Import Competition and Technological Changes: Mobility of Workers and Firms

(Job Market Paper)

Selva B. Baziki[*], Rita Ginja[†] and Teodora Borota Milicevic[‡]

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Abstract

This paper studies the industry labor dynamics in response to recent changes in technology and import competition using detailed matched worker-firm micro data on manufacturing industries in Sweden. Our findings contribute to the explanation of the rise in wage inequality observed in many OECD economies. We focus on the worker-to-firm sorting phenomena which we capture in the data. We analyze the effects of the increase in Chinese import penetration and the ICT (information and communication technologies) adoption as potential drivers of the patterns in the data and we investigate the outcomes of their interactions. We find evidence of increased assortativeness in the matching of heterogenous workers and firms within the high ICT adoption industries, but the sorting patterns are not uniform across industries of this type. In the absence of strong pressure in import competition, the sorting occurs at the low end of the worker-firm distribution, i.e. low-skill workers sorting to low quality firms. On the other hand, ICT technology adoption along with a stronger Chinese import competition results in significant skill upgrade within higher quality firms. Industries with low ICT adoption do not exhibit these sorting patterns. Besides shedding some light on the patterns behind the trends in the wage distribution, this evidence provides a basis for further theoretical and policy analysis on the interactions of technological changes and competitive pressures in globalized markets.

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[*]Corresponding author. Department of Economics, Uppsala University, P.O. Box 513, SE-751 20 Uppsala, Sweden. Phone: (+46)18-471 1562. Fax: (+46)18 - 471 14 78 email: selva.baziki@nek.uu.se

[†]Uppsala University, email: rita.ginja@nek.uu.se

[‡]Uppsala University, email: teodora.borota@nek.uu.se

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1 Introduction

Industrialized OECD economies have been exposed to substantial changes in their economic environments and production processes in the recent three decades. Increasing wage inequality is one of the most notable outcomes of this period documented in the literature.[1] The reported wage distribution changes across countries are very similar down to fine details, but the results on the origins of these changes are still inconclusive and differ across countries. Different explanations for this phenomenon have been proposed: globalization with its numerous faces (increasing global trade, trade between developed and developing nations, outsourcing and offshoring and migration), technological progress with its different characteristics, and finally institutional changes in both labor and product market regulations. Some studies point out that these changes have mostly occurred at the levels *within* industries and *between* firms, as opposed to between industry dispersion dynamics which would have been typical for traditional models of trade and(or) technological differences across sectors. This paper studies how technological changes and trade with developing countries affected the mobility of workers across firms, and in and out of the labor market in Sweden in the 1996 to 2010 period. These movements have determined the industries' labor allocations and may have contributed to the observed changes in the wage distribution. We document significant effects of the technological changes, but also the importance of the interactions between technology and import competition in shaping the distribution of heterogeneous labor across heterogeneous firms.

In recent work, Card et al. (2013) analyze the wage distribution trends in Germany in the 1985-2009 period and identify the contribution of different wage components and their covariances to the overall wage inequality. A significant change documented in this study is the increase in sorting of workers across firms, as measured by the covariance of the individual and firm components in the wage equation. The results show that around one third of the overall increase in wage dispersion in Germany in the analyzed period can be attributed to the increase in the assortativeness of workers matching with firms by their earning and paying potential, respectively. We report very similar changes in the Swedish data in the 1996-2007 period. In the analyzed period, the dispersion of the firm contribution to the individual wage has hardly changed, while the increase in the sorting phenomenon has been notable.[2] This observation motivates our analysis of the main aspects of manufacturing sector dynamics, both on the worker and firm dimensions, which have contributed to the stronger link between the firm and individual characteristics. Relying on the Abowd et al. (1999) methodology (AKM in further text), we start by decomposing individual wages into the contributions of the individual and the firm characteristics. We then construct the joint distribution of individual and firm effects, thus creating a map of the manufacturing sector labor force allocation

[1] As reported in a recent OECD study, since mid-80's, there has been a significant rise in wage dispersion in 17 out of 22 studied economies.

[2] Some of these trends have been presented by Holmlund et al.(2007) and Åkerman et al. (2013), among others.

which we follow over time. Our goal is to provide evidence on the effects of technological change and its interaction with import competition on the allocation of workers across firms, i.e. the sorting patterns. Our goal is not to explain the evolution of wage inequality, but rather to point to various key aspects and dynamics of different industries and to point to potential causes of the differential behavior of the wage distribution we observe across the manufacturing industries. We believe this evidence provides valuable basis for the theoretical explanation of the observed phenomena.

On the one hand, the rise in the adoption of information and communication technologies (ICT, henceforth) has been particularly intense in Sweden since late 90's, and industries in the manufacturing sector have been heterogeneous in their degree of the ICT use. To account for this source of changes in the wage and industry dynamics, we rank the manufacturing industries by their ICT intensity and explore the differences between them. On the other hand, parallel to these changes, Swedish economy has experienced a rapid increase in international trade, measured by both export and import values and driven by changes in international integration policies. The brisk change in the share of trade with less developed, labor intensive countries is of particular interest. We observe a significant increase in trade with China since mid 80's, with these trends accelerating after China joined the WTO in 2001.[3] However, manufacturing industries exhibit different degrees of exposure and changes in Chinese import penetration which allows us to explore these differences to study the effects of import penetration on workers sorting.[4]

The effects of the two forces on industry and labor market dynamics have been analyzed extensively in the previous literature, both theoretically and empirically. With respect to technology, a branch of literature places skill-biased technological change in the center of the theoretical approach and models a particular sorting mechanism where firms which use different type of technology employ labor input of different skills. [5] In a more recent work Autor and Dorn (2013) analyze the changes in employment across skills and find evidence of increasing low and high-skill workers shares relative to the middle, 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, but to the extent that these employment changes are linked to particular types of firms, respectively, they may have an impact on the distribution of workers across firms, i.e. sorting patterns.

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

[3]While the share of different industries in total Swedish imports has remained fairly constant, the share of manufacturing trade with the biggest developing trade partner, China, has increased from 1 to 5%, on average, in the 1988-2012 period.

[4]The choice of China as a representative developing trade partner is justified by two reasons: first, Chinese imports into many developed countries composes the bulk of the growth of imports from developing countries, and secondly, selecting a country helps to get around a potential endogeneity problem in imports' effects on wages (see section 4 for explanations).

[5]See 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.

tive pressures in the less productive end of the firm distribution where the production technologies and the type of good produced are potentially more similar to low wage country technology and exports. Moreover, heterogeneous firm trade models would predict that import competition may cause pressures on the low-skilled labor in the lower productivity end or over the whole firm distribution as firms upgrade their skill composition in response to the pressures.[6] Several recent papers have focused on the effects of increased Chinese import penetration on labor market outcomes of workers, such as: employment, wages, and welfare payments in manufacturing firms/sectors.[7] These papers, however, do not study the effect of these factors on the mobility of workers across firms and industries, and are thus not relating the observed outcomes to the sorting of workers by type. More interestingly, some heterogeneous firm trade studies imply a link between import competition (in general and from developing countries in particular) and technological choices of heterogeneous firms that have not been studied extensively in the empirical literature.

In a recent paper, Autor et al. (2014) attempt to disentangle the two forces, the ICT technology and import competition, in their effect on employment across skills. 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 phenomenon. We also follow this approach, but we add in three important dimensions: (1) since we have access to firm data, we can track changes of firm effects over time and control for firm where the individual works, (2) beyond Autor et al. (2014), we study the impacts of technological changes and trade not only on employment, but on labor allocations, and (3) we study the interaction between technology and import competition and look at movements in the wage distribution.[8]

Within the literature that focuses on the sorting phenomena in particular, Davidson et al. (2013) explore the matching patterns between workers and firms in Swedish manufacturing industries. They find evidence on the effect of trade liberalization on this aspect of the labor market. 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 effect is not present in the comparative-disadvantaged industries (import-competing industries), while the 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

[6]For a review of literature, see e.g. Ashournia et al. (2012)

[7]Autor et al. (2013) analyze the effect of industry level Chinese imports on U.S. local labor markets and find negative effect on wages and employment in import-competing markets. Ashournia et al. (2012) explore both industry level and firm level effects of Chinese import penetration on Danish firms and find that it causes low-skill wage declines at the firm level. Alvarez and Opazo (2011) study the effect on Chilean average firm level wages, and find similar negative wage effects in a developing economy as well.

[8] Previous work on the industry effects of globalization and technology have been placing the two side by side, attempting to determine the relative importance of the two, given that their effects could be disentangled. There are few attempts to define the allocation outcomes of their interactions.

similar approach in the empirical part, but attempt to investigate the sorting phenomenon to greater details, isolating and interacting the effects of trade (import competition) and technological characteristics of the industries. Håkanson et al. (2013) analyze the Swedish data and find a significant increase in workers' sorting to different firms according to their skill levels. They contrast two potential explanations - off-shoring and skill-biased technical change - and find that the latter one seems to have had a more significant impact on sorting and inequality. However, none of this work explores 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).

We start by applying the methodology developed by Abowd, Kramarz and Margolis (1999) (hereafter AKM) on the detailed matched worker-firm micro data of the Swedish manufacturing sector in 1996-2007. We divide the total period into two: 1996-2000 (henceforth Period 1) and 2001-2007 (Period 2). We choose this division into two periods since China entered the WTO in 2001, which we take to be an exogenous trade shock. We then classify manufacturing industries according to their given ICT intensity (low/high) and the change in Chinese imports penetration (low/high) between the two periods. Using the workers and firms fixed effects estimated in the AKM model described above, we construct their joint distribution and analyze the changes in this distribution of workers across firms between the two periods.

When analyzing the industries with high ICT intensity we observe an increase in the share of low fixed effect workers in the low fixed effect firms from Period 1 to Period 2, and a reduction in their shares in the high fixed effects firms. At the same time, the shares of high effect workers in high effects firms increases. This particular allocation pattern, not observed in the low ICT intensive industries, was possibly caused by the nature of the ICT technologies and their non-uniform adoption across firms. However, the documented pattern is not uniform across industries within the high ICT intensity group, which points to the interaction between technology and other factors. In the group of high ICT industries with a high change in the Chinese import penetration, we observe a strong increase in the share of high fixed effect workers in the high fixed effect firms, and a reduction in the shares of low effect workers in the high effect firms. These industries experience a stronger than average[9] 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 one factors effects, but a qualitatively different pattern. To the extent that worker and firm effects represent their skills, i.e. quality, we observe a strong skill upgrade in the high quality firms within this industry type and no change on the low quality end. In the second group (high ICT industries with a low change in the Chinese import penetration), we observe an increase in the share of low fixed effects workers in the low

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

fixed effects firms. We also observe smaller changes in the share of high effects workers in the high effects firms, and the shares of low effects workers in the high effects firms. Thus, these industries resemble the average, but with a significantly smaller change at the high end, and a significantly larger change at the low end of the firm distribution, compared to the average. In the absence of large changes in import competition, the technological change results in a stronger sorting of low skill workers into low quality firms, while the high end of the distribution remains without significant changes. Finally, we do not observe any changes of the above type in the low ICT intensive industries between Period 1 and Period 2, with or without a strong increase in the Chinese import penetration. This last finding again points to the importance of the interactions between the two factors when explaining the aggregate outcomes.

Finally, it is important to note that the choice of Sweden as country of study is interesting for three main reasons. First, the availability of longitudinal data on characteristics of firms (such as, structure of balance sheet, location, form of property) and workers (such as demographic characteristics, information on cognitive and non-cognitive skills, information of workplace and occupation) allows to study in detail the transitions of workers across firms and in-and-out of the labor market. Second, most of the studies on the effects of exposure to trade and technological changes on the wages and employment status of individuals are conducted using US data, which is a large open economy with scope to influence 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, thus sharp international trade flows, such as Chinese exports to the world, are mostly exogenous shocks to Swedish firms. Finally, we focus our study in manufacturing firms, which represent about 1/3 of the total GDP and occupy just over 1/3 of the total of workers in the country. These figures mean that Swedish manufacturing sector is representative of the manufacturing sector of most other countries in the EU, and thus the conclusions drawn from this paper are relevant to other EU countries.

This paper proceeds as follows. In Section (2) we present a brief theoretical background of our empirical study. Then we describe our data in Section (3), and present the empirical strategy in Section (4). Section (5) presents the results, and finally, in Section (6) we summarize our results and conclude.

2 Theoretical background

We provide a brief summary of the theoretical literature relevant to our study. With respect to technology, a branch of the literature places skill-biased technological change in the center of the theoretical approach and models a particular sorting mechanism which results in employment polarization. Acemoglu (1999), among the first, predicts capital skill complementarities and a separating equilibrium. Firms that adopt new technology also resort to hiring high-skill workers while firms using the old technology rely on low skill-workers for production. This results in an equilibrium with two types of firms hiring different types of factors, i.e. in a specific sorting phenomenon. The positive assortative matching occurs at both the high and the low end of the worker-firm distribution.

