Worker Reallocation, Firm Innovation, and Chinese Import Competition*

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December 16, 2020

Abstract

While the nexus between international trade and firms' innovation has recently been documented, the underlying mechanisms explaining firms' innovation in response to import competition are thus far poorly understood. To unmask such mechanisms and their economic relevance, we use longitudinal employer-employee linked data from Denmark (1995–2012) and conduct analyses at both the firm- and worker-levels. We first show that import competition triggers a significant increase in innovation. Around 40 percent of the innovation effect channels through the increase in the share of R&D workers, and 14 percent of this increase in the share of the R&D workers is due to within-firm worker switching to R&D jobs while 80 percent is explained by between-firm worker reallocation. Furthermore, we show that a larger degree of between-firm worker reallocation to R&D jobs relative to within-firm switching is associated with more innovation. The salience of the between-firm reallocation is further confirmed by the worker-level analysis, and its importance to innovation is underscored when we extend our analysis to Portugal.

Key words: Import Competition, Innovation, Between-firm Worker Reallocation, With-firm Worker Reallocation.
JEL code: F12, F14, O31.

*We are extremely thankful to Maggie Chen, Yingyan Zhao, Andrew Bernard, Laura Puzzello and to the seminar participants at George Washington University, University California Santa Cruz, Copenhagen Business School and the FREIT Conference for the helpful comments and suggestions. We are grateful to the data managers at Copenhagen Business School for granting access to the Danish registry data. Funding provided by the Danish Council for Independent Research in Social Sciences, Grant no. DFF–8019-00019B is gratefully acknowledged. The usual disclaimer applies.

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1 Introduction

Over the past two decades, the extraordinary increase of exports from emerging economies, such as China, has presented itself as a new source of competition for firms in advanced countries.[1] While the current literature suggests that firms in advanced economies may respond by increasing R&D efforts and innovation as a protection against import competition (Aghion et al., 2002; Bloom et al., 2013; Hombert and Matray, 2018), it does not yet offer conclusive evidence. Bao and Chen (2018) find, for example, that firms in over 100 countries respond to the threat of foreign competition by raising innovation, whereas Autor et al. (2019) show that imports from China explain 40 percent of a slowdown in innovation among American firms between 1999 and 2007. Meanwhile, Xu and Gong (2017) show that import penetration from China has no adverse effects on innovation in the U.S.[2] Furthermore, the mechanisms through which innovation materializes in response to import competition remain poorly understood.

Our paper aims at filling this gap by looking at: i) whether the innovation responses to import competition can be attributed to the increase in the share of R&D workers; ii) whether internal (within-firm) reallocation of non-R&D workers to R&D jobs is either a weaker or stronger strategy to promote innovation compared to external (between-firm) reallocation, which is achieved by hiring new workers for R&D activities. Because the associated benefits of the within and between-firm channels are potentially different, innovation outcomes can depend on the type of reallocation.

On the one hand, the within-firm workers' reallocation channel is consistent with the assumption that firms face large labor adjustment costs, i.e. due to hiring and firing costs, and/or with the fact that their employees possess firm-specific knowledge.[3] On the other hand, the between-firm workers' reallocation can be interpreted as labor market poaching, i.e. productive firms' hire additional workers from other companies in order to increase innovation and therefore gain a competitive advantage. Domestic firms in developed countries may escape import competition through innovation by either internally reallocating their non-R&D workers to R&D jobs (Bloom et al., 2013), or by hiring external workers for R&D activities (Kaiser et al., 2015), or by doing both. This may then translate into heterogeneous responses to import competition in terms of firms' R&D workers share and innovation.

[1] For instance, European Union's imports from China have increased more than tenfold between 1992 and 2012.

[2] In the similar spirit, Bloom et al. (2016) show that patents, TFP, IT intensity and R&D expenditures increase among European firms who are more exposed to Chinese import competition, although Campbell and Mau (2020) have recently cast doubt on the results regarding patents.

[3] Successful American firms, such as Marlin Steel Wire Products, have for example recently invested in new production technologies and re-trained their own factory workers (mainly machinists) in programming and software skills so that they could help produce new steel products of higher quality in response to increased competition from China (Factory Workers Become Coders, Wall Street Journal, May 17th 2019).

One of major challenges for identifying and estimating the relative importance of the two types of reallocations described above is a lack of sufficiently rich data at both the firm- and worker-levels. We overcome this challenge by using the employer-employee linked data for two countries, Denmark and Portugal. Moreover, we base our empirical analysis on a simple framework, which theorizes with clear and testable predictions the effects of import competition on innovation and the relative importance of the two mechanisms. Specifically, this model features both R&D and non-R&D jobs, as well as firms' heterogeneous products and dynamic innovation decisions.[4] The model captures the costs and benefits of innovation, and workers' reallocation within- and between-firms towards R&D jobs, as well as the associated changes in the amount of innovation in response to an import competition shock, such as the Chinese one. We also perform comparative statics for low- vs high-productive firms and for low- vs high-labor adjustment costs, thus providing theoretical guidance to the cross-country comparison conducted in the empirical analysis.

Armed with our theoretical predictions, we then estimate two sets of empirical analyses. In the first one, we estimate the impact of Chinese import competition on Danish firms' innovation. Similar to Autor et al. (2014) and Keller and Utar (2016), we measure a firm's trade exposure using the change of import penetration by the 4-digit industry, in which the firm is active. To alleviate endogeneity issues, we use the identification strategy in Autor et al. (2014) to isolate the Danish import growth driven by Chinese export-supply growth and not by Danish domestic demand shocks. Regarding innovation, we use patent applications to proxy for innovation at the firm-level (Hall et al., 2005). Furthermore, we test the importance of changes in the share of R&D workers in explaining the trade-innovation relationship at the firm-level. To do so, we use the classification of knowledge-intensive occupations suggested by Bernard et al. (2017, 2020) in order to identify R&D workers in the data. We then assess how import competition affects within- and between-firm reallocation of workers to R&D jobs to dig deeper into the mechanisms behind the impact of import competition on innovation.

In the second set of regressions, we first utilize the worker-level data to study whether import competition impacts the Danish workers' probability of: i) switching to an R&D job, conditional on staying employed at the same firm; ii) moving to another firm and being employed as an R&D worker; iii) moving to a high-productivity/high-tech firm. We then replicate the above analyses at both the firm- and worker-level by using Portuguese data to further explore which type of workers' reallocation matters the most in explaining the effect of import competition on innovation, albeit in a different context.

Our main results can be summarized as follows. Using the firm-level analysis, we find that

[4] See the seminal work by Grossman and Helpman (1990, 1991) and more recent papers by Yeaple (2005) and Atkeson and Burstein (2010) for richer models that provide linkages between trade and innovation.

in Denmark, a 100 percent increase in import competition raises firms' number of patent applications and the share of R&D workers respectively by 7 and 4 percent on average. Around 40 percent of the increase in innovation channels through the total increase in the share of R&D workers resulting from import competition. Moreover, we find that around 14 percent of the increase in the share of R&D workers at the firm level is due to within-firm workers' reallocation to R&D jobs, while 80 percent is due to between-firm workers' reallocation. All these results are more pronounced for high-performance firms, i.e. high-productivity or tech firms. These firms reacts more strongly to import competition in terms of both innovation and the share of R&D workers. They also increase the share of R&D workers more intensively through between-firm hiring compared to the average firm in the sample. Furthermore, we show that a larger degree of between-firm relative to within-firm worker reallocation to R&D jobs is associated with more innovation.

Our worker-level analysis confirms the role of the between-firm channel and of high-performance firms. We find that an increase in Chinese import competition by 100 percent raises the worker's probability to switch to an R&D job by 5.5 percent, conditional on staying employed with the same firm. However, the impact of import competition on the probability of being hired as an R&D worker by another firm is even stronger (a 21 percent increase). Finally, import competition positively affects workers' likelihood of moving to a high-performance (high-productivity/tech) firm. This last result not only confirms our firm-level findings, it is also consistent with firm composition changes in response to Chinese import penetration documented in Bloom et al. (2016) and offers a potential mechanism for why import competition increases innovation among productive firms in Bombardini et al. (2017) and Yamashita and Yamauchi (2020).

When we extend our analysis to Portugal using exactly the same specifications, we find that relative to Denmark the increase in firms' R&D worker share and innovation in response to import competition is smaller. Contrary to the Danish results, most of the increase in the share of R&D workers channels through the within- rather than the between-firm reallocation of labor. This result is in line with Branstetter et al. (2019), who states that Portugal's stringent labor market regulations and low productivity limit firms' potential adjustment in response to competitive shocks. Furthermore, the increase in the share of R&D workers due to import competition has a weak relation to firms' innovation in Portugal. This last result combined with the limited between-firm reallocation of workers to R&D jobs corroborates the importance of the between-firm channel for explaining the relationship between import competition and innovation underscored by the Danish case. While acknowledging that there may be other factors, beside the limited between-firm mobility and low productivity, for the relatively weak innovation response to import competition among Portuguese firms, we find it interesting that the results from our cross-country comparison are consistent with our theoretical insights.

This paper makes several contributions to the existing literature. First, our worker-level analysis enables us to explore in detail the reallocation channels, through which import competition can affect innovation. It complements previous studies, which mainly use firm-level data (e.g., Bloom et al., 2016).[5] Our second contribution is to study both between- and within-firm workers' reallocation to R&D jobs and their relative importance in explaining changes in the share of R&D workers and innovation. This paper also informs the broad literature in international trade. First, it relates to those studies exploring firms' innovation in response to their exposure to the global markets. For instance, Bustos (2011) finds that exporting firms, that operate in industries with higher degree of competition, increase investments in technology faster compared to less exposed firms. The main difference between this study and our paper is that we focus on the impact of import rather than export competition. Second, our paper also refers to the extensive work done on the efficient reallocation of production factors, new-technology adoption and productivity growth in response to trade integration and import competition (Melitz, 2003; Bernard et al., 2003; Tybout, 2008; Aghion et al., 2018).[6] Our paper complements this literature by highlighting a new mechanism behind the relation between trade and innovation: labor reallocation within- and between-firms, although we do not infer the subsequent effects on growth and productivity.

In the next section, we present a simple theoretical model, data and summary statistics are then discussed in Section 3, followed by our empirical strategy in Section 4. Finally, we present our results in Section 5 and conclude in Section 6.

2 Theoretical Hypothesis

We propose a model of firm dynamics to demonstrate the mechanisms through which import competition from a large, low-wage country (such as China) affects the assignment of labor to R&D jobs through workers' within- and between-firm reallocation and the firm innovation in a small open economy. In this model, there are two agents, workers and firms, and there is a permanent shock to the level of import competition.

[5] It is worth noting that in contrast to Bernard et al. (2020), which looks at the effect of offshoring on firms' reallocation of workers to R&D and innovation, we focus on the adjustments to the workforce composition in response to import competition, while controlling for firm-level offshoring.

[6] Other relevant papers include, though not limited to, Frankel and Romer, 1999; Alcalá and Ciccone, 2004; Pavcnik, 2002; Trefler, 2004; Loecker, 2011; Klimek et al., 2010.

2.1 Production and Pricing

There are two types of firms $j = \{1, 2\}$. Both types of firms produce two categories of goods $k = \{N, \Gamma\}$ and have two types of jobs $x = \{n, \gamma\}$. Here we use $\{n, \gamma\}$ for both the job types as well as the number of workers for each job type. Type N goods face import competition from other countries, like China. They are homogeneous, traded internationally, and produced by non-R&D workers n_j, with the production function:

$$y_j^N = zn_j^\alpha,$$

where z is productivity. Their price, p_0, is treated as exogenous to this small open economy and is equal to the given world price plus a tariff (export subsidy) if it is imported (exported) (Artuç et al., 2010; Cameron et al., 2007). The model's only exogenous shock is a permanent import competition shock captured by a decrease in p_0.

Type Γ goods face no foreign competition, despite that they can be traded internationally. They are innovative products that are developed by R&D workers γ_j, with the production function:

$$y_j^\Gamma = a_j\gamma_j^\alpha,$$

where a_j is R&D productivity for firm j.[7] Their prices, p_j, are also treated as exogenous and calibrated from the data.

Two firms are the same except for their productivity to innovate ($a_j = \{a_1, a_2\}$). Without loss of generality, we assume that type $j = 1$ firms are more productive with R&D activities than type $j = 2$ firms, i.e., $a_1 > a_2$.

2.2 Within-firm Labor Reallocation and External Hiring

Firms can reallocate or hire workers into two different jobs, R&D jobs and non-R&D jobs. γ_j and n_j are the number of R&D and non-R&D workers in firms j, respectively. Each period workers separate from their jobs with an exogenous rate $0 < s < 1$ that is assumed to be the same across jobs. These separations ensure that labor reallocation exists even in steady states. Firms can internally switch workers from non-R&D to R&D jobs. We denote such internal switches and their number as $i_j > 0$ for firm j. If $i_j < 0$, it means that firm j internally switches workers from R&D to non-R&D jobs. Firms can also hire external workers from other firms and/or from the pool of unemployed/school graduates.[8]

[7] One can also consider the total number of innovative goods as the total number of varieties, i.e., empirically as the total number of patents (or patent applications) a firm has, and their prices as the total revenue from each variety.

[8] All of our empirical exercise restricts external hires to between-firm (job-to-job) transitions only, except for column 2 of Table A-3 in the appendix.

Such external hires and their number are denoted as m_x where $x = \{n_j, \gamma_j\}$ denotes the job type of the new hires.

The costs of internal switches and external hiring, respectively, are a quadratic function of the number of workers who internally switch occupation or who are externally hired with some parameter ϕ. Specifically, the cost of internal switches is $\frac{\phi}{2} i_j^2$, the cost of hiring workers for R&D jobs is $\frac{\phi}{2} m_{\gamma_j}^2$, and the cost of hiring workers for non-R&D jobs is $\frac{\phi}{2} m_{n_j}^2$.[9]

2.3 Wage Bargaining

Each firm bargains with their R&D workers and non-R&D workers separately. Workers can either work in the firm or be unemployed in a given time period. We assume Nash bargaining, i.e., firm j and each type of workers choose a wage so as to maximize the worker-firm joint surplus:

$$S_x = V_x + W_x \tag{1}$$

where $x = \{n_j, \gamma_j\}$ is for the job type. $W_x = w_x - b_x$ and b_x is a parameter for unemployment benefits for different workers (proportional to their wages), and thus W_x is a worker's net gain from the state of unemployment to the state of employment as an x-type worker at firm j. V_x is the firm's marginal value of hiring an x-type worker.

