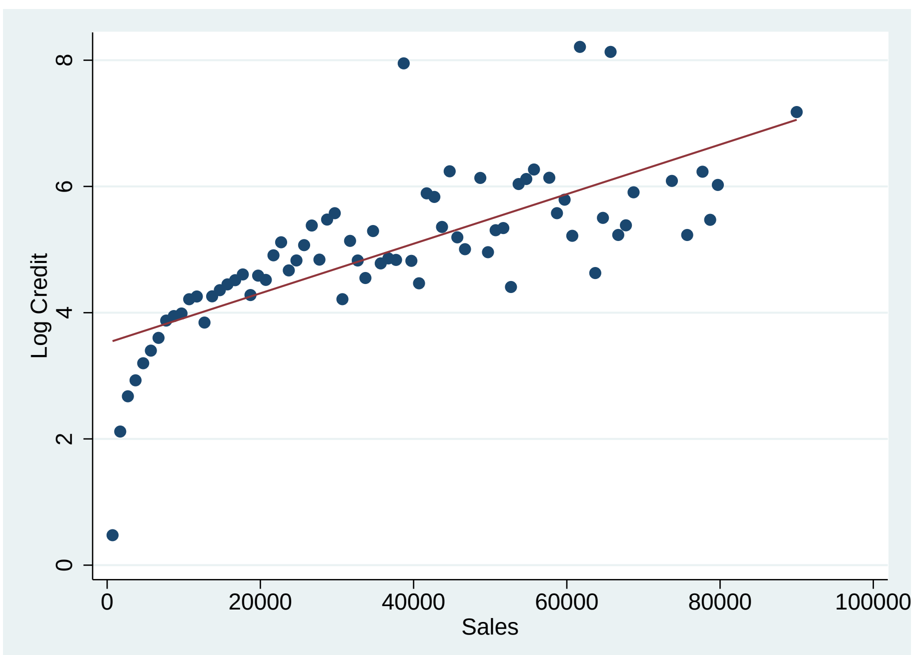


Figure 6: Credit and Sales Correlation

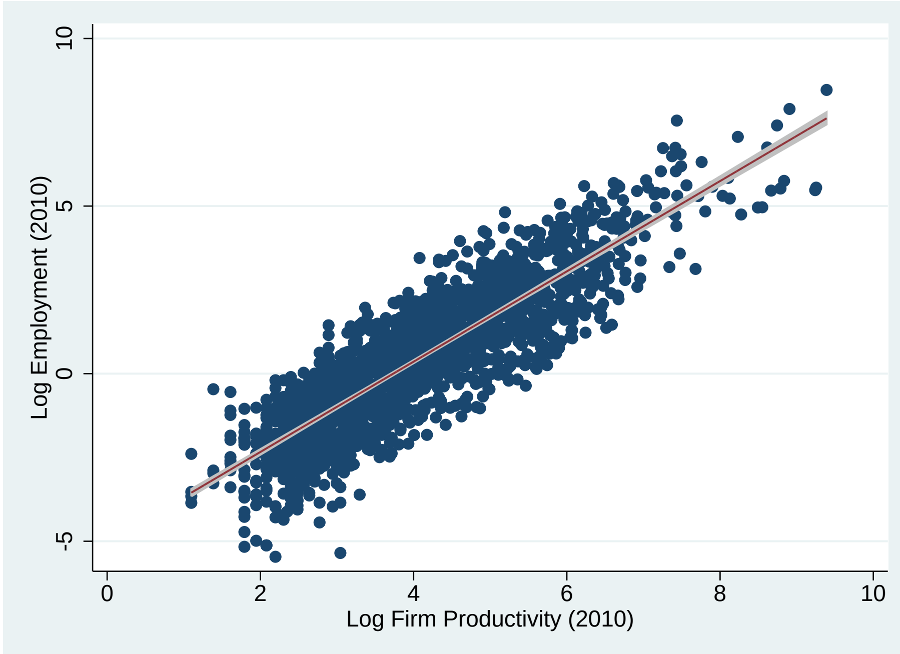


Figure 7: Size and Productivity Correlation

8 Estimating θ and B[36]

We follow Halpern, Koren and Szeidl (2015) and more specifically Zhang (2017) to identify the structural parameters of elasticity of substitution between domestic and foreign inputs θ and foreign input quality shifter B. We later use these parameter estimates to numerically analyze the inequalities governing firms' endogenous production in response to trade costs (equation 34). This involves estimating the firm production function by borrowing key ingredients from the productivity literature.

