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Lasting Effects of an Import Shock: Channels of Adjustment

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Lasting Effects of an Import Shock: Channels of Adjustment[†]

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Abstract

This paper exploits a quasi-natural experiment to study the channels of labor market adjustment to an import shock. Using matched employer–employee data from Sweden, I study workers' adjustment after the removal of quotas set out by the Multi-Fiber Arrangement for Chinese producers upon China's entry into the WTO. I find evidence of substantial losses in terms of earnings and employment. Sectoral mobility mitigates a portion of these losses, but gives rise to substantial adjustment frictions. The largest losses accrue to workers with skills specific to the exposed industry. Some losses are recovered through mobility across labor markets, but only workers in high-skill occupations benefit from this channel. I also show that skill specificity of the local labor market is an important determinant of adjustment and provide evidence of skill upgrading in response to the import shock.

JEL classification: F14, F16, J24, J31
Keywords: Import competition, worker mobility, human capital

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1 Introduction

For decades, the focus of mainstream trade theory has been on the long-term consequences of trade, with little attention to the short- and medium-term adjustment of the affected workers. While it has long been understood that trade has not only benefits but also costs, the reallocation of resources has commonly been assumed to take place without frictions. The Heckscher–Ohlin model and the Ricardian model (and their followers) all assume that workers can reallocate across sectors with no cost. This assumption is at odds with the extensive empirical evidence suggesting that frictions arise when workers move across sectors (Autor et al. 2014; Hakobyan and McLaren 2016), regions (Topalova 2007; Autor et al. 2013a) and occupations (Ebenstein et al. 2014; Hummels et al. 2014).

A recent stream of research has explicitly focused on modelling and evaluating the distributional consequences of trade. The main conclusion emerging from this literature is that the costs of adjustment are substantial.[1] Adjustment appears to be slow, and its negative consequences for workers are long lasting. Autor et al. (2014) show that the effects of the surge in imports from China on workers' earnings in the United States are visible a decade after the shock. Similar findings are documented by Utar (2018) for Denmark. Regional wage differentials linger for as long as 20 years after trade liberalization in Brazil (Dix-Carneiro and Kovak 2017).

The abundant evidence for the long-lasting consequences of trade has given rise , in turn, to a new wave of theoretical literature on dynamic adjustment (Artuç et al. 2010; Artuç and McLaren 2015). A growing subset of this literature incorporates worker heterogeneity in the analysis. For instance, Dix-Carneiro (2014) introduces differential switching costs in the dynamic model of labor mobility and concludes that a substantial portion of adjustment frictions arises due to the low transferability of sector-specific experience. Assuming that human capital is not transferable across occupations, Traiberman (2019) shows that occupation is a more important determinant of the distributional consequences of trade than sector.

Motivated by the recent theoretical literature on dynamic adjustment, this paper studies the channels of adjustment and focuses on the role of worker heterogeneity as an important dimension of adjustment to import shock. Using matched employer–employee data from Sweden from 1997 to 2010, I follow workers after an import shock and document their labor market

[1] See McLaren (2017) for a recent review of the literature focusing on the dynamic adjustment to trade. Overviews of the literature on labor market outcomes in general are provided by Autor et al. (2016) and Muendler (2017).

adjustment in terms of changes to earnings and employment.[2] Identification in this paper builds on the removal of quotas set out by the Multi-Fiber Arrangement (MFA) for Chinese producers upon China's entry into the World Trade Organization (WTO).[3] In 2002, quotas on textile and apparel products were lifted from China inducing a sharp increase in import competition for domestic producers in Sweden. By studying the effects of a single trade shock within one industry, I mitigate the role of technological factors in determining labor market adjustment.[4] I follow the empirical design that has become common in the literature on worker-level effects of import competition; specifically, similar to Autor et al. (2014), Utar (2018) and Dauth et al. (2019), I study the effects of a shock on workers' cumulative earnings and employment over a decade after the shock. I examine how workers adjust to the shock with respect to two channels: mobility across sectors and mobility across labor markets. To pin down the determinants of the differences in workers' adjustment trajectories, I study the estimated effects with respect to workers' education, occupation and task-intensity. I then proceed by assessing the role of the skill composition of the local labor markets in workers' adjustment. Finally, I study the response of workers in terms of the decision to obtain additional training or educational degree.

By studying how workers reallocate across sectors after the import shock, I contribute to the growing literature on the role of sectoral mobility in the labor market adjustment. Autor et al. (2014) examine the effects of import competition from China on labor market outcomes of US manufacturing workers and find that exposed workers can recover some of their losses by transitioning out of the manufacturing sector. Similarly, moving out of the manufacturing sector offsets losses of workers exposed to import competition in Germany (Dauth et al. 2019). A recent study by Utar (2018) on the Danish textile and clothing industry extends this literature by showing that moving out of the exposed sector induces further frictions in the form of longer periods of unemployment and reduced earnings. These frictions are the largest among workers with manufacturing-specific educational degrees and occupations. I expand these findings by showing that task specificity of occupation is yet another important determinant of adjustment. Given that the task-based approach has been able to explain some stylized facts about earnings

[2]The focus of the paper is on studying the effects of an import shock on the subsequent employment trajectories using a reduced-form approach. Hence, the analysis abstracts from the general equilibrium effects of trade.

[3]Examples of other studies that rely on plausible exogeneity of MFA to identity import competition from China are Bloom et al. (2016), Utar (2014, 2018) and Keller and Utar (2018).

[4]See, for instance, the discussion on the overlap between the effects of trade and technology in Autor et al. (2013b).

and employment that the canonical human capital theory could not,[5] bringing the task dimension into the analysis of the distributional consequences of trade is called for.[6]

By examining the mobility across labor markets, I contribute to the literature on worker adjustment through geographic mobility (Kovak 2013; Hakobyan and McLaren 2016; Dix-Carneiro and Kovak 2019). The general conclusion of this literature is that trade induces limited geographic mobility. My contribution is to revisit the definition of geographic mobility by focusing on change in the location of employment instead of on change of residence. This shift of focus allows me to document an interesting, previously unexplored, channel through which import competition influences labor markets: mobility across labor markets. Given that the change of residence is a rare event in the data, the documented mobility across workplaces in different labor markets is an indirect evidence of increased commute in response to the import shock.

Finally, I study how labor market outcomes of the exposed workers are linked to the skill specificity of their local labor markets. This analysis complements the literature on spatial mismatch (Şahin et al. 2014; Andersson et al. 2018a), which assesses the role of access to jobs in workers' labor market outcomes.[7] This paper contributes by highlighting skill specificity of local labor markets as the source of heterogeneity in the adjustment process. Furthermore, bringing insights from the spatial mismatch literature is a useful input to the theoretical literature on dynamic adjustment which ignores the possibility that local labor markets may simply lack jobs corresponding to the skill profiles of displaced workers. To the best of my knowledge, the only other study that connects skill content of local labor markets to the literature on dynamic adjustment after trade shocks is the study by Yi et al. (2016); these authors show that the local industry mix has implications for labor market flexibility (in terms of labor mobility) and that this flexibility influences the adjustment costs of workers affected by trade shocks. I complement these findings by focusing on occupational and task specificity of local labor markets, instead of

[5]For instance, Acemoglu and Autor (2011) show that the task-based approach can better account for trends such as declining real wages of low-skilled workers and polarization of occupational distribution than can the human capital theory; Black and Spitz-Oener (2010) document the high explanatory power of job-task specialization in the dynamics of the gender wage gap; Peri and Sparber (2009) show that the task-based approach can shed light on the substitution mechanism which, in turn, can explain the wage consequences of immigration.

[6]So far the literature on the distributional consequences of trade has focused on the application of the task-based approach in the context of task tradability which has implications for offshoring (Ebenstein et al. 2014; Hummels et al. 2014). The findings presented in this paper show that the task content of jobs is also informative in the context of transferability of skills and its consequences for worker adjustment.

[7]A related stream of literature documents the role of market thickness on worker mobility (see e.g. Moretti 2011; Bleakley and Lin 2012).

industrial composition.

This paper is structured as follows: Section 2 details institutional background, data and empirical specification and documents the effect of quota removal on Swedish producers. Main results are discussed in Section 3. Section 4 examines how workers adjust to import shock through sectoral and geographic mobility. In Section 5 the role of local labor markets is discussed. Section 6 presents the results on skill upgrading and Section 7 concludes.

2 Institutional background, data and specification

2.1 Institutional background: MFA and ATC

Identification in this paper builds on the removal of quotas set out by the Multi-Fiber Arrangement (MFA) for Chinese producers. This section summarizes the regimes under which quotas were set and removed.

The MFA came into place in response to the fast growth of textile and clothing (henceforth TC) industries in Asian economies.[8] After a series of discretionary import restraints imposed by the United States and the United Kingdom in the 1950s, the willingness of the developed countries to protect their TC industries was building up. As a result, in the 1974 the MFA was signed; it governed the trade in textiles and clothing until 1994. The MFA entitled GATT countries to establish quotas limiting imports of TC products.

The MFA was in conflict with the fundamental principles of GATT, in that GATT prohibits quantitative restrictions on trade. Furthermore, by permitting the imposition of quotas against particular countries, the MFA contradicted the most-favoured-nation principle, which promotes equal treatment of trade partners.

In 1995, the MFA was replaced by the Agreement on Textiles and Clothing (ATC). The ATC was designed to integrate TC industries into the GATT/WTO-rules. The ATC stipulated gradual removal of import restrictions. Quota removal was scheduled to take place in four phases: 1995, 1998, 2002 and 2005. Under the ATC, countries had relative freedom in allocating products to the four phases. The EU chose to lift inactive and nonbinding quotas first, retaining quotas on most goods until the very last phase. Thus, in Phase I only one quota was lifted, 14

[8]The main documents relating to the development of the legislation governing trade in textile and clothing can be found at Eur-lex (2017). See Dayaratna-Banda and Whalley (2007) for a detailed overview. Shorter summaries of the MFA and the ATC can be found in Brambilla et al. (2010) and Khandelwal et al. (2013).

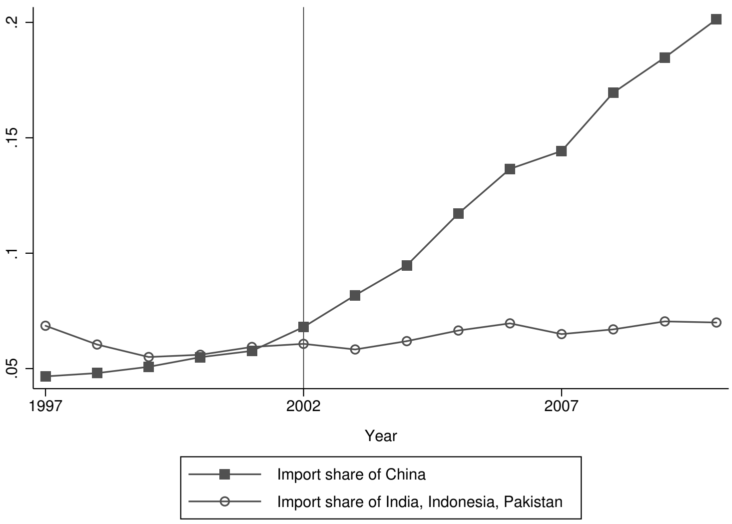

Figure 1: Import share of China and other developing countries in Sweden (largest importers). Products subject to MFA

were removed in Phase II, 36 in Phase III, and more than 140 in Phase IV (Kommerskollegium 2006).

China could not benefit from the liberalization in TC trade until its accession to the WTO in December 2001. Quotas of Phase I, II, and III were all lifted from Chinese TC producers in 2002; Phase IV quota removal followed in 2005.[9]

A number of factors make the first de facto removal of quotas for China a good candidate for identification strategy. First, China's accession to the WTO in 2001 was far from certain during the years of negotiations. Second, just a year after its entry to the WTO, China benefited simultaneously from the first three phases of quota removal, which led to a surge of imports of TC goods by other countries. Moreover, imports from China far surpassed imports from other developing countries following quota removal as is evident from Figure 1.[10]

Removal of quotas is plausibly exogenous to the organization of TC sector in Sweden due to the small size of Swedish TC relative to the EU, which was responsible for the negotiations on behalf of the European countries. The TC sector was, historically, not a the strategic sector of the Swedish economy, due to its small size and enduring decline. Sweden had, in fact, abolished MFA quotas in 1991; however, the quotas were re-imposed in 1995 due to the entry into the EU. This temporary quota removal should not affect the empirical strategy, as the surge in imports

[9] Just after the last phase, the EU has convinced China to "voluntarily" reintroduce some quotas.

[10] Figure B1 illustrates the evolution of MFA-imports from China in terms of multiplies of the domestic value added.

Table 1: Descriptive statistics, 1999

	Exposed		Non-Exposed		Total	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Age	42.58	11.08	39.79	10.95	40.37	11.03
Female	0.56	0.50	0.33	0.47	0.38	0.49
College	0.43	0.50	0.51	0.50	0.50	0.50
Vocational	0.05	0.23	0.06	0.24	0.06	0.24
High-School	0.06	0.24	0.09	0.29	0.09	0.28
Total Earnings	213.53	101.49	251.04	130.11	243.18	125.59
Earnings	176.41	83.18	207.71	105.51	201.16	102.04
No. observations	3019		11401		14420	

Note: Values for 1999. Earnings and Total Earnings in 1000 SEK.

did not take place until 2002.[11] Moreover, if the removal of quotas did induce positive selection among MFA producing firms, this should only dampen the importance of the 2002 import shock for Swedish producers. Nevertheless, as it is evident from the next section, MFA quota removal has intensified the import competition faced by Swedish producers.

