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Trade Competition, Technology and Labor Re-allocation

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TRADE COMPETITION, TECHNOLOGY AND LABOR RE-ALLOCATION

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Trade Competition, Technology and Labor Re-allocation

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January 4, 2016

Abstract

This paper studies the changes in labor allocation across firms and industries in response to changes in technology (captured by the adoption of information and communication technologies, ICT) and import competition, due to increased exposure to trade competition from China. We use detailed matched worker-firm data from the Swedish manufacturing sector. We provide new evidence on the mobility of heterogeneous workers across firms and document increased assortative matching of workers in ICT intensive industries. However, the sorting patterns are not uniform across industries within this group. The adoption of ICT *along* with stronger Chinese import competition results in a significant skill upgrade within high-wage firms. In contrast, in the absence of strong pressures in import competition, sorting occurs at the low end of the worker-firm distribution, i.e. low-skill workers allocate to low-wage firms. Industries with low ICT intensity do not exhibit any of these sorting patterns. We rationalize our empirical findings through a labor market matching model which is able to explain the increased assortative matching in ICT intensive industries through an increase in the relative demand for qualified workers.

JEL Codes: E24, F16, J31, J63, O33

Keywords: Wage Inequality, Employment Dynamics, Assortative Matching, Import Competition, Technological Change.

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1 Introduction

International trade in the last two decades was marked by the rise of China as a major exporter. The Chinese economy also underwent a structural change, and by 2010 China displaced the United States as the largest manufacturing nation¹. On one hand, one of the benefits of China's ascent as a major manufacturing power was the concurrent decline in manufacturing goods prices. On the other hand, recent work has suggested that Chinese exports had disruptive effects on the labor markets of other economies, especially among low skilled workers (see Autor et al., 2013, 2014 and Balsvik et al., 2015). However, it has not yet been studied how individuals (re-)allocate across the full spectrum of firms, which can be exposed to different competitive pressures from the international market and who adopt different types of technologies. We aim to fill this gap in the literature. To do so, we rely on matched worker-firm data covering the entire private Swedish manufacturing sector between 1996 and 2006.

In this paper, we study the labor market effects resulting from increased import competition from low income countries in industries characterized by different technologies. To characterize the workers and firms by their earning/paying potential, we apply the methodology developed by Abowd, Kramarz and Margolis (1999) (hereafter AKM) on detailed administrative matched worker-firm data of the Swedish manufacturing sector for the period of 1996-2006. This rich data allows us to analyze both the changes in the allocation of workers across different firms as well as their movements in and out of the manufacturing sector. We focus on two potential sources of changes in the allocations observed in the labor market: technology and trade. The rise in the adoption of information and communication technologies (ICT) has been intense in developed countries like Sweden since the late 1990's and industries within the manufacturing sector are heterogeneous in their adoption of ICT. Parallel to these changes, the Swedish economy has experienced a rapid increase in international trade, measured by both exports and imports. Of particular interest is the brisk change in the share of trade with less developed, labor-intensive countries.² Following recent work by Autor et al. (2013, 2014) and Balsvik et al. (2015) we focus on the significant increase in trade with China, which accelerated after China joined the WTO in 2001. Swedish imports from China grew 20% annually between 1996 and 2006 and as in many developed countries the growth in Chinese trade stands to represent the bulk of the growth in imports from developing countries. For the case of Sweden, this is also the largest increase among its leading trade partners.³ As manufacturing industries exhibit different degrees of changes in exposure to Chinese imports, we are able to study the differential effects of import penetration on the allocation of workers, as well as interactions between ICT technology and trade with

¹See <http://unstats.un.org/unsd/snaama/resQuery.asp>.

²In fact, given the different specialization patterns in developing and developed economies, the increase in trade with these countries may be viewed as a form of technological change in developed economies (for example, through trade in intermediates or offshoring of some tasks which changes the domestic production process).

³See <http://comtrade.un.org/db/>.

China.

To examine the role of technology, trade, and the interaction between the two, we perform our analysis on the total manufacturing sector segmented on their ICT intensity. Next, we allow for a full interaction of ICT intensity groups with levels of trade exposure gives way to a more detailed analysis. In particular, we divide the data into two overlapping periods: 1996-2001 (Period 1) and 2000-2006 (Period 2), separated by China's entry into the WTO in 2001 which we take to be an exogenous trade shock to a small open economy like Sweden. We classify manufacturing industries according to the change in Chinese imports share (high/low) between the two periods, and according to their ICT intensity (high/low) using the classification developed by Van Ark et al. (2003).

Our results show significant changes in the allocation of different types of workers to different firms between 1996 and 2006. We start by showing that between the two periods the rise in the variance of wages in the Swedish manufacturing sector was low at 2%. Decomposing this change to its components we see that 45% of the overall change in the variance of wages is due to the rise in the variance of the person component, whereas the rise of the firm is equivalent to only 2% of the change. In contrast, the covariance of person and firm fixed effects rises faster and contributes to 10% of the change in wage inequality which is evidence in line with the type-specific sorting phenomena. The focus of this paper is precisely in studying the increase in this covariance of person and firm fixed effects and how that represented a change in the allocation of workers across different firms and industries over time.

We find two main results when examining the changes in allocation patterns within industry groups according to their exposure to trade and ICT intensity. First, the increased sorting is a phenomenon that appears primarily in ICT-intensive industries. Second, we find that the change in the sorting pattern is not uniform within the ICT intensive group. High ICT intensity industries exposed to higher increase in Chinese import penetration show a stronger increase in the share of high-wage workers in high-wage firms, and a reduction in the share of low-wage workers in the high-wage firms. Thus, we see stronger sorting on the high end of the firm distribution in these industries, while there are no significant changes on the low end. In ICT intensive industries with a low change in Chinese import penetration, we also observe increased sorting, but primarily at the other end of the distribution. In these industries, we document an increase in the share of low-wage workers in the low-wage firms.

In fact, when we perform the same wage decomposition exercise on high and low ICT intensity industries separately, we see that the contribution of the covariance of person and firm fixed effects to the variance in wages varies by industries' ICT-intensity: the change in the covariance contributes to 18% of the change in the wage inequality in ICT-intensive industries, whereas in the group of low ICT intensity industries this covariance was nearly unchanged, giving initial support to our first result. We then go on to use the distribution of estimated person and firm fixed effects from the AKM model and construct the joint distribution of person-firm wage components to study the match of person and

firm types within and across periods and industries. This mapping allows us to investigate whether the increased sorting occurs for high/low fixed effects for persons and firms, which, as in AKM, we call high/low wage type workers and firms respectively. Industries which are high ICT adopters see an increase in the share of low-wage persons in low-wage firms between Periods 1 and 2, and a reduction in the share of low-wage persons in high-wage firms. Simultaneously, the share of high-wage persons in high-wage firms increases.⁴ We obtain our second result when we repeat the joint distribution analysis for the interaction of high-ICT industries with different levels of trade exposure.

We then use a simple labor market matching model with both firm and worker heterogeneity to rationalize our empirical findings. The model extends Albrecht and Vroman (2002) by introducing productivity differences across firms within heterogeneous industries to explain the changes in exposure to foreign competition that we observe empirically within industries of different ICT intensity. The baseline version of the model considers an economy where there are two types of workers, *low-skill* and *high-skill* workers. Firms differ in their productivity and they can post one of two types of jobs: an *unqualified* job, which can be performed by either a *low-skill* or a *high-skill* worker, and a *qualified* job, which can only be performed by a *high-skill* worker. The latter jobs are more productive, but they also imply higher fixed costs for firms. In equilibrium, there will be a partitioning of firms: highly productive firms post qualified jobs, less productive firms post unqualified jobs and the least productive firms exit. In the model, high ICT intensity industries are characterized by a higher relative productivity of the *qualified* jobs.

We then simulate the impact of exposing a subset of both high and low ICT industries to an increase in import competition. We assume that this reduces the productivity of unqualified jobs in industries exposed to tougher import competition. As a result of the shock, the least productive firms exposed to trade will exit the market, while firms with higher productivity will upgrade their posts from unqualified to qualified jobs. Consequently, low-skilled workers are pushed out of the exposed industry, low-skill unemployment increases and wages of low-skill workers decrease. Most low-skill workers who leave exposed industries are hired by the non-exposed industries where the number of unqualified jobs increases. Thus, the model explains increased sorting at the high end (upgrading) in the exposed industry by an increase in the relative demand for qualified workers.

On the other hand, in low ICT intensity industries where the relative productivity of the qualified jobs is lower, the responses to a trade shock are significantly weaker. These industries have a wider range of operating firms and a higher share of unqualified jobs, as more firms find it non-profitable to post the high-cost vacancies. Hence, the trade shock makes the job type trade-off and the cross-industry reallocations less pronounced in the low ICT intensity industries.

Finally, the choice of Sweden as the country of study fits the purposes of this paper for four main reasons. First, the availability of longitudinal data on characteristics of firms and workers allows

⁴Throughout the paper, we refer to person or worker fixed effects interchangeable, since an individual needs to be observed working to compute the fixed effect in this setup.

to study in detail the transitions of workers across firms and in-and-out of the labor market. Second, most of the studies of the effects of exposure to trade and technological changes on the wages and employment status of individuals are conducted using U.S data. However, this is a large open economy capable of influencing world prices of goods and it has an independent trade policy. On the contrary, Sweden is part of the EU and it has limited power in international trade agreements. Therefore, sharp changes in international trade flows, such as Chinese exports to the world, are mostly exogenous shocks to Swedish firms. Third, the period covered by our study (1996-2006) has been relatively stable in Sweden. Since 1997, there has been a stable wage setting scheme characterized by collective or local wage agreements in the manufacturing sector, which explain the very low contribution of firms' wage-premium to the change in overall wage inequality (see Nordström Skans, Edin and Holmlund, 2009). This period is also political and economically stable in Sweden, marked by economic growth rates of about 4% per year in the late 1990s and decreasing unemployment rate (the unemployment rate was 8% in 1996 and 4% in 2001).⁵ Finally, we focus our study on manufacturing firms, which represent about 1/3 of the total GDP and occupy just over 1/3 of the total of workers in the Sweden, similar to other EU countries.

In the next section we discuss the literature related to our paper. We present the data sets used in Section 3, we then follow with the empirical strategy in Section 4. In Section 5 we present the results and in Section 6 we present a simple model to rationalize the potential mechanisms behind our findings. Section 7 concludes.

2 Background

Our work relates to several strands of trade and labor literature. The effects of technological changes and trade on industry and labor market dynamics have been analyzed extensively both theoretically and empirically. A branch of literature places skill-biased technological change at the center of the theoretical approach and models a sorting mechanism where firms that use different types of technology employ labor input of different skill levels.⁶ Autor and Dorn (2013) analyze changes in employment across skill groups and they find an increase in the employment share of high- and low-skilled workers relative to the middle-skilled group, which they argue may be linked to the advances in and adoption of ICT related technology. They do not analyze the changes in allocation patterns across firms. To the extent that these employment changes are linked to particular type of firms, they may have an impact on the distribution of workers across firms.

Import competition from low-wage countries, on the other hand, may cause stronger competitive

⁵Despite changes in the early 1990s in the wage setting, Sweden is still characterized by a highly centralized bargaining setting, and 90% of the employees have part of their pay determined by local negotiations (see <http://www.worker-participation.eu/National-Industrial-Relations/Countries/Sweden/Collective-Bargaining>).

⁶See Acemoglu (1999) and Caselli(1999), among the first. Albrecht and Vroman (2002) arrive at a similar prediction in the model with skill-job type complementarities and unemployment.

pressures in the least productive firms if the production technologies and the goods produced are similar to the low-wage country's technology and exports. Moreover, heterogeneous firm trade models predict that import competition may cause pressures on low-skilled labor as firms upgrade their skill composition in response to this pressure.⁷ Several recent empirical studies have focused on the effects of increased Chinese import penetration on labor market outcomes, such as employment, wages, and welfare payments. For example, Autor et al. (2013) analyze the effect of industry-level Chinese imports on U.S. local labor markets and find a negative effect on both wages and employment in import-competing markets. Ashournia et al. (2012) study the effects of Chinese import penetration on Danish firms at industry and firm-level. They find that it decreases low-skilled wages at the firm-level. Alvarez and Opazo (2011) also find negative effects on average wages of firms using Chilean data. These papers, however, do not study the effects on the mobility of workers across firms and industries.

Several studies on heterogeneous firms and trade imply that there is a link between import competition (both in general and from developing countries in particular) and technological and labor input choices of firms. Nevertheless, there is little empirical evidence of such link.⁸ In their theoretical work, Davidson et al. (2008) and Davidson and Matusz (2012) analyze the effect of export and import competition on the choice of technology and the resulting labor market outcomes. They find high end sorting in exporting industries (high skilled workers sort into more productive firms)⁹. In the model developed by Davidson et al. (2008), import competition reduces the gap in revenues of different types of workers, and thus may result in increased negative assortative matching (that is, high-skilled workers accepting jobs in low-performing firms within the import-competing industries). We focus on the same trade channel (import competition), but originating from developing, low-skill countries, which may affect domestic low-skill labor more than the high-skilled. In addition, we study the (re-)allocation patterns across firms exposed to different changes in import competition and with different technological structure.

In a recent paper, Autor et al. (2014) attempt to disentangle the effects of two forces - the ICT technology and import competition - on employment across local labor markets over time between sectors and occupations, and among workers of different education, age and sex categories. They find that technological progress and import competition have rather independent effects, as opposed to some previous hypotheses of the two being just two faces of the same phenomenon¹⁰. We follow an approach similar to Autor et al. (2014), but we add in three important dimensions: (1) since we have

⁷For a review of the literature, see e.g. Ashournia et al. (2012)

⁸See e.g. Kugler and Verhoogen (2011), Bas and Berthou (2013). In the literature that is interested in globalization, technological choice and sorting, but does not necessarily focus on import competition, we note Grossman et al. (2014), Grossman and Maggi (2000), Costinot (2009), Costinot and Vogel (2010) and Yeaple (2005), among others.

⁹Relative to Davidson et al. (2008), Davidson and Matusz (2012) introduces firm heterogeneity as in Melitz (2003) and monopolistic competition

¹⁰For example, Grossman and Rossi-Hansberg (2008) find that with different countries adding value to global supply chains, the task trade results in productivity effect that benefits the factor whose tasks are more easily moved offshore.

access to individual level data, we can track workers' movements across firms, control for the firm where the individual works and thus recover the firm wage-premium; (2) beyond Autor et al. (2014), we study the impacts of technological changes and trade on labor allocations across different types of firms; and (3) the rich administrative data set used allows to document in detail the sorting effects of the interactions between technology and import competition. Previous work on the industry effects of globalization and technology have been placing the two side by side and attempting to determine the relative importance of each factor. Besides our work, we are only aware of three other studies which attempt to study the labor market impacts of both trade and technology (Autor et al., 2014, Håkanson et al., 2015, Bloom et. al, forthcoming).

Within the empirical literature that focuses on the sorting phenomena, Davidson et al. (2014) explore the matching patterns between workers and firms in Swedish manufacturing industries. They find that greater openness in comparative-advantaged industries increases the degree of positive assortative matching, measured by the correlation between the individual and firm components of the wage. This change is not present in the comparative-disadvantaged industries (import-competing industries). Their results are robust to the inclusion of the controls for the technical change across industries, which may have also contributed to the assortativeness of worker-firm matching. We follow a similar approach in the empirical part, but attempt to document the sorting phenomenon across the distribution in greater detail, isolating and interacting the effects of trade and technology. Håkanson et al. (2015) also analyze the Swedish data and they find a significant increase in assortative matching. They contrast two potential explanations - offshoring and skill-biased technical change - and find that the latter seems to have been more important. However, so far no paper has explored the interactions between different forces shaping the labor distribution across firms, nor does it characterize the sorting patterns in detail (e.g. which parts of the distribution are affected).

3 Data

We use firm- and worker-level data from databases either collected or maintained by Statistics Sweden (SCB). The data is confidential as original worker and firm identifiers are stripped and reassigned by SCB, but access to the database is not exclusive. We convert all monetary values to 2010 SEK using the Consumer Price Index information from SCB. Information about Chinese trade figures comes from UN Comtrade (see <http://comtrade.un.org/>). ICT classifications are based on those set by Van Ark et al. (2003). We now explain in detail each of the data sets used in our analysis.

3.1 Firm data

Firm-level balance sheet data is available from the Account Statistics at Statistics Sweden (*Företagsekonomisk Statistik*, FEK). While most of the variables are available from 1980 onwards, this data only covers a

selected sample of large companies until 1996. This restriction motivates our focus on studying the period from 1996 onward. The database includes information on total wage spending, sales, profit, capital, number of employees, and industry classification at the firm level. The data is released with a two year lag, and is composed of only non-imputed information. Industry classification code systems in Sweden were updated once during the period interest, changing the industry code of a firm (the index systems used are SNI1992 and SNI2002). In an effort to have a continuous industry classification, we merge the series at the three digit industry code using the conversion keys supplied by Statistics Sweden where available. If the conversion key was not successful in producing a match between two indices for a particular industry, we then make use of overlapping years in different code systems to generate our own conversion key.¹¹ In our analysis we defined industries using the two digit codes. We supplement this data with the Business Register Database (*Företagsregistret*), which includes information on the legal form and controlling ownership of the firm and municipal location from 1980 onwards.