The production function is Cobb-Douglas in capital, labor and materials, with a nested CES function to combine the domestic and imported intermediate inputs. This follows closely to the structure of our model in 10. The static effect of importing is characterized through the quality effect (B_{jit}) and variety (θ) in the spirit of the Halpern, Koren and Szeidl (2015). The production function is

$$\begin{aligned} Q_{it} &= \exp(\omega_{it} + \xi_{it}) \left[L_{it}^{\alpha_l} M_{it}^{\alpha_m} K_{it}^{\alpha_k} \right] \\ \text{with } M_{it} &= \left[M_{idt}^{\frac{\theta-1}{\theta}} + (BM_{ift})^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} \end{aligned}$$

where ω_{jt} is the productivity observed by plant i itself and ξ_{it} represents the i.i.d measurement error. L_{it} and K_{it} are labor and capital of firm i at date t. M_{idt} and M_{ift} are domestic and imported inputs used to produce the intermediate input M_{it}. θ is the corresponding

[36]Refer to Zhang (2017) for details

elasticity of substitution of domestic and imported inputs. θ represents the input variety effect of imported products showing how easily the imported inputs can be substituted by domestic ones in the production process. When θ is large, domestic and foreign intermediates are more substitutable implying lower variety effect. B represents the average quality effect and following Halpern, Koren and Szeidl (2015), we normalize the domestic quality effect to one. Hence when $B = 1$, there exists no quality effect and when B is greater(lesser) than one, foreign intermediates have relatively higher(lower) quality then domestic intermediates.[37]

The logarithmic production function is:

$$\ln Q_{it} = \alpha_l \ln L_{it} + \alpha_m \frac{\theta}{\theta - 1} \ln \left[M_{idt}^{\frac{\theta-1}{\theta}} + (AM_{ift})^{\frac{\theta-1}{\theta}} d_{it} \right] + \alpha_k \ln K_{it} + \omega_{it} + \xi_{it} \tag{42}$$

where d_{it} is an indicator variable indicating import status of firm i in year t.

Demand is assumed to be the classic Dixit-Stiglitz type:

$$Q_{jt}^{D} = \Phi_t P_{jt}^{\eta},$$

where η is the demand elasticity, which is assumed to be common across products within one industry. P_{jt} is plant j's price. Φ_t is the time-specific demand shifter common for all plants.

It is a well-known fact that estimation of the logarithmic production function in 42 is subject to endogeneity as firms' choice of labor, materials and capital is correlated with their productivity ω_{it}. Following Zhang (2017), we use insights from Olley and Pakes (1996) to use investment as a proxy for firm productivity under the usual condition of monotonicity, $\omega_{it} = \omega_t(i_{it}, k_{it}, d_{it+1})$. Hence we can rewrite equation 42 as:

$$\ln Q_{it} = \alpha_l \ln L_{it} + \alpha_m \frac{\theta}{\theta - 1} \ln \left[M_{idt}^{\frac{\theta-1}{\theta}} + (AM_{ift})^{\frac{\theta-1}{\theta}} d_{it} \right] + \phi(i_{it}, k_{it}, d_{it+1}) + \xi_{it} \tag{43}$$

where $\phi(i_{it}, k_{it}, d_{it+1})$ captures the combined effect of capital and observed productivity. In the standard set up of Olley and Pakes (1996), the static parameter of labor and $\hat{\phi}$ is estimated using OLS. But in this case, due to the nested CES nature of the production function (combining domestic and foreign intermediates), we use GMM to estimate $\hat{\alpha}_l$, $\hat{\alpha}_m$, $\hat{B}$ and $\hat{\theta}$. We parameterize ϕ_{it} a cubic function and estimate productivity $\omega_{it} = \hat{\phi}_{it} - \alpha_k k_{it}$.[38]

The GMM estimates from estimating equation 43 are as follows:

Our estimates of labor and materials are comparable to other estimates in the literature.