2.2 Employer–employee data

This paper uses matched employer–employee data from Sweden from 1997 to 2010, provided by Statistics Sweden. Worker-level data come from the individual register (Longitudinal integrated database for health insurance and labour market studies, LISA) and provide information on demographic and labor market variables for the universe of workers. Only workers who were of working age (i.e., aged 16–67 years) throughout the whole sample period are included in the analysis. Firm-level data are collected from the two sources. The first one is the Swedish Structural Business Statistics (FEK), covering the population of firms. The second data source is Production of Commodities and Industrial Services (IVP), with product-level information for producing firms, which is used to identify which firms were affected by MFA removal and which were not. The IVP dataset provides information on production quantities and values, making it possible to single out domestic producers of TC goods. IVP covers all the firms with at least 20 employees and some firms with at least 10 employees.

To identify which domestic producers were affected by the import shock, I first identify products affected by MFA quota removal. Categories of products under MFA quotas are obtained from Système Intégré de Gestion de Licenses (SIGL), an electronic resource that contains a

[11] In Section 3, I additionally disentangle the effect on producers from the effect on importers of MFA goods.

description of goods protected by the quota together with the quota-utilization levels. To translate the categories of goods listed in SIGL to the Combined Nomenclature (CN) codes, I make use of the document "Council Regulation (EEC) No 3030/93 of 12 October 1993 on common rules for imports of certain textile products from third countries", which contains the correspondence between the descriptions of the goods in SIGL. In combination with the series of CN correspondence tables from RAMON, this document can be matched to the CN2016 8-digit products in the IVP dataset. Following Utar (2018), I measure exposure in 1999 to minimize the anticipation effect.[12] Next, as in Utar (2014, 2018), to define the firms exposed to import shock in 2002, I also use products with quotas removed under Phase IV. This decision is justified by the substantial overlap between firms producing products for which quotas were removed in Phase III and Phase IV (70% of producers in my sample) and by the fact that information about Phase IV quota removal was known in advance, i.e., there was no uncertainty about the products subject to quota removal in 2005.

The TC sector in the EU has traditionally been dominated by a large number of small and medium firms (Stengg 2001). The structure of the Swedish TC sector resembles that of other European nations, with 49 employees being the median size of TC producers in 1999. The TC sector in Sweden, and in Europe overall, had been undergoing restructuring and modernization already from the 1980s, gradually shifting from labor- to more capital-intensive production in response to increasing competition from the low-wage countries (Stengg 2001).

In 1999, there were 198 unique firms in the TC sector, employing 14,420 employees. Around 3,000 of these workers are categorized as exposed and 11,000 as non-exposed. Table 1 reports the descriptive statistics according to exposure group. Mean values of the variables are statistically different between the two groups. This should not, however, imply a problem for the empirical design (difference-in-difference), as it builds on the assumption of parallel trends, which will be discussed in the next section. Moreover, the empirical specification controls for time-invariant worker characteristics, which should account for at least a portion of the differences.

[12]While China's entry into the WTO in 2001 was far from well expected (see, for example, the discussion of the press of the time in Autor et al. 2016; Utar 2018), especially on the level of individual workers, anticipation effects may have occurred. Firms may have dropped the products where the threat of competition from China was especially high, some producers may have exited the market, some workers may have switched jobs. By defining the exposure group based on the portfolios of 1999, I mitigate these selection effects. If, instead, year 1998 is used to define the exposure status of workers, the results are very similar. See replication of main results in Table C1 in the appendix.

2.3 Pre-analysis: Effect of quota removal on import prices and quantities

To what degree did removal of quotas intensify import competition? As a pre-analysis, I evaluate the effects of quota removal on import prices and quantities. I adopt the approach of Utar (2014) and estimate the following equation on the sample of MFA-goods subject to quotas removed in Phases I, II and III:

$$X_{jkt} = \gamma_0 + \gamma_1 China_k \times After_t + \theta_{kj} + \theta_{st} + \epsilon_{jkt}, \tag{1}$$

where X_{jkt} is either log quantity or log unit price of imports of eight-digit product j imported to Sweden from country k in year t. Indicator variable $China_k$ takes value 1 if the exporting country is China. Indicator variable $After_t$ takes value 1 on and after 2002 in specifications for Phase III. In specifications for Phase IV, $After_t$ takes value 1 on and after 2005. Country-product fixed effects θ_{kj} account for the differences in country-specific volumes of imports. Sector-time fixed effects θ_{st} control for sector-specific shocks. Sector here is either textiles or clothing.

I estimate Eq.1 for years 1997-2007.[13] Results are reported in Table 2. Column 1 shows that the removal of quotas in 2002 resulted in a more than a five times increase ($=exp(1.683)$) in quantities imported from China relative to the imports of the same goods imported from other countries. Unit prices of the goods declined by 27% (column 2). After the removal of quotas in 2005, the relative increase in quantities imported from China was three times larger than from other countries (column 3) and relative decline in prices was 12% (column 4). A drop in import prices and increase in import quantities as a result of the removal of MFA quotas is also reported by Brambilla et al. (2010) for the United States and by Utar (2014) for Denmark. These results also mirror the findings of Khandelwal et al. (2013), who find that quota removal increased export values among Chinese producers and decreased export prices. Importantly, Khandelwal et al. (2013) argue that the decline in the unit price of Chinese exports reflects entry of more productive producers and not quality downgrading.

Does the decrease in unit prices and the increase in quantities of imports from China necessarily indicate an increase in import competition? If domestic firms substitute imports from other countries with imports from China, the competition pressure from China can be very

[13] Sample period is chosen to avoid the effects of financial crisis on prices and quantities of imports. If the full sample is used (1997-2010) the estimated increase in quantity is even larger in magnitude, the drop in prices is slightly smaller. The effects are significant at 0.1%

Table 2: Effect of quota removal on import prices and quantities

	(1) Quantity	(2) Price	(3) Quantity	(4) Price	(5) Average price	(6) Average price
	MFA goods				*TC goods*	
$China \times After2002$	1.683***	-0.319***			-0.114***	
	(0.131)	(0.041)			(0.031)	
$China \times After2005$			1.099***	-0.127***		
			(0.118)	(0.033)		
$MFA \times After2002$						-0.067**
						(0.024)
Observations	34717	34717	54009	54009	12767	12767
Adjusted R^2	0.016	0.007	0.008	0.005	0.016	0.016

Note: Specifications in columns 1-4 include country-product and sector-year fixed effects; standard errors clustered on country-product level are in parentheses. Specifications in columns 5-6 include sector-year fixed effects; standard errors for these specifications are clustered on product level. ***p<0.001, **p<0.01, *p<0.5

mild. Eq. 2 quantifies the effect of quota removal on *average* import prices:

$$X_{jt} = \delta_0 + \delta_1 MFA_j \times After2002_t + \theta_{st} + \upsilon_{jt}, \tag{2}$$

X_{jt} is unit price averaged over all exporting countries (in logs). Binary variable MFA_j indicates goods subject to quota removal in Phases I, II and III. $After2002_t$ takes value 1 on and after 2002. As before, θ_{st} are sector-time fixed effects.

The results of estimating Eq. 2 confirm that import competition indeed intensified after quota removal. The coefficient in Table 2 column 5 indicates that the average import prices of MFA-goods declined by 12% after the quotas were removed. The specification in column 6 MFA_j also includes products subject to quota removal under Phase IV. The average decrease in price for all the goods subject to quota removal is 7%. The decline in unit values in the exporting countries is also documented in Brambilla et al. (2010).

Figure B2 in the appendix shows how sharply total value added in TC products declined in Sweden after 2002. In Table C2 in the appendix I additionally estimate the effect of MFA-quota removal on Swedish TC producers. Removal of quotas resulted in a 18% decline in employment in the MFA producers, a 15% drop in sales, a 22% drop in value added and a 50% decline in total investment. Overall, the results of the pre-analysis reported in this section suggest that MFA producers have faced intensified competition once MFA quotas were removed from Chinese producers.

2.4 Empirical Design

I start by analyzing the annual outcomes of workers in terms of earnings and employment and then proceed with the analysis of cumulative outcomes over the nine years after the shock in a difference-in-difference framework.

I start by estimating the following equation on yearly data:

$$E_{it} = \alpha_0 + \alpha_1 MFA_i \times After2002_t + \theta_i + \tau_t + \epsilon_{it}, \tag{3}$$

where E_{it} is an outcome for worker i at time t. Outcome variables include earnings (labor earnings from the main employer), total earnings (labor earnings from all employers), personal income, unemployment benefits and days in unemployment. MFA_i is an indicator variable, which takes value 1 for the workers who in 1999 were employed in firms producing MFA-products. $After2002_t$ takes value 1 for years on and after 2002. To account for the possibility that individuals employed by exposed firms are systematically different from those employed by non-exposed firms, worker fixed effects θ_i are also included. These capture time-invariant characteristics of workers (sex, age at the year of the shock, initial educational level, initial occupation, initial wage, etc.) and of their initial employer (management practices, capital intensity, etc.). Year fixed effects τ_t are included to pick up the labor market trends.

To study the channels of adjustment, I proceed by implementing the empirical design that has become common in the literature on worker-level effects of import competition (Autor et al. 2014; Utar 2018; Dauth et al. 2019)[14] and study the effect of import competition on cumulative earnings and employment of workers. The empirical specification takes the following form:

$$\tilde{E_{ip}} = \beta_0 + \beta_1 MFA_i \times After2002_p + \beta_2 After2002_p + \theta_i + \epsilon_{ip} \tag{4}$$

$\tilde{E_{ip}}$ is cumulative earnings [15] of worker i for period p normalized by worker i's average annual earnings between 1997 and 1999. Period $p = 1$ is the period before the shock (1999–2001). Period $p = 2$ is the period after the shock (2002–2010).[16] Cumulative earnings reflect the history

[14] In its use of MFA quota removal for the identification, my empirical design builds on Utar (2018).

[15] In calculation of cumulative earnings variables, annual values were converted into 2010 Swedish krona using the consumer price index from Statistics Sweden.

[16] As a robustness check, I also used an alternative definition of period 1 as the period from 1997 to 1999. The results when using this alternative definition are in line with the main results reported in the paper, pointing to sizeable losses in earnings and employment and are available upon request.

of labor market activity over the given period. The strength of cumulative earnings relative to annual earnings is that this measure allows decomposing the results with respect to the sources of earnings and disentangles short- or medium-term adjustment from the accumulated outcomes (as further discussed below). When it comes to estimation, the advantage of cumulative earnings over the log earnings is that cumulative earnings overcome the problem of zero values and, in turn, underestimation due to the selection into non-zero earnings. Additionally, cumulative employment is used as the dependent variable. It is calculated as the accumulated amount of years with non-zero earnings from the main employer. Descriptive statistics are reported in Table A1 in the appendix.

Coefficient β_1 will capture the cumulative effect of import competition on exposed workers in the nine-year post-shock period relative to other workers employed in the same industry. As a next step, I will decompose β_1 with respect to the different industries, to study the adjustment through sectoral mobility. That is, I will decompose accumulated earnings into earnings accumulated at the initial employer, other TC employers, other manufacturing employers, employers in the service sector and other sectors (e.g. agriculture, utilities, public sector). To study geographic mobility, I will decompose β_1 according to the mobility status of workers.

The identification strategy relies on the parallel trends assumption. Workers who were in 1999 employed by non-MFA producers are a good counterfactual for the workers of MFA producers if, in the absence of the import shock from China, outcomes for the both groups of workers would have followed the same trend. If the parallel trends assumption holds, the difference-in-difference estimate identifies the causal effect of the import shock on workers' labor market outcomes.

Had the shock been entirely unanticipated, for credible difference-in-difference identification it would suffice to compare the outcomes of workers employed in MFA firms before 2002 and those employed in non-MFA firms, after having assessed the assumption on the common trends until 2002. By defining the exposed workers based on their employment in 1999, I minimize the possibility that workers have engaged in some selection in or out of MFA-firms. I calculate by how much these workers have increased their employment and earnings accumulated over the periods 1999–2001 and 2002–2010 relative to 1997–1999, and compare this value to the corresponding value for the control group — workers who in 1999 were employed by non-MFA producers. Given that the exposure is defined in 1999, the relevant pre-trends are the trends before 1999.

Visual assessment of the trends in employment and earnings provides confidence in the empirical approach. Figure 2 plots labor market outcomes of both workers employed by MFA and non-MFA firms for years 1997–2010.[17] The left panel in the figure plots mean annual earnings normalized by earnings of 1999. The right panel in the figure plots the fraction of workers with non-zero annual earnings in the current year relative to year 1999 (the fraction for both groups is thus 1 in 1999). Both plots exhibit very similar pre-shock trends in 1997–1998 and even in the whole pre-shock period. More formal tests of the internal validity, such as the analysis with unit trends and the falsification test, provide further credibility to the empirical approach. These tests are discussed in Section 3, together with the main results.

In general, the effects of the import shock estimated by Eq.3 and 4 can be seen as the lower-bound effects of trade on workers' labor market outcomes, as the analysis exploits within-industry variation, and the secular declining trend of the industry is to some extent driven by trade. Similarly, if the removal of MFA quotas had a spillover effect on workers of non-MFA firms in terms of worsened labor market opportunities, the effects will be underestimated. At the same time, by studying the effects of trade within industry, I mitigate the risk that the estimates are convoluted by industry-wide shocks.

3 Results

3.1 Average effect of the import shock

Table 3 reports the results of estimating Eq.3. In the reported results *Exp* (for "exposed") denotes the coefficient on $MFA_i \times After2002_p$. The dependent variables for different types of earnings are in logs and include earnings from the main source of employment (Earnings, column 1), earnings from all sources of employment (Total Earnings, column 2), and personal income (column 3). Unemployment variables are unemployment benefits (Unemployment Income, column 4) and days in unemployment (Unemployment Days, column 5). These two variables are log-transformed and 1 is added to keep the individuals without unemployment in the sample. It is evident from Panel A that workers exposed to import competition from China experience a

[17] 1997 is the earliest year in the data.