Defining as $0 < \eta < 1$ the workers' bargaining power in the wage negotiation, the wage arises as a solution to the standard Nash bargaining problem:

$$w_x^* = \text{argmax}_{w_x} \left(V_x\right)^{1-\eta} \left(W_x\right)^{\eta} \tag{2}$$

2.4 Firms' Problem

Each firm j solves the following maximization problem:

$$\begin{aligned}
& V(n_j, \gamma_j, p_0) = \max_{i_j, m_{n_j}, m_{\gamma_j}} \quad \pi_j + E\beta V(n_j', \gamma_j', p_0') \\
s.t. \quad & p_0 z n_j^{\alpha} + p_j a_j \gamma_j^{\alpha} = \pi_j + w_{n_j}^* n_j + w_{\gamma_j}^* \gamma_j + \frac{\phi}{2} m_{n_j}^2 + \frac{\phi}{2} m_{\gamma_j}^2 + \frac{\phi}{2} i_j^2 \quad (budget) \\
& n_j' = (1-s) n_j - i_j + m_{n_j} \quad (law\ of\ motion\ for\ non-R\&D\ workers) \\
& \gamma_j' = (1-s)\gamma_j + i_j + m_{\gamma_j} \quad (law\ of\ motion\ for\ R\&D\ workers) \\
& w_{n_j}^* = \text{argmax}_{w_{n_j}} \left(V_{n_j}\right)^{1-\eta} \left(W_{n_j}\right)^{\eta} \\
& w_{\gamma_j}^* = \text{argmax}_{w_{\gamma_j}} \left(V_{\gamma_j}\right)^{1-\eta} \left(W_{\gamma_j}\right)^{\eta}
\end{aligned}$$

[9] We do not have sufficient data to calibrate specific ϕ for internal switching versus external hiring. However, if ϕ is assumed to be higher for external hiring than for internal switching, all our results below are still valid.

where π_j is firm j's profit and $0 < \beta < 1$ is the discount factor.

2.5 Steady States and Transition Path

To illustrate some of the properties of our model, we first examine the internal switching and external hiring conditions and how an import competition shock analytically affects workers' allocations. Then, we numerically solve the model's steady states before and after a permanent import competition shock (i.e., a reduction of p_0), respectively, as well as the transition path between the two steady states.

We derive the internal switching and external hiring conditions for firm j and wages as follows:

$$\phi m_{n_j} = \beta E[p_0 z \alpha n_j'^{\alpha-1} - w_{n_j}^{*\prime} + (1-s)\phi m_{n_j}'] \quad (1)$$
$$\phi m_{\gamma_j} = \beta E[p_j a_j \alpha \gamma_j'^{\alpha-1} - w_{\gamma_j}^{*\prime} + (1-s)\phi m_{\gamma_j}'] \quad (2)$$
$$\phi i_j = \phi m_{\gamma_j} - \phi m_{n_j} \quad (3)$$
$$w_{n_j}^{*} = \eta[p_0 z \alpha n_j^{\alpha-1} + (1-s)\phi m_{n_j}] + (1-\eta) b_{n_j} \quad (4)$$
$$w_{\gamma_j}^{*} = \eta[p_j a_j \alpha \gamma_j^{\alpha-1} + (1-s)\phi m_{\gamma_j}] + (1-\eta) b_{\gamma_j} \quad (5)$$

In equations (1) and (2), the left hand side is the marginal cost of hiring respectively a non-R&D and an R&D worker. The right hand side is the marginal benefit of an external hire including savings from not having to hire the next period if the new worker does not separate. Equation (3)'s left hand side is the marginal cost of an internal switch, while its right hand side is the net benefit of an internal switch, that is, the marginal benefit of an external hire for an R&D job [according to equation (2)] minus the opportunity cost of losing a non-R&D worker [according to equation (1)]. Wages are obtained as the weighted sum of the benefit firms generate when hiring an additional worker of each job type and the unemployment benefit (see equations 4 and 5).

Under a steady state, when we replace wages in equations (1) and (2) with their expressions from equations (4) and (5), we transform the above five equations to the following three:

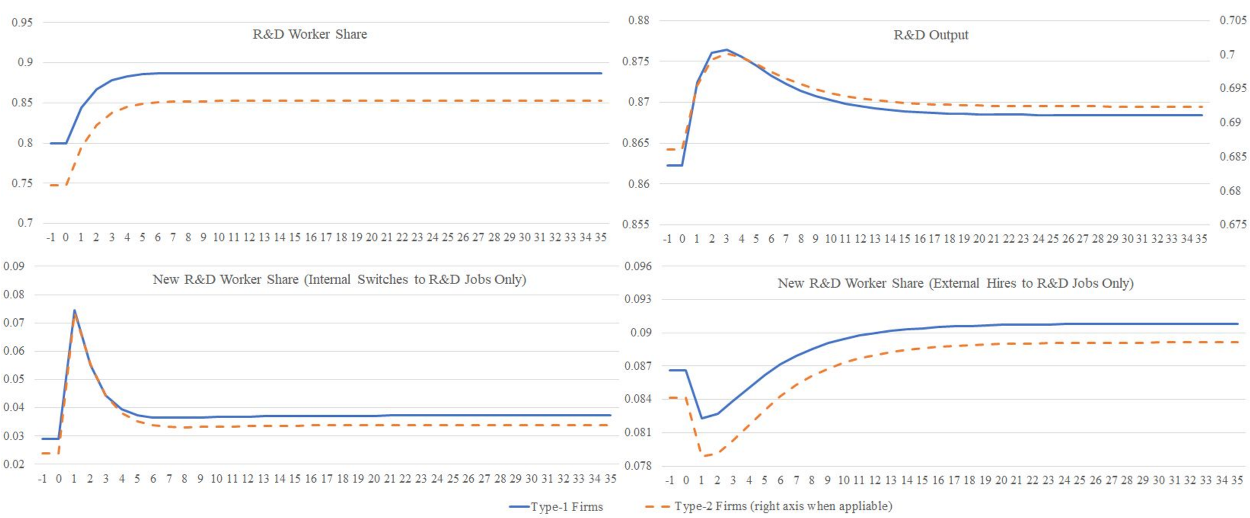
$$\phi i_j = \phi m_{\gamma_j} - \phi m_{n_j} \quad (3)$$
$$[1-\beta(1-s)(1-\eta)]\phi m_{n_j} = \beta(1-\eta)(p_0 z \alpha n_j^{\alpha-1} - b_{n_j}) \quad (6)$$
$$[1-\beta(1-s)(1-\eta)]\phi m_{\gamma_j} = \beta(1-\eta)(p_j a_j \alpha \gamma_j^{\alpha-1} - b_{\gamma_j}) \quad (7)$$

There offers two important results. First, when $i_j > 0$ (i.e., firm j reallocates non-R&D workers to R&D jobs), then $\phi m_{\gamma_j} > \phi m_{n_j}$ according to equation (3). This then implies that

$p_j a_j \alpha \gamma_j^{\alpha-1} > p_0 z \alpha n_j^{\alpha-1}$ according to equations (6) and (7), assuming $b_{\gamma_j} > b_{n_j}$.[10] Therefore, according to equations (4) and (5), $w^*_{\gamma_j} > w^*_{n_j}$. That is, R&D workers have a higher wage than non-R&D workers, which is consistent with the empirical evidence. The second insight is that when the import competition shock strikes, i.e., p_0 decreases, steady state m_{n_j} will decrease according to equation (6). That is, fewer external hires of non-R&D worker. The intuition is that the declining p_0 reduces the marginal benefit of hiring non-R&D workers. Consequently, ϕm_{n_j} decreases, and according to equation (3) i_j will rise, that is, more workers will internally be switched from non-R&D jobs to R&D jobs because the opportunity cost of losing one non-R&D worker becomes smaller. The above responses to the import competition shock will result in a larger ratio of R&D-workers-to-non-R&D-workers in both types of firms than prior to the shock. Even though R&D workers have higher wage costs than non-R&D workers, firms demand more R&D workers because they bring more benefit to the firms than the non-R&D workers, when p_0 decreases.

To see the effects of the trade shock more clearly, we calibrate the model and numerically solve its steady states before and after a permanent negative shock on p_0, and then solve the transition path in between. Notice that our empirical results will mostly capture short-run effects rather than long-run steady state changes. Nevertheless the transition path from the old to the new steady state provides theoretical guidance to the short-run effects. The results are represented in Figure 1. The model's equilibrium conditions and parameter values are detailed in the online appendix.

Figure 1: Labor Transition After a Permanent Trade Shock



Notes: Horizontal axis is time period. The trade shock happens at $t = 0$.

Period $t = -1$ is the steady state before the p_0 shock that strikes at period $t = 0$. Follow-

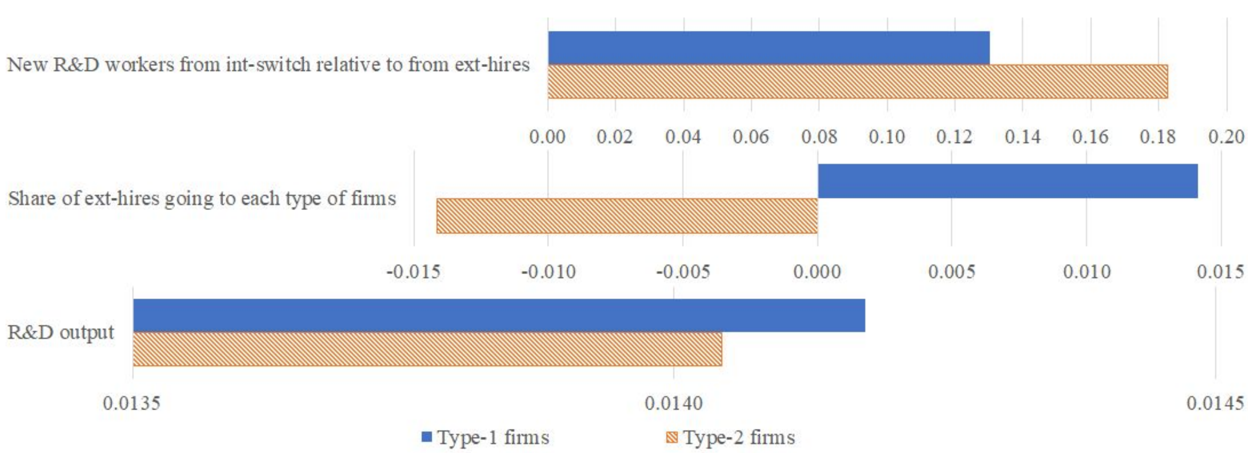
[10] The assumption of $b_{\gamma_j} > b_{n_j}$ is likely to be true as unemployment benefits are proportional to wages and R&D workers have higher wages than non-R&D workers on average in the data.

ing the shock, for both types of firms, the share of R&D workers in the firm's employment increases and so does the number of R&D workers, which leads to a higher R&D output (i.e., the type Γ goods). The latter overshoots a little before converging to a higher steady state than before the shock. Note that, although not being shown in Figure 1, non-R&D workers and their type N goods output decline in the transition path to a lower steady state (see online appendix for more results).

Breaking down the sources of new R&D workers, both the internal switches from non-R&D to R&D jobs and the external hires to R&D jobs as a share of total employment is higher in the after-shock steady state than in the before-shock one. The former is a result of both increasing i_j and decreasing total employment of firm j and the change overshoots in the short run, while the latter is mainly due to decreasing total employment of firm j and declines at first and recoveries eventually. Although we do not show it here, the model also generates declining new non-R&D workers, through both external hiring and internal switching. Hence, an externally hired worker is more likely to be hired to an R&D job.

Because type-1 firms are more productive in R&D than type-2 firms other things being equal, there are important differences in their responses to the import competition shock (Figure 2). Here we discuss short-run effects (3 periods after the shock) as it is the focus of our empirical results. Although both types of firms increase their use of internal worker switching to R&D jobs relative to external hiring, type-2 firms have a larger increase in their reliance on internal worker switching to R&D jobs relative to external hiring than type-1 firms. Moreover, considering all of the external hires, a larger share of them goes to type-1 firms, whereas a smaller share goes to (the least productive) type-2 ones. In other words, an externally hired worker is more likely to be hired by high-productivity firms. Also, type-1 firms have a slightly higher increase in R&D activities (i.e., type Γ goods production) than type-2 firms.

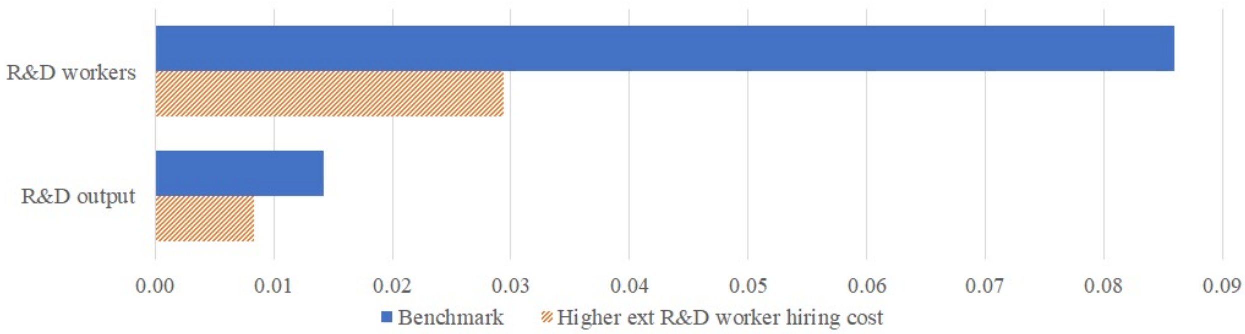
Figure 2: Between-firm Comparison: Changes After a Permanent Trade Shock



Note: The bars plot the changes of the list variables from the pre-shock to post-shock steady state.

Finally, we increase the labor adjustment cost parameter ϕ while leaving all other parameters unchanged, and compare these new results to the benchmark analysis reported above. Figure 3 plots the result differences for type-1 firms. In a nutshell, with higher labor adjustment cost, firms have smaller R&D worker increases and smaller R&D output increases than the benchmark case. More results are available in the online appendix.

Figure 3: Higher Labor Adj. Cost: Post-shock Changes of Type-1 Firms



Note: The bars plot the changes of the list variables from the pre-shock to post-shock steady state.

According to the above switching and hiring conditions and model solutions, we can derive the following proposition:

Proposition 1: *Import competition leads to an increase in the share of R&D workers, both in terms of internal worker switching and external hiring to R&D jobs.*

Proposition 2: *As a result of the increase in R&D workers, import competition increases innovation at the firm-level.*

Proposition 3: *Under import competition, low-productive firms have a larger reliance on internal workers' switching to R&D jobs relative to external hiring compared to high-productive firms, and among all of the external hires an increased share of them goes to high-productive firms and R&D jobs. More productive firms innovate slightly more.*

Proposition 4: *Under import competition, economies with higher labor adjustment costs experience smaller increases in R&D workers and R&D output.*

In the following sections, we will provide empirical tests to the above propositions and estimate the size of the impact with micro-level data. Propositions 1 and 2 will be mainly tested for Denmark in Table 4 of Section 5. The empirical analysis of Proposition 3 will be presented in Tables 5, 7 and 11 of the same section. Finally, in the very last section of the paper, we extend the empirical analysis to Portugal–an economy that has higher labor adjustment cost and features lower average firm productivity than Denmark, whose results represent an empirical test of Propositions 3 and 4.