3.2 Worker data

The matched employer-employee data is gathered by the Swedish Tax Authority (*Skatteverket*) and it is available in Register Based Labor Statistics (*Registerbaserad Arbetsmarknadsstatistik*, RAMS) maintained by Statistics Sweden. This data contains information on total labor earnings collected to compute taxes, and therefore includes the earnings of all employees, including top chief executives (CEOs). The data is available from 1985 onwards, and each individual is linked to a firm (and a plant where applicable). In this database, an individual is tied to a place of work if he/she was employed there in the third week of November, in line with International Labor Organization's definition. For each worker there is information about the annual labor income, main place of employment according to the definition stated above (firm and plant where applicable), age, gender, highest level of education and field of education. We group individuals into three educational groups: less than high school diploma, high school diploma holders, and at least some college based on detailed classification about the education level of individuals.

Sample Selection We restrict our data to include firms that are active from 1996 to 2006, since the firm-level data is based on a sample of companies before 1996. We keep firms with at least 5 employees per year during their entire presence in this range. While we mostly focus on manufacturing firms, we also consider all the other sectors in the descriptive analysis.¹² Finally, we restrict our sample to

¹¹Wherever an industry has been split up into several parts, we assign the firms to the new industry whose description best matches the old industry description. This applies to 3 industries in the conversion from SNI1992 to SNI2002 system.

¹²There are 60,907 firms in the database identified as manufacturing firms in this period. Our restriction of minimum 5 employees drops about 51,000 firms, 72% of which reported an average employment count below one employee. These micro-firms are linked to self-employment, which is beyond the scope of our analysis.

limited liability partnerships or limited liability companies.

We restrict the analysis to workers of 20-65 years of age in each year. The data does not contain information regarding full-time or part-time employment status of individuals or hours workers. Thus, we restrict the baseline sample to individuals with labor earnings of at least SEK 120,000 a year (SEK 10,000 \approx USD 1,570 a month). Next, we drop individuals whose education level is unknown.¹³ Finally, we top coded income at the 99 percentile for the sample period of 1996-2006 (our results are robust to such top coding, but we perform it since the data includes the earnings of all employees, including top chief executives, which is associated with some outliers). More information about the data set can be found in Table A.1 in Appendix.

3.3 Trade and ICT Classifications

Information and Communications Technologies Our measure of ICT adoption follows the classification done by Van Ark et al. (2003) for the U.S. and a group of EU economies¹⁴. In their classification, industries are grouped together as ICT producing, ICT-using and non-ICT manufacturing industries. We group together the ICT producing and using industries as *high ICT intensity* industries for our analysis as they represent a higher rate of ICT adoption than the industries in the non-ICT group which we name as *low ICT intensity*. Details of the classification can be found in Table (A.2) in Appendix A.¹⁵

Chinese Import Penetration We use UN Comtrade data for international trade between Sweden and each of its partners. Comtrade data classifies trade based on product (not industry) level codes, and manufactured goods are indexed by material. To be able to match these product codes to Swedish industry codes from the firm-level data, we use the the description of each product and industry described in Table (A.3) in Appendix A.

To define exposure to Chinese trade competition, we construct a measure of Chinese import penetration (CIP), which is the share of total imports from China for industry k in year $t = 1996, 2001$ in

¹³The income restriction drops 401,074 employees, 51,343 of whom do not have an educational level assigned to them. Of the workers whose income is below the cutoff, about 26% of them earned at most a total of SEK 10,000 (\approx USD 1,570) in a year, and about 67% of them earned at most SEK 50,000 (\approx USD 7,850) annually.

¹⁴The EU countries considered in their study are Austria, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Spain, Sweden and the UK.

¹⁵Note that between ICT producing and intensive categories, two industries are split into two at the three digit level of detail (Scientific Instruments and Insulated Wire). Since we are using industry classifications at the two digit detail level, merging the ICT producing and intensive categories into the same group in our classification of high ICT industries also suits our level of industry detail. We keep low ICT industries exactly the same as Van Ark et al. (2003). The EU-KLEMS database provides continuous measures of consumption and gross fixed capital formation in ICT assets for the period at hand. However, they group several different industries together and present data for a total of 13 industries only. This higher level of aggregation at the industry level does not translate to the level of detail we use in our industry-level analysis.

the total of imports from the world to Sweden for industry k in year t , that is,

$$CIP_{kt} = \frac{Imports_{kt}^{China}}{Imports_{kt}^{World}}. \quad (1)$$

We then obtain the share of Chinese imports to Sweden in 1996 and in 2001 for each of the 21 industries we observe data for (see Table 1). As we are interested in capturing the effect of the change in exposure to Chinese imports on labor outcomes, we rank manufacturing industries according to the percentage change in Chinese import penetration between these two years. We then define *High Exposure Industries* (which we call *T-industries* in our model) as the 10 industries with the largest change in the share of Chinese imports and we define *Low Exposure Industries* (or *N-industries*) the 11 sectors with the smallest change in the share of Chinese imports. By focusing on the change from the first year of data to the last year before full-year Chinese membership to the WTO, we do not rely on any ongoing simultaneous forces within the second period related to firms repositioning in the market as a response to Chinese imports. Our classification is based on potential growth in trade exposure.

We consider two alternative measures of Chinese import penetration. The first approach takes the changes in the first three years in Period 1 to the first three years in Period 2. We then take the median ranking from the following pairings of years: 1996 and 2001, 1997 and 2002, and finally 1998 and 2003 to classify industries as having a low change in CIP (Low Exposure) or high change (High Exposure). The second alternative considers the share of Chinese imports over domestic production and imports net of exports for each industry, i.e. Chinese imports as a share of apparent domestic consumption in the industry. We construct the change in this share from 1996 to 2001 and rank the industries according to the change in their exposure to Chinese imports. We show below in Section 5 that our results are robust by the measure of import penetration used.

Table 1: Manufacturing Industry Trade and Technology Classifications.

Industry	Chinese Share		Industry	Chinese Share	
	(%) 1996	(%) 2001		(%) 1996	(%) 2001
	Δ	Δ		Δ	Δ
Low Exposure			Low ICT		High Exposure
Food	0.09	0.19	Tanning, dressing of leather	110.58	1.06
Textiles	1.16	2.59	Pulp, paper and paper	123.90	1.30
Refined petroleum	0.27	0.46	Rubber and plastic	67.91	0.07
Chemicals	0.25	0.53	Non-metallic minerals	108.81	0.07
Wood	1.60	4.57	Basic metals	185.09	0.79
Motor vehicles	0.05	0.12	Fabricated metal products	161.5	0.11
High ICT			High ICT		
Other transport equipment	0.04	0.04	Machinery and equipment	-3.64	0.15
Furniture	1.77	4.84	Office machinery, computers	173.57	0.12
Wearing apparel	6.99	8.12	Electrical machinery	16.2	0.32
Publishing and printing	0.24	0.43	Radio, television and com.	80.17	0.65
Medical and precision equip.	0.35	0.99		182.94	6.53
					901.7
					351.83
					496.55
					492.47

Note: The ICT classifications follow Van Ark et al. (2003), detailed in Section 3.3 and Table A.2. Chinese Import Penetration measure is as described in Section 3.3.

4 Empirical Strategy

Here we present the basic econometric framework for disentangling the components of wage variation attributable to worker-specific and employer-specific heterogeneity. We follow Abowd et al. (1999) and Card et al. (2013) in our empirical exercise. We assume that the log real annual earnings y_{it} of individual i in year t can be modelled as an additively separable model of the worker time-invariant characteristics α_i , a component specific to the firm j where the individual works in year t (denoted $\theta_{J(i;t)}$), a set of time-varying observable characteristics of the individual $x'_{it}\beta$, and an error component ε_{it} . Then, we estimate the following model:

$$y_{it} = \alpha_i + \theta_{J(i;t)} + x'_{it}\beta + \varepsilon_{it}. \quad (2)$$

In equation (2), α_i subsumes a combination of skills and other time invariant factors specific to the worker i that are rewarded equally regardless of the employer. $x'_{it}\beta$ includes lifecycle components and aggregate shocks that affect a worker's wage in all jobs. In particular, x_{it} includes year fixed effects and cubic polynomial on age fully interacted with maximum lifetime educational attainment. We consider two indicators of completed education of an individual: an indicator for high school degree and an indicator for some college education or more, thereby making workers with at most some high school education the excluded category. The firm effect $\theta_{J(i;t)}$ is a proportional wage premium paid by firm j to all employees (for example, rent-sharing).

We use this simple specification to obtain some descriptive features of the wage dynamics between 1996 and 2006 in Sweden. We start by presenting some descriptive statistics for three estimates from model 2: $\widehat{\alpha}_i$, $\widehat{\theta}_{J(i;t)}$ and $\widehat{\varepsilon}_{it}$. The residual of equation (2) is of particular interest to motivate an additively separable model. We follow Low, Meghir and Pistaferri (2010) and write ε_{it} as

$$\varepsilon_{it} = \psi_{iJ(i,t)} + \phi_{it} + u_{it} \quad (3)$$

where the match effect $\psi_{iJ(i,t)}$ represents an idiosyncratic wage premium earned by individual i at firm j . We assume that $\psi_{iJ(i,t)}$ has mean zero for all i and for all j in the sample interval. The match specific wage component is a productivity component associated with each job match. As it is typical in the earning dynamics literature (see Meghir and Pistaferri, 2004), we assume that ϕ_{it} has mean zero for each person in the sample interval, but it contains a unit root, that captures a drift in the earnings of individuals. Innovations to this component could reflect on-the-job-learning and other unobserved human capital accumulation, promotions/demotions, health shocks, or job mobility. Finally, the transitory component u_{it} represents any mean reverting factors, such as overtime work, piece-rate compensation and bonuses and premia. We assume that u_{it} has mean zero for each person in the sample interval.

To analyze the patterns of workers sorting by type into different types of firms, we construct the

joint distribution of the person and firm effects obtained from the baseline regressions for each of the two periods. We classify industries according to their ICT intensity and the change in their exposure to Chinese import competition as explained in Section 3, and then we track the changes in the joint firm-worker effects distribution between Period 1 and Period 2.

Estimation and assumptions about ε_{it} We estimate equation (2) by OLS. The firm fixed effects in equation (2) are identified by individuals who move between firms and generate a large firm network in which each firm is tied to at least one another firm in the group through at least one worker who moves between them. Thus, we start by constructing the largest of such networks in period which we call the mobility group and our analysis is restricted to this group of interconnected firms (see Abowd, Creedy and Kramarz, 2002). While we base the choice of the largest mobility group to maximize the number of interconnected firms, this also gives us the largest network of interconnected workers. Table A.4 shows that the largest group includes at least 91% of the firms, and 99% of all the workers. For most of our analysis, we focus on firm fixed effects, but we also assess the robustness of our results to focusing instead on plant-level fixed effects. According to Table A.4 in Appendix A there are 865,674 and 890,704 identifiable fixed effects in Periods 1 and 2, respectively.

Abowd et al. (2004) point out that the estimated fixed effects may be subject to a downward bias if the number of workers who switch between firms in the sample are too few; a problem that they call "limited mobility bias." To address this issue the analysis is repeated on two separate samples of firms where the minimum number of movers between firms are restricted either to at least 5 (the main sample) and at least 10 (alternative sample). Our conclusions below are not altered by using this stricter mobility group (results available from the authors).¹⁶

The person and firm fixed effects in equation (2) are identified by OLS if the three components in ε_{it} are (1) orthogonal to the individual and firm fixed effects and (2) if they are orthogonal to the year fixed effects and to the cubic polynomial on age interacted with maximum educational attainment. The assumption (2) is standard, whereas assumption (1) holds since the hypotheses for $\psi_{iJ(i,t)}$, ϕ_{it} and u_{it} stated above ensure that ε_{it} is orthogonal to the individual fixed effects α_i .

By conditioning on individual fixed effects α_i and on $\theta_{J(i,t)}$, we allow for the systematic mobility of workers across firms to be correlated with individual time invariant characteristics and firm specific wage-premia, i.e., we allow high-skilled workers to be more likely to move across firms. However, ε_{it} may not be orthogonal to the firm fixed effects, since there are forms of endogenous mobility that could bias the estimate of firm fixed effects. In section (5.5) we show that endogenous mobility does not pose a threat to identify the firm fixed effects.

¹⁶Our analysis is based on firms, rather than plants, as 85% of the firms in the Swedish manufacturing sector only have 1 plant.

5 Results

For our analysis, we divide the data into two overlapping periods. Period 1 is defined as the years before the Chinese membership in the WTO (1996-2001) and Period 2 as the post-Chinese membership years (2000-2006). We perform our analysis on each period separately.

5.1 Characteristics of the Data

We start by presenting in Table 2 basic characteristics of the individuals in our sample for the first and last years in the data (1996 and 2006). Almost 80% of the individuals employed in the manufacturing sector are males and they are about 40 years old. Panel A shows that about half of the individuals have attended some college, but that in 1996 almost 1/3 of the individuals working did not have a high school degree. This proportion decreased to 19% in 2006. Panels B and C show that the share of individuals with some college is similar when we breakdown the sample according to the industry type (low and high ICT intensity).

In Table A.5 in Appendix A we turn to a more detailed look at some basic characteristics of each industry used in our analysis, grouped according to the definitions of ICT intensity and exposure to import competition for the first and last years in our sample: 1996 and 2006. The table has four characteristics for each industry: share of employment in the industry relative to overall manufacturing sector, share of workers in industry that attended some college, average number of workers per firm and number of firms operating in each industry. The table shows that the share of employment is more or less evenly distributed across the four groups of industries in the table, however three industries employ between 9-16% of the overall manufacturing employment: the machinery and equipment industry (high ICT-high exposure), motor vehicles and trailers (low ICT-low exposure) and fabricated metal products (low ICT-high exposure). Industries classified under low ICT-high exposure branch each employ a smaller share of the total manufacturing employment, but still this group includes 15-17% of the workers in the manufacturing sector. The share of workers with at least some college education is typically higher in the industries classified as high ICT adopters, however, there are industries classified as low ICT with a relative high fraction of workers that attended some college (e.g., refined petroleum and chemicals). Interestingly, all industries increased the share of employed workers with some college, and the mean increase across the four type of industries was similar between 1996 and 2006 (the share of workers that attended some college increased on average by 36% in the low ICT-low exposure, by 53% in the high ICT-low exposure, by 47% in the low ICT-high exposure and by 25% in the high ICT-high exposure industries). The average firm size varies considerably within each industry in the four groups, and only the low ICT-high exposure firms seem to have a smaller size on average.

Finally, the last set of columns presents the number of firms operating by industry. The largest

Table 2: Basic Statistics for 1996 and 2006.

	(1)	(2)	(3)	(4)
	Mean	SD	Mean	SD
	1996		2006	
	Panel A: All			
Share of males	0.78	0.42	0.76	0.43
Age	40.46	11.21	43.10	11.31
Share of workers with some college	0.19	0.39	0.26	0.44
Share of workers with high school degree	0.53	0.50	0.55	0.50
Share of workers with less than high school	0.28	0.45	0.19	0.39
N	453,494		499,914	
	Panel B: Low ICT			
Share of males	0.79	0.41	0.77	0.42
Age	40.39	11.17	42.68	11.38
Share of workers with some college	0.16	0.36	0.22	0.41
Share of workers with high school degree	0.53	0.50	0.57	0.49
Share of workers with less than high school	0.31	0.46	0.21	0.41
N	271,169		294,130	
	Panel C: High ICT			
Share of males	0.76	0.43	0.75	0.43
Age	40.57	11.26	43.70	11.17
Share of workers with some college	0.24	0.43	0.32	0.47
Share of workers with high school degree	0.52	0.50	0.52	0.50
Share of workers with less than high school	0.23	0.42	0.16	0.37
N	182,325		205,784	

Note: The table presents the mean and standard deviation (SD) for the demographic characteristics of the individuals used in our analysis.

decline in the number of operating firms occurred in high ICT industries (the second and fourth panels in Table A.5 in Appendix A). Coincidentally, these are also the industries where the average firm size increased relatively more.

5.2 Variance Decomposition

We start by presenting the results from our main specification (equation 2). The model of wage determination that includes the worker and firm fixed effects is capable of explaining 87-88% of the variation in annual log earnings in each period.¹⁷

To quantify the contribution of person and firm effects for the change in inequality we decompose the variance of observed log earnings (y_{it}) for workers in each sample interval as:

$$\begin{aligned} \text{Var}(y_{it}) = & \text{Var}(\alpha_i) + \text{Var}(\theta_{J(i;t)}) + \text{Var}(x'_{it}\beta) + 2\text{Cov}(\alpha_i, \theta_{J(i;t)}) \\ & + 2\text{Cov}(x'_{it}\beta, \theta_{J(i;t)}) + 2\text{Cov}(\alpha_i, x'_{it}\beta) + \text{Var}(\varepsilon_{it}). \end{aligned} \quad (4)$$

The variance decomposition reveals the changes in the components of the total variation, as well as their relative contributions to the total wage dispersion in each period (see Table 3). In the table we present the decomposition for our full sample (by period), and we also break it down by industry type according to ICT intensity. The main findings in this table can be described as follows. The rise in the variance of earnings across the two periods was low at 2%. The rise in the variance of the person component contributed to 45% of the overall increase in the variance of earnings. The increase in the variance of the firm component contributes only to 2% of the change in the variance in earnings. This is in striking contrast with Card et al., 2013, who document that the increase in the variance of the firm component for Germany contributes to 25% of the change in wage inequality (however they focus on a longer interval period than our study). The rise in the covariance between the firm and person time invariant components contributes to 10% of the change in wage inequality in the period studied. What is remarkable is the difference by industry type. The two panels on the right of the table for "High ICT" and "Low ICT" industries show that the change in the variance of person effects contributes to 50% and 40% of the overall change in earnings inequality in these industries, respectively. The change in the covariance between person and firm fixed effects contributed to 18% of the change in the earnings in "High ICT" industries, whereas in "Low ICT" industries the contribution of the covariance of firm and person fixed lost weight explaining the overall change in the variance of (log) earnings. We view this evidence as supportive of our main objective of focusing on the sorting patterns in the manufacturing sector, within and across its different industries.

