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THREE ESSAYS ON INTERNATIONAL TRADE AND THE LABOR MARKET

Arnaud Joye

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Contents

General Introduction

The past two decades have been an intriguing and exiting period for trade and labor economists trying to better grasp the impact of globalization on labor markets. The combination of major disruptions to the global economy, and the availability of new data sets and new theories, has provided researchers a unique opportunity to explore nuances in understanding the labor-market impact of trade at an unprecedented level of detail. The primary objective of this thesis is therefore to contributing to this lively and policy relevant literature.

Beginning in the 1990s, research by economists showed that skill-biased technical change, especially in the form of rapid automation of routine tasks, played the leading role in the evolution of the wage structure in most advanced economies. On the other hand, international trade, in the form of offshoring at first, was seen to only modestly increase wage inequality. At that time, the attention was particularly centered on the United States and most of the data sets spanned the 1970s and 1980s. (Feenstra and Hanson, 1999; Katz and Autor, 1999). Recent evidence revealed that since the early 1990s, and most particularly since the late 1990s, expanding global trade is playing a much larger role on advanced economies' labor markets. Part of the explanation lies in two different trends happening in the global economy. Those two major developments and the exploration of parts of their influence on the labor market form the common themes of this thesis.

First, we have witnessed an expansion of international trade, which has been mainly propelled by the growing importance of developing countries in the global economy and especially driven by China's spectacular transition to a market-oriented economy. The shift of global manufacturing production networks towards these new global players represents a substantial competitive shock, applying renewed pressure on high-wage countries' labor markets. Production chains have become more and more internationally fragmented, and the availability of cheaper labor abroad might threaten workers and firms in industrialized countries. Part of this issue is explored in the second chapter of my thesis, which looks at the medium-term impact of increased imports from China on workers in the United Kingdom (henceforth UK). In a similar and complementary manner, the third chapter explores the short-term effect of exposure to world trade shocks on wages of Swiss manufacturing workers.

Second, the intensification of merchandise trade has also been accompanied with a rise in bilateral imports and exports matched within sectors. Indeed, at least since the 1960s, the share of intra-industry trade (henceforth IIT) is on an upward trend (Brülhart, 2009). This is interesting at least for two reasons. First, rising IIT shares suggest that national economies worldwide are converging towards similar sector compositions, which in turn could be partially explained by the growing importance of outward processing trade. Besides, increased shares of IIT could be related to lower factor adjustment costs to trade shocks compared to expansions of inter-industry trade. Indeed, if trade integration is mainly driven by the two-way exchange of different varieties of a same sector, then the sectoral composition of factors of production would be potentially less disturbed than if trade was happening across totally different sectors. Unlike inter-industry trade, the two-way exchange of similar products could signal a complementarity in modes of production that might prove beneficial to workers. The first chapter is tightly linked to this issue, since it explores the relationship between expanding IIT and associated worker reallocations both theoretically and empirically. Part of the second chapter also presents new evidence of a positive impact of trade with the European Union, which is mainly in the form of IIT, on workers in the UK.

In this thesis, consisting of three chapters, I have sought to explore these issues with state-of-the-art scientific techniques. Because trade shocks play out in general equilibrium, assessing their causal effects presents a conceptual and empirical challenge. Thus, the thesis is especially focused on identifying the causal impact of international trade on the labor market. To that end, each chapter presents an identification strategy based on the use of instrumental variables.

The first chapter, written with Marius Brülhart, explores the relation between IIT expansion and associated worker flows, taking the latter as an indicator of labor-market adjustment costs. IIT has long interested economists not just because of its incompatibility with neoclassical trade theory but also because of its perceived benign nature. A sizable empirical literature has defined precisely and tested empirically what has become known as the "smooth adjustment hypothesis" (henceforth SAH), according to which IIT expansion is less disruptive than inter-industry trade expansion. The SAH is intuitively compelling but remains rather short of rigorous support and has not yet been couched in a general-equilibrium trade model with pure trade shocks. The difficulty lies in finding a tractable setting that allows both trade flows and factor-market reallocations to be intra-industry and inter-industry to varying degrees, as an exogenous determinant of trade (such as transport costs) is changed. Such a setting has been developed by Bernard, Redding, and Schott (2007), where a differentiated-goods-heterogeneous-firms model yielding intra-industry trade and labor adjustment is embedded in a comparative-advantage framework that generates inter-industry trade and labor adjustment. We show that this model lends itself to simulating inter-industry and intra-industry trade adjustment to a pure trade shock. Moreover, in the empirical section, we seek to improve on the existing literature by instrumenting IIT, which is shown in the theoretical part to be potentially endogenous to productivity shocks. We find that both theoretical and empirical analyses are consistent with the SAH, according to which IIT expansion is less disruptive than inter-industry trade expansion.

The second chapter, written with Marius Brülhart and Joanne Lindley, contrasts the impact of increased import competition coming from China and the European Union (henceforth EU) on workers in the UK over a 15-year period. More specifically, we explore the worker-level impact of increased import penetration in UK manufacturing industries over the period 1997-2011. Our approach borrows the identification strategy of a corresponding analysis for the United States by Autor, Dorn, Hanson, and Song (2014), which we extend in several directions. First, our data permits us to decompose total earnings into hours of work and hourly pay, assessing the relative contribution of each margin in the adjustment process. Second, we look at net as well as gross imports, thus separately examining the effects of increased IIT. Next, we focus on import penetration from EU countries in addition to China. We estimate worker-level outcomes separately by occupations, and finally we look at the indirect impact of import competition on worker-level outcomes along the value chain. The results revealed that gross and net import penetration from China had significantly negative effects on workers' earnings, wages and hours of work in the affected industries. In contrast, increased gross imports from the EU are associated with positive worker-level outcomes, which is largely explained by the fact that increased imports from the EU were mostly offset by increased same-industry exports to the EU. We also find that the adverse worker-level effects of increased imports from China display great heterogeneity across types of job. Finally, we find that increased imports from China exert additional pressure on workers through spillovers to employment and wages in downstream industries.

The third and last chapter is single-authored. I focus on the short-term impact of exposure to trade and real exchange rate shocks on wages for Swiss manufacturing workers over the period 1996-2008. Particular effort is made to consistently estimate the causal effect of trade and exchange rate shocks on wages in using a gravity-type estimation strategy as a first-stage step to construct instrumental variables. The findings show that industry exposure to trade and exchange rate shocks influences wages of manufacturing workers of various groups differently. The trade and exchange rate impacts are concentrated among high-skilled and blue-collar workers almost exclusively. Additional evidence revealed that exchange rate effects are potentially heterogeneous across industries with different market structures. Wages of workers employed in industries that predominantly produce homogeneous goods are shown to be more responsive to exchange rates movements than those working in industries that predominantly produce differentiated varieties.

The three chapters follow.

Chapter 1

Intra-Industry Trade Expansion and Labor Reallocation: Theory and Evidence*

MARIUS BRÜLHART AND ARNAUD JOYE

We study the relation between intra-industry trade (IIT) and associated worker flows, taking the latter as an indicator of labor-market adjustment costs. Our paper proposes two main innovations. First, we generate dynamic IIT in a general-equilibrium trade model featuring heterogeneous firms, and we relate these trade patterns to intra- and inter-industry job reallocations. Second, we test the relationship between IIT and worker flows in panel data and using an instrumental-variable strategy to account for the potential endogeneity of IIT. Our instruments are based on industry-specific real exchange rate indices. Both the theoretical and empirical analyses are consistent with the "smooth adjustment hypothesis", according to which IIT expansion is less disruptive than inter-industry trade expansion. A pure intra-industry trade shock is found to generate less than half as much between-industry worker reallocation than a pure inter-industry trade shock.

JEL Classification: F1, J62, C25
Keywords: intra-industry trade, trade adjustment, job turnover, heterogeneous firms

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1.1 Introduction

Intra-industry trade (IIT) has long interested economists not just because of its incompatibility with neoclassical trade theory but also because of its perceived benign nature. Balassa (1966, p.472) famously conjectured that, in view of rising shares of IIT, “the difficulties of adjustment to freer trade have been generally overestimated”. A sizable empirical literature has since defined precisely and tested empirically what has become known as the “smooth adjustment hypothesis” (SAH). This literature has generally lent support to Balassa’s conjecture, and it is therefore not surprising that IIT indices remain popular first-pass proxies for the adjustment effects of trade expansion.[1]

The SAH is intuitively compelling but remains rather short of rigorous support. There has been considerable discussion on the appropriate measurement of IIT, converging on the conclusion that in the context of trade-related adjustment, measures of “marginal ”IIT (MIIT) are to be preferred to the standard Grubel and Lloyd (1975) index. However, much of this literature has been based on informal reasoning and *ad hoc* empirical specifications.

The SAH has not yet been couched in a general-equilibrium trade model with pure trade shocks. The difficulty lies in finding a tractable setting that allows both trade flows and factor-market reallocations to be intra-industry and inter-industry to varying degrees, as an exogenous determinant of trade (such as transport costs) is changed.[2] Such a setting has been developed by Bernard, Redding, and Schott (2007), where a differentiated-goods-heterogeneous-firms model yielding intra-industry trade and adjustment is embedded in a comparative-advantage framework that generates inter-industry trade and adjustment. We show that this model lends itself to simulating inter-industry and intra-industry trade adjustment to a pure trade shock.

The link between IIT and labor-market adjustment has been investigated empirically in a number of prior studies.[3] None of these analyses considered the possibility that (M)IIT might be endogenous with respect to domestic labor-market conditions. We therefore seek to improve on the existing literature by instrumenting IIT. Moreover, we complement existing studies by drawing on data for Switzerland, which have not been analyzed in this context to date.

Our paper is organized as follows. In Section 1.2, we present the theory and our simulations of the SAH in general equilibrium. Section 1.3 presents our data, our empirical model and the estimation results. Section 1.4 concludes.

[1]For recent policy-related work using IIT as a proxy for non-disruptive trade expansion, see e.g. World Bank (2009), WTO-UNCTAD (2012), or Subramanian and Kessler (2013).

[2]Lovely and Nelson (2000) have shown that, in general equilibrium, MIIT can be associated with inter-industry reallocation of factors if productivity is also allowed to change.

[3]See e.g. Brülhart (2000), Brülhart, Elliott, and Lindley (2006) or Cabral and Silva (2006).

1.2 Theory

1.2.1 Trade and job reallocation in a heterogeneous-firms model

We couch our analysis in the trade model of Bernard, Redding, and Schott (2007) (henceforth BRS). BRS extended the Melitz (2003) framework by adding comparative advantage *à la* Heckscher-Ohlin to firm heterogeneity in general equilibrium.

Assume two countries (Home and Foreign), two differentiated industries (industry 1 producing varieties of good 1 and industry 2 producing varieties of good 2), and two factors of production (skilled and unskilled labor, S and L). Good 1 is assumed to be relatively skill intensive, and Home is assumed to be relatively skill abundant.

Consumer preferences are identical and homothetic, with Cobb-Douglas upper-tier utility across the two goods, and lower-tier utility taking the CES form over a continuum of horizontally differentiated varieties. The Cobb-Douglas industry expenditure shares are denoted α_i. Production technology is assumed to be identical in the two countries, with firms facing fixed costs and constant marginal costs that depend on firm productivity. Technology is homothetic, as fixed and variable costs are assumed to use the two types of labor with the same intensity.

An industry i consists of a continuum of competitive firms. Their sunk entry cost f_{ei} takes the form:

$$f_{ie}(\omega_S)^{\beta_i}(\omega_L)^{1-\beta_i},\ f_{ei} > 0,$$

where ω_S and ω_L stand for skilled and unskilled wage respectively, and β_i represents the skilled labor intensity of sector i. At the time of decision, prospective entrants face uncertainty about their productivity $\varphi \in (0, \infty)$. Once the entry cost is borne, firms draw their productivity level from a common distribution function $g(\varphi)$, assumed to be Pareto with shape parameter $a > 0$. This productivity remains unchanged over the lifetime of the firm. In each period, firms face an exogenous probability of death, δ.

In order to produce its differentiated variety of good i, the firm faces recurrent fixed and variable production costs that share the factor intensities of f_{ei}. The fixed production cost, f_i, is identical across firms, while the variable cost is proportional to productivity φ. The presence of these production costs prevents some firms from producing profitably and leads them to exit the industry immediately after entry. Exporting entails additional fixed and variable costs, denoted by f_{ix} and $\tau_i > 1$ respectively, and sharing the factor intensities of the entry and production costs. Variable exporting costs take the standard iceberg form, meaning that a fraction $\tau_i - 1$ unit of a variety "melts" in transit. Again depending on the productivity draws, some firms within each industry will choose optimally not to export as they could not generate sufficient revenue to cover the fixed costs of exporting.

With profit maximization under monopolistic competition, both domestic and export prices, $p_{id}(\varphi)$ and $p_{ix}(\varphi)$ respectively, depend on firm-specific productivity:

$$p_{ix}(\varphi) = \tau_i p_{id}(\varphi) = \frac{\tau_i (\omega_S)^{\beta_i} (\omega_L)^{1-\beta_i}}{\rho\varphi},$$

where $0 < \rho < 1$ captures the substitutability of varieties within an industry. Given this pricing rule for each firm, equilibrium revenue in the export market, $r_{ix}(\varphi)$, is also proportional to that in the domestic one, $r_{id}(\varphi)$. Relative industry price indices and relative country endowments have an impact on firm revenues such that the latter is different across countries and sectors. Firm profits across the two markets are also proportional and can be separately identified since no firm is ever engaged in exporting without selling on the domestic market. These profits are given by:

$$\pi_{id}(\varphi) = \frac{r_{id}(\varphi)}{\rho} - f_i (\omega_S)^{\beta_i} (\omega_L)^{1-\beta_i},$$

$$\pi_{ix}(\varphi) = \frac{r_{ix}(\varphi)}{\rho} - f_{ix} (\omega_S)^{\beta_i} (\omega_L)^{1-\beta_i},$$

where $\sigma = 1/(1-\rho) > 1$ is the elasticity of substitution. The zero-profit productivity cut-off ${\varphi_i}^*$, below which firms will not embark on production is industry-specific and given by:

$$r_{id}(\varphi_i^*) = \sigma f_i (\omega_S)^{\beta_i} (\omega_L)^{1-\beta_i}.$$

Analogously, firms with draws above the exporting productivity cut-off, ${\varphi_{ix}}^*$, will serve both markets:

$$r_{ix}(\varphi_{ix}^*) = \sigma f_{ix} (\omega_S)^{\beta_i} (\omega_L)^{1-\beta_i}.$$

In each period, a mass of firms, M_{ei}, enters the industry after having incurred the entry cost. A fraction $G(\varphi_i^*)$ draws a productivity level below the zero-profit productivity cut-off, φ_i^* and leaves the industry right away. A fraction $G(\varphi_{ix}^*) - G(\varphi_i^*)$ produces for the domestic market only, and the remaining fraction $1 - G(\varphi_{ix}^*)$ also engage in exporting.

Goods and labor markets need to clear in both countries. The steady-state equilibrium is characterized by a stable mass of entering firms, M_{ei}, and a stable mass of active firms within the industry, M_i. As in Melitz (2003), the mass of entering firms that are productive enough to survive must equal the mass of firms that exogenously dies.

Trade shocks have heterogeneous effects across firms. A fall in variable trade costs, τ_i, for instance, raises the *ex-post* export profits. This will lead to increased firm entry and, hence, more competition within the industry (due to a larger mass of active firms and higher prices for the factor used abundantly) driving least efficient domestic firms' *ex-post* profits down, forcing some of them to exit. This leads to a rise in average aggregate productivity (at industry-levels) and zero-profit productivity cut-off, φ_i^*, below which companies drop out of the industry. Higher export profits at exporters also reduce the exporting productivity threshold, φ_{ix}^*.

Importantly for our analysis, the magnitude of these changes differs across sectors. A fall in trade costs will imply a larger increase in labor demand in the comparative advantage industry than in the comparative disadvantage industry, putting upward pressure on the relative price of the abundant factor. Therefore, the zero-profit productivity cut-off increases by more in the comparative advantage industry and lies closer to the export productivity threshold than in the comparative disadvantage sector.

In sum, this framework not only generates intra- as well as inter-industry trade flows, it also predicts trade liberalization to produce simultaneous job creation and job destruction in all industries, where gross and net job reallocations vary with country and industry characteristics.

1.2.2 Job reallocation within and between industries

The BRS model features between-firm job flows even at steady state through the exogenous firm death rate δ. Our main interest, however, is on job reallocations induced by changes in trade openness, i.e. on transitional dynamics between steady states. Specifically, we study between-industry, within-industry and total job reallocations as trade becomes freer. For each factor-industry pair, we can decompose the change in employment following a fall in variable trade costs into five parts:

(1) the change in employment by firms that enter but do not take up production,

(2) the change in employment by non-exporters that exit the industry after trade liberalization,

(3) the change in employment by non-exporters that survive trade liberalization and remain non-exporters,

(4) the change in employment by non-exporters that turn into exporters after trade liberalization,

(5) the change in employment by surviving exporters.

With those five components in hand, we compute total (TT_{it}), between-industry (BT_{it}) and within-industry (WT_{it}) job reallocations for each industry i and time period t as follows:

$$TT_{it} = |(1)_{it}| + |(2)_{it}| + |(3)_{it}| + |(4)_{it}| + |(5)_{it}|\,,$$

$$BT_{it} = (1)_{it} + (2)_{it} + (3)_{it} + (4)_{it} + (5)_{it},$$

$$WT_{it} = TT_{it} - |BT_{it}|\,.$$

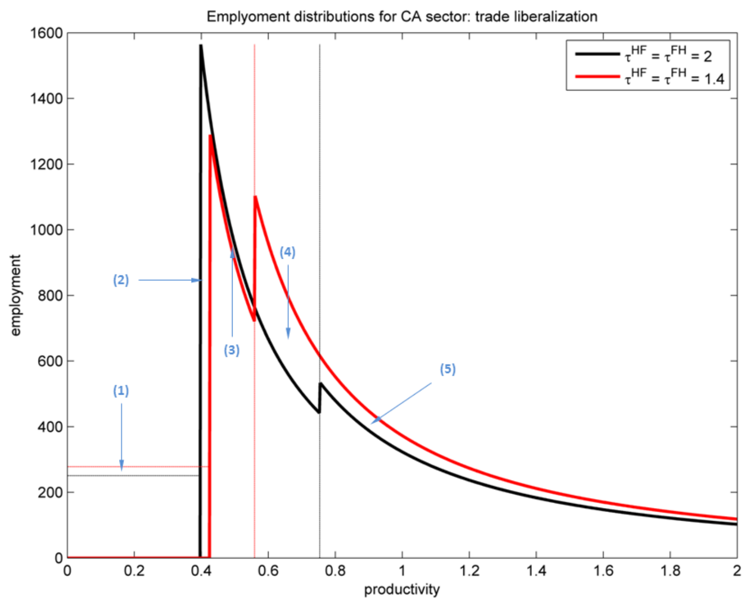
These variables allow us to compute the share of between-industry job reallocation in total job reallocation, BS_{it}, our proxy for labor-market adjustment costs. That is:

$$BS_{it} = \frac{|BT_{it}|}{WT_{it} + |BT_{it}|} = \frac{|BT_{it}|}{TT_{it}} \in (0, 1). \tag{1.1}$$

When $BS_{it} \to 0$, the cost associated with workers changing firms can be assumed to be low, since most between-firm moves occur within a given industry. Alternatively, when $BS_{it} \to 1$, the cost associated with job reallocations will be high, because most displaced workers have to change not only their employer firm but also their industry. We thus rely on the theoretically well grounded and empirically supported assumption that job moves between industries are more costly on average than moves within an industry.[4]

The construction of BS_{it} is best explained graphically, by illustrating a typical simulated transition scenario in the BRS model. Figure 1.1 shows employment densities with high trade costs ($\tau^{HF} = \tau^{FH} = 2$) and for low trade costs ($\tau^{HF} = \tau^{FH} = 1.4$) in the comparative advantage industry at the benchmark equilibrium.[5]

Figure 1.1: Simulated employment effects of trade liberalization in the comparative advantage industry



Notes: Employment distributions for the comparative advantage industry: low trade costs versus high trade costs.
Source: Own simulations based on the model of Bernard, Redding, and Schott (2007).

[4]See e.g. Neal (1995), Couch and Placzek (2010), and, for a comprehensive survey, Carrington and Fallick (2015).

[5]The parameter vector used to simulate the benchmark equilibrium is given in Appendix Table A.1. In Appendix Figure A.1, we trace the corresponding employment distributions for the comparative disadvantage industry.

The five components of employment adjustment distinguished above can be identified in these graphs. It is easy to see that this model implies within-industry as well as between-industry job reallocations. In both industries, jobs are lost in firms that exit because greater trade exposure raises the zero-profit productivity threshold (area (2)) and compresses sales of surviving non-exporting firms (area (3)), but at the same time jobs are gained in firms that switch from being non-exporters to being exporters (area (4)). In other words, jobs are reallocated within industries from low-productivity domestically-oriented firms to higher-productivity export-oriented firms. The other two adjustment components are positive for the comparative advantage industry and negative for the comparative disadvantage industry, thus representing between-industry employment reallocation: after trade liberalization, the comparative advantage industry attracts more entry (area (1)), and its continuing exporters increase their sales and thus employment (area (5)).

1.2.3 Trade shocks, IIT and job reallocation

In the simulations shown above, we model trade shocks as symmetric falls in iceberg-type variable trade costs, to represent bilateral trade liberalization. However, other trade shocks can be considered. For instance the variable cost of exporting (denoted τ^{HF} from Home's perspective) could change differently from the variable cost of importing (τ^{FH}), akin to currency appreciation or depreciation. Alternatively, variable trade costs could remain unchanged but fixed exporting costs (f_{ix}) could change; or features of the foreign economy could evolve at unchanged trade costs.

We now explore the relationship between IIT and the share of between-industry job reallocation for different trade-shock scenarios. Our measure of job reallocation, BS_{it}, is as defined in (1.1). As the relevant measure of IIT, we use the index of "marginal IIT":

$$MIIT_{it} = 1 - \frac{|\Delta X_{it} - \Delta M_{it}|}{|\Delta X_{it}| + |\Delta M_{it}|},$$

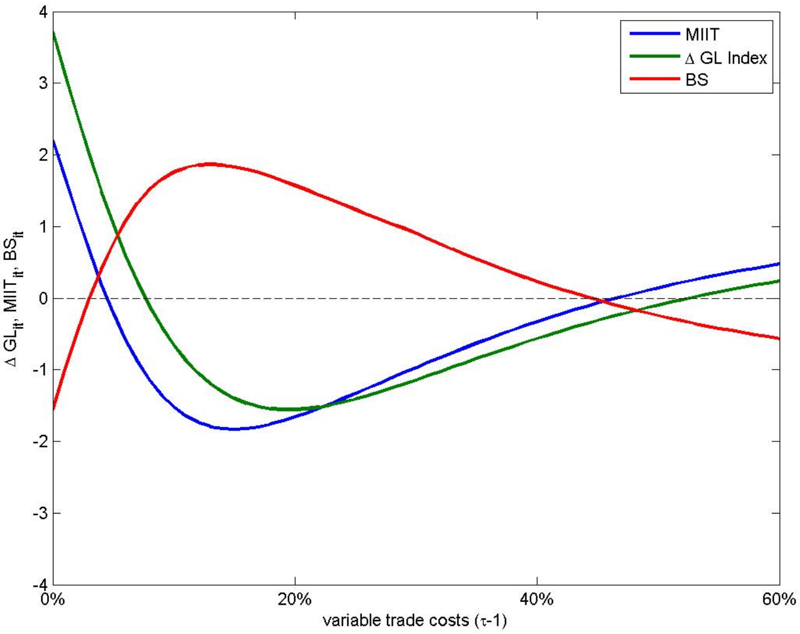
where Δ stands for the difference between year t and $t-1$. This index takes values between zero and one, and it is increasing in the degree of overlap between simultaneous changes in imports and exports.

Given its frequent use in applied studies, and despite the shortcomings of that measure in capturing adjustments pattern (Brülhart, 1994), we also consider changes in the Grubel and Lloyd (1975) index of IIT:

$$\Delta GL_{it} = GL_{it} - GL_{i,t-1}, \quad \text{where } GL_{it} = 1 - \frac{|X_{it} - M_{it}|}{(X_{it} + M_{it})}.$$

We illustrate the relationship between IIT and job reallocation in scatter plots tracing IIT and job reallocation across a range of parameter values. In a first step, we can extend the exercise of Figure 1.1, where we trace employment distributions for one particular change in trade costs, to consider a large number of such changes. Figure 1.2 illustrates the evolution of equilibrium IIT measures and BS_{it} as the variable trade cost $\tau^{HF} = \tau^{FH}$ is lowered in percentage-point steps from 1.6 to 1.0. The graph illustrates that the IIT measures and the share of between-industry job flows co-move with opposite signs for most of the interval, consistent with the SAH. However, the minimum value of ΔGL lies noticeably to the right of the maximum value of BS_{it}, showing that there is an interval of trade costs within which stronger rises in the GL index are associated with greater shares of between-industry job flows - in contradiction with the SAH.

Figure 1.2: IIT, job flows and trade costs

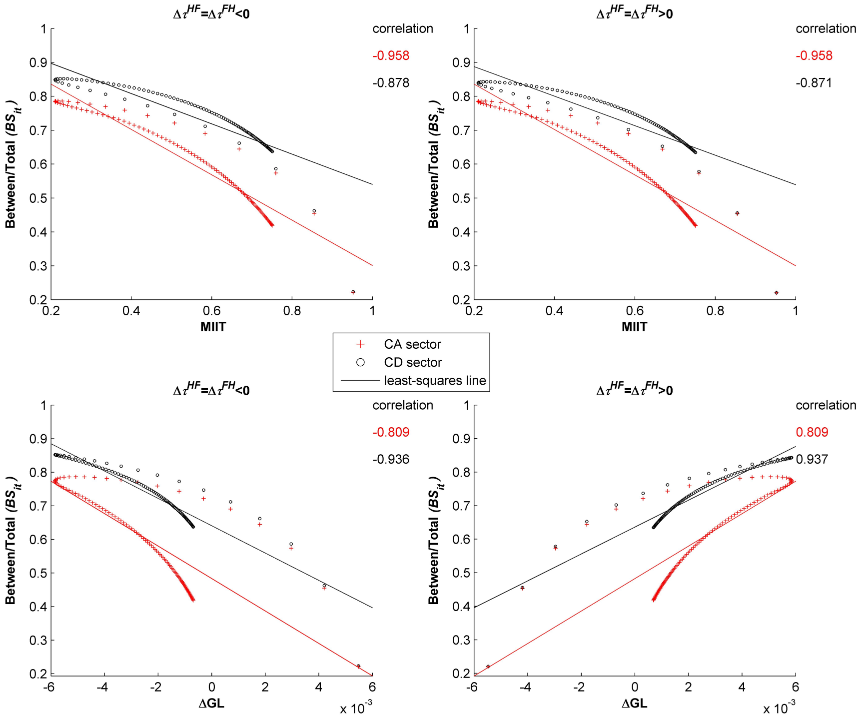


Notes: Comparative advantage industry; baseline parameter values; smoothed equilibrium series in 1 percentage-point steps.
Source: Own simulations based on the model of Bernard, Redding, and Schott (2007).