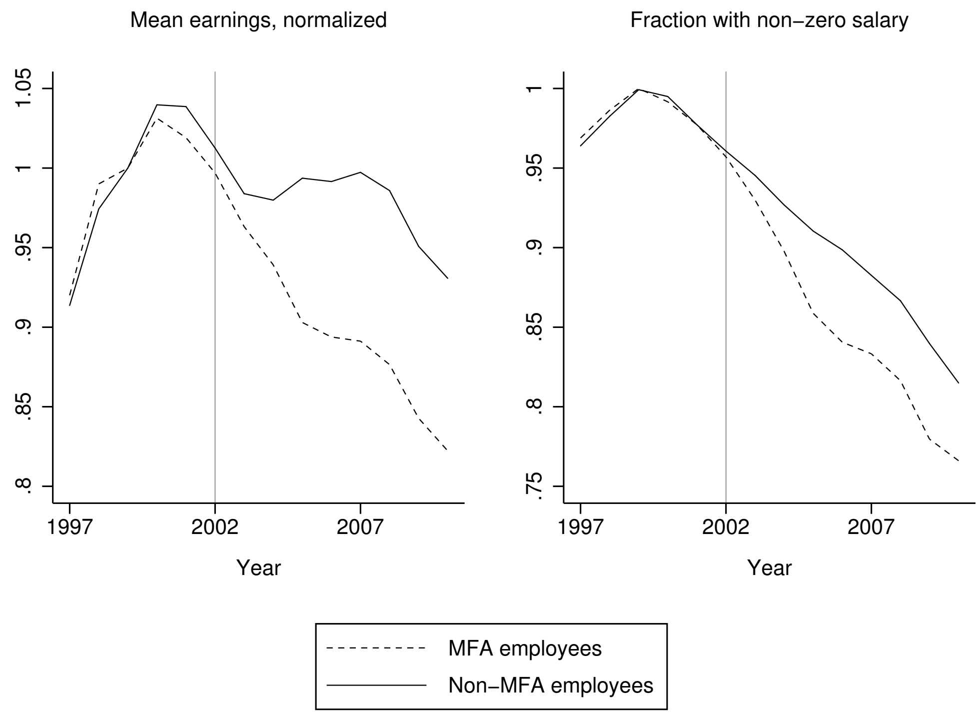

Figure 2: Earnings and employment of workers in TC

disproportionate decline in earnings and a disproportionate increase in unemployment relative to the other workers. Specifically, exposed workers experience a decline of 3.5% (=1-exp(-0.036)) in annual earnings, 3.4% in annual total earnings and 3.2% in personal income. Unemployment benefits rise by 22.0% and days in unemployment by 13.0% (i.e., by approximately 47 days in a given year).

In Panel B, the effect of import competition is captured by the continuous measure of exposure intensity $ExpInt_{ip} = shareMFA_i \times After2002_p$ reflecting the share of MFA products in a firm's portfolio in 1999. The estimated coefficients are larger in absolute magnitudes relative to Panel A, indicating that a greater share of MFA products induces larger losses for employees. The mean value of exposure intensity for exposed workers is 0.53. Thus, workers of an exposed firm, where MFA products comprised 53% of the revenue, experience a 2% drop in their annual earnings (Panel B, column 1).

I now proceed to a few robustness checks to verify the validity of the empirical strategy. First, in an empirical setting with many years of data, difference-in-difference estimation can underestimate standard errors, leading to the erroneous rejection of a null (Bertrand et al. 2004). To ensure that the estimated reduction in earnings and increase in unemployment are not driven

Table 3: Annual effects of import shock, 1999-2010

	(1) Earnings	(2) Total Earnings	(3) Personal Income	(4) Unempl Inc	(5) Unempl Days
Panel A: *Trade Shock indicator variable*					
Exp	-0.036**	-0.035**	-0.033**	0.199***	0.122***
	(0.012)	(0.012)	(0.012)	(0.028)	(0.020)
Adjusted R^2	0.011	0.012	0.012	0.012	0.009
Panel B: *Intensity of Trade Shock*					
ExpInt	-0.039*	-0.046*	-0.045*	0.250***	0.123***
	(0.020)	(0.019)	(0.019)	(0.048)	(0.034)
Adjusted R^2	0.011	0.011	0.011	0.012	0.008
Observations	165058	164010	164985	165058	165058

Note: *Exp* denotes the coefficient on $MFA_i \times After2002_p$. *ExpInt* is the coefficient on $shareMFA_i \times After2002_p$. All specifications include worker and year fixed effects. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5

by serial correlation of the dependent variables, I collapsed the data into two periods as suggested by Bertrand et al. (2004), see Table C3 in the appendix. For this analysis, I split the data into pre-shock and post-shock periods and averaged the outcome variables over these periods. The results support the finding that import shock reduces earnings and increases unemployment of exposed workers and the estimated coefficients are highly statistically significant.

Next, to account for the possibility that workers' labor market outcomes follow differential trends, I performed estimation including unit-level trends in the regressions. The inclusion of the unit-level trends leaves the estimated effects almost unchanged (Table C4). As an additional check, Table C5 in the appendix reports the results of the falsification test, which aims to verify that the identification strategy isolates the effect of the import shock on employees of MFA firms from other confounders. The idea behind the test is to check whether future shock predicts past changes to earnings or employment. Although the pre-sample is fairly short, the results provide support for the validity of the identification strategy, as the coefficient of interest is insignificant in all the specifications.

Finally, quota removal may have benefited firms that were importing MFA goods. Some TC producers may have offshored parts of their production and shifted towards service activities.[18] For MFA producers importing MFA goods or engaging in offshoring, the impact of quota removal

[18] For instance, Lodefalk (2013) shows that the share of services in output by Swedish manufacturing firms has increased from 1995 to 2000.

Table 4: Cumulative effects of import shock, 1999-2010

	(1) Earnings	(2) Total Earnings	(3) Employment
Exp	-0.507+	-0.482*	-0.355***
	(0.292)	(0.204)	(0.047)
Observations	28840	28840	28840
Adjusted R^2	0.331	0.378	0.850

Note: *Exp* denotes the coefficient on $MFA_i \times After2002_p$. All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

is, therefore, expected to be milder. To isolate the effect of imports, I estimate a triple-difference equation where the third "difference variable" is an indicator variable for whether a firm was importing MFA goods in 1999 (see Table C6 in the appendix).[19] The coefficient on the triple difference is highly statistically significant; it is positive for earnings-related outcomes and negative for unemployment variables, indicating that employees of those MFA firms that were also importing MFA goods, indeed do experience milder losses after the import shock.

3.2 Cumulative effect of the import shock

Table 4 reports the results of estimating Eq.4. For the average exposed worker, increased imports from China lead to a decrease in cumulative earnings over nine years of 51% of her pre-shock earnings (column 1).[20] The drop in total earnings amounts to 48% (column 2). The coefficient in column 3 shows that the discrete difference between exposed and non-exposed workers in terms of years with non-zero earnings is 36% of a year (i.e., around one third of a year).

Compared to the results reported by Utar (2018) for Denmark, the average loss in terms of earnings is lower (81%), while the loss in terms of employment is larger (the point estimate is close to zero and is insignificant). It might be tempting to conclude that these differences reflect differences in the flexibility of the Swedish and Danish labor markets. However, as it will become clear in the next section, heterogeneity of workers plays a critical role in the average losses, making it harder to draw conclusions about the role of the institutional context. Moreover, the lower average losses in earnings among workers in Sweden may reflect some selection among

[19] The equation is $E_{it} = \alpha_0 + \alpha_1 MFA_i \times After2002_t + \alpha_2 ImpMFA_i \times After2002_t + \alpha_3 MFA_i \times ImpMFA_i \times After2002_t + \theta_i + \tau_t + \epsilon_{it}$, where $ImpMFA_i$ is 1 if a firm was importing MFA goods in 1999. The coefficient of interest is α_3.

[20] In the remainder of this paper, I use the indicator variable *Exp* for ease of interpretation. The results of estimating Eq.4 using exposure intensity *ExpInt* are reported in the appendix, Tables C7 and C8. The estimated coefficients are in general larger in absolute terms when *ExpInt* is used.

producers due to the temporary quota removal in 1991–1994, which may have forced less efficient producers from the market.

Overall, this section has provided robust evidence that the import shock induces losses for exposed workers. The next section focuses on two channels of adjustment: sectoral mobility and geographic mobility.

4 Channels of adjustment

4.1 Adjustment through sectoral mobility

The results in Table 4 reveal that the exposed workers, on average, experience sizable losses in terms of earnings and employment accumulated over nine years after the shock. Trade shock has the potential to induce workers to search for jobs in other firms, industries or even sectors. This section explores the heterogeneity of accumulated losses with respect to the employment paths chosen by workers. This approach is adapted from Autor et al. (2014), who introduced this type of decomposition.[21] In Table 5 the coefficients for cumulative earnings and cumulative employment are decomposed into five mutually exclusive sources; that is, employment and earnings can be accumulated from the following sources: the initial employer, other TC employer, other employer in manufacturing sector, employer in service sector or employer in other sector (agriculture, utilities, public sector, etc.). By construction, the sum of the coefficients in columns 2-6 should equal the coefficient in column 1. If a worker did not move from her initial employer over the observation period, the coefficients in columns 3-6 would be zero for this worker. All the accumulated outcomes for this worker would be coming from the initial employer and the coefficient in column 1 would then equal the coefficient in column 2. If a worker leaves her initial employer for the service sector in 2005 and stays there until 2010, then the accumulated labor outcomes for this worker are the sum of all the outcomes at the initial employer up till 2005 and the outcomes in the service sector from 2005 to 2010. In general, losses incurred at other employers and in other sectors will affect the amount of losses accumulated over the whole nine-year period after the shock, making the decomposition a useful tool in assessing the channels of adjustment.

It is evident from the decomposition in Panel A that a decline in cumulative earnings for the

[21] Other recent applications of this approach include Utar (2018) and Dauth et al. (2019).

Table 5: Decomposition of the cumulative effects of import shock, 1999-2010

	(1) All Employers	(2) Initial	(3) Other TC	(4) Other Man	(5) Services	(6) Other
Panel A: *Cumulative Earnings*						
Exp	-0.507+	-1.159***	0.379***	-1.280***	0.867***	0.685***
	(0.292)	(0.122)	(0.048)	(0.117)	(0.165)	(0.208)
Panel B: *Cumulative Employment*						
Exp	-0.355***	-0.854***	0.244***	-0.674***	0.518***	0.412***
	(0.047)	(0.065)	(0.026)	(0.046)	(0.050)	(0.046)

Note: Amount of observations is 28,840. All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

exposed workers is much larger at the initial employer (116% of the pre-shock earnings, column 2) than the overall losses accumulated at all employers (column 1). The reason why the losses at the initial employer are larger than the overall losses is that some workers recover a portion of their earnings from other employment sources. That is, workers recover 38% of their pre-shock earnings by moving from the initial employer to other TC employers (column 3). They also recover 87% of a pre-shock annual earnings from employers in the service sector (column 5) and 69% from other employers (column 6). Moving from the initial employer to another employer in manufacturing (non-TC) induces a sizable loss amounting to 129% of the pre-shock annual earnings (column 2).

The results in Panel B complement these findings by showing how workers adjust in terms of years of employment. The import shock causes a substantial loss in employment at the initial employer affected by MFA, amounting to 86% of a year (more than ten months). Notably, the comparison of the losses at the initial employer in terms of earnings (Panel A, column 2) and employment (Panel B, column 2) suggests that workers' earnings *per year* decline as the result of the import shock. This result can reflect the changes at the extensive margin (fewer hours of work) or intensive margin (lower hourly earnings) or both. One fourth of the losses in employment at the initial employer are offset by moving to the other TC employers (column 3). Losses in employment are partly offset in the service sector (52%) and other sectors (41%). Workers who move to other manufacturing employers lose 67% of a year (about eight months).

In the appendix, I additionally report the results of estimating Eq.4 year-by-year, where in a regression for year t the outcome variable is accumulated outcomes until the year t (Figure B3).

From the dynamic visualization of the estimates it is evident that the losses amass over time.

Overall, moving to the manufacturing sector induces larger losses. In Table C19 in the appendix, the cumulative effects of moving to manufacturing are decomposed into two-digit industries. It is evident from the results that moving to none of the more narrowly defined manufacturing industries results in a recovery of either earnings or employment with the exception of other TC and chemicals. Low transferability of skills accumulated at the initial firm may be the reason for why workers choose to stay put in manufacturing and/or in TC firms after the import shock. The role of skill is examined in greater detail in the following section. Although workers can at least partly offset their losses at other TC employers and in other sectors, it is the transition to the service sector that leads to the largest recovery of losses. A more detailed decomposition of the movement to services is presented in Table C20 in the appendix. Wholesale and retail appear to be the main destinations for exposed workers within the service sector.

To summarize, sectoral mobility can offset some losses born at the initial employer. However, is sectoral mobility conductive to stable employment? Table 6 reports the estimates of the effect of the import shock on the accumulated unemployment spells. The dependent variable is based on the amount of days in unemployment, it is expressed in months. The coefficient in column 1 suggests that import shock increases the number of months in unemployment by 1.4 months. In columns 2–4 I decompose this effect with respect to the last sector in which a worker was employed prior to the unemployment spell. The largest increase in unemployment spells is observed in services (column 4). This result suggests that, although services appear to be the main destination where exposed workers can offset their losses, this movement leads to more frequent unemployment spells. Similarly, movement to other TC employers induces more unemployment spells. Unemployment spells are shorter in other manufacturing, which, however, brings losses in terms of earnings (as was shown above). Taken together, these results indicate that sectoral mobility brings further adjustment frictions to the exposed workers.[22] A likely contributor to these results is the "last-in-first-out" principle established by paragraph 22 of the Swedish Employment Protection Act (Lag om anställningsskydd, SFS, 1982:80), which favors workers with longer tenure at a firm in the event of workforce downsizing.