¹⁷These results are available upon request.

Table 3: Variance Decomposition

	Total			High ICT			Low ICT					
	Period 1		Period 2		Period 1		Period 2		Period 1		Period 2	
	Variance	Share	Variance	Share	Variance	Share	Variance	Share	Variance	Share	Variance	Share
Log Earnings Variance	0.121		0.140		0.135		0.161		0.111		0.124	
<u>Breaking down the variance</u>												
Person Effect	0.083	68.8	0.092	65.7	0.092	67.9	0.105	65.0	0.077	69.6	0.082	66.5
Firm Effect	0.005	3.7	0.005	3.5	0.005	3.4	0.006	3.5	0.004	4.0	0.004	3.6
Covariates (X)	0.015	12.4	0.012	8.8	0.016	12.0	0.013	8.1	0.014	12.8	0.012	9.4
Residual	0.014	11.7	0.018	12.8	0.015	11.0	0.018	11.2	0.014	12.3	0.018	14.3
2xCov(Person,Firm)	0.0003	0.3	0.002	1.49	0.001	0.9	0.006	3.6	-0.0003	-0.3	-0.001	-0.5
2xCov(Person+Firm,X)	0.004	3.1	0.011	7.7	0.006	4.4	0.014	8.7	0.002	1.9	0.008	6.6

Note: The data is limited to workers aged 20-65, earning at least SEK10,000 a month with the top 1% assigned the value of the 99th percentile, employed in LLP or LLC manufacturing firms of at least 5 workers and 5 movers within the largest mobility group of inter-connected firms. The high and low ICT definitions follow the assignments by Van Ark et al (Put the reference of the section later, saying detailed in Section ()).

5.3 Changes in the Distribution of Workers and Firms between 1996 and 2006

To illustrate workers' sorting patterns into different types of firms, we start by mapping the joint distribution of the person and firm effects obtained from the baseline regressions for each period as well as for the total period. We first rank the firm and person effects, and then group them into deciles. Each firm bin, therefore, contains 10% of all the firms in that period, and the person bins are constructed analogously. Next, for each firm and person effect decile bin intersection, we calculate the share of worker-year matches to firms that fall into that particular bin, as a share of total possible firm-worker-year outcomes in the period. This is represented by a bar in the graph. Within each period, the sum of the shares adds up to 100%. This ranking allows us to focus on the relative positioning of the firm and person effects compared to the pool of other workers and firms rather than the absolute value of these effects. We are, in other words, focusing on the *shape* of the joint firm-work effects distribution.

The first two panels of Figure 1 present the joint distribution of the worker-firm effects over the two periods (left: 1996-2001, right: 2000-2006) and the difference (bottom panel) in the share of workers in each worker-firm bin between the periods. The comparison of the graphs in the top panel shows a change in the distribution of worker-firm effects. This comparison is visualised in the difference graph in the bottom panel of the Figure, and shows that the very lowest and the very highest paying deciles of firms do not exhibit any change in the share of workers. However, in the remaining ranges of firm types, we observe positive sorting, that is, larger masses of workers in the bins associated to high wage-worker and high-wage firms (on the top-right quadrant of the Figure) and also an increase in share of low-wage workers in low-wage firms (on the bottom-left quadrant of the Figure). Finally, there are also overall losses in the employment shares of the middle deciles of the firm effect. When interpreting the results, one should note that these comparisons are not in absolute terms as the support sets of the person and firm fixed effects may be different in range and dispersion. These are instead an exploration of the changes in the *shape* of the distribution relative to their respective supports.

In the Appendix (see Figure B.1), we also provide the dissection of the distribution for the total period by the two education groups in the workforce (at most high school - which includes those that that have high school diploma or less - and attendance of some college). This figure shows that high school workers are distributed more or less evenly across the whole support of the worker-firm effects, with some degree of positive assortative matching on both ends. College workers, on the other hand, concentrate in the highest paying firms and a large share of these workers are also high-wage individuals.

5.4 Comparing the Results for Different Industries: ICT and Trade Exposure

We now focus on the empirical and economic explanations of the changes observed in the data. We attempt to provide some evidence on the potential sources of the changes in joint distribution of

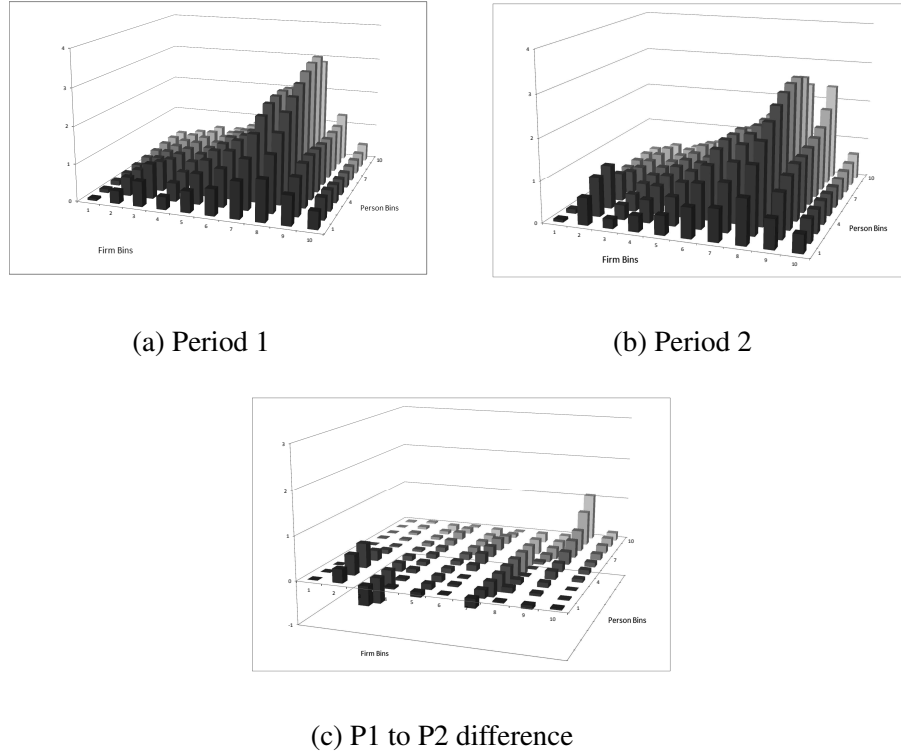
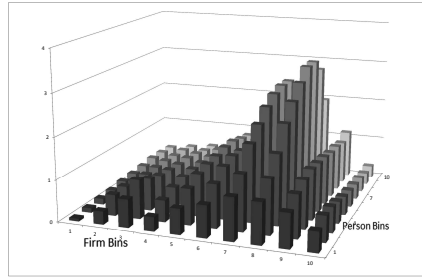


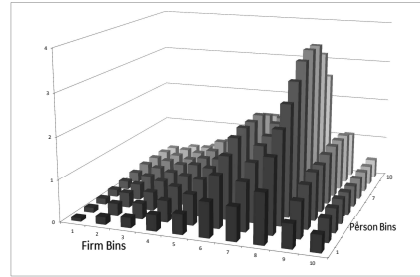
Figure 1: Distributions of worker and firm fixed effects.

worker and firm effects.

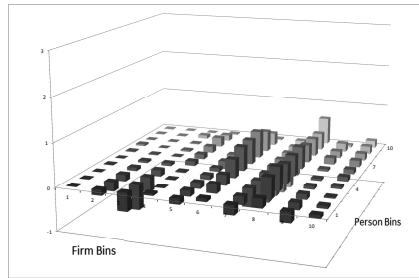
ICT We first focus on the heterogeneity by ICT intensity. When analyzing changes from Period 1 to Period 2 for the group (and also within the group) of industries with low ICT intensity (see Figure 2), we do not observe any significant changes in the joint distribution of firm and worker type. However, when we turn to analyze changes for the group of industries with high ICT intensity (see Figure 3), the changes in the joint distribution from Period 1 to 2 become more pronounced. We observe a large increase in the share of low-wage workers in low-wage firms, and a reduction in their shares in high-wage firms. At the same time, the share of high-wage workers in high-wage firms increases significantly. This particular allocation pattern could be caused by the very nature of ICT technologies and could also be due to non-uniform adoption across firms. Although this finding may be in line with the theoretical predictions of the skilled-biased technological change literature, we are concerned as to whether this phenomenon occurs uniformly across all industries with high adoption of the ICT. In particular, our main question is whether there are other factors - i.e. the increase in Chinese import penetration (intermediate or final goods) - that contribute to these mobility patterns when interacted with the change in technology.



(a) Period 1

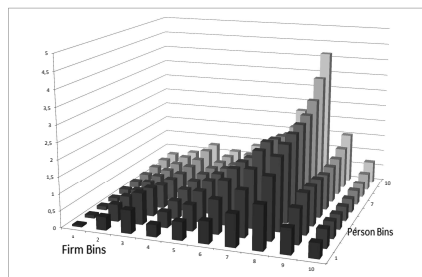


(b) Period 2

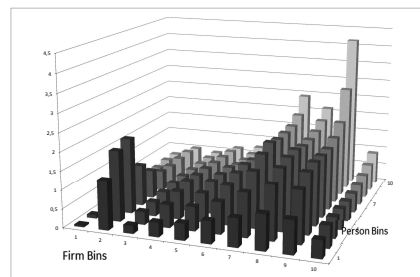


(c) P1 to P2 difference

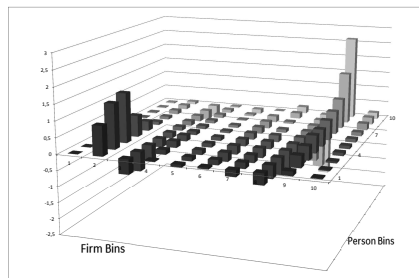
Figure 2: Distributions of worker and firm fixed effects: Low ICT Industries.



(a) Period 1



(b) Period 2



(c) P1 to P2 difference

Figure 3: Distributions of worker and firm fixed effects: High ICT Industries.

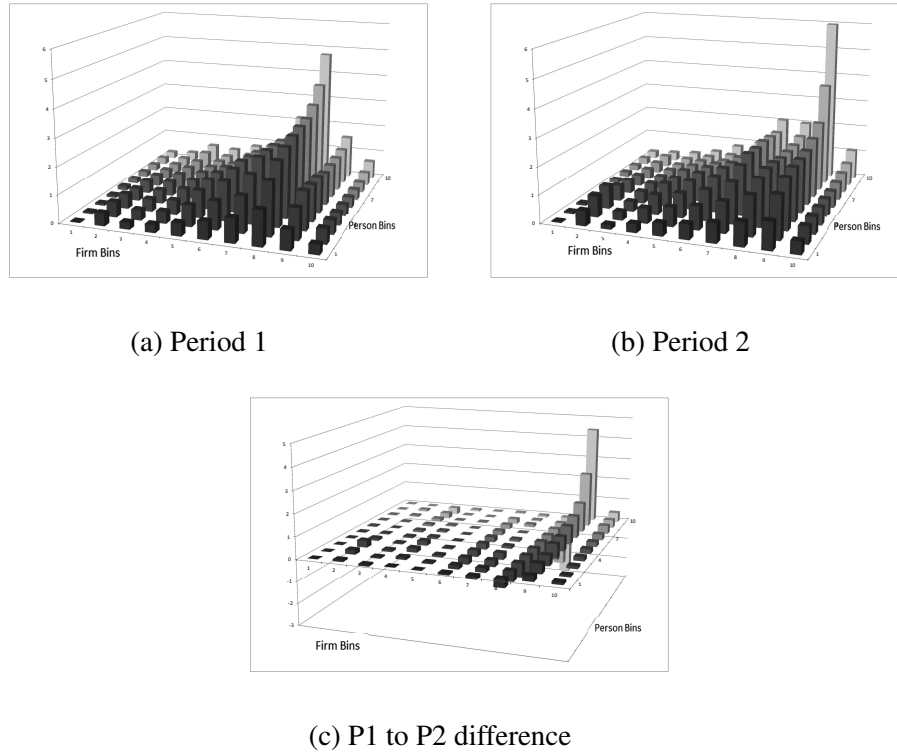


Figure 4: Distributions of worker and firm fixed effects: High ICT-High China Industries.

Technology and Import Competition Interactions To analyze this phenomenon in more detail, we proceed with the analyses within the group of the high ICT intensity industries. We distinguish between two subgroups of industries depending on their exposure to changes in competition from China (see Section 3.3).

The results reveal that the pattern observed in the aggregate for ICT intensive industries is not uniform across industries within this group, which suggests some interaction between technology and trade. In the first group - high ICT intensity industries with a high change in Chinese import penetration - we observe a strong increase in the share of high fixed effect workers in high fixed effect firms (Figure 4). These industries experience a stronger than average¹⁸ sorting on the high end of the firm distribution, while there are no significant changes on the low end. The interaction of import competition and technological change is not merely producing intensification or dampening of either one of the factors' effects, but a qualitatively different pattern. We view this result as an indication of the joint contribution of the two forces in skill upgrading of high quality firms, while leaving employment shares at the low end of the distribution unchanged.

In the second group of industries - high ICT intensity industries with a low change in Chinese import penetration - we observe an increase in the share of low-wage workers in low-wage firms

¹⁸We take the magnitude of the effects that we observe for the aggregate of all high ICT intensity industries as the average.

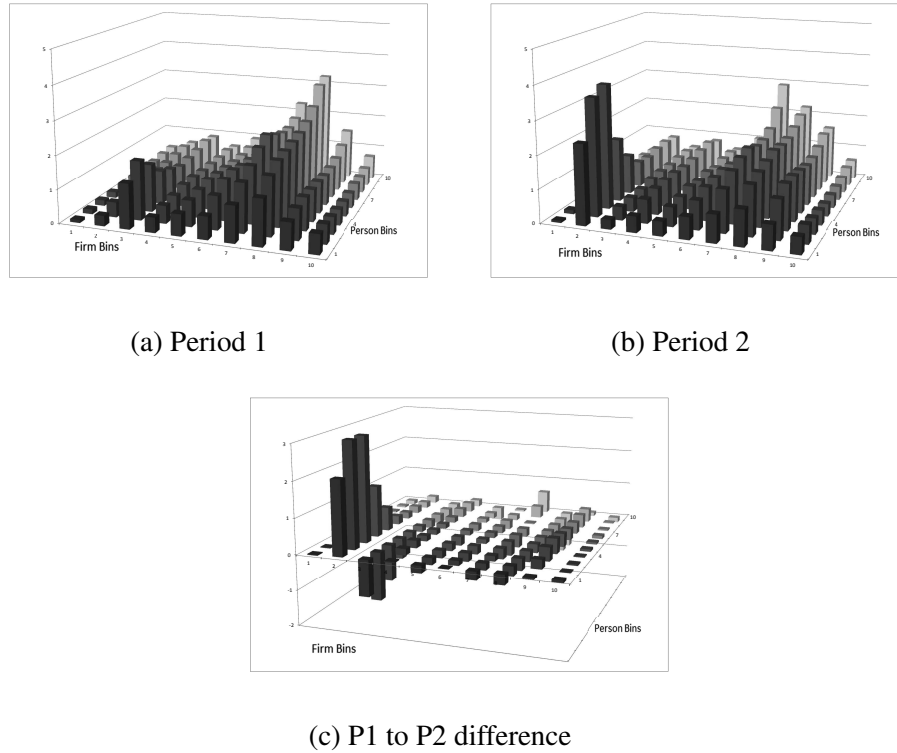


Figure 5: Distributions of worker and firm fixed effects: High ICT-Low China Industries.

(Figure 5). We also observe smaller changes in the share of high-wage workers in high-wage firms, and the shares of low-wage workers in high-wage firms. This effect resembles the aggregate results ICT industries, but with a much smaller change at the high end, and a much larger change at the low end of the firm distribution. The increase in low-wage employment shares at the low end of the firm distribution indicates that these types of firms, within industries with less exposure to import competition, may have served as the shelter firms for within industry low-skilled labor as well as of other more exposed industries.¹⁹ We wish to stress that the presence of the high ICT intensity still remains important, as we do not observe the similar "shelter" effects in non-exposed low ICT intensive industries (see Figure B.2 in the Appendix).