Next, we repeat the exercise that underlies Figure 1.2 but we plot MIIT against BS_{it}. In the two left-hand-side panels of Figure 1.3, we simulate a symmetric and linear reduction in variable trade costs from a 100 percent *ad valorem* equivalent ($\tau^{HF} = \tau^{FH} = 2$) to zero ($\tau^{HF} = \tau^{FH} = 1$). The relationship between the two IIT measures and BS_{it} is monotonically negative, consistent with the SAH. On the right-hand-side of Figure 1.3, we simulate the reverse scenario, i.e. a move from free trade to very costly trade. In this case, the negative relationship between MIIT and BS_{it} is unchanged, whereas for ΔGL it turns positive, thus illustrating the unstable relationship between the latter measure and the pattern of labor-market adjustment.

Changes in trade costs can be unilateral, e.g. through exchange-rate fluctua-

Figure 1.3: IIT and job reallocation when trade costs change symmetrically



Source: Own simulations based on the model of Bernard, Redding, and Schott (2007).

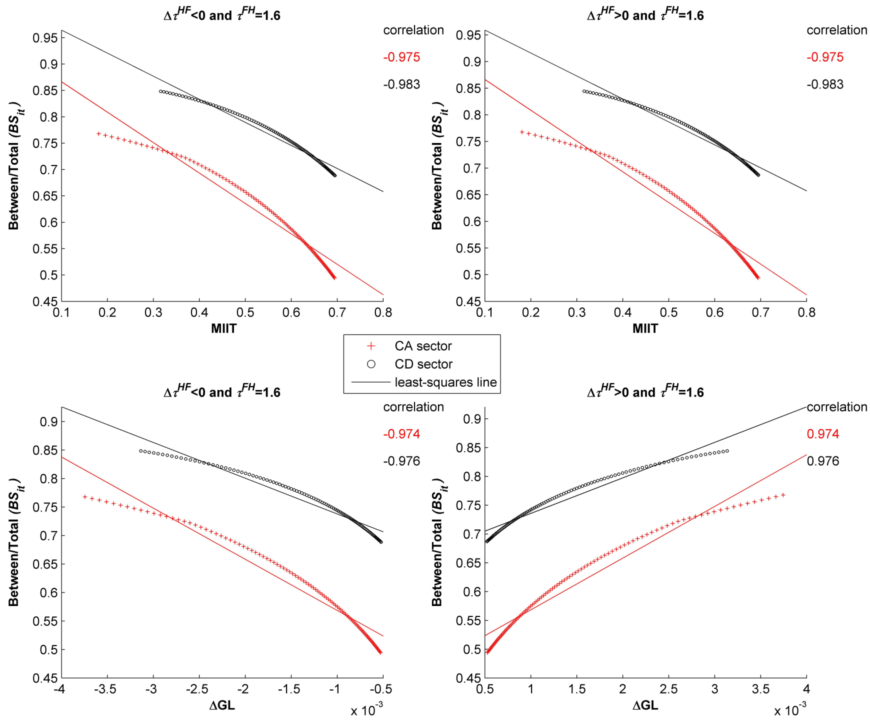
tions. We simulate such asymmetric trade shocks in Figure 1.4, where we let τ^{HF} change in constant steps from 2 to 1 (left-hand panels) and from 1 to 2 (right-hand panels) while τ^{FH} remains at 1.6. This could be thought of as representing a devaluation or revaluation of Home's currency, respectively. The same qualitative result is found here as for symmetric changes in trade costs: MIIT and BS_{it} covary in opposite directions, as posited by the SAH. For ΔGL, however, the sign of the correlation depends on the sign of the change in trade costs.[6]

We consider as a "trade shock" also a change in exogenous parameters affecting Home's trade partner while trade costs remain constant. Three representative cases are illustrated in Figure 1.5: we track trade and labor-market changes following an increase in the size of Foreign N^F (from 1,300 to 3,700, left-hand panels), following an increase in the homogeneity of firm productivity draws in Foreign a^F (from 3.4 to 4.4), and following a decrease in minimum *ex ante* firm productivity k^F (from 0.9 to 0.2). In all three cases we again detect clear negative correlations between MIIT and BS_{it} but no systematic relationship between ΔGL and BS_{it}.[7]

[6]Qualitatively equivalent patterns are found for symmetric and asymmetric variations in fixed exporting costs.

[7]We have also simulated changes in factor intensities affecting only Foreign and found analogous results.

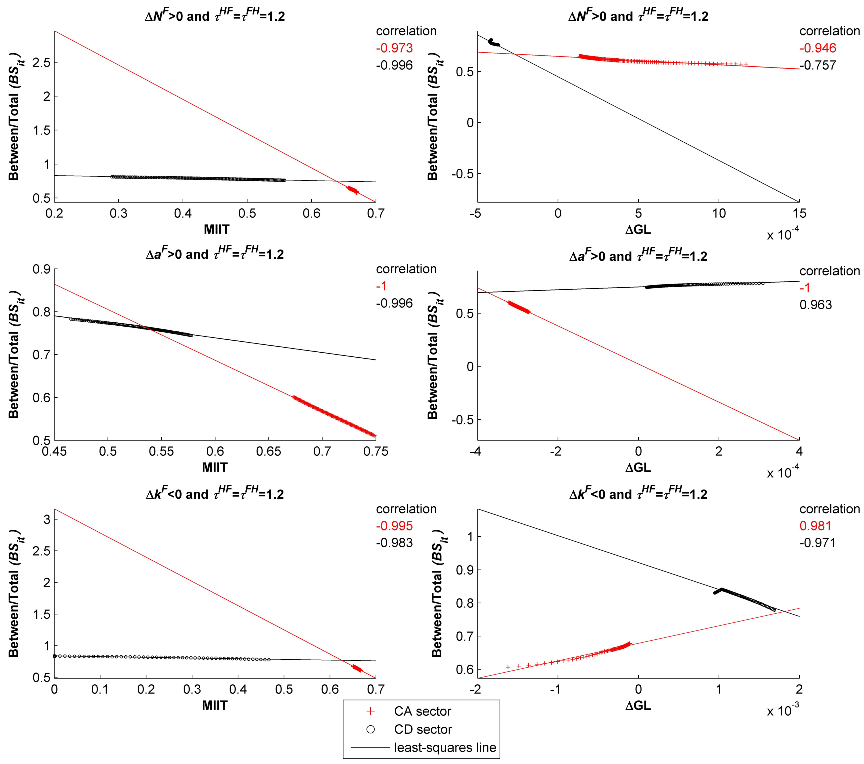
Figure 1.4: IIT and job reallocation when trade costs change asymmetrically



Source: Own simulations based on the model of Bernard, Redding, and Schott (2007).

Figures 1.3 to 1.5 are indicative of a robust negative relationship between MIIT and BS_{it} irrespective of the trade shock considered, as posited by the SAH. However, these simulations show that there are exceptions. The top-left panel of Figure 1.3, for instance, shows a small segment over which the relationship between MIIT and BS_{it} is positive. It is therefore possible in the BRS framework that the SAH does not hold. To determine the likelihood of this possibility, we have run comprehensive simulations across the full range of parameter combinations that are compatible with equilibrium. Specifically, we track symmetric decreases in the variable trade cost, letting τ go from 1.6 to 1 in steps of 0.01. We conduct this exercise for 1,192 combinations of the nine other exogenous parameters in the model (see Table A.1 for details). Given that we have two industries, this leaves us with 2,384 equilibrium paths analogous to those illustrated in Figures 1.3 to 1.5. Across these simulations, we find that *all* correlations between MIIT and BS_{it} are negative, with an average value of -0.97. Some three percent of correlations with ΔGL, however, are positive, for an average value of -0.77. When we do the reverse exercise, letting trade costs rise from free trade to 60 percent *ad valorem*, the same correlations are found between MIIT and BS_{it}, whereas the sign of the correlations with ΔGL in fact turns out to be positive on average. These simulations strongly suggest that the relationship between MIIT and the share of inter-industry job reallocation, while not universally negative, is predominantly negative. No such generalization is possible with respect to ΔGL.

Figure 1.5: IIT and job reallocation when the foreign economy changes



Source: Own simulations based on the model of Bernard, Redding, and Schott (2007).

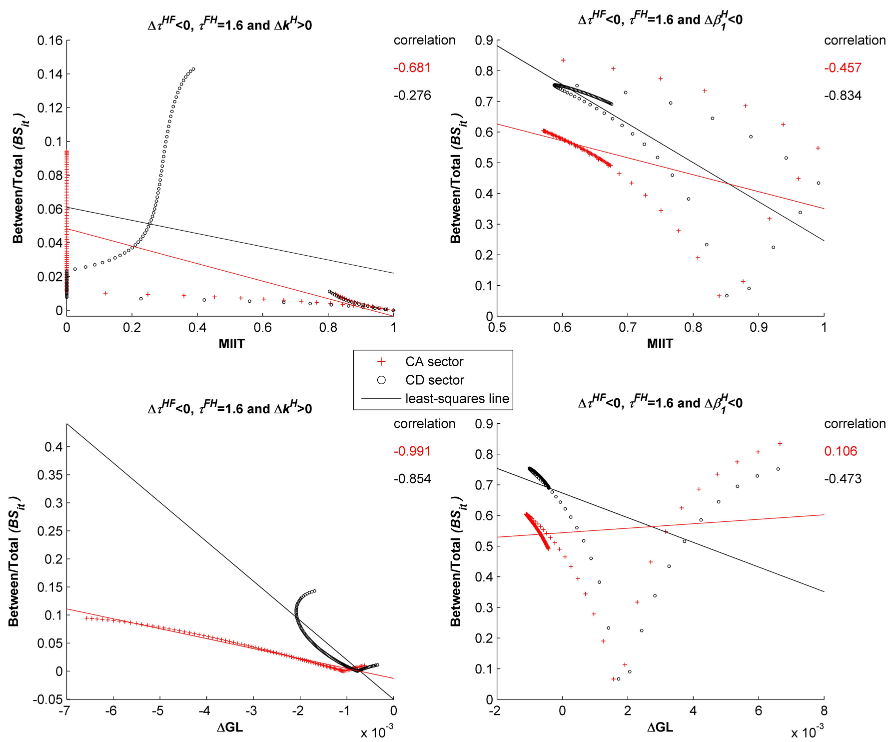
1.2.4 Trade and technology shocks combined

In the real economy, exogenous trade shocks likely coincide with endogenous changes in domestic production and consumption that in turn affect trade patterns and job reallocations. This could affect the observed link between IIT and labor-market adjustment. For that reason, we run some additional simulations in which we model simultaneous shocks to trade costs and to parameters of the Home production function.

Two representative scenarios are illustrated in Figure 1.6. In the left-hand-side panel, we lower τ^{HF} in constant steps from 2 to 1 (as in Figure 1.4), and we simultaneously increase Home's minimum *ex ante* firm productivity (k^H) from 0.2 to 1.2. In the right-hand-side panel, we again gradually lower τ^{HF}, and we simultaneously reduce β_1^H, the share Home's abundant factor in its production function (from 0.96 to 0.51, while β_2^H increases from 0.04 to 0.49). In both cases it becomes clearly apparent that these combinations of domestic and trade-related changes blur the relationship between MIIT and BS_{it}, making it highly nonlinear and non-monotonic. These graphs are indicative of a general pattern we find in our wide-ranging simulations: as soon as we consider trade shocks jointly with domestic technology shocks, the strong relationship between MIIT and BS_{it} found when considering trade shocks alone disappears.

This result is of course not surprising: while the causal effect of MIIT (as a manifestation of an exogenous trade shock) on labor reallocation is overwhelmingly negative as stated by the SAH, simultaneously allowing for other forces to affect labor reallocation and trade flows will weaken the empirical correlation. To uncover the causal effect of MIIT on labor reallocation, MIIT therefore ought to be instrumented with variables representing exogenous trade shocks. This is what we endeavor to achieve in our empirical section.

Figure 1.6: IIT and job reallocation when trade costs and domestic technology change



Source: Own simulations based on the model of Bernard, Redding, and Schott (2007).

1.3 Empirical test

1.3.1 Estimation

We now seek to explore the relationship between IIT and job reallocation empirically. Our best hope of finding such effects is by looking at a highly trade-oriented economy. By working with data for Switzerland, whose trade-to-GDP ratio averaged 84.3% over our sample period 1991-2008, we have what should be a propitious setting.

Like many prior studies, we regress our measure of inter-industry job reallocation, BS_{it}, on an appropriate measure of IIT, the interaction of IIT with sectoral trade openness, and a number of controls. Given that the theory implies no specific functional forms, and our simulations suggest linear approximations to work well, we focus on linear additive regression models.

Specifically, we consider the following baseline panel model:

$$\begin{aligned} BS_{it} = \beta_0 + \beta_1 IIT_{it} + \beta_2 IIT_{it} \times |\Delta STO|_{it} + \beta_3 |\Delta STO|_{it} \\ + \mathbf{\Psi}'_{it}\lambda_{it} + \eta_i + \nu_t + \varepsilon_{it} \end{aligned} \quad (1.2)$$

where

$$\mathbf{\Psi}'_{it} = [|\Delta AD|_{it} \quad FIRM_{it-1} \quad EMPLOY_{it-1}] \,.$$

IIT_{it} is defined as the Brülhart (1994) MIIT index, but we shall also explore the implications of using ΔGL instead. $|\Delta STO|_{it}$ is the absolute change in sectoral trade openness between $t-1$ and t, where $STO_{it} = \frac{X_{it}+M_{it}}{GVA_{it}}$, and GVA_{it} is gross value added. For the main effect of IIT, β_1, to be interpretable as the effect of IIT on an industry with average trade openness, $|\Delta STO|_{it}$ is centered around its industry mean. In order to control for domestic inter-industry demand shocks, we include the variable $|\Delta AD|_{it}$, the absolute change in sectoral apparent demand between $t-1$ and t, where $AD_{it} = GVA_{it} + X_{it} - M_{it}$ (in CHF bn at constant prices). $FIRM_{i,t-1}$ and $EMPLOY_{i,t-1}$ denote the number of firms and workers respectively (in thousands). Finally, η_i and ν_t are industry and year fixed effects, respectively, purging our regressions from the effects of all time-invariant and industry-invariant unobservables. As an alternative to including industry fixed effects, we systematically also estimate the model in first differences.

One issue that has not been addressed in the existing empirical literature is the potential endogeneity of IIT. As our simulations show, unobserved shocks affecting both IIT and job reallocations might confound the causal effect of IIT.

We therefore propose to instrument for IIT in the following way. Building on Goldberg (2004), we construct industry-level trade-weighted real exchange rates for Switzerland:

$$trer_t^i = \sum_c \omega_{t-1}^{ic} \times rer_t^c,$$

where

$$\omega_{t-1}^{ic} = \frac{M_{t-1}^{ic} + X_{t-1}^{ic}}{\sum_c (M_{t-1}^{ic} + +X_{t-1}^{ic})},$$

and rer_t^c is the Swiss-franc real exchange rate with respect to the currency of country c in year t.[8] As an instrument for IIT, we take the absolute change in $trer_t^i$, $\left|\Delta trer_t^i\right|$. This variable is expected to be inversely related to IIT, as exchange-rate-induced idiosyncratic changes in industry-level price competitiveness are likely associated with inter-industry adjustments in sales and thus employment. Since the effects on domestic employment of exchange rate fluctuations will be fully mediated by changes in trade flows and apparent demand, the exclusion restriction plausibly holds. Moreover, since $\left|\Delta trer_t^i\right|$ depends on lagged country-level changes in exchange rates and trade shares, we can safely rule out reverse causation from the industry-level variable IIT.

1.3.2 Data

We construct our dependent variable BS_{it} using individual-level data from the Swiss Labor Force Survey, available annually from 1991 to 2008. This is a rotating panel with participants interviewed in five consecutive years, allowing us to observe between-industry and within-industry inter-firm moves which, in turn, are used to construct the labor adjustment cost variable according to definition (1.1).

The finest level of sectoral disaggregation we can attain consistently over the sample period in the Labor Force Survey data is the NACE Rev. 1.0 four-digit level. We concord those data from NACE Rev. 1.0 to ISIC Rev. 3 in order to merge them with the trade data. Bilateral trade data are taken from the UN COMTRADE database at the 5-digit SITC level, which we concord to corresponding ISIC sectors.[9] After concording, we are left with 108 manufacturing industries. As a robustness check, we also estimate our models at the three-digit level of the ISIC classification, featuring 54 manufacturing industries. We have 29,940 individual observations in manufacturing firms and for which we can identify whether or not a move has taken place, yielding 17 individual-level observations per four-digit industry and year.

To compute changes in sectoral trade openness ($|\Delta STO|_{it}$) and apparent demand ($|\Delta AD|_{it}$), we use sectoral gross value added data from the Swiss Federal Statistical Office. Because these data are available at the NACE two-digit level only, we use disaggregate census-based total employment to apportion value added to four-digit industries. Firm numbers ($FIRM_{i,t-1}$) are also available from the Federal Statistical Office's multi-annual census.[10]

Bilateral nominal exchange rates, needed to construct industry-specific exchange rates as an instrument for IIT ($\left|\Delta trer_t^i\right|$), were extracted from the website oanda.com. Summary statistics for all variables are reported in Table 1.1.

[8] We consider Switzerland's 30 largest trade partners: Australia, Austria, Belgium-Luxembourg, Brazil, Canada, China, Hong Kong, Czech Republic, Denmark, Finland, France, Germany, Hungary, India, Ireland, Israel, Italy, Japan, Netherlands, Poland, Republic of Korea, Russia, Saudi Arabia, Singapore, Spain, Sweden, Thailand, Turkey, USA and UK.

[9] Trade flows are measured in constant CHF (base year 2005), using the Swiss CPI deflator.

[10] In our sample period, a firm census was conducted in 1995, 2001, 2005 and 2008. We complete the missing years through linear interpolation.

Table 1.1: Descriptive statistics: ISIC rev. 3, four-digit

	Pooled and Fixed-Effects Samples				*First-Difference Sample*			
	mean	sd	min	max	mean	sd	min	max
Adjustment Cost: (BS_{it})	0.908	0.226	0	1	0.899	0.220	0	1
$MIIT$	0.442	0.339	0	0.999	0.457	0.331	0	0.999
$MIIT \times \|\Delta STO\|$	0.020	0.489	-2.866	8.990	0.004	0.314	-2.866	2.786
ΔGL	0.000	0.055	-0.345	0.573	-0.001	0.049	-0.322	0.250
$\Delta GL \times \|\Delta STO\|$	0.007	0.233	-0.630	7.240	-0.002	0.042	-0.630	0.372
$\|\Delta STO\|$	0.002	0.792	-3.461	12.646	-0.008	0.538	-3.461	4.914
$\|\Delta AD\|$	0.137	0.286	0.000	5.227	0.154	0.315	0.000	5.227
Firms	495.8	848.9	10	6,117	597.6	953.7	14	6,117
Employment	8,973.5	8221.6	25	47,458	10,775.7	8592.8	288	47,458
$\|\Delta TWRER\|$	0.059	0.130	0.000	0.931	0.031	0.048	0.000	0.662
$\|\Delta TWRER\| \times \|\Delta STO\|$	-0.004	0.154	-1.953	3.440	0.002	0.052	-0.428	0.803
$\|\Delta TWRER2\|$	0.058	0.129	0.000	1.013	0.030	0.047	0.000	0.552
$\|\Delta TWRER2\| \times \|\Delta STO\|$	-0.003	0.147	-1.957	3.181	0.003	0.055	-0.400	0.858
Observations	1,002				693			

Source: Own calculations based on merged COMTRADE-SLFS database.

1.3.3 Results

Our baseline fixed-effects and first-difference IV estimation results are shown in Table 1.2. They support the empirical relevance of the SAH. The effect of MIIT on between-industry labor reallocation is consistently and statistically significantly negative. This effect is more pronounced in sector-years subject to stronger trade shocks as measured by $|\Delta STO|_{it}$. The coefficients are remarkably stable across the eight specifications. The estimated coefficient on MIIT is around -0.55. This suggests that compared to a pure inter-industry trade shock (MIIT=0), a pure intra-industry trade shock (MIIT=1) will reduce the share of between-industry job flows by fully 55 percentage points. Or, put differently, a one-standard-deviation increase in MIIT will lower the share of between-industry job flows by 0.83 standard deviations.[11]

Our instruments perform well overall. First-stage F statistics according to Angrist and Pischke (2009), while on the low side for the fixed-effects model, are satisfactory in the first-differenced specification. Stock-Wright LM statistics for the significance of the endogenous regressors are satisfactory throughout, suggesting that MIIT is indeed a relevant structural variable. Perhaps most reassuringly, the first-stage regressions confirm that our instrument behaves in the expected way: exchange-rate variability is consistently negatively related to MIIT, and in most cases statistically significantly so (see Appendix Table A.3). The estimated coefficients on our measure of domestic demand shocks, $|\Delta AD|_{it}$, are negative throughout, in line with our prior.

In Table 1.3, we show a range of alternatives to our baseline specification. In the first two columns, we report the main fixed-effects and first-difference estimates from Table 1.2, for comparison.

One potential issue are different sample sizes for our dependent variable across industries: BS_{it} is computed over small numbers of observations for some sectors. We have therefore explored a range of different weighting schemes.[12] It turns out that our results are robust to re-weighting. As a representative example, we show results based on weighting industries by their total trade in columns (3) and (4) of Table 1.3. These estimates are larger in absolute terms and more precisely measured than our baseline results, which is not surprising given the fact that the variance of the disturbance term is likely to be smaller in larger (and thus better measured) industries.

Next, we explore the sensitivity of our baseline results to changing industry definitions. In columns (5) and (6) of Table 1.3, we report estimates based on our baseline regression specifications applied to three-digit industries. These estimates are somewhat noisier than the four-digit results, but the coefficients all have the same signs and similar magnitudes.

[11] See Table 1.1 for the standard deviations needed to make these calculations.

[12] We have weighted industries by the number of years for which the dependent variable is observed; by their time-averaged shares in total employment and firm numbers; and by their time-averaged shares in total imports, exports and total trade. Detailed results are available on request.

Table 1.2: Adjustment costs and MIIT (IV estimates, 2^{nd} stage)

	Fixed-effects models				First-difference models			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$MIIT$	-0.650	-0.563*	-0.563*	-0.521*	-0.663**	-0.583**	-0.550*	-0.465*
	(0.414)	(0.341)	(0.340)	(0.299)	(0.331)	(0.264)	(0.326)	(0.267)
$MIIT \times \lvert\Delta STO\rvert$			-0.175	-0.171			-0.256***	-0.277**
			(0.193)	(0.184)			(0.095)	(0.109)
$\lvert\Delta STO\rvert$		0.032	0.105	0.109		0.055**	0.157***	0.179**
		(0.019)	(0.091)	(0.092)		(0.028)	(0.057)	(0.070)
$\lvert\Delta AD\rvert$		-0.136		-0.144		-0.175*		-0.145
		(0.105)		(0.108)		(0.095)		(0.100)
Firms		0.003		0.006		-0.151		0.045
		(0.210)		(0.206)		(0.434)		(0.423)
Employment		-0.001		-0.001		-0.007		-0.010
		(0.009)		(0.009)		(0.014)		(0.014)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	No	No	No	No
N	994	994	994	994	693	693	693	693
No. industries	100	100	100	100	84	84	84	84
First-Stage Statistics								
K-P LM test (p.val.)	0.091	0.055	0.082	0.052	0.051	0.033	0.049	0.029
SW LM S test (p.val.)	0.046	0.046	0.138	0.135	0.059	0.049	0.075	0.074
AP F test $MIIT$	2.989	3.810	3.894	4.660	6.895	8.946	6.987	10.878
AP F test interaction			1.945	1.992			18.884	18.854

Notes: The dependent variable is BS_{it}, the share of between-industry job reallocation in total job reallocation. All regressions include year fixed effects and a constant term (not reported). Robust standard errors reported in parentheses are clustered at the four-digit industry level. *Firms* and *Employment* are lagged one year in all regressions. *K-P LM test* is the Kleibergen-Paap underidentification LM test. *SW LM S test* is the Stock-Wright LM S statistic for weak-instrument robust inference. *AP F test* is the Angrist-Pischke first-stage F statistic for weak identification of individual endogenous regressors. * p<0.10, ** p<0.05, *** p<0.01.
Source: Own estimations based on merged COMTRADE-SLFS database.

In columns (9) to (12) of Table 1.3, we provide estimates corresponding to our baseline specifications but without instrumenting the MIIT variable. These results turn out to be qualitatively equivalent to our IV estimates, but the estimated magnitudes are considerably smaller. This is consistent with our theoretical simulations that suggest confounding domestic effects to potentially bias the observed relationship between MIIT and labor-market adjustment towards zero.

In columns (13) and (14), we present estimates with an alternative dependent variable. Instead of the share of between-industry job reallocation in total job reallocation, BS_{it} as defined in (1.1), we use the share of between-industry job reallocation in total job (thus including movers *and* stayers), ABS_{it}. That is:

$$ABS_{it} = \frac{|BT_{it}|}{WT_{it} + |BT_{it}| + STAY_{it}} = \frac{|BT_{it}|}{TT_{it} + STAY_{it}} \in (0, 1).^{13} \qquad (1.3)$$

[13] See Appendix Table A.2 for descriptive statistics of estimation samples when using ABS_{it}.

Table 1.3: Adjustment costs and IIT (various IV and OLS estimates)

	IV								OLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	FE	FD	FE	FD	FE	FD	FE	FD	FE	FD	FE	FD	FE	FD
$MIIT$	-0.521*	-0.465*	-0.628**	-0.590**	-1.14	-0.758			-0.066***	-0.082***	-0.049*	-0.063**	-0.021**	-0.01
	(0.299)	(0.267)	(0.249)	(0.297)	(0.699)	(0.545)			(0.025)	(0.029)	(0.026)	(0.030)	(0.010)	(0.015)
$MIIT \times \lvert\Delta STO\rvert$	-0.171	-0.277**	-0.347	-0.479**	-0.140	-0.248**			-0.003	-0.031	-0.023	-0.032*	-0.018	-0.002
	(0.184)	(0.109)	(0.329)	(0.232)	(0.237)	(0.114)			(0.016)	(0.024)	(0.019)	(0.018)	(0.029)	(0.021)
ΔGL							-2.280	-6.830						
							(2.299)	(7.579)						
$\Delta GL \times \lvert\Delta STO\rvert$							0.015	-0.340						
							(1.113)	(1.881)						
$\lvert\Delta STO\rvert$	0.109	0.179**	0.184	0.245**	0.117	0.181**	0.006	-0.020	0.012	0.037	0.024	0.029	0.017	0.002
	(0.092)	(0.070)	(0.130)	(0.117)	(0.121)	(0.077)	(0.008)	(0.065)	(0.012)	(0.029)	(0.016)	(0.020)	(0.017)	(0.012)
$\lvert\Delta AD\rvert$	-0.144	-0.145	-0.153**	-0.130*	-0.250	-0.177	0.029	0.045	0.011	-0.012	-0.010	-0.011	-0.003	-0.009
	(0.108)	(0.100)	(0.060)	(0.079)	(0.180)	(0.136)	(0.050)	(0.128)	(0.026)	(0.022)	(0.012)	(0.009)	(0.005)	(0.005)
Dependent variable	BS	BS	BS	BS	BS	BS	BS	BS	BS	BS	BS	BS	ABS	ABS
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
N	994	693	994	693	616	481	994	693	1002	693	1002	693	1628	1470
No. industries	100	84	100	84	53	45	100	84	108	84	108	84	112	108
Level of disaggregation	4D	4D	4D	4D	3D	3D	4D	4D	4D	4D	4D	4D	4D	4D
Weights	None	None	Trade share	Trade share	None	None	None	None	None	None	Trade share	Trade share	Trade share	Trade share
First-Stage Statistics														
K-P LM test	0.052	0.029	0.024	0.027	0.079	0.110	0.112	0.326						
SW LM S test	0.135	0.074	0.088	0.102	0.053	0.046	0.135	0.074						
AP F-test $MIIT$	4.660	10.878	9.302	8.719	2.711	4.132	2.199	1.273						
AP F-test interaction	1.992	18.854	1.623	22.053	1.407	9.277	2.950	3.096						

Notes: BS_{it} is the share of between-industry job reallocation in total job reallocation. ABS_{it} is the share of between-industry job movers in all observed workers. All regressions include year fixed effects and a constant term (not reported). Robust standard errors reported in parentheses are clustered at the four-digit industry level (three-digit in columns 5 and 6). Column 1 is the same as column 4 of Table 3. Column 2 is the same as column 8 of Table 3. * p<0.10, ** p<0.05, *** p<0.01.
Source: Own estimations based on merged COMTRADE-SLFS database.