3 Data

Information about firms and workers is collected from three registers at the Danish official statistical institute (Denmark Statistics): the "Integrated Database for Labor Market Research" (*IDA*), the "Accounting Statistics Registers" (*FirmStat*) and the "Foreign Trade Statistics Register" (*Udenrigshandelsstatistikken*). Furthermore, we integrate these registers with a database of patent applications by Danish firms (PATSTAT). From the population of all firms, we only retain private firms that are included in first two databases over the period from 1995 to 2012 and that were ever part of the manufacturing industry.[11] We now provide further details about how we process the data in each database.

IDA is a longitudinal employer-employee register, containing information on the age, gender, place of work, education, labor market status and occupation of each individual aged 15-74 between 1980 and 2012. The information is updated once a year in week 48. From this register, we only keep individuals who are employed full time every year in the period from 1995 to 2012. The individual information in *IDA* is used in the worker-level regressions but also to measure a number of workforce characteristics at the firm-level, such as the share of R&D workers.

Our second database is Firm Statistics Register (FirmStat henceforth), which covers the universe of private-sector firms over the years 1995-2012. It provides the annual value of firm productivity[12] and the 4-digit level classification of the Danish Industrial Activities.

The third database is the *Foreign Trade Statistics Register* and is available from 1993 through 2012.[13] It contains data on import and export sales and the number of imported and exported products at the firm-level for the same period as *FirmStat*. This database provides data both by specific destination and at an aggregated level. Imports and exports are recorded in Danish kroner (DKK) according to the 8-digit Combined Nomenclature as long as the transaction is worth at least 7500 DKK or involves goods that weigh at least 1000 kg.[14] From the trade transactions database, we calculate the export share of each

[11]Specifically, we focus on firms that were ever part of the manufacturing sector, because it is possible that former manufacturing firms offshore most or all of their production activities and thus are now classified as a service firm. These "factoryless goods producing" firms (FGPFs) are firms that no longer control production and assembly in-house but are still involved in other tasks such as design, R&D, and marketing (Bernard and Fort, 2015). Firms switching from manufacturing to service industries is important in explaining the decline in Danish manufacturing employment (Bernard et al., 2017). For these firms, we measure import competition at the industry that they used to be affiliated to (i.e., one of the manufacturing industries) before switching out to a service industry.

[12]Firm productivity, is calculated as turnover per employee in logarithmic scale (i.e., labor productivity). We deflate all monetary values using the World Bank's GDP deflator with 2005 as the base year.

[13]We use 1993 as a pre-sample year in the construction of our instrumental variables as explained in the next section. The sample period used in all regressions goes from 1995 through 2012.

[14]7500 DKK is equivalent to approximately 1000 euros at the time of writing. Since the introduction of the euro, the Danish Central Bank has adopted a fixed exchange rate policy vis-a-vis the euro.

product in the corresponding industry that is used in the construction of our measure of import competition at the 4-digit industry level, as explained in the next section.[15] To construct our import competition variable and its instrument, we merge the export share of each product in the corresponding industry to the U.N. COMTRADE data.[16]

The final database is a collection of patent applications sent to the European Patent Office (PATSTAT, 2015) by Danish firms. The 2015 PATSTAT patent dataset from the European Patent Office contains detailed information on all patent applications from every patent office in the world by year 2015. We count every patent owned by Danish firms, regardless of the patent office that granted the patent rights. We combine the firm-level data with patent applications through matching by name and address of the head-quarter as in Bloom et al. (2016).[17]

3.1 Descriptive Statistics

The first panel of Table 1 reports the descriptive statistics of the main dependent variables at the firm-level used in the empirical analysis. We measure the intensive margin of innovation as the number of patent applications (Hall et al., 2005).[18] Its average is reported in the first row of Table 1 and it is very close to zero. Furthermore, our sample comprises around 2 percent of firms that apply for at least a patent over the whole sample period. Those firms are classified as tech firms in the remainder of the analysis. Patents as a measure of innovation, like any other innovation indicators, present both advantages and disadvantages. On the positive side, patent applications (i) are a direct outcome of the innovation process

[15] We map international import data at the product level to the 4-digit industry level by merging the trade transactions data with *FirmStat*, where for each firm we observe product and industry codes.

[16] The first 6-digits of the Combined Nomenclature in the *Foreign Trade Statistics Register* are the same as the product classification in the COMTRADE data, i.e., the HS classification. However, we use the 4-digit level aggregation to considerably improve consistency over time.

[17] This type of match presents many challenges, notably arising from the way applicants are stored in PATSTAT. The first issue is the lack of harmonized names, which means that the same entity may have several separate database entries (due also to the many different spellings of a single organization or name changes over time). Another issue is the lack of comprehensive information about applicants (only address information is available, and still this piece of information is not standardized and often partial or missing). In the name match phase, four criteria are combined in order to increase match accuracy: 1) perfect match: where names, removing legal designation, are exactly the same; 2) Alphanumeric match: where the names, keeping only [A-Z] and [0-9] are the same (e.g.: I.B.M. = IBM = I B M); 3) Jaro-Winkler distance: names are broken into tokens and the similarity score is computed by the number of tokens in common, weighted on the inverse of frequency. The higher the Jaro-Winkler distance for two strings, the more similar the strings. Only results above a threshold value have been considered valid matches; 4) Levensthein distance: this measure is an edit distance counting the number of changes needed to transform the former name into the latter. For a full description of the methodology please refer to Tarasconi and Menon (2017).

[18] In one of our refinements, we use the number of patent grants as a measure of innovation. Furthermore, we prefer to use the number of patent applications instead of its log transformation to avoid the issues highlighted in Campbell and Mau (2020). For completeness, we also report in columns 12 and 13 of Table A1 in the online appendix the main results obtained by using respectively the log of (patent applications+1) and the negative hyperbolic sine of patent applications as dependent variables.

and (ii) can be documented. On the other side, not all inventions are necessarily patentable or linked to patent applications, and firms may present different propensity to apply for a patent. Though with some important limitations, we believe that patent applications is a rather conservative and objective measure of innovation, and thus a plausible and suitable proxy for our purpose.

In order to validate our measure of innovation, we plot in the first panel of Figure 4 the total number of patent applications against the total R&D expenditures retrieved from all the available waves of the Danish R&D and Innovation Survey (FUIS, henceforth) over the period from 1995 through 2012.[19] We find a positive and strong correlation between the two proxies for innovation measured at the industry and year levels. That is, industry-year pairs, that report large number of patent applications, feature at the same time high levels of R&D expenditure.

[Insert Figure 4 about here]

We use the classification of knowledge-intensive occupations suggested by Bernard et al. (2017) in order to identify workers involved with R&D activities, excluding technicians.[20] For instance, such R&D workers are engaged in medical jobs, natural sciences, social sciences, programming, or in using the highest skills in their professional area. According to this definition, the average share of R&D workers at the firm-level is approximately 3 percent with a standard deviation of approximately 0.08. We validate our classification of R&D, by comparing the industry-year total number of R&D workers from the register to the one calculated from the FUIS data. In the second panel of Figure 4, reassuringly the data show a strong and positive association between the two measures. This lends support to our measure of R&D workers.

[Insert Table 1 about here]

The remainder of Table 1 shows the descriptive statistics of the independent variables used in our regression models at the firm-level. As we explain more extensively in the next section, the key variable of the empirical analysis is import competition from China at the industry level, which is measured as the log of the weighted sum of imports for all HS products from China to Denmark, EU15, and the USA. The instrument of our import competition variable is reported in the next row. Similar to Hummels et al. (2014), it is based on the shocks to 4 high-income countries' import demand for Chinese goods. Those countries

[19]Further details the FUIS data can be found in this link: $https://www.dst.dk/da/Statistik/Publikationer/VisPub?cid = 17627$

[20]Similar results (reported in column 2 of Table A-2 in the online appendix) are obtained by using the complete classification of R&D, i.e. the one that includes technicians.

are Australia, Japan, New Zealand and Canada. In an alternative definition, we calculate the import competition from new EU members, instead of China, by using import values from Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, the Slovak Republic, Slovenia, Cyprus, and Malta who joined the EU in 2004 and Bulgaria, and Romania who joined in 2007. Its instrument is calculated as the total import values of the above mentioned 4 high-income countries from these new EU member countries.

Figure 5 shows basic time-series variation in the total number of patent applications (top panel), the share of R&D workers (middle panel) and the import competition variable (bottom panel) over the sample period. The top panel shows a steep long-run upward trend in the total number of patent applications, which in 2012 was about six times as large as it was in 1995. There is also a positive trend in the share of R&D workers, which increased from slightly more than 2 percent in 1995 to approximately 4 percent in 2012. The same holds true for import competition from China. Over the same sample period, our import competition variable increased from about 19 to 21, which is a 200 percent increase.

[Insert Figure 5 about here]

In order to corroborate our findings on the effects of Chinese import competition on labor reallocations within- and between-firms, we examine a broad set of worker-level outcomes. Specifically, we estimate the impact of import competition on: i) worker's probability of switching to an R&D job, conditional on staying employed at the same manufacturing firm for at least 3 years ("Stayers"); ii) worker's probability of being hired as an R&D worker by another manufacturing firm ("Move def.1"); iii) worker's probability of moving from a non-tech or non-high-productivity firm to a tech or high-productivity firm in the manufacturing industry ("Move def.2"). The first worker outcome captures labor adjustments within the same firm in response to import competition. Its sample average is around 1 percent, as reported in Table 2. The other worker-level outcomes are calculated conditionally on moving from one firm to another one. Those variables have an average within a range of 4.5 ("Move def.2") to 6 percent ("Move def.1") and are used to measure workers' between-firm reallocation in response to the increased import competition from China. The remainder of Table 2 shows the descriptive statistics of the individual variables used in the worker-level analysis, such as workers' labor market experience and tenure.

[Insert Table 2 about here]

To provide preliminary insight into the relationships of interest, we plot the number of patent applications at the 4-digit industry level against Chinese import competition (Figure 6), after accounting for 2-digit sector and year fixed effects. We also plot the share of R&D workers at the 4-digit industry level against Chinese import competition (Figure 7). In both scatter plots, a significant positive relationship is evident, consistent with the notion that import competition increases the innovation and the share of R&D workers at the firm-level. In the next section, we examine whether these relationships hold in more rigorous empirical specifications. Finally, Figure 8 shows that innovation is positively correlated with share of R&D workers. Hence, below we also analyze how much of the increase in innovation triggered by import competition is mediated through the increase in the share of R&D worker.

[Insert Figures 6,7 and 8 about here]

4 Empirical Strategy

4.1 Firm-level Analysis

We use the following specification to examine the impact of Chinese import competition on firm-level outcomes, i.e., the intensive margin of innovation and the share of R&D workers:

$$Outcome_{ijt} = \alpha_0 + \beta_1 Imp^{CH}_{jt-1} + X'_{ijt-1}\gamma_1 + \delta_i + \delta_m + \delta_t + \epsilon_{ijt} \tag{3}$$

where the dependent variable, $Outcome_{ijt}$, is the outcome of firm i, in the 4-digit industry j and in year t.[21] Our main independent variable, Imp^{CH}_{jt-1}, measures the level of Chinese import competition and is calculated as follows:

$$Imp^{CH}_{jt-1} = log(\sum_{p=1}^{P} \frac{exports_{jp1995}}{exports_{j1995}} Imp^{CH-EU15-US}_{pt-1}) \tag{4}$$

where $Imp^{CH-EU15-US}_{pt-1}$ is the total purchases of product p by the EU-15 countries (including Denmark) and the USA from China at time $t-1$.[22] We include the imports from the other EU-15 countries (beside Denmark) and the USA to capture the fact that the rise

[21] It is important to note that the linear specification may be problematic when we use the number of patent applications because it contains a large number of zeros (Campbell and Mau, 2020). To address this issue it would be appropriate to use a negative binomial count model instead. However, it is not straightforward to take into account both the endogeneity of the import competition variable and the numerous fixed effects in a count model. When in fact we try to estimate a negative binomial model with all of the fixed effects and in a specification in which we address the endogeneity of import competition by adding the residuals obtained from our first-stage IV regression, this model does not converge by using the canned routine "xtnbreg" in stata (see column 10 of Table A1). However, we report in the online appendix (column 11 of Table A1) the results obtained from a count model in which we rule out sector fixed effects but we keep the firm and year fixed effects and the first-stage residuals. It's encouraging that the coefficient estimated from this simplified negative binomial model on the import competition variable is in line with the one reported in the main results. We take this as suggestive evidence that the linear specification estimated in the main analysis does not provide a misleading result on the effect of Chinese import competition on firms' patent applications.

[22] As an alternative definition, we calculate our import competition variable by using import values by the EU-15 countries and the USA from new EU members as in Dauth et al. (2014).

of Chinese exports affects Danish firms not only through intensifying competition in the domestic market, but also in foreign markets where Danish firms export to and therefore compete with China.[23] The weights, $\frac{exports_{jp1995}}{exports_{j1995}}$, are export shares, which are time invariant and industry-specific.[24] The variable $export_{jp1995}$ represents Danish industry j's export value of product p to the world market in year 1995, whereas $export_{j1995}$ denotes Danish industry j's total exports to the world market in the same year. One important reason for using export shares is to ensure an industry actually is involved in the production of the item (at the 4-digit level of the HS classification) for which it also faces import competition. For instance, if an industry imports tea but it does not export tea, then the import competition variable is set to zero for this specific item. Also, note that import competition and the other independent variables are lagged to account for the fact that firms cannot, for example, immediately respond to changing economic conditions.[25]

The vector X_{ijt-1} includes a set of firm characteristics that could influence our firm-level outcomes, such as firm-level productivity, labor turnover rates, offshoring status, robot adoption, import and export values.[26] Specifically, the inclusion of productivity and import values in our estimating equation controls for the potential "productivity effect" on innovation associated with getting access to cheaper or better foreign inputs. The firm-level offshoring controls for the reorganization effects highlighted in Bernard et al. (2020). A recent study for Denmark (Humlum, 2019) shows that the adoption of industrial robots induces manufacturing firms to hire R&D workers and increase innovation. To control for this channel, we include a dummy variable equal to 1 if the firm imports robots.[27] The export values control for the market size effect brought by export liberalization, as in Aghion et al. (2018) and Coelli et al. (2016).

Furthermore, we incorporate firm fixed effects (δ_i) and 2-digit-manufacturing-sector and year fixed effects (δ_m and δ_t). All these additional control variables allow us to focus more carefully on the effects of foreign competition.[28]

[23] Danish export sales to the other EU-15 countries and the USA represent in total more than 70 percent of total exports over the sample period (OECD, 2015).

[24] In the baseline regressions, we use industry-specific export shares instead of firm-specific export shares as weights to reduce endogeneity. However, qualitatively similar results are obtained when using firm-specific export shares in the calculation of alternative import competition measures. These additional results are reported in column 3 of Table A-1 and column 7 of Tables A-3 in the online appendix.