To strengthen our results with an alternative investigation, we divide the plan of worker and firm effects into low (bins 1 through 4) and high (bins 7 through 10) areas, giving us 4 quadrants: Low Firm-Low Person, Low Firm-High Person, High Firm-Low Person, and High Firm-High Person. In Appendix (Table A.6) we present logit regression results where we control for a set of firm and worker observables, as well as interactions of Chinese Import Penetration level with ICT level. Column 1 of Table A.6 shows that, compared to the "High China-High ICT" scenario, all the other combinations of China and ICT levels become more likely to have a Low Firm-Low Person outcome in Period 2, rel-

¹⁹We find similar patterns using alternative definitions of exposure to import competition; see Figures B.4-B.7 in the Appendix.

ative to Period 1, where the differences were smaller. Low China-High ICT industries are most likely to produce an Low Firm-Low Person outcome in Period 2, which fits well with our expectations on the positive sorting on the low end for this group of industries. On the other hand, all industries are less likely to produce a High Firm-High Person outcome compared to High China-High ICT industries, and again these differences become more pronounced in Period 2 relative to Period 1. Relatively, the least likely contribution comes from the Low China-High ICT industries, which supports the findings presented in the distribution graphs (see Column 2 of Table A.6).

Mobility: Origin and Destination Table 4 presents the movements of individuals into different industry and firm groups in Period 2 relative to their industry group in Period 1. The table presents row-percentages, which are a share of the Period 1 industry group of the individuals (see Table A.7 in Appendix for the number of individuals in each cell). The sample used to construct this table is restricted to those individuals and firms used in our main analysis (see Table A.4). As above, we group industries according to their ICT and exposure to import competition from China in Periods 1 and 2 (see Table 1 for the industries classified as "Low/High China" and "Low/High ICT"). The table has four horizontal panels (Panels A-D) where individuals are grouped into four possible groups (LFLP, LFHP, HFLP, HFHP). The two first letters denote the firm type and the two last letters denote the person type. "LF (HF)" is a firm with fixed effects in bins 1-4 (7-10) of Figure 1 in Period 1. "LP (HP)" is a person with fixed effects in bins 1-4 (7-10) of Figure 1 in Period 1. Since the individual effects are stable over the whole period for those individuals present in both Periods 1 and 2 (see Section 5.5), and as we are interested in studying the transition of individuals across firm types and in and out of the manufacturing sector, in Period 2 we consider only the firm type (high vs low). Within manufacturing, individuals may switch jobs across sectors within each period (ie, within Period 1 and Period 2), thus we assign as job and firm type to each individual the last affiliation of employment within each period. Individuals in column "Switch" are those that were employed in a manufacturing job in Period 1, but switched to a non-manufacturing job in Period 2. For individuals in column "Exit" we do not observe any work related income for the whole of Period 2, in neither manufacturing nor non-manufacturing industries and consider them as having exited the sample which could be due to a leave to unemployment or the labor force altogether, retirement or death, as well as due to our sample selection; an income below the income restriction of 120000SEK/year in Period 2, or aging beyond 65 years. "Stayers" are individuals present in Periods 1 and 2. "Newcomers" are individuals who were not in our sample in Period 1 (either because they did not meet the income restriction, were younger than 20 years old, were out of the labor force, unemployed or working outside the manufacturing sector), but who enter the manufacturing sector in Period 2.

Panel A ("Low ICT-Low China") of the table presents the largest proportion of switchers out of manufacturing sector, whereas in "High ICT" industries (Panels C and D), the switching out of manufacturing (but not exit) is relatively uniform across persons and firms types, regardless of the

exposure to import competition from China.

The row that refers to "Stayers" shows that the largest share of individuals present in Periods 1 and 2 corresponds to industries classified as "Low ICT-Low China" (Panel A). On the other hand, Panel A and C show that exit rates are higher in firms exposed to low import competition from China. Remarkably, Panel D ("High ICT-High China") shows the largest heterogeneity in pattern of exit rates within industry type. The highest rate of leavers is among low-wage workers in low-wage firms and the smallest among high-wage workers in high-wage firms in Period 1.

5.5 Assessing the Empirical Strategy

Endogenous Mobility Here we assess whether endogenous mobility of workers across firms may invalidate the identification of firm fixed effects. First, individuals may sort into firms based on an individual worker-firm match component $\psi_{ij(i,t)}$. To address this concern, we estimate a fully saturated model, which includes an indicator variable for each individual-job combination. The fully saturated model explains 90% and 89% of the variation in log earnings in the Periods 1 and 2, respectively, as opposed to 88% and 87% explained by the double fixed effect model. This shows that the improvement in the fit with the individual-job match model is relatively small compared to our baseline specification which is additive on firm and worker fixed effects.

Second, ϕ_{it} will be correlated with the firm fixed effects if wage growth predicts transitions across jobs. In other words, if permanent shocks to wage growth are correlated with job-to-job transitions. To address this concern, we perform a basic event-study as suggested in Card et al. (2013). In particular, we study the change in the mean earnings of workers who change jobs within each interval and who were employed in their old and new firms for two years in a row before and after the switch. We then classify the firms into high- and low-paying firms based on the mean earnings of co-workers. Figures (B.9) and (B.10) in Appendix present the change in the mean average earnings by type of firms for individuals who switch firms within Period 1 and Period 2. These figures show that there was no pre-switch trend in the earnings of workers who leave either high- or low-pay firms, regardless of the type of firm where they end up.

Finally, if u_{it} is correlated with job-to-job transitions, firm fixed effects will be biased. In particular, there will be attenuation bias if individuals facing positive (negative) transitory income shocks are more likely to move to high (low) wage firms. By using the same event-study described above, we can address this concern. For both Periods 1 and 2 we are unable to detect a dip or a jump in period -1 for the earnings of workers who leave either high- or low-pay firms independently of the type of firm in which they end up. Then, it is likely that transitory shocks are not correlated with job-to-job transitions.

Table 4: Transition of Workers between Period 1 and Period 2 by Industry Type (row percentages, as a share of P1).

Firm Type	Period 2									
	Low ICT				High ICT				Switch	Exit
	Low China		High China		Low China		High China			
Low	High	Low	High	Low	High	Low	High			
Period 1										
Panel A: Low ICT-Low China										
LFLP	31.8	16.3	1.1	1.2	1.1	0.5	0.4	0.7	18.4	28.5
LFHP	39.3	17.7	1.2	1.0	0.5	0.4	0.2	1.0	19.3	19.6
HFLP	4.4	56.4	0.5	1.1	0.3	0.6	0.3	1.0	14.6	20.7
HFHP	2.9	71.0	0.3	0.9	0.1	0.5	0.2	1.1	12.9	10.1
Panel B: Low ICT-High China										
LFLP	0.7	0.7	23.0	8.4	36.0	0.2	0.6	0.6	8.2	21.6
LFHP	1.0	1.0	39.6	14.8	7.1	0.2	1.4	1.2	12.2	21.4
HFLP	0.6	1.5	8.0	50.8	0.4	0.4	0.5	1.3	12.6	23.7
HFHP	0.3	1.2	11.5	64.1	0.1	0.4	0.3	1.3	7.7	13.0
Panel C: High ICT-Low China										
LFLP	0.5	0.6	0.5	0.5	45.9	9.8	0.2	0.4	13.5	28.1
LFHP	0.3	0.5	0.6	0.4	44.2	13.2	0.4	0.5	15.7	24.1
HFLP	0.3	1.1	0.4	0.8	6.0	49.4	0.3	3.1	16.1	22.3
HFHP	0.1	1.0	0.3	0.5	6.4	58.6	0.4	7.1	13.2	12.4
Panel D: High ICT-High China										
LFLP	0.4	0.7	1.4	1.5	25.3	0.5	24.8	14.3	10.2	20.9
LFHP	0.3	0.7	1.6	1.4	3.3	1.3	28.5	26.4	17.4	19.1
HFLP	0.3	1.4	0.6	1.6	0.4	3.9	4.8	56.3	12.9	17.7
HFHP	0.2	1.4	0.4	1.4	0.2	5.9	3.0	68.2	11.1	8.2
Stayers Total	4.4	23.9	6.7	16.0	9.6	12.9	3.5	23.0		
Newcomers	6.6	19.6	8.3	15.8	5.2	12.0	5.2	27.4		
TOTAL	3.5	17.2	5.1	11.8	6.6	9.4	2.8	17.6	11.1	14.9

Note: See Table 1 for the industries classified as "Low/High China" and "Low/High ICT". Since individuals may switch jobs across sectors within each period, we assign them to the last firm (and sector) affiliation of employment within each period. We divided individuals into four possible groups (LFLP, LFHP, HFLP, HFHP) in Panels A-D, where the two first letters denote the firm type and the two last denote the person type. "LF (HF)" is a firm with fixed effects in bins 1-4 (7-10) of Figure 1 in Period 1. "LP (HP)" is a person with fixed effects in bins 1-4 (7-10) of Figure 1 in Period 1. Individuals in column "Switch" are employed in a manufacturing job in Period 1, but switched to a non-manufacturing job in Period 2. Individuals in column "Exit" leave the sample for whole Period 2, which can be due to an income below the income restriction of 120,000SEK/year, become older than 65, leave to unemployment, leave labor force, retire or die. "Stayers" are individuals present in Periods 1 and 2. "Newcomers" are individuals out of our sample in Period 1 (either because they did not meet the income restriction, were younger than 20 years old, were out of the labor force, unemployed or working outside the manufacturing sector), but who enter the manufacturing sector in Period 2.

Worker and Firm Fixed Effects Across Periods To assess if worker and firm fixed effects switch rank for individuals and firms present in our sample across the two periods, we plot in Figure B.11 the joint distribution in Period 1 and 2 of effects for workers (panel a) and firms (panel b). The figure does not show significant transitions of workers across different person effect deciles, nor of firms across different firm effect deciles for those workers and firms that we observed in both Periods 1 and 2. This points to the stability of the ranking of the relative returns to individual skills and firm unobserved time-invariant characteristics. This suggests that both worker and firm effects are a reasonably stable representation of their earning and paying unobserved potentials (i.e. their skills and productivity).

Furthermore, to understand to which extent the firm fixed effects correlate with observable characteristics, we regress the estimated fixed effects on a set of firm characteristics. In particular, we take one observation per firm and we correlate the firm estimated fixed with the average firm's capital intensity (log capital per worker), exporter intensity, log profits per worker, share of high school graduates and the share of college graduates in the labor force of the firm. We find that when we control for industry indicators, all of these variables correlate positively with the firm fixed effects, except export intensity. Since a firm's information on export it is only available after 2000, we performed this inspection only for the second period in our sample (results available upon request).

Note that some recent papers criticize the methodology of Abowd et al. (1999) on the grounds that the economic interpretation of the estimated worker and firm fixed effects is unclear; see Hagedorn, Law and Manovskii (2012), Eeckhout and Kircher (2011) and Lise, Meghir and Robin (2013). In light of this, we see the AKM decomposition into worker and firm fixed effects primarily as a description of the covariance structure of the wages/earnings. We do not take a stand on the underlying economic factors (complementarities, matching, individual and collective bargaining, etc.) that generate these correlations.

6 The Model

6.1 Setup

In this section, we present a theoretical model which we use to provide an explanation of the observed industry dynamics and labor market outcomes. We rely on a simple labor market matching model with both firm and worker heterogeneity, based on Albrecht and Vroman (2002), which we modify to introduce productivity differences across firms within heterogeneous industries.

We assume that there are two types of workers that differ in their skill levels. Both live forever and are risk neutral. We normalize the population measure to 1 and assume that a fraction p of the population has low skill of level s^1 , while a fraction $(1 - p)$ has a high skill level s^2 .

To study the potentially heterogeneous effect of changes in import penetration across industries, we use a two-industry model. In this model one of the industries faces an import shock and we are

able to study the changes in the affected industry, as well as the implications for the neutral industry and potential cross-industry reallocations.

We consider two industries k , with $k = T, N$. Industry T is exposed to a change in import competition, while industry N is not. The two industries are ex-ante identical. There is a measure z^{max} of firms in each industry. Firms differ in their productivity level, each taking up a productivity value z (which we use to index the firms) from a uniform distribution in the range $[0, z^{max}]$. Each firm is represented by one job position and filled jobs break up at an exogenous rate δ . Each firm may choose between two types of jobs: an unqualified or a qualified job. There are minimum skill requirements for each job type. For the unqualified job the low skill requirement is given by y_k^1 and the qualified job requires a higher skill level given by y_k^2 , with $y_k^2 > y_k^1$. When a job in industry k is filled, the resulting output $f(s, y_k, z_k)$ is a function of the job skill requirement y_k , worker's skill s and firm productivity z_k , and is given by

$$f(s, y_k, z_k) = \begin{cases} y_k^\alpha z_k & \text{if } s \geq y_k \\ 0 & \text{if } s < y_k. \end{cases} \quad (5)$$

The skill requirement thus represents the skill input or productivity of the worker hired for the job and cannot be higher than the worker's own skill level. If producing, firms pay their worker a wage $w(s, y_k, z_k)$ and also incur a fixed cost $c(y_k)$. We assume that the same fixed cost is also incurred when the job is vacant and that it is higher for qualified jobs, but same across industries (i.e. $c(y_k^1) = c^1 < c(y_k^2) = c^2$). Firms choose the job skill requirements to maximize the value of the vacancy, and will thus require $y_k^1 = s^1$ and $y_k^2 = s^2$ for the two types of jobs, respectively. This implies that the unqualified jobs can hire workers of any skill and have output $(s^1)^\alpha z$, and the qualified jobs will hire only high skill workers and have output $(s^2)^\alpha z$.

The labor market is not segmented and open jobs and unemployed workers meet randomly. The number of meetings is determined by a matching function $m(u, v)$, where u represents the unemployment rate and v stands for vacancies. The matching function exhibits constant returns to scale and can be expressed as $m(\theta)u$ where $\theta = v/u$ stands for the labor market tightness.²⁰ Low-skill workers meet vacancies at the effective rate $\phi m(\theta)$ where ϕ is the share of vacancies that accept the low-skill worker, while high-skill workers meet the available vacancies at the rate $m(\theta)$. We define ϕ_k to be the share of industry k 's unqualified vacancies in the total number of vacancies in the economy. Likewise, unqualified vacancies meet unemployed workers at the rate $m(\theta)/\theta$, while this rate is $(1 - \gamma)m(\theta)/\theta$ for qualified vacancies, with $(1 - \gamma)$ representing the share of high-skill workers in the pool of unemployment.

Matches between vacancies and unemployed workers are formed whenever the total surplus created by the match is non-negative. Denoting the value of unemployment for a worker of type s by

²⁰We assume $m'(\theta) > 0$ and $\lim_{\theta \rightarrow 0} m(\theta) = 0$, as well as $\lim_{\theta \rightarrow 0} \frac{m(\theta)}{\theta} = \infty$.

$U(s)$, the value of k -industry's vacancy of type y_k for the firm with productivity z_k by $V(y_k, z_k)$, the value of employment for a worker of type s at job y_k in firm z_k by $N(s, y_k, z_k)$ and the value of filled job y_k with worker s for a firm z_k by $J(s, y_k, z_k)$, then a match is formed if

$$N(s, y_k, z_k) + J(s, y_k, z_k) \geq U(s) + V(y_k, z_k). \quad (6)$$

Next, we define the expressions for the value functions. The value of employment for a worker of type s at job y_k in firm z_k ($N(s, y_k, z_k)$) and the value of filled job y_k with worker s for a firm z_k ($J(s, y_k, z_k)$) are given by

$$rN(s, y_k, z_k) = w(s, y_k, z_k) + \delta[U(s) - N(s, y_k, z_k)] \quad (7)$$

$$rJ(s, y_k, z_k) = f(s, y_k, z_k) - w(s, y_k, z_k) - c + \delta V(y_k, z_k) \quad (8)$$

where r represents the interest rate (common for workers and firms) and δ is the exogenous match dissolution rate. The values of unemployment for a worker of type s^1 and s^2 ($U(s^1)$ and $U(s^2)$), respectively, are given by

$$\begin{aligned} rU(s^1) &= b + \phi_N m(\theta) [\bar{N}(s^1, y_N^1, z_N) - U(s^1)] \\ &+ \phi_T m(\theta) [\bar{N}(s^1, y_T^1, z_T) - U(s^1)] \end{aligned} \quad (9)$$

$$\begin{aligned} rU(s^2) &= b + m(\theta) [\phi_N \max\{\bar{N}(s^2, y_N^1, z_N) - U(s^2), 0\}] \\ &+ \left(\frac{v_N}{v} - \phi_N\right) (\bar{N}(s^2, y_N^2, z_N) - U(s^2)) \\ &+ m(\theta) [\phi_T \max\{\bar{N}(s^2, y_T^1, z_T) - U(s^2), 0\}] \\ &+ \left(\frac{v_T}{v} - \phi_T\right) (\bar{N}(s^2, y_T^2, z_T) - U(s^2)) \end{aligned} \quad (10)$$

where b is the fixed unemployment benefit and $\frac{v_k}{v}$ represents the share of each k -industry's vacancies in the total number of vacancies in the economy. The max operator in the value of unemployment for the high skill worker denotes this worker's choice of forming the match depending on the expected surplus when matched with an unqualified vacancy. $\bar{N}(s^j, y_k^j, z_k)$ stands for the expected value of employment for the worker of skill $j = 1, 2$ and it is a function of the expected (average) productivity of the firm that the worker may be matched to.