[22] Figure B4 illustrates the yearly estimates of the cumulative effect on unemployment spells. The slope of the curve reassures that the main estimates reported in Table 4 are not driven by the financial crisis of 2008.

Table 6: Cumulative unemployment after moving across sectors, 1999-2010

	(1) All Unempl Spells	(2) TC	(3) Man	(4) Services
Exp	1.440***	0.869***	-0.395***	0.939***
	(0.171)	(0.093)	(0.100)	(0.106)

Note: Amount of observations is 28,840. All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5

4.2 Heterogeneity in sectoral mobility

The results discussed in Section 3 show that workers can offset their losses by moving out of an exposed firm and even out of the manufacturing sector. However, sectoral mobility gives rise to the adjustment frictions in terms of longer unemployment spells, loss of earnings and employment. Borrowing the insights from the extensive literature on job switching, recent theoretical literature on dynamic adjustment stresses the role of human capital transferability in these frictions (Dix-Carneiro 2014; Traiberman 2019).[23] Job switching can render skills tied to the previous jobs redundant, making it costly for workers to switch employment. These skills can be firm specific (Becker 1964), industry specific (Neal 1995; Parent 2000), occupation specific (Shaw 1984; Kambourov and Manovskii 2009) or even task specific (Poletaev and Robinson 2008; Gathmann and Schönberg 2010). The ability to adjust to a trade shock hinges upon the overlap between worker's skills and the profile of skills demanded by a new employer. If skills are rendered obsolete due to the displacement, starting in a new firm or even sector may require new investment in skills. In what follows, I study the role of skills in the adjustment process. The analysis with respect to education and occupation confirms the findings reported in Utar (2018); the empirical analysis of task specificity adds novel insights to this stream of literature.

4.2.1 Adjustment and education

To study the role of skills in the adjustment process, I start with a variable which is commonly used to approximate human capital in the empirical studies of trade — educational attainment (see e.g. Menezes-Filho and Muendler 2011; Dix-Carneiro 2014; Hakobyan and McLaren 2016). In Table 7, I split the data with respect to the highest-attained degree in 1999. The results show that losses in terms of earnings and employment at the initial employer are not that different

[23] The alternative explanations of frictions arising after job switching include search and matching frictions (Helpman et al. 2010), firing and hiring costs (Kambourov 2009) and information frictions (Allen 2014).

Table 7: Sectoral mobility by educational level, 1999-2010

	(1) All Employers	(2) Initial	(3) Other TC	(4) Other Man	(5) Services	(6) Other
			I. High-school degree *(N=14294)*			
A. Cumulative Earnings						
Exp	0.223	-1.135***	0.453***	-1.259***	1.527***	0.636***
	(0.323)	(0.180)	(0.076)	(0.191)	(0.253)	(0.172)
B. Cumulative Employment						
Exp	-0.195***	-0.890***	0.304***	-0.782***	0.789***	0.384***
	(0.058)	(0.098)	(0.043)	(0.070)	(0.081)	(0.071)
			II. Vocational degree *(N=1790)*			
A. Cumulative Earnings						
Exp	-1.096	-1.668**	0.491+	-1.882***	1.067	0.896
	(1.273)	(0.547)	(0.271)	(0.531)	(0.920)	(0.880)
B. Cumulative Employment						
Exp	-0.030	-0.888**	0.165*	-0.723***	0.702**	0.714**
	(0.122)	(0.288)	(0.077)	(0.206)	(0.241)	(0.218)
			III. University degree *(N=2494)*			
A. Cumulative Earnings						
Exp	-0.939	-1.556**	0.527+	-1.352**	1.658**	-0.217
	(0.722)	(0.522)	(0.272)	(0.418)	(0.541)	(0.300)
B. Cumulative Employment						
Exp	-0.154	-0.744**	0.171*	-0.558**	0.873***	0.104
	(0.133)	(0.256)	(0.070)	(0.194)	(0.222)	(0.159)

Note: All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

across the three groups (column 2 in each panel). There are, however, some differences in the adjustment process. Workers with high-school degrees and workers with university degrees are successful at recouping their initial losses by transitioning into the service sector (column 5, Panels I and III). For workers with vocational education, the effect of moving to the service sector on earnings is, however, insignificant (column 5, Panel II).

I proceed by focusing on the field of study to capture industry-specificity of skills. In Table 8, workers with university degrees are split into two groups with respect to their field of study — workers with manufacturing-oriented degrees and those with non-manufacturing degrees.[24] It is evident from the results that workers with manufacturing degrees are hit harder by the shock than workers with non-manufacturing degrees (column 1). The difference in the accumulated outcomes comes from differences in adjustment. Workers with manufacturing degrees experience larger losses at the initial employer (column 2, Panel I) and do much worse in services (column

[24] All degrees where the field of study is in a category other than "Technology and Manufacturing" are classified as non-manufacturing.

Table 8: Sectoral mobility by field of education, university degree only, 1999-2010

	(1) All Employers	(2) Initial	(3) Other TC	(4) Other Man	(5) Services	(6) Other
			I. Manufacturing degrees *(N=1276)*			
A. Cumulative Earnings						
Exp	-2.057*	-1.600+	0.275	-1.172+	0.795	-0.354
	(0.919)	(0.886)	(0.195)	(0.671)	(0.781)	(0.295)
B. Cumulative Employment						
Exp	-0.224	-0.818+	0.170	-0.402	0.614+	0.211
	(0.226)	(0.448)	(0.117)	(0.344)	(0.350)	(0.261)
			II. Non-Manufacturing degrees *(N=1218)*			
A. Cumulative Earnings						
Exp	0.018	-1.090+	0.629	-1.398*	2.197**	-0.320
	(1.008)	(0.648)	(0.410)	(0.542)	(0.720)	(0.444)
B. Cumulative Employment						
Exp	-0.033	-0.445	0.159+	-0.605*	0.980***	-0.123
	(0.169)	(0.312)	(0.088)	(0.237)	(0.288)	(0.207)

Note: All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

5, Panel I). Similar findings with respect to the field of study are reported for workers with vocational education (Table C9 in the appendix): total losses are much larger for workers with manufacturing-oriented vocational degrees (column 1, Panel I) and these workers do not offset their losses by moving to services (column 5, Panel I).

To summarize, these results suggest that a focus on level of education in interpreting the effects of import shock might be misleading. That workers with manufacturing degrees are less successful in the service sector is consistent with the notion that transitioning into services forces workers to abandon their manufacturing-specific skills, which makes the experience of these workers less valuable to the service sector. In other words, industry-specific human capital makes it costly to switch industries (Neal 1995; Parent 2000).

4.2.2 Adjustment and occupation

Another way to assess the importance of skills in labor market adjustments is to focus on workers' pre-shock occupations. Specifically, I will focus on six broadly defined occupational groups based on the International Standard Classification of Occupations (ISCO-88).[25]

[25] To study how the adjustment diverges for workers who had different occupations in 1999, I would ideally have to use the data on occupations in 1999. A shortcoming in my data, however, is that occupations are recorded only from 2001, i.e. two years after the desired date. Although, there is a risk that occupation records from 2001 do already reflect some anticipatory actions taken by workers, I choose to use these data motivated by the observation that occupational mobility across occupational groups is very low. This fact is evident from Table C10 in the appendix, which reports the probabilities

I split occupations into six broad groups: managers (includes production, administration managers, directors), professionals and technicians (engineers, personnel professionals, finance professionals), clerks and service workers (stock clerks, shop salespersons), craft workers (industrial-machinery mechanics, tailors, sewers), machine operators (sewing-, knitting-, spinning-machine operators) and laborers (manufacturing laborers, building caretakers). Table 9 reports the results for earnings across the six groups.[26] Estimates show that all occupational groups except for craft workers incur losses amounting to more than 120% of their pre-shock annual earnings at the initial employer (column 2). Adjustment after the shock, however, leads to the different accumulated outcomes. Differences in gains accumulated at other TC employers do not exhibit any sharp contrasts across the occupational groups (column 3); it is the ability to recover losses in services (column 5) and the amount of losses incurred in other manufacturing (column 4) that appear to be critical for earnings accumulated after the shock.

Laborers experience the largest reduction in earnings accumulated after the shock amounting to more than 200% of the pre-shock annual earnings (Panel VI, column 1). This substantial decline accrues from large losses borne from moving to other jobs in manufacturing (Panel VI, column 4) and relatively low recovery at all the other employers (Panel VI, column 6). Professionals and technicians seem to benefit from the trade shock, as their gains from moving to the service sector are almost a double of their losses at the initial employer (Panel II, column 5). Recovery of lost earnings in services is also quite successful for clerks and service workers who make up for almost three quarters of their initial losses (Panel III, column 5). Other occupational groups are less successful at offsetting their initial losses through sectoral mobility. For instance, managers make up for 45% of their initial losses in services, resulting in an overall decline in earnings of 164% of the pre-shock earnings (Panel I). Machine operators recover less than 20% of their initial losses in services, with a total loss amounting to 117% of the pre-shock earnings (Panel IV). From the results on adjustment in terms of employment (Table C11 in the appendix) it is evident that the largest accumulated losses are borne by craft workers, machine operators and laborers.

of remaining within the same occupational group in any given three years. Column 1 shows the probabilities for the whole working population of Sweden. In every given period the probability of staying in the same occupational group is around 93%. In column 2, the probabilities of staying in the same occupational group are reported only for individuals who, in the first year of the given period, were employed in TC; and in column 3 for individuals who, in the first year of the given period, were employed in manufacturing. Across all three samples less than 8% change occupational groups. Given that 2001 is still a year before the shock and that mobility across occupational groups is very low, I use occupations recorded for year 2001 as a proxy for occupations in 1999.

[26] To save space, results for employment are reported in the appendix Table C11.

Table 9: Sectoral mobility by occupational group, cumulative earnings, 1999-2010

	(1) All Employers	(2) Initial	(3) Other TC	(4) Other Man	(5) Services	(6) Other
I. Managers *(N=1398)*						
Exp	-1.638***	-1.437**	0.430**	-1.131**	0.636+	-0.137
	(0.469)	(0.440)	(0.162)	(0.414)	(0.347)	(0.122)
II. Professionals and Technicians *(N=4850)*						
Exp	0.632	-1.746***	0.631***	-1.563***	2.948***	0.361
	(0.756)	(0.356)	(0.186)	(0.255)	(0.659)	(0.321)
III. Clerks and Service workers *(N=2490)*						
Exp	-1.016	-1.621***	0.345*	-1.189***	1.225*	0.224
	(0.683)	(0.413)	(0.137)	(0.341)	(0.550)	(0.221)
IV. Craft Workers *(N=2656)*						
Exp	-0.543	0.087	0.258*	-1.467***	0.159	0.419
	(0.493)	(0.439)	(0.110)	(0.247)	(0.268)	(0.277)
V. Machine Operators *(N=10900)*						
Exp	-1.172***	-1.396***	0.384***	-0.692**	0.304*	0.228
	(0.315)	(0.221)	(0.081)	(0.242)	(0.152)	(0.156)
VI. Laborers *(N=2020)*						
Exp	-2.074***	-1.219**	0.398**	-2.104***	0.385	0.465+
	(0.503)	(0.372)	(0.151)	(0.305)	(0.339)	(0.243)

Note: All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

Overall, the results in Table 9 (and Table C11) show that the adjustment costs are unevenly distributed across the six occupational groups. The outcomes accumulated nine years after the shock depend on the ability to recover losses in the service sector and the amount of losses incurred in other manufacturing. The most successful transition out of the declining manufacturing sector is experienced by the two groups: professionals and technicians, and clerks and service workers. In fact, both these occupational groups are service-specific: in 2001, 95.5% of clerks and service workers were employed in the service sector; 76.9% of all professionals and technicians were employed in the service sector.[27] The finding that workers with occupations specific to the service sector are successful at transitioning into services is consistent with the importance of occupational human capital for job mobility (Shaw 1984; Kambourov and Manovskii 2009).

[27]The importance of occupational human capital can be studied even further by estimating how outcomes depend on an occupation's specificity to the manufacturing sector using the measure proposed in Utar (2018). As in Utar (2018), I find that an occupation's specificity to the manufacturing sector diminishes the ability of workers to recover losses in the service sector. The results are available upon request.

4.2.3 Adjustment and tasks

In the context of skill transferability, the differential adjustment costs across occupations documented in the previous section can be interpreted as indicating the differences in skill transferability of occupations or, in other words, the importance of occupation-specific human capital (Shaw 1984; Kambourov and Manovskii 2009). Yet, skill transferability can be traced to the even finer level of tasks. According to the task-based view on job mobility, occupations embody task portfolios and the ability of individuals to transfer their skills across occupations depends on the distance between the task portfolios of the occupations (Poletaev and Robinson 2008; Gathmann and Schönberg 2010). The central idea of the task-based approach is that skills obtained in occupations are productive in other occupations embodying similar tasks. In contrast to occupation-specific human capital, task-specific capital is not necessarily destroyed by job mobility. Given that the task-based approach has already advanced several strands of literature studying wage structure, it is informative to examine how tasks relate to worker adjustment after import shock. In this section, I focus on the role of tasks to scrutinize the determinants of workers' adjustment frictions.