Albrecht and Vroman (2002) arrive at a similar prediction in a model with skill-job type complementarities and unemployment. Skill-biased technical change implies an increased productivity for high-skill workers when they are employed at high-skill jobs. A strong technical change can result in a shift away from a pooling equilibrium to the one where worker types are segregated by job types. While firms with multiple jobs are not modeled, the mechanism implies high and low-end sorting patterns. This framework also provides some intuition on the effect of import competition from developing countries, which, in this technological setup, is interpreted as a decrease in the productivity of the low skill workers on the low-skill jobs.

In a more recent work Autor and Dorn (2013) link the specific changes in employment across skills (increase in low and high-skill workers shares relative to the middle-skill, i.e. "the polarization phenomenon") to the advances and adoption of ICT technology. The polarization literature does not explore the firm heterogeneity dimension, but focuses on the workers heterogeneity in the skill/occupation dimension and the degree of complementarities between these different skills and modern technologies and tasks. To the to the extent that different tasks are linked to particular types of firms, technological progress may have an impact on the distribution of workers across firms.

Recent papers in international trade literature with heterogenous firms and workers have established several theoretical mechanisms through which globalization may have had an effect on labor market outcomes. The focus on intra-industry trade has made it possible to investigate both the differences across firms within industries, and also how trade liberalization reinforces the contribution of these differences to the labor market outcomes. Trade and international competition create certain mechanisms that affect the allocation of workers of different skills across firms of heterogeneous performance. For example, Verhoogen (2008) exploit the quality upgrade mechanism through which the most competitive firms hire the most capable workers as a response to the increased profit opportunities and incentives to upgrade product quality. This paper, however, did not account for the firm effect on the wage of otherwise identical workers. Helpman et al. (2010) incorporate the workforce composition effect, but also account for the firm effects in the wages of identical workers. Theoretical mechanisms of that study predict that more productive and internationally more successful firms also become more selective in the choice of the labor input and hire a mix of workers with better average capabilities. A common effect in the papers which rely on the workforce composition effects is that they predict an increase in matching of high skill workers to high performing firms as a response to export liberalization. We refer to this effect as the high-end matching.

However, there has not been much theoretical exploration on the effect of import competition on workforce composition across heterogeneous firms. In lines with the selection mechanisms of the heterogeneous firm models, import competition from low-wage countries may cause stronger competitive pressures in the less productive end of the firm distribution. The production technologies and the type of products are potentially more similar to technologies and products of the low wage countries, and thus more exposed to substitution for cheaper imports. Moreover, low-wage countries import competition might cause stronger pressures on the low-skilled labor relative to the high-skilled, in the lower productivity end or over the whole firm distribution, as firms upgrade their skill composition and product quality in response to the competitive pressures.

More interestingly, these latter theories imply a link between import competition (in general and from developing countries in particular) and technological choices of heterogeneous firms that have not been studied extensively in the empirical literature. Several trade papers link the trade liberalization phenomenon to technological choices of firms. To the extent that different technologies require different types of labor to operate, these choices will naturally result in particular sorting patterns (see Yeaple (2005), Bustos (2011)). Davidson et al. (2008) analyze the effect of trade on technology choice and the resulting labor market outcomes (high end sorting in exporting industries), but also addresses the import-competing industries. Import competition reduces the gap in revenues of different types of workers, and thus may result in increased negative matching, i.e. high-skill workers accepting jobs in low performing firms within the import-competing industries. We focus on the similar trade channel (import competition) but originated from developing countries and therefore affecting worker types non-uniformly. Furthermore, we explore the trade and technology channels as exogenous to each other, as well as their interactions, in order to identify the exact sorting patterns these two sources may produce.

3 Data

Our firm and worker level data comes 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 supplement this database with publicly available Consumer Price Index information, again from SCB to convert nominal monetary values to real, taking 2010 as the baseyear. For Chinese trade figures, we use data from UN Comtrade, and base our ICT classifications on those set by Van Ark et al. (2003).

Firm data Firm level balance sheet data is available in Statistics Sweden's Account Statistics (FEK). While data is available from 1980 onwards, it only covers a selective sample of large companies until 1996. This database carries information on total wage spending, sales, profit, capital, number of employees, firm age, and industry classification at the firm level. The database is released with a two year lag, and only includes non-imputed companies and data. Industry classification code systems were updated three times during the entire time period of the series, changing the industry code index system of a firm after each update (the index systems used are SNI1969, SNI1992, SNI2002 and SNI2007). In an effort to have a continuous industry classification under one index, we first use the conversion keys supplied to us from Statistics Sweden where available. If the conversion key was not successful in producing a match between two indices for a particular industry, then we make use of overlapping years in different code systems to generate our own conversion key. In instances where an industry has been split up into parts, we assign the firms to the new industry whose description best matches the old industry description.[10] We do this exercise at the four digit detail level industry code, but in the regressions use only the two digit codes.

We supplement this database with the Business Register Database (Företagsregistret) which carries information on the legal form and controlling ownership of the firm as well as its municipal location from 1980 onwards. Firm level trade statistics of exporter/importer status, and the associated trade value and destination are available from the Foreign Trade Database (Utrikeshandel) from 2000 onwards. For intra-European Union trade, the database has a minimum requirement of 4.5 million SEK ($\approx$ \$610,000) in value to be registered as an importer or exporter, thus we do not observe any within-EU trade less than this cutoff in the data.

Worker data Matched employer employee data comes from the Swedish Tax Authority (Skatteverket) and is available in Register Based Labor Statistics (RAMS) maintained by Statistics Sweden. Data is available from 1985 onwards, where 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 Organisation's definition. For each worker registered, we have information on 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. While the education levels are detailed into 5 groups from pre high school to graduate work, we chose to group individuals into the following three educational groups: less than high school diploma, high school diploma holders, and at least some college based on the more detailed classification.

[10] The number of industries subject to this assignment are: 11 industries from the SNI1969 to SNI2002 matching, 3 industries from SNI1992 to SNI2002 matching, and 2 industries from the SNI2007 to SNI2002 matching.

Trade and ICT data We use UN Comtrade data for international trade between Sweden and her partners. Comtrade data classifies trade based on product (not industry) level codes and manufactured goods are chiefly indexed by material. To be able to match these product codes to Swedish industry codes from the firm level data, we have performed a match between the two indices based on index descriptions as shown in the Appendix. Since Recycling is not an industry that product level trade information allows us to identify, we have left out Recycling firms (67 of them in Period 2, and 33 in Period 3) from the analysis on Chinese import penetration. For all the other industries, we have taken the share of Chinese imports over all imports into Sweden, and computed the change in this share over periods as can be seen in Appendix (B).

The ICT classifications are based on Van Ark et al. (2003) and included ICT producing, ICT Intensive and Less Intensive ICT categories. Between ICT producing and Intensive categories two industries are split into three digit level of detail. Since we are using industry classifications at the two digit detail level, we merge the ICT producing and intensive categories into the same group in our classification of high ICT industries, while keeping low ICT industries exactly the same as Van Ark et al. (2003). Details of the classification can be seen in Figure (B.3) in Appendix.

Sample Selection We restrict our data to include firms that are active between 1996 to 2010 since the firm level data is based on a sample of companies before 1996. We keep firms with at least 5 employees 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.

The data does not contain information about full time or part time employment status of individuals. Therefore, we restrict the baseline sample to those who earn at least 120,000SEK a year (10,000SEK $\approx$\$1,570 a month). Next we drop individuals whose education level is unknown and those who are born before 1920 or after 1991.

More information about the databases, and individual series can be found in Appendix (C).

4 Empirical Strategy

4.1 Setup

We now turn to our basic econometric framework for disentangling the components of wage variation attributable to worker-specific and employer-specific heterogeneity. We define, our data set contains N^* person-year observations on N workers and J firms. The function $J(i;t)$ gives the identity of the unique firm that employs worker i in year t. We assume that the log real annual wage y_{it} of individual i in year t is the sum of a worker time-invariant component α_i, a firm component $\theta_{J(i;t)}$, a set of of time-varying observable worker characteristics $x'_{it}\beta$, and an error component ε_{it}:

$$y_{it} = \alpha_i + \theta_{J(i;t)} + x'_{it}\beta + \varepsilon_{it}. \tag{1}$$

As in Abowd et al.(1999), α_i is a combination of skills and other factors that are rewarded equally across employers; $x'_{it}\beta$ is a combination of lifecycle and aggregate factors that affect worker's productivity in all jobs. We include in x_{it} an unrestricted set of year dummies as well as quadratic and cubic terms in age fully interacted with maximum lifetime educational attainment, in particular, we consider two indicators for an individuals' completed education: an indicator for high school degree and an indicator for some college education or more, and thus the excluded category is high dropout. Finally, we interpret the firm effect $\theta_{J(i;t)}$ as a proportional pay premium (or discount) that is paid by firm j to all employees (i.e., all those with $J(i;t) = j$). Such a premium could represent rent-sharing, an efficiency wage premium, or strategic wage posting behavior (e.g., Burdett and Mortensen (1998), Moscarini and Postel-Vinay (2012)).

We use this simple specification to obtain some descriptives features of the wage dynamics between 1996 and 2010 in Sweden. In particular, we start by present some descriptive statistics for three estimates from model 1: $\widehat{\alpha_i}$, $\widehat{\theta_{J(i;t)}}$ and $\widehat{\varepsilon_{it}}$. Note that the residual of equation 1 includes a job specific matching effect, in particular, following Low, Meghir and Pistaferri (2010),

$$\varepsilon_{it} = \psi_{iJ(i,t)} + \phi_{it} + u_{it} \tag{2}$$

where the match effect $\psi_{iJ(i,t)}$ represents an idiosyncratic wage premium (or discount) earned by individual i at firm j, relative to the baseline level $\alpha_i + \theta_j$. We assume that $\psi_{iJ(i,t)}$ has mean zero for all i and for all j in the sample interval.[11] Match specific wage components arise in models in which there is an idiosyncratic productivity component associated with each potential job match, and workers receive some share of the rents from a successful match (e.g., Mortensen and Pissarides (1994)). ϕ_{it} is a unit root component that captures a drift in individuals earnings power. Innovations to this component could reflect (market-wide) employer learning, unobserved human capital accumulation, health shocks, or the arrival of outside offers. As typical of 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 contains a unit root. Finally, the transitory component u_{it} represents any left-out mean reverting factors. 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 start by con-

[11]The AKM methodology has been criticized on the grounds that excluding the match effect from the main specification may lead to biased estimates in the fixed effects. In the Appendix, we address the criticism and present the results of a different empirical specification that includes (a) the individual worker-firm match component, and (b) the firm effect in addition to the match component in the main regression and compare the findings. We provide the wage variance decomposition for the model that includes the match component in the main specification (See Section (D.3)).

structing the joint distribution of the person and firm effects obtained from the baseline regressions for each period as well as the total period. We classify industries according to their ICT intensity and their exposure to Chinese import competition and track the changes in the joint firm-worker effects distribution across periods. We define two measures of the Chinese import penetration, [CMP]. The choice of China as a focus of analysis is an ideal one on two accounts. First, Chinese imports into many developed countries composes the bulk of the growth of imports from developing countries and that makes it a good proxy of cheap imported goods from the rest of the world. Secondly, selecting a country helps to get around the endogeneity problem of imports' effects on wages by instrumenting Chinese imports to the country of interest by Chinese exports to the rest of the world, or a selection of similar countries (rest of high income EU for instance). By this account, the increase in Chinese exports to the rest of the world can be seen as a result of either more productive Chinese production, or Chinese trade reforms (such as the 2001 World Trade Organization (WTO) membership which could serve as an infliction point) and independent of firm wage decisions in the country of interest.

First, we use the ratio of Chinese (CM) to total imports (M) for each industry j and year t as:

$$CMP_{jt} = \frac{CM_{jt}}{M_{jt}} \tag{3}$$

This measure captures the changes in the importance of China as an import trade partner. Second, we use the measure of Chinese penetration in the market in industry j and year t as:

$$CMP_{jt} = \frac{CM_{jt}}{M_{jt} + Q_{jt} - X_{jt}} \tag{4}$$

where Q_{jt} and X_{jt} represent domestic total production and exports in industry j and year t, respectively. This measure shows the Chinese market shares in particular domestic industry at time t.

We rank the industries by their change in Chinese import penetration from the beginning of one period into the next to group them into high-penetration change and low-penetration change groups (Table (B.2)). Similarly, we also rank the industries based on their ICT usage into high and low group, and separate the ICT producing industries.

We divide the data into two periods for our analysis. Period 1 is defined as the years before Chinese membership to the WTO (1996-2000) and Period 2 as post-Chinese membership years (2001-2007). We perform our analysis on each period separately, as well as on the total time frame titled as the Total Period.

The firm fixed effects in our main wage equation (1) are identified by individuals who move between firms and generate a large firm network in which each firm is tied to at least one other firm in the group through at least one worker who moves between them. We determine the largest such network called the Mobility Group in each period that maximises the number of firms that are connected, and restrict the analysis that follows to this group of interconnected firms (and therefore their employees). As can be seen in Table C.2 this method includes between 82.7-94.9% of the firms, and 97.5-99.5% of all the workers. When we identify plant level fixed effects later on in the analysis as a comparison, we drop single person plants from our Largest Mobility Group by Plants. This is means the mobility group configuration disregards 594, 525, and 387 plants for periods 1-3 and 830 plants in the total period. We also have very rare cases where the plant assignment for the employee is unknown. We have also dropped these people from our last block, amounting to 7, 2, 7, and 16 employees respectively for periods 1-3 and the total period.