While the effect of MIIT not surprisingly appears less distinctly with this alternative dependent variable that incorporates the large number of stayers, it is still apparent even in this specification.

Finally, we return to the baseline regression specification but replace the MIIT index by the change in the GL index, ΔGL_{it}. These estimates are shown in columns (7) and (8) of Table 1.3. The estimated coefficients are statistically insignificant and do not have stable sign. These results confirm that Grubel-Lloyd based measures are not helpful for inferring the adjustment implications of trade expansion.

One issue left unexplored in Table 1.3 is timing. Our baseline estimates are predicated on one-year intervals are the relevant time horizon over which to measure trade and labor-market adjustments, but theory is silent as to the appropriate timing. We have therefore experimented widely with different interval lengths and lag structures and found the strong and robust effects observed for year-on-year changes to weaken considerably with any departure from that dynamic structure. As an example, we present results computed over two-year intervals in Appendix Table A.4. No statistically significant findings emerge at two-year horizons, even though the IV estimates retain their signs and approximate magnitudes. Our estimates therefore confirm previous research suggesting that the link between MIIT and labor-market adjustment primarily applies to annual frequencies.

1.4 Conclusion

We have studied the relation between intra-industry trade (IIT) and associated worker flows, taking the latter as an indicator of labor-market adjustment costs, proposing two main innovations. First, we have generated dynamic IIT (MIIT) in a general-equilibrium trade model featuring heterogeneous firms, and related these trade patterns to intra- and inter-industry job reallocations. Second, we have tested the relationship between IIT and worker flows in panel data for Switzerland, using an instrumental-variable strategy to account for the potential endogeneity of MIIT. Our instruments are based on industry-specific real exchange rate indices. Both the theoretical and empirical analyses are consistent with the "smooth adjustment hypothesis", according to which IIT expansion is less disruptive than inter-industry trade expansion. Although there are specific theoretical cases in which higher MIIT is associated with a higher share of between-industry job flows, our simulations suggest an overwhelming dominance of the reverse relationship. In our empirical estimations, a pure intra-industry trade shock is found to generate less than half as much between-industry worker reallocation than a pure inter-industry trade shock. Our analysis confirms that in the context of adjustment, measures of MIIT are more informative than Grubel-Lloyd indices.

Chapter 2

Net Imports, Gross Imports and Individual Workers: Evidence from the United Kingdom

MARIUS BRÜLHART, ARNAUD JOYE AND JOANNE LINDLEY

We explore the worker-level impact of increased import penetration in UK manufacturing industries over the period 1997-2011. Our approach borrows the identification strategy of a corresponding analysis for the US by Autor, Dorn, Hanson, and Song (2014), which we extend in five directions: (i) our data permits us to decompose total earnings into hours of work and hourly pay; (ii) we look at net as well as gross imports, thus separately examining the effects of increased intra-industry trade; (iii) we focus on import penetration from EU countries in addition to China; (iv) we estimate worker-level outcomes separately by occupations; and (v) we look at the indirect impact of import competition on worker-level outcomes along the value chain. We find that gross and net import penetration from China had significantly negative effects on workers' earnings, wages and hours of work in the affected industries. In contrast, increased gross imports from the EU are associated with positive worker-level outcomes. We also find that the adverse worker-level effects of increased imports from China are most pronounced among managers and skilled trades and least pronounced among professionals, clerical staff and plant operators. Finally, we find that increased imports from China in an industry located further down the value chain (i.e. a *downstream* industry) have adverse worker-level effects in the sourcing (i.e. a *upstream*) industry.

JEL Classification: F16, J23, J31, J62
Keywords: gross imports, net imports, labor demand, wages, earnings

2.1 Introduction

Traditionally, the empirical evidence for detrimental wage effects from international trade has been sparse, with only a modest increase in the skilled-unskilled wage gap being found as a consequence of foreign outsourcing (Feenstra and Hanson, 1999). Skill biased technical change, on the other hand, has been shown to have a bigger impact on the US wage and earnings inequalities (Katz and Autor, 1999). So even though trade theory identifies that free trade with countries at any income level may affect individual worker outcomes such as domestic wages, earnings and employment evidence suggests that imports from developing economies were generally too small to have any major impact on US employment or wage inequality, especially during the period of rapid inequality growth that occurred during the 1980s and 1990s (Krugman, 2000).

More recently however, the growing importance of low-wage countries in the global economy has put new pressure on high-wage countries (e.g. Freeman, 1995; Feenstra, 2010), and this has provided a unique opportunity to examine the impact of international trade on worker adjustment. Most of the recent growth in global manufacturing output has come from China, as a consequence of its transition to a market-oriented economy. Indeed, Hanson (2012) reports that since 1990 China has accounted for more than 75% of the growth in manufacturing value added engendered by low- and middle-income economies. Moreover, China has dramatically improved its share of world manufacturing exports which has rapidly increased from around 2% in 1990 to 16% in 2011 (Autor et al., 2014).

Until now, most of the recent research looking for detrimental employment and earnings effects in developed countries that might have occurred from increased imports from China has been undertaken for the US. This is mainly as a consequence of its trade imbalances with developing countries, like China, and the rise in the share of total US spending on low-income countries' goods (see for example Bernard, Jensen, and Schott, 2006; Autor, Dorn, and Hanson, 2013a).[1] However, the spectacular Chinese export boom is expected to hit workers in the United Kingdom (henceforth UK) in a somewhat similarly disruptive way.

Of course the UK already has close trade ties with the European Union (henceforth the EU) which might also be expected to have had a sizable impact on its labor market. Trade theory predicts that trade with countries at any income level my affect domestic workers, yet the impact will depend on *where* imports originate (Bernard, Jensen, and Schott, 2006). Consequently, it is important to make the distinction between gross and net imports (or whether bilateral trade patterns are mainly in the form of *inter-* or *intra-*industry trade) in order to fully understand trade competition and its impact on medium- to long-run workers' career paths. The recent availability of new micro-level data, especially administrative data, enables researchers to better investigate the causal effect of enhanced trade

[1] According to Autor et al. (2014), the share of US total spending on Chinese goods rose from 0.6% in 1991 to 4.6% in 2007.

competition on labor market outcomes at the individual level.

In this paper, we analyze the effect of exposure to increasing trade integration on UK manufacturing workers' wages, employment and earnings. We focus on trade integration, mainly in the form of increased import competition from China (i.e. low-income countries) but also from (more similar countries like) the EU. We use the econometric approach of Autor et al. (2014) by using, as a measure of trade exposure, the growth in UK imports from China, or the EU, over the period 1997 to 2011 that took place in a worker's initial industry. Using individual-worker level panel data from the UK New Earnings Survey Panel Dataset (NESPD) we can analyze the medium- to long-run consequences of exposure to import competition on earnings, employment spells, hourly pay and hours worked of UK manufacturing workers.

We add five dimensions to the approach of Autor et al. (2014). First, our data permit us to decompose total earnings into hours of work and hourly pay, hence allowing us to assess the relative contributions of each part in the adjustment process to trade shocks. Second, we look at net as well as gross import competition, thus separately examining the effects of increased intra-industry trade. Third, we contrast the impact of imports coming from China to those coming from the EU. We would expect a different impact on worker outcomes whether import competition stem from China or the EU. Fourth, unlike Autor et al. (2014) we are able to control for the worker's occupation and evaluate import competition effects within occupation groups. One would expect workers employed in low-skill intensive occupations to exhibit declining earnings profiles as a consequence of trade compared to other workers within the same occupation; and not just workers relative to all workers across all occupations, which could be a consequence of skill biased technical change instead of pure trade effects. Indeed, within occupation groups, workers employed in industries that face higher subsequent exposure to import competition, say from China, would be expected to exhibit a worse earnings trajectory.[2] Finally, we also look at the indirect impact of import competition on worker-level outcomes along the value chain.[3] We are interested in capturing the effects of import competition, not only on workers within the affected industries, but also on workers in neighbouring downstream or upstream industries; effects that could be transmitted through the demand for or supply of intermediate inputs.

Regarding UK trade exposure with China, we find that, on average, workers more exposed to import competition see a fall in cumulative earnings, a drop in cumulative wages and cumulative hours of work over the sample period from 1997 to 2011. The implied differential decrease in earnings over the 15-year sample period, between workers at the 75$^{\text{th}}$ percentile of industry trade exposure relative

[2]Unfortunately, we do not observe individual education attainment in the NESPD, so we cannot directly capture skills of workers at the initial period. However, as it will be clear, we control for occupation at the 2-digit level and for a bunch of (pre-shock) individual observable characteristics. Thus, even though we cannot observe worker skills, we argue that we do control (somehow indirectly) for skill/ability in the best way we can.

[3]We are greatly indebted to Olivier Cadot for suggesting this idea.

to workers at the 25^{th} percentile is 48% of initial annual earnings. The drop in wages is equal to 69.2% of initial total wages and the drop in hours worked is equal to 33.6% of total hours worked in the initial year. When considering changes in *net* imports, rather than changes in *gross* imports to account for the potential new export opportunities that China's economic opening might offer, the results imply a bigger negative impact on earnings, wages and employment relative to gross imports. This suggests that what really hurts UK manufacturing workers is the difference in nature of imports and exports.

The trade competition impact differs across occupation groups, which highlights great heterogeneity in trade adjustment by job characteristics. Occupations such as managers, skilled trade and elementary production are most adversely affected by the rise in Chinese imports. Somewhat unexpected, we find that the adverse effects of increased imports from China are most pronounced among managers and among production workers performing less routine tasks. Managers are the only occupation group that sees a drop in both margins of employment, whereas clerks and secretaries suffer in terms of hours worked and skilled trades and plant/machine operators' wages are negatively affected by the rise in Chinese import competition.

Not only are workers affected by increased exposure to Chinese imports within their own industry, they are also sensible to a rise in exposure to China's trade in the industry that purchases the highest value of intermediate inputs from theirs. From the perspective of a worker employed in a given industry, higher trade competition in an industry located further down the value chain has a significant and negative impact on her wages and employment. Indeed, higher *downstream* exposure to import competition results in an additional implied 75^{th}-25^{th} percentile drop of 46.9% of initial total wages and a drop of 24.8% of initial total hours worked for a worker employed in the sourcing industry.

Unlike China, increased imports from the EU are associated with positive earnings, wages and employment, a finding that is largely explained by the fact that increased imports from the EU were mostly offset by increased same-industry exports to the EU, and that the former might not substitute to UK domestic production, but rather complement them.

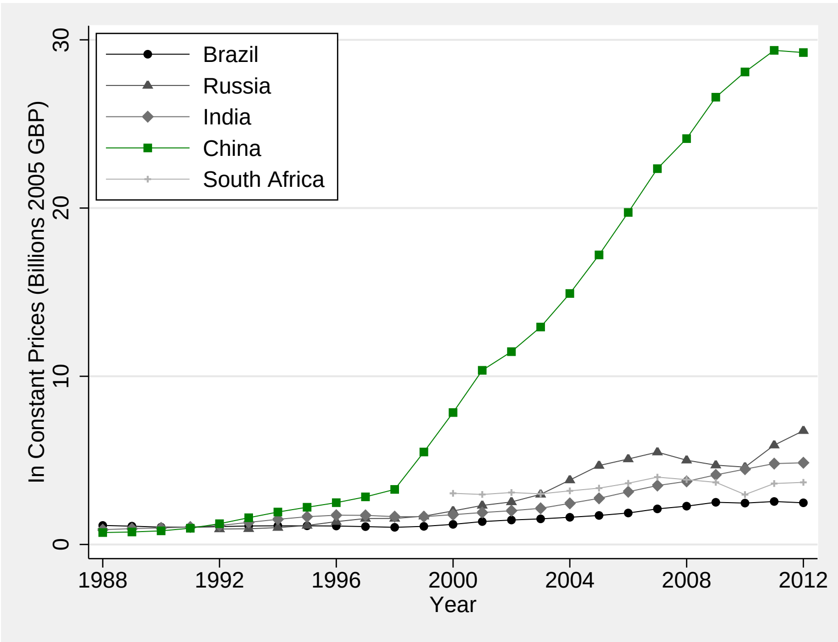
We begin in Section 3.5 by documenting some facts about UK bilateral trade patterns with China and with the EU. Section 2.3 then provides an overview of recent work, along with previous studies, analyzing trade shocks on labor markets. Section 2.4 describes our empirical methodology to estimating the impact of exposure to trade competition, and documents facts about UK industry exposure to imports from China and the EU. The data used and the main estimating equation are discussed in Section 2.5, while Section 2.6 and Section 2.7 present the core results for the labor market effects of increased exposure to import competition from China and the EU respectively. Section 3.7 concludes.

2.2 UK bilateral trade patterns

We begin in this section by providing descriptive evidence showing why China, among emerging economies, is UK's most interesting (and potentially disruptive) trading partner. We then document UK bilateral trade patterns with China and contrast them with those associated with the EU.

Figure 2.1, which shows UK import values from the 5 BRICS countries taken individually, carries two main facts. First, as evident in the figure, the growth rate of imports from China exhibits, by far, the biggest increase over time. Second, imports from China took off abruptly around 2001, when China joined the WTO, largely surpassing UK import values from other BRICS countries.

Figure 2.1: UK import values from individual BRICS countries, 1988-2012

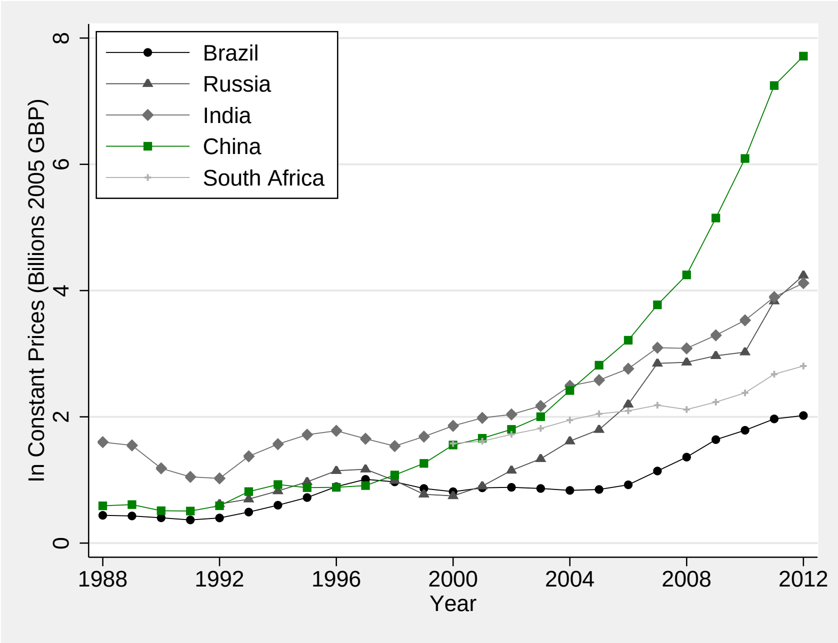


Source: Using data from UN Comtrade for total manufacturing industries.

Adding to the picture, we can see in Figure 2.2, which replicates Figure 2.1 but plotting export values instead of imports, that China has become (since 2004) the most important export destination for the UK among BRICS economies; even surpassing India. These two pictures highlight the growing importance of China as a major trading partner for the UK, both in terms of imports and exports.

Isolating UK trade patterns with China, Figure 2.3, which plot values of imports from and exports to China, illustrates the strong asymmetric evolution of both trade flows. The growth rate of UK imports from China is far bigger than the corresponding growth rate for exports signifying that Chinese imports may put a bigger pressure on UK workers than the potential beneficial effects of export opportunities in China. Moreover, the fact that imports took off around 2001, when

Figure 2.2: UK export values from individual BRICS countries, 1988-2012



Source: Using data from UN Comtrade for total manufacturing industries.

China joined the WTO, suggests (along with the first fact) that the Chinese export boom may be mainly driven by a combination of its internal-fostered transition to a market-oriented economy and of trade tariff reductions following WTO accession (something we cannot distinguish from this figure).

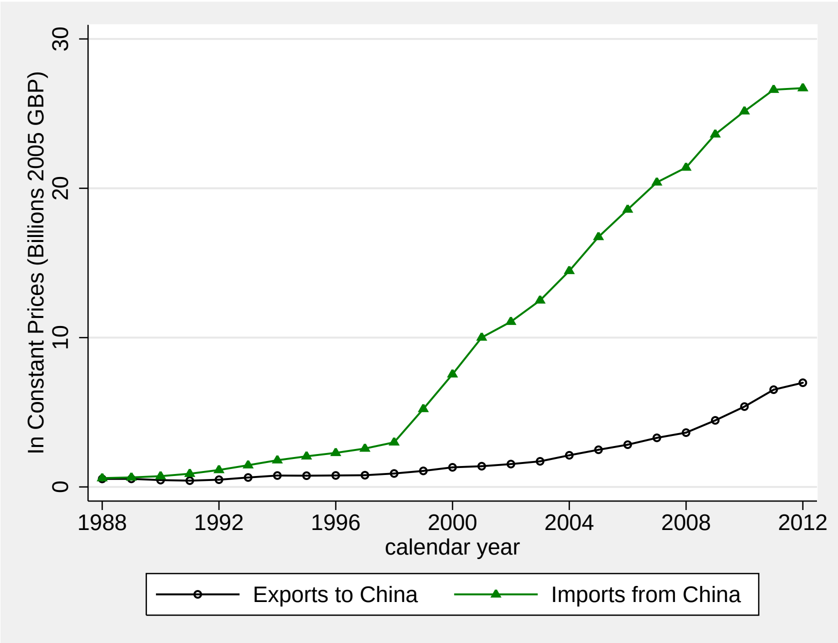
From the perspective of the UK, the rise of China in the world economy is expected to have similar qualitative impact on its domestic workers than in the US. Indeed, bilateral trade relationships with China appear to be qualitatively similar in both countries. (Figures B.2 in the Appendix, which displays similar trends for both trade flow types for the US.). Note the magnitude differences between the UK and the US of both trade flow types roughly correspond to the US/UK population ratio (around 5).[4] Thus, as in the US, we can think of UK industries having been confronted to a major rise in import competition from China without a counterbalancing rise in demand for UK exports.[5]

Concerning the UK trade relationship with the EU, we can see in Figure 2.4

[4]When looking in proportion rather than in volumes, we reach the same observations; the growth rate of the share of UK imports from China, relative to UK total imports, increases much more rapidly than the corresponding one for export share, with an inflexion point around 2001 (see Figure B.1 in the Appendix), and that is qualitatively similar for the US (see Figure B.3).

[5]Adding to the picture, we can observe the same declining path in the share of UK working age population employed in manufacturing industries as in the US, which negative trend accelerated in the late-1990s and continued through the 2000s. Indeed, Figure B.11 in the Appendix shows that the share of UK employment in manufacturing has fallen from 19% in 1994 to 10% in 2011.

Figure 2.3: Trade between the UK and China, 1988-2012



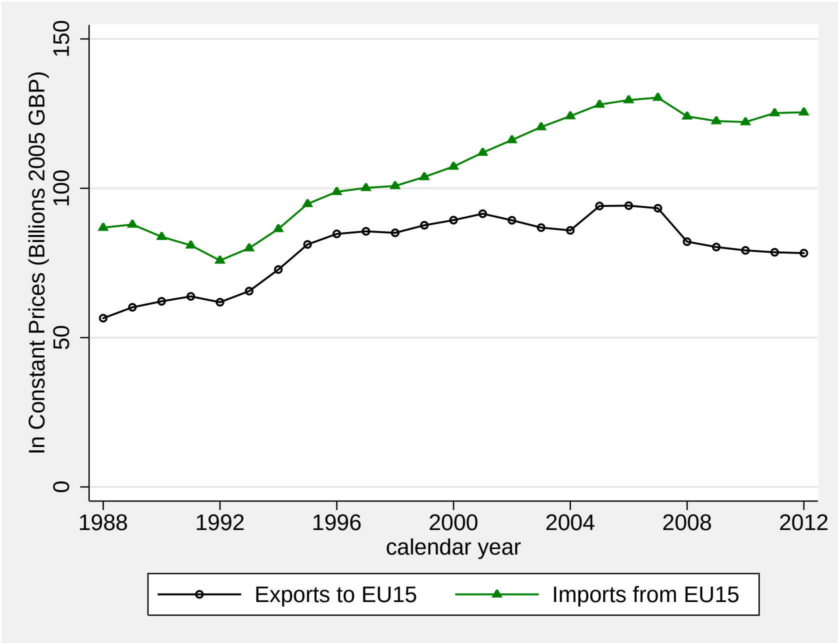
Source: Using data from UN Comtrade for 166 consistently defined manufacturing industries.

that imports from and exports to the EU have increased over time with much similar growth rates than the corresponding ones with China.[6] We can see that trade with the EU happens to be more balanced and of a different nature than with China, which will matter for its impact on the labor market (more on this in Section 2.7).[7] This is where the distinction between gross and net imports (or whether bilateral trade patterns are mainly in the form of *inter-* or *intra-*industry trade) becomes crucial in understanding the trade competition impact on workers' career paths. Indeed, we can reasonably think that imports from the EU might not be as detrimental to workers as imports originating from China, because of potential complementaries between imports coming from the EU and the UK domestic production structure.

[6]Our definition of the European Union comprises the first 15 countries that entered the union before 2004 less the UK. The countries are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain and Sweden.

[7]As with China, UK bilateral trade patterns, in volumes, with the EU are qualitatively similar than those of the US with the EU (Figure B.5 in the Appendix). Moreover, UK (and US) exports and imports shares with the EU are closely match as well but slightly declining over time (see Figure B.4 for the UK and Figure B.6 for the US in the Appendix). Note that the proportion of imports coming from the EU and exports going to the EU is 2 to 3 times bigger for the UK than for the US highlighting the relative importance of the EU as a key trading partner for the UK.

Figure 2.4: Trade between the UK and the EU, 1988-2012



Source: Using data from UN Comtrade for 166 consistently defined manufacturing industries. UK is omitted from the EU.

2.3 Literature background

Mainly because of its trade imbalances with developing countries and the rise in the share of total US spending on low-income countries' goods, the focus has been primarily set on the US and on the adverse effect of increased import competition from low-income countries on workers' employment and earnings. Low-income countries export growth in 1990 onwards is mainly due to China's transition to a market-oriented economy. The main events that made China more open include a massive rural-to-urban migration of more than 150 million workers (see Chen, Jin, and Yue, 2010); the access of domestic industries to previously banned foreign technologies, capital goods and intermediate inputs (see Hsieh and Klenow, 2009); the permission for multinational firms to operate in China (see Naughton, 2007, which is a great source of information about China and its transition to a market-oriented economy); and its accession the WTO in 2001.[8]

This has led to a number of papers investigating the impact of increased imports from China on labor markets. As already discussed, Autor et al. (2014) is the most similar to ours since they use individual worker data to look at the impact of increased exposure to import competition from China on cumulative earnings

[8]For additional sources on China and its transition to a market-oriented economy, see for example Hanson (2012), Feenstra and Wei (2010), Harrison, McLaren, and McMillan (2010), Hsieh and Ossa (2011), and Brandt, Van Biesbroeck, and Zhang (2012).

and employment of US workers over the period 1992-2007. They use individual-level administrative data in manufacturing industries. Their findings suggest that workers who initially were employed in manufacturing industries which experienced high subsequent import growth from China cumulate lower earnings; are at bigger risk of exiting the labor force and obtaining public disability benefits; spend less time employed for their initial employers; spend less time in their initial industry; and spend more time employed elsewhere in manufacturing and outside manufacturing. Moreover, earnings losses are greater for workers with low initial wages; low initial tenure; low attachment to the labor force; and for those employed at larger firms with lower than industry-average wage levels. Trade competition in terms of exposure to import competition also induces substantial job churning among high-wage workers, yet they are better able than low-wage workers to move across employers with minimal earnings losses, and they are less likely to leave their initial employer during a mass layoff.

Dauth, Findeisen, and Südekum (2014) explore the impact of rising trade between Germany and China (and Eastern Europe) on employment in German local labor markets over the period 1988 to 2008. They have a section discussing the impact of Chinese and Eastern European countries import and export competition on individual workers. They find that trade has a stabilizing effect on employment relationships (within regions, local industries and plants). Bloom, Draca, and Van Reenen (2011) examine the impact of firm exposure to Chinese import competition on patenting, IT, R&D and TFP using a panel of up to half a million firms over 1996-2007 across twelve European countries (Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK). The identification strategy they use is related to the one we use here in the sense that in one of their specifications they use initial industry exposure to Chinese imports as an instrument for subsequent Chinese import growth.

One further strand of the trade literature that looks at the impact of trade on wages takes a structural approach by estimating general equilibrium models. This literature generally assumes perfect labor mobility across industries. Accordingly, labor market adjustments after (trade) shocks are very rapid and thus changes in wages can be identified across (and not within) skill groups.[9] A more recent approach to this modelling moves away from perfect worker mobility by introducing search frictions, costly firm entry and exit, and industry-specific human capital. These works primarily explore the effect of trade liberalization on labor market dynamics and wage inequalities for developing countries.[10] Our analysis is closely related to this branch of the trade literature.

Another closely related strand of trade literature estimates the short- and medium-run impacts of trade exposure on wages, employment, firm dynamics, worker

[9]See for example Feenstra and Hanson (1999), Harrigan (2000) and Blum (2008) for the US, and Robertson (2004) for Mexico.

[10]See Helpman, Itskhoki, Muendler, and Redding (2012), Coşar (2013), and Dix-Carneiro (2011) which use Brazilian data, whereas Coşar, Guner, and Tybout (2011) uses data on Columbia. These works analyse firm dynamics and labor market responses after a certain type of trade liberalization.

turnover and inequality at different levels of aggregation.[11] Workers are assumed to face barriers to mobility across firms, occupations, industries or geographical regions. Thus, the labor market adjustments to trade shocks are not immediate implying costly transitory effects. However contrary to our study, this approach does not permit the observation of effects which prevail after the reallocation process has taken place.

2.4 Industry exposure to trade competition

2.4.1 Industry trade shocks

Following Autor et al. (2014), we use as a measure of trade exposure the change in the import penetration ratio for a UK industry *j* over the period 1997-2011, controlling for the industry pre-shock domestic absorption (or size of the industry *j* before the shock occurs). More specifically, we define the change in industry trade exposure as,

$$\Delta IP_{j,\tau} = \frac{\Delta M_{j,\tau}^{UK,C}}{Y_{j,96} + M_{j,96} - E_{j,96}}, \tag{2.1}$$

where $\Delta M_{j,\tau}^{UK,C}$ is the change in gross (net) imports between 1996 and 2011 from China or from the EU to the UK in industry *j*, whilst $Y_{j,96}$ is turnover, $M_{j,96}$ are imports and $E_{j,96}$ are exports for industry *j* in 1996. The denominator represents UK initial industry *j* absorption in 1996; that is before the shock occurs. The idea is to capture the growth in UK gross (net) imports from China or from the EU that is exclusively accounted by domestic supply shocks within the partner country or changes in its trade cost structure.

