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Abstract

While recent work has documented a nexus between international trade and firm innovation, the underlying mechanisms explaining firms' innovation in response to import competition are thus far poorly understood. To identify such mechanisms and their economic relevance, we use longitudinal linked employer-employee 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. Approximately 40 percent of the innovation effect is attributable to the increase in the share of R&D workers; 14 percent of this increase in the share of 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 having 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 between-firm reallocation is further confirmed by a 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.

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1 Introduction

Over the past two decades, the extraordinary increase in exports from emerging economies, such as China, has emerged 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 to protect themselves against import competition (?Hombert and Matray, 2018; Kromann and Sørensen, 2019), 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. (2020) show that imports from China explain 40 percent of the slowdown in innovation among American firms between 1999 and 2007. However, 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.

The aim of our paper is to fill this gap by examining i) whether the innovation responses to import competition can be attributed to the increase in the share of R&D workers and 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 than 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 at work.

On the one hand, the within-firm workers' reallocation channel is consistent with the assumption that firms face high 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, between-firm worker reallocation can be interpreted as labor market poaching, i.e., productive firms hire additional workers from other companies 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), hiring external workers for R&D activities (Kaiser et al., 2015), or doing both. This may then translate into heterogeneous responses to import competition in terms of firms' R&D worker share and innovation.

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

[2] In a similar spirit, Bloom et al. (2016) show that patents, TFP, IT intensity and R&D expenditures increase among European firms that are more exposed to Chinese import competition, although recent findings obtained by Campbell and Mau (2020) have 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 retrained 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 17, 2019).

One of the 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 linked employer-employee 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 heterogeneous firm products and dynamic innovation decisions.[4] The model captures the costs and benefits of innovation and workers' reallocation within and between firms to 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 shock. We also perform comparative statics for low- vs. high-productivity firms and for low- vs. high-labor adjustment costs, thus providing theoretical guidance for 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, 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 in 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. 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) to identify R&D workers in the data. We then assess how import competition affects the within- and between-firm reallocation of workers to R&D jobs to delve deeper into the mechanisms behind the impact of import competition on innovation.

In the second set of regressions, we first utilize worker-level data to study whether import competition impacts Danish workers' probability of i) switching to an R&D job, conditional on remaining employed at the same firm; ii) moving to another firm and being employed as an R&D worker; and iii) moving to a high-productivity/high-tech firm. We then replicate the above analyses at both the firm and worker levels by using Portuguese data to further explore which type of worker 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 in Denmark, a 100 percent increase in import competition raises firms' number of patent

[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.

applications and the share of R&D workers by 7 and 4 percent on average, respectively. Approximately 40 percent of the increase in innovation is attributable to the total increase in the share of R&D workers resulting from import competition. Moreover, we find that approximately 14 percent of the increase in the share of R&D workers at the firm level is due to within-firm worker reallocation to R&D jobs, while 80 percent is due to between-firm worker reallocation. All these results are more pronounced for high-performance firms, i.e., high-productivity or tech firms. These firms react 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 than 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 a 100 percent increase in Chinese import competition raises a worker's probability of switching to an R&D job by 5.5 percent, conditional on remaining 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 but 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 is attributable to 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 weaker relation to firms' innovation in Portugal than in Denmark. 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, in addition to 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; Kromann and Sørensen, 2019).[5] Our second contribution is to study both within- and between-firm worker 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 on international trade. First, it relates to those studies exploring firms' innovation in response to their exposure to global markets. For instance, Bustos (2011) finds that exporting firms that operate in industries with a higher degree of competition increase investments in technology faster than less exposed firms. The main difference between that 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, and 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 the paper 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 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] Note that in contrast to Bernard et al. (2020), which examines the effect of offshoring on firms' reallocation of workers to R&D and innovation, we focus on the adjustments to 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 and the number of workers for each job type. Type-N goods face import competition from other countries, such as China. They are homogeneous, traded internationally, and produced by non-R&D workers n_j with the production function:

$$y_j^N = z n_j^\alpha,$$

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, although 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 in innovation ($a_j = \{a_1, a_2\}$). 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 state. 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 $i_j < 0$, 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] Such external hires and

[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] Our empirical exercises restrict external hires to between-firm (job-to-job) transitions only, except for column 2 of Table A-3 in the appendix.

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 are a quadratic function of the number of workers who internally switch occupation or who are externally hired with some parameter ϕ, respectively. 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 separately with its R&D workers and non-R&D workers. Workers can either work for the firm or be unemployed in a given time period. We assume Nash bargaining, i.e., firm j and each type of worker chooses a wage to maximize worker-firm joint surplus:

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

where $x = \{n_j, \gamma_j\}$ denotes the job type. $W_x = w_x - b_x$ and b_x are parameters 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 by $0 < \eta < 1$ worker 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:

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

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

[9] If ϕ is assumed to be higher for external hiring than for internal switching, all our results below remain valid.

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 for the model's steady states before and after a permanent import competition shock (i.e., a reduction of p_0), 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:

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

The left-hand side of equations (1) and (2) represents the marginal cost of hiring a non-R&D and an R&D worker, respectively. The right-hand side is the marginal benefit of an external hire, including savings from not having to hire in 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 that firms generate when hiring an additional worker of each job type and the unemployment benefit (see equations 4 and 5).

In 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:

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

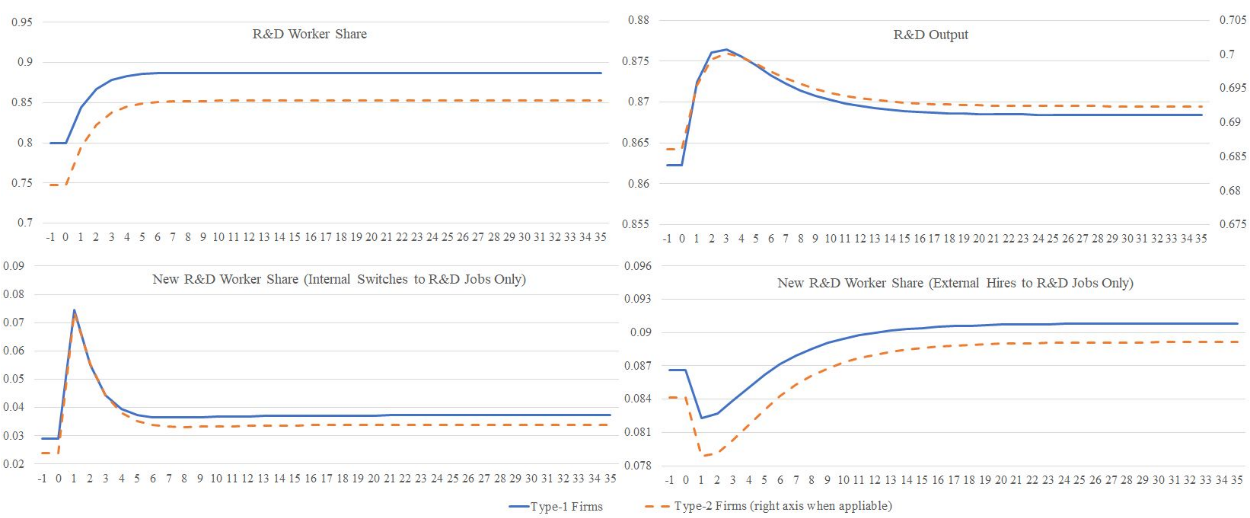
This presents two important results. First, when $i_j > 0$ (i.e., firm j reallocates non-R&D workers to R&D jobs), then $\phi m_{\gamma_j} > \phi m_{n_j}$ according to equation (3). This then implies that $p_j a_j \alpha \gamma_j^{\alpha-1} > p_0 z \alpha n_j^{\alpha-1}$ according to equations (6) and (7), assuming $b_{\gamma_j} > b_{n_j}$.[10] Therefore,

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

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, the steady-state m_{n_j} will decrease according to equation (6). That is, fewer external hires of non-R&D workers. 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 decreases. 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 firms than non-R&D workers when p_0 decreases.