Finally, the the value of k -industry's vacancy of type y_k for the firm with productivity z_k ($V(y_k, z_k)$) is given by

$$\begin{aligned}
rV(y_k^1, z_k) &= -c^1 + \frac{m(\theta)}{\theta} [\gamma(J(s^1, y_k^1, z_k) - V(y_k^1, z_k)) \\
&\quad + (1 - \gamma)\max\{J(s^2, y_k^1, z_k) - V(y_k^1, z_k), 0\}] \tag{11}
\end{aligned}$$

$$rV(y_k^2, z_k) = -c^2 + \frac{m(\theta)}{\theta} (1 - \gamma)[J(s^2, y_k^2, z) - V(y_k^2, z)] \tag{12}$$

Again, the max operator in the value of the unqualified vacancy denotes the choice of the firm with this type of vacancy to form the match with a high skill worker depending on the size of the respective surplus. We will focus on the equilibria in which the parameters of the model are such that the matches between unqualified vacancies and high skill workers are profitable and the high-skill workers accept the unqualified jobs.

Substituting the value functions into (6), the match is formed if and only if

$$f(s, y_k, z_k) - c_k \geq r(U(s) + V(y_k, z_k)). \tag{13}$$

The wages for each industry, job type, firm and worker type are determined by Nash bargaining condition

$$N(s, y_k, z_k) - U(s) = \beta[N(s, y_k, z_k) + J(s, y_k, z_k) - U(s) - V(y_k, z_k)], \tag{14}$$

with β as the worker's share of surplus, which yields the wage expression as

$$w(s, y_k, z_k) = \beta(f(s, y_k, z_k) - c - rV(y_k, z_k)) + (1 - \beta)rU(s).$$

In the steady-state equilibrium, the flows into and out of unemployment are equal for each type of worker, low skill and high skill respectively,

$$\delta(p - \gamma u) = \phi m(\theta) \gamma u \tag{15}$$

$$\delta((1 - p) - (1 - \gamma)u) = m(\theta)(1 - \gamma)u, \tag{16}$$

and the flows into and out of vacancy pools are equal for each type of vacancy (unqualified and qualified, respectively) and given by

$$\delta(z_k^2 - z_k^1 - v_k^1) = \frac{m(\theta)}{\theta} v_k^1 \tag{17}$$

$$\delta(z_k^{max} - z_k^2 - v_k^2) = (1 - \gamma) \frac{m(\theta)}{\theta} v_k^2. \tag{18}$$

The two productivity thresholds in each k -industry, z_k^2 and z_k^1 , represent the qualified job cutoff and the

exit cutoff productivity, respectively, i.e. the lowest productivity firm opening the qualified vacancy and the lowest productivity firm operating. The two conditions above define the number of each type of vacancies (v_k^1 and v_k^2) across the two industries as the functions of labor market tightness θ and the productivity thresholds. One can then substitute the vacancy conditions above and the total number of vacancies in the economy $v_N^1 + v_T^1 + v_N^2 + v_T^2 = v = \theta u$ into the expressions for the shares of each industry's unqualified vacancies in the economy as

$$\phi_N = \frac{v_N^1}{\theta u} = \frac{\delta(z_N^2 - z_N^1)}{\frac{m(\theta)}{\theta} + \delta} \frac{1}{\theta u} \quad (19)$$

$$\phi_T = \frac{v_T^1}{\theta u} = \frac{\delta(z_T^2 - z_T^1)}{\frac{m(\theta)}{\theta} + \delta} \frac{1}{\theta u} \quad (20)$$

Similarly, one also defines the shares of qualified vacancies in each industry as a share of the total number of vacancies in the economy. Lastly, we need to define the remaining two steady state conditions in each industry for the cutoff productivity levels that determine the k -industry's selection of firms into exit, firms that open only unqualified jobs, and, finally, the firms that open the qualified jobs in equilibrium. Provided that the value of unqualified vacancy is larger than the value of qualified vacancy for lower z firms, the marginal exiting firm z_k^1 in industry k is defined as the one for which the value of opening the unqualified vacancy equals zero,

$$V(y_k^1, z_k^1) = 0. \quad (21)$$

For higher values of productivity, there exists a firm z_k^2 for which the value of opening an unqualified vacancy is equal to the value of opening a qualified vacancy (i.e. it is indifferent between the two types of vacancies),

$$V(y_k^2, z_k^2) = V(y_k^1, z_k^2). \quad (22)$$

This condition then defines the second productivity cutoff, which together with the exit cutoff productivity determines the firms partitioning in each industry. We then substitute the value functions (11) and (12) for the values of vacancies in the above conditions (see Figure B.8 in Appendix for the illustration of these productivity cutoffs).

We use the equilibrium conditions for unemployment flows (15 and 16), vacancy flow conditions (17 and 18), and the productivity cutoff conditions for each industry k (21 and 22) to solve for the eight equilibrium variables: unemployment rate u , labor market tightness θ , the share of unqualified vacancies ϕ , share of low-skill workers in unemployment pool γ , industry exit cutoff productivity z_k^1 and the industry job-type cutoff productivity z_k^2 .

The effect of an increase in Chinese import penetration Following our empirical analysis, we study the effect of the change in Chinese import penetration *within* the group of ICT intensive industries, which we distinguish from the low ICT intensity industry group by assigning it a higher return to skill in the production function, α . We expose one of the two ex-ante identical ICT intensive industries to an increase in the import competition (non-exposed industry denoted by N and trade exposed industry denoted by T) in the following way. We assume that a decrease in the productivity of the unqualified jobs in industry T , (y_T^1), may be used to represent the change brought about by a stronger Chinese presence in the industry market which substitutes the local unqualified jobs. In other words, it lowers the productivity of the unqualified jobs, rendering them less valuable, while it leaves the productivity of the qualified jobs unchanged. The results of the numerical exercise are presented in the following section. We discuss the relationship of the model’s prediction to the empirical findings on the changes in labor distribution within the group of high ICT intensity industries.

6.2 Numerical analysis

Model parameters We use the numerical exercise to provide the intuition for the mechanisms that may underlie the changes observed in the data. In that sense, we do not employ a formal full model calibration, but set most of the model parameters based on their empirical counterparts and calibrate the remaining ones to match a few aggregate data moments.

First, we set the values of 7 parameters ($r, p, \beta, \delta, b, z^{max}, \alpha$) and the form of the matching function $m(\bullet)$. The interest rate (r) is set to 0.035 based on the data on the Swedish average interest rate provided by the Eurostat (short to long run rates averages range from 3.29 to 4.72 in the 1996-2006 period). The share of workers with low skill in the total population (p) is set to 0.58, for which we refer to our dataset and calculate the share of workers with estimated individual fixed effect at or below the percentile 60 of the overall distribution of individual fixed effects²¹. Following Albrecht and Vroman (2002) we set $\beta = 0.5$ (workers bargaining power) and $b = 0.1$ (unemployment benefits). Following Stadin (2015) who analyzes the Swedish employment dynamics, we set $\delta = 0.1$ (job separation rate) and assume a matching function of the form $m(\theta) = 2 * \theta^{0.5}$. The highest value of firm productivity in both industries (z^{max}) is set to 1.95. Finally, the parameter α is measuring the returns to skill in the production function. We vary α from 1 to 1.4 to represent the difference in ICT intensity across industries, where high α (1.4) represent the group of ICT intensive industries and the value of 1.2 is used for the benchmark calibration.

We calibrate the relative skill s^2/s^1 and the relative vacancy cost c^2/c^1 to match the labor market tightness and the unemployment rate in the Swedish data. Stadin (2015) reports the aggregate labor

²¹Since we classify workers as low or high skill based on their individual components in the wage, our measure does not include individuals unemployed. As the share of low skill labor in the pool of unemployed may be higher, our value of the low skill share in the total labor force is possibly biased downwards. However, we observe similar values for the share of low skill in the total number of workers switching to unemployment between Period 1 and Period 2

market tightness in Sweden in 1992-2011 to be 0.1, while it varies between very small values and 0.6 in the three largest labor markets in Sweden over the analyzed period. The aggregate economy unemployment rate in 1996-2006 varied between 6% and 11% (the Statistics Sweden database). Given our model set-up and the two main restrictions, namely the lack of an outside (service) sector to absorb the labor reallocation from manufacturing, and the lack of low skill labor in high productivity firms (qualified jobs), the equilibrium unemployment rates are higher. We refer to our data and find that the ratio of workers who leave the manufacturing jobs between Period 1 and Period 2 (switch to services, unemployment or leave the labor force) to total Period 1 employment is 0.3 and to total employment in both periods (which includes the newly employed in Period 2) is 0.26. Based on this evidence and the model limitations, we allow for a higher unemployment rate in our calibration (0.2-0.3, depending on the industry type) than the one reported for the aggregate Swedish economy. The calibration yields $s^2/s^1 = 3.3$ and $c^2/c^1 = 4.4$. Given the lack of linear vacancy cost estimates for Sweden, we follow Stadin (2015) where the vacancy cost is 32% of the equilibrium wage. A 0.4 cost for the unqualified vacancy is consistent with this measure, which yields the qualified vacancy cost of 3.5. Finally, we set the two skill levels at 1.5 and 5 for s^1 and s^2 , respectively.

Numerical results As noted above, to represent the effect of an increase in imports from China in high ICT intensity industries, we employ the two-industry framework (two high ICT intensity industries, N and T) in which only industry T is exposed to an increase in the Chinese import penetration. This is represented by a decrease in the productivity of unqualified jobs in industry T (i.e. y_T^1 falls). Figure (6) illustrates the effects on each industry's equilibrium variables and on the wages different worker types earn at different types of jobs. The solid lines in the figure refer to the industries not exposed (N), whereas the dashed lines refer to the exposed industries (T).

A decline in the productivity of unqualified jobs in industry T results in an increase in the exit cutoff productivity (z_T^1) as only more productive firms now find it optimal to open these types of vacancies. Unemployment rises, as well as the share of low-skill workers in the unemployment pool. Higher unemployment reduces the labor market tightness which makes the qualified job vacancies relatively more valuable, pushing the qualified job cutoff productivity z_T^2 down. The average wage of high-skill workers in these jobs falls due to a lower average productivity of firms posting qualified jobs. However, for a given range of high z (top 40% of z), the average wage of high skill workers increases as their outside option (i.e. the value of being unemployed) rises. The average wage of low skill workers falls. In industry N , the results show opposite movements. A higher share of low-skill workers in the unemployed pool and a reduction in labor market tightness makes unqualified jobs in this industry more profitable, given that their productivity is unchanged. Thus, z_N^1 falls while z_N^2 increases. The movements in the cutoff conductivities in turn affect the employment shares across skills and job types. Average wage of low skill at unqualified jobs experience a weaker decline compared to industry T , but as opposed to industry T , the average wage at qualified jobs rises due to

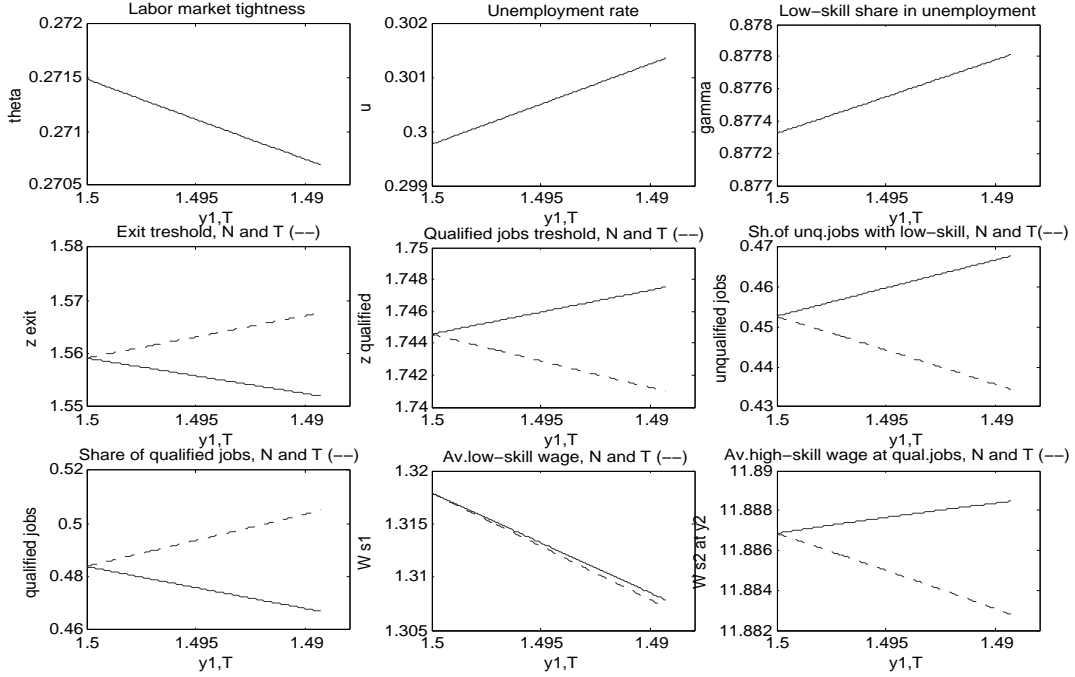


Figure 6: The effect of an increase in imports from China on the steady-state variables: two ICT intensive industries (N and T) of which only T industry is exposed to an increase in Chinese import penetration, represented by a decrease in the productivity of unqualified jobs, y_T^1 .

higher average productivity of those firms²².

The main results are summarized below:

Results. *A decrease in productivity of the unqualified jobs in industry T produces the following effects:*

- i. *Productivity thresholds in the two industries move in the opposite directions - the range of firms opening unqualified jobs in industry T reduces from both ends (z_T^1 increases and z_T^2 falls), while the range of firms opening unqualified jobs in industry N expands on both ends (z_N^1 falls while z_N^2 increases).*
- ii. *In industry T , the share of low-skill employment in low productivity firms (unqualified jobs) in total industry employment decreases, while it rises in industry N .*
- iii. *In industry T , the share of high skill-qualified job type employment in total industry employment increases. The share of this employment category decreases in industry N .*
- iv. *In industry T , total employment drops, while it increases in industry N .*

²²However, the average wage of high skill workers at qualified jobs for a given range of high z (top 40% of z), falls.

Tables (A.8), (A.9) and (A.10) in the Appendix summarize the quantitative effect of a 1% decrease in y_T^1 on employment shares and wages across skills in the two industries, and also report their empirical counterparts.

As we are interested in the distribution of heterogeneous workers across heterogeneous firms, we follow the changes in the employment shares of high (low) skill workers employed at high (low) paying firms in total industry employment. In the data, we then track the changes in the share of low skill workers on the bottom 40 percent of jobs of industry k (i.e. jobs in the low paying firms) in total industry employment, as well as the share of high skill workers on the top 40 percent of jobs of industry k (jobs in the high paying firms) in total industry employment. We define low (high) skill workers as those workers who in each period have an estimated individual effect in the bottom (top) 40 percent of the distribution of person effects.

Relating the model to the data, the model counterparts of person fixed effects are given by the workers skill levels, i.e. the two levels in the model, s^1 and s^2 . The firm-wage component is a function of the productivity z and the choice of the job type, y^1 or y^2 . We focus on three different measures of firm “quality” (translating into the firm wage component) in the model: 1) by the job type (which is a function of the productivity z in equilibrium), with the two values, y^1 and y^2 , 2) top and bottom 40% of firms in the distribution across productivity z , and 3) firms with the top paying 40% (or 60%) and bottom paying 40% of the total industry jobs. The model employment shares are then calculated as the shares of different skills, $s^{1,2}$, at different firms/jobs (according to the three measures), in the total industry employment.

In both the model and the data, we observe an absolute and a relative increase in the share of high-skill employment in the high quality firms in the industry exposed to import competition (T)²³. On the other hand, in the non-exposed industry (N), we observe an absolute and a relative increase in the share of low-skill employment in the low quality firms²⁴. Comparing the exposed and non-exposed industries, the model results confirm the observed right tail and left tail sorting in the exposed and non-exposed industries, respectively, both being in the group of high ICT intensity industries. The only case when the model does not capture all the effects is when we use the third measure of firm quality as top paying 40% and bottom paying 40% of industry jobs, since the top paying 40% of jobs are always filled with the high skill workers (i.e. there is no change in their share with the increase in Chinese import penetration). However, if we consider the top paying 60% and bottom paying 40% of industry jobs, we capture the empirically observed changes, similarly as with the other measures of firm quality.

Within and across industry reallocations The two (high ICT intensity) industry framework implies that most low-skill workers who leave industry T get hired in industry N , where they work in

²³Relative to the other employment category (i.e. low-skill employment in the low quality firms).

²⁴Again, relative to the other employment category (i.e. high-skill employment in the high quality firms).

unqualified jobs of unchanged productivity. The new qualified jobs in industry T are filled with high skill labor from the same industry's exiting firms and, to a lesser extent, from the N industry firms which are switching to unqualified jobs²⁵. In this sense, the model supports increased within industry sorting at the high end in the industry affected by increased import competition, as well as the across industry reallocation of low-skill workers to unqualified jobs in industries that are not affected by the trade shock. These results are supported by the empirical evidence on the within and across industry labor reallocations reported in Table (4). In the *high* ICT intensity industries group, 26.4% of high skill labor in low-wage firms in industries with a large increase in the share of Chinese imports is reallocated to high-wage firms within the same industries²⁶. At the same time, 25.3% of low skill labor in low-wage firms in industries with a high change in import competition is reallocated to low-wage firms in industries not exposed to the trade shock. One interesting empirical fact, which we do not capture in our framework, reveals that 36% of low skill labor in low-wage firms in *low* ICT intensity industries with a high change in import competition is reallocated to the low-wage firms in *high* ICT intensity industries with low changes in Chinese import penetration.