5 Results

5.1 Job Switchers

Our AKM specification requires the firms in our estimation to be interlinked in a mobility group via workers that move between them. Since movers are essential in determining the firm effect (firm premia) relative to a reference firm, in this section we pay special attention to workers who move within each period and present some basic wage facts. We only follow workers who were employed in their old and new firms for two years in a row before and after the switch, and align all such moves at time zero in our graphs. In the event the worker moves multiple times within the period (about 1% of movers in Period 1 and 3% in Period 2), we assign the last move as the time zero.

Since workers are assigned to firms they are employed at in November, our data does not separately identify the different sources of wage income on the year of the move. Thus, we do not report movers' average wage for the year of the move at time zero which could be coming from different firms, but instead plot their average wage for the year that they are solely employed at the new firm, at t+1. Next, we assign firms into quartiles at t-1 and zero according to the average wages of all workers at those firms excluding the movers themselves. In the following graphs, we only present the results for workers who are leaving quartile 1 (left panel) and quartile 4 (right panel) firms to move to any of the four possible quartiles in their next employment. Further details on the population and movers are presented in Tables D.1 and D.2.

The left panels in Figures 1 for Period 1 and 2 for Period 2 show that for the workers who start off in the lowest quadrant, there is an upward trend in wages as they switch firms. This is expected, since these workers are moving to firms that are at least as good as the one they left behind. The share of college educated population monotonically increases as the destination quartile goes up (from 10% to 27% in Period 1, and from 10% to 26% in Period 2) which could explain part of the difference in wages across destination groups.

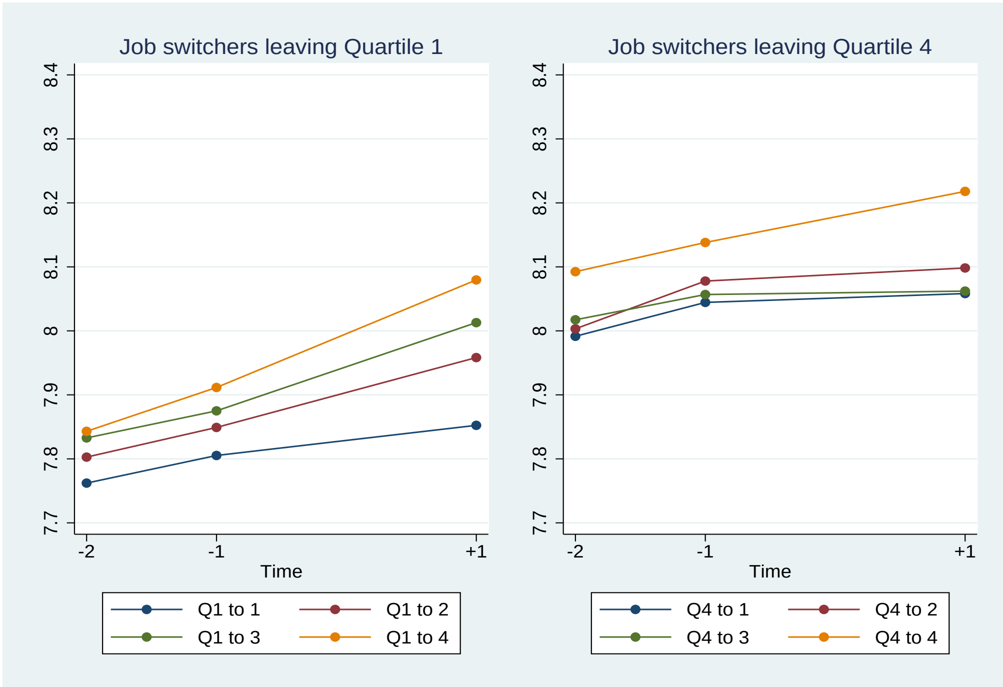


Figure 1: Average wages of job switchers within Period 1, with all the shifts aligned at time zero.

For the workers who start off in the firms with the highest average wages in Period 1, the right panel in Figure 1 shows that workers who find employment at another firm in the highest quadrant are getting rewarded higher in their new firms. Those who switch to lower quadrants have been receiving lower wages even when they worked in the best firm before the move at time t-2 and t-1, and continue on a relatively lower-and flat-wage trend after the move compared to those who move to another quartile 4 firm. The story is different when we examine the quartile 4 switchers in Period 2. The right panel in Figure 2 shows that the workers who switch to higher quadrants are on a higher trend than the other two, increasing the wage gap between the groups. Furthermore, workers who switch from the best to the worst average wage firms are getting a negative reward in their wages in Period 2, a trend we do not see in Period 1.

To sum up, the average wage graphs in this section show how movers are rewarded differently across the two periods. We have seen that for workers who leave quartile 4 jobs, the wage gap between those who go to better firms and those who downgrade increases, and the relative payoff of switching to a high firm is higher. Relating this result to worker characteristics, we see that higher skill-as captured by the share of college educated in each panel-is rewarded relatively higher in

Figure 2: Average wages of job switchers within Period 2, with all the shifts aligned at time zero.

Period 2 compared to Period 1[12]. Within this group, those switching to the lowest firms get a lower wage in their new firm only in Period 2, even though the share of college educated in this group is equivalent in both periods at about 30%. The specific skillset of the worker which includes not only education level, but also ability is an important part of explaining the change in the relative returns in Period 2. To gain more insight into the way both the quality of the worker and firm play a role in the distribution of workers into high and low rewarding firms, we proceed to our AKM estimations where the firm premium is simultaneously estimated with the person effect.

5.2 Variance Decomposition

In this section we present the results of our main specification analysis. The model of wage determination that includes the worker and firm fixed effects is capable of explaining 88.20% of the variation in the data. When estimated separately, the fixed effect components seem to contribute equally to the explanation of total variance of wages in the whole sample period: 49% of the variation is explained by the variation in the worker fixed effect, while the variation in the firm effects explain the remaining 51%. The largest connected set includes 99.77% of the sample workforce and provides similar results: 49.5% the worker effect variation contribution and 50.5% the firm

[12]Firms in quadrant 1 have on average a smaller share of college educated workers (12% and 13% in Periods 1 and 2) compared to firms in quadrant 2 (34% in Period 1 and 49% in Period 2).

effect variation contribution.[13]

Table 1: LOG REAL WAGE VARIANCE DECOMPOSITION

	Period 1 1996-2000		Period 2 2001-2007		Period 3 2008-2010		Total Period 1996-2010	
	Variance	Share	Variance	Share	Variance	Share	Variance	Share
Variance of Log Real Wages	0.118		0.143		0.152		0.142	
Breaking down the variance:								
Variance of Person Effect	0.312	263.6	0.108	75.1	0.413	272.2	0.095	66.9
Variance of Firm Effect	0.010	8.2	0.008	5.7	0.026	16.9	0.006	4.1
Variance of Covariates	0.360	303.9	0.035	24.3	0.479	316.2	0.067	46.7
Variance of the Residual	0.012	10.2	0.018	12.6	0.012	8.2	0.024	17.0
2*Covariance of Person and Firm Effects	-0.017	-14.5	-0.004	-2.5	-0.048	-31.6	-0.001	-0.8
2*Covariance of Person+Firm Effects and Covariates	-0.558	-471.4	-0.022	-15.3	-0.730	-481.9	-0.048	-34.0

Note: The data is restricted to the total period mobility group employees with single jobs born between 1920 and 1991, earning a work salary of at least 120,000SEK a year.

Variance decomposition of log real wages reveals the changes in the components of the total variation, as well as their relative contributions to the total wage dispersion in each period. To avoid the discussion on the effects of the financial crisis 2008-2009, we focus our attention on the first two periods, i.e 1996-2007. While person effects exhibit increased dispersion from Period 1 to Period 2, their contribution to total wage variance has declined over the periods. By contrast, the firm effect dispersion has remained roughly the same and contributes minimally to overall variance in wages. At the same time, between Period 1 and 2, the covariance of the two components is increasing. Since the covariance term captures the sorting of workers across firms by their person and firm fixed components, 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.

5.3 Worker-firm fixed effects distribution and its change over time

To better illustrate workers sorting by type 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 the total period. We first rank the firm and person effects, and then group them

[13] These results available upon request.

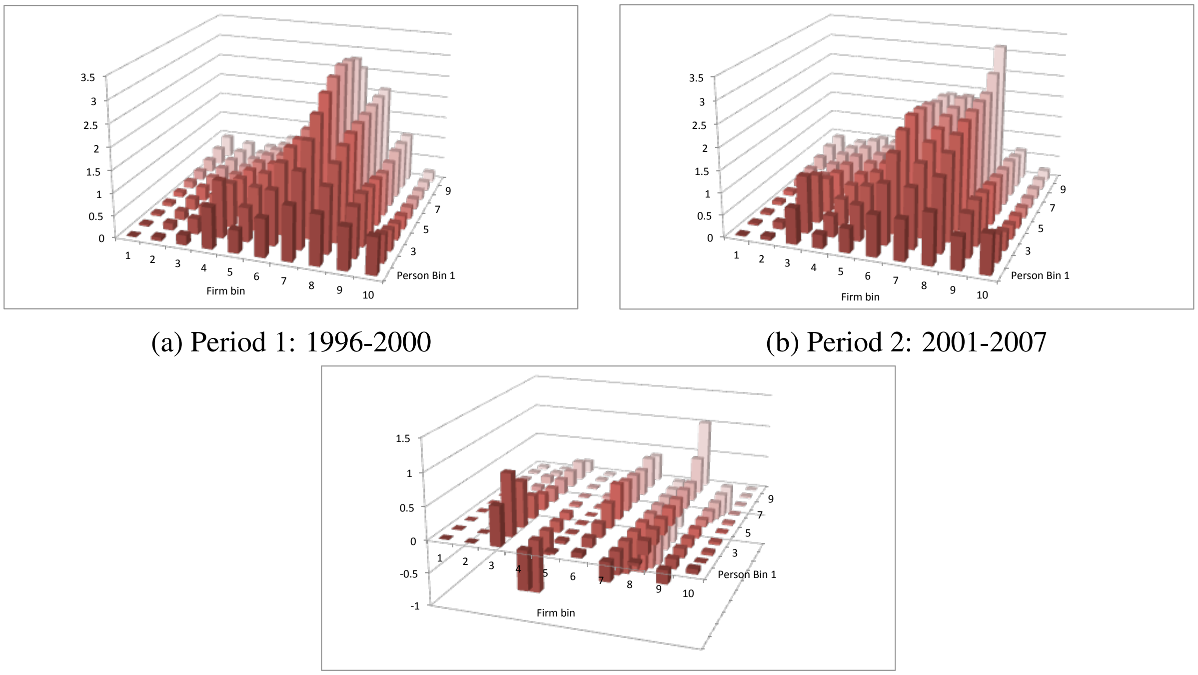
into deciles.[14] Next, for each firm and person effect decile bin intersection we calculate the share of worker-year matches to firms that fall into that particular bin, as a share of total possible firm-worker-year outcomes in the period. This is represented by a bar in the graph. Within each period the sum of the shares add up to 100. The ranking method 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, i.e we are focusing on the *shape* of the joint firm-work effects distribution.

The first two panels of Figure (3) presents the joint distribution of the worker-firm effects over the two periods (left:1996-2000, right:2001-2007) and the difference (bottom panel) in the share of workers in each worker-firm bin between the periods. We document a significant change in the distribution of worker-firm effects, with noticeable changes in the share of workers allocated to particular bins. The difference graph reveals 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 firms characteristics, we observe both positive sorting (larger masses of workers in the bins with high worker and firm effects correlation, and particularly in the low worker-low firm effect bins) and the overall losses and gains in the employment of the middle deciles of the firm effect. When interpreting the results, it should be noted 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 merely exploration of the changes in the *shape* of the distribution relative to their respective supports.

In the Appendix (see Figure D.2), we also provide the dissection of the distribution in Period 2 by the two education groups in the workforce (by highest education level obtained during the working life). The results show that high school graduates distribute over the whole support of the worker-firm effects and their distribution closely resembles the distribution of the overall workforce, with some degree of positive assortative matching on both ends. College graduates, on the other hand, concentrate in the highest paying firms and large share of these workers also have high person effects. This may add additional strength to the high end positive matching explanation.

Next, in Figure (4) we document the distribution of residuals over the worker-firm effect deciles constructed using the same methodology as the joint distributions for the two periods (left:1996-2000, right:2001-2007), as well as the difference (bottom sub-panel) between the first two periods. The residual component contains a part representing the idiosyncratic match quality in the worker-firm pairs. The exploration of the significance in this component and how it changes over time reveals little evidence on the importance of the idiosyncratic match component. There is a certain rise in the match effect for the low-paying firms with certain worker effect groups, and for the high-

[14]Each firm bin therefore contains 10% of all the firms in that period, and the person bins are constructed analogously.