[25] Very similar results are obtained by using longer lags (see columns 6-9 of Table A-1 and columns 9-12 of Table A-3 in the online appendix).

[26] We identify the firms' offshoring status by using the narrow definition suggested by Hummels et al. (2014) and Hummels et al. (2018). Very similar results are obtained if we exclude offshoring firms from our sample. These additional findings are reported in column 5 of Table A-1 and column 8 of Table A-3 in the online appendix.

[27] Similarly to Humlum (2019), we construct robot adoption on the basis of information on imported robots.

[28] In a robustness check reported in column 3 of Table A-2 in the online appendix we augment the baseline specification with a proxy for firm-level liquidity, i.e. the log of total assets. Unfortunately this variable is

One possible threat to the identification of β_1 is that Chinese import competition is likely to be endogenous in regression (3), as innovation or technology shocks may affect imports. To address this endogeneity issue, we instrument China's import competition in Denmark, the EU-15, and the USA with China's import competition in other high-income countries (Australia, Canada, Japan and New Zealand), similarly to Hummels et al. (2014).[29] Specifically, the instrumental variable Imp^{IV}_{jt-1} is calculated as follows:

$$Imp^{IV}_{jt-1} = log(\sum_{p=1}^{P} \frac{export_{jp\_1993}}{export_{j\_1993}} Imp^{CH-HI}_{pt-1}) \tag{5}$$

where Imp^{CH-HI}_{pt-1} is the four high income countries' total purchases of product p from China at time t, weighted by Danish product export shares in the pre-sample base year (1993), which are constant, industry-specific, calculated two years before our sample period starts.[30]

While our instrument is centered on the base year export shares and thus is not subject to the same contemporaneous forces that affect the firms' outcomes explored in this study, we require our instrument to be also independent from any expectations in future trends of the same outcomes. We test such restriction by regressing the change in our instrument from 1995 to 1998 on the change in the firms' outcomes at the 4 digit industry level in the pre-sample period, i.e., 1993-1995.[31] Column 1 of Table 3 shows that we cannot reject the hypothesis of no correlation between our instrument and pre-sample growth of the main outcome variables used in the empirical analysis at the firm-level, such as the share of R&D workers and the number of patent applications. This result is robust to alternative periods used to calculate the growth rate of our instrumental variable (see columns 2-4 of Table 3).

In addition, we check whether the base-year (1993) export shares of each selected 4-digit product within each 4-digit industries ($\frac{exp_{jp\_1993}}{exp_{j\_1993}}$) are systematically correlated with potential

available only for a shorter period from 2001 through 2012. It is reassuring that the coefficient estimated on our import competition variable is not affected by this inclusion.

[29]In a refinement exercise reported in Tables A-1 (column 5) and A-3 (column 6), we instrument our endogenous variable with the (value weighted) proportion of products in the four-digit industry that were covered by a quota restriction on China in 2000 (prior to China's WTO accession) and that were planned to be removed by 2005 (Bloom et al., 2016). This identification strategy limits the estimation of equation (3) to the sample of firms in the textile and clothing industry over the period 1995-2005. It is encouraging to see that our main results are confirmed for a narrower sample of firms and with an alternative instrument.

[30]A threat to this identification strategy is that product demand shocks are correlated across high-income countries, in which case using cross-industry variation in China's penetration of other high-income markets as an instrument for the import competition faced by Danish firms may confound import growth with unobserved components of demand. Autor et al. (2013) implements a gravity-based strategy that differences out import demand in the purchasing country, thereby retaining supply-driven changes in China's export performance. The results obtained with the gravity-based strategy are similar to those with the IV approach. Hence, Autor et al. (2013) concludes that correlated import demand shocks across high-income countries don't seem to play an important role for the estimation of the effects of Chinese import competition.

[31]For the firm outcome variables, we use the pre-sample period because it is the period for which the data was available to form expectations about the outcome variables for the post-1995 period.

industry characteristics in the same year (Jaeger et al., 2018; Goldsmith-Pinkham et al., 2018). In columns 5-14 of Table 3 we focus on the 12 products with the highest Rotemberg weights, i.e. on the products that contribute the most to the identifying variation exploited in our empirical analysis. For none of these products we find a systematic cross-industry correlation in 1993 between the product's export share and the industry characteristics, such as average firms' productivity, capital intensity and share of workers with tertiary education. These results suggest that the base-year export share used in our instrument is very likely to be exogenous.

[Insert Table 3 about here]

4.2 Worker-level Analysis

In order to analyze workers' reallocation in response to import competition, we first estimate the following worker-level regression:

$$Outcome_{wijt} = \alpha_0 + \beta_1 Imp^{CH}_{jt-1} + Z'_{wt-1}\gamma_2 + X'_{ijt-1}\gamma_2 + \delta_w + \delta_m + \delta_t + \epsilon_{wijt} \tag{6}$$

where $Outcome_{wijt}$ is a dummy variable equal to 1 if a worker w is employed at firm i in manufacturing industry j between $t-2$ and t ("stayer") and switches to an R&D job in the same firm at time t (i.e., within-firm switches).[32] As in the firm-level analysis, our main independent variable is Imp^{CH}_{jt-1}, which measures the level of Chinese import competition at the industry j in which the worker is employed at time $t-1$. The vector X_{ijt-1} includes a set of firm characteristics, as described in the previous section about the firm-level empirical strategy, whereas Z_{wt-1} consists of a whole host of worker variables, such as workers' age and tenure. Further, we augment equation (6) with worker fixed effects δ_w and 2-digit-sector (δ_m) and year (δ_t) fixed effects. Last, we instrument Imp^{CH}_{jt-1} with exogenous shocks to other countries' import demand of Chinese goods in a 2SLS estimation similar to the firm-level analysis. This regression is first estimated on the sample of stayers.

We also estimate specification (equation 6) on the sample of workers who move between firms. In this case, the dependent variable $Outcome_{wijt}$ is equal to 1 if a worker w moves to another firm i and is hired as an R&D worker at time t, and 0 for all the other types of transitions within the manufacturing industry (i.e., movers def. 1 in Table 2). Then, we study a worker's probability of moving from a non-tech or non-high-productivity firm to a tech- or a high-productivity firm within the manufacturing industry regardless of the resulting job type (i.e, movers def. 2 in Table 2).[33]

[32] The dummy variable returns to 0 after a worker's job change until his/her next job change.

[33] In def.1 and def.2 we don't condition on the worker's previous job type, unless otherwise mentioned.

5 Results

This section presents our findings about the effects of import competition on firms' innovation and workers' reallocation towards R&D jobs. Using these estimated effects, we quantify how much of the firms' increase in innovation channels through an increase in its share of R&D workers. To highlight the underlying mechanisms, we study to what extent import competition induces a reallocation of workers towards R&D jobs within- and between-firms using both firm- and worker-level data. Our results show that the between-firm reallocation is a salient margin of adjustment in response to import competition in Denmark. Finally, we draw on an alternative labor market setting where between-firm reallocation is arguably more restricted by using Portuguese data. This extension corroborates the importance of the between-firm mechanism in the import competition-innovation relationship.

5.1 Main Analysis

We first explore whether Chinese import competition affects firms' innovation. Column 1 of Table 4 shows a positive association between import competition at time $t-1$ and the number of patent applications in the subsequent year, after controlling for firm characteristics, firm, sector and year fixed effects. In column 2, we turn to our instrumental variable approach to address endogeneity concerns. The first-stage result shows that the instrument has a significant positive impact on import competition (see bottom panel of Table 4). The first stage F-stat is well above 10, indicating a strong first stage. The second stage result in column 2 reveals that a 100 percent increase in the lagged import competition from China raises the number of patent applications by 0.002, which corresponds to a 7 percent increase.[34] This finding confirms the positive impact of import competition on innovation at the firm-level found in previous studies (Bloom et al., 2016; Bao and Chen, 2018; Bombardini et al., 2017; Yamashita and Yamauchi, 2020).[35]

We also estimate the impact of Chinese import competition on the share of R&D workers at the firm level. In the results reported in column 3 of Table 4, we find that Chinese import competition is positively related to the share of R&D workers. The import competition coefficient of 0.0007 implies that a 100 percent increase in import competition in year $t-1$ is associated with a 2.4 percent increase in the share of R&D workers in year t, after controlling for firms' characteristics and numerous fixed effects. Our IV approach shows that Chinese

[34] This figure is calculated from 0.002/0.028, where the denominator is the sample mean of the innovation measure reported in the bottom panel of Table 4.

[35] Similar results are reported in Table A-1 of the online appendix when: i) we exclude either newly established or incumbent firms; ii) we focus on a sample of exporting firms and use a firm-specific measure of import competition; iii) we use longer lags for the import competition variable.

import competition significantly increases the share of R&D workers.[36] Specifically, a 100 percent increase in import competition in year $t-1$ leads to a 0.0012 increase in the share of R&D workers in year t, which corresponds to a 4.2 percent increase.[37]

Note that for both firm-level outcomes the import competition coefficients in the IV specifications (columns 2 and 4) are larger in magnitude than the analogous OLS coefficients (column 1 and 3). This is consistent with the endogeneity concern, which predicts that unobserved technology shocks that increase innovation and the share of R&D workers are negatively correlated with imports. Finally, both sets of results are in line with Proposition 1 from our theoretical model.

We then examine how much of the total effect of import competition on innovation channels through the exogenous increase in the share of R&D workers, i.e. we test Proposition 2 from our model. According to the coefficient reported in column 6 of Table 4, a one percentage point increase in the share of R&D workers at time $t-1$ that is exogenously induced by import competition shocks raises the number of patent applications by 0.0066. Given that a 100 percent increase in import competition raises the share of R&D workers by 0.12 percentage points (see column 4 of Table 4), we can conclude that about 40 percent of the total increase in the number of patent applications due to import competition (0.002) channels through the exogenous increase in the share of R&D workers also due to import competition ($0.66\times0.0012=0.0008$).

[Insert Table 4 about here]

5.1.1 Refinements

We test the robustness of the main findings reported in columns 5 and 6 of Table 4 on the role played by the share of R&D workers in the import competition-innovation relationship by conducting the following refinements in Table 5. First, we obtain similar results by using the number of patent grants as a measure of innovation (column 1) or resorting to our alternative measure of import competition shocks based on new EU countries (column 2).[38]

[36] We find similar results reported in the online appendix if we exclude workers with less than secondary education from the share of R&D workers (column 1 of Table A-2) or if we use the total number of R&D workers instead of its share as dependent variable (column 1 of Table A-3).

[37] Incumbent firms have on average a larger share of R&D workers and a higher number of patent applications compared to firms that exit or enter the market over the sample period. They also feature slightly different trends in the outcome variables as reported in Table A-0 of the online appendix. Comparable results are obtained by focusing on either incumbent or newly established firms (see columns 3 and 4 of Table A-3 in the online appendix).

[38] The EU-15 countries, including Denmark, experienced an unprecedented increase in trade with these new EU members over the course of the sample period (Dauth et al., 2014). The new-EU countries include Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, the Slovak Republic, Slovenia, Cyprus, and Malta who joined the EU in 2004 and Bulgaria, and Romania who joined in 2007. The corresponding instrumental variable is calculated as the total import values by Australia, Canada, New Zealand and Japan from the

Second, we augment the main specification with an interaction between the share of R&D workers and a dummy for high-performance firm (type-1 firms in the theoretical model) in column 3. Specifically, we classify firms as high-performance ones if they feature a productivity above the 75th percentile of the industry distribution (i.e., high-productivity firms) and/or they apply for at least a patent over the sample period (i.e., tech firms). The interaction specification reveals that the impact of an exogenous increase in the share of R&D workers on innovation is larger for the high-productivity/tech firms compared to the other firms (33 versus 23 percent increase in the number of patent applications for each percentage point increase in the share of R&D workers). This lends empirical support to the second part of Proposition 3: type-1 firms benefit the most from increases in the share of R&D workers due to import competition in terms of innovation outcomes.

[Insert Table 5 about here]

Danish firms react to Chinese import competition by filing a larger number of patent applications or grants. This does not necessarily imply that Danish firms are becoming more innovative. In fact, these patents might not capture new products but rather protect firms' intellectual property rights for existing products. We now examine whether this is the case by using information on firm product from the Danish custom data. Specifically, in columns 4 and 5 of Table 5 we investigate how Danish firms respond to Chinese import competition by adjusting product composition, i.e., adding and dropping exported products. We find that Danish firms are more likely to both add and drop products, conditional on exporting. Specifically, a 100 percent increase in Chinese import competition at time $t-1$ raises the probability of both adding and dropping at least one product by 2 percent.

We then estimate how much of this increase in product mix channels through the increase in the share of R&D workers driven by Chinese import competition shocks in columns 6 and 7. One percentage point increase in the share of R&D workers due to import competition at time $t-1$ triggers an 11 percent increase in the likelihood of the firm starting or quitting at least one exporting product (columns 6 and 7). Given that a 100 percent increase in import competition raises the share of R&D workers by 0.12 percentage points, we can argue that more than half of the increase in the likelihood of adding or dropping exported products due to import competition channels through the exogenous increase in the share of R&D workers.[39] These results confirm Proposition 2 that import competition induces domestic firms to become more innovative, i.e., to add new products thanks to the increase in the share of R&D workers at the firm level (Bernard et al., 2010).

new EU countries.

[39]Specifically, $11\times0.0012=0.0132$, which is approximately 70 percent of the total effect of import competition on the likelihood of adding new exported products.

5.1.2 Mechanisms: Within- and Between-firm Worker Reallocations

After having established that changing the share of R&D workers is important to innovation, we now examine how two types of worker reallocation, within- and between-firm, affect the share of R&D workers and thus innovation.

We first focus on the firm's share of R&D workers as dependent variable. In columns 1 and 2 of Table 6 we report again the estimated impact of import competition on the share of R&D workers from Table 4 for easy comparison. In column 3, we re-calculate the same share by only including the stock of stayers who switch to R&D jobs within the same firm. The impact of import competition is now about 14 percent of the one reported in column 2, i.e. a 100 percent increase in import competition in year $t-1$ increases the share of R&D workers (focusing on the stock of internal switchers) in year t by 0.6 percent. In column 4, we re-calculate the share of R&D workers by only including in the numerator the stock of between-firm R&D hires. The impact of import competition is 80 percent of the one reported in column 2, i.e., a 100 percent increase in import competition in year $t-1$ increases the share of R&D workers (focusing on between-firm R&D hires) in year t by 3.4 percent. From these results we can therefore conclude that about 14 percent of the increase in the share of R&D workers due to import competition is achieved by reallocating workers within firms. Around 80 percent is instead achieved by between-firm hiring.[40]

In column 5 of Table 6, we re-define the import competition variable by focusing on imports from Eastern European countries. The results show that import competition defined in this way still has a significant positive impact on share of R&D workers, which is of similar magnitude to the one estimated from our baseline specification in column 2.