To more clearly depict the effects of the trade shock, we calibrate the model and numerically solve for its steady states before and after a permanent negative shock on p_0 and then solve for the transition path in between. Note 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 for both the long-run and 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



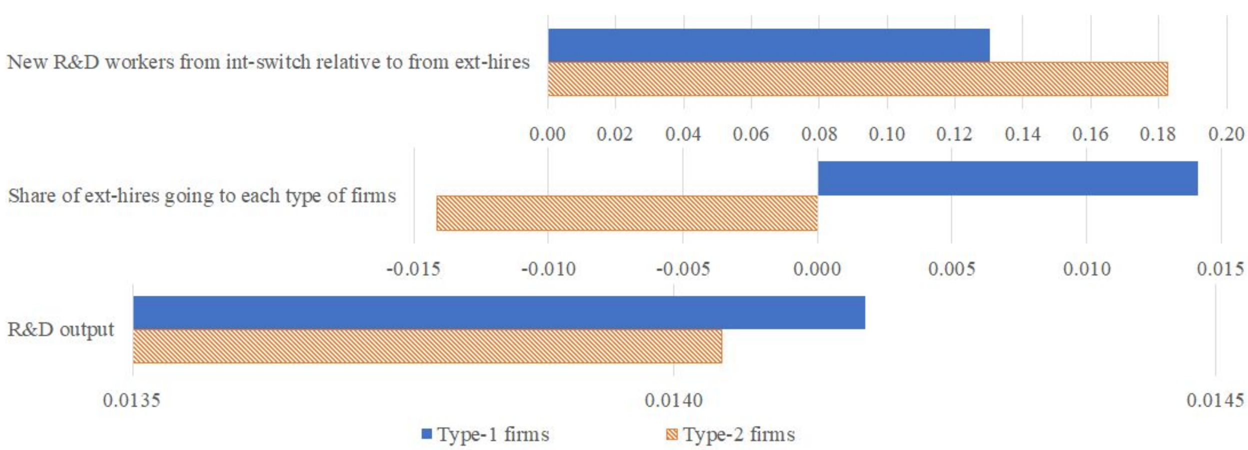
Notes: The horizontal axis represents the time period. The trade shock occurs at $t = 0$.

Period $t = -1$ is the steady state before the p_0 shock that strikes in period $t = 0$. Following the shock, for both types of firms, the share of R&D workers in the firm's employment increases, as does the number of R&D workers, which leads to higher R&D output (i.e., the type-Γ goods). The latter overshoots slightly before converging to a higher steady state than before the shock. Note that although not shown in Figure 1, non-R&D workers and their type-N goods output decline on the transition path to a lower steady state (see the 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 are higher in the post-shock steady state than in the pre-shock state. The former is a result of both increasing i_j and decreasing the total employment of firm j, while the latter is mainly due to the decreasing total employment of firm j. 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 for 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 they are 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 of R&D workers than type-1 firms. Moreover, considering all of the external R&D hires, a larger share of them goes to type-1 firms, whereas a smaller share goes to (the least productive) type-2 firms. In other words, an externally hired worker is more likely to be hired by a high-productivity firm. Additionally, type-1 firms have a slightly higher increase in R&D activities (i.e., type-Γ goods production) than type-2 firms.

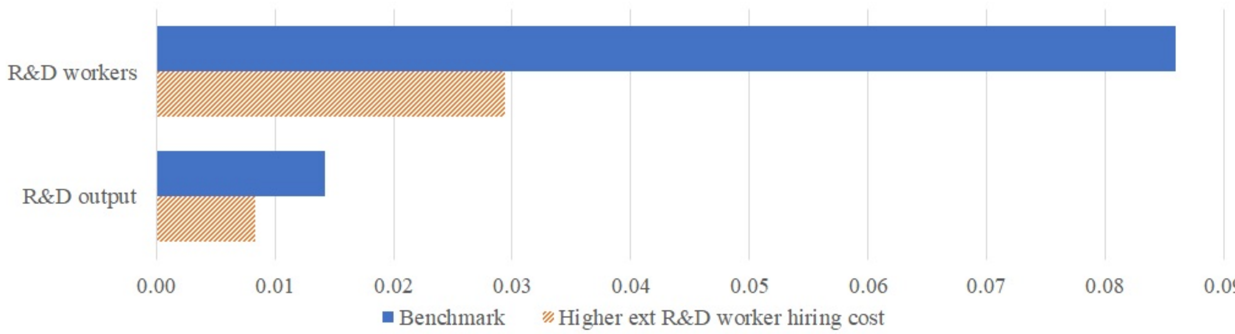
Figure 2: Between-firm Comparison: Changes After a Permanent Trade Shock



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

Finally, we increase the labor adjustment cost parameter ϕ while holding 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 summary, with higher labor adjustment costs, firms have smaller R&D worker increases and smaller R&D output increases than the benchmark case. Additional results are available in the online appendix.

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



Note: The bars plot the changes in 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 for 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-productivity firms are more reliant on internal workers' switching to R&D jobs relative to external hiring than high-productivity 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 of 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 is presented in Tables 5, 7 and 11 of the same section. Finally, in the last section of the paper, we extend the empirical analysis to Portugal, i.e., to an economy that has a higher labor adjustment cost and features lower average firm productivity than Denmark. These last 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 the 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 retain 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 and to measure a number of workforce characteristics at the firm level, such as the share of R&D workers.

Our second database is the 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 aggregate 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 offshored most or all of their production activities and thus are now classified as service firms. 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 in the industry with which they were formerly affiliated (i.e., one of the manufacturing industries) before switching to a service industry.

[12] Firm productivity is calculated as turnover per employee on a 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 runs 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 by Danish firms to the European and the Danish Patent Office (PATSTAT, 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 the name and address of the headquarters as in Bloom et al. (2016).[17]

3.1 Descriptive Statistics

The first panel of Table 1 reports the descriptive statistics of the main firm-level dependent variables 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 is very close to zero. Furthermore, our sample comprises approximately 2 percent of firms that apply for at least one patent over the whole sample period. Those firms are classified as tech firms in the remainder of the analysis. The use of patents as a measure of innovation, like any other innovation indicator, presents both advantages and disadvantages. On the positive side, patent applications (i) are a direct outcome of the innovation process and (ii) can be documented. On the other hand, not all inventions are necessarily patentable

[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 4-digit level aggregation to considerably improve consistency over time.

[17]This type of match presents many challenges, notably those arising from how 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 this information is not standardized and often partial or missing). In the name match phase, four criteria are combined to increase match accuracy: the first if perfect match, where names, removing legal designation, are exactly the same. The second is alphanumeric match, where the names, keeping only [A-Z] and [0-9], are the same (e.g., I.B.M. = IBM = I B M). The third is the Jaro-Winkler distance, where the 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 is, the more similar the strings are. Only results above a threshold value have been considered valid matches. The fourth is the 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 the log of (patent applications+1) and the negative hyperbolic sine of patent applications as dependent variables, respectively.

or linked to patent applications, and firms may present different propensities to apply for a patent. Albeit with some important limitations, we believe that patent applications are a rather conservative and objective measure of innovation and thus a plausible and suitable proxy for our purpose.

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 a large number of patent applications feature 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) to identify workers involved in 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 that 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 for 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, the EU15, and the USA. The instrument for 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. These countries 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 the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, the Slovak

[19] Further details of the FUIS data can be found at 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., one that includes technicians.

Republic, Slovenia, Cyprus, and Malta, which joined the EU in 2004, and Bulgaria and Romania, which joined in 2007. Its instrument is calculated as the total import values of the abovementioned 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 approximately 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 approximately 19 to 21, which is a 200 percent increase.

[Insert Figure 5 about here]

To corroborate our findings on the effects of Chinese import competition on within- and between-firm labor reallocations, we examine a broad set of worker-level outcomes. Specifically, we estimate the impact of import competition on i) workers' probability of switching to an R&D job, conditional on remaining employed by the same manufacturing firm for at least 3 years ("Stayers"); ii) workers' probability of being hired as R&D workers by another manufacturing firm ("Move def.1"); and iii) workers' 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 approximately 1 percent, as reported in Table 2. The other worker-level outcomes are calculated conditional on moving from one firm to another. 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 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 the share of R&D workers. Hence, below, we also analyze how much of the increase in innovation triggered by import competition is mediated by the increase in the share of R&D workers.

[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:

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

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

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

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 (other than Denmark) and the USA to capture the fact that the increase in Chinese exports affects Danish firms not only through intensifying competition in the domestic market but also in foreign markets to which Danish firms export and therefore

[21]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 account for both the endogeneity of the import competition variable and the numerous fixed effects in a count model. When we attempt 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 (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 remove sector and municipality fixed effects but retain the firm and year fixed effects and the first-stage residuals. It is encouraging that the coefficient estimated from this simplified negative binomial model on the import competition variable is in line with that 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 about 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 for the EU-15 countries and the USA from new EU members as in Dauth et al. (2014).