We are concerned about estimating the causal effect of trade exposure on UK workers' career paths. More precisely, we are interested in isolating and estimating the causal effect of internal domestic factors within the partner economy (China or the EU) that caused their exports to grow substantially. Our measure of industry trade exposure, as defined in (3.16), may be contaminated by domestic demand shocks to the UK economy that might influence import demand. Indeed, part of the observed changes in the import penetration ratio might be due to UK import demand shocks that have nothing to do with factors driving China's export growth or trade relationship patterns with the EU.

[11] Articles analyzing trade shocks (i) *at the plant level* include Bernard, Jensen, and Schott (2006) for the US, Verhoogen (2008) on Mexico, Amiti and Davis (2012) on Indonesia and Hummels, Jorgensen, Munch, and Xiang (2010) using Danish data; (ii) *at the industry level*, see Goldberg and Pavcnik (2003), Artuc, Chaudhuri, and McLaren (2010), McLaren and Hakobyan (2010), Ebenstein, Harrison, McMillan, and Phillips (2011), and Menezes-Filho and Muendler (2011); and (iii) *at the regional level*, see Autor, Dorn, and Hanson (2013a) who look at the impact of rising import competition from China on employment in US local labor markets. See also Chiquiar (2008), Kovak (2011, 2013) and Topalova (2005, 2010) analyzing primarily labor market consequences of trade reforms in developing countries. See Brülhart, Carrère, and Trionfetti (2012) who analyze regional wages and employment responses of trade liberalization in Austria following the fall of the Iron Curtain.

So, in order to capture internal supply shocks transmitted into UK imports on individual outcomes, we instrument $\Delta IP_{j,\tau}$ with:

$$\Delta IPO_{j,\tau} = \frac{\Delta M^{O,C}_{j,\tau}}{Y_{j,92} + M_{j,92} - E_{j,92}}, \tag{2.2}$$

where, $\Delta M^{O,C}_{j,\tau}$ is the change in gross (net) imports between 1996 and 2011 from China (the EU) to non-UK high income countries in industry *j*, controlling for the size of the UK industry in which the worker was working in 1992, four years prior to the base period in (3.16).[12] Consistent with the approach in Autor et al. (2014), we use 1992 instead of 1996 to account for the potential sorting of workers across industries in anticipation of future trade with China or with the EU.

The identification strategy relies on the idea that China's export growth and EU trade growth similarly affect other high income economies than the UK, provided that supply shocks come from within the partner country, and that domestic demand shocks are weakly correlated across high income countries. Therefore, constructing an industry measure of trade exposure in the UK by using the one of other high income countries identifies the supply-driven components of China's export growth and EU trade growth without any confounding effect of other shocks that simultaneously impact UK imports and workers' outcomes (for example shocks originating from other common trade partners that are not China, the EU, the non-UK high income economies or the non-UK OECD countries used in the instruments).

The quality of the identification strategy could be altered if three important conditions are not fulfilled. First the explanatory power of the instruments must be high enough in order to avoid a *weak instrument* problem (we present the first stage statistics in each table to show that this is not the case). Second, if product demand shocks are correlated across high-income economies, the IV estimates would be potentially correlated with unobserved components of product demand. If this is the case, our main estimators would tend to be biased toward zero and would not be exempt from domestic shocks. In other words, the effect of import exposure on earnings, employment and wages would be weaker than it truly is. Reassuringly for us, Autor et al. (2014) find that this does not consist of a serious threat (see their estimation based on a gravity-based model in their Table 11, p.1848).

The last and potentially the most serious threat to the identification strategy may come from technological shocks affecting all high-income economies. If import growth from China (the EU) is predominantly due to some global technological shocks that push employment away from labor-intensive industries (i.e. industries in which China has a strong comparative advantage) or from more capital-intensive industries (i.e. some industries in which the EU has a comparative advantage), then we would not be able to identify and isolate pure trade competition

[12] Non-UK high income countries to instrument for UK import penetration ratio from China are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland as in Autor et al. (2014). Non-UK OECD countries (Australia, Canada, Chile, Japan, Mexico, New Zealand, Republic of Korea, Switzerland and the US) are used to instrument for UK import penetration ratio from the EU.

effects. In our estimation, we will try to control for this by including a large set of initial-year industry and occupation characteristics. The novelty with respect to Autor et al. (2014) is that our data permit us to control for the worker's occupation which will help us to discriminate between pure trade competition effects and pure technological effects. Nonetheless, recent evidences suggest that advances in technology (e.g. automation) are not the main drivers of rising import competition from low-income countries, and furthermore suggest that it is import competition from China that enhances innovation in high-income countries rather than the converse as shown by Bloom, Draca, and Van Reenen (2011).

In addition to evaluating the direct impact of import competition on worker-level outcomes, we are also interested in examining the impact of import competition shocks that might be potentially transmitted through the purchase/sale of intermediate inputs from/to other domestic neighbouring industries. To take an example, imagine that industry *j* sells its largest share of intermediate inputs to domestic industry *k*; we call industry *k* the neighbouring downstream industry. From the perspective of a worker *i* employed in industry *j*, an increase in import penetration in industry *k*, *ceteris paribus*, might be potentially detrimental in terms of earnings, wages and employment. Indeed, if industry *k* is hit hard by import competition, then some firms in industry *k* might decrease their purchases of intermediate inputs from industry *j* because of lower revenues and, thus, might negatively affect workers in the neighbouring industry *j*. To identify such an effect, from the perspective of industry *j*, we define the change in the neighbouring *downstream* industry *k* trade exposure as,

$$\Delta IP^{down}_{jk,\tau} = \frac{\Delta M^{UK,C}_{jk,\tau}}{Y_{k,96} + M_{k,96} - E_{k,96}}, \tag{2.3}$$

where, from the perspective of industry *j*, $\Delta M^{UK,C}_{jk,\tau}$ is the change in imports between 1996 and 2011 from China to the *downstream* industry *k*, controlling for initial downstream industry *k* domestic absorption. The neighbouring downstream industry *k* is identified as the industry purchasing the largest value of intermediate inputs from industry *j*. Analogously, we can define the change in the neighbouring *upstream* industry *l* trade exposure as,

$$\Delta IP^{up}_{jl,\tau} = \frac{\Delta M^{UK,C}_{jl,\tau}}{Y_{l,96} + M_{l,96} - E_{l,96}}, \tag{2.4}$$

where, from the perspective of industry *j*, $\Delta M^{UK,C}_{jl,\tau}$ is the change in imports between 1996 and 2011 from China to the *upstream* industry *l*, controlling for initial *upstream* industry *l* domestic absorption. The neighbouring upstream industry *l* is identified as the one selling the largest value of intermediate inputs to industry *j*.

Our measures of indirect industry trade exposure, as defined in (2.3) and (2.4), may also be contaminated by domestic demand shocks to the UK economy for the exact same reasons than the measure of direct industry trade exposure, as defined in (3.16). Therefore, we employ an analogous type of instruments as in (3.18). More precisely, we instrument $IP^{down}_{jk,\tau}$ and $IP^{up}_{jl,\tau}$ with respectively,

$$\Delta IPO^{down}_{jk,\tau} = \frac{\Delta M^{O,C}_{jk,\tau}}{Y_{k,92} + M_{k,92} - E_{k,92}}, \tag{2.5}$$

and,

$$\Delta IPO^{up}_{jl,\tau} = \frac{\Delta M^{O,C}_{jl,\tau}}{Y_{l,92} + M_{l,92} - E_{l,92}}, \tag{2.6}$$

where, $\Delta M^{O,C}_{jk,\tau}$ and $\Delta M^{O,C}_{jl,\tau}$ are the change in imports between 1996 and 2011 from China to non-UK high income countries in the neighbouring downstream industry *k* and in the neighbouring upstream industry *l* respectively, controlling for the size of the downstream and upstream industry in 1992, four years prior to the base period in (3.16).[13]

2.4.2 The anatomy of gross imports from China

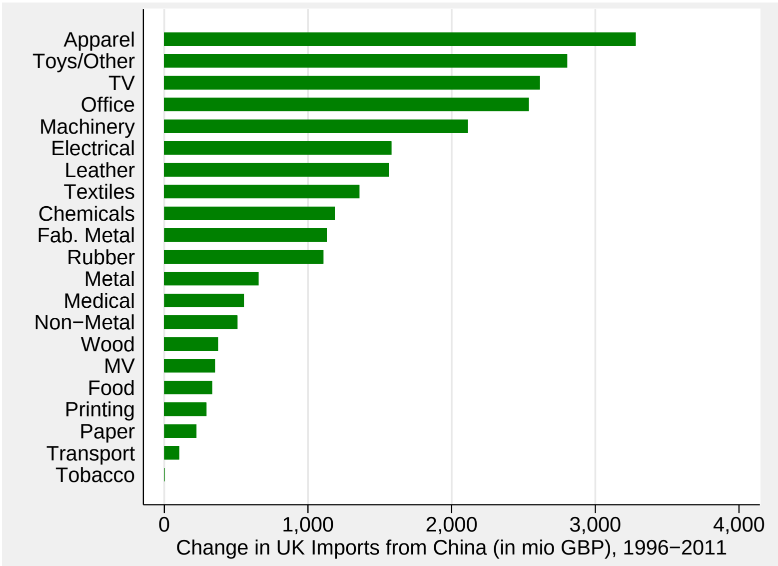
As first evidence of huge variations in UK industry gross import exposure from China, Figure 2.5 shows the change in UK gross import values, in constant (2005) millions of British pounds, from China over 1996 to 2011 for 21 broad manufacturing sectors. On the one hand, we can see that the biggest increases in imports are in sectors such as apparel (+£3280 million), toys and miscellaneous manufacturing (+£2803 million), TVs (+£2613 million), office machinery and computers (+£2536 million), electronics (+£2112 million), leather (+£1562 million) and textile (+£1357 million). These sectors are those that intensively use production workers (sectors in which China has a strong comparative advantage). On the other hand, in sectors such as tobacco (-£0.5 million), transport equipment (+£102 million), pulp, paper and paperboard (+£222 million), printing and publishing (+£292 million), and food (+£333 million) the increase in imports have been far more modest. Those sectors intensively use more natural resources or physical capital inputs.

Interestingly, we can see that the sectors that have exhibited high imports from China are very similar to those in the US (see Figure B.7 in the Appendix). Indeed, the cross-country correlation coefficient between industry changes in gross imports from China to the UK and from China to the US is 0.785 (p-value of 0.000).

To shed more light on the apparent relationship between UK industry import exposure from China and the share of production workers employed, we plot in Figure 2.6 on the horizontal axis the growth of industry import penetration from China from 1996 to 2011 and on the vertical axis the share of production workers in total industry employment in 1996. Each point on the graph represents a single (5-digit) industry, whereas each label corresponds to one of the corresponding 21

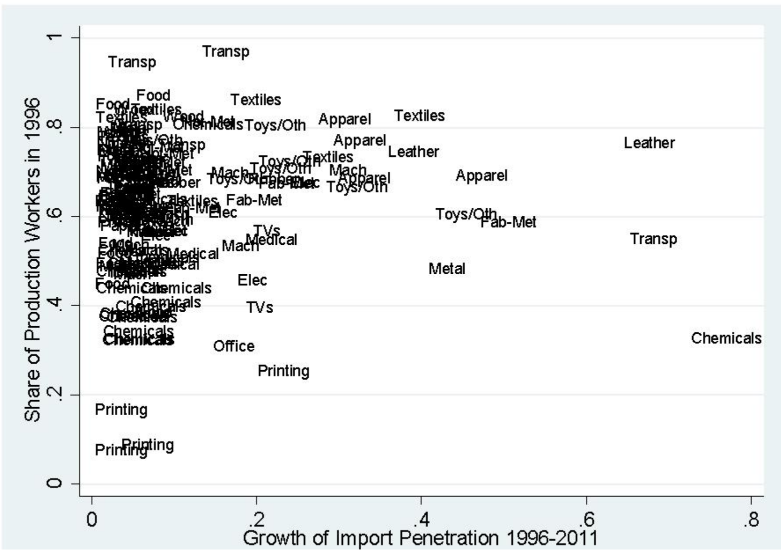
[13] We use the same non-UK high income countries as in (3.18) to instrument for UK indirect import penetration ratio from China.

Figure 2.5: The change in imports from China to the UK, 1996-2011



Source: Using data from UN Comtrade for 21 consistently defined manufacturing sub-sectors.

Figure 2.6: Growth in trade exposure from China and the share of UK production workers



Notes: For 166 consistently defined manufacturing industries. The sub-sectors are labeled at the two-digit level. Import penetration is constructed using imports and exports from UN Comtrade and turnover from the Annual Business Inquiry (ABI). The share of production workers is taken from the 1995/6 Quarterly Labor Force Survey (QLFS).

broad manufacturing sectors. Focusing first on the broad sectors, the evidence suggests that sectors with the biggest increase in import exposure from 1996 to 2011 tend to be those that were initially (i.e. in 1996) intensive in the use of production workers. Accordingly, sectoral patterns of import growth are broadly consistent with China's comparative advantage in sectors that use intensively production workers (Amiti and Freund, 2010).

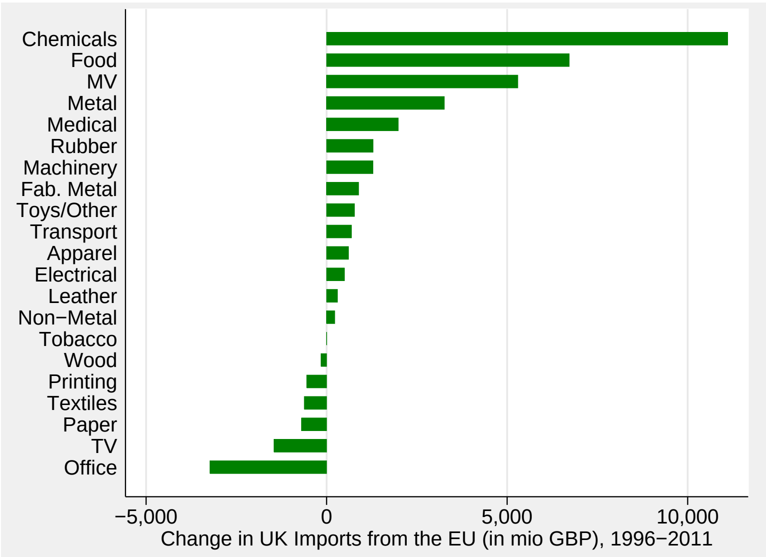
However, differences in factor intensity cannot be the entire story. Figure 2.6 shows a large variation in the change in import penetration *within* the broad manufacturing sectors (which tend to be quite similar in terms of production worker intensity use). In the empirical analysis, we will include controls for eight broad manufacturing sectors, leading to an identification of the effect of trade competition on medium- to long-run outcomes among industries with similar skill-intensity requirement in production. Autor et al. (2014) provides similar evidence for the US between 1991 and 2007. In their study, they also identify sectors intensive in the use of production worker as being exposed to high import growth from China (pp10-11).

2.4.3 The anatomy of gross imports from the European Union

Along with the emergence of China, UK's close trade ties with the EU are expected to have a sizable impact on the dynamics of its labor market. Figure 2.7 replicates Figure 2.5 but using import growth from the EU (instead of China). A totally different pattern emerges. The change in gross import values from the EU to the UK is high in sectors such as chemicals (+£11107 million), food products (+£6720 million), motor vehicles (+£5296 million) and metals (+£5296 million), whereas sectors such as office machinery (-£3229 million), TVs (-£1456 million), pulp, paper and paperboard (-£694 million) and textiles (-£619 million) experienced a negative change in gross import values from the EU.

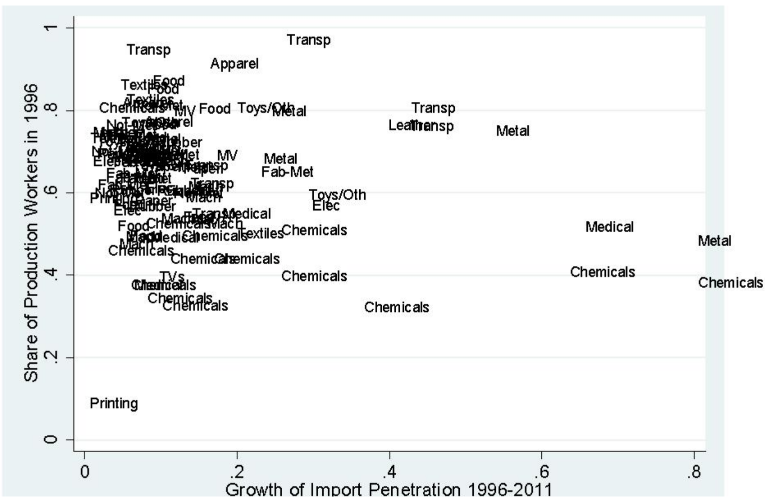
Again, UK industry trade patterns with the EU look similar to those in the US (see Figure B.8 in the Appendix) with a cross-country correlation coefficient between industry changes in gross imports from the EU to the UK and from the EU to the US equals to 0.865 (p-value of 0.000). These figures imply that the sectors that experienced high growth in gross imports from the EU differ to those that faced high imports from China in terms of the intensity of their use of production workers. Indeed, this observation is confirmed by Figure 2.8, which replicates Figure 2.6 with the growth of gross import penetration ratio coming from the EU (instead of China) on the horizontal axis. Industries with the biggest increase in import exposure from 1996 to 2011 tended to be those that were initially (i.e. in 1996) not that intensive in the use of production workers, but more intensive in the use of capital or natural resources.

Figure 2.7: The change in imports from the EU to the UK, 1996-2011



Source: Using data from UN Comtrade for 21 consistently defined manufacturing sub-sectors.

Figure 2.8: Growth in trade exposure from the EU and the share of UK production workers



Notes: For 166 consistently defined manufacturing industries. The sub-sectors are labeled at the two-digit level. Import penetration is constructed using imports and exports from UN Comtrade and turnover from the ABI. The share of production workers is taken from the 1995/6 QLFS. To make the figure comparable with figure 8, import penetration from the EU for the manufacture of essential oils (2463) is 0.990 but set to 0.8, also precious metal production (2741) is set to 0.8 but is 2.26. The correlation coefficient between UK IP from China and Europe is 0.264 with a p-value of 0.001.

2.5 Empirical methodology and data

2.5.1 Data sources

Our primary source of data are taken from the New Earnings Survey Panel Dataset (NESPD) which is a one percent random sample of UK workers who have the same last two digits in their National Insurance number. This data set is made available by the Office for National Statistics (ONS) and began in 1975. The NESPD follows workers throughout their working life collecting information on their earnings, number of hours worked, place of work, age, gender, industry and occupation of employment. More importantly, the NESPD picks up workers after an unemployment spell. Thus if they leave employment they leave the survey but when they re-enter employment again they re-enter the survey.

Following Autor et al. (2014), we select a sample of workers with high labor market attachment. This consists of full-time workers age 21 to 64, who were born between 1947 and 1975, with non-zero earnings in 1992-1994 and 1995-1997. Most of our estimations for the impact of trade exposure on worker's career outcomes are based on workers observed between 1997 and 2011. We use data from pre-sample years in order to construct control variables. We use five main worker outcomes over the sample period: cumulative earnings, the number of years with positive earnings, cumulative earnings per year in years with non-zero earnings, cumulative hourly pay and cumulative hours of work. Table B.1 in the Appendix provides detailed summary statistics.

International bilateral trade data are taken from the United Nations Commodity Trade Statistics Database (UN Comtrade). We use detailed bilateral commodity import and export flows from 1988 to 2011 for most partner countries. Product values are classified according to the Standard International Trade Classification, revision 3 (SITC, rev.3) at the 5-digit level in current US dollars. To concord these data to 5-digit 1992 UK Standard Industrial Classification (UKSIC 1992) industries, we constructed a crosswalk table that maps any 5-digit SITC product to at least one 5-digit UKSIC 1992 industry (see the Appendix Section B.3 for more details). Trade flows were converted into constant (2005) GBP using historical exchange rates and the UK Consumer Price Index (CPI).[14]

In order to assess the indirect worker-level impact of import competition along the value chain, we need to identify for each industry their respective closest upstream and downstream manufacturing neighbour. For this purpose, we use the 1995 Analytical Input-Output Tables (I-O) from the ONS. The I-O Tables report information on production linkages between industries at a disaggregated level based on Input-Output industry groups (called IO123).[15] For an industry j, we define

[14] Historical yearly GBP/USD exchange rates are provided by oanda.com. UK CPI is taken from the World Bank.

[15] The IO123 classification is based on an aggregated version of UKSICs with 123 different industries in total (of which 77 are manufacturing industries). Thus, the level of disaggregation is less detailed than 5-digit UKSIC industries. See Section 2.6.3 for an explanation on how this impact on our results.

its closest downstream (upstream) neighbouring industry as the industry that buys (sells) the largest value of intermediate inputs from (to) industry *j*.

2.5.2 Estimating equation

Direct impact of import competition

Following Autor et al. (2014), we estimate the effect of trade exposure on individual worker outcomes with the following specification:

$$E_{ij,\tau} = \beta_0 + \beta_1 \Delta IP_{j,\tau} + \beta_2 IP_{j,96} + X^{'}_{ij,96}\beta_3 + Z^{'}_{j,96}\beta_4 + \varepsilon_{ij,\tau}, \qquad (2.7)$$

where, $E_{ij,\tau}$ is one of the five main worker outcomes between 1997 and 2011 for worker *i* in industry *j*. $\Delta IP_{j,\tau}$ is the change in gross (net) import penetration from China (the EU) over the period 1996 to 2011 in industry *j* as defined in (3.16). $IP_{j,96}$ is import penetration in 1996 in industry *j*; $X_{ij,96}$ is a vector of worker characteristics in 1996; and $Z_{j,96}$ is a vector of industry/occupation controls in 1996.

The vector of worker characteristics include the worker's birth year, gender, indicators for the size of the primary firm (4 dummies), indicators for job tenure at the initial firm (4 dummies) in 1996, mean log annual earnings over 1990 to 1996 (also interacted with age) and the change in log earnings over the period 1990 to 1996.

The vector of industry/occupation controls include the industry net capital stock, the industry share of production workers, the industry average log wage, the industry share of imported intermediate inputs in total intermediate consumption, the industry share of IT equipment in total domestic output, the industry share of computer equipment in total domestic output, import penetration by countries other than China (the EU), eight sub-sector dummies and two-digit occupation dummies (more details to follow). All of our controls are measured in 1996. Standard errors are clustered at the 3-digit industry level. Following Autor et al. (2014), we model the cumulative shock due to trade exposure as a function of import penetration ratio in 1996 (the initial condition) plus the subsequent growth in import penetration ratio over 1996 to 2011 (the average annual change).

The biggest challenge in estimating equation (2.7) is that industries that face increasing import competition might be exposed to other shocks that could be wrongly attributed to trade. To control for such confounding factors, we include a large set of industry and occupation (initial-year) controls observed in 1996. Our main specification includes the industry net capital stock, the industry share of IT equipment in total domestic output, the industry share of computer equipment in total domestic output and the industry share of production workers in employment, all of which might indicate the degree of industry exposure to technical change (Doms, Dunne, and Troske, 1997; Autor, Katz, and Krueger, 1998). Moreover, the specification includes the industry share of imported intermediate inputs in total intermediate consumption, as in Feenstra and Hanson (1999), and import penetration by countries other than China (the EU) in order to capture overall industry exposure to trade in final goods and offshoring. Finally, we also include the industry average log wage, eight sub-sector dummies and two digit occupation dummies. The inclusion of the occupation controls is a novelty which enables us to evaluate import competition effects within detailed occupation groups. One would expect workers employed in low-skill intensive occupations to exhibit declining earnings profiles as a consequence of trade compared to other workers within the same occupation; and not just workers relative to all workers across all occupations, which could be a consequence of skill biased technical change instead of pure trade effects.

Our analysis compares workers with similar individual characteristics, similar initial earnings, similar initial experience on the job, similar initial employer size, who are initially employed in similar occupation and with similar average industry characteristics, some of whom work in industries that face increases in trade competition and some of whom do not.

Indirect impact of import competition

To examine the indirect impact of import competition on workers employed in neighbouring industries, we augment the main estimating equation (2.7) as follows:

$$\begin{aligned} E_{ij,\tau} = \gamma_0 &+ \gamma_1 \Delta IP_{j,\tau} + \gamma_2 \Delta IP^{down}_{jk,\tau} + \gamma_3 \Delta IP^{up}_{jl,\tau} \\ &+ C^{'}_{j,96}\gamma_4 + X^{'}_{ij,96}\gamma_5 + Z^{'}_{j,96}\gamma_6 + \mu_{ij,\tau}, \end{aligned} \tag{2.8}$$

where, *k* indexes the neighbouring *downstream* industry relative to industry *j* and *l* indexes the neighbouring *upstream* industry relative to industry *j*. Along with the direct change in gross import penetration in industry *j*, $\Delta IP_{j,\tau}$, we include the two additional measures of indirect exposure to import competition, namely $\Delta IP^{down}_{jk,\tau}$ and $\Delta IP^{up}_{jl,\tau}$ as defined in (2.3) and (2.4) respectively. $X_{ij,96}$ and $Z_{j,96}$ are respectively the same vectors of worker characteristics and industry/occupation controls in 1996 as those used in equation (2.7) except that the 8 sub-sector dummies are not included (more on this in Section 2.6.3). $C_{j,96}$ is a vector containing import penetration in industry *j*, import penetration in downstream neighbouring industry *k* and import penetration in upstream neighbouring industry *l* in 1996.

2.6 The labor market effect of increased exposure to import competition from China

2.6.1 Baseline results

Table 2.1 presents our estimates for the relationship between UK gross import exposure from China and cumulative earnings over 1997 to 2011 based on equation (2.7). We restrict the sample to full time workers (as noted in section 3.2.1). Initially, we regress cumulative earnings on the change in gross import penetration from China and a full set of birth-year dummies to account for life-cycle variations in earnings. Column 1 provides the OLS estimates and column 2 the 2SLS estimates using the variable defined in equation (3.18) as our instrument. In both columns, we find a negative and statistically significant relationship between the change in gross import penetration and cumulative earnings over 1997 to 2011. Thus, higher exposure to gross import competition from China (based on a worker's initial industry) is related to lower cumulative earnings over the subsequent 15 years.

In order to quantify our results we compare a manufacturing worker at the 75th percentile of the change in trade exposure with a manufacturing worker at the 25th percentile. The value of the change in gross import penetration from China is 0.26 percentage points at the 25th percentile and is 5.97 percentage points at the 75th percentile. So using column 1, the implied differential for a reduction in earnings over the 15 year sample period, between workers at the 75th percentile relative to the 25th percentile is 63.7% of initial annual earnings.[16]Using the 2SLS estimates from column 2, the implied differential increases to 76.7% of initial annual earnings.[17]The 2SLS estimate is substantially higher than the OLS estimate suggesting that the potential positive correlation between UK industry import demand shocks and UK industry labor demand should not to be ignored.