In columns 6 and 7, we re-estimate the regressions from columns 3 and 4 by augmenting the main specification with the interaction between import competition and a dummy for high-productivity/tech firms, i.e., for type-1 firms in our theoretical model. We find evidence that both types of firms reallocate to the same extent existing workers to R&D jobs in response to import competition (column 6). However, when we examine the share of R&D workers that includes in the numerator only newly hired R&D workers from other firms (between-firm movers def.1), we find that type-1 firms engage in external hiring in order to increase their share of R&D workers to a larger extent compared to the other firms (4.4 versus 3.2 percent, see column 7). These results combined together are consistent with the first part of Proposition 3 from our theoretical model, according to which high-productivity firms achieve a larger increase in the share of R&D workers through external hires rather

[40]Note that less than 3 percent of the total impact goes through the hiring of newly hired workers from either long-term unemployment or school graduates. For long term unemployment, we mean a spell of unemployment that lasts more than a year. The coefficient obtained from including only these transitions in the share variable is reported in column 2 of Table A-3 in the online appendix.

than by reallocating existing workers to R&D jobs.

[Insert Table 6 about here]

Finally, we confirm the relevance of the "between-firm" channel in the last three columns of table 6 by conducting two additional refinements. In columns 8 and 9, we re-estimate our innovation regression by augmenting the specification from column 6 of table 4 with an additional variable that captures the intensity of the between-firm reallocation. This is calculated as the number of R&D workers hired from other firms (i.e., between-firm movers def.1) divided by the number of R&D workers resulting from both within- and bewteen-firms reallocation. The estimated coefficient on this variable suggests that, controlling for the share of R&D workers in a firm's total employment, a larger degree of worker reallocation to R&D jobs achieved through between-firms hiring is associated with more firm innovation. Specifically, according to the IV specification reported in column 9 in which we instrument the share of R&D workers in a firm's total employment, a percentage point increase in the intensity variable is associated with 0.0027 increase in the number of patent application, i.e. a 10 percent increase.

In column 10, we re-estimate the specification from column 6 of table 4 by replacing the share of R&D workers with its equivalent calculated by focusing on between-firm R&D hires. The estimated coefficient from this refinement suggests that a large fraction of the total increase in the number of patent applications due to import competition is explained by the increase in the share of R&D workers obtained from between-firms hiring. Specifically, a one percentage point increase in the share of R&D workers that is induced through the hiring of new workers from other firms in response to import competition shocks raises the number of patent applications by 0.012. This result suggests that newly hired R&D workers from other firms explain 25 percent of the total increase in the number of patent applications due to import competition,[41] or more than 60 percent (=25%/40%) of the increase in innovation that mediates through the total increase in the share of R&D workers.

5.2 The Salience of the Between-Firm Reallocation

In table 6 we have established the relevance of the between-firm reallocation using firm-level data for Denmark. We now further study this channel as follows. First, we conduct a worker-level analysis in order to provide further insights on the dynamics of workers' reallocation in response to import competition in Denmark. Second, we repeat both the firm and worker-level analyses using analogous employer-employee data from Portugal, where due to labor

[41] This number is obtained as follows: 1.20×0.00041 (from column 4 in Table 6) / 0.002 (from column 2 in Table 4)=0.0005/0.002=25 percent.

market rigidities and low productivity the between-firm reallocation in response to import competition is potentially more restricted compared to the Danish case. Such an extension provides us an additional opportunity to test the importance of the between-firm reallocation channel in explaining the nexus between import competition and innovation.

5.2.1 Worker-level Analysis Results

In the worker-level analyis, we first estimate the probability of switching to R&D jobs for workers who stay employed at the same firm (i.e., within-firm switches). Column 1 of Table 7 shows that an increase in Chinese import competition at time $t-1$ is positively related to the probability that a worker who stays employed with the same firm between $t-2$ and t switches to an R&D job at time t, after accounting for workers' and firms' characteristics, and sector and year fixed effects in a probit model. Column 2 reports an alternatively estimated marginal effect from a linear probability specification, in which we also control for worker fixed effects. Reassuringly, we find that the import competition coefficients in both columns are positive and statistically significant.[42]

While the numerous controls and fixed effects reduce endogeneity concerns, they do not eliminate them entirely, and thus we turn to our instrumental variable approach in column 3. The first-stage coefficient on the instrument is significant and positive as expected (see the bottom panel of column 3) and the first-stage F-stat on the instrument is well above 10. The second-stage IV result shows that Chinese import competition has a significantly positive impact on the likelihood that a "stayer" switches to an R&D job within the same firm. A 100 percent increase in import competition at time $t-1$ increases the probability of switching to R&D jobs at time t by 5.5 percent.[43] This is especially true for male workers, workers with tertiary education and workers with a long tenure at the current firm.[44]

Similar results are obtained by using our alternative measure of import competition (column 4). The interaction results in column 5 confirm that all firms included in the sample on average reallocate their existing workers to R&D. However, workers in high-performance

[42]Following the existing literature (Damm and Dustmann, 2014; Miguel et al., 2004), we prefer the flexibility of the linear probability model, because of the worker fixed effects and our instrument for import competition, which are more challenging in a probit specification. The linear probability model is unbiased and consistent as long as few of the predicted probabilities lie outside the unit interval (Horrace and Oaxaca, 2006). Moreover, Angrist and Pischke (2010) deem the linear probability model a preferable approach, when the nature of the non-linear model is unknown.

[43]Additional findings reported in column 1 of Tables A-4 (or A-5) in the online appendix reveal that import competition does not affect the reversed reallocation within the same (or in a different) firm, i.e., workers' switching out of R&D jobs.

[44]These additional results are reported in Table A-4 in the online appendix. The same table also reveals that there are no systematic differences in the effect of import competition across workers with different age or work experience. We also don't find heterogenous effects depending on whether the stayer is employed at an incumbent or a newly established firm.

firms feature a smaller probability of being reallocated to R&D jobs compared to stayers in other firms (1 versus 5 percent).

[Insert Table 7 about here]

In Table 6, we show that a significant fraction of the increase in the share of R&D workers due to import competition channels through between-firm worker reallocation to R&D jobs. We now further document this channel by examining how import competition affects a worker's probability of being hired as an R&D employee by another firm. The first two columns reveal that Chinese import competition at time $t-1$ is positively related to a worker's probability of moving to another firm and being employed in an R&D job at time t. Using our IV approach (column 3), we estimate that a 100 percent increase in Chinese import competition raises a worker's probability of being hired by another firm as an R&D worker by 21 percent, conditionally on moving. This is much larger than the increase of within-firm switching probability (5.5 percent). Additional results in the online appendix also show that the effect of import competition on the between-firm worker reallocation towards R&D jobs is stronger for male workers, workers with tertiary education and workers with long tenure.[45]

When we specifically examine a worker's probability of switching from a non-R&D to an R&D job when moving to another firm, we find a similar effect (column 4). It appears that firms increase the share of R&D workers by hiring workers from other firms, no matter whether these workers were already employed in R&D jobs. The estimated impact of import competition is fairly similar if we focus on the alternative definition of import competition based on new EU countries (column 5). Note that all these results are estimated on the import competition of the hiring firm's manufacturing industry and we neglect the role played by the import competition of the sending firm's manufacturing industry for cases in which a worker makes a between-industry transition but remains employed in the manufacturing sector. When we focus on this type of transitions and we try to include both measures of import competition, only the receiving firm's competition retains its significance.[46] Interenstingly, however, when we examine workers' transitions from the manufacturing to the service industry, import competition of the manufacturing industry positively affects the probability of being hired as an R&D worker in a service firm (column 6). A 100 percent increase in import competition at time $t-1$ raises the likelihood that a non-R&D worker from a manufacturing firm switches to an R&D job in a service firm at time t by approximately 6 percent. This result is consistent with Utar (2018) and Xu and Gong (2017), who

[45] These additional results are reported in Table A-5 in the on-line appendix. The same table also reveals that there are no systematic differences in the effect of import competition across workers with different age or work experience. We also estimate a stronger effect for the sample of newly established companies compared to the one comprising incumbent firms.

[46] These additional results are available upon request from the authors.

find that a non-negligible fraction of workers moves from the manufacturing to the service industry in response to increased import competition from China.

[Insert Table 8 here]

To dig deeper in the between-firm margin of adjustment and to test more explicitly Proposition 3 in the theoretical model, we then examine in Table 9 whether import competition affects workers' transitions from low- to high-performance firms. Specifically, as we did in the previous analysis we classify firms as high-performance ones if they feature a productivity above the 75th percentile of the industry distribution or if they apply for at least a patent over the sample period. The instrumented coefficient in column 3 reveals that a 100 percent increase in import competition raises workers' probability of moving from a low- to a high-performance firm by approximately 33 percent, conditionally on moving. This result supports the second half of Proposition 3 in the theoretical model, according to which externally hired workers are more likely to join high-performance firms.

When we further condition the above transition on being hired as an R&D worker, a 100 percent increase in import competition raises this type of worker reallocation by around 4 percent (column 4). We estimate a similar effect of import competition by using import competition from new EU countries (column 5). Finally, we also find a positive (although imprecisely estimated) impact of import competition on workers' transition to high-performance firms in the service industry (see column 6)

[Insert Table 9 about here]

5.2.2 The Case of Portugal

Our results so far show that Chinese import competition increases the share of R&D workers among Danish firms, and that 14 percent of this increase is due to within-firm workers' reallocation to R&D jobs while about 80 percent is due to the between-firm reallocation. We also find that 40 percent of the total impact of import competition on innovation is explained by the increase in the share of R&D workers, 60 percent of which is from between-firm workers' reallocation. We also show that a larger degree of between-firm relative to within-firm reallocation to R&D occupation is associated with more innovation at the firm-level.

Can we conclude from all these results that the between-firm reallocation of workers to R&D jobs is more important than within-firm reallocation in explaining the observed link between innovation and import competition? To corroborate this interpretation of the main results obtained for Denmark, we now extend our empirical analysis to Portugal. This extension allows us to further investigate the relevance of the between-firm worker reallocation channel to innovation and to test Propositions 3 and 4 in the theoretical model by examining a context in which firms' productivity is generally low and workers' transitions across firms are constrained by high adjustment costs, such as labor market frictions due to high firing and hiring costs.

Portugal provides an excellent comparison to Denmark for the following two reasons. First, both countries are small and trade-oriented and have very similar exposure to Chinese import competition (Figure 9). Second, they are extremely different in terms of firms' average productivity and labor market institutions. On the one hand, Denmark has a flexible labor market with few frictions that hinder labor reallocation across firms. On the other hand, Portugal is characterized by one of the most rigid labor markets in the world (Botero et al., 2004), with a restrictive employment protection legislation and high labor market frictions (Card et al., 2016). Furthermore, in our estimation samples Danish firms' average productivity is almost 4 times as large as Portuguese firms' one over the same period.[47] Due to these differences and similar exposures to Chinese import competition across the two economies, we expect labor reallocation towards R&D jobs (especially between-firm) and the response in terms of innovation to be weaker in Portugal compared to Denmark, consistently with Propositions 3 and 4. Therefore, estimating the same empirical specifications with Portuguese data will enable us to examine more carefully the relative importance of between- vs within-firm worker reallocation in explaining the innovation responses to import competition.

We conduct the empirical analysis using "Quadros de Pessoal" *(QP)*, a matched employer-employee dataset for Portugal. The *QP* dataset is comparable to the IDA dataset for Denmark in its structure and content (Buhai et al., 2014). It is an annual, mandatory employment survey administered by the Portuguese Ministry of Employment and covers all firms (with at least one wage earner) and their establishments and employees. The analysis of the Portuguese case is based on all active firms ever part of the manufacturing industry over the period 1995–2012.[48] Worker-level data files are used to estimate the worker-outcomes (such as the probability of switching to R&D jobs) and workforce characteristics (such as the share of R&D workers), whereas firm-level data allows us to measure firm characteristics (such as productivity). Custom trade data at the firm level[49] is obtained from Statistics

[47] The average log sales per worker (sd) in our sample of Danish firms is 13.780 (0.764) with a min of 1.973 and a max of 20.113. The same statistic is 10.887 (1.961) in the sample of Portuguese firms, with min of 0 and max of 17.70. The median of log productivity is 13.681 and 11.111 respectively in the Danish and Portuguese samples

[48] Note that the year 2001 is missing, as no data were collected at the worker-level in that year by the Portuguese Ministry of Employment.

[49] The Portuguese Classification of Economic Activities (CAE, comparable to NACE) underwent several changes over the period considered. To perform the empirical analysis over the same period covered by the Danish data (1995–2012), we standardize all industry classifications according to the earlier versions of NACE rev. 1.1, which is more aggregated than later versions (NACE rev. 2). This corresponds to

Portugal and merged with the QP dataset. Following the Danish case, we construct Chinese import competition and its instrument at the industry-level by using the export shares from the Portuguese custom data and information from U.N. COMTRADE at the product level. Finally, we combine the firm-level data with the patent applications from PATSTAT by matching names and addresses of firms' head-quarters, as we did for Danish firms.

Figure 9 shows basic time-series variation in the share of R&D workers (top panel), the total number of patent applications (middle panel) and the import competition variable (bottom panel) over the sample period for the manufacturing industry in Portugal. There is a positive trend in the share of R&D workers, which increased from less than 1 percent in 1995 to above 2 percent in 2012. The middle panel shows that the total number of patent applications more than doubled over the sample period. The same holds true for import competition, it increased from about 20 to 23, a 300 percent increase, even larger than the Danish case.

[Insert Figure 9 about here]

The main results for Portugal are presented in Table 10. In column 1, we examine the impact of import competition on innovation. In general, Chinese import competition has a positive effect on innovation: a 100 percent increase in the former increase the number of patent applications at the firm-level by 0.00016, which corresponds to a 1.33 percent increase, which is much smaller than Denmark's 7 percent increase and not as precisely estimated as in the Danish context. In column 2, we estimate the impact of Chinese import on the firm-level share of R&D workers. A 100 percent increase in import competition triggers a 3.5 percent increase in the share of R&D workers, which is slightly smaller than Denmark's 4.2 percent increase. Both sets of results are consistent with Proposition 4, i.e. an economy characterized by higher adjustment costs feature lower increase in the share of R&D workers and R&D output in response to a import competition shock.

Furthermore, in column 3, we find that a 100 percent increase in the share of R&D workers at time $t-1$, that is exogenously driven by import competition shocks, raises the number of patent applications by 0.16. Given that a 100 percent increase in import competition raises the share of R&D workers by 0.05 percentage points, we find that only 6 percent of the increase in the number of patent applications due to import competition channels through the exogenous increase in the share of R&D workers in Portugal.[50] For Denmark, this number is 40 percent.

When we focus on the share of R&D workers that focuses on internal switchers to R&D as dependent variable (column 4), a 100 percent increase in import competition leads to a

approximately 80 (3-digit) industries every year.