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 the 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 that an industry is actually 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. Additionally, 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, and import and export values.[26] Specifically, the inclusion of productivity and import values in our estimation equation controls for the potential "productivity effect" on innovation associated with obtaining access to less expensive or better foreign inputs. Firm-level offshoring controls for the reorganization effects highlighted in Bernard et al. (2020). A recent study on 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 generated by export liberalization, as in Aghion et al. (2018) and Coelli et al. (2020).

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

One possible threat to the identification of β_1 is that Chinese import competition is

[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 6 of Table A-3 in the online appendix.

[25] Very similar results are obtained when using longer lags (see columns 6-9 of Table A-1 and columns 8-11 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 7 of Table A-3 in the online appendix.

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

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), similar to Hummels et al. (2014).[29] Specifically, the instrumental variable (IV) 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} represents 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, and 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 firm outcomes explored in this study, we require our instrument to also be independent of any expectations in future trends of the same outcomes. We test this 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 the 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 using alternative periods to calculate the growth rate of our IV (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 industry ($\frac{exp_{jp\_1993}}{exp_{j\_1993}}$) are systematically correlated with potential

[29]In a refinement exercise reported in Tables A-1 (column 4) and A-3 (column 5), 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 that our main results are confirmed for a narrower sample of firms and with an alternative instrument, although the coefficients are imprecisely estimated.

[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 obtained with the IV approach. Hence, Autor et al. (2013) concludes that correlated import demand shocks across high-income countries do not seem to play an important role in 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 were 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 do we find a systematic cross-industry correlation in 1993 between the product's export share and industry characteristics, such as average firm 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

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

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

where $Outcome_{wijt}$ is a dummy variable equal to 1 if worker w is employed by 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 in 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 on the firm-level empirical strategy, whereas Z_{wt-1} consists of a host of worker variables, such as age and tenure. Furthermore, we augment equation (6) with worker fixed effects δ_w, 2-digit-sector (δ_m), municipality (δ_c) and year (δ_t) fixed effects. Finally, we instrument Imp^{CH}_{jt-1} with exogenous shocks to other countries' import demand for 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 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 do not 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 firm innovation and worker reallocation to R&D jobs. Using these estimated effects, we quantify the extent to which the increase in a firm's innovation is attributable to an increase in its share of R&D workers. To highlight the underlying mechanisms, we study the extent to which import competition induces a reallocation of workers to R&D jobs within and between firms using both firm- and worker-level data. Our results show that 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 firm 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 and firm, sector, municipality and year fixed effects. In column 2, we turn to our IV approach to address endogeneity concerns. The first-stage result shows that the instrument has a significant positive impact on import competition (see the 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 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 firm 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; and 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 (columns 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 the extent to which the total effect of import competition on innovation is attributable to 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 conclude that approximately 40 percent of the total increase in the number of patent applications due to import competition (0.002) is attributable to the exogenous increase in the share of R&D workers due to import competition ($0.66 \times 0.0012 = 0.0008$).

[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 considering the following refinements in Table 5. First, we obtain similar results when 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 obtain similar results, as 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 the 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 than 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 the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, the Slovak Republic, Slovenia, Cyprus, and Malta, which joined the EU in 2004, and Bulgaria and Romania, which joined in 2007. The corresponding IV is calculated as the total import values for Australia, Canada, New Zealand and Japan from the new EU

Second, we augment the main specification with an interaction between the share of R&D workers and a dummy for high-performance firms (type-1 firms in the theoretical model) in column 3. Specifically, we classify firms as high-performance firms if they feature productivity above the 75th percentile of the industry distribution (i.e., high-productivity firms) and/or if they apply for at least one 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 high-productivity/tech firms than for 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. In the mechanisms section below, we will show that this is due to type-1 firms' greater reliance on external (between-firm) hiring of new R&D workers than other firms.

[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 products from 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 is attributable to the increase in the share of R&D workers driven by Chinese import competition shocks in columns 6 and 7. A 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 export 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 argue that more than half of the increase in the likelihood of adding or dropping exported products is 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

countries.

[39]Specifically, $11 \times 0.0012 = 0.0132$, which is approximately 70 percent of the total effect of import competition on the likelihood of adding newly exported products.

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).

5.1.2 Mechanisms: Within- and Between-firm Worker Reallocation

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 firms, affect the share of R&D workers and thus innovation.

We first focus on the firm's share of R&D workers as the dependent variable. In columns 1 and 2 of Table 6, we again report the estimated impact of import competition on the share of R&D workers from Table 4 to facilitate comparison. In column 3, we recalculate the same share by including only the stock of stayers who switch to R&D jobs within the same firm. The impact of import competition is now approximately 14 percent of that 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 recalculate 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 that 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 therefore conclude that approximately 14 percent of the increase in the share of R&D workers due to import competition is achieved by reallocating workers within firms. Approximately 80 percent is instead achieved by between-firm hiring.[40]

In column 5 of Table 6, we redefine 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 the share of R&D workers, which is of similar magnitude to that 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 only newly hired R&D workers from other firms in the numerator (between-firm movers def.1), we find that type-1 firms engage in external hiring to increase their share of R&D workers to a larger extent than the other firms (4.4 versus 3.2 percent; see column 7). Together, these results are consistent with the first part of Proposition 3

[40]Note that less than 3 percent of the total impact is attributable to the hiring of newly hired workers from either long-term unemployment or school graduates. By 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.

from our theoretical model, according to which type-1 firms achieve a larger increase in the share of R&D workers through external hires than type-2 firms.

[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-firm reallocation. The estimated coefficient on this variable suggests that, when 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-firm 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 one-percentage-point increase in the intensity variable is associated with a 0.0027 increase in the number of patent applications, 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-firm 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 is mediated through the total increase in the share of R&D workers.

5.2 The Salience of Between-firm Reallocation

In Table 6, we established the relevance of between-firm reallocation using firm-level data for Denmark. We now further study this channel as follows. First, we conduct a worker-level analysis to provide further insights into the dynamics of worker reallocation in response to import competition in Denmark. Second, we repeat both the firm- and worker-level analyses

[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.

using analogous employer-employee data from Portugal, where due to labor market rigidities and low productivity, the between-firm reallocation in response to import competition is potentially more restricted than in the Danish case. Such an extension provides us with 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 analysis, we first estimate the probability of switching to R&D jobs for workers who remain employed by 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 remains employed by the same firm between $t-2$ and t switches to an R&D job at time t after accounting for worker and firm characteristics and sector, municipality 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 IV 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, workers older than 50 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 reallocate their existing workers to R&D on average. 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 nonlinear 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 work experiences. We also do not find heterogeneous effects depending on whether the stayer is employed by an incumbent or a newly established firm.

firms feature a lower probability of being reallocated to R&D jobs than 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 is due to import competition attributable to 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, conditional on moving. This is much larger than the increase in the 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 to R&D jobs is stronger for male workers, workers with tertiary education, workers younger than 50 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, regardless of 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 transition and attempt to include both measures of import competition, only the receiving firm's competition retains its significance.[46] Interestingly, however, when we examine workers' transitions from the manufacturing industry to the service industry, import competition in 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

[45]These additional results are reported in Table A-5 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 work experiences. We also estimate a stronger effect for the sample of newly established companies than for that comprising incumbent firms.

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

percent. This result is consistent with Utar (2018) and Xu and Gong (2017), who find that a nonnegligible fraction of workers move from the manufacturing to the service industry in response to increased import competition from China.

[Insert Table 8 here]

To delve deeper into the between-firm margin of adjustment and to more explicitly test Proposition 3 in the theoretical model, we examine in Table 9 whether import competition affects worker transitions from low- to high-performance firms. Specifically, as we did in the previous analysis, we classify firms as high-performance firms if they feature productivity above the 75th percentile of the industry distribution or if they apply for at least one 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, conditional on moving. 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 approximately 4 percent (column 4). All these results support the second half of Proposition 3 in the theoretical model, according to which externally hired workers are more likely to join high-performance (type-1) firms. 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 thus 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 worker reallocation to R&D jobs, while approximately 80 percent is due to 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 worker reallocation. We also show that a larger degree of between-firm relative to within-firm reallocation to R&D occupations 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 firm productivity is generally low and worker 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 average firm 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 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' productivity over the same period.[47] Due to these differences and similar exposures to Chinese import competition across the two economies, we expect labor reallocation to R&D jobs (especially between-firm) and the response in terms of innovation to be weaker in Portugal than in Denmark, consistent with Propositions 3 and 4. Therefore, estimating the same empirical specifications with Portuguese data will enable us to more carefully examine 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 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 allow us to measure firm characteristics (such as productivity). Custom trade data at the firm level[49] are obtained from Statistics Portugal

[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 log productivity is 13.681 and 11.111 in the Danish and Portuguese samples, respectively.