Varying ICT intensity In the next exercise, we analyze the effects of an increase in Chinese import penetration in low ICT industries. We use the same two-industry framework (N and T), but we use a lower value of α , measuring the return to skill in the production function, to represent a lower degree of ICT intensity. Having in mind the production technology $f(s, y^1, z) = (y^1)^\alpha z = (s^1)^\alpha z$ for unqualified and $f(s, y^2, z) = (y^2)^\alpha z = (s^2)^\alpha z$ for qualified jobs, a lower $\alpha > 1$ implies a lower productivity of both job types for any given z iff $s^1, s^2 > 1$. A reduction in α is also implying, for a given z , a reduction in relative productivity of the qualified job with respect to the unqualified job, $(s^2/s^1)^\alpha$, for any $s^2 > s^1$. Thus, a lower α industries represent the low ICT intensity industries that exhibit a lower return to any skill due to lower technological level. More importantly, the relative return of high to low skill in these industries is lower compared to high α (high ICT intensity) industries, representing a lower relative benefit of hiring a high skill worker to complement the installed technology. In high ICT intensity industries, a high skill worker is complementing an ICT intensive technology and produces a relatively higher return, compared to a low skill worker. As shown in Figure (B.12) in Appendix, a higher α implies higher labor market tightness, unemployment rate and the share of low skill workers in unemployment. The range of firms with qualified jobs increases (exit threshold productivity rises while the job type threshold falls). The share of qualified jobs in total industry employment increases and the share of unqualified jobs with low skill labor falls. The average wages of low skill labor on unqualified jobs and the skilled labor on qualified jobs rise. We believe these features may well capture the nature of the ICT technology and its complementarity to skill.

²⁵These firms will still hire a certain share of high skill labor for unqualified jobs and thus less of these workers will reallocate to industry T

²⁶In low ICT intensity industries group this effect is weaker, 14.8%

To represent an increase in Chinese import penetration within the two *low* ICT intensity industries (low α) framework, we again reduce the productivity of unqualified jobs in industry T (y^1), leaving the jobs productivity in industry N unchanged. With $\alpha, y^1 > 1$, the first derivative of the production function with respect to job productivity is positive and, for y^1 not too small, this derivative is higher for a higher α (see footnote²⁷). Moreover, the derivative is increasing faster with y^1 for higher α (second derivative is positive and increasing in α)²⁸. This insures that the output reacts more strongly to the job productivity changes in the high ICT intensity industries, making the two choices individual firms are facing (to operate or exit and the choice of job type) more sensitive to the variation in unqualified jobs productivity.

While the effects of a 1% decrease in y^1_T within the low ICT intensity industries group are of the same nature and sign as in the high ICT intensity industries group, the magnitude of the changes is lower. Figure (B.13) in Appendix presents the change in the main variables of interest in the two low ICT intensity industries. The changes in the employment shares of interest under different values of α are presented in Table (A.11) in Appendix. Not all the effects are monotone for the very high or very low α , but in general, the employment shares changes become weaker with a decrease in α . The results point to the interactions of the ICT technology and Chinese import penetration, as defined in our theoretical exercise.

7 Conclusion

In this paper, we presented the analysis of the labor dynamics in the manufacturing sector in response to recent changes in technology and import competition, using detailed matched worker-firm micro data from Sweden. We focused on the worker-to-firm sorting phenomena, which we capture in the data, between 1996 and 2006. We focused on the effects of the increase in Chinese import penetration and ICT adoption as potential culprits for the sorting phenomena, and, we investigated the outcomes of the interactions of these two forces. In the group of high ICT intensity industries, we observe an increase in the share of low-wage workers in the low-wage firms, and a reduction in their shares in the high-wage firms. At the same time, the share of high-wage workers in high-wage firms increases. This particular allocation pattern, not observed in the low ICT intensity industries, corresponds to the theoretical predictions of skilled-biased technological change literature, caused by the nature of ICT technologies and their non-uniform adoption across firms.

However, the documented pattern is not uniform across industries within the high ICT intensity

$$27 \quad \frac{d(y^1)^\alpha}{dy^1} = \alpha(y^1)^{(\alpha-1)} > 0$$

$$\frac{d[\alpha(y^1)^{(\alpha-1)}]}{d\alpha} = (y^1)^{\alpha-1} [1 + \alpha \ln(y^1)] > 0 \text{ for } y^1 > e^{-1/\alpha}$$

$$28 \quad \frac{d^2(y^1)^\alpha}{dy^1} = \alpha(\alpha-1)(y^1)^{(\alpha-2)} > 0 \text{ for } \alpha > 1$$

$$\frac{d[\alpha(\alpha-1)(y^1)^{(\alpha-2)}]}{d\alpha} = (y^1)^{\alpha-2} [(2\alpha-1) + (\alpha^2 - \alpha) \ln(y^1)] > 0 \text{ for } y^1 > e^{\frac{-2\alpha+1}{\alpha^2-\alpha}}$$

group, which points to the interaction between technology and trade. In the group of high ICT industries with a high change in Chinese import penetration, we observe a strong increase in the share of high-wage workers in high-wage firms, and a reduction in the shares of low-wage workers in high-wage firms, while there are no significant changes on the low end of the firm distribution. To the extent that worker and firm effects represent their time-invariant skills we document strong skill upgrading in high quality firms within this industry type and no change on the low quality end. In contrast, in the second group (high ICT industries with a low change in the Chinese import penetration) of industries, we observe an increase in the share of low-wage effects workers in the low-wage effects firms (i.e. "sheltering" effects of the low-skill workers). The interaction of import competition and technological change is not merely producing intensification or dampening of either one of the factors' effects, but a qualitatively different pattern. This last finding again points to the importance of the interactions between the two factors when explaining the aggregate outcomes.

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TRADE COMPETITION, TECHNOLOGY AND LABOR RE-ALLOCATION

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ONLINE APPENDIX

NOT FOR PUBLICATION

A Tables

Table A.1: Description of Variables in Data.

Firm Data	
Total Wages	Sum of personnel costs for the year (Summa personalkostnader)
Total Sales	Sum of revenues for the year (Nettomsättning)
Profit	Reported profit for the year (Redovisat Resultat)
Firm age	Calculated from years active in the dataset
Capital (K)	Sum of the following reported tangible assets for the year: Land and Buildings Machinery and Equipment Ongoing Construction and Advance payments for tangible fixed assets
Total Employees (N)	Total employees (Antal Anställda)
Capital Intensity	Calculated as K/N
Industry Classification	Industry Codes are reported in two different systems (1992, 2002) which all have been converted to SNI2002 at the 5-digit and 2-digit level
Business Register	
Legal Form	Classification by type of legal entity
Controlling Ownership	Standard Classification by ownership control
Municipality	Municipality where the firm (headquarters) is registered. Municipality of the main plant is only available from 2000 onwards.
Employee Data	
Annual Wage	Taxed wage income (Kontant Bruttolön)
Age	As reported
Gender	As reported
Level of Highest Education	Under the old SUN code, the following categories: Pre High School Some High School without a diploma High School diploma Less than 2 years of University More than 2 years of University, includes those with diploma Postgraduate Studies
Targeted Field of Education	Targeted diploma subject

Notes: The source of **Firm Data** is the Account Statistics (FEK). Only non-imputed companies are included.

Business Register data comes from the Business Register Database (*Fretagsregistret*). Data available from 1980 onwards.

The source of **Employee Data** is the Register Based Labor Statistics (RAMS). Each individual is linked to a firm, and a plant where applicable.

Table A.2: Information and Communication Technology Classifications

Van Ark et al.(2003) Classifications	Our own ICT Classifications
ICT Producing Industries	High ICT Industries
30- Office machinery, computers	18-Wearing apparel
313-Insulated Wire	22-Publishing and printing
32-Radio, TV and comunic. equip.	29-Machinery and Equipment
331-3-Medical and precision equip.	30- Office machinery, computers
	31-Electrical machinery
ICT-using Industries	32-Radio, TV and comunic. equip.
18-Wearing apparel	33-Medical and precision equip.
22-Publishing and printing	35-Other transport equipment
29-Machinery and Equipment	36-Furniture
31(ex313)-Electrical machinery	
334-5-Other Instruments	
35-Other transport equipment	
36-Furniture	
37-Recycling	
Non-ICT Industries	Low ICT Industries
15-Food	15-Food
16-Tobacco	16-Tobacco
17-Textiles	17-Textiles
19-Tanning, dressing of leather	19-Tanning, dressing of leather
20-Wood	20-Wood
21-Pulp, paper and paper products	21-Pulp, paper and paper products
23-Refined petroleum	23-Refined petroleum
24-Chemicals	24-Chemicals
25-Rubber and plastic products	25-Rubber and plastic products
26-Other non-metallic minerals	26-Other non-metallic minerals
27-Basic metals	27-Basic metals
28-Fabricated metal products	28-Fabricated metal products
34-Motor vehicles and trailers	34-Motor vehicles and trailers

Notes: For our own classification, we keep the Non-ICT industries from van Ark et al. (2003) as Low ICT Industries, and group the rest together into High ICT Industries. Since Recycling is not an industry we can identify with Chinese imports at the product level from UNComtrade, we drop it from our ICT grouping.

Table A.3: Matching UN Comtrade SITC Codes to Swedish Industries (SNI)

SITC	SITC Name	SNI	SNI Name
1 4 6 7 9 11	Meat and meat preparations Cereals and cereal preparations Sugars, Sugar preparations and honey Coffee, tea, cocoa, spices, and manufactures thereof Miscellaneous edible products and preparations Beverages	15	Manufacture of food products and beverages
12	Tobacco and tobacco manufactures	16	Manufacture of tobacco products
65	Textile yarn, fabrics, made-up articles, n.e.s., and related products	17	Manufacture of textiles
84 85	Articles of apparel and clothing accessories Footwear	18	Manufacture of wearing apparel; dressing and dyeing of fur
61	Leather, leather manufactures, n.e.s., and dressed furskins	19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear
63	Cork and wood manufactures (excluding furniture)	20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
64	Paper, paperboard and articles of paper pulp, of paper or of paperboard	21	Manufacture of pulp, paper and paper products
892 898	Printed matter Musical instruments and parts and accessories thereof; records, tapes and other sound or similar recordings	22	Publishing, printing and reproduction of recorded media
325 33	Coke and semi-coke (including char) of coal, of lignite or of peat, whether or not agglomerated; retort carbon Petroleum, petroleum products and related materials	23	Manufacture of coke, refined petroleum products and nuclear fuel
5 excl 57&58	Chemicals and related products, n.e.s.	24	Manufacture of chemicals and chemical products
62 57 58	Rubber manufactures, n.e.s. Plastics in primary forms Plastics in non-primary forms	25	Manufacture of rubber and plastic products
66	Non-metallic mineral manufactures, n.e.s.	26	Manufacture of other non-metallic mineral products
67 68	Iron and steel Non-ferrous metals	27	Manufacture of basic metals
69	Manufactures of metals, n.e.s.	28	Manufacture of fabricated metal products, except machinery and equipment
74	General industrial machinery and equipment, n.e.s., and machine parts, n.e.s.	29	Manufacture of machinery and equipment n.e.c.
75	Office machines and automatic data-processing machines	30	Manufacture of office machinery and computers
77	Electrical machinery, apparatus and appliances, n.e.s., and electrical parts thereof	31	Manufacture of electrical machinery and apparatus n.e.c.
76	Telecommunications and sound-recording and reproducing apparatus and equipment	32	Manufacture of radio, television and communication equipment and apparatus
88 872	Photographic apparatus, equipment and supplies and optical goods, n.e.s.; watches and clocks Instruments and appliances, n.e.s., for medical, surgical, dental or veterinary purposes	33	Manufacture of medical, precision and optical instruments, watches and clocks
78	Road vehicles (including air-cushion vehicles)	34	Manufacture of motor vehicles, trailers and semi-trailers
79	Other transport equipment	35	Manufacture of other transport equipment
82	Furniture, and parts thereof; bedding, mattresses, mattress supports, cushions and similar stuffed furnishings	36	Manufacture of furniture; manufacturing n.e.c.
—	—	37	Recycling

Notes: Recycling is not an industry that product level trade information from UN Comtrade allows us to identify.

Table A.4: Summary Statistics of The Manufacturing Industries, and Largest Mobility Groups

	Total Population			Largest Mobility Group - Firms		
	No of Firms	No of People	Log Real Earnings	No of Firms	No of People	Log Real Earnings
Total Period: 1996-2006	12653	1064274	10.36 (0.36)	12181	1059438	10.36 (0.36)
Percent of Mobility Group vs Total (%)				96.3%	99.5%	
Period 1: 1996-2001	10596	866743	10.31 (0.35)	9632	856043	10.31 (0.35)
Percent of Mobility Group vs Total (%)				90.9%	98.8%	
Period 2: 2000-2006	10363	889919	10.40 (0.37)	9596	881109	10.40 (0.37)
Percent of Mobility Group vs Total (%)				92.6%	99.0%	

Note: Standard deviation of log earnings in parentheses.

Table A.5: Characteristics of Industries (2006 vs. 1996).

Classification	Exposure	ICT	Employment		Share of College		Average Firm Size		Number of Firms	
			1996	2006	1996	2006	1996	2006	1996	2006
Food	L	L	7.0%	6.8%	11.3%	16.4%	681	839	599	597
Textiles	L	L	1.2%	0.7%	11.6%	17.2%	152	179	151	102
Refined petroleum	L	L	0.5%	0.3%	38.5%	44.9%	672	446	9	10
Chemicals	L	L	4.8%	6.6%	33.4%	47.0%	1418	4158	199	202
Wood	L	L	5.3%	5.1%	8.4%	11.4%	342	322	698	598
Motor vehicles and trailers	L	L	13.2%	13.2%	21.0%	27.2%	6667	7120	227	244
Other transport equipment	L	H	3.1%	3.6%	26.3%	36.6%	1742	3257	115	116
Furniture	L	H	2.8%	5.4%	8.8%	9.9%	110	7995	400	360
Wearing apparel	L	H	0.3%	0.1%	7.8%	20.3%	71	88	54	31
Publishing and printing	L	H	6.4%	4.9%	23.9%	33.8%	209	174	876	645
Medical and precision equip.	L	H	3.1%	2.9%	38.7%	43.6%	1232	331	249	250
Tanning, dressing of leather	H	L	0.2%	0.2%	5.4%	12.2%	94	158	33	22
Pulp, paper and paper products	H	L	7.1%	5.7%	14.6%	20.0%	1094	730	157	156
Rubber and plastic products	H	L	3.4%	3.2%	15.0%	16.4%	369	156	393	385
Other non-metallic minerals	H	L	2.8%	2.4%	11.7%	16.0%	375	336	199	168
Basic metals	H	L	5.7%	5.2%	11.8%	17.1%	2257	1345	134	151
Fabricated metal products	H	L	8.6%	9.3%	9.9%	13.0%	113	139	1732	1733
Machinery and equipment	H	H	15.8%	15.3%	19.5%	26.7%	621	778	1144	991
Office machinery, computers	H	H	0.5%	0.5%	48.5%	34.7%	225	229	51	39
Electrical machinery	H	H	4.0%	3.7%	24.5%	32.1%	709	1993	302	265
Radio, television and com.	H	H	4.2%	4.4%	40.4%	64.6%	4995	12229	122	93

Note: The table includes some basic characteristics of for each industry in the manufacturing sector, grouped according to the definitions of intensity of ICT adoption and exposure to import competition for the first and last years in our sample: 1996 and 2006. There are four characteristics for each industry: share of employment in the industry relative to overall manufacturing sector, share of workers in industry that attended some college, average number of workers per firm and number of firm operating in each industry.

Table A.6: Logit for the probability of being in the Low Firm-Low Person (LFLP) or High Firm-High Person quadrants (HFHP) quadrants.

Dependent Variable	(1) LFLP	(2) HFHP
<i>Period 1</i>		
Low China×Low ICT	0.506*** (0.016)	-0.251*** (0.009)
Low China×High ICT	0.604*** (0.016)	-0.232*** (0.010)
High China×Low ICT	0.398*** (0.015)	-0.180*** (0.010)
Observations	669.986	669.986
<i>Period 2</i>		
Low China×Low ICT	-0.054*** (0.014)	-0.443*** (0.009)
Low China×High ICT	0.582*** (0.013)	-0.189*** (0.009)
High China×Low ICT	0.114*** (0.013)	-0.185*** (0.009)
Observations	729.514	729.514

Note: Regressions include year dummies and control for the individual's gender, highest education, age, tenure in firm and the following firm characteristics: capital per worker, profit per worker, share of high school and college graduates on the firm side. Period 2 workers are restricted to those who were present in Period 1. The coefficients in the table are marginal effects. Reference interaction group is High China-High ICT. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.7: Industry Type Breakdown of Firms and Workers between Period 1 and Period 2 (Person count).