[50]Specifically, $0.16 \times 0.0005 = 0.00001$, which is around 6 percent of the total effect of import competition on the number of patent applications (0.00016).

2.8 percent increase in the share of such R&D workers, explaining about 60 percent of the total increase in the share of R&D workers that is reported in column 2. This implies that, contrary to the Danish case, the increase in the share of R&D workers resulting from import competition is mainly explained by within-firm reallocation of workers towards R&D jobs. Not surprisingly, the within-firm reallocation of labor towards R&D activities is stronger in Portugal than in Denmark. This is consistent with Proposition 3 and the fact that Portuguese firms are on average less productive than Danish ones.

These findings at the firm-level are corroborated by the worker-level regressions. We find that import competition raises the stayers' probability of switching to R&D jobs: a 100 percent increase in Chinese import competition triggers a 30 percent increase in the probability that a stayer switches to an R&D job (column 5). The counterpart effect for Danish workers is 5.5 percent. Furthermore, contrary to the Danish case, import competition insignificantly affects workers' probability of being hired to an R&D job by another firm (column 6).

[Insert Table 10 about here]

These results for Portugal combined with the Danish findings reported in Table 6 and discussed in Section 5.1.2 are consistent with Propositions 3 and 4 in the theoretical model that, although within-firm worker adjustments increase the share of R&D workers at the firm-level, they seem less effective in promoting innovation compared to between-firm adjustments in a context characterized by a larger share of low-productivity firms and higher labor adjustment costs. These results also corroborate the idea that Portugal's stringent labor market regulations limit the economy's ability to adjust to competitive shocks in the most efficient way (Branstetter et al., 2019). While acknowledging other non-labor market factors behind this cross-country difference, we are reassured by the fact that we estimate exactly the same empirical strategy applied to comparable databases and that we interpret our empirical comparison in light of the theoretical framework presented in Section 2.

6 Conclusions

Our paper shows that Chinese import competition triggers increases in innovations and the share of R&D workers among Danish firms. A 100 percent increase in import competition raises firms' number of patent applications by 7 percent, and in the Danish data the import competition has increase by 200 percent. Around 40 percent of this increase channels through the increase in the total share of R&D workers resulting from import competition. About 14 percent of the R&D worker share increase is due to existing workers switching to R&D jobs within firms and 80 percent is achieved through between-firm reallocation of workers.

Furthermore, we show that a larger degree of between-firm worker reallocation to R&D jobs relative to within-firm switching is associated with more firm innovation. These results are confirmed by a broad set of worker-level analyses.

When we extend the empirical analysis to Portugal, we find that, contrary to Denmark, import competition has a smaller positive effect on innovation and the increase in the share of R&D workers affects only marginally patent applications by Portuguese firms in response to import competition from China. Most of the increase in the R&D worker share is in the form of within-firm worker reallocation to R&D jobs instead of between-firm reallocation. These results together with the main findings for Denmark provide suggestive evidence that within-firm worker reallocation to R&D matters less for import-competition-driven innovation compared to between-firm worker reallocation.

Although not being directly tested in this paper, there are some possible explanations behind this important result that between-firm hiring may be a more effective way of improving innovation at the firm-level than within-firm job switching. For one, a firm's ability to attract external workers and to tap into a larger pool of talents than those within the firm can help expand innovation output. For another, between-firm hiring may help companies broaden their knowledge base (Kaiser et al., 2015). These are suitable agendas for future research.

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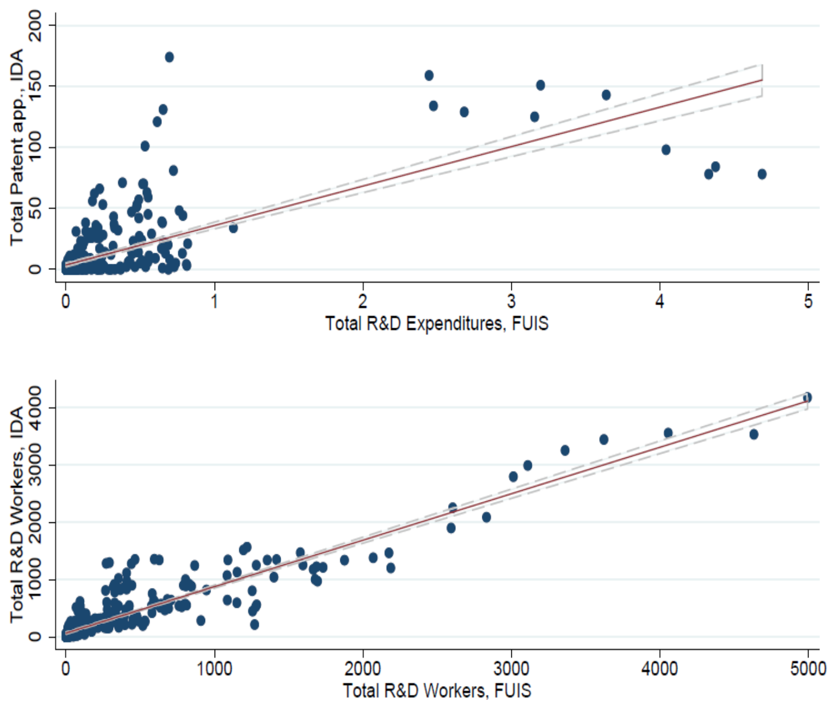
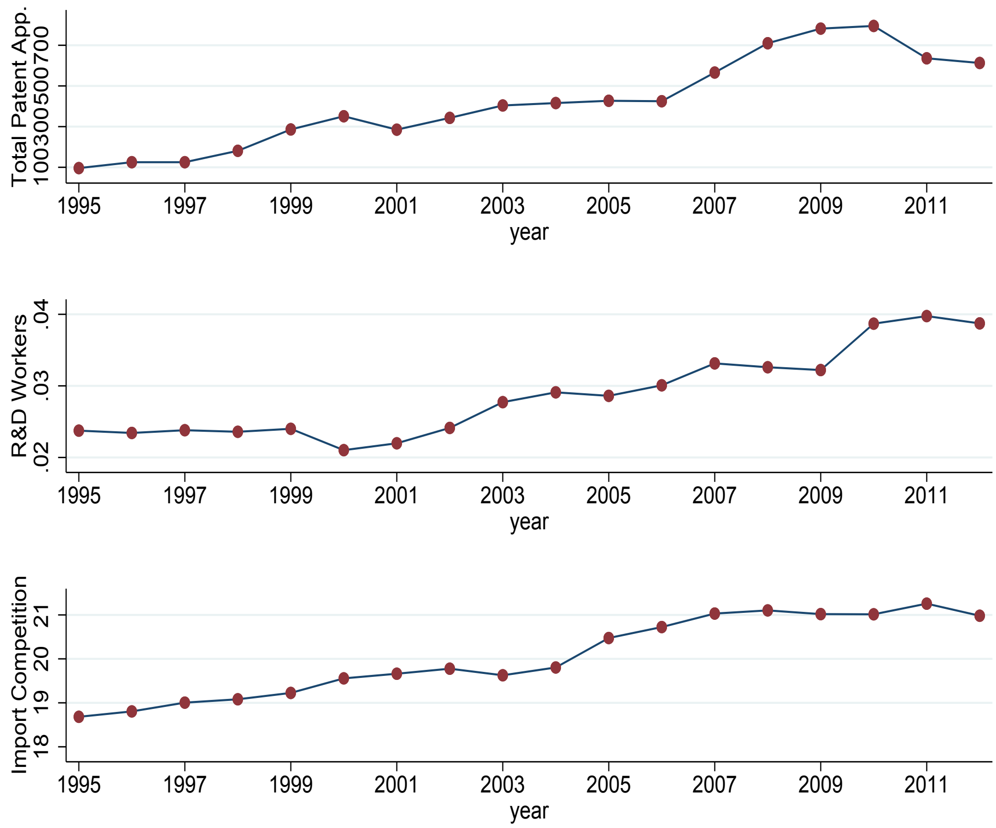
Figure 4: Validation of our measures of innovation and R&D workers



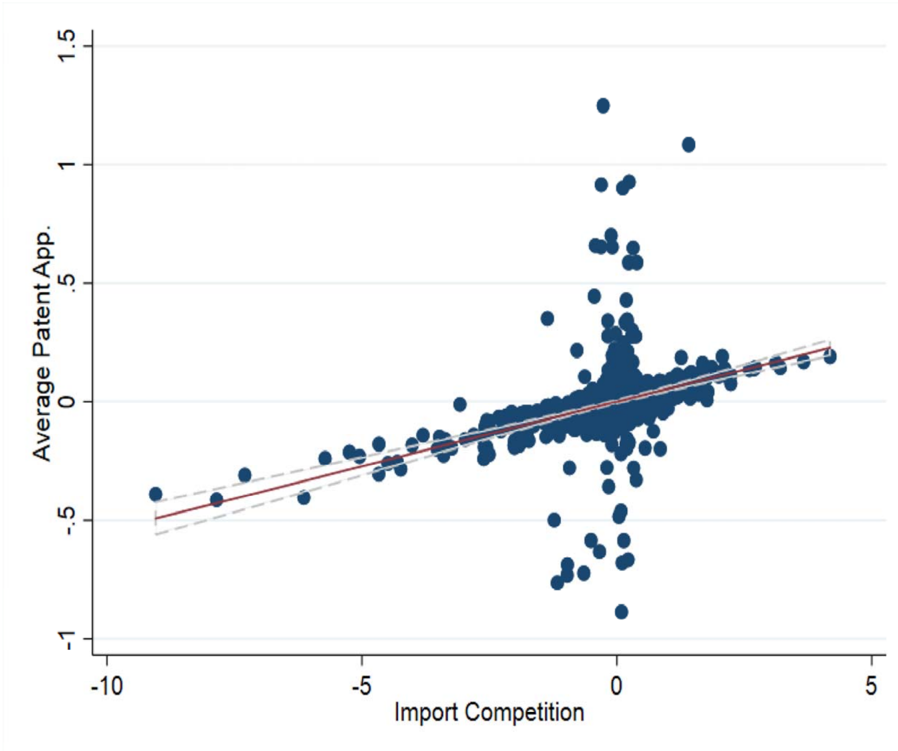
Notes: Total Patent app., IDA is calculated from the register data by adding up the firm-level number of patent applications for each year and 2 digit industry. Total R&D Expenditures, FUIS are the year-2 digit industry specific total real R&D Expenditures in billions of Danish kr. calculated from the Danish Innovation Survey data. Total R&D Workers, IDA are the year-2 digit industry specific total number of R&D workers calculated from the register data and according to our main definition. Total R&D Workers, FUIS are the year-industry specific total number of R&D workers calculated from the Danish Innovation Survey data.

Figure 5: Import Competition, R&D Workers, Patent Applications: Time Series Variation (Denmark)



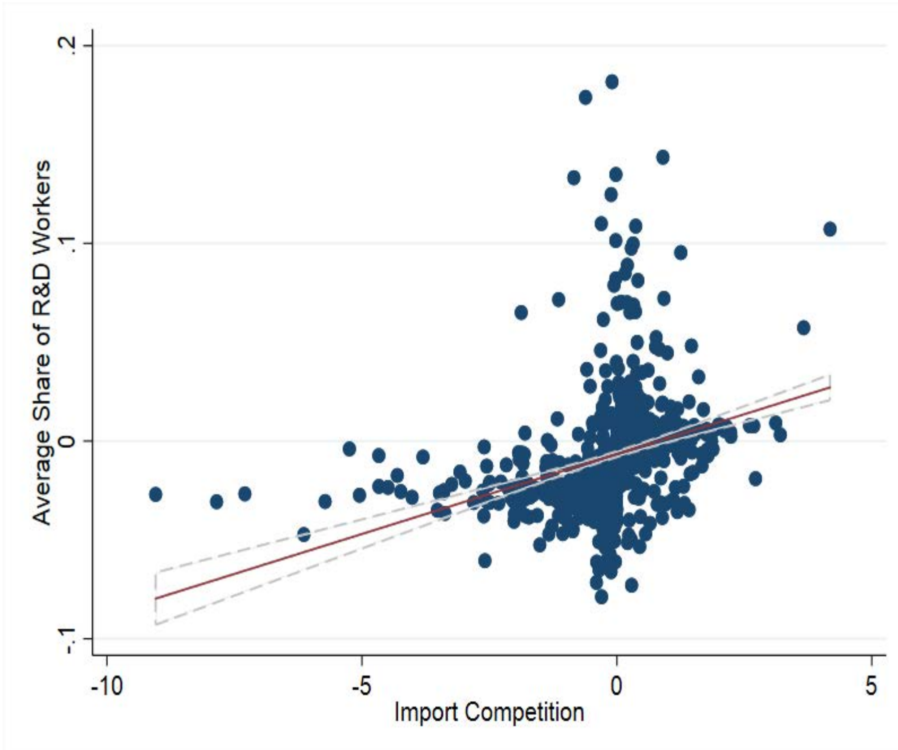
Notes: R&D Workers are the year-specific average share of R&D workers at the firm-level. Total Patent app. is calculated by adding up for each year the firm-level number of patent applications. Import Competition is the year specific average log of the weighted sum of import values of all HS products from China.

Figure 6: Innovation and Import Competition



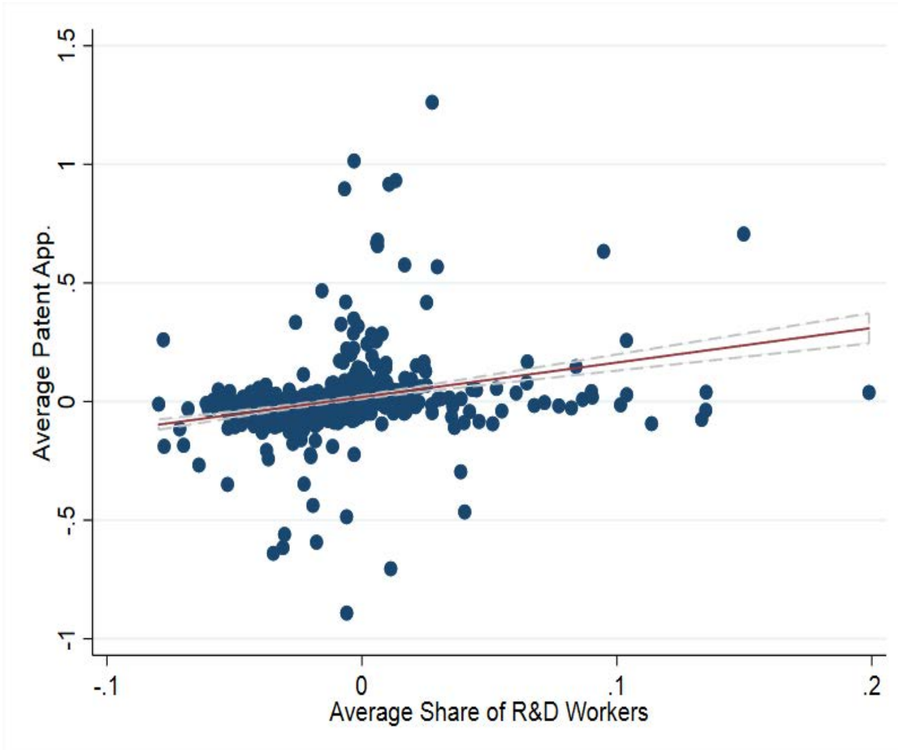
Notes: The average residuals at the 4-digit industry from regressing the number of patent applications on two-digit-sector and year fixed effects are reported on the vertical axis. The average residuals at the 4-digit industry from regressing the Chinese import competition variable on two-digit-sector and year fixed effects are reported on the horizontal axis.