[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

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 Portuguese customs 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 the names and addresses of firms' headquarters, 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 for import competition, which increased from approximately 20 to 23, a 300 percent increase, even larger than in 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 increases 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 imports 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 features a lower increase in the share of R&D workers and R&D output in response to an import competition shock.

Furthermore, in column 3, we find that a 100 percent increase in the share of R&D workers at time $t-1$, which is exogenously driven by import competition shocks, raises the number of patent applications by 0.048. 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 15 percent of the increase in the number of patent applications is 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 captures internal switchers to R&D as the dependent variable (column 4), a 100 percent increase in import competition leads

approximately 80 (3-digit) industries every year.

[50] Specifically, $0.048 \times 0.0005 = 0.000024$, which is approximately 15 percent of the total effect of import competition on the number of patent applications (0.00016).

to a 2.8 percent increase in the share of such R&D workers, explaining approximately 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 to R&D jobs. Unsurprisingly, the within-firm reallocation of labor to R&D activities is stronger in Portugal than in Denmark. This is consistent with Proposition 3 and the fact that there is a larger share of low-productivity firms in Portugal than in Denmark.

These findings at the firm level are corroborated by worker-level regressions. We find that import competition increases 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 for 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 than 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 influence this cross-country difference, we are reassured by the fact that we employ 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 innovation 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, import competition increased by 200 percent. Approximately 40 percent of this increase is attributable to the increase in the total share of R&D workers resulting from import competition. Approximately 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 that the increase in the share of R&D workers only marginally affects 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 than between-firm worker reallocation.

Although not directly tested in this paper, there are some possible explanations for 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. First, a firm's ability to attract external workers and tap into a larger pool of talent than those within the firm can help expand innovation output. In addition, 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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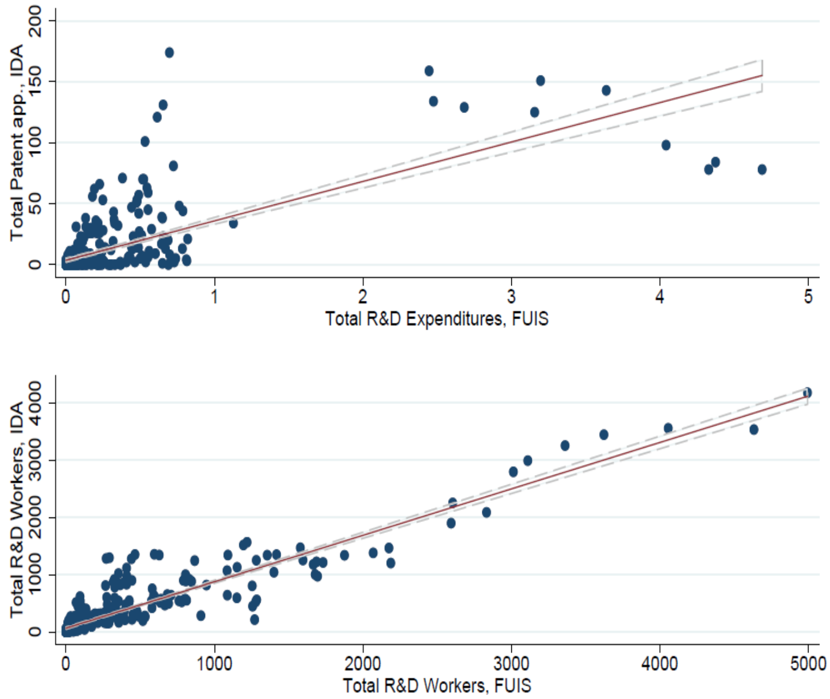
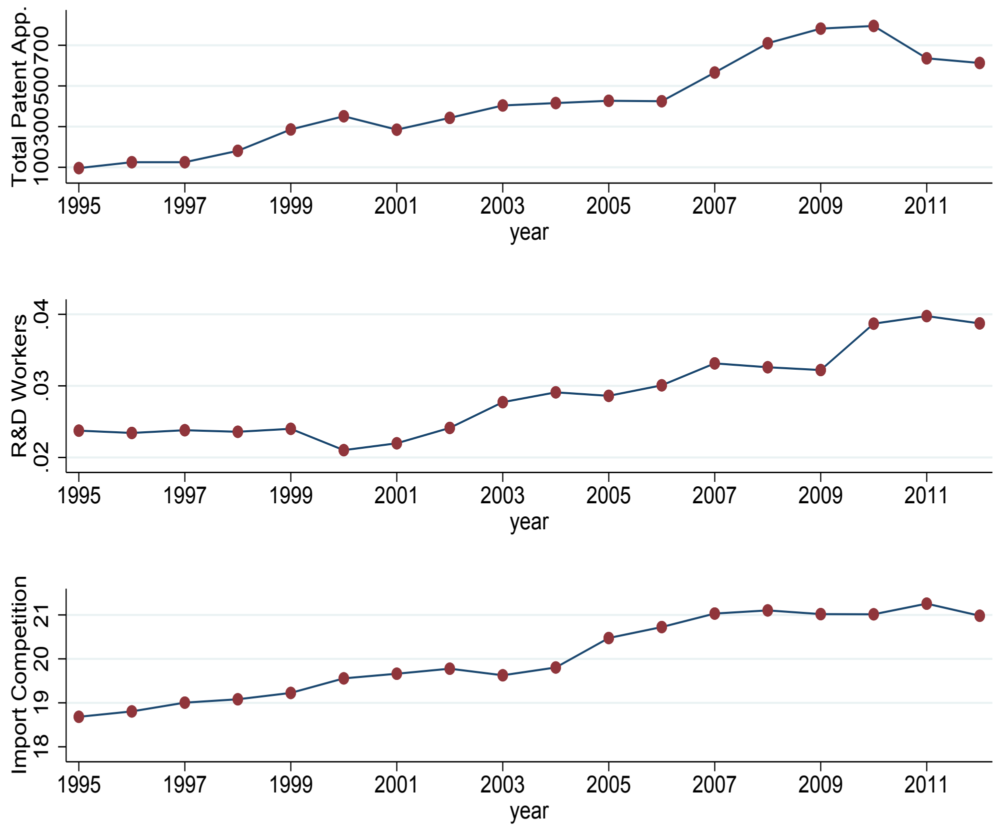
Figure 4: Validation of our measures of innovation and R&D workers



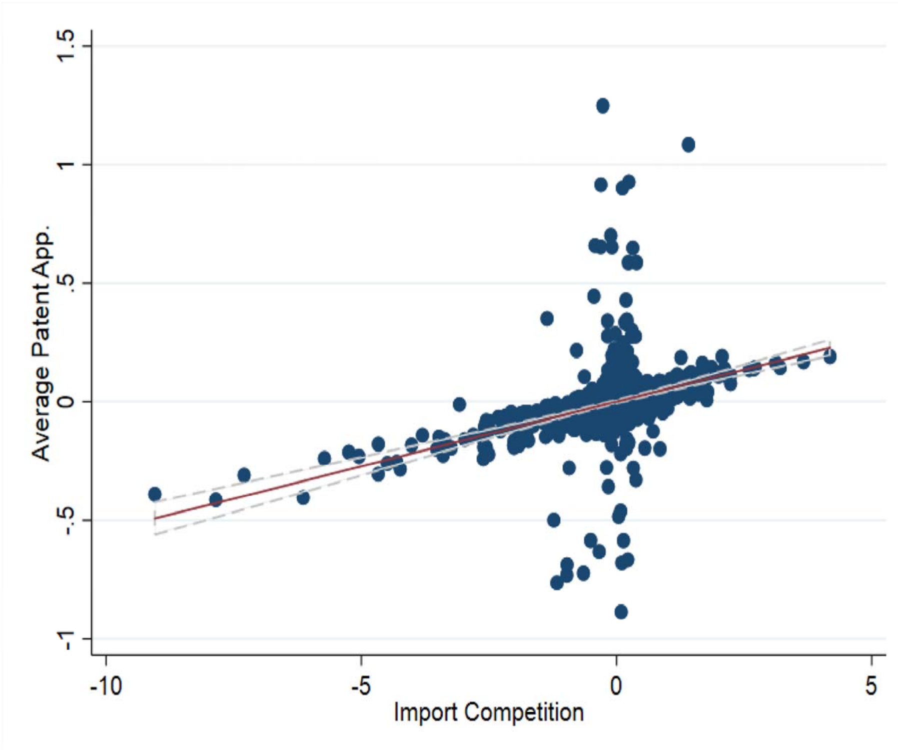
Notes: Total Patent app., IDA is calculated from the register data by summing the firm-level number of patent applications for each year and 2-digit industry. Total R&D Expenditures, FUIS are the year-2-digit-industry-specific total real R&D expenditures in billions of Danish kr. calculated from the 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)