In the three subsequent columns, we add controls for whether the worker is female (column 3), the size of the worker's initial firm and the worker's work experience at the initial firm (column 4). We also add controls for the worker's earnings histories (column 5) including their mean log annual earnings and the change in their log earnings over the period 1990 to 1996. Note that the inclusions of the gender dummy and earnings history have a notable impact on the estimates.

In order to control for cross-industry heterogeneity in exposure to other shocks that might be confounded with import shocks, we add an extensive list of industry and occupation-level control variables in the four subsequent columns. Column 6 includes the initial gross import penetration from China and from all other countries except China to account for overall industry exposure to trade in final goods. In column 7, we add initial industry controls such as average industry log wage, industry net capital stock, industry share of IT equipment in total domestic output, industry share of computer equipment in total domestic output and industry

[16]The computation is $11.162 \times (5.97 - 0.26) = 63.73$.

[17]The computation is $13.439 \times (5.97 - 0.26) = 76.74$.

share of production workers in employment, all of which might indicate the degree of industry exposure to technical change (Doms, Dunne, and Troske, 1997; Autor, Katz, and Krueger, 1998). Moreover, column 7 includes the industry share of imported intermediate inputs in total intermediate consumption (as in Feenstra and Hanson, 1999) which (roughly) controls for industry exposure to offshoring. Column 8 adds two-digit level occupation dummies and thus in this column we are comparing the outcomes of manufacturing workers who are initially performing different tasks within the same detailed occupation. Finally, column 9 adds dummies for eight manufacturing sub-sectors, so that we are comparing outcomes for manufacturing workers who are initially working in different industries within the same sub-sector. This is our preferred specification and provides an estimate of -8.410 which is strongly significant.[18]The first stage is also strong and demonstrates an F-statistic of 55.583 supporting the use of Chinese imports to other high income countries as an instrument for Chinese imports to the UK.

From column 9 the implied differential for a reduction in earnings over the 15 year sample period, between workers at the 75^{th} percentile relative to the 25^{th} percentile of the change in import penetration is 48%.[19]This is very similar, albeit slightly larger, to that found by Autor et al. (2014) even though our estimate compares workers within two digit occupation. For the US, Autor et al. (2014) find an implied differential for a reduction in earnings over 16 years, between workers at the 75^{th} percentile relative to the 25^{th} percentile of around 46%.

[18]The inclusion of the industry dummies in column 9 does substantially change the estimates. The coefficient on the change in gross import penetration from China in column 9 is roughly 40% lower than that in column 8 suggesting, that even controlling for input intensity use, a lot of variation remains. Also the coefficient on the change in import exposure from column 9 is smaller than that from column 2 whereas Autor et al. (2014) find the converse. This suggests that conditional on our demographic measures (which are controlled for in each column), workers with somewhat lower potential earnings are initially employed in industries that experienced higher import exposure in subsequent years.

[19]The computation is $8.410 \times (5.97 - 0.26) = 48.02$.

Table 2.1: Gross imports from China and cumulative earnings (1997-2011) for full time workers: OLS and 2SLS estimates

	OLS	2SLS							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(ΔChina Imports)/UK Consumption$_{96}$	-11.162**	-13.439**	-11.492**	-10.879**	-12.851**	-12.935**	-12.107**	-13.171**	-8.410**
	(3.235)	(3.613)	(3.452)	(3.076)	(3.312)	(3.238)	(3.592)	(3.681)	(4.362)
(China Imports$_{96}$)/UK Consumption$_{96}$						-6.254	-9.223	-6.223	-0.522
						(6.451)	(6.523)	(6.834)	(8.660)
(Non-China Imports$_{96}$)/UK Consumption$_{96}$						0.606	1.092	0.605	-0.131
						(1.068)	(1.074)	(1.128)	(1.412)
1st stage statistics									
(ΔHI Imports)/UK Consumption$_{92}$		0.131**	0.129**	0.129**	0.128**	0.145**	0.173**	0.173**	0.160**
		(0.004)	(0.001)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Robust F-stat		28.727**	30.854**	31.196**	31.300**	30.934**	58.366**	61.997**	55.583**
Shea's partial R-squared		0.509	0.504	0.505	0.504	0.515	0.538	0.543	0.506
Birth-Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gender			Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Size & Job Tenure				Yes	Yes	Yes	Yes	Yes	Yes
Earnings History					Yes	Yes	Yes	Yes	Yes
Industry Controls							Yes	Yes	Yes
Two Digit Occ. Dummies								Yes	Yes
8 Sub-Sector Dummies									Yes
% diff. for Δ IP at 75th v.s. 25th percentile	-63.74**	-76.74**	-65.62**	-62.22**	-73.38**	-73.86**	-69.13**	-75.22**	-48.02**

Notes: For a sample of 19,949 workers born between 1947 and 1975, with non-zero earnings in 1992-1994 and 1995-1997. All regressions include a constant and birth dummies. Where ** (*) denotes statistically significant at the 5 (10) percent level. Robust standard errors are clustered on start of period 3 digit industry. Using change in trade exposure from China with respect to the Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland over the period 1996-2011 (with initial absorption in 1992) as an instrument for the change in trade exposure from China with respect to the UK over the period 1996-2011. The mean (standard deviation) of $(\Delta\text{China Imports})/\text{UK Consumption}_{96}$ is 0.0593 (0.0942), whilst the median is 0.0222, the value at the 25th percentile is 0.0026 and the 75th percentile is 0.0597.
Source: Own estimations based on merged COMTRADE-NESPD database.

As an alternative labor market outcome measure, we use the number of years (between 1997 and 2011) that workers have experienced non-zero earnings. The intention here is to roughly capture the extensive margin of employment (and to compare our results with those in Autor et al. (2014)). If an individual works a single day in a year, they will have non-zero earnings in that year. Consequently, any periods of unemployment that are less than a year in duration are unobserved. The specifications in columns 1 to 9 of Table 2.2 are directly comparable to those in Table 2.1. Again, we find a strongly significantly negative relationship between the change in gross import exposure and years of non-zero earnings. Again column 9 is our preferred specification and this implies that Chinese import exposure reduces subsequent employment. The employment differential for a manufacturing worker at the 75th percentile of import exposure relative to a worker at the 25th percentile is 18.8% of a year, which is 69 days or almost 10 weeks lost during the 15-year sample period.[20]

In Table 2.3, we further consider three additional outcome measures, namely cumulative earnings per year, cumulative hourly pay and cumulative hours of work. Hourly pay captures the intensive margin of gross annual earnings and cumulative hours of work captures the extensive margin of gross annual earnings more accurately than the number of years with non-zero earnings. We also now consider changes in *net* import penetration (rather than gross import penetration) from China in the lower panel. Focusing first on the upper panel, we can see that increased gross import exposure has a negative and significant impact on cumulative earnings per year (column 3), on average hourly pay (column 4) and on cumulative hours of work (column 5), with a bigger magnitude on the wage than on hours of work. Indeed, the implied reduction in total wage earnings for a manufacturing worker at the 75th percentile of import exposure relative to a worker at the 25th percentile is 69.2% of initial wage (in 1996), whereas the fall in employment is 33.6% of the total number of hours worked in 1996. This suggests that the adjustment to trade shocks is more severe at the intensive margin relative to the extensive margin. To account for the potential new export opportunities that China's economic opening might offer (which might temper some of the loss incurred by gross import competition), the lower panel shows that for net imports each point estimate is larger (in absolute value) and with larger 75th-25th percentile differentials. This suggests that what really hurts UK manufacturing workers is the difference in the nature of imports and exports. Worth mentioning, the point estimates of net import growth on hourly pay and on hours of work are respectively 89.8% and 50.7% larger than the corresponding ones using gross import growth.

[20]The computation is $3.288 \times (5.97 - 0.26) = 18.78$.

Table 2.2: Gross imports from China and years of non-zero earnings (1997-2011) for full time workers: OLS and 2SLS estimates

	OLS	2SLS							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(ΔChina Imports)/UK Consumption$_{96}$	-4.800**	-5.374**	-4.298**	-4.320**	-4.071**	-4.039**	-4.324**	-4.406**	-3.288**
	(1.236)	(1.519)	(1.362)	(1.425)	(1.418)	(1.389)	(1.288)	(1.248)	(1.302)
(China Imports$_{96}$)/UK Consumption$_{96}$						-1.709	-3.196	-2.230	-0.868
						(2.274)	(2.006)	(1.903)	(1.959)
(Non-China Imports$_{96}$)/UK Consumption$_{96}$						0.149	0.373	0.220	-0.050
						(0.360)	(0.323)	(0.306)	(0.308)
1st stage statistics									
(ΔHI Imports)/UK Consumption$_{92}$		0.131**	0.129**	0.129**	0.128**	0.145**	0.173**	0.173**	0.160**
		(0.004)	(0.001)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Robust F-stat		28.727**	30.854**	31.196**	31.300**	30.934**	58.366**	61.997**	55.583**
Shea's partial R-squared		0.509	0.504	0.505	0.504	0.515	0.538	0.543	0.506
Birth-Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gender			Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Size & Job Tenure				Yes	Yes	Yes	Yes	Yes	Yes
Earnings History					Yes	Yes	Yes	Yes	Yes
Industry Controls							Yes	Yes	Yes
3-Digit Occ. Dummies								Yes	Yes
8 Sub-Sector Dummies									Yes
% diff. for Δ IP at 75th v.s. 25th percentile	-27.41**	-30.69**	-24.54**	-24.67**	-23.25**	-23.06**	-24.69**	-25.16**	-18.78**

Notes: As per Table 2.1.
Source: Own estimations based on merged COMTRADE-NESPD database.

Table 2.3: Gross and net imports from China (1997-2011) for full time workers: 2SLS estimates for various labor market outcomes

	Cumulative Annual Earnings (1)	Years of Non-Zero Earnings (2)	Cumulative Annual Earnings/Year (3)	Cumulative Hourly Pay (4)	Cumulative Hours of Work (5)
Gross Imports:					
(ΔChina Imports)/UK Consumption$_{96}$	-8.410**	-3.288**	-0.561**	-12.114**	-5.888**
	(4.362)	(1.302)	(0.291)	(5.008)	(2.473)
% diff. for Δ IP at 75th v.s. 25th percentile	-48.02**	-18.78**	-3.203**	-69.196**	-33.631**
1st stage statistics					
(ΔHI Imports)/UK Consumption$_{92}$	0.160**	0.160**	0.160**	0.160**	0.160**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Robust F-stat	55.583**	55.583**	55.583**	55.562**	55.562**
Shea's partial R-squared	0.506	0.506	0.506	0.506	0.506
Number of observations	19,949	19,949	19,949	19,778	19,778
Net Imports:					
(ΔChina Imports)/UK Consumption$_{96}$	-11.084**	-5.031**	-0.739**	-18.982**	-10.715**
	(5.288)	(1.521)	(0.353)	(5.549)	(2.773)
% diff. for Δ IP at 75th v.s. 25th percentile	-52.44**	-23.79**	-3.49**	-89.79**	-50.69**
1st stage statistics					
(ΔHI Imports)/UK Consumption$_{92}$	0.069**	0.069**	0.069**	0.069**	0.069**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Robust F-stat	19.039**	19.039**	19.039**	19.167**	19.167**
Shea's partial R-squared	0.314	0.314	0.314	0.315	0.315
Number of observations	19,946	19,946	19,946	19,775	19,775

Notes: For a sample of workers born between 1947 and 1975, with non-zero earnings in 1992-94 and 1995-97. All regressions include the full vector of controls from column 9 of Table 2.1. Where ** (*) denotes statistically significant at the 5 (10) percent level. Robust standard errors are clustered on start of period 3 digit industry. Using change in trade exposure from China with respect to the Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland over the period 1996-2011 as an instrument for the change in trade exposure from China with respect to the UK over the period 1996-2011.
Source: Own estimations based on merged COMTRADE-NESPD database.

In order to explore the dynamics within our observed period, we again follow Autor et al. (2014) by plotting the estimated impact of gross import exposure on specific worker outcomes by year for the years 1993 through 2011 using our preferred specification. The upper panel in Figure 2.9 illustrates the estimated impact of gross import exposure on worker earnings per year on average. As expected, the trade effects are zero before the trade shock in 1996. But thereafter trade exposure has an adverse effect (though not significantly different from zero for most of the year) on earnings between 1996 and 2011 (except in 1998), although this does exhibit some degree of convergence after approximately nine years. The second panel provides the results for the probability of having non-zero earnings in each year. This suggests a similar pattern to earnings loss which again starts to converge back to zero after around eight years. The third panel provides earnings losses for a sub-sample of workers who never exhibit zero earnings. For these workers, relative earnings continue to decline, with no signs of convergence.

Figure 2.10 plots hourly pay by year (upper panel) and hours of work by year (lower panel). For both, we can see that rising imports from China adversely affect annual wages and employment for the entire sample period, with wages suffering slightly more than employment (which is consistent with the findings of Table 2.3). Interestingly, wages seem to stabilize from 2004 onwards, whereas employment shows a converging path from 2000 onwards.

2.6.2 Results by one-digit occupation

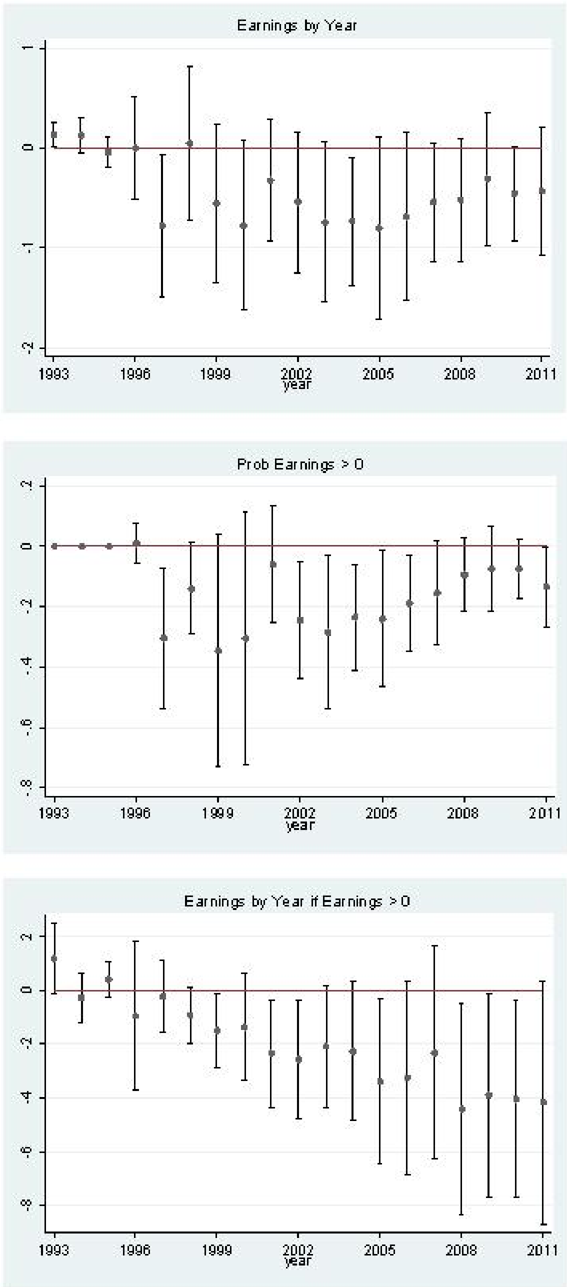
One advantage that the NESPD has over the data used in Autor et al. (2014) is that it contains information on the occupations of workers enabling us to look at trade exposure effects separately by occupation. Table 2.4 provides estimates for gross import exposure from China on our five main worker outcome measures (as per the upper panel of Table 2.3) estimated separately by one-digit occupation. In order to maintain sensible sample sizes it was necessary to combine personal service occupations, sales and customer service and elementary occupations into one composite group. This provides seven one-digit occupation groups for managers, professionals, associate professionals, clerical/secretarial, skilled trades, plant/machine operators and personal/sales/ elementary occupations.

In column 1, increased trade exposure adversely affects the cumulative earnings of managers, skilled trades and personal/sales/elementary occupations. Managers and skilled trades suffer substantially from import competition with an implied differential of 107% and 102% respectively. However, as it could be expected personal/sales/elementary occupations experience the biggest reduction in cumulative earnings, with an implied differential of 157%. For the other occupation groups, increased import growth seems to exert a negative effect on earnings as well, although the estimates are not statistically significant.

Looking at cumulative wages in column 4, we can see a similar pattern emerging as in column 1. Namely, managers and skilled trades are mostly affected by increased import exposure with an implied 75^{th}-25^{th} percentile differential is 149%

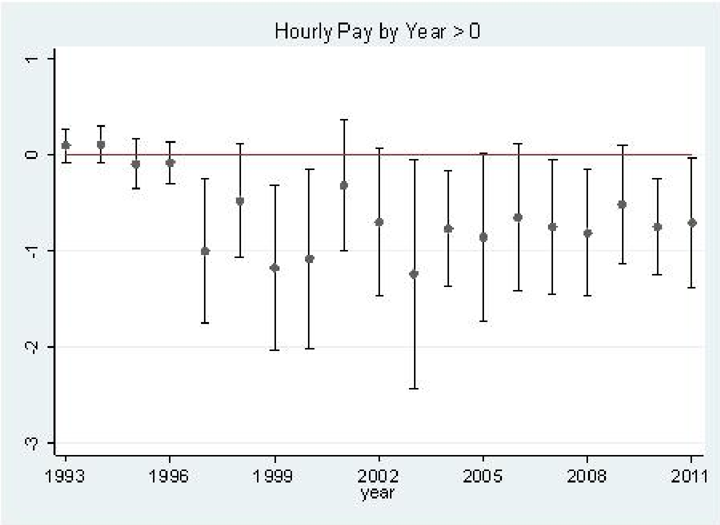
and 127% respectively, whereas in the bottom of the occupation distribution only plant/machine operators see their wages declining in response to Chinese import competition (-41%). Moreover, as seen in column 5, managers also see their employment decreasing in response to rising trade competition, highlighting the fact that "white-collar" workers seem those suffering the most relative to all other occupation groups. The implied differential for a reduction in employment over the 15 year-sample period is 82.5% of total hours of work in 1996 for managers. In column 5, employment for clerical and secretarial occupations is also negatively affected, whereas their wages (in column 4) do not seem to react to import competition shocks suggesting an adjustment only at the extensive margin for this group of workers. Interestingly, managers are the only occupation group seeing a decrease in both margins.

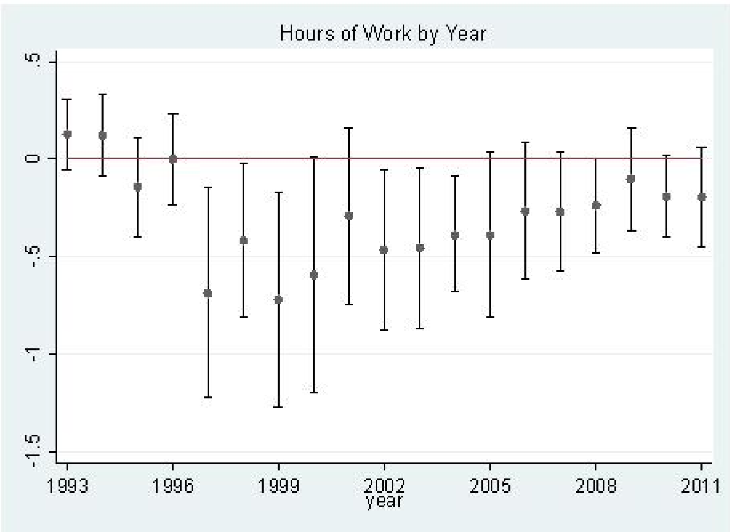
Figure 2.9: Year-by-year regression results for main outcomes, 1993-2011



Source: Own estimations based on merged COMTRADE-NESPD database.

Figure 2.10: Year-by-year regression results for additional outcomes, 1993-2011





Source: Own estimations based on merged COMTRADE-NESPD database.

In Table 2.5, as an alternative to occupation dummies, we include a measure of routine tasks intensity in 1996 for each occupation at the three-digit level of disaggregation. The routine intensity measure is defined as the share of routine task inputs for each occupation as in Autor, Levy, and Murnane (2003). We used information about the content of tasks from the US Dictionary of Occupational Titles (DOT). Autor, Levy, and Murnane (2003) made available a dataset containing five different measures of task activity for each job based on 1980 US Census Code.[21] In order to take advantage of those task measures, we constructed a crosswalk that matches any 1980 Census Code to their nearest 3-digit UK 2000 Standard Occupational Classification (UKSOC 2000) code.[22] The estimates suggest that controlling for the routine intensity of a job does not alter the results qualitatively and quantitatively. Indeed, the main coefficients and the 75th-25th implied differentials are not greatly affected compared to what is found in the upper panel of Table 2.3 (which controls for two digit occupations).

These results are consistent with those found in the US since Autor, Dorn, and Hanson (2013b) also find large negative effects from Chinese trade competition on US non-production jobs. In their paper, they explore the effects of technology and trade on employment in US local labor markets and find that Chinese import competition has an adverse employment effect on non-production workers (alongside a less surprising negative employment effect on production workers).[23]

Again we can plot the estimated impact of gross import exposure on specific worker outcomes by year for each occupation group, although we can only look at earnings and non-zero earnings probabilities as a consequence of smaller sample sizes. The upper panel in Figure 2.11 supports the findings of Table 2.4 that trade exposure has the largest adverse effect on earnings at both ends of the occupation distribution (for white-collar and low-skilled blue-collar workers). The lower panel shows that the decline in earnings is partly due to a rise in zero-earnings years, again we find a larger decline for managers, professionals, associate professionals an elementary workers. Interestingly, both the earnings and the probability of being in employment never fully converge for professionals, associate professionals and elementary workers. This is not the case for managers and skilled trades whose earnings and employment likelihood seem to converge to zero in 2011. Somewhat surprisingly, Figure 2.11 shows that the group least affected by Chinese import competition, in terms of earnings and non-zero earnings probabilities by year, is plant/machine operators. A result that is in line with the findings of Table 2.4

[21] The resource used is called DOT means by occupation and is available on David Autor's MIT webpage, in the Data Archive section. The task measures were derived from 1991 revised 4th edition of the DOT. See Autor, Levy, and Murnane (2003) for more information.

[22] We used the online CASCOT tool (Computer Assisted Structured COding Tool) freely provided by the University of Warwick. Click *here* for the link. Cascot "is a computer program designed to make the coding of text information to standard classifications simpler, quicker and more reliable" (Warwick Institute for Employment Research).

[23] See their Table 4 on page 20.

Table 2.4: Gross imports from China (1997-2011) for full time workers: 2SLS estimates by one-digit occupation (continues on the next page)

	Cumulative Annual Earnings (1)	Years of Non-Zero Earnings (2)	Cumulative Annual Earnings/Year (3)	Cumulative Hourly Pay (4)	Cumulative Hours of Work (5)
Managers	-18.826** (6.940)	-6.680** (2.168)	-1.255** (0.463)	-26.143** (8.329)	-14.449** (4.120)
N	2419	2419	2419	2401	2401
% diff. for ΔIP (75^{th} p. v.s. 25^{th} p.)	-107.49**	-38.14**	-7.17**	-149.28**	-82.50**
1^{st} stage statistics					
Main coefficient (s.e.)	0.163** (0.007)	0.163** (0.007)	0.163** (0.007)	0.162** (0.007)	0.162** (0.007)
Robust F-stat (Shea's partial R-squared)	57.117** (0.449)	57.117** (0.449)	57.117** (0.449)	56.899** (0.449)	56.899** (0.449)
Professionals	-12.756 (13.702)	-7.485** (3.222)	-0.851 (0.913)	-13.025 (11.728)	-8.007 (5.708)
N	1035	1035	1035	1030	1030
% diff. for ΔIP (75^{th} p. v.s. 25^{th} p.)	-72.84	-42.74* *	-4.86	-74.37	-45.72
1^{st} stage statistics					
Main coefficient (s.e.)	0.099** (0.004)	0.099** (0.004)	0.099** (0.004)	0.099** (0.004)	0.099** (0.004)
Robust F-stat (Shea's partial R-squared)	48.563** (0.456)	48.563** (0.456)	48.563** (0.456)	48.839** (0.457)	48.839** (0.457)
Associate Professionals	-13.649 (12.619)	-8.208** (3.133)	-0.910* (0.525)	-17.308 (16.077)	-10.362 (6.820)
N	1134	1134	1134	1129	1129
% diff. for ΔIP (75^{th} p. v.s. 25^{th} p.)	-77.94	-46.87**	-5.20*	-98.83	-59.17
1^{st} stage statistics					
Main coefficient (s.e.)	0.131** (0.009)	0.131** (0.009)	0.131** (0.009)	0.131** (0.009)	0.131** (0.009)
Robust F-stat (Shea's partial R-squared)	41.426** (0.455)	41.426** (0.455)	41.426** (0.455)	41.418** (0.454)	41.418** (0.454)
Clerical/Secretarial	-4.266 (8.502)	-4.069* (2.384)	-0.284* (0.150)	-9.457 (9.523)	-7.518** (3.832)
N	2187	2187	2187	2180	2180
% diff. for ΔIP (75^{th} p. v.s. 25^{th} p.)	-24.36	-23.23 *	-1.62*	-54.00	-42.93**
1^{st} stage statistics					
Main coefficient (s.e.)	0.115** (0.004)	0.115** (0.004)	0.115** (0.004)	0.115** (0.004)	0.115** (0.004)
Robust F-stat (Shea's partial R-squared)	53.534** (0.470)	53.534** (0.497)	53.534** (0.470)	53.825** (0.471)	53.825** (0.471)

Table 2.4 (continued): Gross imports from China (1997-2011) for full time workers: 2SLS estimates by one-digit occupation

	Cumulative Annual Earnings (1)	Years of Non-Zero Earnings (2)	Cumulative Annual Earnings/Year (3)	Cumulative Hourly Pay (4)	Cumulative Hours of Work (5)
Skilled Trades	-17.784* (9.494)	-5.631** (2.278)	-1.816** (0.633)	-22.166* (12.407)	-7.693 (6.157)
N	4851	4851	4851	4813	4813
% diff. for ΔIP (75th p. v.s. 25th p.)	-101.55*	-32.15**	-10.37**	-126.57*	-43.93
1st stage statistics					
Main coefficient (s.e.)	0.118** (0.004)	0.118** (0.005)	0.118** (0.004)	0.118** (0.004)	0.118** (0.004)
Robust F-stat (Shea's partial R-squared)	29.001** (0.415)	29.001** (0.415)	29.001** (0.415)	29.258** (0.416)	29.258** (0.416)
Plant/Machine Operators	3.646 (6.722)	-1.010 (1.255)	0.243 (0.448)	-7.224* (4.231)	-3.281 (2.725)
N	6856	6856	6856	6771	6771
% diff. for ΔIP (75th p. v.s. 25th p.)	-20.82	-5.77	1.39	-41.25*	-18.74
1st stage statistics					
Main coefficient (s.e.)	0.171** (0.004)	0.171** (0.004)	0.171** (0.004)	0.171** (0.004)	0.171** (0.004)
Robust F-stat (Shea's partial R-squared)	71.696** (0.557)	71.696** (0.557)	71.696** (0.557)	71.158** (0.558)	71.158** (0.558)
Personal/Sales/Elementary Occupations	-27.506* (15.736)	-7.817* (4.034)	-1.834 (1.923)	-16.463 (17.443)	-5.496 (8.369)
N	1467	1467	1467	1454	1454
% diff. for ΔIP (75th p. v.s. 25th p.)	-157.06*	-44.64*	-10.47	-94.00	-31.38
1st stage statistics					
Main coefficient (s.e.)	0.097** (0.020)	0.097** (0.020)	0.097** (0.020)	0.096** (0.020)	0.096** (0.020)
Robust F-stat (Shea's partial R-squared)	13.095** (0.224)	13.095** (0.224)	13.095** (0.224)	13.198** (0.222)	13.198** (0.222)