To pin down the role of tasks, I follow Autor et al. (2003) and Spitz-Oener (2006) and use three categories of tasks: manual (e.g. operating machines, repairing, packing), analytical (e.g. researching, programming, executing laws) and interactive (e.g. selling, advertising, teaching).[28] I use the data on task-intensity reported in Gathmann and Schönberg (2010) to match task intensity to two-digit ISCO occupations. Gathmann and Schönberg (2010) obtain a task-intensity measure from the German Qualification and Career Survey, which contains information on tasks performed in different jobs. Task intensity is calculated as the mean use of tasks by occupation. Table A2 in the appendix shows the results of mapping task intensity to ISCO-88 occupations. There is a substantial overlap between analytical and interactive tasks in many occupations, whereas intensity of both analytical and interactive tasks tends to be low for occupations intensive in manual tasks.[29]

[28] Literature on task usage further splits manual, analytical and interactive tasks into *routine* and *non-routine* tasks to designate which jobs can be more easily performed by computers (Autor et al. 2003; Spitz-Oener 2006), offshored or substituted by imports (Ebenstein et al. 2014). In the context of skill transferability, however, this split is not very meaningful, as routinenes of tasks is not necessarily informative of the distance between occupations.

[29] To assess the robustness of my results, I have additionally used an alternative classification of occupations developed by Becker et al. (2013). This classification is also based on the German Qualification and Career Survey, but it exploits information on the tools used in different occupations to assess how intensive occupations are in interactive tasks. Using this classification leads to a similar conclusion: that losses are larger for workers performing a lower fraction of interactive tasks and that the difference is driven by the service sector.

Table 10: Task specificity and workers' earnings, 1999-2010

	(1) All Employers	(2) Other TC	(3) Services
A. Manual tasks			
Exp	-0.084	0.633**	3.486***
	(0.846)	(0.216)	(0.673)
Exp × TaskSpec (β_4)	-1.138	-0.287	-3.310***
	(0.998)	(0.255)	(0.737)
TaskSpec × After2002	-3.248***	0.139*	-2.591***
	(0.483)	(0.064)	(0.326)
B. Analytical tasks			
Exp	-1.833***	0.194	-1.005**
	(0.550)	(0.141)	(0.372)
Exp × TaskSpec (β_4)	1.689	0.389	3.602***
	(1.029)	(0.264)	(0.804)
TaskSpec × After2002	3.333***	-0.155*	2.237***
	(0.460)	(0.064)	(0.306)
C. Interactive tasks			
Exp	-1.435***	0.306**	-0.342
	(0.433)	(0.107)	(0.280)
Exp × TaskSpec (β_4)	0.976	0.208	2.566***
	(0.885)	(0.211)	(0.703)
TaskSpec × After2002	3.155***	-0.114*	2.559***
	(0.454)	(0.053)	(0.358)

Note: Amount of observations is 24,324. All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5

For tailors and knitters (two-digit occupation title "Other craft and related workers"), the mean use of manual tasks is 96.6%; of analytical tasks, 33.0%; and of interactive tasks, 34.0%. For accountants ("Other professionals"), the mean task use is correspondingly 52.3%, 90.0% and 82.0%.[30] Looking at task intensity by sector, in 1999 in the manufacturing sector the mean use of manual tasks was 78.3%; of analytical skills, 56.7%; and of interactive tasks, 50.3%. In services, the task use was correspondingly 65.5%, 63.8% and 66.1%.[31] Hence, the manufacturing sector is relatively more intensive in manual tasks, while analytical and interactive tasks are more prevalent in services. At the same time, for all workers in the top quartile of manual-task intensity, in 1999 59.0% were employed in manufacturing and 22.4% in services; the corresponding shares are 21.4% and 75.2% for workers in the top quartile of analytical-task intensity; and 18.5% and 77.0% for those in the top quartile of interactive-task intensity, indicating that manual tasks are more specific to the manufacturing sector, whereas analytical and interactive are more

[30] Gathmann and Schönberg (2010) argue that there is little evidence that there exists variation in the tasks performed by the same occupations belonging to different sectors (e.g. accountants in manufacturing and in services). This observation justifies the use of occupation data to compare tasks across sectors.

[31] The distribution of task-intensity across sectors is quite stable over time.

specific to the service sector.

To pin down the importance of task content of jobs for adjustment, I estimate the following triple-difference equation:

$$\begin{aligned}\tilde{E_{ip}} = \beta_0 + \beta_1 MFA_i \times After2002_p + \beta_2 After2002_p + \beta_3 After2002_p \times TaskInt_i \\ + \beta_4 MFA_i \times After2002_p \times TaskInt_i + \theta_i + \epsilon_{ip}\end{aligned} \tag{5}$$

The effect of the task specificity is captured by the coefficient of the triple interaction (β_4), where $TaskInt$ refers to the intensity in manual, analytical or interactive tasks of worker i's occupation. Table 10 presents the results for the effect on earnings across all employers (column 1) and the destinations with the potential to recover losses: other TC (column 2) and services (column 3). It is evident that workers in occupations that are more intensive in manual tasks are not able to recover their losses in services (Panel A, column 3). In contrast, the gains from the service sector are amplified for occupations with higher intensity in analytical (Panel B, column 3) and interactive tasks (Panel C, column 3). There is no significant effect of task specificity on the recovery in other TC. Although the coefficients on the interaction terms are insignificant for earnings accumulated from all employers (column 1), they are highly significant for employment (Table C17 in the Appendix), indicating that the magnifying effect of task intensity has implications for the employment accumulated nine years after the shock.

In summary, individuals who in 1999 were employed in occupations more intensive in manual tasks, bear disproportionately higher losses than those with occupations more intensive in analytical or interactive tasks. The differences in accumulated earnings and employment stem primarily from the ability to recover losses in the service sector. Given that analytical and interactive skills are more specific to the service sector than are manual tasks, these results are consistent with the interpretation that wage losses from job mobility are associated with difference in task requirements between the jobs (Poletaev and Robinson 2008; Gathmann and Schönberg 2010). Given that the task-based approach has been able to explain some stylized facts about earnings and employment that the canonical human capital theory could not, documenting the role of the task dimension provides an important insight for the literature on the dynamic adjustment.

Table 11: Cumulative effects of import shock and mobility across labor markets, 1999-2010

	(1) All Employers	(2) Same labor market	(3) Other labor market
A. Cumulative Earnings			
Exp	-0.507+	-0.948***	0.441
	(0.292)	(0.170)	(0.277)
B. Cumulative Employment			
Exp	-0.355***	-0.551***	0.196***
	(0.047)	(0.069)	(0.059)

Note: Amount of observations is 28,840. All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

4.3 Adjustment through geographic mobility

Neoclassic models of trade assume not only perfect sectoral mobility, but also geographic. Nevertheless, it has been repeatedly documented in the literature that trade shocks induce minimal geographic mobility (Kovak 2013; Hakobyan and McLaren 2016; Dix-Carneiro and Kovak 2019), suggesting that geographic mobility is not an important channel of adjustment. These findings are also at odds with the broader literature arguing that labor mobility is an important mechanism of reestablishing equilibrium after a labor-demand shock (Topel 1986; Blanchard and Katz 1992; Bound and Holzer 2000), but are in line with the findings that worker mobility across regions tends to be low. For instance, evidence on low regional mobility in European countries is discussed in Beyer and Smets (2015) and House et al. (2018); low mobility across Swedish labor markets is documented in Lundholm (2007) and Eriksson et al. (2008). In general, low mobility is explained by substantial mobility costs, arising, for instance, due to liquidity constraints on the housing market or from the costs associated with family ties (Kennan and Walker 2011; Head and Lloyd-Ellis 2012; Alesina et al. 2015). But is change of residence a relevant margin of adjustment? While geographic mobility appears to be low in many countries, there is evidence of growing number of job commuters (see, for instance, evidence for Sweden in Andersson et al. 2018b). Even when the costs of moving to another locations are high, workers may accept those cost to recover losses incurred due to trade shock.

Given that a change of residence is a very rare event in the sample,[32] I use change in the

[32]Change of residence is assessed using municipality of residence, as municipality is the only variable in the data referring to residence. 91% of individuals in the sample reside in the same municipality in 2005 as in 1999. If short-distance moves to municipalities in close neighbourhood are excluded from the definition of mobility, the share of individuals residing in the same municipality in 2005 as they did in 1999 goes up to 97%.

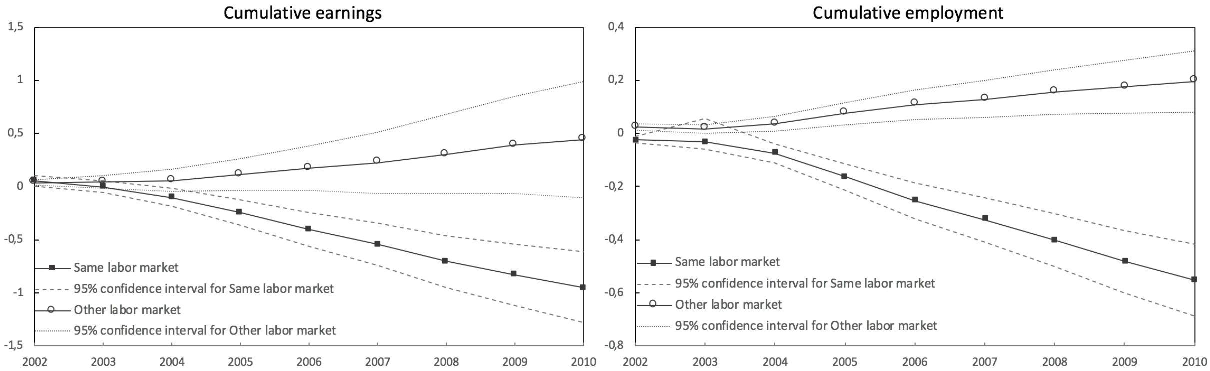

Figure 3: Cumulative earnings and employment since 2002. Each point represents the estimated coefficient β_1 from Eq. 4 estimated on the annual basis for the corresponding sub-sample of workers

location of the main employer to assess whether geographic mobility is an important channel of adjustment to the trade shock. Local labor market is a logical geographic demarcation for studying the change of workplace location,[33] as a change of workplace municipality can reflect a very short-distance change that represents hardly any mobility. During 1999–2010, 35.2% of individuals in the sample have changed their local labor market at least once.[34]

In the TC context, the role of geographic mobility may be especially relevant, given the high geographic concentration of the sector within many countries (Stengg 2001). Workers in a small town in Sweden — e.g. Borås — hit by the trade shock may find it difficult to adjust, simply because of the limited supply of jobs on the local labor market. However, residents of Borås ready to commute 65 km to the large city of Gothenburg (another local labor market) may enjoy a larger pool of available jobs while still living in Borås.

The decomposition of the effects of import shock with respect to mobility across labor markets is presented in Table 11. "Same labor market" refers to the earnings and employment accumulated on the local labor market where a worker was employed at the time of the import shock. "Other labor market" denotes earnings and employment accumulated from employers located in other local labor markets. The results indicate that work in other labor markets makes up for more than a half of the losses in cumulative employment (Panel B, column 3). Relative to the losses at the initial employer (Table 5, Panel B, column 2), work in other labor market makes up for approximately one fourth of the lost employment. Although the estimated

[33]Local labor markets in the data are recorded in accordance with the classification from 1997, when there was 105 local labor markets in Sweden.

[34]Descriptive statistics for movers and stayers are reported in the appendix, Table A3.

Table 12: Cumulative unemployment after moving across sectors, 1999-2010

	(1) All Un Spells	(2) Same labor market	(3) Other labor market
Exp	1.440***	1.385***	0.055
	(0.171)	(0.161)	(0.055)

Note: Amount of observations is 28,840. All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5

recovery of earnings losses through this channel is not statistically significant at a p-value of 11% (Panel A, column 3), the magnitude of the estimate is relatively large, amounting to more than 85% of the losses at all employers. As it will become evident from the next section, the insignificant coefficient reflects the heterogeneous outcomes within this group of movers. At the same time, staying in the same labor market brings losses in both earnings and employment (column 2). Figure 3 illustrates how earnings and employment develop over time for workers who change labor market and for those who stay on the same labor market. The figure shows that labor market outcomes of stayers steadily deteriorate over time relative to movers.

Is movement across labor markets conductive to stable employment? Table 12 reports the estimated effects of the import shock on accumulated unemployment spells. Around 96% of the total unemployment time (column 1) is driven by stayers (column 2). The contribution of movers to the length of unemployment spells is close to zero (column 3). Hence, by moving to other labor markets workers succeed in securing stable employment; staying put increases the length of time in unemployment.

Together, these findings suggest that although mobility across labor markets is moderate, it represents a channel of adjustment to the import shock that allows offsetting a portion of losses. Given that the change of the residence is a rare event in the sample, the increased mobility across the labor markets after the import shock is an indirect evidence of increased commute of the workers. This finding points to an interesting, previously unexplored channel through which import competition influences labor markets.

4.4 Heterogeneity in geographic mobility

The previous section established that mobility across labor markets is a channel through which workers can partially recover their losses in earnings and employment. But is this channel

Table 13: Geographic mobility by occupational groups, cumulative earnings, 1999-2010

	(1) All Employers	(2) Same labor market	(3) Other labor market
I. Managers *(N=1398)*			
Exp	-1.638***	-0.693	-0.945*
	(0.469)	(0.478)	(0.457)
II. Professionals and Technicians *(N=4850)*			
Exp	0.632	-1.463**	2.095**
	(0.756)	(0.477)	(0.768)
III. Clerks and Service workers *(N=2490)*			
Exp	-1.016	-0.696	-0.320
	(0.683)	(0.583)	(0.483)
IV. Craft Workers *(N=2656)*			
Exp	-0.543	-0.373	-0.171
	(0.493)	(0.473)	(0.317)
V. Machine Operators *(N=10900)*			
Exp	-1.172***	-0.967**	-0.205
	(0.315)	(0.297)	(0.205)
VI. Laborers *(N=2020)*			
Exp	-2.074***	-1.587***	-0.487
	(0.503)	(0.472)	(0.335)

Note: All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

available to all the workers? Are some groups of workers more likely to gain from geographic mobility than others?