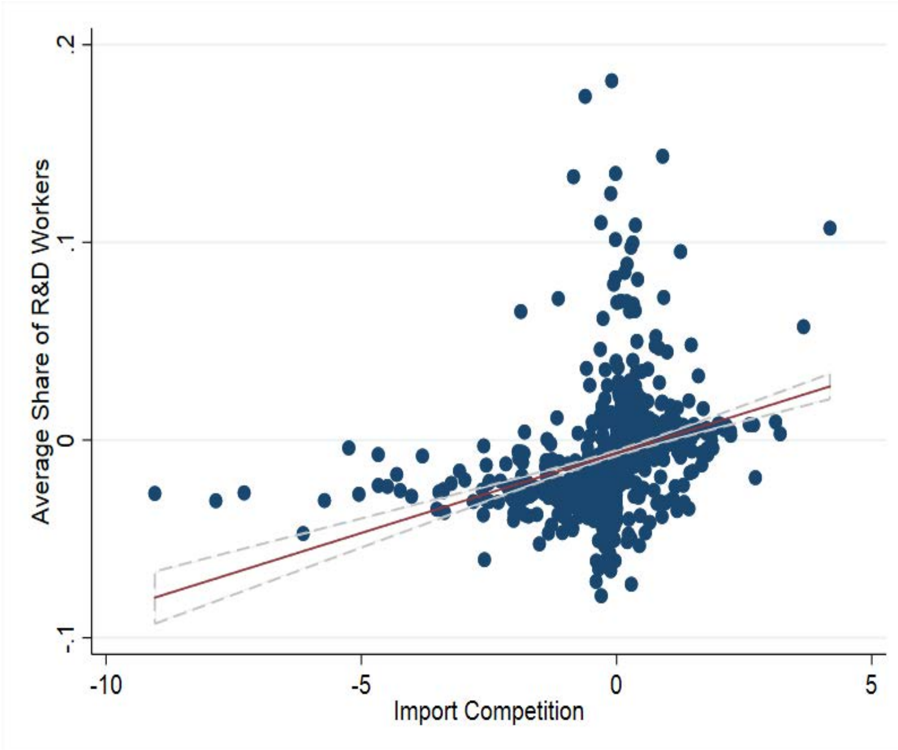
Notes: R&D workers are the year-specific average share of R&D workers at the firm level. Total Patent app. is calculated by summing for each year the firm-level number of patent applications. Import competition is the year-specific average log of the weighted sum of import values of all HS products from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

Figure 6: Innovation and Import Competition



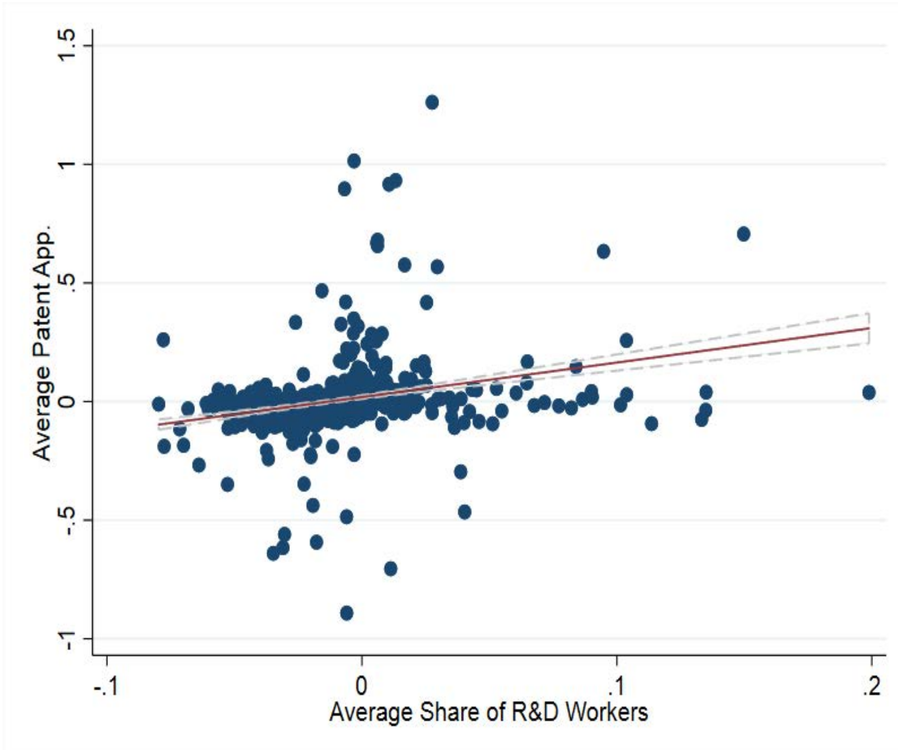
Notes: The average residuals at the 4-digit-industry level from regressing the number of patent applications on two-digit-sector and year fixed effects are reported on the vertical axis. The average residuals at the 4-digit-industry level from regressing the Chinese import competition variable on two-digit-sector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

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



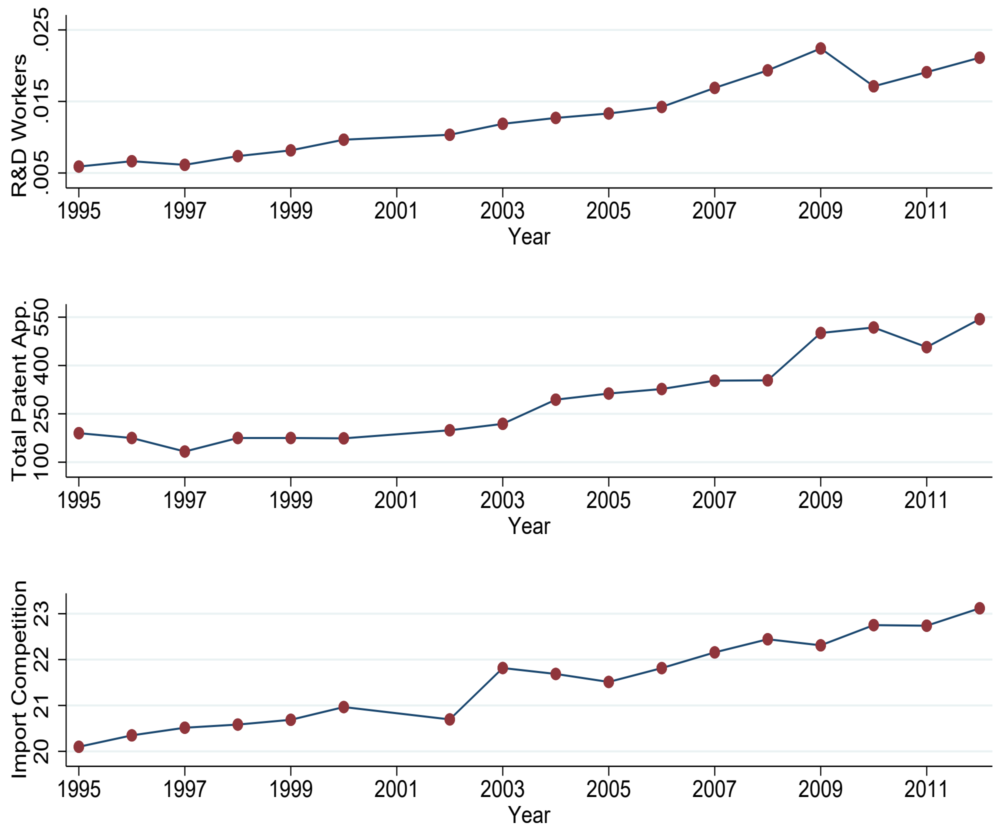
Notes: The average residuals at the 4-digit-industry level from regressing the share of R&D workers on two-digit-sector and year fixed effects are reported on the vertical axis. The average residuals at the 4-digit-industry level from regressing the Chinese import competition variable on two-digit-sector 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 level 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 level 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. The total number of patent applications is calculated by summing 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, Mun. 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, Mun. 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, Mun. 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**	**OLS**	**IV**	**IV: IC Alt. Def.**	**IV**
	(1)	**(2)**	**(3)**	**(4)**	**(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, Mun. 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, Mun. 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, Mun. 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$_{t-1}$			0.04861*
			(0.02709)
Firm Fixed Effects	yes	yes	yes
Worker Fixed Effects	no	no	no
Sector, Province and Year Fixed Effects	yes	yes	yes
Firm Characteristics	yes	yes	yes
Worker Characteristics	no	no	no
Mean Y	0.01200	0.01478	0.01200
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, Province 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%.