(a) Period 1: 1996-2000

(b) Period 2: 2001-2007

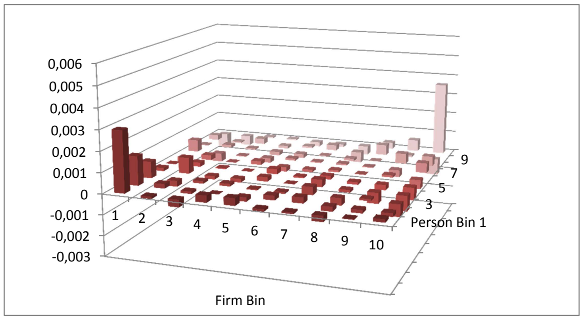
(c) P1 to P2 difference

Figure 3: Worker-firm fixed effects distributions.

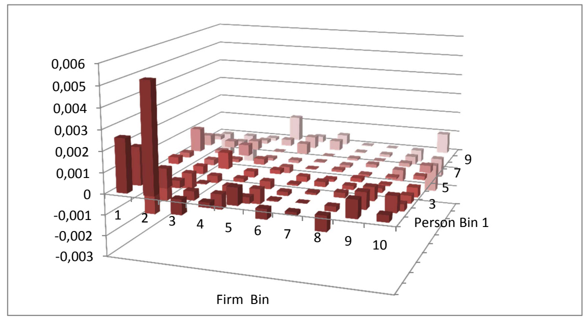
paying firms who seem to exhibit a decrease in the match effect when coupled with employees with higher worker effects. However, there are no significant patterns of the residual behavior in the remaining areas of the distribution, lending support to our empirical specification.

Correlation between firm fixed effects and observable characteristics of firms Investigating the background of the fixed effects as the characteristics of firms, we shed light on how firm fixed effects correlate with firm specific observables. In Table (2) we show how firm's capital intensity, exporter status, profitability, share of high school graduates and the share of college graduates in its labor force predict the fixed effect of firms. We find that all of these factors have a significant positive effect on the firm fixed effects. Moreover, we also test the importance of these factors in determining the probability of a firm falling into the top 20% and the bottom 20% of the firms by the firm fixed effects (see Tables D.3 and D.4 in Appendix). We find significant effects of all factors in determining presence in the top and bottom quintiles, with the sign reversed between the groups: higher capital intensity, exporting, profitability and the share of skilled employees, all increase (lower) the probability that a firm belongs to the top 20% (bottom 20%) firms in the distribution of firm effects.

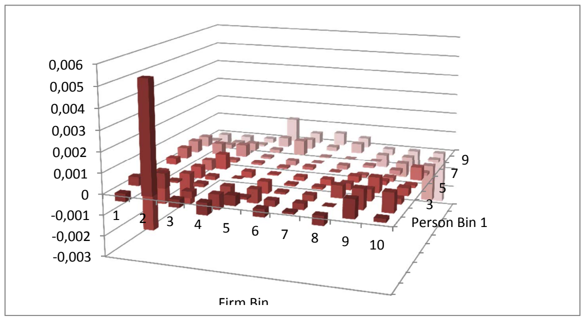
Transitions of workers and firms Figures (5) and (6) present the between-periods transitional patterns of workers, into unemployment and also across the worker-firm effects distribution, and



(a) Period 1: 1996-2000



(b) Period 2: 2001-2007



(c) P1 to P2 difference

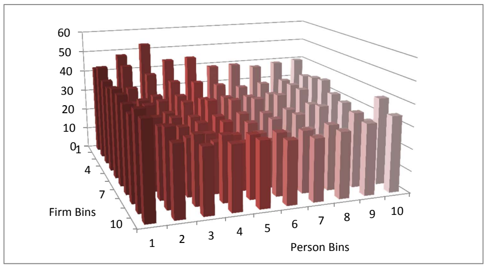
Figure 4: Match-effect distribution distributions.

Table 2: FACTORS INFLUENCING THE FIRM FIXED EFFECTS

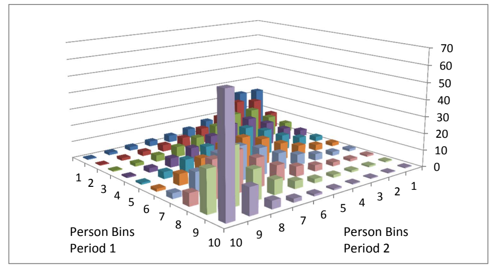
VARIABLES	(1) Firm Effect	(2) Firm Effect	(3) Firm Effect	(4) Firm Effect
Log Capital per Worker	0.00554***	0.00510***	0.00496***	0.00766***
	(0.000382)	(0.000240)	(0.000236)	(0.000256)
Firm Export Intensity		7.86e-09***	4.21e-09***	-8.96e-10
		(2.76e-10)	(9.48e-10)	(8.16e-10)
Profit per Worker			1.70e-09***	1.06e-09***
			(3.95e-10)	(2.90e-10)
Share of HS graduates				0.000498***
				(2.63e-05)
Share of College+				0.00182***
				(4.46e-05)
Constant	-0.100***	-0.0861***	-0.0846***	-0.178***
	(0.00384)	(0.00327)	(0.00322)	(0.00543)
Observations	107,403	55,938	55,938	55,938
Number of year	15	11	11	11

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

Note: All robust errors. Regressions include year dummies. Sample is restricted to agents above 17 years of age, holding a full time job in manufacturing firms. Share of HS shows the share of High School graduates working within the firm in a year, Share of College+ are share of workers that have at least some college education. The reference group for education is those without a High School degree. Firm Export Intensity is export values over total sales in each year. Export value variable is only available for the last 11 years of the panel.



(a) Out of employment



(b) Across worker fixed effects

Figure 5: Transition probabilities of workers, Period 1 to Period 2, percent.

Firm Dynamics Between Periods - Exits
As a share of the firms in the earlier period Firm Bins, percent

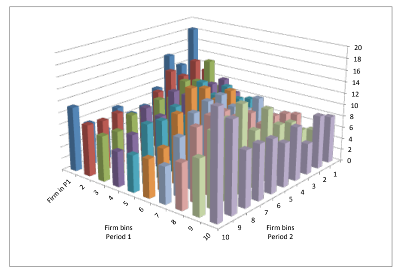
Firm Bins	P1 to P2 Exits	P2 to P3 Exits
1	49.82	32.84
2	38.50	29.55
3	34.81	25.80
4	32.10	26.70
5	31.37	26.07
6	26.69	25.94
7	28.91	27.77
8	29.89	26.60
9	33.95	32.75
10	42.12	36.90

(a) Firm exits

Firm Dynamics Between Periods - Entries
As a share of the current period Firm Bins, percent

Firm Bins	Period2 New Entries	Period 3 New Entries
1	43.26	44.23
2	31.82	30.63
3	28.61	25.69
4	25.50	24.86
5	24.06	19.64
6	24.46	19.92
7	20.69	19.92
8	23.53	20.88
9	30.21	25.69
10	39.71	39.61

(b) Firm Entries

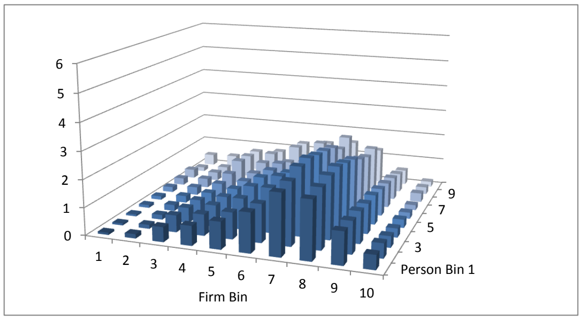


(c) Across firm fixed effects

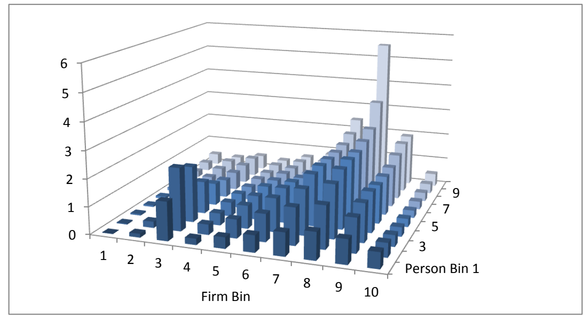
Figure 6: Transition probabilities of firms, Period 1 to Period 2

of firms in/out of the active market (firm entry/exit) and across the worker-firm effects distribution.

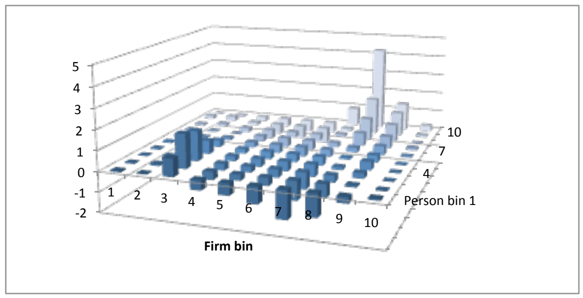
While we do not observe much flow of workers across different person effect deciles, which points to the stability of the ranking of the relative returns to their individual skills, the same is not true for the firms. We observe a larger movement of firms across the firm effect deciles. This points to a high volatility in the estimated firm performance component in the workers wage (to the extent that there has been no significant change in the wage setting regime). However, when we restrict the sample to exclude firms who have less than 5 (or 10) movers, the firm effects become more stable across periods and the joint distributions look qualitatively similar. Therefore, we use these findings as a justification that both worker and firm effects are a reasonably stable representation of their earning and paying potentials, i.e. their skills and productivity.



(a) Period 1: 1996-2000



(b) Period 2: 2001-2007

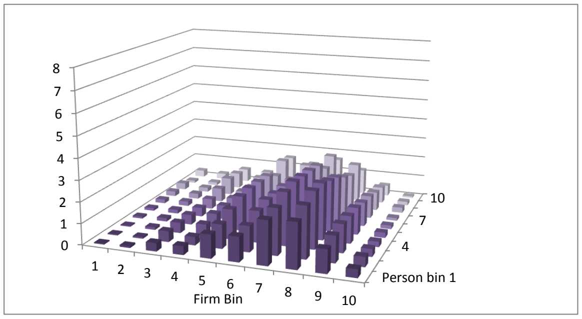


(c) P1 to P2 difference

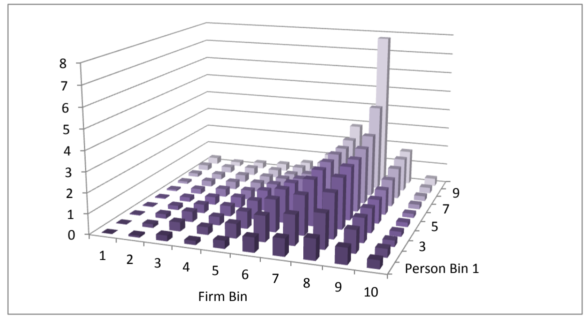
Figure 7: High ICT Industries worker-firm fixed effects distributions.

5.4 Sources of distribution changes

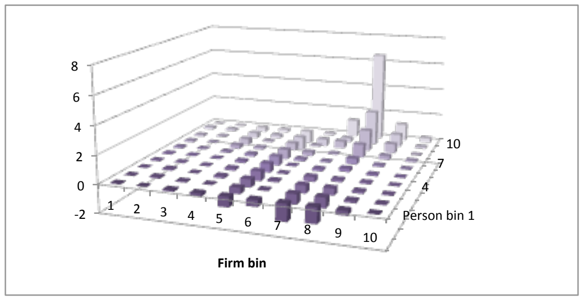
In this section we focus on the empirical and economic explanations of the effects we observe. We attempt to provide some evidence on the potential sources of the changes in firm-worker effect distributions. We first focus on the role of the adoption of new technologies. When analyzing changes for the group of industries with high ICT intensity from Period 1 to Period 2 (Figure 7) we observe an increase in the share of low fixed effect workers in the low fixed effect firms, and a reduction in their shares in the high fixed effect firms. At the same time, the shares of high fixed effect workers in the high fixed effect firms increases. This particular allocation pattern (sorting) was possibly caused by the nature of the ICT technologies and their non-uniform adoption across firm. This type of movement is not present in the low ICT intensive industries. Although this finding may be in line with the theoretical predictions of the skilled-biased technological change literature, we are concerned about whether the 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. Although we don't investigate these interactions further, but focus on their identification only, the background story of the particular specialization patterns, compatible with the new technologies, may indeed only be possible under the increased import of goods regarded as competitively disadvantaged in the new environment.



(a) Period 1: 1996-2000



(b) Period 2: 2001-2007



(c) P1 to P2 difference

Figure 8: High ICT High China Industries worker-firm fixed effects distributions.

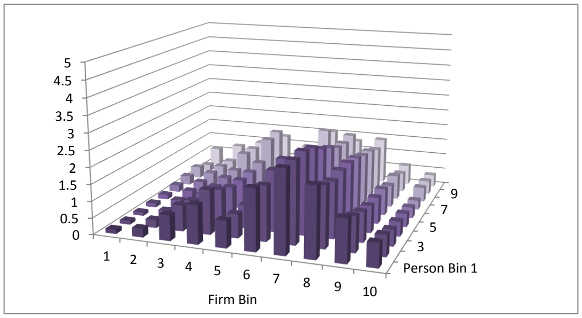
5.4.1 Technology and import competition interactions - across Periods 1 and 2

To analyze the phenomenon in more details, we proceed with the analyses within the group of the high ICT intensity industries. We distinguish between two subgroups of industries, depending on the industries' exposure to changes in competition from China.