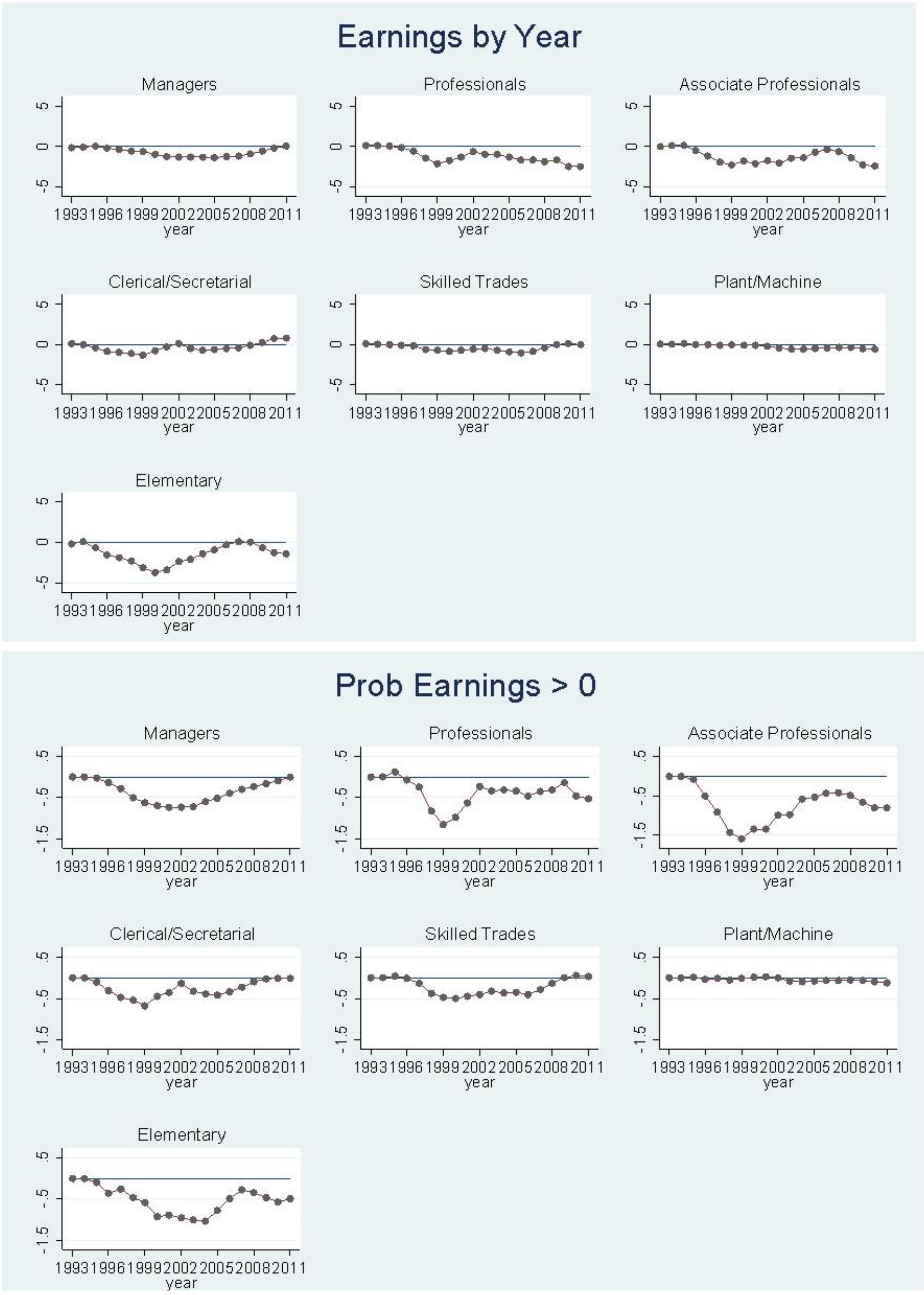
Notes: As per Table 2.3. The differentials are evaluated at the 25th and 75th percentile of the total distribution of import penetration.
Source: Own estimations based on merged COMTRADE-NESPD database.

Table 2.5: Gross imports from China (1997-2011) and routine tasks for full time workers: 2SLS estimates for various labor market outcomes

	Cumulative Annual Earnings (1)	Years of Non-Zero Earnings (2)	Cumulative Annual Earnings/Year (3)	Cumulative Hourly Pay (4)	Cumulative Hours of Work (5)
(ΔChina Imports)/UK Consumption$_{96}$	-7.901*	-3.121**	-0.527**	-11.586**	-5.464**
	(4.450)	(1.260)	(0.297)	(4.897)	(2.481)
Routine Task Intensity in 1996	-0.2959*	0.388**	-0.020*	0.122	0.4889**
	(0.155)	(0.344)	(0.010)	(0.151)	(0.083)
% diff. for Δ IP at 75th v.s. 25th percentile	-47.33*	-18.69**	-3.16**	-69.40**	-32.73**
1st stage statistics					
(ΔHI Imports)/UK Consumption$_{92}$	0.161**	0.161**	0.161**	0.160**	0.160**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Robust F-stat	55.183**	55.183**	55.183**	55.127**	55.127**
Shea's partial R-squared	0.506	0.506	0.506	0.506	0.506
Number of observations	19,935	19,935	19,935	19,767	19,767

Notes: For a sample of workers born between 1947 and 1975, with non-zero earnings in 1992-1994 and 1995-1997. All regressions include the full vector of control variables from column 9 of Table 1 except for the two-digit occupation dummies. Where ** (*) denotes statistically significant at the 5 (10) percent level. Robust standard errors are clustered on start of period 3 digit industry. Using change in trade exposure from China with respect to the Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland over the period 1996-2011 (with initial absorption in 1992) as an instrument for the change in trade exposure from China with respect to the UK over the period 1996-2011. The mean (standard deviation) of (ΔChina Imports)/UK Consumption$_{96}$ is 0.0593 (0.0942), whilst the median is 0.0224, the value at the 25th percentile is 0.0026 and the 75th percentile is 0.0625.
Source: Own estimations based on merged COMTRADE-NESPD database.

Figure 2.11: Year-by-year regression results for main outcomes by one-digit occupation, 1993-2011



Source: Own estimations based on merged COMTRADE-NESPD database.

2.6.3 Indirect effect

Table 2.6 presents our estimates when including *downstream* and *upstream* neighbouring industry's gross import exposure from China on our five main worker outcome measures over 1997 to 2011 based on equation (2.8). Important to note is that the 8 sub-sector dummies are not included as controls. The reason is that due to the level of disaggregation of the I-O Tables, the majority of identified downstream and upstream industries are in different sub-sectors than their corresponding sourcing and purchasing industry.[24]Therefore, constrained by the data we are only able to capture *between*, rather than *within*, sub-sectors effects.[25]

We can see that the negative relationship between the direct change in gross import penetration and each of the five dependent variables remains highly significant. In fact, the inclusion of the two indirect measures of Chinese import competition slightly increases the precision of each point estimate. Moreover, each coefficient on direct change in import exposure seems unaffected by the inclusion of indirect change in gross import penetration.[26]

Increased import growth in the *upstream* neighbouring industry tends to have a positive effect on cumulative annual earnings and negative ones on cumulative hourly pay and hours of work, although the point estimates are not statistically significant. In contrast, the findings in columns 4 and 5 suggest that increased import competition in the *downstream* industry has a negative and significant impact on wages and hours of work. The implied 75^{th}-25^{th} percentile differential for wages and hours of work are respectively -46.9% and -24.8%, suggesting that, from the perspective of a given industry, increased import competition in the industry that purchases the biggest amount of inputs from them leads to a additional detrimental effect on both margins of employment.

[24]Of the 73 identified downstream and upstream sectors, respectively 77.8% and 75.3% are in different 1-digit UKSIC industries than their corresponding neighbour.

[25]As expected, if we include the eight sub-sector dummies, the coefficients on both indirect import exposure measures turn insignificantly different from zero, whereas the coefficients on the direct effect of import exposure are unaffected in all columns relative to those in the upper panel of Table 2.3.

[26]We now have to contrast those point estimates with the corresponding ones in columns 8 of Table 2.1 and Table 2.2. That is the column estimating the impact of Chinese import competition without controlling for the eight sub-sector dummies.

Table 2.6: Direct and indirect gross imports from China (1997-2011) for full time workers: 2SLS estimates for various labor market outcomes

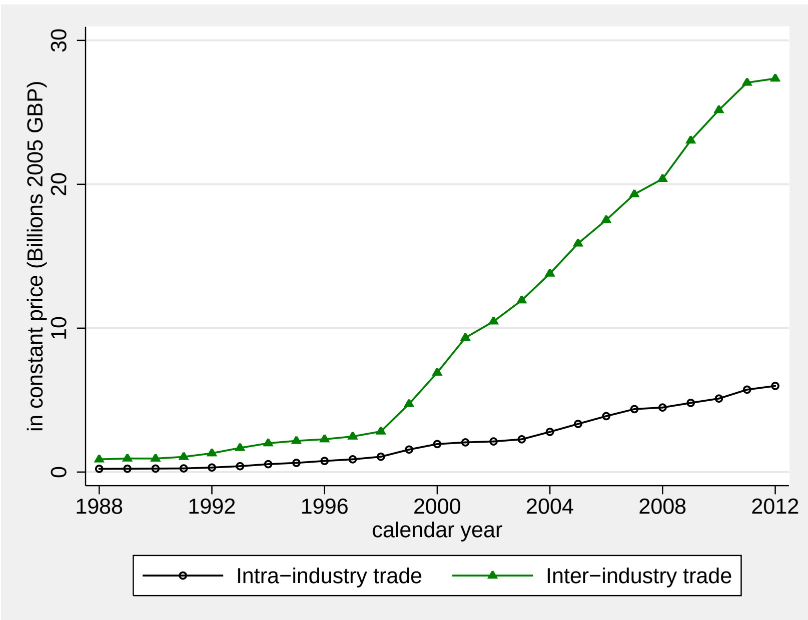
	Cumulative Annual Earnings (1)	Years of Non-Zero Earnings (2)	Cumulative Annual Earnings/Year (3)	Cumulative Hourly Pay (4)	Cumulative Hours of Work (5)
(ΔChina Imports)/UK Consumption$_{96}$	-13.678** (3.552)	-4.372** (1.199)	-0.912** (0.237)	-18.263** (4.448)	-8.410** (2.261)
Upstream (ΔChina Imports)/UK Consumption$_{96}$	3.543 (15.305)	-1.178 (5.203)	0.236 (1.020)	-19.188 (15.690)	-7.543 (7.948)
Downstream (ΔChina Imports)/UK Consumption$_{96}$	-11.740 (10.877)	-5.612** (2.414)	-0.783 (0.725)	-23.620** (8.983)	-12.945** (4.724)
% diff. for ΔIP (75th p. v.s. 25th p.)	-72.22**	-23.08**	-4.82**	-95.92**	-44.17**
% diff. for ΔUpstream IP (75th p. v.s. 25th p.)	12.05	-4.01	0.80	-65.24	-25.65
% diff. for ΔDownstream IP (75th p. v.s. 25th p.)	-23.25	-11.11**	-1.55	-46.93**	-24.83**
1st stage statistics: (ΔChina Imports)/UK Consumption$_{96}$					
(ΔHI Imports)/UK Consumption$_{92}$	0.187** (0.002)	0.187** (0.002)	0.187** (0.002)	0.187** (0.002)	0.187** (0.002)
Upstream (ΔHI Imports)/UK Consumption$_{92}$	-0.121** (0.004)	-0.121** (0.004)	-0.121** (0.004)	-0.121** (0.004)	-0.121** (0.004)
Downstream (ΔHI Imports)/UK Consumption$_{92}$	-0.042** (0.002)	-0.042** (0.002)	-0.042** (0.002)	-0.042** (0.002)	-0.042** (0.002)
Robust F-stat (Shea's partial R-squared)	29.599** (0.5805)	29.599** (0.5805)	29.618** (0.5805)	29.551** (0.5795)	29.551** (0.5795)
1st stage statistics: Upstream Imports from China					
(ΔHI Imports)/UK Consumption$_{92}$	0.007** (0.0004)	0.007** (0.0004)	0.007** (0.0004)	0.007** (0.0004)	0.007** (0.0004)
Upstream (ΔHI Imports)/UK Consumption$_{92}$	0.076** (0.002)	0.076** (0.002)	0.076** (0.002)	0.076** (0.002)	0.076** (0.002)
Downstream (ΔHI Imports)/UK Consumption$_{92}$	0.009** (0.001)	0.009** (0.001)	0.009** (0.001)	0.009** (0.001)	0.009** (0.001)
Robust F-stat (Shea's partial R-squared)	7.412** (0.5026)	7.412** (0.5026)	7.412** (0.5026)	7.412** (0.5012)	7.412** (0.5012)
1st stage statistics: Downstream Imports from China					
(ΔHI Imports)/UK Consumption$_{92}$	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Upstream (ΔHI Imports)/UK Consumption$_{92}$	-0.012** (0.001)	-0.012** (0.001)	-0.012** (0.001)	-0.012** (0.001)	-0.012** (0.001)
Downstream (ΔHI Imports)/UK Consumption$_{92}$	0.148** (0.001)	0.148** (0.001)	0.148** (0.001)	0.148** (0.001)	0.148** (0.001)
Robust F-stat (Shea's partial R-squared)	36.242** (0.6902)	36.242** (0.6902)	36.242** (0.6902)	36.124** (0.6890)	36.124** (0.6890)
Number of observations	19,257	19,257	19,257	19,091	19,091

Notes: For a sample of workers born between 1947 and 1975, with non-zero earnings in 1992-94 and 1995-97. All regressions include the vector of controls from column 9 of Table 2.1 except the eight sub-sector dummies. Where ** (*) denotes statistically significant at the 5 (10) percent level. Robust standard errors are clustered on start of period 3 digit industry. The mean (sd) of (ΔChina Imports)/UK Consumption$_{96}$ is 0.0586 (0.0951), the median is 0.0221, the value at the 25th perc. is 0.0026 and the 75th perc. is 0.0554. The mean (sd) of Upstream (ΔChina Imports)/UK Consumption$_{96}$ is 0.0357 (0.0518), the median is 0.0243, the value at the 25th perc. is 0.0031 and the 75th perc. is 0.0371. The mean (sd) of Downstream (ΔChina Imports)/UK Consumption$_{96}$ is 0.0389 (0.0836), the median is 0.0079, the value at the 25th perc. is 0.0071 and the 75th perc. is 0.0269.
Source: Own estimations based on merged COMTRADE-NESPD database.

2.7 The labor market effect of increased exposure to import competition from the European Union

In this section, we explore the nature of trade with China and compare that to trade with the EU. Figure 2.12 shows that UK bilateral trade patterns with China are mainly in the form of *inter*-industry trade, whereas Figure 2.13 shows that UK bilateral trade relationships with the EU are mainly in the form of *intra*-industry trade. This makes the EU an interesting point of reference, given that overall trade has increased in a similar way to that with China. This is also the case for the US as shown in Figures B.9 and B.10 in the Appendix. We would then expect a different impact on worker-level outcomes whether import competition stem from China or the EU.

Figure 2.12: The nature of trade between the UK and China, 1988-2012

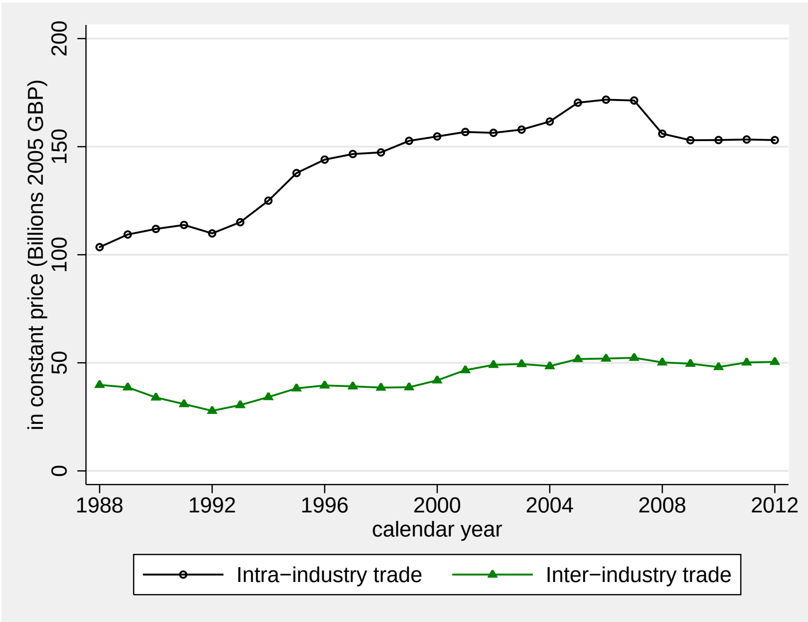


Source: Using data from UN Comtrade for 166 consistently defined manufacturing industries.

In order to compare the impact of import penetration from China with that from the EU we re-estimate our preferred specification for all five of our outcome variables further conditioning on the change in import penetration from the EU (over 1996 to 2011) and the import penetration from the EU in 1996. This is analogous to Table 2.3 where we look at gross imports in the upper panel and net imports in the lower panel.

Table 2.7 presents the results using the change in gross import penetration from China and from the EU simultaneously. On the one hand, the table shows that the impact of gross Chinese import growth on all outcomes is still negative and significant and these estimates remain mostly unaffected by the inclusion of gross import

Figure 2.13: The nature of trade between the UK and the EU, 1988-2012



Notes: The EU consists of Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain and Sweden.
Source: Using data from UN Comtrade for 166 consistently defined manufacturing industries.

from the EU. On the other hand, increased gross imports from the EU are associated with positive worker-level outcomes with the estimates being statistically significant in all columns. However, the positive effects of import competition from the EU are not large enough to compensate for the negative effects of Chinese competition.

The estimates in Table 2.8 show that the adverse effect of net import competition from China is much larger than for gross imports, confirming that UK industries have been exposed to a major rise in imports from China without a counterbalancing rise in demand from China for exports. However, net import growth from the EU now implies positive or negative exposure shocks, though these are largely not statistically different from zero.[27] Overall, the findings suggest that imports from the EU might not be substitutes to domestic production, but are rather complements.[28]

[27] Moreover, as one can see in Table 2.8, the F-stat on the excluded instrument for EU import growth is low at 4.4, suggesting that the point estimates might suffer from a weak instrument issue.

[28] We use the change in trade exposure from the EU with respect to non-UK OECD countries (i.e. Australia, Canada, Chile, Japan, Mexico, New Zealand, Republic of Korea, Switzerland and the US) as an instrument for the change in trade exposure from the EU with respect to the UK. In unreported results in which we use as an instrument the change in trade exposure from the EU with respect to the Denmark, we find similar results.

Table 2.7: Gross imports from China and the EU (1997-2011) for full time workers: 2SLS estimates for various labor market outcomes

	Cumulative Annual Earnings (1)	Years of Non-Zero Earnings (2)	Cumulative Annual Earnings/Year (3)	Cumulative Hourly Pay (4)	Cumulative Hours of Work (5)
(ΔChina Imports)/UK Consumption$_{96}$	-9.261** (4.148)	-3.009** (1.096)	-0.617** (0.277)	-11.196** (4.503)	-5.241** (2.145)
(ΔEU Imports)/UK Consumption$_{96}$	4.771** (1.355)	1.263** (0.517)	0.318** (0.090)	4.854** (1.763)	2.675** (1.044)
% differential for ΔChina IP (75th p. v.s. 25th p.)	-52.88**	-17.18**	-3.52**	-63.93**	-29.93**
% differential for ΔEU IP (75th p. v.s. 25th p.)	42.03**	11.13**	2.80**	42.73**	23.57**
1st stage statistics: ΔChina Imports					
(ΔHI Imports)/UK Consumption$_{92}$	0.162** (0.003)	0.162** (0.003)	0.162** (0.003)	0.162** (0.003)	0.162** (0.003)
(ΔOECD Imports)/UK Consumption$_{92}$	0.015** (0.001)	0.015** (0.001)	0.015** (0.001)	0.015** (0.001)	0.015** (0.001)
Robust F-stat	30.462**	30.462**	30.462**	30.462**	30.462**
Shea's partial R-squared	0.484	0.484	0.484	0.484	0.484
1st stage statistics: ΔEU Imports					
(ΔHI Imports)/UK Consumption$_{92}$	0.059** (0.005)	0.059** (0.005)	0.059** (0.005)	0.059** (0.005)	0.059** (0.005)
(ΔOECD Imports)/UK Consumption$_{92}$	0.166** (0.005)	0.166** (0.005)	0.166** (0.005)	0.166** (0.005)	0.166** (0.005)
Robust F-stat	17.202**	17.202**	17.202**	17.203**	17.203**
Shea's partial R-squared	0.565	0.565	0.565	0.565	0.565
Number of observations	19,946	19,946	19,946	19,775	19,775

Notes: For a sample of workers born between 1947 and 1975, with non-zero earnings in 1992-94 and 1995-97. All regressions include the full vector of control variables from column 9 of Table 1. Where ** (*) denotes statistically significant at the 5 (10) percent level. Robust standard errors are clustered on start of period 3 digit industry. Using change in trade exposure from China with respect to the Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland over the period 1996-2011 as an instrument for the change in trade exposure from China with respect to the UK over the period 1996-2011. We use the change in trade exposure from the EU with respect to non-UK OECD countries (i.e. Australia, Canada, Chile, Japan, Mexico, New Zealand, Republic of Korea, Switzerland and the US) as an instrument for the change in trade exposure from the EU with respect to the UK. The mean (sd) of (ΔChina Imports)/UK Consumption$_{96}$ is 0.0592 (0.0939), the median is 0.0222, the value at the 25th percentile is 0.0026 and the 75th percentile is 0.0597. The mean (sd) of (ΔEU Imports)/UK Consumption$_{96}$ is 0.0492 (0.2052), the median is 0.0401, the value at the 25th percentile is -0.0004 and the 75th percentile is 0.0877.
Source: Own estimations based on merged COMTRADE-NESPD database.

Table 2.8: Net imports from China and the EU (1997-2011) for full time workers: 2SLS estimates for various labor market outcomes

	Cumulative Annual Earnings (1)	Years of Non-Zero Earnings (2)	Cumulative Annual Earnings/Year (3)	Cumulative Hourly Pay (4)	Cumulative Hours of Work (5)
(ΔChina Imports)/UK Consumption$_{96}$	-13.199** (4.261)	-4.745** (1.507)	-0.880** (0.284)	-21.850** (4.861)	-11.899** (2.774)
(ΔEU Imports)/UK Consumption$_{96}$	3.928 (9.549)	-1.509 (3.256)	-0.262 (0.637)	14.136 (9.153)	4.144 (5.900)
% differential for ΔChina IP (75th p. v.s. 25th p.)	-62.43**	-22.44**	-4.16**	-103.37**	-56.29**
% differential for ΔEU IP (75th p. v.s. 25th p.)	31.07	-11.94	-2.07	111.82	32.78
1st stage statistics: ΔChina Imports					
(ΔHI Imports)/UK Consumption$_{92}$	0.068** (0.001)	0.068** (0.001)	0.068** (0.001)	0.068** (0.001)	0.068** (0.001)
(ΔOECD Imports)/UK Consumption$_{92}$	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Robust F-stat	10.429**	10.429**	10.429**	10.511**	10.511**
Shea's partial R-squared	0.2389	0.2389	0.2389	0.2405	0.2405
1st stage statistics: ΔEU Imports					
(ΔHI Imports)/UK Consumption$_{92}$	0.022** (0.001)	0.022** (0.001)	0.022** (0.001)	0.022** (0.001)	0.022** (0.001)
(ΔOECD Imports)/UK Consumption$_{92}$	-0.024** (0.003)	-0.024** (0.003)	-0.024** (0.003)	-0.024** (0.003)	-0.024** (0.003)
Robust F-stat	4.359**	4.359**	4.359**	4.366**	4.366**
Shea's partial R-squared	0.096	0.096	0.096	0.097	0.097
Number of observations	19,946	19,946	19,946	19,775	19,775

Notes: As per Table 2.7. The mean (standard deviation) of net(ΔChina Imports)/UK Consumption$_{96}$ is 0.0489 (0.0982), whilst the median is 0.0124, the value at the 25th percentile is 0.0011 and the 75th percentile is 0.0484. The mean (standard deviation) of net (ΔEU Imports)/UK Consumption$_{96}$ is 0.0639 (0.1564), whilst the median is 0.0429, the value at the 25th percentile is 0.0096 and the 75th percentile is 0.0887.
Source: Own estimations based on merged COMTRADE-NESPD database.

2.8 Conclusion

The emergence of low and middle-income countries in the global economic landscape, mainly driven by China's transition to a market-oriented economy, has revived academic interest in the effects of trade competition on worker adjustment. China is an economy that converges toward the global technology frontier in response to major changes in domestic policy. Using a unique longitudinal dataset of individual worker characteristics for the UK over an extended period of time, we have exploited this recent surge in exports to analyze how UK manufacturing workers adjust to trade competition.

The UK's close trade ties with the EU have had a sizable impact on its labor market. Indeed, as trade theory predicts, trade with countries of any income level my affect domestic workers, although the impact largely depends on the nature of trade and *where* the imports originate from. We provide unique evidence that the effects of import competition from the EU did not have an adverse effect on the labor market outcomes of UK workers, and moreover may even have had a complementary effect. This is largely a consequence of the nature of trade being *intra-* rather than *inter*-industry. Conversely trade exposure from China has led to lower cumulative earnings, wages and hours of work between 1997 and 2011. The implied differential for a reduction in earnings over the 15 year sample period, between workers at the 75$^{\text{th}}$ percentile of industry trade exposure relative to workers at the 25$^{\text{th}}$ percentile is 48% of initial annual earnings. The drop in wages is equal to 69.2% of initial total wages and hours worked are lower by 33.6% of total hours worked in the initial year.

The impact of trade competition differs across occupation groups, which highlights the great heterogeneity in trade adjustment by job characteristics. Occupations such as managers, skilled trades and elementary production are most adversely affected by the rise in Chinese imports. Somewhat unexpectedly we find that the adverse effects of increased imports from China are most pronounced among managers and least pronounced among plant/machine operators.

Finally, we provide evidence of import competition shocks being transmitted through the purchase of intermediate inputs into worker-level outcomes in the sourcing industry. We have found that increased imports from China in an industry located further down the value chain (i.e. the *downstream* industry) have adverse effects on wages and hours worked in the sourcing (i.e. *upstream*) industry. Such an effect might be explain by the fact that firms in the *downstream* industry are hit by a negative revenue shock, which is potentially transmitted to the sourcing industry through lower purchases of intermediate inputs. The additional implied differential for a reduction in wages and hours worked over the 15 year sample period, between workers at the 75$^{\text{th}}$ percentile of *downstream* industry trade exposure relative to workers at the 25$^{\text{th}}$ percentile is respectively 46.9% and 24.8%.