Online Appendix Workers' Reallocation, Innovation and Chinese Import Competition

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1 Parameterization of the Theoretical Model

In order to solve the model numerically, we simplify the model by assuming that all type-Γ goods share the same price, i.e., $p_1 = p_2$. Parameters are detailed in the following table.

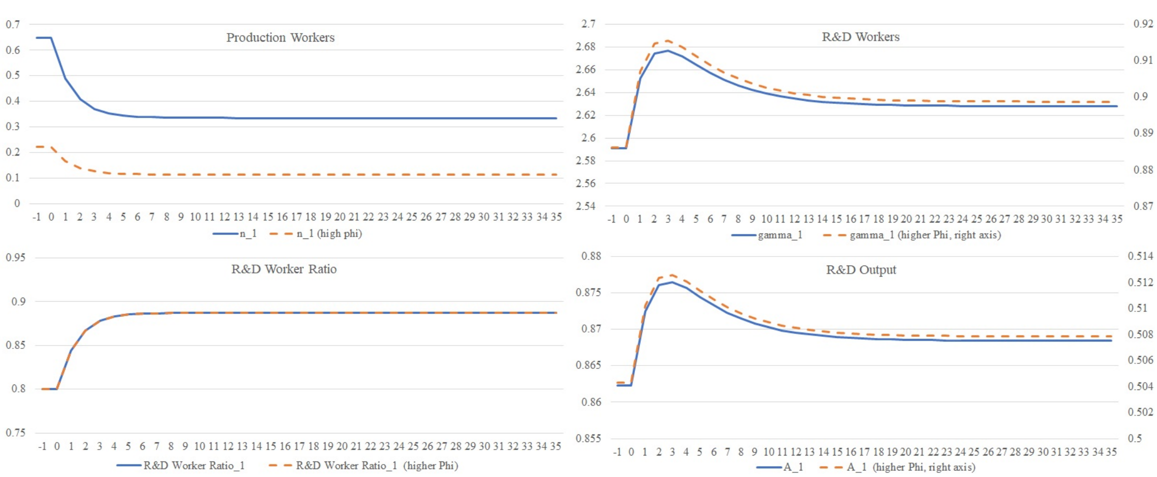
Table A: Model Parameters

Parameter	Explanation	Target
$\beta = 0.99$	Standard in the macro literature	-
$z = 1$	Normalized	-
$a_1 = 0.5357$	Type-1 firms' R&D productivity	R&D to non-R&D worker wage ratio = 1.5
$a_2 = 0.4556$	Type-2 firms' R&D productivity	High-perf. to low-perf. firm worker wage ratio = 1.1
$\alpha = 0.5$	Decreasing return to scale in prod function	-
$p_0 = 1$	Normalized before-shock type-N goods price	-
$p_1 = p_2 = 5.6$	Type-Γ goods prices	Before-2001 low-IC to high-IC goods price=5.6
$p_0' = 0.7$	After-shock type-N goods prices	After-2001 high-IC to low-IC goods price ratio relative to before-2001 ratio=0.7
$\phi = 1$	Normalized for labor adjustment cost	-
$\phi' = 5$	For comparison: higher labor adjustment cost	The increase of R&D workers in Denmark is about 3 times as that in Portugal
$s = 0.075$	Separation rate	Hobijn and Şahin (2009)
$\eta = 0.5$	Worker bargaining power	-
$b_{n_2} = 0.4680$	Unemp. benefit for type-2 firms' prod workers	83% of low-perf. firm production workers' wages
$b_{n_1} = b_{n_2} \times 1.1 = 0.5148$	Unemp. benefit for type-1 firms' prod workers	High-perf. to low-perf. firm worker wage ratio = 1.1
$b_{\gamma_1} = b_{n_1} \times 1.5 = 0.7722$	Unemp. benefit for type-1 firms' R&D workers	R&D to non-R&D worker wage ratio = 1.5
$b_{\gamma_2} = b_{n_2} \times 1.5 = 0.7020$	Unemp. benefit for type-2 firms' R&D workers	R&D to non-R&D worker wage ratio = 1.5

Notes: The targeted statistics are averages from various data sources. The targeted wage statistics come from the "Integrated Database for Labor Market Research" (*IDA*) database. The targeted price statistics are from Statistics of Denmark's Industry Sales of Goods. The targeted unemployment benefits are from OECD. High-IC goods are products exposed to high import competition (import competition above 75th percentile), and low-IC goods are products exposed to low import competition (import competition below 25th percentile).

In the comparative static exercise, we increase the labor adjustment cost parameter ϕ while leaving all other parameters unchanged and compare to the benchmark economy. Figure A1 plots the result differences across the two economies for type-1 firms. The differences for type-2 firms are similar and are not plotted here for brevity. With higher labor adjustment cost, type-1 firms have lower production and share of R&D workers than the benchmark economy both before and after the trade shock, as well as smaller increases in R&D output in response to the trade shock.

Figure A1: Transition Path for Type-1 firms with Higher Labor Adjustment Costs



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

2 Additional Empirical Results

Table A-0: Share of R&D Workers and Innovation by Firm-Type

	Incumbent Firms	**Newly Established Firms**	**Exiting Firms**
Year		R&D Workers	
1995	0.018	-	0.018
1996	0.021	0.017	0.015
1997	0.022	0.018	0.015
1998	0.023	0.018	0.015
1999	0.022	0.019	0.017
2000	0.019	0.017	0.016
2001	0.018	0.019	0.019
2002	0.017	0.018	0.020
2003	0.013	0.015	0.013
2004	0.012	0.014	0.011
2005	0.012	0.013	0.012
2006	0.013	0.015	0.011
2007	0.015	0.016	0.015
2008	0.016	0.018	0.014
2009	0.017	0.018	0.012
2010	0.025	0.025	0.020
2011	0.026	0.026	0.021
2012	0.027	0.028	-
	Incumbent Firms	**Newly Established Firms**	**Exiting Firms**
year		Intensive Margin of Innovation	
1995	0.007	-	0
1996	0.005	0	0
1997	0.006	0	0
1998	0.007	0	0.009
1999	0.009	0	0.009
2000	0.005	0.001	0.015
2001	0.006	0.001	0.002
2002	0.008	0.001	0.002
2003	0.005	0.002	0.002
2004	0.006	0.002	0.003
2005	0.007	0.004	0.003
2006	0.008	0.005	0.004
2007	0.01	0.006	0.005
2008	0.012	0.005	0.007
2009	0.007	0.007	0.009
2010	0.009	0.015	0.005
2011	0.012	0.009	0.004
2012	0.01	0.008	-

Notes: Incumbent firms are firms that are active from 1995 through 2012. Newly established firms are firms that enter the market over the sample period. Exiting firms are firms that exit the market over the sample period.