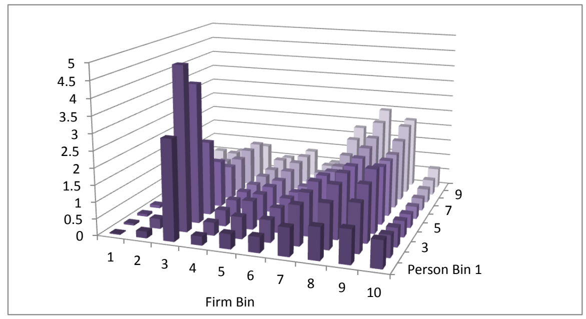
The results reveal that the observed aggregate pattern for the high ICT intensity industries is not uniform across industries within this group, which points to the interaction between technology and other factors. In the first group (high ICT industries with a high change in the Chinese import penetration), we observe a strong increase in the share of high fixed effect workers in the high fixed effect firms, and a reduction in the shares of low fixed effect workers in the high fixed effect firms (Figure 8). These industries experience a stronger than average[15] 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.

In the second group (high ICT industries with a low change in the Chinese import penetration), we observe an increase in the share of low fixed effect workers in the low fixed effect firms (Figure 9). We also observe smaller changes in the share of high fixed effect workers in the high fixed

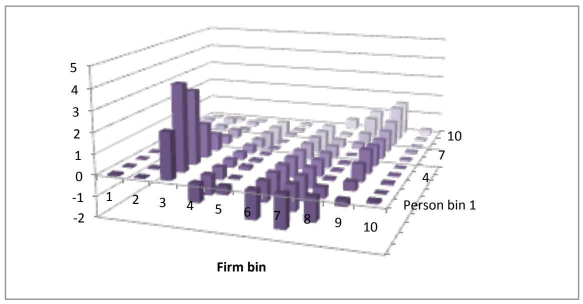
[15]We take the magnitude of the effects that we observe for the aggregate of all high ICT intensity industries as the average.



(a) Period 1: 1996-2000



(b) Period 2: 2001-2007



(c) P1 to P2 difference

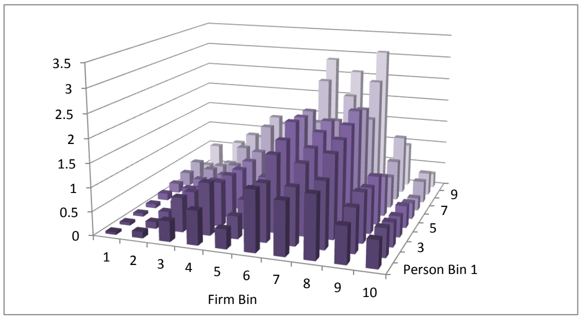
Figure 9: High ICT Low China Industries worker-firm fixed effects distributions.

effect firms, and the shares of low fixed effect workers in the high fixed effect firms. Thus, this effect resembles the average, but with a much smaller change at the high end, and a much larger change at the low end of the firm distribution, compared to the average.

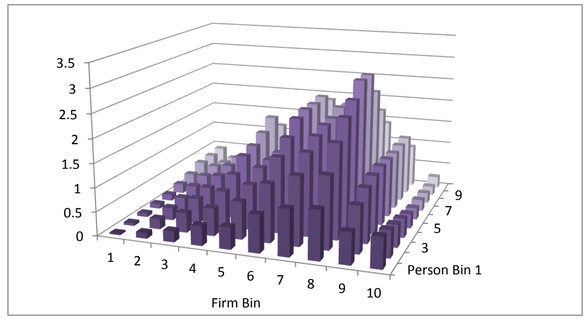
Finally, we do not observe any changes of the above type in the low ICT intensive industries between Period 1 and Period 2, with (Figure 10) or without a strong increase in the Chinese import penetration. This last finding again points to the importance of the interactions between the two factors when explaining the aggregate outcomes.

To strengthen our results with an alternative investigation, we divide the plane of worker and firm effects into low (bins 1 through 5) and high (bins 6 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 Section (D.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.

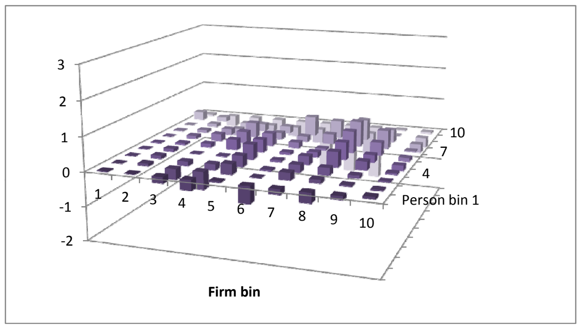
Table D.9 shows that compared to the "High China-High ICT" scenario, all other scenarios of interactions between Chinese competition and ICT contribute positively to the Low Firm-Low Person outcome in Period 1, whereas in Period 2 (Table D.10) only the Low China-High ICT scenario is more likely to have an outcome in the Low Firm-Low Person quadrant. This again supports the positive assortative matching we have observed in the lower end of the person-firm effect distributions. Next, Tables (D.11) and (D.12) show that the "High China-High ICT" scenario is more likely to produce an outcome in the High Firm-High Person quadrant in both periods



(a) Period 1: 1996-2000



(b) Period 2: 2001-2007



(c) P1 to P2 difference

Figure 10: Low ICT High China Industries worker-firm fixed effects distributions.

compared to other combinations of industry type interactions. In Period 2, the strongest negative outcome comes from the Low China-High ICT industries.

Thus the results in logit regressions confirm the illustrations from earlier in this section that (a) Period 2 positive sorting on the high end is strongest in High China-High ICT industries, weakest in Low China-High ICT, and (b) Period 2 assortative matching on the low end is strongest in Low China-High ICT industries and weakest in High China-High ICT industries.

6 Conclusion

In this paper we presented the analysis of the industry labor dynamics in response to recent changes in technology and import competition using detailed matched worker-firm micro data on manufacturing industries in Sweden. We focused on the worker-to-firm sorting phenomena which we capture in the data and which may have contributed to the rise in the wage inequality in the 1996-2007 period. We concentrated on the effects of the increase in Chinese import penetration and the ICT adoption as potential culprits for the sorting phenomena, and, in particular, we investigated the outcomes of these two forces' interactions. In the group of the high ICT intensity industries, we observe an increase in the share of low fixed effect workers in the low fixed effect firms, and a reduction in their shares in the high fixed effects firms. At the same time, the shares of high effect workers in high effect firms increases. This particular allocation pattern, not observed in the low ICT intensive industries, corresponds to the theoretical predictions of the skilled-biased technological change literature, caused by the nature of the ICT technologies and their non-uniform adoption across firms.

However, the documented pattern is not uniform across industries within the high ICT intensity group, which points to the interaction between technology and other factors. In the group of high ICT industries with a high change in the Chinese import penetration, we observe a strong increase in the share of high fixed effect workers in the high fixed effect firms, and a reduction in the shares of low effect workers in the high effect firms, while there are no significant changes on the low end of the firm distribution. The interaction of import competition and technological change is not merely producing intensification or dampening of one factors effects, but a qualitatively different pattern. To the extent that worker and firm effects represent their skills, i.e. quality, we observe a strong skill upgrade in the high quality firms within this industry type and no change on the low quality end. However, in the second group (high ICT industries with a low change in the Chinese import penetration), we observe an increase in the share of low fixed effects workers in the low fixed effects firms. In the absence of large changes in import competition, the technological change results in a stronger sorting of low skill workers into low quality firms, while the high end of the distribution exhibits less significant changes. Finally, we do not observe any changes of the above type in the low ICT intensive industries, with or without a strong increase in the Chinese import penetration. This last finding again points to the importance of the interactions between the two factors when explaining the aggregate outcomes.

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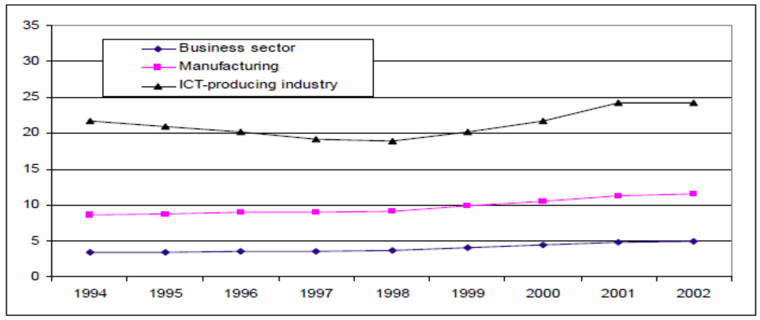
A Changes in technology and Chinese import penetration

ICT-capital stock as a share of the Swedish total capital stock for different industries 1994–2002



Note: The following industries are defined as ICT-producing: Office, accounting and computing machinery (ISIC 30), Electric machinery and apparatus (ISIC 31), vision and communication equipment (ISIC 32) and Medical, precision and optical instruments (ISIC 33).

Source: Statistics Sweden (2006).

Figure A.1: ICT share of total capital, 1994-2002

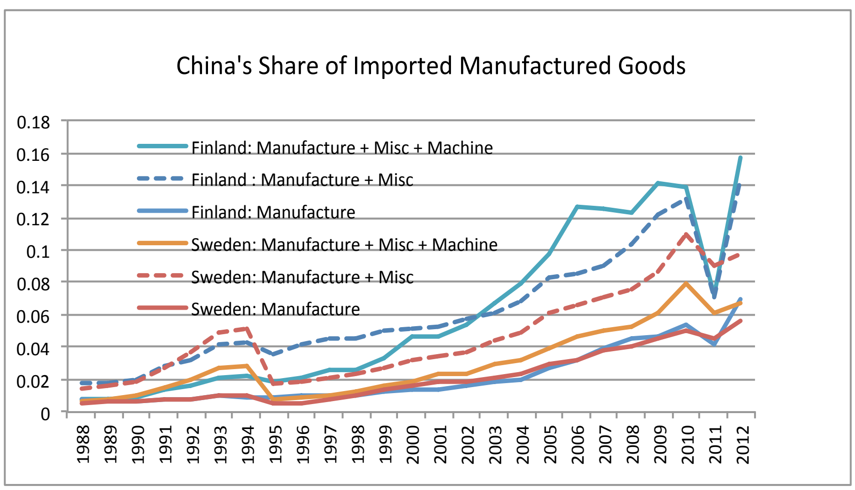


Figure A.2: Imports from China, 1988-2012

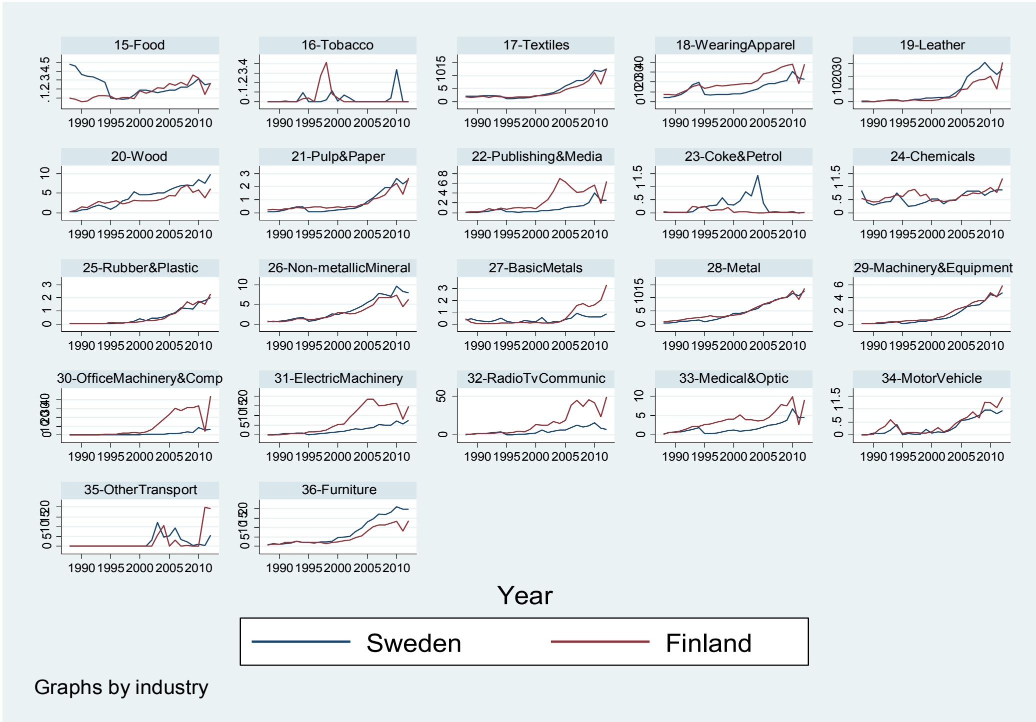


Figure A.3: Swedish and Finish Imports from China as a Share of Total Imports, by industry, 1988-2012.