A few interesting observations emerge from the heterogeneity analysis.[35] First, gains both in earnings and employment from moving to other labor markets are to a large extent driven by one occupational group — professionals and technicians. This group doubles their pre-shock annual earnings by moving (Table 13, Panel II, column 3). At the same time, professionals and technicians lose substantially from staying put (Panel II, column 2), with losses amounting to around 150% of their pre-shock annual earnings. The pattern is quite similar for this group in terms of employment (see Table C15 in the appendix). The most substantial earnings and employment reductions from staying are experienced by machine operators and laborers (Tables 13 and C15, Panels V and VI, column 2).

Second, geographic mobility benefits workers with more interactive- and analytical-task intensive occupations (see Tables C16). Benefits from mobility, however, do not materialize for

[35] Additional tables with the heterogeneity analysis not mentioned in this section are reported in Appendix C.

workers with manual-task-intensive occupations.

Third, the findings document some mobility across labor markets for workers in the lowest educational group (Table C12, Panel I, column 3). The coefficient of employment is positive and highly significant, indicating that this group spends more time working for employers located in other labor markets. This observation is in contrast with the general conclusion from the literature that geographic mobility (defined in terms of residence) is minimal among this educational group (Topel 1986; Bound and Holzer 2000; Notowidigdo 2019). Although the mobility across labor markets does not fully offset the losses of this group of workers, the increased mobility in terms of employment signifies that import shock does, in fact, induce mobility among workers in the lowest educational group. This finding underlines that geographic mobility (in terms of workplace location) is a relevant margin of adjustment.

Overall, the gains from geographic mobility are largely driven by workers from one occupational group: professionals and technicians. In addition, the benefits accrue to individuals with more analytical- and interactive-task specific occupations. These findings are broadly consistent with the standard result, that benefits of geographic mobility are concentrated among more highly skilled individuals (Topel 1986; Bound and Holzer 2000), although my findings also document some mobility across the lowest educational group. The standard explanation, that the differential geographic mobility is driven by the opportunity costs, does not accord with these findings. It is, however, plausible that the observed heterogeneity is driven by search costs (as discussed, for example, in Van den Berg and Van Vuuren 2010).[36]

5 Skill specificity of local labor market

The results discussed in Section 4 show that adjustment to the trade shock depends on how specific workers' skills are to the exposed sector. But is having the "right" skills sufficient for recovery? To interpret the results in previous subsections as the pure indication of non-transferability of skills, one has to implicitly assume that possessing a certain set of skills is sufficient for a match with employers searching for that set of skills. However, what if there is no possibility of such a match on the job market where a worker is searching?

[36] An alternative explanation for the differential geographic mobility costs is the role of compensating factors (social transfers and costs of housing) as discussed in the model by Notowidigdo (2019)). This mechanism, however, does not align with the institutional context of this paper.

Imagine two tailors (i.e., workers in a manufacturing-specific occupation) searching for jobs in the service sector after the import shock, each searching on her own local labor market. Say, skills possessed by the tailors are valuable in the role of a personal shopping assistant in the sense that they do not depreciate fully after the switch from a tailor to a personal shopping assistant and, therefore, there is no substantial loss in earnings after the job switch. However, if only one of the two local markets has open vacancies for personal shopping assistants, then only one of the tailors will be able to find such a match; the other tailor will have to accept a match that may result in a greater depreciation of worker's human capital, and, therefore, a substantial reduction in earnings. This reduction in earnings is, therefore, a combination of lower human capital transferability and lower availability of good matches.

To pin down the importance of local labor markets for post-shock adjustment, I analyze worker outcomes with respect to skill specificity of local labor market. The first measure of skill specificity is based on occupations: I use the ratio of employment in the manufacturing-specific occupations to the total employment in the labor market in 1999.[37] Manufacturing specificity of occupations is defined using the ratio of number of workers in an occupation employed in manufacturing in 1999 to total number of workers in this occupation in 1999.[38] To single out manufacturing-specific occupations, I use three-digit occupations in the top quartile of the manufacturing-specificity measure.[39] The second measure is based on tasks. In light of the earlier results documented for tasks, I use mean task intensity of local labor market to determine how specific the market is in manual tasks.[40]

Given that both measures use the 1999 data and the full sample of workers (irrespective of whether they move across labor markets or not), the results can be interpreted as eliciting the role of the worker's initial local labor market in the magnitude of trade-induced adjustment costs.

I assess the role of skill specificity of labor markets in workers' adjustment to import shocks

[37]The share of employment is a standard way of approximating specialization, see e.g. Rosenthal and Strange (2004) for a discussion. Relative to a more common approach, where the share is calculated as a headcount of employees in manufacturing firms, my measure is more precise. The results presented in this section also hold if manufacturing specificity is defined as the density of workers employed in manufacturing in 1999 or as the location quotient (the ratio between the regional concentration of workers in manufacturing and the national concentration).

[38]Using this measure, Utar (2018) shows that workers in more manufacturing-specific occupations experience worse adjustment driven by the inability to recover losses in services.

[39]The three most manufacturing-specific occupations in the population according to this definition are plant and machine operators, craft workers and manufacturing laborers. The most manufacturing-specific labor markets include Värnamo, Trollhättan and Borås.

[40]The most manual-task-intensive labor markets in the population are Vansbro, Fagersta and Hällefors.

by estimating the triple-difference equation:

$$\begin{aligned}\tilde{E_{ip}} = \beta_0 + \beta_1 MFA_i \times After2002_p + \beta_2 After2002_p + \beta_3 After2002_p \times LMSpec_i \\ + \beta_4 MFA_i \times After2002_p \times LMSpec_i + \theta_i + \epsilon_{ip}\end{aligned} \tag{6}$$

The effect of skill specificity is captured by the coefficient on the triple interaction (β_4), where $LMSpec$ is either manufacturing-specificity measure based either on occupation ($OSpec$) or on manual-task intensity ($TSpec$). Given that the specification includes worker fixed effects, the unobserved characteristics of the initial local labor markets are controlled for.

Table 14 presents the results for the effect on earnings across all employers and the destinations with a potential to recover losses: other TC and services. The results indicate that the gains from the service sector do not accrue to workers who in 1999 worked in more manufacturing-specific labor markets (Panel A, column 3). Although manufacturing-specificity of local labor markets implies better recovery in other TC (Panel A, column 2), these gains do not compensate for the losses in other sectors (Panel A, column 1). The pattern is even stronger for employment (Table C18 in the appendix), where it is evident that larger losses in the service sector result in larger accumulated losses in terms of employment (i.e., the coefficient in the first column is significant). Similar findings emerge from the task-based definition. Panel B of Table 14 confirms the conclusion that specificity of local labor markets is an important determinant of post-shock labor market adjustments, as individuals who in 1999 were working in labor markets with higher manual-task intensity do not gain from moving to services.

Hence, even when the level of analysis is shifted from labor-market level (Autor et al. 2013a; Kovak 2013; Topalova 2007) to worker level, there is evidence that local labor markets play an important role in adjustment. That skill specificity of local labor markets is relevant adds an important nuance to the interpretation of adjustment costs. In particular, adjustment costs of sectoral mobility do not necessarily reflect workers' ability to find use for their skills in other sectors, they may rather reflect workers' ability to find a match for their skills. If the possibility that a match between a worker and a firm does not happen due to the limited access to relevant jobs in the local labor market is ignored, the role of transferability of workers' skills can be overstated (as long as the definition of transferability does not take job accessibility into account).

Table 14: Skills specificity of local labor markets and workers' earnings, 1999-2010

	(1) All Employers	(2) Other TC	(3) Services
A. Occupation-based definition			
Exp	-0.104	-0.059	2.374***
	(1.167)	(0.129)	(0.691)
Exp × OSpec (β_4)	-4.460	2.946***	-8.502+
	(7.162)	(0.868)	(4.354)
OSpec × After2002	-0.056	0.352*	-5.124*
	(2.990)	(0.151)	(2.518)
B. Task-based definition			
Exp	12.178	-4.079***	15.109*
	(18.198)	(1.130)	(7.128)
Exp × TSpec (β_4)	-17.126	6.426***	-19.621*
	(25.165)	(1.593)	(9.836)
TSpec × After2002	-18.971***	0.490+	-23.909***
	(4.263)	(0.260)	(2.863)

Note: Amount of observations is in Panel A is 25,288, in Panel B 22,418. All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

More broadly, the findings discussed in this section suggest that skill specificity of local labor markets should be an important element of the analysis of the distributional effects of trade.

6 Skill upgrading

Previous sections have established a link between the adjustment costs of exposed workers and their skills. Workers with skill profiles specific to the exposed sector are less successful at transitioning to the other sector. But does import shock induce skill upgrading?

In this section, I study how the import shock influences the decision to acquire additional training and education. More specifically, I look at three outcomes. The first is the number of days in training provided by the Swedish Public Employment Service,[41] the second is the probability of obtaining an educational degree, the third is the probability of obtaining an educational degree in a non-manufacturing discipline.

Panel A of Table 15 presents the estimates of Eq. 4, where the dependent variable is one of the following variables: days in training provided by the Public Employment Service, the probability of obtaining an additional educational degree or the probability of obtaining an

[41] Training ("åtgärdsstudier") can take the form of a variety of programs and measures such as competence training, IT-education, traineeships, etc.

Table 15: Skill upgrading, 1999-2010

	(1) Days in training	(2) Degree	(3) Non-manu degree
A. Full sample			
Exp	17.953***	0.013*	0.018***
	(3.964)	(0.006)	(0.005)
B. More manual-intensive occupations, (N=21926)			
Exp	21.849***	0.019*	0.021***
	(5.119)	(0.007)	(0.006)
C. Less manual-intensive occupations, (N=6914)			
Exp	11.521*	0.004	0.013
	(4.775)	(0.010)	(0.009)

Note: The threshold for manual-intensity of occupations is the median value of manual-intensity of occupations in the population of workers. Amount of observations in the full sample is 28,840. All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5

additional educational degree in a non-manufacturing discipline. The estimate in column 1 indicates that the import shock increases the number of days in training taken by exposed workers by about 18 days. Column 2 suggests that the import shock increases the probability of obtaining an education degree, and column 3 shows that the probability of obtaining a non-manufacturing degree also increases.

In light of the previous findings on the low transferability of manufacturing skills, it is informative to examine the decision to upgrade skills with respect to the skill profiles of workers. In Panels B and C of Table 15, I split the sample with respect to how intensive workers occupations were in manual tasks. In the reported results, the median value of manual-task intensity is used as a threshold.[42] It is evident from Panel B that the skill upgrading in response to the import shock is largely driven by workers in occupations of greater manual-task intensity.

In general, the evidence on skill upgrading is in line with trade models with endogenous skill acquisition (Findlay and Kierzkowski 1983; Falvey et al. 2010), which predict acquisition of skill in response to trade shocks. More broadly, trade-induced skill upgrading is consistent with the evidence that firms respond to foreign competition by upgrading their technologies and products (Bloom et al. 2016; Eckel et al. 2015), which requires access to a more skilled workforce.

[42]The conclusions of this sample split remain unchanged if top tercile or top quartile are used as the threshold.

7 Conclusions

While it has long been understood that trade has not only benefits but also costs, quantification of the consequences of trade for worker adjustment has only recently drawn significant attention of trade economists. In this paper, I study the effect of a Chinese import shock on the employment trajectories of Swedish employees and contribute to the discussion with the detailed evidence on the channels of adjustment. Exploiting rich micro data from Sweden, I follow workers in the TC sector after an import shock and document their adjustment in terms of changes to earnings and employment. The import shock in focus is the removal of quotas set out in the MFA for Chinese producers, which induced a sharp increase in import competition for domestic producers in Sweden in 2002. I show that this import shock reduced earnings of the exposed workers and increased job churning. Sectoral mobility is an important channel of adjustment. Similar to the results in Autor et al. (2014), Utar (2018) and Dauth et al. (2019), I show that moving out of the exposed sector is critical to the ability to make up for the losses after the shock, but the ability to offset losses in services is limited for workers with manufacturing-specific skills. More specifically, gains from moving to services do not offset the losses incurred at the initial employer for workers with educational degrees in manufacturing, workers with occupations more specific to the manufacturing sector and workers with occupations more intensive in manual tasks.

I also find evidence of mobility across labor markets through changes on employment location. Given that few individuals change residence during the period of observation, the documented mobility across labor markets is an indirect evidence of increased commute of the workers in response to the shock — a novel channel previously unexplored in the literature on the dynamic adjustment. Gains from geographic mobility are, however, concentrated among the workers in one occupational group (professionals and technicians).

I further show that the skill specificity of labor market has important consequences for how successful the transition out of the exposed sector is. In particular, I show that workers on more manufacturing-specific labor markets accumulate larger losses. Finally, I provide evidence of skill upgrading in response to the import shock. Exposed workers spend more days in the training provided by the Public Employment Service; they are also more likely to obtain an additional educational degree and to obtain an educational educational degree in non-manufacturing fields. These results are largely driven by individuals in occupations of higher manual-task intensity.

That skills influence the ability of workers to gain from sectoral and geographic mobility points to the important role of labor market institutions providing education and training. As costs of adjustment are tied to the skill specificity, policies directed towards skill acquisition seem more promising than measures aimed at facilitating entry into the growing sector. At the same time, reducing costs of mobility in general (and of commute in particular), may facilitate transition, by improving accessibility to the better matching jobs. Assessing the potential of various measures aimed at reducing mobility costs and facilitating smooth transition into new sectors is an important direction for future work.

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Appendix

A Descriptive Statistics

Table A1: Descriptive statistics.