Table A-1: Import Competition and Innovation, Additional Results

Dep. Var: Intensive Margin of Innovation	**IV: Incumbent Firms** (1)	**IV: New Firms** (2)	**IV: Firm-specific Import Competition** (3)	**IV: Quota Instrument** (4)
Import Competition$_{t-1}$	0.00121*	0.00045*	0.00125*	0.00122
	(0.00073)	(0.00023)	(0.00071)	(0.00102)
Firm Fixed Effects	yes	yes	yes	yes
Sector, Mun. and Year Fixed Effects	yes	yes	yes	yes
Firm Characteristics	yes	yes	yes	yes
Mean Y	0.036	0.024	0.029	0.016
First Stage F-stat on Instruments	313.195	340.166	299.05	275.31
First Stage- Import Competition IV Coeff.	0.57391*** (0.0491)	0.58701*** (0.0501)	0.57603*** (0.01284)	2.414*** (0.1454)
R-sq	0.09176	0.08711	0.11098	0.12345
N	98,796	84,146	215,656	17,342

Dep. Var: Intensive Margin of Innovation	**IV: Excl. Offshoring Firms** (5)	**IV** (6)	**IV** (7)	**IV** (8)	**IV** (9)
Import Competition$_{t-1}$	0.00178*				
	(0.00091)				
Import Competition$_{t-2}$		0.00103*			
		(0.00054)			
Import Competition$_{t-3}$			0.00108*		
			(0.00057)		
Import Competition$_{t-4}$				0.00063**	
				(0.00032)	
Import Competition$_{t-5}$					0.00034
					(0.00030)
Firm Fixed Effects	yes	yes	yes	yes	yes
Sector, Mun. and Year Fixed Effects	yes	yes	yes	yes	yes
Firm Characteristics	yes	yes	yes	yes	yes
Mean Y	0.014	0.030	0.032	0.033	0.034
First Stage F-stat on Instruments	435.54	409.86	407.78	449.99	430.87
First Stage- Import Competition IV Coeff.	0.65324*** (0.0129)	0.64089*** (0.0151)	0.65034*** (0.0162)	0.62307*** (0.0147)	0.75905*** (0.03821)
R-sq	0.10907	0.11678	0.11709	0.09145	0.07651
N	191,537	184,830	154,830	133,258	115,486

Dep. Var: Intensive Margin of Innovation	**Negative Binomial** (10)	**Negative Binomial** (11)	**IV: Ln(Patents+1)** (12)	**IV: Asinh(Patents)** (13)
Import Competition$_{t-1}$	0.07234*	*It does not converge*	0.00069**	0.00085**
	(0.03899)		(0.00034)	(0.00043)
Firm Fixed Effects	yes	yes	yes	yes
Sector and Mun. Fixed Effects	no	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes
Firm Characteristics	yes	yes	yes	yes
First Stage Residuals	yes	yes	no	no
Mean Y	1.04428		0.00582	0.00738
First Stage F-stat on Instruments	-		435.65	435.65
First Stage- Import Competition IV Coeff.	0.65620*** (0.0130)	*It does not converge*	0.65620*** (0.0130)	0.65620*** (0.0130)
LL/R-sq	-4203.4992		0.21098	0.18187
N	17,339		229,844	229,844

Notes: The dependent variable is the number of patent applications at the firm level in columns 1-11. In column 1, the sample excludes newly established firms and firms that exit over the sample period. In column 2, the sample only includes newly established firms. In column 3, import competition is calculated by using firm-product export shares and the sample only includes exporting firms. In column 4, the sample only includes firms in the textile and clothing industry over the period 1995-2005. In the same column, the instrumental variable is calculated as 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) that were planned to be removed by 2005. In column 5, the sample excludes offshoring firms. In columns 6-9, we use alternative lags for the import competition variable. In column 12, the dependent variable is the log(patent applications+1). In column 13, the dependent variable is asinh(patent applications+1). Firm characteristics include the lag of firm's size, offshoring status (not in column 6), 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 A-2: Import Competition and the Share of R&D Workers, Additional Results (1)

Dep. Var: R&D Workers	**IV: Excl. Low Skilled (1)**	**IV: Broad Def. (2)**	**IV: Incl. Liquidity Constraints (3)**
Import Competition$_{t-1}$	0.00057**	0.01101**	0.00211**
	(0.00028)	(0.00504)	(0.00091)
Firm Fixed Effects	yes	yes	yes
Sector, Mun. and Year Fixed Effects	yes	yes	yes
Firm Characteristics	yes	yes	yes
Mean Y	0.034	0.054	0.030
First Stage F-stat on Instruments	435.65	435.65	455.39
First Stage- Import Competition IV Coeff.	0.65620*** (0.0130)	0.65620*** (0.0130)	0.70228*** (0.02422)
R-sq	0.22363	0.22363	0.29561
N	229,844	229,844	183,008

Dep. Var: R&D Workers	**IV: Excl. Exporting Firms (4)**	**IV: Excl. Foreign Owned Firms (5)**	**IV: Excl. Copenhagen (6)**	**IV: Excl. Small Firms (7)**
Import Competition$_{t-1}$	0.00055**	0.00071**	0.00069**	0.00146*
	(0.00027)	(0.00031)	(0.00032)	(0.00085)
Firm Fixed Effects	yes	yes	yes	yes
Sector, Mun. and Year Fixed Effects	yes	yes	yes	yes
Firm Characteristics	yes	yes	yes	yes
Mean Y	0.023	0.028	0.028	0.044
First Stage F-stat on Instruments	333.39	435.65	409.11	606.98
First Stage- Import Competition IV Coeff.	0.641223*** (0.0127)	0.65620*** (0.0130)	0.627781*** (0.0121)	0.70897*** (0.0198)
R-sq	0.22363	0.22363	0.22363	0.22363
N	157,976	220,154	198,188	58,461

Notes: The dependent variable is the share of R&D workers at the firm level. In column 1, the dependent variable exclude low-skilled workers in the calculation of the share of R&D workers. In column 2, the dependent variable is calculated by including technicians in the definition of R&D workers. In column 3, we include log of total assets in the specification as a proxy of firm-level liquidity, which is only available for the sub-period 2001-2012. In column 4, the sample excludes exporting firms. In column 5, the sample excludes foreign-owned firms. In column 6, the sample excludes firms located in Copenhagen and Frederiksberg. In column 7, the sample excludes firms with fewer than 50 employees. Firm characteristics include the lag of firm's size, offshoring status, 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 A-3: Import Competition and the Share of R&D Workers, Additional Results (2)

Dep. Var: R&D Workers	**IV: Count** (1)	**IV: Newly Hired from Unemp/Edu** (2)	**IV: Incumbent Firms** (3)	**IV: New Firms** (4)	**IV: Quota Instrument** (5)
Import Competition$_{t-1}$	0.4087*	0.00001*	0.00108*	0.00233*	0.00208
	(0.2309)	(0.00001)	(0.00064)	(0.00127)	(0.00141)
Firm Fixed Effects	yes	yes	yes	yes	yes
Sector, Mun. and Year Fixed Effects	yes	yes	yes	yes	yes
Firm Characteristics	yes	yes	yes	yes	yes
Mean Y	1.46	0.00501	0.029	0.029	0.023
First Stage F-stat on Instruments	435.65	435.65	313.195	340.166	275.31
First Stage- Import Competition IV Coeff.	0.65620*** (0.0130)	0.65620*** (0.0130)	0.57391*** (0.0491)	0.58701*** (0.0501)	2.414*** (0.1454)
R-sq	0.12432	0.11433	0.10237	0.15609	0.12345
N	229,844	229,844	98,796	84,146	17,342

Dep. Var: R&D Workers	**IV: Firm-specific Import Comp.** (6)	**IV: Excl. Offshoring Firms** (7)	**IV** (8)	**IV** (9)	**IV** (10)	**IV** (11)
Import Competition$_{t-1}$	0.00287**	0.00101*				
	(0.00143)	(0.00057)				
Import Competition$_{t-2}$			0.00171**			
			(0.00081)			
Import Competition$_{t-3}$				0.00163**		
				(0.0079)		
Import Competition$_{t-4}$					0.00145*	
					(0.0077)	
Import Competition$_{t-5}$						0.00112
						(0.0077)
Firm Fixed Effects	yes	yes	yes	yes	yes	yes
Sector, Mun. and Year Fixed Effects	yes	yes	yes	yes	yes	yes
Firm Characteristics	yes	yes	yes	yes	yes	yes
Mean Y	0.035	0.019	0.029	0.029	0.029	0.029
First Stage F-stat on Instruments	245.11	435.54	409.86	407.78	449.99	430.87
First Stage- Import Competition IV Coeff.	0.61673*** (0.01018)	0.65324*** (0.0129)	0.64089*** (0.0151)	0.65034*** (0.0162)	0.62307*** (0.0147)	0.75905*** (0.03821)
R-sq	0.25671	0.17301	0.12448	0.11747	0.09356	0.09335
N	43,873	191,537	184,830	154,830	133,258	115,486