B Industry classifications

Table B.1: MATCHING UN COMTRADE SITC CODES TO SWEDISH INDUSTRIES

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 B.2: CHINESE IMPORTS BY INDUSTRIES: SHARES IN AND CHANGES OVER THE BEGINNING OF EACH PERIOD

	Chinese Share in 1996, % (P1)	Chinese Share in 2001, % (P2)	Chinese Share in 2008, % (P3)	Change in Chinese Share, % (P1 to P2)	Rank in Change Low to High (P1 to P2)	Change in Chinese Share, % (P2 to P3)	Rank in Change Low to High (P2 to P3)
Industries							
15-Food	0.089	0.189	0.220	110.58	6	16.91	3
16-Tobacco		0.069	0.000		-	-99.88	1
17-Textiles	1.159	2.594	8.013	123.90	7	208.89	12
18-WearingApparel	6.986	8.117	20.528	16.20	2	152.89	9
19-Leather	1.055	3.165	25.929	199.91	12	719.13	21
20-Wood	1.602	4.566	7.097	185.09	11	55.44	6
21-Pulp&Paper	0.069	0.252	1.918	267.28	15	660.89	20
22-Publishing&Media	0.237	0.427	1.477	80.17	4	245.92	15
23-Coke&Petrol	0.272	0.456	0.025	67.91	3	-94.43	2
24-Chemicals	0.254	0.531	0.819	108.81	5	54.45	5
25-Rubber&Plastic	0.072	0.257	1.163	259.01	14	352.67	17
26-Non-metallicMineral	0.788	2.944	7.483	273.37	16	154.23	10
27-BasicMetals	0.112	0.566	0.684	404.11	18	20.90	4
28-Metal	1.294	4.165	9.927	221.87	13	138.37	8
29-Machinery&Equipment	0.151	0.681	2.885	351.83	17	323.88	16
30-OfficeMachinery&Comp	0.118	0.707	3.666	496.55	20	418.63	18
31-ElectricMachinery	0.318	1.882	5.141	492.47	19	173.20	11
32-RadioTvCommunic	0.652	6.532	10.637	901.70	21	62.84	7
33-Medical&Optic	0.349	0.988	3.093	182.94	10	213.05	13
34-MotorVehicle	0.045	0.119	0.751	161.50	8	533.05	19
35-OtherTransport	0.040	0.039	2.271	-3.64	1	5729.36	22
36-Furniture	1.769	4.839	16.736	173.57	9	245.86	14

Note: The imports data is from Comtrade at the product level. The Authors have performed a match between imported products and Swedish industry codes. The cutoff industries between high and low ranking are Industry 20 for the Change from P1 to P2, and Industry 31 from P2 to P3. In the Ranking we have taken the lowest 11 sectors as Low, and the rest as High Chinese Share industries. The industries that always remain Low in both rankings are: 18, 23, 24, 15, and 20. The industries that always remain High in both rankings are: 19, 25, 21, 29, and 30.

Table B.3: INFORMATION AND COMMUNICATION TECHNOLOGY CLASSIFICATIONS

Van Ark et al.(2003) Classifications	Our own ICT Classifications
ICT Producing Industries	**High ICT Industries**
30-OfficeMachinery&Comp	18-WearingApparel
313-Insulated Wire	22-Publishing&Media
32-RadioTvCommunication	29-Machinery&Equipment
331-3-Scientific Instruments	30-OfficeMachinery&Comp
	31-ElectricMachinery
Intensive ICT-using Industries	32-RadioTvCommunication
18-WearingApparel	33-Scientific Instruments
22-Publishing&Media	35-OtherTransport
29-Machinery&Equipment	36-Furniture
31(ex313)-ElectricMachinery	
334-5-Other Instruments	
35-OtherTransport	
36-Furniture	
37-Recycling	
Less Intensive ICT-using Industries	**Low ICT Industries**
15-Food	15-Food
16-Tobacco	16-Tobacco
17-Textiles	17-Textiles
20-Wood	20-Wood
21-Pulp&Paper	21-Pulp&Paper
23-Coke&Petrol	23-Coke&Petrol
24-Chemicals	24-Chemicals
25-Rubber&Plastic	25-Rubber&Plastic
26-Non-metallicMineral	26-Non-metallicMineral
27-BasicMetals	27-BasicMetals
28-Metal	28-Metal
34-MotorVehicle	34-MotorVehicle

Notes: For our own classification, we keep the Less intensive 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 Comtrade, we drop it from our ICT grouping.

C Data

Table C.1: DATA DESCRIPTION

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 four different systems (SNI1969, 1992, 2002, 2007) 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
Trade Data	
Imports and Exports	Indicator available for each year when there is foreign trade
Value	Reported value of foreign trade
Country	Code for the destination or source country

Notes: **Firm Data** source is Account Statistics (FEK). Data for 1980-1996 are for a sample of companies. Data comes with a 2 year lag. Only non-imputed companies included. **Business Register** data is sourced from the Business Register Database (Fretagsregistret). Data available from 1980 onwards. **Employee Data** source is Register Based Labor Statistics (RAMS). Data available from 1985 onwards. Each individual is linked to a firm, and a plant where applicable. **Trade Data** source is the Foreign Trade Database (Utrikeshandel). Data available from 2000 onwards. Partial data available between 1997-2000. For intra-EU trade, minimum of 4.5 million SEK ($\approx$610,000USD) required to register as importing or exporting.

Table C.2: SUMMARY STATISTICS OF THE MANUFACTURING INDUSTRIES, AND LARGEST MOBILITY GROUPS

	Total Population			Largest Mobility Group - Firms		
	No of Firms	No of People	Log Real Wage	No of Firms	No of People	Log Real Wage
Total Period: 1996-2010	13716	1141174	12.404	13072	1135928	12.404
			(0.383)			(0.383)
Percent of Mobility Group vs Total (%)				95.30	99.54	
Period 1: 1996-2000	9838	769461	12.407	8300	752618	12.410
			(0.358)			(0.359)
Percent of Mobility Group vs Total (%)				84.37	97.81	
Period 2: 2001-2008	9782	831740	12.511	8769	820603	12.513
			(0.340)			(0.340)
Percent of Mobility Group vs Total (%)				89.64	98.66	
Period 3: 2008-2010	8467	589293	12.677	5140	540436	12.690
			(0.400)			(0.401)
Percent of Mobility Group vs Total (%)				60.71	91.71	

Note: Wage standard deviation in parentheses. The Population is restricted to agents born after 1920 and before 1992 holding a full time job (defined as earning at least 120,000SEK in 2010 SEK annually) in manufacturing firms.

D Results

Table D.1: JOB SWITCHERS LEAVING QUARTILE 1 AND 4 FIRMS - PERIOD 1

	(1) Quartile 1 at time t-1	(2) Percent (%)	(3) Quartile 4 at time t-1	(4) Percent (%)
Quartile at time zero				
1	6,172	74.7	287	3.5
2	1,361	16.5	648	7.8
3	336	4.1	2,434	29.5
4	395	4.8	4,892	59.2
Total	8,264		8,261	

Note: The population is restricted to only Period 1 (1996-2000). The table only present outcomes for those who move, but, the quartile assignments for firms take into account all the coworkers (excluding the mover themselves) at the old (t=-1) and new (t=0) firms. The total population in Period 1 is 739,416 workers. 85% of those never move between firms. Of the movers (112,032 people, 15% of total), only 6% move more than once. In the calculations, we assign the last firm moved to as the firm at time zero and onwards. Of the movers, 33,049 of them are present in all four years: two years in the older firm, and two years in the final firm. This subpopulation covers 4366 firms (out of 9509) that employ 631,992 people together with the movers.

Table D.2: JOB SWITCHERS LEAVING QUARTILE 1 AND 4 FIRMS - PERIOD 2

	(1) Quartile 1 at time t-1	(2) Percent (%)	(3) Quartile 4 at time t-1	(4) Percent (%)
Quartile at time zero				
1	7,757	60.60	537	4.20
2	2,903	22.68	1,307	10.21
3	1,578	12.33	1,361	10.63
4	562	4.39	9,594	74.96
Total	12,800		12,799	

Note: The population is restricted to only Period 2 (2001-2007). The table only present outcomes for those who move, but, the quartile assignments for firms take into account all the coworkers (excluding the mover themselves) at the old (t=-1) and new (t=0) firms. The total population in Period 2 is 814,858 workers. 82% of those never move firms. Of the movers (144,397 people, 18% of total), 12% move more than once. In the calculations, we assign the last firm moved as the firm at time zero and onwards. Of the movers, 51,201 of them are present in all four years, two years in the older firm, and two years in the final firm. This subpopulation covers 6485 firms (out of 9519) that employ 760,464 people together with the movers.

D.1 Firm Fixed effect regressions

Table D.3: PROBABILITY OF FALLING INTO THE BOTTOM 20% PAYING FIRMS

VARIABLES	(1) Bottom20	(2) Bottom20	(3) Bottom20	(4) Bottom20
Log Capital per Worker	-0.0267***	-0.0229***	-0.0228***	-0.0241***
	(0.000737)	(0.000660)	(0.000662)	(0.000634)
Firm Export Intensity		-7.48e-09***	-6.62e-09***	-9.10e-11
		(5.08e-10)	(6.37e-10)	(5.48e-10)
Profit per Worker			-4.05e-10**	3.21e-10***
			(1.67e-10)	(8.83e-11)
Share of HS graduates				-0.000439***
				(6.54e-05)
Share of College+				-0.00208***
				(9.83e-05)
Industries				
Tobacco	-0.291***	-0.189***	-0.189***	-0.171***
	(0.00419)	(0.00362)	(0.00357)	(0.00381)
Textiles	-0.0565***	0.0365***	0.0365***	0.0356***
	(0.00826)	(0.00855)	(0.00856)	(0.00841)
WearingApparel	0.0313*	0.110***	0.110***	0.110***
	(0.0170)	(0.0141)	(0.0141)	(0.0121)
Leather	-0.0868***	0.00657	0.00658	-0.00574
	(0.00883)	(0.0132)	(0.0132)	(0.0125)
Wood	-0.0630***	-0.0286***	-0.0287***	-0.0361***
	(0.00524)	(0.00432)	(0.00432)	(0.00464)
Pulp&Paper	-0.247***	-0.143***	-0.142***	-0.142***
	(0.00304)	(0.00418)	(0.00414)	(0.00419)
Publishing&Media	-0.193***	-0.105***	-0.105***	-0.0914***
	(0.00293)	(0.00339)	(0.00338)	(0.00344)
Coke&Petrol	-0.136***	-0.0334***	-0.0334***	-7.82e-05
	(0.00703)	(0.00956)	(0.00957)	(0.00885)
Chemicals	-0.201***	-0.101***	-0.101***	-0.0683***
	(0.00567)	(0.00267)	(0.00266)	(0.00161)
Rubber&Plastic	-0.140***	-0.0537***	-0.0537***	-0.0528***
	(0.00490)	(0.00433)	(0.00432)	(0.00442)
Non-metallicMineral	-0.175***	-0.0849***	-0.0848***	-0.0821***
	(0.00292)	(0.00755)	(0.00755)	(0.00738)
BasicMetals	-0.203***	-0.140***	-0.140***	-0.139***
	(0.00420)	(0.00630)	(0.00625)	(0.00642)
Metal	-0.153***	-0.0721***	-0.0721***	-0.0730***
	(0.00350)	(0.00280)	(0.00280)	(0.00257)
Machinery&Equipment	-0.219***	-0.140***	-0.140***	-0.125***
	(0.00343)	(0.00474)	(0.00473)	(0.00399)
OfficeMachinery&Comp	-0.143***	-0.0370**	-0.0369**	0.00258
	(0.00873)	(0.0158)	(0.0158)	(0.0162)
ElectricMachinery	-0.182***	-0.0943***	-0.0942***	-0.0783***
	(0.00488)	(0.00498)	(0.00499)	(0.00558)
RadioTvCommunication	-0.234***	-0.125***	-0.125***	-0.0853***
	(0.00431)	(0.00554)	(0.00555)	(0.00623)
Medical&Optic	-0.187***	-0.0955***	-0.0954***	-0.0559***
	(0.00588)	(0.00523)	(0.00524)	(0.00533)
MotorVehicle	-0.242***	-0.139***	-0.139***	-0.135***
	(0.00281)	(0.00225)	(0.00225)	(0.00192)
OtherTransport	-0.159***	-0.0697***	-0.0697***	-0.0636***
	(0.00508)	(0.00796)	(0.00797)	(0.00778)
Furniture	-0.116***	-0.0273***	-0.0273***	-0.0299***
	(0.00653)	(0.00544)	(0.00544)	(0.00521)
Recycling	-0.0224***	0.0675***	0.0675***	0.0599***
	(0.00754)	(0.0134)	(0.0134)	(0.0129)
Observations	107,403	55,938	55,938	55,938
Number of years	15	11	11	11

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

Note: See Notes from Table D.4.