Firm Type	Period 2										
	Low ICT				High ICT				Switch	Exit	Sum
	Low China		High China		Low China		High China				
Low	High	Low	High	Low	High	Low	High				
Period 1											
Panel A: Low ICT-Low China											
LFLP	3630	1865	124	134	123	54	48	82	2106	3249	11415
LFHP	3784	1698	112	94	44	35	24	92	1852	1882	9617
HFLP	1712	21701	190	441	112	218	104	392	5623	7980	38473
HFHP	1419	34544	140	425	47	259	112	545	6255	4909	48655
Panel B: Low ICT-High China											
LFLP	163	152	5181	1886	8126	55	125	145	1838	4877	22548
LFHP	114	122	4657	1736	838	28	169	141	1438	2513	11756
HFLP	172	440	2315	14643	127	106	143	384	3645	6840	28815
HFHP	93	406	3757	20874	46	132	103	408	2522	4248	32589
Panel C: High ICT-Low China											
LFLP	57	73	61	57	5779	1238	30	55	1695	3541	12586
LFHP	27	46	51	32	3880	1160	37	47	1378	2112	8770
HFLP	66	241	96	177	1292	10697	72	679	3490	4827	21637
HFHP	36	273	86	136	1700	15602	94	1901	3507	3309	26644
Panel D: High ICT-High China											
LFLP	40	77	147	161	2665	53	2621	1506	1077	2203	10550
LFHP	26	61	137	119	280	111	2418	2236	1470	1614	8472
HFLP	114	472	214	532	132	1281	1576	18638	4285	5864	33108
HFHP	74	696	201	690	92	2868	1451	33110	5391	3958	48531
Stayers Total	11527	62867	17469	42137	25283	33897	9127	60361			262668
Newcomers	3607	10765	4556	8715	2863	6597	2852	15049			55004
TOTAL	15134	73632	22025	50852	28146	40494	11979	75410	47572	63926	429170

Note: The sample is restricted to those individuals and firms used in our main analysis (see Table A.4). See Table 1 for the industries classified as "Low/High China" and "Low/High ICT". Since individuals may switch jobs across sectors within each period, we assign them to the last firm (and sector) affiliation of employment within each period. We divided individuals into four possible groups (LFLP, LFHP, HFLP, HFHP) in Panels A-D, where the two first letters denote the firm type and the two last denote the person type. "LF (HF)" is a firm with fixed effects in bins 1-4 (7-10) of Figure 1 in Period 1. "LP (HP)" is a person with fixed effects in bins 1-4 (7-10) of Figure 1 in Period 1. Individuals in column "Switch" are employed in a manufacturing job in Period 1, but switched to a non-manufacturing job in Period 2. Individuals in column "Exit" leave the sample for whole Period 2, which can be due to an income below the income restriction of 120,000SEK/year, become older than 65, leave to unemployment, leave labor force, retire or die. "Stayers" are individuals present in Periods 1 and 2. "Newcomers" are individuals out of our sample in Period 1 (either because they did not meet the income restriction, were younger than 20 years old, were out of the labor force, unemployed or working outside the manufacturing sector), but who enter the manufacturing sector in Period 2.

Table A.8: Employment effect of a 1% decrease in the productivity of unqualified jobs (y_T^1) in exposed (T) industry vs. non-exposed (N) industry for the high ICT intensity industries.

	(1)	(2)	(3)	(4)
y_T^1	$\frac{e_N^s}{e_N}$	$\frac{e_T^s}{e_T}$	$\frac{e_{y2,N}^s}{e_N}$	$\frac{e_{y2,T}^s}{e_T}$
Panel A: Model				
	skill shares, by job types in total			
1.500	0.453	0.453	0.484	0.484
1.495	0.460	0.444	0.475	0.494
1.489	0.468	0.434	0.467	0.505
change (% point)	1.512	-1.827	-1.693	2.110
Panel B: Data				
Period 1	0.393	0.393	0.244	0.273
Period 2	0.466	0.396	0.238	0.302
change (% point)	6.341	-0.644	-1.637	2.942

Note: The model employment shares represent the shares of different skills, $s^{1,2}$, on different job types, $y^{1,2}$, in the total industry employment, where the share of s^1 on y^2 is 0 by construction. The figures from the data are constructed as follows. $\frac{e_k^s}{e_k}$, $k = N, T$, is the share of low skill workers on the bottom 40 percent of jobs of industry k (i.e. jobs in the low paying firms) in the total industry employment. $\frac{e_{y2,k}^s}{e_k}$, $k = N, T$, is the share of high skill workers on the top 40 percent of jobs of industry k (jobs in the high paying firms) in the total industry employment. In the data, we define low (high) skill workers as those workers who in each period have an estimated individual effect in the bottom (top) 40 percent of the distribution of person effects.

Table A.9: Alternative employment shares: Employment effect of a 1% decrease in the productivity of unqualified jobs (y_T^1) in exposed (T) industry vs. non-exposed (N) industry for the high ICT intensity industries.

	(1)	(2)	(3)	(4)
Panel C: Top (z^{t40}) and bottom (z^{b40}) 40% of z				
y_T^1	$\frac{e^{s1}(z^{b40},N)}{e_N}$	$\frac{e^{s1}(z^{b40},T)}{e_T}$	$\frac{e^{s2}(z^{t40},N)}{e_N}$	$\frac{e^{s2}(z^{t40},T)}{e_T}$
1.500	0.382	0.382	0.368	0.368
1.495	0.387	0.376	0.368	0.369
1.489	0.391	0.371	0.367	0.369
change (% point)	0.947	-1.120	-0.113	0.122
Panel D: Top (e^{t40}) and bottom (e^{b40}) 40% of filled jobs				
y_T^1	$\frac{e^{s1}(e^{b40},N)}{e_N}$	$\frac{e^{s1}(e^{b40},T)}{e_T}$	$\frac{e^{s2}(e^{t40},N)}{e_N}$	$\frac{e^{s2}(e^{t40},T)}{e_T}$
1.500	0.351	0.351	0.000	0.000
1.495	0.351	0.351	0.000	0.000
1.489	0.351	0.351	0.000	0.000
change (% point)	0.020	0.020	0.000	0.000
Panel E: Top 60% (e^{t60}) and bottom 40% (e^{b40}) of filled jobs				
y_T^1	$\frac{e^{s1}(e^{b40},N)}{e_N}$	$\frac{e^{s1}(e^{b40},T)}{e_T}$	$\frac{e^{s2}(e^{t60},N)}{e_N}$	$\frac{e^{s2}(e^{t60},T)}{e_T}$
1.500	0.351	0.351	0.498	0.498
1.495	0.351	0.351	0.491	0.507
1.489	0.351	0.351	0.483	0.517
change (% point)	0.020	0.020	-1.492	1.847

Note: The model employment shares represent the shares of different skills, $s^{1,2}$, employed at: 1) Panel C: top (z^{t40}) and bottom (z^{b40}) 40% productive firms, 2) Panel D: top (e^{t40}) and bottom (e^{b40}) 40% of filled jobs, and 3) Panel E: top 60% (e^{t60}) and bottom 40% (e^{b40}) of filled jobs, in the total industry employment.

Table A.10: Wage effect of a 1% decrease in the productivity of unqualified jobs in exposed (T) industry vs. non-exposed (N) industry for the high ICT intensity industries.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Model, relative wages by skill and job type								
y_T^1	$\frac{\bar{w}_{y1,N}^{s2}}{\bar{w}_N^{s1}}$	$\frac{\bar{w}_{y1,T}^{s2}}{\bar{w}_T^{s1}}$	$\frac{\bar{w}_{y1,N}^{s2}}{\bar{w}_{y2,N}^{s1}}$	$\frac{\bar{w}_{y1,T}^{s2}}{\bar{w}_{y2,T}^{s1}}$	$\frac{\bar{w}_N^{s2}}{\bar{w}_N^{s1}}$	$\frac{\bar{w}_T^{s2}}{\bar{w}_T^{s1}}$	$\frac{\bar{w}^{s2}}{\bar{w}^{s1}}$	$\frac{\bar{w}_T^{s2}}{\bar{w}_N^{s2}}$
1.500	4.772	4.772	0.529	0.529	6.896	6.896	6.896	0.500
1.495	4.788	4.789	0.529	0.529	6.921	6.922	6.921	0.500
1.489	4.803	4.805	0.528	0.529	6.947	6.948	6.947	0.500
change (%)	0.646	0.689	-0.138	-0.101	0.737	0.755	0.746	-0.035
Panel B: Model, relative wage by skill and top (z^{t40}) / bottom (z^{b40}) 40% of z								
y_T^1	$\frac{\bar{w}^{s2}(z^{b40},N)}{\bar{w}_N^{s1}}$	$\frac{\bar{w}^{s2}(z^{b40},T)}{\bar{w}_T^{s1}}$	$\frac{\bar{w}^{s2}(z^{b40},N)}{\bar{w}^{s2}(z^{t40},N)}$	$\frac{\bar{w}^{s2}(z^{b40},T)}{\bar{w}^{s2}(z^{t40},T)}$	$\frac{\bar{w}_N^{s2}}{\bar{w}_N^{s1}}$	$\frac{\bar{w}_T^{s2}}{\bar{w}_T^{s1}}$	$\frac{\bar{w}^{s2}}{\bar{w}^{s1}}$	$\frac{\bar{w}_T^{s2}}{\bar{w}_N^{s2}}$
1.500	4.775	4.775	0.527	0.527	6.916	6.916	6.916	0.500
1.495	4.790	4.765	0.527	0.527	6.941	6.905	6.923	0.500
1.489	4.806	4.755	0.527	0.526	6.966	6.894	6.930	0.500
change (%)	0.652	-0.422	-0.098	-0.151	0.716	-0.323	0.194	0.027
Panel B: Data								
Period 1	1.635	1.655	0.846	0.842	1.651	1.689	1.673	1.041
Period 2	1.636	1.737	0.831	0.826	1.673	1.784	1.735	1.077
change (%)	0.017	4.927	-1.765	-1.992	1.300	5.606	3.676	3.497

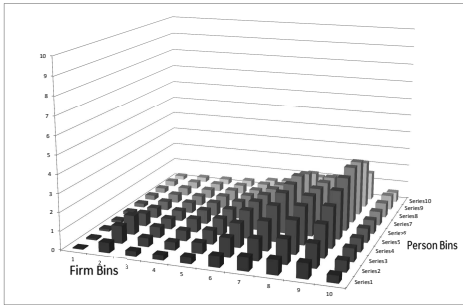
Note: The model figures represent the relative wages of different skills, $s^{1,2}$, on different job types, $y^{1,2}$ (Panel A), or on jobs in top (z^{t40}) and bottom (z^{b40}) 40% productive firms (panel B), within and across industries. The figures from the data are constructed using wages of workers with different skill on the bottom/top 40 percent of jobs of industry k (i.e. jobs in the low/high paying firms).

Table A.11: Employment effect of a 1% decrease in the productivity of unqualified jobs in exposed (T) industry vs. non-exposed (N) industry under different ICT intensity (represented by α , return on skill in the production function, varying from 1 to 2.)

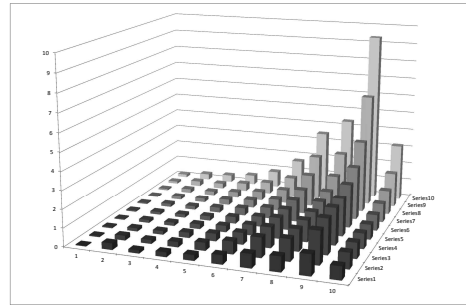
	(1)	(2)	(3)	(4)
Panel A: Unqualified and qualified jobs				
α	$\frac{e_N^s}{e_N}$	$\frac{e_T^s}{e_T}$	$\frac{e_{y^2,N}^s}{e_N}$	$\frac{e_{y^2,T}^s}{e_T}$
1.0	1.398	-1.613	-1.686	2.139
1.1	1.430	-1.665	-1.682	2.094
1.2	1.455	-1.713	-1.678	2.077
1.4	1.512	-1.827	-1.693	2.110
1.6	1.599	-1.992	-1.755	2.229
2.0	1.956	-2.619	-2.091	2.819
Panel B: Top (z^{t40}) and bottom (z^{b40}) 40% of z				
α	$\frac{e^s(z^{b40},N)}{e_N}$	$\frac{e^s(z^{b40},T)}{e_T}$	$\frac{e^s(z^{t40},N)}{e_N}$	$\frac{e^s(z^{t40},T)}{e_T}$
1.0	0.888	-0.944	-1.319	1.659
1.1	0.902	-0.999	-0.623	0.061
1.2	0.917	-1.045	-0.081	0.080
1.4	0.947	-1.120	-0.113	0.122
1.6	0.974	-1.523	-0.150	0.173
2.0	1.956	-2.619	-0.259	0.334
Panel C: Top (e^{t40}) and bottom (e^{b40}) 40% of filled jobs				
α	$\frac{e^s(e^{b40},N)}{e_N}$	$\frac{e^s(e^{b40},T)}{e_T}$	$\frac{e^s(e^{t40},N)}{e_N}$	$\frac{e^s(e^{t40},T)}{e_T}$
1.0	0.043	0.043	-1.333	1.678
1.1	0.034	0.034	-1.380	0.920
1.2	0.027	0.027	0.000	0.000
1.4	0.020	0.020	0.000	0.000
1.6	0.015	0.015	0.000	0.000
2.0	1.956	-2.619	0.000	0.000
Panel D: Top 60%(e^{t60}) and bottom 40%(e^{b40}) of filled jobs				
α	$\frac{e^s(e^{b40},N)}{e_N}$	$\frac{e^s(e^{b40},T)}{e_T}$	$\frac{e^s(e^{t60},N)}{e_N}$	$\frac{e^s(e^{t60},T)}{e_T}$
1.0	0.043	0.043	-1.354	1.656
1.1	0.034	0.034	-1.396	1.698
1.2	0.027	0.027	-1.428	1.741
1.4	0.020	0.020	-1.492	1.847
1.6	0.015	0.015	-1.584	2.007
2.0	1.956	-2.619	0.000	0.000

Note: The reported figures present the % point changes in the model employment shares of different skills, $s^{1,2}$, employed at: 1) Panel A: unqualified (y^1) and qualified (y^2) jobs, 2) Panel B: top (z^{t40}) and bottom (z^{b40}) 40% productive firms, 3) Panel C: top (e^{t40}) and bottom (e^{b40}) 40% of filled jobs, and 4) Panel D: top 60% (e^{t60}) and bottom 40% (e^{b40}) of filled jobs, in the total industry employment.

B Figures

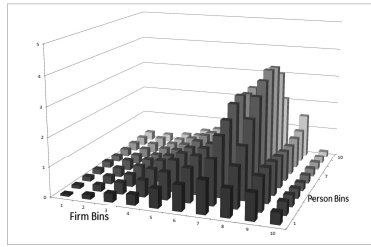


(a) High School graduates

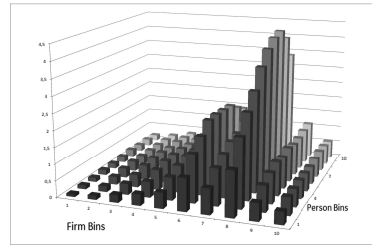


(b) College graduates

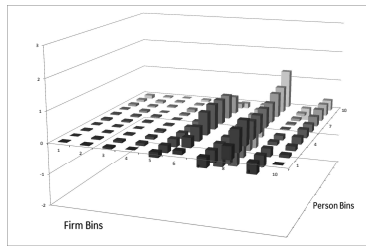
Figure B.1: Distributions of worker and firm fixed effects by education, 1996-2006.



(a) Period 1

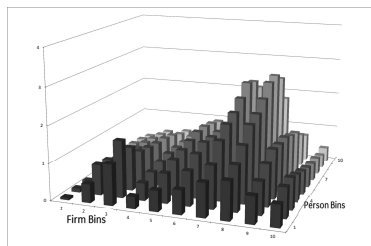


(b) Period 2

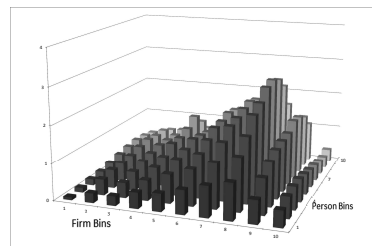


(c) P1 to P2 difference

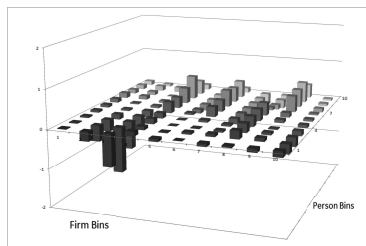
Figure B.2: Distributions of worker and firm fixed effects: Low ICT-Low China Industries.



(a) Period 1



(b) Period 2



(c) P1 to P2 difference

Figure B.3: Distributions of worker and firm fixed effects: Low ICT-High China Industries.