Notes: In column 1, the dependent variable is the number of R&D workers at the firm level. In columns 2-8, the dependent variable is the share of R&D workers at the firm level. In column 2, the dependent variable only includes newly hired workers from unemployment or education in the calculation of the share of R&D workers. In column 3, the sample excludes newly established firms and firms that exit over the sample period. In column 4, the sample only includes newly established firms. In column 5, the sample only includes firms in the textile and clothing industry over the period 1995-2005. In the same column, the instrumental variable is calculated as 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) that were planned to be removed by 2005. In column 6, import competition is calculated by using firm-product sales shares. In column 7, we exclude offshoring firms. In columns 8-11, we use alternative lags for the import competition variable. Firm characteristics include the lag of firm's size, offshoring status (not included in column 8), 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 A-4: Import Competition and the Probability of Switching to R&D Jobs Within a Firm at the Worker Level

	IV: Reverse Switching	IV: With Tertiary Education	IV: Less Than Tertiary Education	IV: More Than 50 Years Old	IV: 50 Years Old or Younger
Dep. Var.: R&D Switch	(1)	(2)	(3)	(4)	(5)
Import Competition$_{t-1}$	0.0001	0.00274**	0.00031*	0.00123**	0.00152*
	(0.0002)	(0.00135)	(0.00018)	(0.00064)	(0.00068)
Worker Fixed Effects	yes	yes	yes	yes	yes
Sector, Mun. and Year Fixed Effects	yes	yes	yes	yes	yes
Worker Characteristics	yes	yes	yes	yes	yes
Firm Characteristics	yes	yes	yes	yes	yes
Mean Y	0.00473	0.02421	0.00529	0.00370	0.01569
First Stage F-stat on Instruments	607.14	507.14	599.03	509.06	603.17
First Stage- Import Competition IV Coeff.	0.6283*** (0.0168)	0.5613*** (0.0117)	0.6261*** (0.0153)	0.5787*** (0.0123)	0.6309*** (0.0165)
R-sq	0.21485	0.2135	0.2071	0.23088	0.23297
N	3,732,144	1,058,738	2,598,010	1,020,969	2,683,323

	IV: More Than 5 Years of Tenure	IV: 5 Years of Tenure or Less	IV: More Than 10 Years of Work Experience	IV: 10 Years of Work Experience or Less	IV: Male Workers
Dep. Var.: R&D Switch	(6)	(7)	(8)	(9)	(10)
Import Competition$_{t-1}$	0.00028**	0.00102	0.00034*	0.00043**	0.00109*
	(0.00014)	(0.00088)	(0.00018)	(0.00021)	(0.00056)
Worker Fixed Effects	yes	yes	yes	yes	yes
Sector, Mun. and Year Fixed Effects	yes	yes	yes	yes	yes
Worker Characteristics	yes	yes	yes	yes	yes
Firm Characteristics	yes	yes	yes	yes	yes
Mean Y	0.00782	0.01663	0.00653	0.01792	0.01667
First Stage F-stat on Instruments	612.11	580.23	612.56	580.22	601.01
First Stage- Import Competition IV Coeff.	0.6356*** (0.0195)	0.6048*** (0.0125)	0.6355*** (0.0195)	0.6046*** (0.0124)	0.6298*** (0.0155)
R-sq	0.23060	0.24876	0.22852	0.20826	0.23328
N	2,983,525	720,764	2,809,081	895,201	2,625,213

	IV: Female Workers	IV: Incumbent Firms	IV: New Firms
Dep. Var.: R&D Switch	(11)	(12)	(13)
Import Competition$_{t-1}$	0.00019**	0.00057*	0.00044*
	(0.00004)	(0.00031)	(0.00023)
Worker Fixed Effects	yes	yes	yes
Sector, Mun. and Year Fixed Effects	yes	yes	yes
Worker Characteristics	yes	yes	yes
Firm Characteristics	yes	yes	yes
Mean Y	0.00836	0.01171	0.01134
First Stage F-stat on Instruments	510.02	631.19	504.22
First Stage- Import Competition IV Coeff.	0.5795*** (0.0125)	0.6402*** (0.0209)	0.5523*** (0.0115)
R-sq	0.14361	0.23442	0.14155
N	1,079,071	2,347,499	1,150,962

Notes: In column 1, the dependent variable is equal to 1, if a worker i who remains employed in the same firm between $t-2$ and t and switches out of an R&D occupation at time t. In all the other columns, the dependent variable is equal to 1, if a worker i who remains employed in the same firm between $t-2$ and t and switches to an R&D job 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, 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 A-5: Import Competition and the Probability of Being Hired by Another Firm to an R&D Job at the Worker Level

	IV: Reverse Switching	IV: With Tertiary Education	IV: Less Than Tertiary Education	IV: More than 50 Years Old	IV: 50 Years Old or Younger
Dep. Var.: Move def. 1	(1)	(2)	(3)	(4)	(5)
Import Competition$_{t-1}$	-0.00072	0.11424**	0.00258*	0.01404	0.01944**
	(0.00086)	(0.06006)	(0.00138)	(0.02556)	(0.00852)
Sector, Mun. and Year Fixed Effects	yes	yes	yes	yes	yes
Worker Characteristics	yes	yes	yes	yes	yes
Firm Characteristics	yes	yes	yes	yes	yes
Mean Y	0.00661	0.29761	0.05358	0.05994	0.06654
First Stage F-stat on Instruments	756.11	576.76	744.48	345.08	759.05
First Stage- Import Competition IV Coeff.	0.6179*** (0.0239)	0.5261*** (0.0227)	0.61193*** (0.0230)	0.4567*** (0.0154)	0.64509*** (0.0292)
R-sq	0.05199	0.06902	0.12921	0.05194	0.11772
N	939,386	177,832	761,554	161,838	777,548
	IV: More than 5 Years of Tenure	IV: 5 Years of Tenure or Less	IV: More Than 10 Years of Work Experience	IV: 10 Years of Work Experience or Less	IV: Male Workers
Dep. Var.: Move def. 1	(6)	(7)	(8)	(9)	(10)
Import Competition$_{t-1}$	0.02178**	0.01236	0.00798*	0.02112**	0.01854**
	(0.00871)	(0.01014)	(0.00481)	(0.00978)	(0.00906)
Sector, Mun. and Year Fixed Effects	yes	yes	yes	yes	yes
Worker Characteristics	yes	yes	yes	yes	yes
Firm Characteristics	yes	yes	yes	yes	yes
Mean Y	0.08058	0.06072	0.06228	0.06486	0.06942
First Stage F-stat on Instruments	565.03	742.98	687.11	570.11	740.02
First Stage- Import Competition IV Coeff.	0.5209*** (0.0225)	0.61076*** (0.0229)	0.59113*** (0.0195)	0.5254*** (0.0227)	0.61054*** (0.0229)
R-sq	0.10617	0.12397	0.10059	0.15531	0.11738
N	173,700	684,470	430,544	508,842	701,188
	IV: Female Workers	IV: Incumbent Firms		IV: New Firms	
Dep. Var.: Move def. 1	(11)	(12)		(13)	
Import Competition$_{t-1}$	0.00512	0.01248*		0.01698**	
	(0.00604)	(0.00605)		(0.00558)	
Sector, Mun. and Year Fixed Effects	yes	yes		yes	
Worker Characteristics	yes	yes		yes	
Firm Characteristics	yes	yes		yes	
Mean Y	0.04566	0.07032		0.05826	
First Stage F-stat on Instruments	564.05	569.23		572.87	
First Stage- Import Competition IV Coeff.	0.5205*** (0.0225)	0.5268*** (0.0227)		0.5260*** (0.0227)	
R-sq	0.13567	0.13779		0.12991	
N	238,198	475,918		325,178	

Notes: In column 1, the dependent variable is equal to 1, if a worker i moves to another manufacturing firm and switches out of an R&D job. In the other columns, the dependent variable is equal to 1, if a worker i moves to another manufacturing firm and is employed in an R&D job. 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, education, tenure, and work experience. Firm characteristics include the lag of firm's size, offshoring status, 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%.