Chapter 3

The Effect of Trade and Exchange Rate Shocks on Wages in Switzerland

ARNAUD JOYE

I explore the impact of industry-level exposure to trade and real exchange rate shocks on individual-level wages for Swiss manufacturing workers over the period 1996-2008. This study proposes three main complements from the existing literature. First, I propose a gravity-type estimation strategy as a first-stage step to construct instrumental variables designed to consistently estimate the causal effect of changes in trade on workers' wages. Second, I focus on individual-level data, which enables to analyze the impact of trade and exchange rates within skill groups, occupations and industry characteristics. Third, I focus on a small open economy by drawing on data for Switzerland. This study shows that industry exposure to trade and exchange rate shocks influences wages of manufacturing workers of various groups differently. I show that the impact is concentrated among high-skilled and blue-collar workers almost exclusively. I also provide evidence that exchange rate effects are potentially heterogeneous across industries with different market structures. Wages of workers employed in industries that predominantly produce homogeneous goods are shown to be more responsive to exchange rates movements than those working in industries that predominantly produce differentiated varieties.

JEL Codes: F14, F16, J31
Keywords: wage, import competition, export share, real exchange rates, market structure

3.1 Introduction

At least since Stolper and Samuelson (1941), economists have been interested in studying the effect of globalization on the labor market. The literature to date has been somewhat US centric and focused mainly on aggregate outcomes (e.g. Feenstra and Hanson, 1999). However, exposure to foreign shocks are expected to have more sizeable effects on small open economies such as Switzerland. Indeed the Swiss economy is highly dependent on exports and imports, and exposed to significant currency swings. According to the Open Markets Index report from the International Chamber of Commerce, Switzerland was the 11$^{\text{th}}$ most open economy out of 75 countries in 2013. The importance of exports and imports in the Swiss economy coupled with the recent abandon of the exchange rate ceiling by the Swiss National Bank call for a better comprehension of the effects of trade and exchange rates. Alas, to my knowledge no study exploring the impact of trade and exchange rate shocks on Swiss workers has been carried out.[1]

Therefore, this paper explores the impact of industry-level exposure to trade and exchange rate movements on individual-level wages of Swiss manufacturing workers over the period 1996-2008. Focusing on individual-level data is particularly appropriate for studying the relationship between wages, and trade and exchange rate shocks as analyses relying on more aggregated data could miss heterogeneous effects in workers with different characteristics. The standard approach to estimating the effect of import competition is to use fluctuation in the prices or quantities of imported goods across industries over time as an exogenous shock and explore the impact on industry-specific labor-market outcomes.[2] This study explores a similar route, yet the individual-level information at hand enables to analyze the impact of trade and exchange rates on wages of workers sharing similar characteristics in many dimensions, as well as the effect within skill groups, occupations and industry characteristics.

This paper contributes to a rapidly growing literature estimating the labor-market consequences of globalization at the individual, firm, industry or region level.[3] At the individual level, Autor, Dorn, Hanson, and Song (2014) looks at the medium-term impact of increased import competition from China on earnings and employment in the US economy, whereas Brülhart, Joye, and Lindley (2015) explores similar effects stemming from China or the European Union for the United Kingdom. In both studies, it is shown that increased import growth coming from China has significant and negative effects on workers' earnings. On the contrary, Brülhart et al. (2015) find that increased gross imports from the European Union

[1] A recent paper by Kaiser and Siegenthaler (2014) explores the relationship between real exchange rate movements and firms' skill demand in Switzerland. However, their data do not permit them to look at the individual-level consequences of exchange rate swings.

[2] See for example Feenstra and Hanson (1999) and Harrigan (2000) for the US.

[3] See for example Bernard, Jensen, and Schott (2006) or Amiti and Davis (2012) on trade and firms; Revenga (1992) or Artuc, Chaudhuri, and McLaren (2010) on trade and industries; and Brülhart, Carrère, and Trionfetti (2012) or Autor, Dorn, and Hanson (2013a) on trade and regions.

are associated with positive worker-level outcomes, while increase in net imports are not. My work complements theirs by using data for Switzerland, which is of particular interest for two reasons. First, Switzerland's trade-to-GDP ratio is high (91.2% over the sample period 1996-2008) suggesting that the average manufacturing industry relies heavily on exports and imports. Second, the movements of the swiss currency can be safely regarded as exogenous shocks to Swiss industries, as the swiss franc acts as a safe haven currency in times of economic and financial instability.

Ebenstein, Harrison, McMillan, and Phillips (2014) study the short-term impact of industry and occupational exposure to trade and offshoring shocks on wages of US workers. They find that occupational exposure is associated with significant wage effects, while industry exposure has no significant impact. My work is closely related to their study, since it also focuses on the short-term impact of trade on wages, yet I additionally propose a gravity-type estimation strategy as a first-stage step to construct instrumental variables designed to consistently estimate the causal effect of trade shocks on wages. Indeed, the estimated impact of trade may be potentially contaminated by domestic demand shocks to the Swiss economy that might influence import demand and export opportunities. Part of the observed fluctuations in trade might be due to changes in the domestic labor market that have nothing to do with factors driving foreign competition. If changes in trade flows partly reflect domestic shocks to Swiss industries, then this reverse causality would undermine the interpretation of the results.

Another potential threats that might invalidate our estimates is the probable correlation between technological change and trade shocks. One usual suspect is automation; for example if the wage of low-skilled workers are disproportionately affected by automation and, at the same time, those workers suffer relatively more, say, from import competition, then it would cast doubts on the causal interpretation of the results and bias the OLS estimation towards zero. I attempt to address the potential correlation between technological change and trade shocks by controlling for time-varying industry characteristics, as well as including individual-level characteristics, and 4-digit occupation and education fixed-effects.

My work also contributes to the literature that estimates the link between exchange rate movements and employment or wages (e.g. Campa and Goldberg, 2001, at the industry level). A closely related strand of literature examines the effect of exchange rate movements on workers using household survey data, as I do. The number of papers that explore these effects is relatively small and focuses mainly on the US (Goldberg and Pavcnik, 2003) and Mexico (Robertson, 2003, 2004). I therefore complement existing studies by drawing on data for Switzerland which have not been analyzed in this particular context to date.

Another related branch of the literature is interested in the relationship between exchange rate fluctuations and labor demand. Nucci and Pozzolo (2010, 2014) estimate the implications for firm-level wages and employment of changes in exchange rate for Italy. In a similar manner, Kaiser and Siegenthaler (2014) explore the relationship between real exchange rate movements and firms' skill demand in

Switzerland. My study is complementary to the latter, because their data do not permit them to look at the individual-level consequences of exchange rates swings.

This study shows that industry real exchange rate movements and trade exposure influence wages of manufacturing workers of various groups differently. When averaged across all workers, the overall impact of trade on wages appears small but statistically significant: a 10% increase in import penetration leads to a drop of 0.39% in wages, while a 10% increase in the export share implies a 0.53% increase in wages. In contrast, exchange rates movements do not seem to influence average wages. However, for some specific groups, effects can be larger. The impact of import penetration ratios, export shares and exchange rates swings are concentrated among high-skilled and blue-collar workers almost exclusively. Overall, the net effect of trade shocks on wages is positive, ranging from an increase of 0.42% for high-skilled workers' wages to 0.66% for blue-collar workers' wages after a rise of 10% in import penetration ratio and export share. For high-skilled workers, the results imply an average exchange rate elasticity of -0.22: the effect of a 1% currency appreciation on the hourly wage for a hypothetical high-skilled worker employed in an industry with average import exposure is a 0.220% wage expansion, potentially channeled through reductions in the cost of imported intermediate inputs. Concerning blue-collar workers, the estimated elasticity of hourly wage to exchange rate change is equal to 0.158. This means that the effect of a 1% currency depreciation on the hourly wage for a hypothetical blue-collar worker employed in an industry with average foreign exposure is a 0.158% wage rise. These results, highlighting the asymmetric effect of exchange rates on wages of workers of different skills or employed in different occupations, are in line with the findings of Goldberg and Pavcnik (2003). One potential explanation is that a currency appreciation puts pressure on costs which may push producers to invest in processes that are substitutes to blue-collar/low-skilled workers and/or complementary to white-collar/high-skilled workers (e.g. Acemoglu, 1998).

Exchange rate effects are potentially heterogeneous across industries with different market structures (Nucci and Pozzolo; 2010, 2011). A number of papers show that exchange rate pass-through elasticities depend on market structure and in particular on the extent to which products are differentiated and the substitution among different variants (Yang, 1997). Thus, I present results exploring the influence of market structure on shaping the response of wages to exchange rate shocks. Preliminary evidence show that wages of workers employed in industries that predominantly produce homogeneous goods are more responsive to exchange rates movements than those working in industries that predominantly produce more differentiated varieties.

The paper is organized as follows. Section 3.2 describes the data and presents the definition of the trade and exchange rates variables. Section 3.3 explains the instrumental variable strategy to consistently estimate the causal impact of trade on wages, while Section 3.4 presents the empirical specification. Section 3.5 presents the main findings regarding the impact of trade on domestic wages, while Section 3.6 shows the impact of exchange rates on wages. Section 3.7 concludes.

3.2 Data sources and variables description

3.2.1 Data sources

The data on workers, trade and exchange rates are drawn from several sources. At the core is the Swiss Labor Force Survey (SLFS) conducted each year by the Federal Statistical Office (FSO). I have data for the period 1991-2008. The dataset provides extensive information about individual-level earnings, normal hours worked per week, the industry and occupational status of each worker, and numerous socio-economic characteristics. The SLFS uses industry description based on various revisions of the Swiss Economic Activity Nomenclature (NOGA85, 95, 02 and 08).[4] The finest level of disaggregation I can consistently attain over the sample period is the NOGA95 4-digit level, or equivalently the NACE Rev.1.0 4-digit level. The occupation variable is based on the International Standard Classification of Occupations (ISCO-88). As outcome measure, I focus on individual-level (hourly) wages. The wage is calculated as annual gross earnings, transformed in weekly gross earnings, and then divided by total hours worked per week. In addition, I use control variables such as age, sex, highest education attainment (5 classes), tenure (continuous, in years), marital status, nationality (swiss or foreign), firm size (2 categories; with < 20 or ≥ 20 employees), location (26 cantons), occupation (225 groups) and industry (193 manufacturing). The sample is restricted to individuals between 15 and 65 years old working in manufacturing industries.

Trade data are drawn from two distinct sources. Total swiss imports and exports data by industry are taken from the UN COMTRADE database at the 5-digit SITC Rev.3 level (Standard International Trade Classification). I constructed a concordance table to convert SITC Rev.3 products to NACE Rev.1.0 sectors at the most detailed level (4-digit level).[5] Expressed in current US dollar, the data are converted to constant Swiss Franc (base = 2011).[6] Bilateral trade flows for 193 countries, used to construct the gravity-type instruments and the industry-specific effective exchange rates, are extracted from CEPII. The database is called BACI and provides bilateral values of exports at the HS 6-digit product level, from 1995, for more than 200 countries.[7] Export values were then concorded from 6-digit HS92 to 4-digit NACE Rev.1.0.[8]

In order to instrument for time-varying trade shocks at the industry level, I use a structural gravity equation as a first-stage step to estimate the predicted values of total export and import values. Details on the construction of the instruments

[4]The NOGA nomenclature is equivalent to the NACE nomenclature up to the 4-digit level of disaggregation. NOGA95 corresponds to NACE Rev.1.0, NOGA02 corresponds to NACE Rev.1.1 and NOGA08 corresponds to NACE Rev.2.

[5]See the Appendix, section C.3 for details about how the concordance has been constructed.

[6]Swiss GDP deflator is used.

[7]See Gaulier and Zignago (2010) for details on the BACI database construction.

[8]Matching 6-digit HS92 products into SITC Rev.3 5-digit products is relatively straightforward with the help of official concordance provided by the UN Statistical Office. Then, I used my own SITC-NACE concordance as described in section C.3 in the Appendix.

are described in section 3.3. For this task, I use the GeoDist database provided by CEPII, which makes available the set of gravity variables developed in Mayer and Zignago (2005). The dataset contains country-specific geographical variables for 225 countries, including variables such as the geographical coordinates of their capital cities, the language spoken in the country under different definitions and a variable indicating whether the country is landlocked. The dataset also incorporates dyadic variables (valid for pairs of countries) such as bilateral distances, whether pairs of countries were or are still part of the same country, whether countries are contiguous, and their colonial ties. Finally, I also make use of an additional CEPII dataset called *language* that provides separate measures of common official language, common spoken language, common native language and linguistic proximity between different native languages, available for 195 countries.[9]

Other relevant data include gross production value per industry (GPV) obtained from FSO. The data are only available at the 2-digit NACE level, so to construct estimates of GPV at finer levels of disaggregation, I used total employment data by 4-digit industry. Industry employment data are not available for every year as they come from a firm census which was conducted for 1995, 2001, 2005 and 2008. As a consequence, in-between-year total industry employment are estimated by linear interpolation. Then, I estimated 4-digit GPV by weighting 2-digit values by the share of employment in each 4-digit sub-industries. Finally, swiss nominal exchange rates with respect to its 28 most important trading partners were extracted from the website fxtop.com, and then converted to real exchange rates using Swiss and corresponding trading partners CPI (base year 2010).[10]

After merging data on workers, trade flows and industry-specific real effective exchange rates (henceforth industry-specific REERs), I end up with a combined dataset covering the sample period 1996-2008 which sample is described in table C.1 in the Appendix.

3.2.2 Variable definitions

This paper explores the impact of globalization on wages of manufacturing workers in the short run. I have four globalization variables that are industry-specific and time-varying; import penetration ratio (IP), export share (XS), import-weighted REER index, and export-weighted REER index.

Industry-specific import penetration ratio captures the industry exposure to import competition. For worker *i* employed in industry *k* at time *t*, the ratio is calculated as follows:

$$\mathrm{IP}_{k,t} = \frac{\mathrm{M}_{k,t}}{\mathrm{DA}_{k,t}} \qquad \text{where} \qquad \mathrm{DA}_{k,t} = \mathrm{Y}_{k,t} + \mathrm{M}_{k,t} - \mathrm{X}_{k,t}; \tag{3.1}$$

[9] See Melitz and Toubal (2014) for details on the *language* database.

[10] The most important trading partners are Australia, Austria, Belgium-Luxembourg (treated as one country), Brazil, Canada, China, Denmark, Finland, France, Germany, Hong-Kong, Hungary, India, Ireland, Israel, Italy, Japan, South Korea, the Netherlands, Poland, Saudi Arabia, Singapore, Spain, Sweden, Thailand, Turkey, the United Kingdom and the United States.

where $\mathrm{DA}_{k,t}$ denotes the apparent domestic absorption of industry *k* in year t, $\mathrm{Y}_{k,t}$ is gross production per industry *k* in year t, and $\mathrm{M}_{k,t}$ and $\mathrm{X}_{k,t}$ are respectively total import and export values by industry *k* in year t.

Export share movements capture changes in comparative advantage for the exporting country, whether arising from changes in production price, product quality or variety. For worker *i* employed in industry *k* at time *t*, the export share, relative to production, is calculated as follows:

$$\mathrm{XS}_{k,t} = \frac{\mathrm{X}_{k,t}}{\mathrm{Y}_{k,t}}. \tag{3.2}$$

The industry-specific REER movements can be considered as shocks either to the delivered price of foreign goods or to the offered price of (domestic) outputs sold abroad. Thus, constructing two different measures of industry-specific REER, one reflecting the geographic composition of each industry's main import competitors and one capturing the composition of each industry's main export markets, allows to separately estimate shocks to input and output prices respectively. Indeed, industries can be substantially different in their mix of trading partners such that swings in a specific bilateral exchange rate lead to an asymmetric effect on workers.

The industry-specific REERs are constructed by weighting movements in the real exchange rate of the most important trading partners of Switzerland. The import-weighted REER is constructed as a weighted geometric 3-year-moving-average as follows:

$$\mathrm{ER}^{M}_{k,t} = \exp\left[\prod_{c} \overline{\theta}_{c,k,t-1} \times \ln(\mathrm{RER})_{c,t}\right], \tag{3.3}$$

$$\text{where} \qquad \overline{\theta}_{c,k,t-1} = \frac{\sum\limits_{i=t-1}^{t-3} M_{c,k,i}}{\sum\limits_{i=t-1}^{t-3} \sum\limits_{c} M_{c,k,i}}. \tag{3.4}$$

$RER_{c,t}$ denotes the Swiss bilateral real exchange rate index with country c in year t. In a similar fashion, the export-weighted REER is constructed as:

$$\mathrm{ER}^{X}_{k,t} = \exp\left[\prod_{c} \overline{\eta}_{c,k,t-1} \times \ln(RER)_{c,t}\right], \tag{3.5}$$

$$\text{where} \qquad \overline{\eta}_{c,k,t-1} = \frac{\sum\limits_{i=t-1}^{t-3} X_{c,k,i}}{\sum\limits_{i=t-1}^{t-3} \sum\limits_{c} X_{c,k,i}}. \tag{3.6}$$

The weights are lagged by one year in order to mitigate the potential correlation between exchange rate fluctuations and the geographic composition of trade flows.

3.3 Instrumental variable strategy

Exogenous globalization shocks likely coincide with endogenous changes in domestic production and consumption that in turn affect trade patterns and labor-market conditions. On the one hand, the industry-specific REER movements can be considered as exogenous shocks either to the delivered price of foreign goods or to the offered price of domestic outputs sold abroad. I assume that, in the case of Switzerland, swings in exchange rates can arguably be taken as exogenous shocks to domestic workers as movements in the swiss currency are mainly due to external forces external to the swiss domestic market.[11] On the other hand, unlike exchange rates, the estimated impact of trade may be potentially contaminated by domestic demand shocks to the Swiss economy that might influence import demand and export opportunities. Part of the observed fluctuations in trade might be due to changes in the domestic labor market that have nothing to do with factors driving foreign competition. If changes in trade flows partly reflect domestic shocks to Swiss industries, then this reverse causality would undermine the interpretation of the results. Another potential threats that might invalidate our estimates is the probable correlation between technological change and trade shocks. One usual suspect is automation; for example if the wage of low-skilled workers are disproportionately affected by automation and, at the same time, those workers suffer relatively more, say, from import competition, then it would cast doubts on the causal interpretation of the results and bias the OLS estimation towards zero.

I attempt to address these issues in several manners. First, I hope to neutralized reverse causality and mitigate skill-biased technological change (SBTC) by linking industry-level trade and exchange rate variables with individual-level data on wages and detailed socio-demographic characteristics. Indeed, a worker may hardly influence industry-level outcomes. Second, controlling for industry characteristics such as the annual industry average wage, controlling for the occupation of each worker at a detailed level and also for individual education attainment is a further attempt to mitigate coefficient biases. Third, I control for 4-digit industry and 2-digit sector $\times$ time fixed effects. I therefore compare workers within 4-digit industries controlling for 2-digit time-varying sectoral shocks in order to mitigate the effect of technological change. Finally, I use a gravity-type estimation strategy as a first-stage step to construct instrumental variables designed to consistently estimate the causal effect of trade on manufacturing workers.

This gravity methodology consists of aggregating up across a country's partners the prediction of a regression that aims to estimate trade flows with distance, language, land-border, colonial ties, landlocked status, and industry-level directional (origin and destination) fixed-effects. Gravity estimates are valid instruments since they are based on geographical and cultural variables which are plausibly exogenous (at least in the short term) and yet, when aggregated across all bilateral trading partners, correlated with a country's overall trade patterns. However, in-

[11] The same plausible assumption is made in Kaiser and Siegenthaler (2014).

stead of using predicted trade flows for Switzerland with respect to all its trading partners, I use average values of estimated trade flows from third countries to construct instruments for trade flows of Swiss industries.[12] The underlying hypothesis is that the estimated trade flows from third countries are correlated with the actual Swiss flows through geography and cultural characteristics, which are less likely to be related to economic outcomes through any channel other than trade.

The structural gravity model used is based on Anderson (1979) and follows from the model at the industry level as in Anderson and Van Wincoop (2004). The detailed derivation of the structural gravity model can be found in section C.2 of the Appendix. In short, the structural model is derived under the assumptions of a CES demand specification with product differentiation by place of origin (i.e. Armington type). Further assumptions are the inclusion of budget constraints (one for each destination in each industry) and market clearance equations (one for each origin in each industry). I abstract from the time subscript *t* to ease notation. At the industry level, the resulting model is:

$$T_{o,d,k} = \frac{E_{d,k} Y_{o,k}}{Y_k} \left(\frac{t_{o,d,k}}{\Pi_{o,k} P_{d,k}} \right)^{1-\sigma_k} \tag{3.7}$$

$$(\Pi_{o,k})^{1-\sigma_k} = \sum_d \left(\frac{t_{o,d,k}}{P_{d,k}} \right)^{1-\sigma_k} \frac{E_{d,k}}{Y_k} \tag{3.8}$$

$$(P_{d,k})^{1-\sigma_k} = \sum_o \left(\frac{t_{o,d,k}}{\Pi_{o,k}} \right)^{1-\sigma_k} \frac{Y_{o,k}}{Y_k}, \tag{3.9}$$

where $T_{o,d,k}$ is the value of shipments at destination prices from origin *o* to destination *d* in industry *k*. $E_{d,k}$ denotes the expenditure at destination *d* on goods in industry *k* from all origins. $Y_{o,k}$ represents sales of goods at destination prices from origin *o* in industry *k* to all destinations, whereas Y_k is the total output of goods in industry *k* at delivered prices. $t_{o,d,k} \geq 1$ is the variable trade cost on shipment of goods from origin *o* to destination *d* in industry *k*. σ_k represents the elasticity of substitution across goods in industry *k*. The term $\Pi_{o,k}$ represents outward multilateral resistance, which captures the average sellers' "frictions" faced in all destination countries. Finally, $P_{d,k}$ represents inward multilateral resistance (and is also the CES sectoral price index for the demand system), which then measures the average buyers' "frictions" faced in all origin markets.[13]

Turning to the estimation of the fundamental structural gravity equation in (3.7), and following the standard practice in the gravity literature, bilateral trade costs $t_{o,d,k}$ are approximated by a set of observable proxy variables. For each in-

[12] I use 9 non-European OECD countries' bilateral trade statistics with 193 countries (excluding Switzerland) for the estimation of the gravity regression. The 9 countries are Australia, Canada, Chile, Israel, Japan, Korea, Mexico, New-Zealand and the US (incl. Virgin Islands and Puerto Rico). The results are robust to using alternative sets of countries.

[13] See Anderson and Van Wincoop (2003).

dustry k, the specification is of the form:

$$(t^k_{o,d})^{1-\sigma_k} = exp[\gamma^k_1 \ln DIST_{o,d} + \gamma^k_2 BRDR_{o,d} + \gamma^k_3 CLNY_{o,d} + \gamma^k_4 CLNY45_{o,d} + \gamma^k_5 SMCTRY_{o,d} + \gamma^k_6 COL_{o,d} + \gamma^k_7 CSL_{o,d} + \gamma^k_8 CNL_{o,d} + \gamma^k_9 LP_{o,d}] \quad (3.10)$$

where ln $DIST_{o,d}$ is the logarithm of bilateral distance between origin country *o* and destination country *d*. $BRDR_{o,d}$ captures the presence of contiguous borders. $CLNY_{o,d}$ and $CLNY45_{o,d}$ accounts whether pairs have *ever* been or have been *post* 1945 in a colonial relationship respectively. $SMCTRY_{o,d}$ is a variable equal to 1 if pairs were or still are the same country. $COL_{o,d}$, $CSL_{o,d}$ and $CNL_{o,d}$ stands for common official, spoken and national language respectively. Finally, $LP_{o,d}$ is a variable representing language proximity between different native languages for pair of countries. As documented by Melitz and Toubal (2014), the use of common official language alone underestimate the impact of language and fails to capture the fact that the primary source of linguistic influence on bilateral trade is information rather than ethnicity or trust.

The next step toward estimation is to use (3.10) to substitute for the power transform of bilateral trade costs in (3.7) and add origin-time and destination-time fixed effects for each industry *k*. The Poisson pseudo-maximum-likelihood (PPML) estimator of Santos Silva and Tenreyro (2006) is used in order to to address the issues of heteroskedasticity and zeros in bilateral trade flows.[14] The PPML technique is used to estimate the following econometric specification of the gravity model for each industry *k* (220 manufacturing industries):

$$T^k_{o,d,t} = exp[\gamma^k_0 + \gamma^k_1 \ln DIST_{o,d} + \gamma^k_2 BRDR_{o,d} + \gamma^k_3 CLNY_{o,d} + \gamma^k_4 CLNY45_{o,d} + \gamma^k_5 SMCTRY_{o,d} + \gamma^k_6 COL_{o,d} + \gamma^k_7 CSL_{o,d} + \gamma^k_8 CNL_{o,d} + \gamma^k_9 LP_{o,d} + \alpha^k_{o,t} + \omega^k_{d,t}] + \epsilon^k_{o,d,t} \quad (3.11)$$

where $\alpha^k_{o,t}$ represents the set of time-varying origin-country industry-specific fixed effects which controls for the outward multilateral resistances $\Pi_{o,k,t}$ along with total sale $Y_{o,k,t}$. Finally, $\omega^k_{d,t}$ denotes the set of time-varying destination-country industry-specific fixed effects that controls for the inward multilateral resistances $P_{d,k,t}$ along with total expenditures $E_{d,k,t}$.[15]

For the purpose of illustration, Table 3.1 provides gravity coefficients, estimated by (3.11), by broad sector for years 1995-2008. I have to remind that the sourcing (origin) countries are the 9 non-European OECD countries [16], whereas the trading (destination) partners include 193 countries (excluding Switzerland) for which I have complete and consistent gravity and trade data.

[14] Results are robust with or without zero trade flows included and with alternative estimator such as OLS.

[15] See the work of Anderson and Yotov (2010, 2010 and 2012) for similar developments.

[16] To remind the reader, the countries are Australia, Canada, Chile, Israel, Japan, Korea, Mexico, New-Zealand and the US (incl. Virgin Islands and Puerto Rico).

Without going too much into details, let me briefly summarize the most salient features of the PPML gravity estimates reported in table 3.1. The coefficient on distance is always negative and statistically significant except for Transport.[17] Distance is hence a major obstacle to trade, but its magnitude displays significant variability across sectors, with low value/weight ratio sectors, such as Fuels and Wood, potentially more impacted than sectors with higher value/weight ratio. Contiguity also matters for most sectors. Having a common border significantly boosts trade flows in 9 out of 14 sectors.[18] Surprisingly, *post*-1945 colonial ties have a depressing effect on trade for almost all sectors except Food as shown by the coefficients on *CLNY45*. On the other hand, the sign of the coefficients on *CLNY*, whether countries have *ever* been in a colonial relationship, are not stable across sectors and have varying degrees of statistical significance. Finally, the impact of language, and the relative contributions of the different sources of linguistic influence, vary widely across sectors. On the one hand, having a common spoken language, which intends to capture the ease of communication, seems to facilitate trade as the only significant coefficients have a positive sign. On the other hand, estimates show that countries sharing common national languages tend to trade less in 7 out of 17 sectors. Surprisingly, and maybe driven by the 9 countries selected in the sample, greater linguistic proximity is not always a guarantee towards larger trade flows.

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[17] One explanation for the non-significance of distance could come from the fact that trade in the Transport sector are disproportionately arising between neighboring countries, and especially between Canada, Mexico and the US, as suggested by the large positive and significant coefficient estimates on the contiguity variable, *BRDR*, and on the language proximity variable *LP*.

[18] As mentioned in the previous footnote, the effect of *BRDR* may be potentially driven by Canada, Mexico and the US.