	Non-Exposed		Exposed	
	Mean	S.D.	Mean	S.D.
A. Outcome variables, post-shock period (N1=11401, N2=3019)				
Cumulative Earnings	12.526	13.255	11.884	16.056
Cumulative Total Earnings	10.436	10.204	9.862	11.184
Cumulative Employment (non-zero salary)	8.052	2.083	7.695	2.381
Cumulative Unemployment spells	3.374	7.597	4.886	8.727
Days in training	38.437	157.619	56.909	205.394
Additional Degree, dummy	0.085	0.279	0.098	0.297
Additional Non-manuf. degree, dummy	0.053	0.224	0.071	0.256
B. Exposure to the import shock (N1=11401, N2=3019)				
Exposure Intensity	0.000	0.000	0.532	0.335
C. Worker characteristics in 1999, dummies (N1=11401, N2=3019)				
High-school degree	0.330	0.470	0.453	0.498
Vocational degree	0.513	0.500	0.432	0.495
University degree	0.064	0.245	0.055	0.228
Manufacturing Degree	0.356	0.479	0.220	0.414
Non-Manufacturing Degree	0.258	0.437	0.265	0.441
Managers	0.047	0.211	0.055	0.229
Professionals	0.178	0.383	0.131	0.337
Clerks	0.076	0.265	0.126	0.331
Craft workers	0.088	0.284	0.107	0.309
Machine Operators	0.396	0.489	0.310	0.462
Laborers	0.067	0.250	0.081	0.273
D. Task intensity, 1999 (N1=9717, N2=2445)				
Manual tasks intensity	0.790	0.201	0.772	0.214
Analytic tasks intensity	0.551	0.208	0.550	0.222
Interactive tasks intensity	0.487	0.244	0.500	0.261
E. Manufacturing specificity, 1999, def.1 (N1=10019, N2=2625)				
Occupation-based definition (OSpec)	0.149	0.052	0.159	0.037
F. Manufacturing specificity, 1999, def.2 (N1=8992, N2=2217)				
Task-based definition (TSpec)	0.719	0.039	0.714	0.028

Note: N1 and N2 refer the amount of observation for the Non-Exposed and Exposed workers respectively.

Table A2: Task intensity in 2-digit occupations

Occupation title	Task-intensity Manual	Analytical	Interactive
Legislators and senior officials	0.453	0.924	0.908
Corporate managers	0.429	0.844	0.932
General managers	0.431	0.835	0.875
Physical, mathematical and engineering science professionals	0.524	0.922	0.868
Life science and health professionals	0.417	0.849	0.898
Teaching professionals	0.476	0.698	0.964
Other professionals	0.532	0.900	0.820
Physical and engineering science associate professionals	0.610	0.710	0.638
Life science and health associate professionals	0.610	0.710	0.638
Other associate professionals	0.552	0.850	0.825
Office clerks	0.460	0.846	0.792
Customer services clerks	0.514	0.422	0.789
Personal and protective services workers	0.647	0.460	0.497
Models, salespersons and demonstrators	0.573	0.696	0.958
Market-oriented skilled agricultural and fishery workers	0.918	0.450	0.648
Extraction and building trades workers	0.925	0.365	0.404
Metal, machinery and related trades workers	0.924	0.551	0.449
Precision, handicraft, printing and related trades workers	0.901	0.589	0.460
Other craft and related trades workers	0.966	0.330	0.340
Stationary-plant and related operators	0.933	0.497	0.392
Machine operators and assemblers	0.943	0.408	0.304
Drivers and mobile-plant operators	0.917	0.348	0.360
Sales and services elementary occupations	0.848	0.244	0.248
Laborers in mining, construction, manufacturing and transport	0.903	0.305	0.199

Note: Based on task-intensity data from Gathmann and Schönberg (2010)

Table A3: Movers and Stayers

	Mean Movers	Mean Stayers	Mean Difference	t-test
Female	0.39	0.38	-0.01	-1.37
Age	37.92	42.08	4.16***	22.25
University degree	0.10	0.08	-0.02***	-3.44
Vocational degree	0.08	0.05	-0.02***	-5.44
High-school degree	0.53	0.47	-0.05***	-6.09
Manufacturing Degree	0.32	0.33	0.01	0.93
Non-Manufacturing Degree	0.31	0.23	-0.08***	-10.20
Managers	0.07	0.04	-0.02***	-5.69
Professionals	0.21	0.18	-0.03***	-4.34
Clerks	0.11	0.10	-0.01*	-2.46
Craft workers	0.09	0.11	0.02**	3.06
Machine Operators	0.36	0.44	0.08***	9.09
Laborers	0.08	0.08	-0.00	-0.89
No. observations	5266	9694		

Note: ***p<0.01, **p<0.05, *p<0.1

B Figures

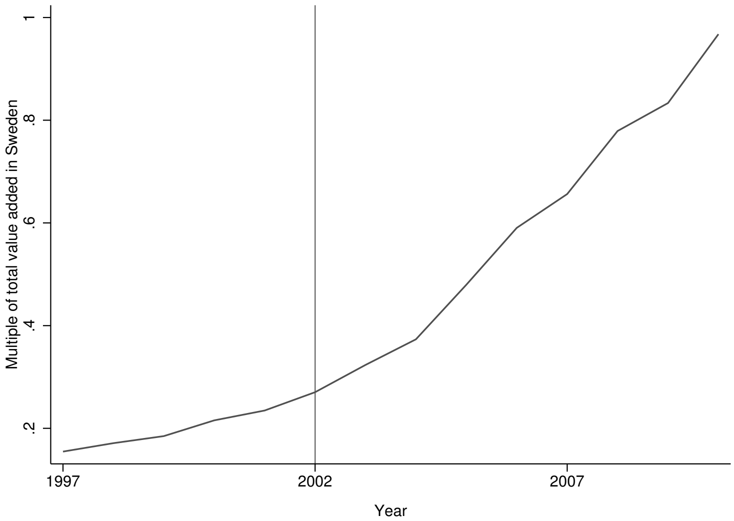

Figure B1: Total imports of MFA-goods from China as a multiple of 1999 total value added in Sweden

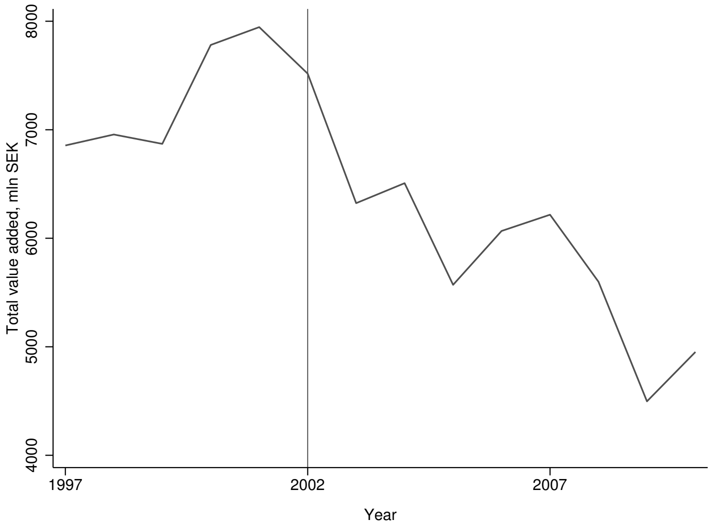

Figure B2: Total value added in TC products, mln SEK

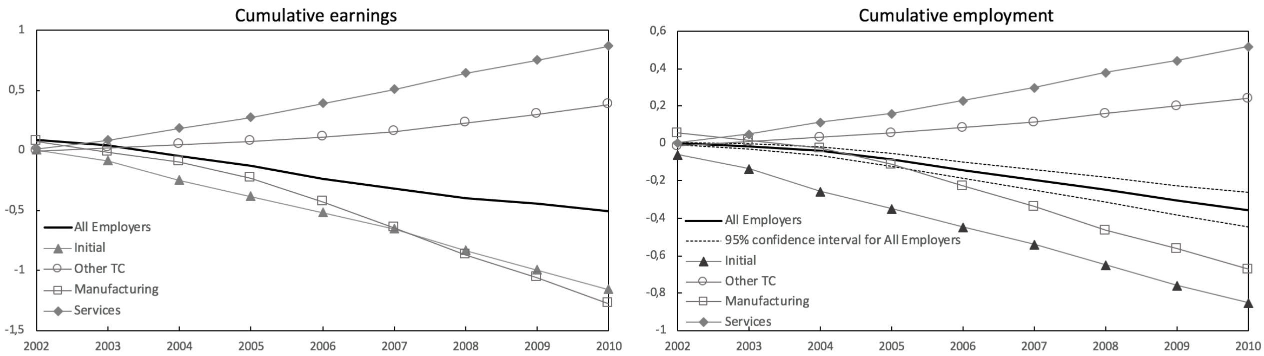

Figure B3: Cumulative earnings and employment since 2002. Each point represents the estimated coefficient β_1 from Eq. 4 estimated on the annual basis.

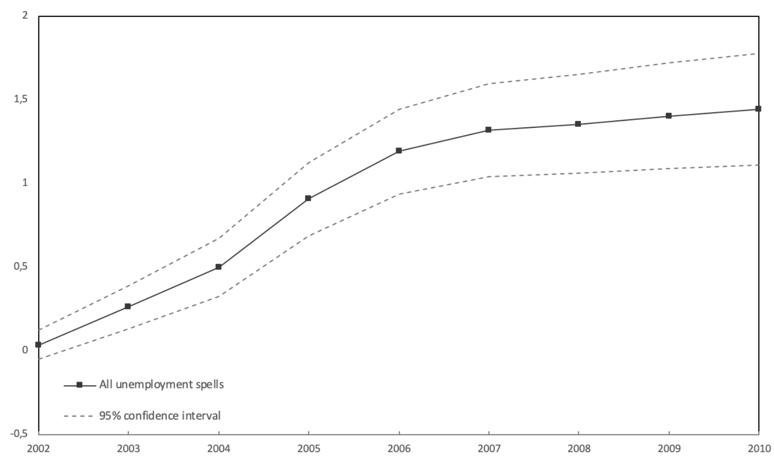

Figure B4: Cumulative unemployment spells since 2002. Each point represents the estimated coefficient β_1 from Eq. 4 estimated on the annual basis.

C Additional results and robustness

Table C1: Cumulative effects of import shock, 1998-2010. Exposure status defined for 1998

	(1) Earnings	(2) Total Earnings	(3) Employment
Exp	-1.787***	-1.454***	-0.693***
	(0.194)	(0.147)	(0.047)
Observations	33852	33852	33852
Adjusted R^2	0.274	0.299	0.675

Note: Exposure status of workers is defined with respect to their employment in 1999 (instead of 1999) as in the main analysis. The amount of observations is larger than in the main sample, as there were more workers in TC om 1998, than in 1999. All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

Table C2: Firm-level effect of MFA-quotas removal

	(1) Employment	(2) Sales	(3) Value Added	(4) Investment
Exp	-0.179**	-0.136*	-0.174*	-0.496*
	(0.062)	(0.057)	(0.070)	(0.222)
Observations	1392	1394	1392	1316
Adjusted R^2	0.086	0.149	0.049	0.063

Note: Table reports results of estimating Eq.3 on firm level. All specifications include firm fixed effects and year fixed effects. The dependent variable is in the column title (all in logs). Standard errors clustered on firm level are in parentheses. ***p<0.001, **p<0.01, *p<0.5

Table C3: Effects of import shock, 1999-2010. Data collapsed into pre- and post-shock

	(1) Earnings	(2) Total Earnings	(3) Personal Income	(4) Unempl Inc	(5) Unempl Days
Exp	-0.082***	-0.084***	-0.084***	0.496***	0.322***
	(0.018)	(0.018)	(0.018)	(0.052)	(0.038)
Observations	28587	28567	28595	28840	28840
Adjusted R^2	0.010	0.013	0.011	0.134	0.110

Note: All specifications include worker and year fixed effects. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5

Table C4: Annual effects of import shock on firms and workers, unit-level trends included

	(1) Earnings	(2) Total Earnings	(3) Personal Income	(4) Unempl Inc	(5) Unempl Days
Exp	-0.034**	-0.036**	-0.035**	0.197***	0.122***
	(0.012)	(0.013)	(0.013)	(0.028)	(0.020)
Individual trends	YES	YES	YES	YES	YES
Observations	160409	160409	160409	160409	160409
Adjusted R^2	0.012	0.007	0.008	0.012	0.009

Note: All specifications include worker fixed effects. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5

Table C5: Annual effects of import shock in the pre-sample, 1997-1998

	(1) Earnings	(2) Total Earnings	(3) Personal Income	(4) Unempl Inc	(5) Unempl Days
Exp	0.018	0.003	0.002	0.009	0.016
	(0.011)	(0.011)	(0.011)	(0.010)	(0.017)
Observations	29742	29711	29742	29742	29742
Adjusted R^2	0.049	0.060	0.060	0.000	0.012

Note: Regressions are run on the pre-sample (1997-1998). All specifications include worker and year fixed effects. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5

Table C6: Annual effects of import shock and the role of own imports, 1999-2010.