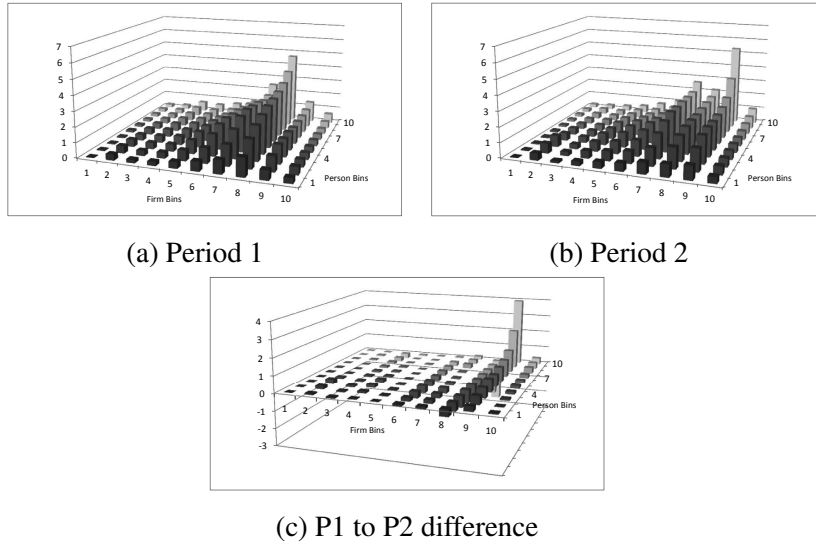


Figure B.4: Distributions of worker and firm fixed effects: High ICT - High China industries, using an alternative definition of import competition, which is the median ranking of the change in the share of Chinese imports to Sweden in first three years of Period 1 vs. Period 2.

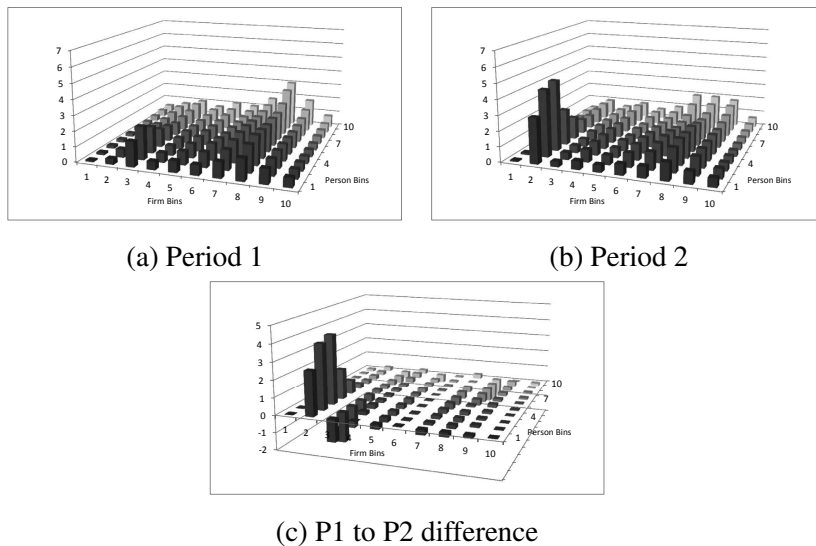


Figure B.5: Distributions of worker and firm fixed effects: High ICT - Low China industries, using an alternative definition of import competition, which is the median ranking of the change in the share of Chinese imports to Sweden in first three years of Period 1 vs. Period 2.

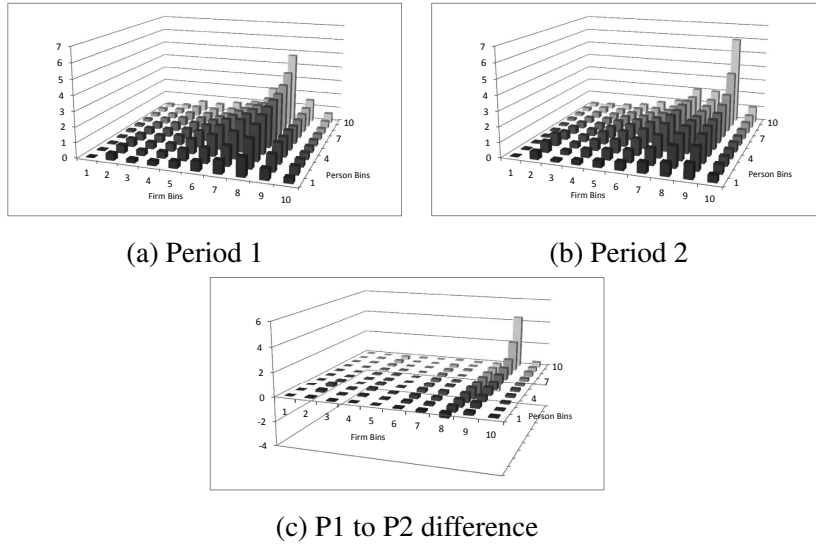


Figure B.6: Distributions of worker and firm fixed effects: High ICT - High China industries, using an alternative definition of import competition, where the share of Chinese imports taken over domestic production and imports net of exports for each industry.

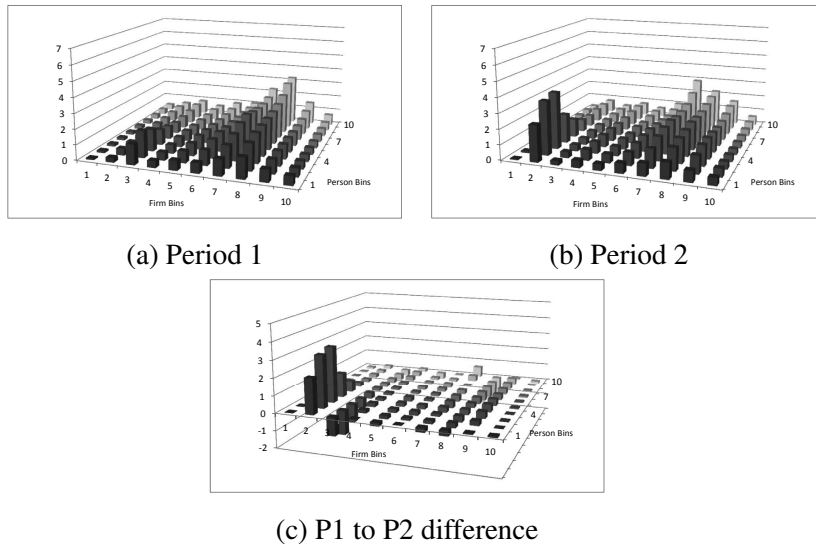


Figure B.7: Distributions of worker and firm fixed effects: High ICT - Low China industries, using an alternative definition of import competition, where the share of Chinese imports taken over domestic production and imports net of exports for each industry.

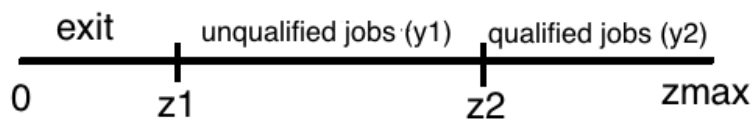


Figure B.8: Productivity cutoffs: the productivity of the marginal exiting firm, z_k^1 in industry k , and the productivity of the firm for which the value of opening an unqualified vacancy is equal to the value of opening a qualified vacancy (i.e. it is indifferent between the qualified and unqualified vacancies), z_k^2 .

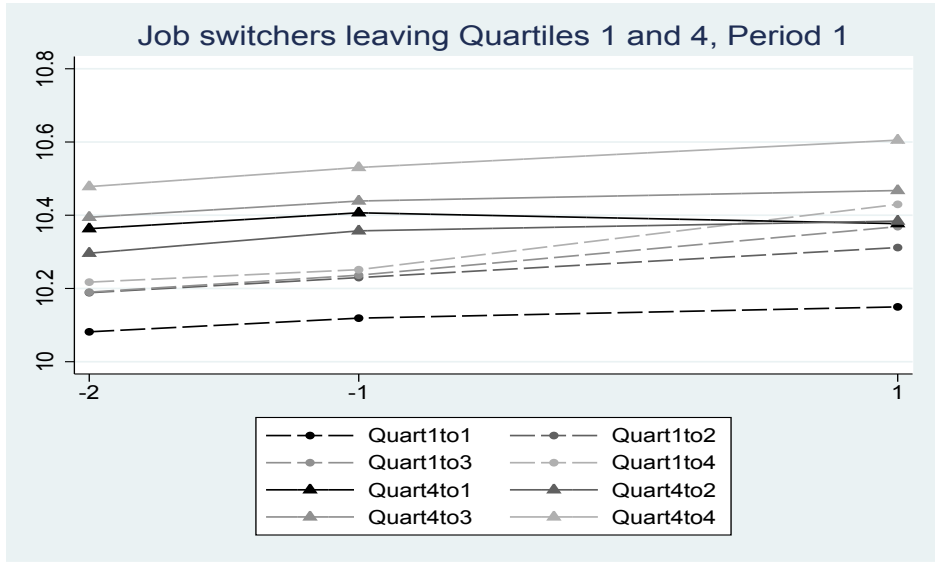


Figure B.9: Average wages at old and destination firms of workers who switch from Quartile 1 (dashed) and Quartile 4 (solid) firms to all possible quartiles within Period 1. Firm quartiles are determined by the average wage of the coworkers of the switchers the year before and the year of the switch.

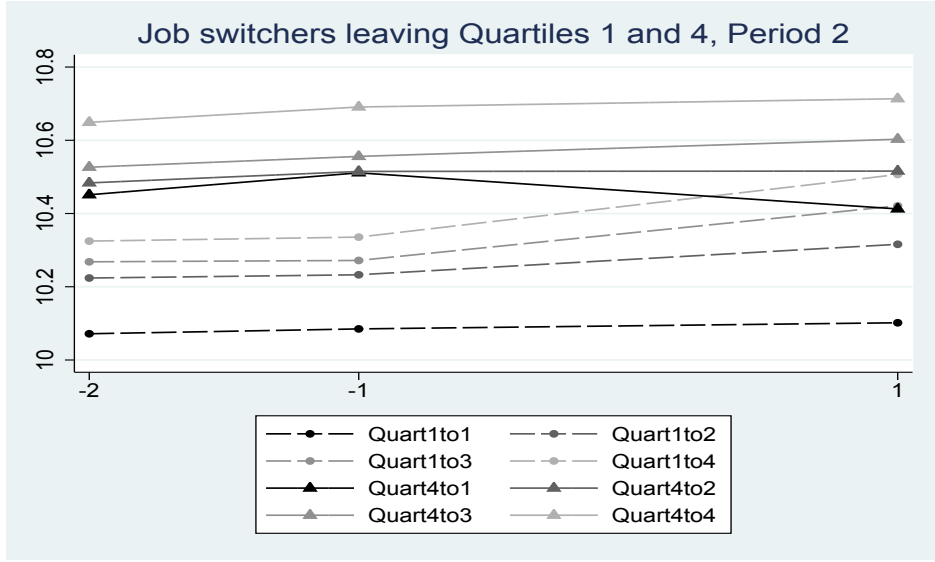
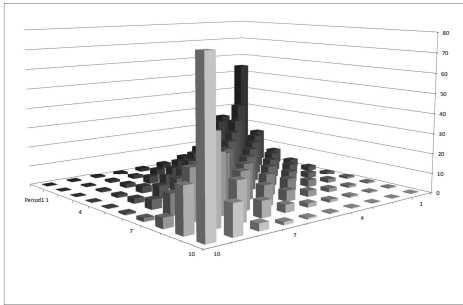
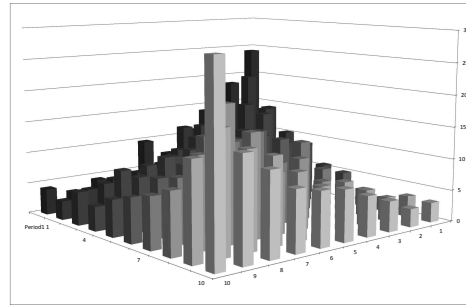


Figure B.10: Average wages at old and destination firms of workers who switch from Quartile 1 (dashed) and Quartile 4 (solid) firms to all possible quartiles within Period 2. Firm quartiles are determined by the average wage of the coworkers of the switchers the year before and the year of the switch.



(a) Across worker fixed effects



(b) Across firm fixed effects

Figure B.11: Transition probabilities across deciles of the distribution of fixed effects for workers and firms that remain in the sample in Periods 1 and 2.

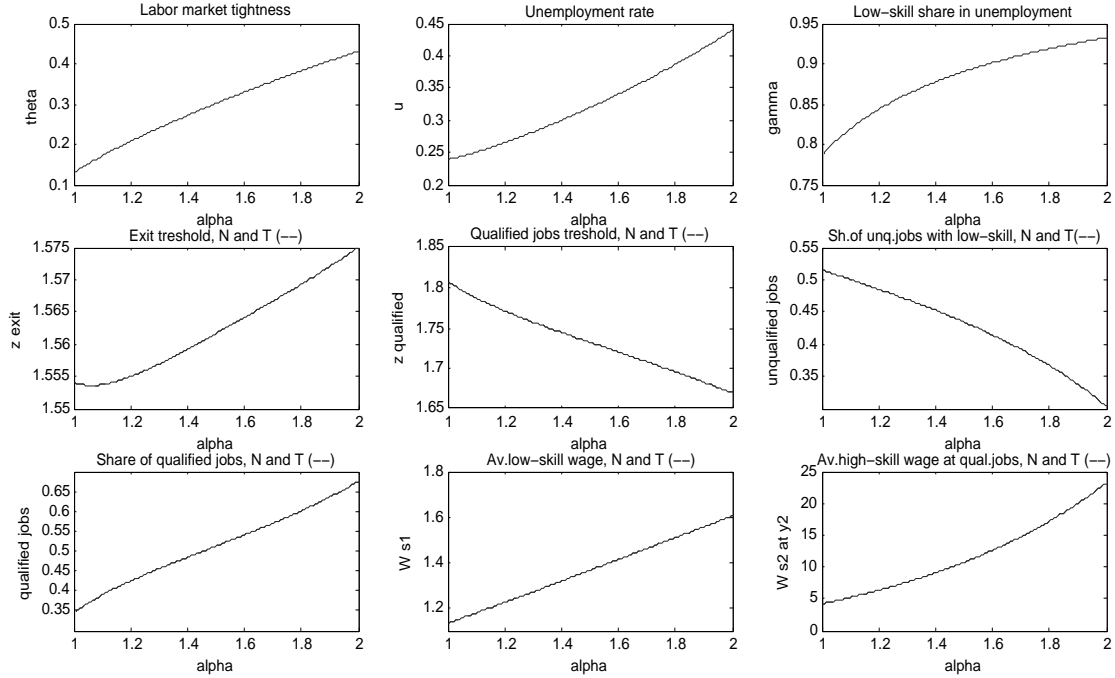


Figure B.12: The effect of increasing ICT intensity represented by a rise in α , return on skill in the production function, on the steady-state variables.

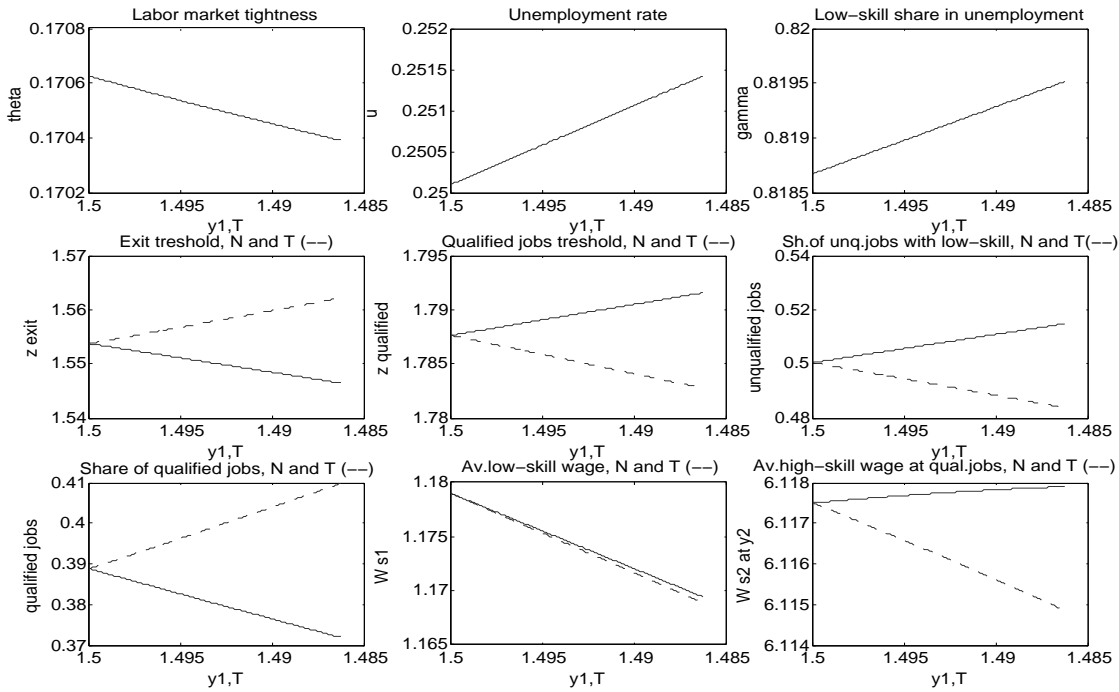


Figure B.13: The effect of an increase in imports from China on the steady-state variables: two low ICT intensive industries (N and T) of which only T industry is exposed to an increase in Chinese import penetration, represented by a decrease in the productivity of unqualified jobs, y_T^1 .

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