[37] Without information on quantities of M_{jdt} and M_{jft}, the parameter B reflects the real quality effect as well as the price differential between the two.

[38] Following standard practice in the literature, we assume productivity evolves according to a first order Markov process.

Table 21: First Stage GMM estimates:

Parameter	Estimate	Standard Error
α_l	0.21	0.01
α_l	0.77	0.01
$(\theta - 1)/\theta$	0.86	0.10
B	0.85	0.17

Similar to Halpern, Koren and Szeidl (2015), our dependent variable in the production function is log total sales and not value added, as a result of which coefficients of capital and labor are smaller than in the more common value-added specifications, while material costs have a large coefficient.[39] The two key parameters of interest to us are B and θ for the purpose of understanding and plotting inequalities given in equation 36. $(\theta - 1)/\theta = 0.86 \Rightarrow \theta \approx 7$ and the estimate of $B = 0.85$. We use these estimates in Figure 3.3.

It is true that without price and quantity data, we cannot differentiate between real input quality effect and the price difference between domestic and imported inputs. However the ESEE data is remarkably rich in providing information about prices of intermediates for the individual firms. It provides data on firm level changes in prices across all intermediates that firms use (both domestic and imported) In Figure 8, we show that the distribution of average change in intermediate prices for firms who started offshoring in 2010[40] is very close to firms who did not offshore in either 2009 or 2010.

This provides descriptive evidence that firms are not really importing significantly cheaper intermediates but rather intermediates which are lower in quality. More disaggregate product and price data at the firm level can further shed light on the margins of adjustment for firms when they source foreign intermediates.

[39] Halpern, Koren and Szeidl (2015) estimates $\alpha_l = 0.198$ and $\alpha_m = 0.752$ which are quite close to what we find in Table 21. We also estimate these parameters for separate industries. Results are available upon request.

[40] We denote firms as offshorers who did not import (according to the narrow definition) in 2009 but did import in 2010.

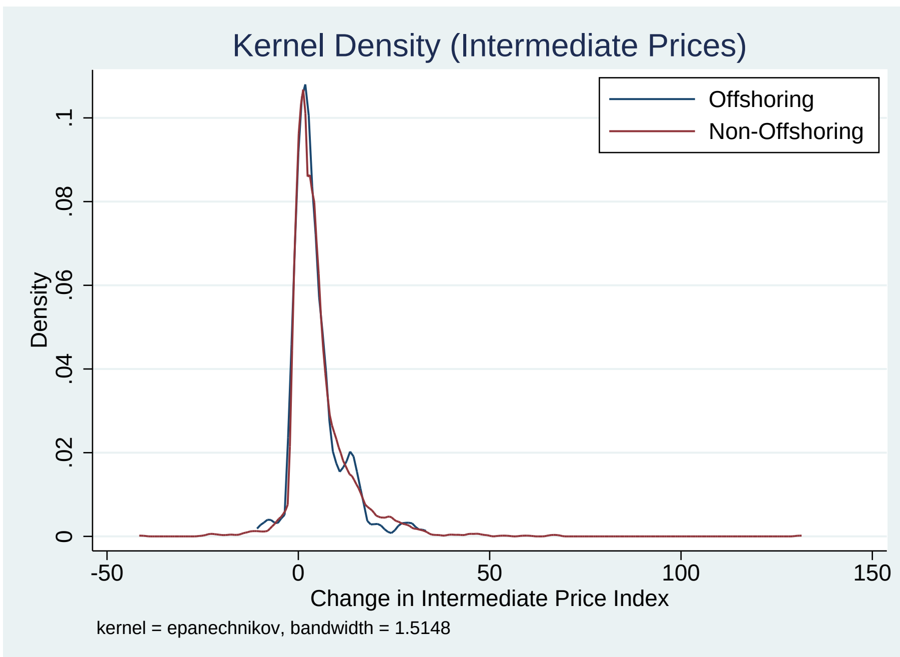


Figure 8: Change in Intermediate Prices: Offshorers v/s Non-Offshorers