Table D.4: PROBABILITY OF FALLING INTO THE BOTTOM 20% PAYING FIRMS

VARIABLES	(1) Top20	(2) Top20	(3) Top20	(4) Top20
Log Capital per Worker	0.00612***	0.0107***	0.0102***	0.0136***
	(0.00127)	(0.00133)	(0.00135)	(0.00125)
Firm Export Intensity		6.70e-08***	5.66e-08***	3.88e-08***
		(1.12e-09)	(3.03e-09)	(2.41e-09)
Profit per Worker			4.88e-09***	2.91e-09***
			(1.14e-09)	(7.52e-10)
Share of HS graduates				0.000542***
				(7.62e-05)
Share of College+				0.00523***
				(0.000161)
Industries				
Tobacco	0.575***	0.498***	0.494***	0.451***
	(0.0657)	(0.0690)	(0.0694)	(0.0691)
Textiles	0.0112**	0.00344	0.00329	0.00344
	(0.00460)	(0.00756)	(0.00761)	(0.00671)
WearingApparel	-0.0221***	-0.0205***	-0.0204***	-0.0241**
	(0.00618)	(0.00740)	(0.00745)	(0.0106)
Leather	-0.00454	0.000420	0.000341	0.0264***
	(0.0100)	(0.00888)	(0.00900)	(0.00951)
Wood	0.0200***	0.00959**	0.00972**	0.0288***
	(0.00225)	(0.00479)	(0.00481)	(0.00384)
Pulp&Paper	0.209***	0.196***	0.193***	0.191***
	(0.00762)	(0.00790)	(0.00798)	(0.00782)
Publishing&Media	0.187***	0.180***	0.179***	0.145***
	(0.0114)	(0.0201)	(0.0203)	(0.0207)
Coke&Petrol	0.352***	0.349***	0.349***	0.260***
	(0.0208)	(0.0255)	(0.0254)	(0.0240)
Chemicals	0.240***	0.233***	0.233***	0.147***
	(0.00587)	(0.00555)	(0.00565)	(0.00718)
Rubber&Plastic	0.0273***	0.00825***	0.00823***	0.00703**
	(0.00587)	(0.00268)	(0.00267)	(0.00313)
Non-metallicMineral	0.0606***	0.0354***	0.0348***	0.0278***
	(0.00344)	(0.00525)	(0.00528)	(0.00504)
BasicMetals	0.131***	0.104***	0.102***	0.102***
	(0.00581)	(0.00821)	(0.00829)	(0.00770)
Metal	0.0201***	0.00404	0.00390	0.0103***
	(0.00205)	(0.00437)	(0.00441)	(0.00361)
Machinery&Equipment	0.0976***	0.0864***	0.0858***	0.0504***
	(0.00300)	(0.00443)	(0.00449)	(0.00424)
OfficeMachinery&Comp	0.120***	0.111***	0.111***	0.00959
	(0.0138)	(0.0182)	(0.0182)	(0.0193)
ElectricMachinery	0.0635***	0.0510***	0.0502***	0.0118**
	(0.00383)	(0.00466)	(0.00464)	(0.00526)
RadioTvCommunication	0.220***	0.201***	0.200***	0.0975***
	(0.0125)	(0.0193)	(0.0196)	(0.0199)
Medical&Optic	0.163***	0.182***	0.181***	0.0797***
	(0.00973)	(0.00586)	(0.00621)	(0.00518)
MotorVehicle	0.0405***	0.0197**	0.0185**	0.0119
	(0.00502)	(0.00814)	(0.00839)	(0.00766)
OtherTransport	0.156***	0.177***	0.176***	0.163***
	(0.00906)	(0.00688)	(0.00690)	(0.00756)
Furniture	0.00606	-0.00614	-0.00634	0.000886
	(0.00396)	(0.00548)	(0.00553)	(0.00525)
Recycling	0.171***	0.118***	0.118***	0.139***
	(0.0115)	(0.00889)	(0.00889)	(0.00738)
Observations	107,403	55,938	55,938	55,938
Number of years	15	11	11	11

*** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Note: All robust errors. Regressions include year dummies. Sample is restricted to agents above 17 years of age. Share of HS shows the share of High School graduates working within the firm in a year, Share of College+ are share of workers that have at least some college education. The reference group for education is those without a High School degree. The base industry is Manufacture of Food Products and Beverages. Firm Export Intensity is export values over total sales in each year. Export value variable is only available for the last 11 years of the panel.

D.2 Plant level analysis

Table D.5: SUMMARY STATISTICS OF THE MANUFACTURING INDUSTRIES, AND LARGEST MOBILITY GROUPS

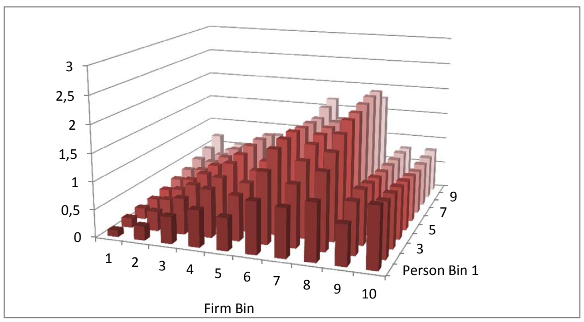
	Total Population				Largest Mobility Group - Firms				Largest Mobility Group - Plants			
	No of Firms	No of Plants	No of People	Log Real Wage	No of Firms	No of Plants	No of People	Log Real Wage	No of Firms	No of Plants	No of People	Log Real Wage
Total Period: 1996-2010	13716	19733	1141174	12.404 (0.383)	13072	19062	1135928	12.404 (0.383)	13040	17913	1134342	12.404 (0.383)
Percent of Total (%)					95.30	96.60	99.54		95.07	90.78	99.40	
Period 1: 1996-2000	9838	13797	769461	12.407 (0.358)	8300	12195	752618	12.410 (0.359)	8277	11078	748385	12.410 (0.359)
Percent of Total (%)					84.37	88.39	97.81		84.13	80.29	97.26	
Period 2: 2001-2008	9782	14245	831740	12.511 (0.340)	8769	13203	820603	12.513 (0.340)	8720	12174	817411	12.513 (0.340)
Percent of Total(%)					89.64	92.69	98.66		89.14	85.46	98.28	
Period 3: 2008-2010	8467	11597	589293	12.677 (0.400)	5140	8055	540436	12.690 (0.401)	5046	6818	531624	12.690 (0.401)
Percent of Total(%)					60.71	69.46	91.71		59.60	58.79	90.21	

Note: Wage standard deviation in parentheses. The Population is restricted to agents born after 1920 and before 1992 holding a full time job (defined as earning at least 120,000SEK in 2010 SEK annually) in manufacturing firms. We have dropped single person plants from our Largest Mobility Group by Plants, amounting to 594, 525, and 387 plants for periods 1-3 and 830 plants in the total period. We also have very rare cases where the plant assignment for the employee is unknown. We have also dropped these people from our last block, amounting to 7, 2, 7, and 16 employees respectively for periods 1-3 and the total period.

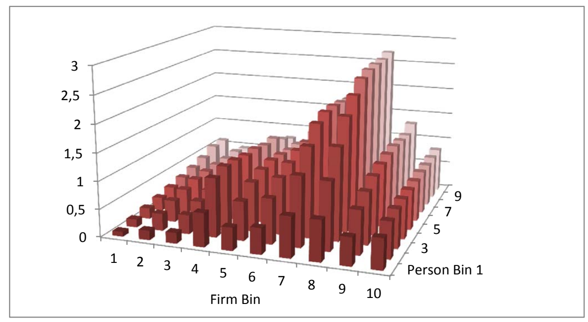
Table D.6: Distribution of Plants, by Firms

	Period 1 : 1996-2000		Period 2: 2001-2007		Period 3: 2008-2010		Total Period : 1996-2010	
	No of Firms	Percent (%)	No of Firms	Percent (%)	No of Firms	Percent (%)	No of Firms	Percent (%)
Number of Plants in the same Firm								
1	8160	82.94	8044	82.23	7299	86.21	10913	79.56
2	685	6.96	707	7.23	501	5.92	1163	8.48
3	413	4.20	410	4.19	277	3.27	646	4.71
4	175	1.78	189	1.93	124	1.46	281	2.05
5	96	0.98	110	1.12	56	0.66	192	1.40
6	75	0.76	71	0.73	53	0.63	108	0.79
7	54	0.55	57	0.58	43	0.51	81	0.59
8	28	0.28	34	0.35	17	0.20	56	0.41
9	26	0.26	29	0.30	11	0.13	36	0.26
10	26	0.26	22	0.22	16	0.19	41	0.30
11+	100	1.02	109	1.11	70	0.83	199	1.45

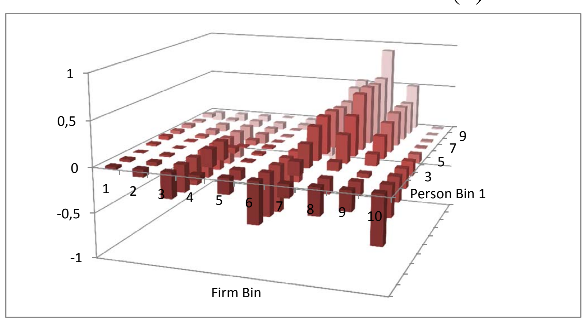
Note: Wage standard deviation in parentheses. The Population is restricted to agents born after 1920 and before 1992 holding a full time job (defined as earning at least 120,000SEK in 2010 SEK annually) in manufacturing firms. We have dropped single person plants from our Largest Mobility Group by Plants, amounting to 594, 525, and 387 plants for periods 1-3 and 830 plants in the total period. We also have very rare cases where the plant assignment for the employee is unknown. We have also dropped these people from our last block, amounting to 7, 2, 7, and 16 employees respectively for periods 1-3 and the total period.



(a) Period 1: 1996-2000



(b) Period 2: 2001-2007



(c) P1 to P2 difference

Figure D.1: Worker-firm effects distribution, plant level analysis

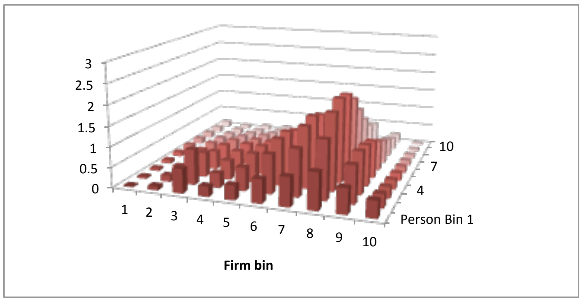
D.3 Empirical specification with the match component

Table D.7: Log Real Wage Variance Decomposition - Match Effect

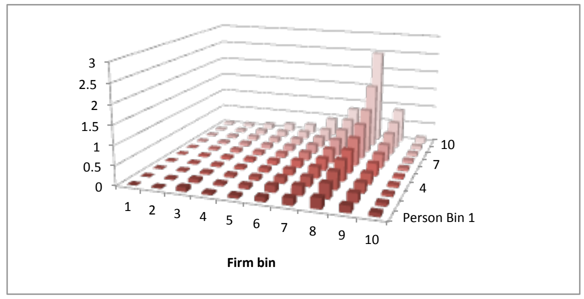
	Period 1 1996-2000		Period 2 2001-2007		Period 3 2008-2010		Total Period 1996-2010	
	Variance	Share	Variance	Share	Variance	Share	Variance	Share
Variance of Log Real Wages	0.118		0.143		0.152		0.142	
Breaking down the variance:								
Variance of Match Effect	0.290	245.14	0.181	126.24	0.326	214.83	0.112	78.54
Variance of Covariates	0.344	290.66	0.052	36.08	0.385	254.09	0.049	34.73
Variance of the Residual	0.011	8.99	0.016	11.25	0.012	7.79	0.020	14.18
2*Covariance of Match Effect and Covariates	-0.526	-444.80	-0.105	-73.57	-0.571	-376.71	-0.039	-27.45
The Match Effect Model:								
R2	91.01		90.52		92.21		85.82	
Std Dev of Match Effect	0.539		0.453		0.571		0.334	

Note: The data is restricted to the total period mobility group employees with single jobs born between 1920 and 1991, earning a work salary of at least 120,000SEK (real, in 2010 SEK) a year. The wage equation used to get the Match Effects has age, age2, age3, a dummy for High School Diploma, a dummy for Some college and more, and the interactions of all age variables and education dummies as covariates. The age dummies are lifetime maximum schooling variables, the person need not have obtained a diploma or attended college in the particular period that is being examined. The Match effect is a dummy that takes on the value one for each firm and person specific match.

D.4 Distribution by education levels



(a) High School graduates



(b) College graduates

Figure D.2: Worker-firm effects distribution by education, 2001-2007

D.5 Across-industry distribution differences

Table D.8: EMPLOYMENT BY INDUSTRY GROUPS, ALL PERIODS

	Period 1: 1996-2000			Period 2 : 2001-2007			Period 3 : 2008-2010		
	Firms	People in First Job	People in Last Job	Firms	People in First Job	People in Last Job	Firms	People in First Job	People in Last Job
Low ICT Low China	1686	240778	243572	2093	264284	263466	2393	192360	192456
Low ICT High China	2808	201431	198689	3084	204172	202801	702	124958	123384
High ICT Low China	1766	123710	125361	1752	133963	143325	305	52223	52651
High ICT High China	1740	183527	181824	1802	203342	196169	1727	168355	169405
Total	8300	749446	749446	8731	805761	805761	5127	537896	537896

Note: The data is restricted to the total period mobility group employees born between 1920 and 1991, earning a work salary of at least 120,000SEK a year and firms of at least 5 employees each year they are active in the database. Low and High Chinese penetration industries are constructed using our Chinese penetration measure between periods 1-2 and 2-3. Since we identify high and low Chinese Import Penetration as the change in Chinese imports over periods, we group Period 1 industries into the same low and high Chinese Import Penetration groups as those in Period 2 for comparison. ICT classifications are fixed across all time periods. As workers may switch jobs across sectors within the period, we present the population breakdown across industry types of their first job and also their last job within the period in the given ICT and China interaction sector.