	(1) Earnings	(2) Total Earnings	(3) Personal Income	(4) Unempl Inc	(5) Unempl Days
Exp	0.043**	0.057***	0.066***	0.299***	0.076*
	(0.016)	(0.016)	(0.015)	(0.046)	(0.032)
Imp × After2002	-0.548***	-0.552***	-0.566***	0.619***	0.537***
	(0.014)	(0.013)	(0.014)	(0.026)	(0.020)
Exp × Imp (α_3)	0.221***	0.206***	0.202***	-0.545***	-0.268***
	(0.023)	(0.023)	(0.022)	(0.053)	(0.039)
Observations	160996	159968	160923	160996	160996
Adjusted R^2	0.068	0.072	0.077	0.024	0.025

Note: The triple difference coefficient is denoted as Exp × Imp (α_3). All specifications include worker and year fixed effects. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5

Table C7: Cumulative effects of import shock, 1999-2010. Exposure Intensity as the measure of import competition

	(1) Earnings	(2) Total Earnings	(3) Employment
ExpInt	-0.498	-0.667+	-0.553***
	(0.579)	(0.364)	(0.076)
Observations	28840	28840	28840
Adjusted R^2	0.331	0.378	0.850

Note: All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

Table C8: Decomposition of the cumulative effects of import shock, 1999-2010. Exposure Intensity as the measure of import competition

	(1) All Employers	(2) Initial	(3) Other TC	(4) Other Man	(5) Services	(6) Other
Panel A: *Cumulative Earnings*						
ExpInt	-0.498	-1.904***	0.667***	-1.536***	1.176***	1.099*
	(0.579)	(0.186)	(0.108)	(0.153)	(0.274)	(0.443)
Panel B: *Cumulative Employment*						
ExpInt	-0.553***	-1.438***	0.530***	-0.837***	0.615***	0.578***
	(0.076)	(0.098)	(0.063)	(0.064)	(0.076)	(0.073)

Note: Amount of observations is 28,840. All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

Table C9: Sectoral mobility by field of education, vocational degree only, 1999-2010

	(1) All Employers	(2) Initial	(3) Other TC	(4) Other Man	(5) Services	(6) Other
			I. Manufacturing degrees *(N=1196)*			
A. Cumulative Earnings						
Exp	-2.631*	-1.418*	0.181	-2.087***	-0.022	0.715
	(1.155)	(0.640)	(0.114)	(0.564)	(0.947)	(0.607)
B. Cumulative Employment						
Exp	-0.240	-0.803*	0.128+	-0.877***	0.382	0.930***
	(0.154)	(0.360)	(0.076)	(0.260)	(0.280)	(0.270)
			II. Non-Manufacturing degrees *(N=594)*			
A. Cumulative Earnings						
Exp	2.129	-2.197*	1.134	-1.459	3.330+	1.320
	(3.024)	(1.024)	(0.793)	(1.140)	(2.007)	(2.379)
B. Cumulative Employment						
Exp	0.393*	-1.080*	0.243	-0.422	1.372**	0.280
	(0.194)	(0.465)	(0.177)	(0.331)	(0.438)	(0.367)

Note: All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

Table C10: Occupational mobility, 2001-2010

	Occupational group			3-digit Occupations		
	Population	TC	Manufacturing	Population	TC	Manufacturing
2001-2003	94.38	94.93	94.29	90.49	92.76	90.29
2002-2004	91.88	89.97	90.44	85.69	83.94	82.73
2003-2005	91.67	89.48	89.95	84.80	81.95	80.85
2004-2006	93.39	93.56	92.99	88.52	89.98	87.83
2005-2007	93.36	93.80	93.35	89.17	91.06	88.98
2006-2008	93.74	94.59	94.19	89.92	92.48	90.60
2007-2009	93.94	93.34	94.18	90.20	90.74	90.75
2008-2010	93.95	94.26	93.64	90.13	91.83	89.76

Note: Columns 1-3 report the probability of remaining in the same occupational group within given three years; columns 4-6 report probability of remaining in the same 3-digit occupation. In columns 2 and 5, only the individuals who in the first year of the given period were employed in TC are included in the sample, in columns 3 and 6 - only the individuals who in the first year of the given period were employed in manufacturing.

Table C11: Sectoral mobility by occupational group, employment, 1999-2010

	(1) All Employers	(2) Initial	(3) Other TC	(4) Other Man	(5) Services	(6) Other
I. Managers *(N=1398)*						
Exp	-0.261	-0.807**	0.321**	-0.627**	0.698**	0.153
	(0.168)	(0.277)	(0.105)	(0.212)	(0.227)	(0.143)
II. Professionals and Technicians *(N=4850)*						
Exp	-0.061	-0.922***	0.280***	-0.814***	1.153***	0.243*
	(0.079)	(0.178)	(0.062)	(0.112)	(0.157)	(0.095)
III. Clerks and Service workers *(N=2490)*						
Exp	-0.059	-1.154***	0.201**	-0.475***	1.111***	0.257*
	(0.115)	(0.194)	(0.073)	(0.126)	(0.170)	(0.119)
IV. Craft Workers *(N=2656)*						
Exp	-0.359*	-0.260	0.198**	-0.971***	0.236+	0.438**
	(0.141)	(0.218)	(0.076)	(0.133)	(0.123)	(0.137)
V. Machine Operators *(N=10900)*						
Exp	-0.579***	-1.132***	0.269***	-0.389***	0.254***	0.418***
	(0.079)	(0.117)	(0.048)	(0.094)	(0.071)	(0.074)
VI. Laborers *(N=2020)*						
Exp	-0.431*	-0.917***	0.302**	-1.262***	0.674***	0.773***
	(0.172)	(0.234)	(0.094)	(0.122)	(0.157)	(0.159)

Note: All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

Table C12: Geographic mobility by educational level, 1999-2010

	(1) All Employers	(2) Same labor market	(3) Other labor market
	I. High-school degree *(N=14294)*		
A. Cumulative Earnings			
Exp	0.223	-0.393	0.616*
	(0.323)	(0.259)	(0.298)
B. Cumulative Employment			
Exp	-0.195***	-0.537***	0.342***
	(0.058)	(0.103)	(0.093)
	II. Vocational degree *(N=1790)*		
A. Cumulative Earnings			
Exp	-1.096	-0.703	-0.393
	(1.273)	(0.884)	(1.186)
B. Cumulative Employment			
Exp	-0.030	-0.066	0.036
	(0.122)	(0.291)	(0.273)
	III. University degree *(N=2494)*		
A. Cumulative Earnings			
Exp	-0.939	-1.915**	0.977
	(0.722)	(0.625)	(0.700)
B. Cumulative Employment			
Exp	-0.154	-0.590*	0.436+
	(0.133)	(0.272)	(0.252)

Note: All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

Table C13: Geographic mobility by educational field, university degrees, 1999-2010

	(1) All Employers	(2) Same labor market	(3) Other labor market
	I. Manufacturing degrees *(N=1276)*		
A. Cumulative Earnings			
Exp	-2.057*	-2.468*	0.411
	(0.919)	(0.980)	(0.933)
B. Cumulative Employment			
Exp	-0.224	-0.725	0.501
	(0.226)	(0.457)	(0.433)
	II. Non-Manufacturing degrees *(N=1218)*		
A. Cumulative Earnings			
Exp	0.018	-1.127	1.145
	(1.008)	(0.813)	(0.961)
B. Cumulative Employment			
Exp	-0.033	-0.280	0.247
	(0.169)	(0.344)	(0.316)

Note: All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

Table C14: Geographic mobility by educational level, vocational degrees, 1999-2010

	(1) All Employers	(2) Same labor market	(3) Other labor market
		I. Manufacturing degrees *(N=1196)*	
A. Cumulative Earnings			
Exp	-2.631*	-0.890	-1.741
	(1.155)	(0.749)	(1.154)
B. Cumulative Employment			
Exp	-0.240	-0.041	-0.199
	(0.154)	(0.344)	(0.318)
		II. Non-Manufacturing degrees *(N=594)*	
A. Cumulative Earnings			
Exp	2.129	-0.306	2.435
	(3.024)	(2.231)	(2.693)
B. Cumulative Employment			
Exp	0.393*	-0.140	0.533
	(0.194)	(0.531)	(0.508)

Note: All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

Table C15: Geographic mobility by occupational groups, employment, 1999-2010

	(1) All Employers	(2) Same labor market	(3) Other labor market
I. Managers *(N=1398)*			
Exp	-0.261	0.191	-0.452+
	(0.168)	(0.279)	(0.258)
II. Professionals and Technicians *(N=4850)*			
Exp	-0.061	-0.739***	0.678***
	(0.079)	(0.175)	(0.166)
III. Clerks and Service workers *(N=2490)*			
Exp	-0.059	-0.291	0.232
	(0.115)	(0.196)	(0.173)
IV. Craft Workers *(N=2656)*			
Exp	-0.359*	-0.405*	0.046
	(0.141)	(0.191)	(0.146)
V. Machine Operators *(N=10900)*			
Exp	-0.579***	-0.722***	0.143
	(0.079)	(0.112)	(0.089)
VI. Laborers *(N=2020)*			
Exp	-0.431*	-0.617**	0.187
	(0.172)	(0.224)	(0.179)

Note: All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

Table C16: Geographic mobility and task specificity, earnings, 1999-2010

	(1) All Employers	(2) Same labor market	(3) Other labor market
A. Manual tasks			
Exp	-0.084	-1.161+	1.077
	(0.846)	(0.689)	(0.739)
Exp × TaskSpec (β_4)	-1.138	0.158	-1.296
	(0.998)	(0.851)	(0.822)
TaskSpec × After2002	-3.248***	-1.073*	-2.175***
	(0.483)	(0.422)	(0.364)
B. Analytical tasks			
Exp	-1.833***	-0.901+	-0.932*
	(0.550)	(0.483)	(0.427)
Exp × TaskSpec (β_4)	1.689	-0.214	1.903*
	(1.029)	(0.830)	(0.900)
TaskSpec × After2002	3.333***	1.473***	1.860***
	(0.460)	(0.404)	(0.355)
C. Interactive tasks			
Exp	-1.435***	-0.853*	-0.582+
	(0.433)	(0.383)	(0.322)
Exp × TaskSpec (β_4)	0.976	-0.361	1.337+
	(0.885)	(0.696)	(0.771)
TaskSpec × After2002	3.155***	1.062**	2.093***
	(0.454)	(0.358)	(0.344)

Note: Amount of observations is 28,840. All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

Table C17: Task specificity and workers' employment, 1999-2010

	(1) All Employers	(2) Other TC	(3) Services
A. Manual tasks			
Exp	0.289+	0.282**	1.868***
	(0.157)	(0.104)	(0.228)
Exp × TaskSpec (β_4)	-0.868***	-0.026	-1.634***
	(0.207)	(0.132)	(0.266)
TaskSpec × After2002	-0.334***	0.115**	-1.245***
	(0.087)	(0.039)	(0.106)
B. Analytical tasks			
Exp	-0.845***	0.217**	-0.212
	(0.129)	(0.076)	(0.140)
Exp × TaskSpec (β_4)	0.853***	0.077	1.528***
	(0.198)	(0.125)	(0.263)
TaskSpec × After2002	0.417***	-0.122**	1.096***
	(0.083)	(0.037)	(0.103)
C. Interactive tasks			
Exp	-0.700***	0.264***	-0.011
	(0.107)	(0.062)	(0.108)
Exp × TaskSpec (β_4)	0.638***	-0.006	1.249***
	(0.173)	(0.105)	(0.224)
TaskSpec × After2002	0.348***	-0.092**	1.121***
	(0.071)	(0.031)	(0.090)

Note: Amount of observations is 28,840. All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

Table C18: Occupational specificity of local labor markets and workers' employment, 1999-2010

	(1) All Employers	(2) Other TC	(3) Services
A. Occupation-based definition			
Exp	-0.085	0.029	1.389***
	(0.175)	(0.096)	(0.261)
Exp × OSpec (β_4)	-1.820+	1.468*	-4.534**
	(1.072)	(0.598)	(1.573)
OSpec × After2002	2.040***	0.284***	-3.700***
	(0.298)	(0.081)	(0.396)
B. Task-based definition			
Exp	-2.135**	-2.766***	5.455**
	(0.687)	(0.469)	(1.699)
Exp × TSpec (β_4)	2.899**	4.335***	-6.715**
	(0.952)	(0.676)	(2.367)
TSpec × After2002	0.467*	0.246+	-9.945***
	(0.226)	(0.145)	(0.605)

Note: Amount of observations is 28,840. All specifications include worker fixed effects and dummy for the period after 2002. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

Table C19: Manufacturing: decomposition of the cumulative effects of the import shock

	All Manu (1)	Food Beverages (2)	Textiles & Clothing (3)	Wood & Paper (4)	Petroleum Chemicals (5)	Plastic & Non-metal (6)	Metals (7)	Machines (8)	Transport (9)	Furniture (10)	Other (11)
Panel A: *Cumulative Earnings*											
Exp	-1.280***	-0.014	0.379***	0.031	0.250***	-0.019	-0.215***	-0.201***	-0.493***	-0.474***	-0.142**
	(0.117)	(0.025)	(0.048)	(0.035)	(0.048)	(0.026)	(0.030)	(0.042)	(0.059)	(0.032)	(0.045)
Panel B: *Cumulative Employment*											
Exp	-0.674***	0.002	0.244***	0.005	0.205***	-0.016	-0.111***	-0.111***	-0.261***	-0.328***	-0.059**
	(0.046)	(0.010)	(0.026)	(0.013)	(0.026)	(0.011)	(0.014)	(0.013)	(0.018)	(0.016)	(0.019)

Note: Amount of observations is 28,840. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1

Table C20: Services: decomposition of the cumulative effects of the import shock

	All Services (1)	Wholesale & retail (2)	Transport (3)	Hotels & restaurant (4)	Inf. & commun. (5)	Finance & insurance (6)	Real estate (7)	Prof. activities (8)	Support activities (9)	Education (10)	Health & & social (11)	Arts & Entert. (12)	Other (13)
Panel A: *Cumulative Earnings*													
Exp	0.636***	0.662***	-0.015	-0.013	-0.066	0.003	0.019	-0.077+	0.090+	-0.018+	0.013	-0.012	0.051*
	(0.159)	(0.125)	(0.044)	(0.013)	(0.041)	(0.004)	(0.016)	(0.044)	(0.050)	(0.010)	(0.021)	(0.011)	(0.021)
Panel B: *Cumulative Employment*													
Exp	0.364***	0.343***	-0.005	0.005	-0.029***	-0.001	0.017+	-0.042**	0.035**	0.000	0.015+	-0.001	0.025**
	(0.047)	(0.036)	(0.016)	(0.007)	(0.009)	(0.001)	(0.010)	(0.015)	(0.013)	(0.005)	(0.009)	(0.004)	(0.008)

Note: Amount of observations is 28,840. Standard errors clustered on individual level are in parentheses. ***p<0.001, **p<0.01, *p<0.5, +p<0.1