Figure 7: Share of R&D Workers and Import Competition



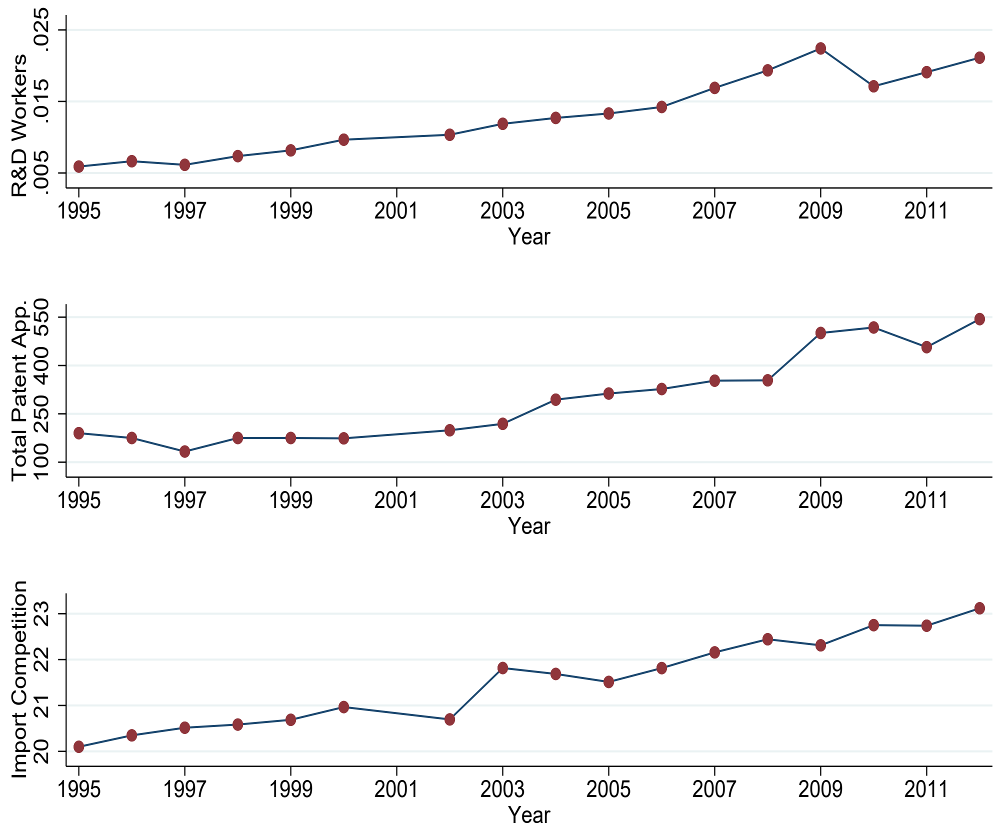
Notes: The average residuals at the 4-digit industry from regressing the share of R&D workers on two-digit-sector-and-year fixed effects are reported on the vertical axis. The average residuals at the 4-digit industry from regressing the Chinese import competition variable on two-digit-sector and year fixed effects are reported on the horizontal axis.

Figure 8: Innovation and Share of R&D Workers



Notes: The average residuals at the 4-digit industry from regressing the number of patent applications on two-digit-sector-and-year fixed effects are reported on the vertical axis. The average residuals at the 4-digit industry from regressing the share of R&D workers on two-digit-sector and year fixed effects are reported on the horizontal axis.

Figure 9: Import Competition, R&D Workers, Patent Applications: Time Series Variation (Portugal)



Notes: R&D Workers are the year-specific average share of R&D workers at the firm-level. Total number of patent applications is calculated by adding up for each year the firm-level number of patent applications. Import Competition is the year-specific average log of the weighted sum of import values of all HS products from China.

Table 1: Descriptive Statistics

Variables	Definition	Mean	SD
Outcome variables			
Intensive Margin of Innovation	number of patent applications	0.028	1.073
R&D Workers	share of R&D workers in a firm's total employment	0.029	0.079
Import competition variables			
Import Competition	log of the weighted sum of import values of all HS products by EU-15 and USA from China	20.179	2.048
Import Competition Instrument	log of the weighted sum of import values of all HS products by 4 high-income countries from China	19.240	2.048
Import Competition (alt. def.)	log of the weighted sum of import values of all HS products by EU-15 and USA from new EU countries	20.100	1.478
Import Competition Instrument (alt. def.)	log of the weighted sum of import values of all HS products by 4 high-income countries from new EU countries	17.196	1.767
Firm variables			
Exports	log of export (merchandise) sales	5.091	7.027
High Skilled Workers	share of workers with tertiary education	0.086	0.176
Imports	log of import (merchandise) purchases	5.317	7.105
Labor Turnover	number of newly hired workers over total number of employees	0.343	0.307
Offshoring	1, if firm offshoring production	0.198	0.398
Productivity	log of sales per worker	13.671	0.726
Size	log of total number of employees	3.441	12.311
Robot Adoption	1, if firm adopts industrial robots	0.002	0.037
Tech	1, if the firm applies for a patent in the sample period	0.023	0.048
N		229,844	
Average Number of Firms		12,973	

Notes: The four high-income countries used for the import competition instrument are Australia, Canada, Japan, and New Zealand. All descriptive statistics are calculated as averages over the period 1995-2012. Firm variables are in real Danish Kroner (using 2005 as the base year).

Table 2: Main Workers' Characteristics

	Definition	Stayers	Movers
Outcome Variables			
Stayers' within-firm switches	1, if a worker remains employed with the same firm between $t-2$ and t and switches from a non-R&D to an R&D job at time t	0.012	
Between-firm movers: def.1	1, if a worker moves to another firm and is employed in an R&D job at time t		0.060
Between-firm movers: def.2	1, if a worker moves from a non-tech or non-high-productivity firm to a tech or high-productivity firm at time t regardless of the job type after the move, unless otherwise mentioned		0.045
Workers' Variables			
Age	worker's age	43.133	37.832
Secondary Education	1, if worker with secondary education	0.586	0.555
Tertiary Education	1, if worker with tertiary education	0.127	0.114
Work Experience	worker's experience	20.581	15.368
Tenure	worker's tenure at a given firm	10.011	5.663
N		3,732,144	939,386

Notes: The dummy variable is 0 before and after a worker's job change until his/her next job change. Between-firm movers: def.1 and def.2 disregard a worker's previous job type, unless otherwise mentioned. All descriptive statistics are calculated as averages over the period 1995-2012.

Table 3: Pre-trend Tests and Base-Year Share Exogeneity

	Instrumental Variable Growth Rates			
	1998-1995	2000-1995	2005-1995	2012-1005
	(1)	(2)	(3)	(4)
R&D Workers$_{1995}$-R&D Workers$_{1993}$	0.01405	-0.00208	-0.00155	0.00270*
	(0.01120)	(0.00166)	(0.00153)	(0.00161)
R-sq	0.00336	0.00004	0.00002	0.00005
N	417	417	417	417
IntMargInno$_{1995}$- IntMargInno$_{1990}$	0.54393	0.48513	0.45135	0.12249
	(0.44079)	(0.52507)	(0.59921)	(0.51626)
R-sq	0.00104	0.00104	0.00006	0.00028
N	417	417	417	417
	Correlation Between Base-Year Share and Industry Characteristics			
	Product (4013)	Product (8211)	Product (3920)	Product (8308)
	(5)	(6)	(7)	(8)
Productivity	-0.00000	0.00000**	-0.00001	0.00001
	(0.00000)	(0.00000)	(0.00002)	(0.00001)
Capital Intensity	0.00000	-0.00000	0.00001	-0.00001
	(0.00000)	(0.00000)	(0.00001)	(0.00001)
High Skilled Workers	-0.00001	0.00000	-0.00005	0.00002
	(0.00000)	(0.00000)	(0.00005)	(0.00001)
Size	-0.00000	-0.00000	-0.00000	0.00001
	(0.00000)	(0.00000)	(0.00001)	(0.00001)
R-sq	0.01137	0.01015	0.03403	0.11703
N	417	417	417	417
	Product (5608)	Product (8434)	Product (8414)	Product (7314)
	(9)	(10)	(11)	(12)
Productivity	0.00002*	-0.00083	-0.00070	0.00003
	(0.00001)	(0.00085)	(0.00048)	(0.00002)
Capital Intensity	-0.00000	0.00040	0.00044	-0.00003
	(0.00001)	(0.00065)	(0.00034)	(0.00003)
High Skilled Workers	-0.00012	0.00002	-0.00228	0.00000
	(0.00011)	(0.00086)	(0.00217)	(0.00003)
Size	-0.00002	0.00103	0.00068	0.00000
	(0.00003)	(0.00094)	(0.00063)	(0.00001)
R-sq	0.01236	0.00874	0.04394	0.03566
N	417	417	417	417
	Product (8434)	Product (8416)	Product (0511)	Product (0303)
	(13)	(14)	(15)	(16)
Productivity	-0.00003	-0.00003	-0.00123	-0.00032
	(0.00005)	(0.00005)	(0.00137)	(0.00026)
Capital Intensity	-0.00012	0.00000	0.00059	0.00010
	(0.00014)	(0.00002)	(0.00102)	(0.00012)
High Skilled Workers	-0.00010	-0.00013	-0.01031	-0.00009
	(0.00009)	(0.00016)	(0.01095)	(0.00042)
Size	0.00027	-0.00002	0.00125	0.00027
	(0.00027)	(0.00002)	(0.00109)	(0.00017)
R-sq	0.00888	0.02853	0.03724	0.02046
N	417	417	417	417

Notes: In columns 1-4, the dependent variable is the growth rate of the instrumental variable and the explanatory variable is the change in the shares of R&D workers at the 4-digit industry level during the pre-sample period 1993-1995. In columns 5-16, the dependent variable is the export share of a selected product at the industry level in the base year 1993, and all explanatory variables are corresponding industries' characteristics in 1993. The products with the highest Rotemberg weights are selected. Product codes: 4013 (Inner Tubes of Rubber); 8211 (Knifes); 3920 (Polymers of Terephthalate); 8308 (Pliers of Leg Steel and Rivets); 5608 (Fishnets and Net Fabrics of Twine); 8434 (Machines for Milk and Cheese); 8414 (Vacuum Pumps and Compressors); 7314 (Wire Mesh, Tablecloths); 8438 (Machines for Bread, Meat); 8416 (Furnace Burners); 0511 (Animal Products Unfit for Human Consumption); 0303 (Frozen Fish). In columns 5-14, results are weighted by the number of firms in each industry at the base year. Robust standard errors are in parentheses. Significance levels are ***1%, **5%, *10%.

Table 4: Import Competition, Innovation and the Share of R&D Workers

Dependent Variable	**Intensive Margin of Innovation**		**R&D Workers**		**Intensive Margin of Innovation**	
	OLS (1)	**IV (2)**	**OLS (3)**	**IV (4)**	**OLS (5)**	**IV (6)**
Import Competition$_{t-1}$	0.00108*	0.00182**	0.00072**	0.00123**		
	(0.00053)	(0.00086)	(0.00031)	(0.00063)		
R&D Workers$_{t-1}$					0.03384**	0.66352*
					(0.01596)	(0.34908)
Firm Fixed Effects	yes	yes	yes	yes	yes	yes
Sector and Year Fixed Effects	yes	yes	yes	yes	yes	yes
Firm Characteristics	yes	yes	yes	yes	yes	yes
Mean Y	0.028	0.028	0.029	0.029	0.028	0.028
First Stage F-stat on Instruments	.	435.65	.	435.65	.	21.45
First Stage Import Comp. IV Coeff.	.	0.65620*** (0.0130)	.	0.65620*** (0.0130)	.	0.00160** (0.0008)
R-sq	0.11718	0.11708	0.28158	0.28150	0.11708	0.11999
N	229,844	229,844	229,844	229,844	229,844	229,844

Notes: In columns 1, 2, 5, and 6 the dependent variable is the number of patent applications at the firm level. In columns 3 and 4 the dependent variable is the share of R&D workers at the firm level. Firm characteristics include the lag of firm's size, offshoring status, robot adoption, share of high skilled workers, labor turnover, log of export sales, log of import sales and log of sales per employee. Robust standard errors clustered at the industry-year level are in parentheses. Significance levels are ***1%, **5%, *10%.

Table 5: Share of R&D Workers Explaining the Import Competition-Innovation Relation

	Intensive Margin of Innovation			Add Product	Drop Product	Add Product	Drop Product
	IV: Patent Grants (1)	**IV: IC Alt. Def. (2)**	**IV (3)**	**IV (4)**	**IV (5)**	**IV (6)**	**IV (7)**
R&D Workers$_{t-1}$	0.41207*	0.70494**	0.62768*			7.56349**	7.11285**
	(0.24220)	(0.30954)	(0.33709)			(3.00987)	(3.00765)
R&D Workers$_{t-1}$*HighPerf			0.30176*				
			(0.17123)				
Import Competition$_{t-1}$				0.01349***	0.01268**		
				(0.00511)	(0.00549)		
Firm Fixed Effects	yes	yes	yes	yes	yes	yes	yes
Sector and Year Fixed Effects	yes	yes	yes	yes	yes	yes	yes
Firm Characteristics	yes	yes	yes	yes	yes	yes	yes
Mean Y	0.030	0.028	0.028	0.67484	0.65184	0.67484	0.65184
First Stage F-stat on Instruments	21.45	15.31	21.45; 9.80	245.11	245.11	14.77	14.77
First Stage Import Comp. IV Coeff.	0.00160**	0.00185**	0.00160**; 0.00189**	0.61673***	0.61673***	0.00163***	0.00163***
	(0.0008)	(0.0009)	(0.0008); (0.0007)	(0.01018)	(0.01018)	(0.00028)	(0.00028)
R-sq	0.11161	0.11161	0.13156	0.37300	0.38190	0.48869	0.34530
N	229,844	229,844	229,844	43,873	43,873	43,873	43,873

Notes: In columns 2 and 3, the dependent variable is the number of patent applications at the firm level. In column 1, the dependent variable is the number of patent grants at the firm level. In columns 4 and 6, the dependent variable is a dummy equal to 1 if the firm exports at least one new product at time t. In columns 5 and 7, the dependent variable is a dummy equal to 1 if the firm quits exporting at least one product at time t. The "HighPerf" dummy is equal to 1 for firms who apply for at least a patent (i.e. tech firms) or whose average productivity is above the 75th percentile of the within-industry productivity distribution (i.e., high-productivity firms). Import Competition$_{t-1}$ is the log of the weighted sum of import values of all HS products by EU-15 and USA from China at time $t-1$. Instrumental variable is the log of the weighted sum of import values of all HS products from China by the following high-income countries: Australia, Canada, Japan and New Zealand. Firm characteristics include the lag of firm's size, offshoring status, robot adoption, share of high skilled workers, labor turnover, log of export sales, log of import sales, and log of sales per employee. Robust standard errors clustered at the industry-year level are in parentheses. Significance levels are ***1%, **5%, *10%.