Distributions in groups of industries, Period 1, 1996-2000

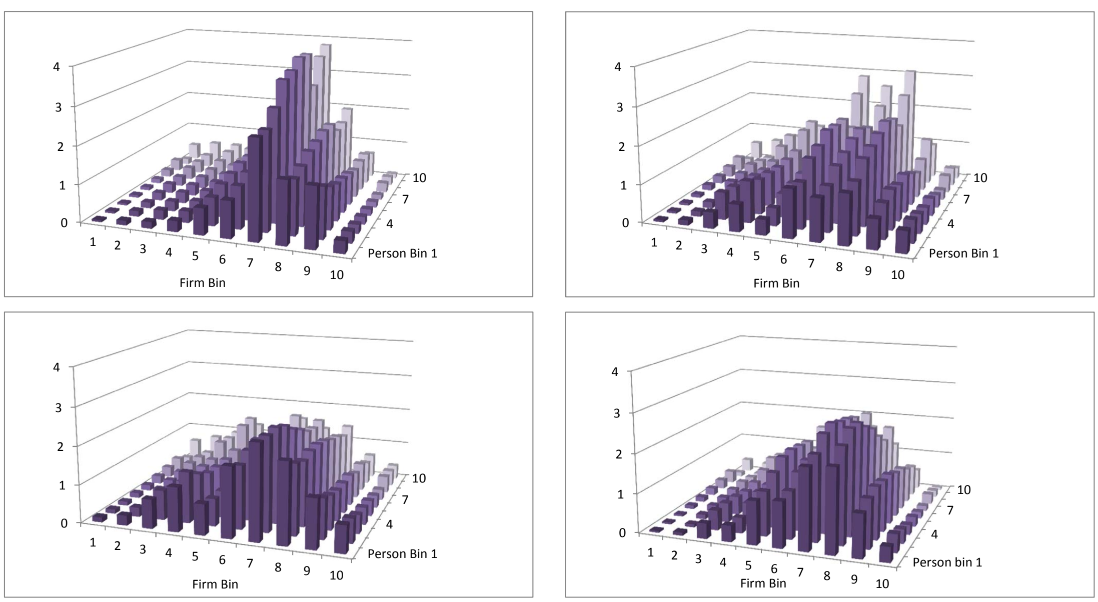


Figure D.3: Industries with low (top) / high (bottom) ICT intensity and low (left) / high (right) change in Chinese import penetration, Period 1

D.6 Logit Regressions on Quadrant Outcomes

Table D.9: Logit on the outcome of being in the Low Firm-Low Person quadrant, Period 1

	(1)	(2)	(3)	(4)
VARIABLES	LFLPP1	LFLPP1	LFLPP1	LFLPP1
Log Capital per Worker	-0.527***	-0.535***	-0.544***	-0.530***
	(0.0105)	(0.0111)	(0.0112)	(0.0112)
Firm Export Intensity	-0.00300***	-0.00289***	-0.00296***	-0.00224***
	(0.000478)	(0.000478)	(0.000480)	(0.000482)
Profit per Worker	-0.0872***	-0.0886***	-0.0878***	-0.0870***
	(0.00540)	(0.00539)	(0.00541)	(0.00542)
Share of HS graduates	-0.0141***	-0.0145***	-0.0133***	-0.0101***
	(0.00128)	(0.00128)	(0.00129)	(0.00132)
Share of College+	-0.0613***	-0.0597***	-0.0596***	-0.0576***
	(0.00119)	(0.00124)	(0.00124)	(0.00124)
Female	0.546***	0.556***	0.547***	0.538***
	(0.0262)	(0.0262)	(0.0262)	(0.0263)
Age	0.0269***	0.0265***	0.0268***	0.0265***
	(0.00109)	(0.00109)	(0.00109)	(0.00110)
LowChina*LowICT				0.295***
				(0.0378)
LowChina*HighICT				0.490***
				(0.0390)
HighChina*LowICT				0.380***
				(0.0354)
LowChina in P1	0.159***		0.159***	
	(0.0251)		(0.0251)	
LowICT in P1		0.131***	0.130***	
		(0.0271)	(0.0270)	
Constant	6.706***	6.797***	6.747***	6.221***
	(0.235)	(0.235)	(0.235)	(0.240)
Observations	67,077	67,077	67,077	67,077

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

Note: Regressions include year dummies and control for the individual's education level. The sample is restricted to firms where agents born after 1920 and before 1992, holding a full time job in manufacturing firms. Share of HS shows the share of High School graduates working within the firm in a year, Share of College+ are share of workers that have at least some college education. Firm Export Intensity is export values over total sales in each year. Export value variable is only available for the last 11 years of the panel. Reference Interaction group is high China High ICT.

Significantly more Low Firm Low Person outcomes from all the other interactions but High China-High ICT by very similar magnitudes. The strongest effect is from Low China-High ICT, fitting with our expectations on the positive sorting on the low end for this group of industries.

Table D.10: LOGIT ON THE OUTCOME OF BEING IN THE LOW FIRM-LOW PERSON QUADRANT, PERIOD 2

VARIABLES	(1) LFLPP2	(2) LFLPP2	(3) LFLPP2	(4) LFLPP2
Log Capital per Worker	-0.267***	-0.227***	-0.228***	-0.228***
	(0.00341)	(0.00370)	(0.00371)	(0.00370)
Firm Export Intensity	-0.00999***	-0.0105***	-0.0103***	-0.00979***
	(0.000159)	(0.000158)	(0.000160)	(0.000160)
Profit per Worker	-0.0929***	-0.0914***	-0.0897***	-0.0853***
	(0.00158)	(0.00158)	(0.00159)	(0.00161)
Share of HS graduates	-0.00853***	-0.00973***	-0.00905***	-0.00732***
	(0.000440)	(0.000434)	(0.000441)	(0.000445)
Share of College+	-0.0552***	-0.0579***	-0.0577***	-0.0560***
	(0.000440)	(0.000450)	(0.000450)	(0.000453)
Female	0.669***	0.674***	0.667***	0.662***
	(0.00872)	(0.00870)	(0.00873)	(0.00875)
Age	0.00390***	0.00323***	0.00332***	0.00289***
	(0.000354)	(0.000354)	(0.000355)	(0.000355)
Firm Tenure	-0.0885***	-0.0901***	-0.0899***	-0.0920***
	(0.00221)	(0.00221)	(0.00221)	(0.00222)
LowChina*LowICT				-0.126***
				(0.0128)
LowChina*HighICT				0.359***
				(0.0131)
HighChina*LowICT				-0.00921
				(0.0125)
LowChina in P1	0.0745***		0.0761***	
	(0.00838)		(0.00841)	
LowICT in P1		-0.250***	-0.250***	
		(0.00908)	(0.00908)	
Constant	2.698***	2.531***	2.445***	2.142***
	(0.0572)	(0.0573)	(0.0581)	(0.0590)
Observations	665,262	665,262	665,262	665,262

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

Note: Regressions include year dummies and control for the individual's education level. The sample is restricted to firms where agents born after 1920 and before 1992, holding a full time job in manufacturing firms. Share of HS shows the share of High School graduates working within the firm in a year, Share of College+ are share of workers that have at least some college education. Firm Export Intensity is export values over total sales in each year. Export value variable is only available for the last 11 years of the panel. Reference Interaction group is high China High ICT. Firm tenure counts how many years an employee has been working at a particular firm, and the regression is only looking at the first time a worker is matched to a firm.

Compared to High China-High ICT industries, Low China-High ICT industries have a lot more LFLP in Period 2, again supporting the positive sorting theory on the low end for this group of industries.

Table D.11: LOGIT ON THE OUTCOME OF BEING IN THE HIGH FIRM-HIGH PERSON QUADRANT, PERIOD 1

VARIABLES	(1) HFHPP1	(2) HFHPP1	(3) HFHPP1	(4) HFHPP1
Log Capital per Worker	0.364***	0.401***	0.416***	0.412***
	(0.00903)	(0.00990)	(0.0100)	(0.0101)
Firm Export Intensity	-0.00141***	-0.00144***	-0.00130***	-0.00165***
	(0.000348)	(0.000347)	(0.000347)	(0.000352)
Profit per Worker	0.0445***	0.0502***	0.0486***	0.0472***
	(0.00471)	(0.00473)	(0.00473)	(0.00474)
Share of HS graduates	0.00534***	0.00472***	0.00367***	0.00205*
	(0.00115)	(0.00115)	(0.00116)	(0.00119)
Share of College+	0.0343***	0.0310***	0.0313***	0.0302***
	(0.000885)	(0.000912)	(0.000915)	(0.000933)
Female	-0.960***	-0.967***	-0.959***	-0.959***
	(0.0214)	(0.0214)	(0.0214)	(0.0214)
Age	-0.0407***	-0.0402***	-0.0403***	-0.0403***
	(0.000909)	(0.000909)	(0.000910)	(0.000910)
LowChina*LowICT				-0.471***
				(0.0280)
LowChina*HighICT				-0.342***
				(0.0323)
HighChina*LowICT				-0.397***
				(0.0289)
LowChina in P1	-0.205***		-0.178***	
	(0.0194)		(0.0195)	
LowICT in P1		-0.304***	-0.282***	
		(0.0224)	(0.0225)	
Constant	-2.545***	-2.877***	-2.918***	-2.659***
	(0.130)	(0.134)	(0.134)	(0.141)
Observations	81,289	81,289	81,289	81,289

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

Note: Regressions include year dummies and control for the individual's education level. The sample is restricted to firms where agents born after 1920 and before 1992, holding a full time job in manufacturing firms. Share of HS shows the share of High School graduates working within the firm in a year, Share of College+ are share of workers that have at least some college education. Firm Export Intensity is export values over total sales in each year. Export value variable is only available for the last 11 years of the panel. Reference Interaction group is high China High ICT.

For High Firm High Person outcomes in Period 1, all ICT and Chinese exposure interactions are equally less likely to have HFHP outcomes compared to High China-High ICT industries.

Table D.12: LOGIT ON THE OUTCOME OF BEING IN THE HIGH FIRM-HIGH PERSON QUADRANT, PERIOD 2

VARIABLES	(1) HFHPP2	(2) HFHPP2	(3) HFHPP2	(4) HFHPP2
Log Capital per Worker	0.229***	0.206***	0.217***	0.220***
	(0.00264)	(0.00290)	(0.00293)	(0.00294)
Firm Export Intensity	1.34e-08	2.95e-09	9.33e-09	9.57e-09
	(4.48e-08)	(4.48e-08)	(4.48e-08)	(4.47e-08)
Profit per Worker	0.0744***	0.0804***	0.0739***	0.0714***
	(0.00143)	(0.00142)	(0.00143)	(0.00144)
Share of HS graduates	0.00734***	0.00866***	0.00769***	0.00621***
	(0.000394)	(0.000394)	(0.000395)	(0.000399)
Share of College+	0.0372***	0.0373***	0.0379***	0.0359***
	(0.000293)	(0.000302)	(0.000303)	(0.000309)
Female	-1.095***	-1.116***	-1.097***	-1.093***
	(0.00729)	(0.00728)	(0.00730)	(0.00730)
Age	-0.00254***	-0.00206***	-0.00239***	-0.00191***
	(0.000267)	(0.000267)	(0.000267)	(0.000268)
Firm Tenure	0.106***	0.106***	0.106***	0.107***
	(0.00160)	(0.00159)	(0.00160)	(0.00160)
LowChina*LowICT				-0.185***
				(0.00870)
LowChina*HighICT				-0.475***
				(0.00953)
HighChina*LowICT				-0.140***
				(0.00928)
LowChina in P1	-0.212***		-0.219***	
	(0.00596)		(0.00602)	
LowICT in P1		0.0320***	0.0665***	
		(0.00705)	(0.00713)	
Constant	-4.409***	-4.400***	-4.333***	-4.148***
	(0.0452)	(0.0457)	(0.0459)	(0.0463)
Observations	665,262	665,262	665,262	665,262

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

Note: Regressions include year dummies and control for the individual's education level. The sample is restricted to firms where agents born after 1920 and before 1992, holding a full time job in manufacturing firms. Share of HS shows the share of High School graduates working within the firm in a year, Share of College+ are share of workers that have at least some college education. Firm Export Intensity is export values over total sales in each year. Export value variable is only available for the last 11 years of the panel. Reference Interaction group is high China High ICT. Firm tenure counts how many years an employee has been working at a particular firm, and the regression is only looking at the first time a worker is matched to a firm.

All the ICT and Chinese exposure interactions are again equally less likely to have High Firm High Person outcomes in Period 2 compared to High China-High ICT industries, but we see that the Low China-High ICT are the strongest in this effect.