Table 6: Import Competition, Innovation and the Share of R&D Workers, Mechanisms

	R&D Workers							**Intensive Margin of Innovation**		
	OLS	**IV**	**IV: Stayers' Within-firm Switches**	**IV: Between-firm Movers Def.1**	**IV: IC Alt. Def.**	**IV: Stayers' Within-firm Switches**	**IV: Between-firm Movers Def.1**	**OLS**	**IV**	**IV: Between-firm Movers Def.1**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Import Competition$_{t-1}$	0.00072**	0.00123**	0.00004*	0.00041**		0.00003*	0.00038*			
	(0.00031)	(0.00063)	(0.00002)	(0.00020)		(0.00002)	(0.00021)			
Import Competition$_{t-1}$*HighPerf						-0.00002	0.00015**			
						(0.00002)	(0.00008)			
Import Competition (alt. def.)$_{t-1}$					0.00112**					
					(0.00057)					
R&D Workers$_{t-1}$								0.03282**	0.61134**	1.19772**
								(0.01548)	(0.31081)	(0.54566)
Intensity of Between-firm Moves$_{t-1}$								0.25183**	0.27379**	
								(0.10874)	(0.11827)	
Firm Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sector and Year Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm Characteristics	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Mean Y	0.029	0.029	0.007	0.012	0.029	0.007	0.012	0.028	0.028	0.028
First Stage F-stat on Instruments	.	435.65	435.65	435.65	367.26	465.20; 689.05	435.65; 702.13	-	22.11	8.11
First Stage Import Comp. IV Coeff.	.	0.65620***	0.65620***	0.65620***	0.62652***	0.70078***; 0.88123***	0.65620***; 0.80477***	.	0.00166**	0.00023**
	.	(0.0130)	(0.0130)	(0.0130)	(0.00948)	(0.0294); (0.05681)	(0.0130); (0.05265)	.	(0.0081)	(0.0012)
R-sq	0.28158	0.28150	0.21682	0.10124	0.272825	0.23543	0.11591	0.11766	0.12007	0.11934
N	229,844	229,844	229,844	229,844	229,844	229,844	229,844	229,844	229,844	229,844

Notes: In columns 1-7, the dependent variable is the share of R&D workers at the firm level. In columns 3 and 6, the dependent variable only includes the number of stayers who switched to an R&D job (i.e., within-firm switches) in the numerator of the share. In column 4 and 7, the dependent variable only includes the number of new hires from other firms employed in an R&D job (i.e., between-firm movers def.1) in the numerator of the share, where stayers are defined as workers who remain employed in the same firm between $t-2$ and t. The "HighPerf" dummy is equal to 1 for firms who apply for at least a patent (i.e. tech firms) or whose average productivity is above the 75th percentile of the within industry productivity distribution (i.e. high-productivity firms). In column 5, the regression uses the new-EU member import competition instrument. Import Competition$_{t-1}$ (or alt. def.) is the log of the weighted sum of import values of all HS products by EU-15 and USA from China (or new EU countries) at time $t-1$. Instrumental variable is the log of the weighted sum of import values of all HS products from China (or new EU countries for the alt. def.) by the following high-income countries: Australia, Canada, Japan and New Zealand. In columns 8-10, the dependent variable is the number of patent applications at the firm level. Intensity of Between-firm Moves$_{t-1}$ is as the number of R&D workers hired from other firms (i.e., between-firm movers def.1) divided by the number of R&D workers resulting from both within- and between-firms reallocation. Firm characteristics include the lag of firm's size, offshoring status, robot adoption, share of high skilled workers, labor turnover, log of export sales, log of import sales, and log of sales per employee. Robust standard errors clustered at the industry-year level are in parentheses. Significance levels are ***1%, **5%, *10%.

Table 7: Import Competition and Switching to R&D Jobs Within a Firm at the Worker Level

Dep. Var.: Stayers' Within-firm Switches	**Probit (1)**	**OLS (2)**	**IV (3)**	**IV: IC Alt. Def. (4)**	**IV (5)**
Import Competition$_{t-1}$	0.05542*	0.00016*	0.00067**		0.00059*
	(0.02891)	(0.00009)	(0.00032)		(0.00032)
Import Competition$_{t-1}$*HighPerf					-0.00048**
					(0.00023)
Import Competition (alt. def.)$_{t-1}$				0.00072*	
				(0.00038)	
Worker Fixed Effects	no	yes	yes	yes	yes
Sector and Year Fixed Effects	yes	yes	yes	yes	yes
Worker Characteristics	yes	yes	yes	yes	yes
Firm Characteristics	no	yes	yes	yes	yes
Mean Y	0.012	0.012	0.012	0.012	0.012
First Stage F-stat on Instruments	.	.	607.14	338.95	607.14; 653.91
First Stage Import Comp. IV Coeff.	.	.	0.6283*** (0.0168)	0.3424*** (0.0064)	0.6283*** (0.0168); 0.65432*** (0.01876)
Pseudo R-sq; R-sq	0.18420	0.22642	0.22642	0.22642	0.24776
N	3,732,144	3,732,144	3,732,144	3,732,144	3,732,144

Notes: The dependent variable is equal to 1, if a worker i who remains employed in the same firm between $t-2$ and t (stayer) switches to an R&D job at time t (i.e., within-firm switches). The "HighPerf" dummy is equal to 1 for firms who apply for at least a patent (i.e. tech firms) or whose average productivity is above the 75th percentile of the within industry productivity distribution (i.e., high-productivity firms). Import Competition$_{t-1}$ (or alt. def.) is the log of the weighted sum of import values of all HS products by EU-15 and USA from China (or new EU countries) at time $t-1$. Instrumental variable is the log of the weighted sum of import values of all HS products from from China (or new EU countries) by the following high-income countries: Australia, Canada, Japan and New Zealand. Worker characteristics include the lagged value of age, tenure and work experience. Firm characteristics include the lag of firm's size, offshoring status, robot adoption, share of high skilled workers, labor turnover, log of export sales, log of import sales, and log of sales per employee. In column 1 the reported coefficient is the marginal effect. Robust standard errors clustered at the industry-year level are in parentheses. Significance levels are ***1%, **5%, *10%.

Table 8: Import Competition and the Probability of Being Hired by Another Firm to an R&D Job at the Worker Level

Dep. Var.: Between-firm Movers Def. 1	**Probit (1)**	**OLS (2)**	**IV (3)**	**IV: Switch to R&D (4)**	**IV: IC Alt. Def. (5)**	**IV: From Manuf. to Service (6)**
Import Competition$_{t-1}$	0.04859**	0.00366	0.01295**	0.00307**		0.00456*
	(0.02312)	(0.00252)	(0.00603)	(0.00136)		(0.00258)
Import Competition (alt. def.)$_{t-1}$					0.01188**	
					(0.00372)	
Worker Fixed Effects	no	yes	yes	yes	yes	yes
Sector and Year Fixed Effects	yes	yes	yes	yes	yes	yes
Worker Characteristics	yes	yes	yes	yes	yes	yes
Firm Characteristics	yes	yes	yes	yes	yes	yes
Mean Y	0.06043	0.06043	0.06043	0.01021	0.06043	0.07712
First Stage F-stat on Instruments	.	.	356.11	356.11	304.77	267.11
First Stage Import Comp. IV Coeff.	.	.	0.6179*** (0.0239)	0.6179*** (0.0239)	0.56101*** (0.01382)	0.4678*** (0.0085)
R-sq	0.15678	0.10200	0.10199	0.10199	0.10155	0.03147
N	939,386	939,386	939,386	939,386	939,386	99,692

Notes: In columns 1, 2, 3, and 5, the dependent variable is equal to 1, if a worker i moves to another firm within the manufacturing industry and is employed in an R&D job, regardless of the job type before the move. In column 4, the dependent variable is equal to 1, if a worker i moves to another firm within the manufacturing industry and switches from a non-R&D to an R&D job. In column 6 the dependent variable is equal to 1, if a worker i moves to a firm in the service industry at time t and is employed in an R&D job. Import Competition$_{t-1}$ (alt. def.) is the log of the weighted sum of import values of all HS products by EU-15 and USA from China (new EU countries) at time $t-1$. Instrumental variable is the log of the weighted sum of import values of all HS products from China (or new EU countries for the alt. def.) by the following high-income countries: Australia, Canada, Japan, and New Zealand. Worker characteristics include the lagged value of age, tenure and work experience. Firm characteristics include the lag of firm's size, offshoring status, robot adoption, share of high skilled workers, labor turnover, log of export sales, log of import sales, and log of sales per employee. In column 1 the reported coefficient is the marginal effect. Robust standard errors clustered at the industry-year level are in parentheses. Significance levels are ***1%, **5%, *10%.

Table 9: Import Competition and the Probability of Being Hired by a Tech or a High Productivity Firm at the Worker Level

Dep. Var.: Between-firm Movers Def. 2	**Probit (1)**	**OLS (2)**	**IV (3)**	**IV: Hired as an R&D Worker (4)**	**IV: IC Alt. Def. (5)**	**IV: From Manuf. to Service (6)**
Import Competition$_{t-1}$	0.01377**	0.00201*	0.01505**	0.00054*		0.00599
	(0.00681)	(0.00112)	(0.00749)	(0.00028)		(0.00437)
Import Competition (alt. def.)$_{t-1}$					0.01843**	
					(0.00802)	
Worker Fixed Effects	no	yes	yes	yes	yes	yes
Sector and Year Fixed Effects	yes	yes	yes	yes	yes	yes
Worker Characteristics	yes	yes	yes	yes	yes	yes
Firm Characteristics	yes	yes	yes	yes	yes	yes
Mean Y	0.04529	0.04529	0.04529	0.01203	0.04529	0.07462
First Stage F-stat on Instruments	.	.	356.11	356.11	304.77	267.11
First Stage Import Comp. IV Coeff.	.	.	0.6179*** (0.0239)	0.6179*** (0.0239)	0.56101*** (0.01382)	0.4678*** (0.0085)
R-sq	0.15678	0.10200	0.10199	0.10199	0.10155	0.03147
N	939,386	939,386	939,386	939,386	939,386	99,692

Notes: In columns 1, 2, 3, and 5, the dependent variable is equal to 1, if a worker i moves from a non-tech or non-high-productivity firm to a tech or high-productivity firm within the manufacturing industry at time t, regardless of the job type before and after the move. In column 4, the dependent variable is equal to 1, if a worker i moves from a non-tech or non-high-productivity firm to a tech or high-productivity firm within the manufacturing industry and is employed in an R&D job at time t, regardless of the job type before the move. In column 6, the dependent variable is equal to 1, if a worker i moves to a tech or a high-productivity firm in the service industry at time t. Import Competition$_{t-1}$ (or alt. def.) is the log of the weighted sum of import values of all HS products by EU-15 and USA from China (or new EU countries) at time $t-1$. Instrumental variable is the log of the weighted sum of import values of all HS products from China (or new EU countries for the alt. def.) by the following high-income countries: Australia, Canada, Japan, and New Zealand. Worker characteristics include the lagged value of age, tenure and work experience. Firm characteristics include the lag of firm's size, offshoring status, robot adoption, share of high skilled workers, labor turnover, log of export sales, log of import sales, and log of sales per employee. In column 1 the reported coefficient is the marginal effect. Robust standard errors clustered at the industry-year level are in parentheses. Significance levels are ***1%, **5%, *10%.

Table 10: Import Competition, R&D Workers and Innovation, Results for Portugal

	Dep. Var: Intensive Margin of Innovation	**Dep. Var: R&D Workers**	**Dep. Var: Intensive Margin of Innovation**
	IV	**IV**	**IV**
	(1)	**(2)**	**(3)**
Import Competition$_{t-1}$	0.00016*	0.00051**	
	(0.00009)	(0.00024)	
R&D Workers$_{t-1}$			0.16201*
			(0.09037)
Firm Fixed Effects	yes	yes	yes
Worker Fixed Effects	no	no	no
Sector and Year Fixed Effects	yes	yes	yes
Firm Characteristics	yes	yes	yes
Worker Characteristics	no	no	no
Mean Y	0.012	0.01478	0.012
First Stage F-stat on Instruments	476.11	476.11	9.89
First Stage- Import Competition IV Coeff.	0.68419*** (0.01558)	0.68419*** (0.01558)	0.0004*** (0.00009)
R-sq	0.1023	0.22344	0.0451
N	123,918	123,918	123,918
	Dep. Var.: R&D Workers (Excl. New Hires)	**Dep. Var.: R&D Switch**	**Dep. Var.: Move def. 1**
	IV	**IV**	**IV**
	(4)	**(5)**	**(6)**
Import Competition$_{t-1}$	0.00018*	0.00201**	0.00028
	(0.00010)	(0.00063)	(0.00231)
Firm Fixed Effects	yes	no	no
Worker Fixed Effects	no	yes	yes
Sector and Year Fixed Effects	yes	yes	yes
Firm Characteristics	yes	yes	yes
Worker Characteristics	no	yes	yes
Mean Y	0.00639	0.00685	0.00221
First Stage F-stat on Instruments	476.11	546.11	344.83
First Stage- Import Competition IV Coeff.	0.68419*** (0.01558)	0.78945*** (0.02308)	0.59151*** (0.01317)
R-sq	0.22344	0.3523	0.12311
N	123,918	1,036,333	711,128

Notes: In columns 1 and 3, the dependent variable is the number of patent applications at the firm level. In column 2, the dependent variable is the share of R&D workers at the firm level. In column 4, the dependent variable is the share of R&D workers calculated by only including the number of stayers who switched to an R&D job (i.e., within-firm switches) in the numerator of the share. In column 5, the dependent variable is equal to 1, if a worker i who remains employed in the same firm between $t-2$ and t (stayer) and switches to an R&D job at time t (within-firm switch). In column 6, the dependent variable is equal to 1, if a worker i moves to another firm in the manufacturing industry and is employed in an R&D job (between-firm movers def. 1). Firm characteristics include the lag of firm's size, offshoring status, robot adoption, share of high skilled workers, labor turnover, log of export sales, log of import sales, and log of sales per employee. Worker characteristics include the lagged value of age, tenure, and work experience. Robust standard errors clustered at the industry-year level are in parentheses. Significance levels are ***1%, **5%, *10%.