Table 3.1: PPML gravity estimations for export values by broad sector, 1995-2008

	Food	Textile	Leath./Shoes	Wood	Paper/Print/Publ.	Fuels	Chemicals
LNDIST	-0.823***	-1.338***	-1.092***	-1.665***	-1.004***	-1.898***	-1.067***
	(0.089)	(0.146)	(0.139)	(0.156)	(0.184)	(0.131)	(0.077)
BRDR	0.865***	0.821**	0.742*	0.345	0.915***	0.153	0.118
	(0.207)	(0.359)	(0.429)	(0.293)	(0.353)	(0.327)	(0.170)
CLNY	-0.328	-0.270	-0.112	0.781*	0.129	0.713	-0.074
	(0.283)	(0.265)	(0.272)	(0.450)	(0.189)	(0.489)	(0.146)
CLNY45	0.099	-1.159*	-0.880**	-2.388***	-1.522***	-3.231***	-1.395***
	(0.320)	(0.647)	(0.351)	(0.794)	(0.411)	(0.645)	(0.298)
SMCTRY	-0.226	0.774	0.182	0.182	0.439	0.650	0.513*
	(0.288)	(0.796)	(0.779)	(0.731)	(0.374)	(0.468)	(0.306)
COL	-0.240	0.887**	0.439	-1.123**	-0.153	-0.032	-0.048
	(0.268)	(0.351)	(0.473)	(0.479)	(0.280)	(0.406)	(0.221)
CSL	0.660	-0.760	0.584	2.082***	0.469	1.848**	2.117***
	(0.464)	(0.723)	(0.848)	(0.751)	(0.618)	(0.777)	(0.409)
CNL	-0.455	-1.041	-1.816**	-0.741	-0.098	-2.829***	-1.648***
	(0.680)	(0.924)	(0.815)	(0.878)	(0.805)	(0.991)	(0.506)
LP	-0.338**	-0.049	-0.221	-0.670***	-0.180	-0.380	-0.331***
	(0.137)	(0.202)	(0.158)	(0.229)	(0.230)	(0.295)	(0.121)
Constant	9.535***	11.498***	8.503***	13.684***	7.341***	17.937***	8.325***
	(0.859)	(1.379)	(1.220)	(1.447)	(1.968)	(1.224)	(0.793)
R-squared	0.937	0.941	0.888	0.980	0.986	0.918	0.963
Observations	23338	23338	23338	23338	23338	23338	23338
	Rub./Plast.	Minerals	Metals	Machinery	Electric	Transport	Miscell.
LNDIST	-1.063***	-1.295***	-0.912***	-0.991***	-0.856***	-0.075	-1.266***
	(0.105)	(0.147)	(0.116)	(0.073)	(0.102)	(0.188)	(0.181)
BRDR	1.135***	0.523*	1.259***	0.351**	0.408	2.493***	0.093
	(0.198)	(0.278)	(0.227)	(0.162)	(0.330)	(0.493)	(0.590)
CLNY	-0.323*	-0.139	0.688**	-0.243**	-0.101	0.729***	-0.119
	(0.165)	(0.140)	(0.291)	(0.109)	(0.108)	(0.188)	(0.258)
CLNY45	-0.772*	-1.311***	-1.810***	-0.938***	-1.062***	-2.166***	-1.799***
	(0.414)	(0.408)	(0.384)	(0.225)	(0.256)	(0.411)	(0.309)
SMCTRY	0.492*	1.074**	-1.975***	0.553	-2.063***	-0.992	0.928
	(0.258)	(0.478)	(0.412)	(0.914)	(0.710)	(1.055)	(0.787)
COL	0.169	0.200	0.510**	0.247*	0.180	0.489**	1.990***
	(0.150)	(0.202)	(0.258)	(0.149)	(0.147)	(0.218)	(0.345)
CSL	1.345***	0.764**	-0.580	0.279	0.235	-0.241	-0.979
	(0.294)	(0.386)	(0.534)	(0.275)	(0.341)	(0.500)	(0.767)
CNL	-1.464***	-0.499	0.479	-0.620*	-0.528*	0.053	-1.632**
	(0.448)	(0.596)	(0.635)	(0.357)	(0.294)	(0.620)	(0.745)
LP	-0.400***	-0.214**	0.292**	-0.269***	-0.171**	0.400***	-0.113
	(0.094)	(0.104)	(0.143)	(0.074)	(0.079)	(0.142)	(0.187)
Constant	6.872***	9.400***	9.162***	8.867***	6.518***	-0.496	11.518***
	(1.108)	(1.411)	(1.336)	(0.768)	(1.049)	(1.922)	(1.710)
R-squared	0.978	0.972	0.950	0.958	0.919	0.965	0.945
Observations	23338	23338	23338	23338	23338	23338	23338

Notes: Robust standard errors (clustered by country pair) are reported in parentheses. Each estimation is performed with directional (source and destination) and year fixed effects. Dependent variable is always the value of exports. *p≤0.10, **p≤0.05, ***p≤0.01.

Sources: Own estimations based on the BACII database.

Let me turn back to the construction of the instrumental variables. I obtain the bilateral predicted export values from (3.11), $\widehat{T}^{k}_{o,d,t}$ for each industry k and period t. Then, I sum them over destination (origin) countries to get an estimate of exports for each origin (imports for each destination) for each industry k. Finally, I take the average values over origin or destination countries to get the estimated total exports, $\widehat{X}_{k,t}$, and total imports, $\widehat{M}_{k,t}$ for each sector k in each year t respectively. To be precise:

$$\widehat{X}_{k,t} = \frac{1}{n_o}\sum_{o}\left(\sum_{d}\widehat{T}_{o,d,k,t}\right), \tag{3.12}$$

$$\widehat{M}_{k,t} = \frac{1}{n_d}\sum_{d}\left(\sum_{o}\widehat{T}_{o,d,k,t}\right), \tag{3.13}$$

where n_d and n_o denote the number of destination and origin countries respectively. $\widehat{X}_{k,t}$ is then used as the instrument for total swiss exports in industry k and year t, whereas $\widehat{M}_{k,t}$ is used as the instrument for total swiss imports in industry k and year t. The instrumental variables are therefore constructed in the following manner:

$$\mathrm{IP}^{IV}_{k,t} = \frac{\widehat{\mathrm{M}}_{k,t}}{\mathrm{DA}_{k,t}} \tag{3.14}$$

$$\mathrm{XS}^{IV}_{k,t} = \frac{\widehat{\mathrm{X}}_{k,t}}{\mathrm{Y}_{k,t}}. \tag{3.15}$$

3.4 Empirical strategy: 2^{nd} stage equation

The empirical strategy is to regress worker i-level wage, in industry k in period t on lagged measures of trade and weighted REER indexes using annual data from 1996 to 2008. I present two different equation specifications. The first one estimates the direct impact of trade inspired from studies such as Ebenstein et al. (2014), while the second one estimates the impact of exchange rates movements in a similar fashion than Campa and Goldberg (2001) or Nucci and Pozzolo (2010, 2014). The first specification, estimated either with ordinary least squares (OLS) or two-stage least squares (2SLS), is of the form:

$$\begin{aligned}\mathrm{w}_{i,k,t} =& \beta_0 + \mathbf{T}'_{\mathbf{k},\mathbf{t-1}}\beta_1 + \mathbf{X}'_{\mathbf{i},\mathbf{k},\mathbf{t}}\beta_2 + \mathbf{Z}'_{\mathbf{k},\tau}\beta_3 \\ &+ \beta_4 D_t + \beta_5 I_k + \beta_6 O_j + \beta_7 DI_{l,t} + \varepsilon_{i,k,t}.\end{aligned} \tag{3.16}$$

The dependent variables $\mathrm{w}_{i,k,t}$, for individual i working in industry k in year t, is the log of real hourly wage. $\mathbf{T}_{\mathbf{k},\mathbf{t-1}}$ is a vector containing the trade variables and is given by:

$$\mathbf{T_{k,t-1}} = \begin{bmatrix} \ln(\text{IP})_{k,t-1} \\ \ln(\text{XS})_{k,t-1} \end{bmatrix}; \tag{3.17}$$

where $\ln(\text{IP})_{k,t-1}$ is the value of the log of import penetration ratio in industry k in year $t-1$ as defined by (3.1) in section 3.2.2. It captures the industry exposure to import competition. In the IV specifications, $\ln(\text{IP})_{k,t-1}$ is instrumented by the import penetration ratio constructed with the gravity-predicted imports in (3.14) from third countries as illustrated in section 3.3.

$\ln(\text{XS})_{k,t-1}$ is the value of the log of export share in industry k in year $t-1$ as defined by (3.2) in section 3.2.2. It intends to capture the export exposure of each industry relative to production. In the IV specifications, $\ln(\text{XS})_{k,t-1}$ is instrumented by the export share constructed with the gravity-predicted exports in (3.15) from third countries as illustrated in section 3.3.

$\mathbf{X_{i,k,t}}$ is a vector of individual characteristics including age, age squared, age cubed, sex, marital status, whether the worker is swiss, tenure in the establishment (continuous, in years), highest education attainment (5 classes), firm size (2 categories; with < 20 or ≥ 20 employee) and location (26 cantons). Trade variables are lagged one period in order to mitigate the problem of reverse causality and also because wage adjustments are not likely to be instantaneous.

$\mathbf{Z_{k,\tau}}$ is a vector of industry characteristics comprising the industry *k* average hourly wage in years t, $t-1$ and $t-2$. Finally, D_t represents time fixed effects (13 years), I_k represents 4-digit industry fixed effects (193 manufacturing), O_j represents 4-digit occupation fixed effects (225 groups) and finally $DI_{l,t}$ represents 2-digit sector $\times$ time fixed effects. Robust standard errors are clustered at the 4-digit industry level.

The second specification looks at the effect of exchange rates movements on wages. As in Campa and Goldberg (2001) or Nucci and Pozzolo (2010, 2014), I test whether wage adjustments after an exchange rate shock are stronger depending on the external orientation of each industry. It is expected that an appreciation of the domestic currency would impact workers more, through revenues, the higher is the industry's exposure to sales from exports. On the contrary, on the cost side, an appreciation of the domestic currency may induce a cut in imported input expenditures and the effect is supposed to be larger the higher is the industry exposure to import competition.[19] Therefore, I include both changes in industry-specific REER indexes as well as the interactions between import penetration ratio, in year $t-1$, and the change in import-weighted REER index on the one hand, and between export share, in year $t-1$, and the change in export-weighted REER index on the other hand. In light of the non-stationarity of the exchange rate time series, the

[19]One would suggest for example to use the industry's share of cost stemming from imported intermediate inputs instead. Unfortunately, I lack such data. However, an OECD study ranked Switzerland 16th in Global Value Chain participation amongst OECD and BRICS economies in 2009. It suggests that the share of imported intermediate inputs in total imports is potentially significant among manufacturing industries.

specification is estimated in first differences.

It has to be noted that estimating in first-differences result in a loss of observations. Indeed, even though the SLFS dataset includes information for workers observed over consecutive years (up to five years), a little less than 40% of individuals drop out of the sample after one year. The first-difference specification is of the form:

$$\begin{aligned}\Delta \mathrm{w}_{i,k,t} =& \gamma_0 + \mathbf{G}'_{\mathbf{k,t-1}}\gamma_1 + \Delta\mathbf{P}'_{\mathbf{k,t}}\gamma_2 + \Delta\mathbf{GP}'_{\mathbf{k},\tau}\gamma_3 + \mathbf{X}'_{\mathbf{i,k,t}}\gamma_4 + \Delta\mathbf{Z}'_{\mathbf{k,t}}\gamma_5 \\ &+ \gamma_6 D_t + \gamma_7 I_k + \gamma_8 O_j + \gamma_9 DI_{l,t} + \varepsilon_{i,k,t}\end{aligned} \tag{3.18}$$

where $\mathbf{G_{k,t-1}}$ is a vector containing the industry import penetration ratio and export share in period $t-1$ as follows:

$$\mathbf{G_{k,t-1}} = \begin{bmatrix} \mathrm{IP}_{k,t-1} \\ \mathrm{XS}_{k,t-1} \end{bmatrix}. \tag{3.19}$$

$\Delta\mathbf{P_{k,t-1}}$ is a vector containing the two different industry-specific REER indexes and is as follows:

$$\Delta\mathbf{P_{k,t}} = \begin{bmatrix} \Delta \mathrm{ER}^M_{k,t} \\ \Delta \mathrm{ER}^X_{k,t} \end{bmatrix}, \tag{3.20}$$

where $\Delta\mathrm{ER}^M_{k,t}$ is the log change, between t and $t-1$, in the import-weighted industry-specific REER index as defined by (3.3) in section 3.2.2. A higher rate means a real depreciation of the swiss currency relative to the industry-specific foreign basket. Finally, $\Delta\mathrm{ER}^X_{k,t}$ is the log change in the export-weighted industry-specific REER index as defined by (3.5) in section 3.2.2.

$\Delta\mathbf{GP}_{\mathbf{k},\tau}$ is a vector containing the interaction between the trade variables and the change in industry-specific REER indexes as follows:

$$\Delta\mathbf{GP}_{\mathbf{k},\tau} = \begin{bmatrix} \mathrm{IP}_{k,t-1} \times \Delta \mathrm{ER}^M_{k,t} \\ \mathrm{XS}_{k,t-1} \times \Delta \mathrm{ER}^X_{k,t} \end{bmatrix}. \tag{3.21}$$

Finally, $\Delta\mathbf{Z_{k,t}}$ includes the change in industry average (log) wage and the change in individual (log) annual hours of work. As in equation (3.16), I also include the full vector of individual characteristics, as well as time, region, industry, occupation and time $\times$ 2-digit sector fixed-effects. Therefore, the estimating equations as specified in (3.16) and (3.18) capture the short term effect of trade and exchange rates shocks on wages for workers *(i)* sharing similar characteristics in terms of age, sex, education, nationality, location and marital status; *(ii)* having the same experience on the job, within similar occupation ; *(iii)* with similar average industry characteristics; and *(iv)* being employed in different sub-industries of the same sector. An important point to note is that I am only able to capture the wage effect for workers that remain employed in the manufacturing sector. I am therefore unable to gauge the wage consequence for workers switching out of manufacturing, or for those that become unemployed.

3.5 The effect of trade on wages

The OLS and 2SLS estimates of wage determinants of equation (3.16) for all workers are shown in Table 3.2. Columns 1 to 5 present various estimations performed with OLS. In column 1, I perform the estimation without control variables and including only time and industry fixed effects. The effect of import penetration on wage is consistently and significantly negative, with a coefficient of -0.054 suggesting a small impact on wage; a 10% increase in industry exposure from import competition is associated with a 0.54% decline in wage. The impact of export share is positive and significant with a point estimate of 0.062; a 10% increase in export share is associated with a 0.62% increase in wage. Therefore, in net, the effect of trade shocks on wage is small but significantly positive.

The subsequent columns present the estimation with additional controls and fixed effects. In column 2, I add region and education fixed-effects. Column 3 adds the full set of control variables. Finally, columns 4 and 5 add sector $\times$ year fixed effects and occupation fixed effects respectively. The coefficients are remarkably stable, yet with lower coefficients on both import penetration and export share, across the five specifications. The last column is the equivalent of column 5 but estimated using 2SLS, in which import penetration ratio and export share are instrumented by (3.14) and (3.15) respectively. This is the preferred specification. The coefficient on the import penetration is unchanged relative to the one estimated using OLS. On the contrary, the coefficient on the export share is roughly 40% larger. This is consistent with there being a positive correlation between industry trade shocks and industry characteristics that seems to slightly bias OLS estimates towards zero. In column 6, point estimates suggest that a 10% increase in import penetration leads to a drop of 0.39% in wages, while a 10% increase in the export share implies a 0.53% increase in wages; the net effect is therefore positive but modest. Overall, these results contrast with those in Ebenstein et al. (2014). Indeed contrasting industry and occupation exposure to trade, they do not find any impact of increased industry trade exposure on wages.

Concerning individual-level characteristics, Table 3.2 presents results that are fairly expected. Wages are higher for males, for married and older workers, for workers with higher tenure at the firm and for those working in larger firms. Moreover, the contemporaneous average industry wage is positively related with individual wage, whereas the two corresponding lagged measures do not seem to significantly influence workers' wages. Finally, the number of annual hours of work is negatively related to wage.[20]

The instruments perform well overall. The F-stat on the excluded instruments is equal to 36.3, which indicates that the 2SLS estimation does not suffer from a weak-instrument issue.[21] Most reassuringly, the first-stage regressions in Ta-

[20] Controlling for the number of annual hours worked means that if I estimate equation (3.16) using the log of annual gross earnings instead of wages, results are equivalent.

[21] The F-stat on the excluded instruments is the Kleibergen-Paap F-stat, which is a Wald test for weak-identification.

ble C.2, columns 1 and 2, in the Appendix, confirm that the instruments behave in the expected way: third countries' trade flows estimated with the gravity procedure are positively and significantly related to swiss trade flows. Therefore, the instrumental variables are good predictors of the endogenous variables.

When averaged across all workers, the overall impact of trade on wages appears small, as shown in Table 3.2. However, for some specific group of workers, the effect can be larger. Table 3.3 presents the OLS and corresponding 2SLS regressions, as in columns 5 and 6 of Table 3.2, separately for different groups of workers. Panel A presents estimations of equation (3.16) separating workers based on their highest education attainment; high-skilled workers in columns 1 and 2, and low-skilled workers in columns 3 and 4.[22] Panel B shows the corresponding estimations based on the worker's occupation.[23] Results for white collar workers are presented in columns 1 and 2, while results for blue collar workers can be found in columns 3 and 4. [24]

What emerges from Panel A of Table 3.3 is that the impact of import penetration ratios and export shares are concentrated among high-skilled workers almost exclusively. Indeed, as suggested by the point estimates, import penetration and export shares have a larger impact on wages for high-skilled workers relative to low-skilled workers. For the former group, the coefficients in column 2 indicates that a 10% increase in industry exposure to import competition is associated with a 0.75% decline in wages. In contrast, a 10% increase in export share is related to a 1.16% increase in wages. Columns 3 and 4 shows lower point estimates for both trade shocks when low-skilled workers are considered, yet they are not significantly different from zero in the IV specification.[25]

Turning to Panel B of Table 3.3, workers employed in blue-collar occupations see their wages respond more to trade shocks than workers employed in white-collar occupations. The results in column 4 indicate that a 10% increase in import penetration ration leads to a drop of 0.89% in wages. On the contrary, a 10% increase in industry exposure from exports is associated with a 1.5% increase in wages.[26] Overall, the net effect of trade shocks on wages is positive, ranging from an increase of 0.42% for high-skilled workers' wages to 0.66% for blue-collar workers' wages after a rise of 10% in import penetration ratio and export share.

[22] High-skilled workers are those that have either graduated from a university, from a professional school, or have a Maturité. The low-skilled workers corresponds to those that have finished an apprenticeship or less.

[23] The occupation classification is ISCO-88.

[24] White-collar workers are those in occupations such as legislators, senior officials and managers, professionals, technicians and associate professionals, clerks, service workers, and shop and market sales. Blue-collar workers are those in occupations such as skill agricultural and fishery workers, and craft and related workers, plant and machine operators, assemblers and elementary occupations.

[25] The corresponding first-stage regressions of column 2, for high-skilled workers, can be found in columns 3 and 4 in Table C.2 in the Appendix, whereas the corresponding first-stage estimates for low-skilled workers can be found in columns 5 and 6.

[26] Again, the corresponding first-stage regressions of column 2, for white-collar workers, can be found in columns 7 and 8 in Table C.2 in the Appendix, whereas the corresponding first-stage estimates for blue-collar workers can be found in columns 9 and 10.

Table 3.2: OLS and 2SLS estimates of wage determinants (1996-2008): overall workers

	OLS					IV
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(\mathrm{IP})_{k,t-1}$	-0.054***	-0.045**	-0.042***	-0.041***	-0.039***	-0.039***
	(0.021)	(0.019)	(0.014)	(0.013)	(0.012)	(0.013)
$\ln(\mathrm{XS})_{k,t-1}$	0.062**	0.048**	0.045**	0.044**	0.038**	0.053**
	(0.025)	(0.021)	(0.019)	(0.018)	(0.017)	(0.023)
$\overline{\mathrm{w}}_{k,t}$			0.398***	0.397***	0.351***	0.350***
			(0.036)	(0.036)	(0.033)	(0.033)
$\overline{\mathrm{w}}_{k,t-1}$			0.007	0.013	-0.002	-0.002
			(0.017)	(0.018)	(0.018)	(0.018)
$\overline{\mathrm{w}}_{k,t-2}$			-0.012	-0.012	-0.014	-0.013
			(0.021)	(0.022)	(0.021)	(0.021)
$\ln(\mathrm{hours})_t$			-0.107***	-0.107***	-0.103***	-0.103***
			(0.027)	(0.027)	(0.026)	(0.026)
Age			0.075***	0.075***	0.075***	0.075***
			(0.011)	(0.011)	(0.011)	(0.011)
Age^2 ($\times$ 1000)			-1.387***	-1.387***	-1.392***	-1.393***
			(0.282)	(0.282)	(0.276)	(0.277)
Age^3 ($\times$ 1000)			0.008***	0.008***	0.008***	0.008***
			(0.002)	(0.002)	(0.002)	(0.002)
Married			0.011	0.011	0.018***	0.018**
			(0.007)	(0.007)	(0.007)	(0.007)
Foreign			-0.030***	-0.031***	-0.009	-0.009
			(0.009)	(0.009)	(0.009)	(0.009)
Female			-0.199***	-0.200***	-0.233***	-0.233***
			(0.011)	(0.011)	(0.012)	(0.012)
Tenure			0.003***	0.003***	0.004***	0.004***
			(0.000)	(0.000)	(0.000)	(0.000)
Firm Size			0.106***	0.107***	0.086***	0.086***
			(0.012)	(0.012)	(0.012)	(0.012)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes	Yes
Education FE	No	Yes	Yes	Yes	Yes	Yes
Sector$\times$Year FE	No	No	No	Yes	Yes	Yes
Occupation FE	No	No	No	No	Yes	Yes
R-squared	0.001	0.001	0.163	0.163	0.168	0.168
F	4.198	3.642	157.471	164.979	208.670	194.700
N	22,633	22,633	22,633	22,633	22,633	22,633
No. Clusters	193	193	193	193	193	193
F-test on IVs						36.259

Notes: The dependent variables in all columns is the log of hourly wage. All regressions include a constant term. Standard errors are clustered at the industry 4-digit level. Columns (1) to (5) are estimated with OLS, while column (6) is estimated using 2SLS. Column (1) controls for year and industry 4-digit fixed effects. Columns (2) and (3) add regional and education fixed effects. Column (4) adds 2-digit sector $\times$ year fixed effects. Columns (5) and (6) add occupation 4-digit fixed effects. The F-stat on the excluded instruments is the Kleibergen-Paap F-stat, which is a Wald test for weak-identification. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.
Sources: Own estimations based on merged BACII-SLFS database.

Table 3.3: OLS and 2SLS estimates of wage determinants: various groups of workers

Panel A: education	High-skilled		Low-skilled	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
$\ln(\text{IP})_{k,t-1}$	-0.056***	-0.074***	-0.033*	-0.017
	(0.019)	(0.026)	(0.018)	(0.019)
$\ln(\text{XS})_{k,t-1}$	0.050**	0.116***	0.048**	0.036
	(0.023)	(0.038)	(0.022)	(0.034)
$\overline{\text{w}}_{k,t}$	0.369***	0.361***	0.332***	0.333***
	(0.052)	(0.051)	(0.040)	(0.040)
$\overline{\text{w}}_{k,t-1}$	0.071*	0.075*	-0.042	-0.041
	(0.040)	(0.040)	(0.029)	(0.030)
$\overline{\text{w}}_{k,t-2}$	-0.023	-0.016	-0.019	-0.017
	(0.030)	(0.031)	(0.029)	(0.029)
$\ln(\text{hours})_t$	-0.114***	-0.114***	-0.095***	-0.095***
	(0.032)	(0.032)	(0.029)	(0.029)
R-squared	0.194	0.193	0.159	0.159
F	66.543	65.634	118.677	110.707
N	7,979	7,979	14,654	14,654
No. Clusters	173	173	186	186
F-test on excluded IVs		34.794		27.257
Panel B: occupation	White-collar		Blue-collar	
$\ln(\text{IP})_{k,t-1}$	-0.029**	-0.020	-0.049*	-0.086*
	(0.012)	(0.017)	(0.030)	(0.051)
$\ln(\text{XS})_{k,t-1}$	-0.001	-0.005	0.091***	0.152**
	(0.022)	(0.037)	(0.034)	(0.063)
$\overline{\text{w}}_{k,t}$	0.364***	0.364***	0.345***	0.343***
	(0.034)	(0.034)	(0.060)	(0.059)
$\overline{\text{w}}_{k,t-1}$	0.005	0.005	-0.014	-0.016
	(0.021)	(0.021)	(0.037)	(0.037)
$\overline{\text{w}}_{k,t-2}$	0.012	0.013	-0.060*	-0.062*
	(0.022)	(0.023)	(0.033)	(0.033)
$\ln(\text{hours})_t$	-0.118***	-0.118***	-0.091***	-0.092***
	(0.037)	(0.037)	(0.032)	(0.032)
R-squared	0.221	0.221	0.130	0.129
F	147.852	144.324	74.148	66.520
N	11,864	11,864	10,761	10,761
No. Clusters	181	181	182	182
F-test on excluded IVs		41.624		14.933

Notes: The dependent variable in all columns is the log of hourly wage. All regressions include a constant term and all control variables that are included in Table 3.2 (not shown, but available on request). Standard errors are clustered at the industry 4-digit level. All regressions control for regional, year, education, industry 4-digit level, occupation 4-digit level and 2-digit industry $\times$ year fixed effects. Panel A shows results for workers according to their highest education attainment. Columns (1) and (2) present results for high-skilled workers, while columns (3) and (4) show results for low-skilled workers. Panel B shows results for workers according to their occupation. Columns (1) and (2) present results for white-collar workers, while columns (3) and (4) show results for blue-collar workers. The F-stat on the excluded instruments is the Kleibergen-Paap F-stat. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.
Sources: Own estimations based on merged BACII-SLFS database.

3.6 The effect of exchange rates on wages

As in Campa and Goldberg (2001) and Nucci and Pozzolo (2010, 2014), in this section, I test whether individual-level wage adjustments after an exchange rate shock are stronger depending on the external orientation of each industry and the geographic composition of each industry's trading partners. It is expected that an appreciation of the domestic currency would impact workers more, through revenues, the higher is the industry's share of exports. On the contrary, on the cost side, an appreciation of the domestic currency may induce a cut in foreign imported intermediate input expenditures and the effect is potentially larger the higher is the industry exposure to import competition. Accordingly, Table 3.4 presents the OLS estimates of the impact of exchange rate movement on wages using equation (3.18) over the period 1996-2008. Column 1 reports estimates of equation (3.18) including all workers. Columns 2 and 3 shows results for high-skilled and low-skilled workers respectively. Finally, columns 4 and 5 present the corresponding results for white-collar and blue-collar workers respectively.

The results in the first column shows a limited role of exchange rate movements in explaining changes in real wages when all workers are considered. However, when the sample is split by highest education attainment, we can see that exchange rates movements affect high-skilled workers only (column 2). This is further evidence that the wages of high-skilled workers are more responsive to trade and exchange rate shocks than workers with lower education attainments. One potential reason is that high-skilled workers are more likely to be employed in trade-oriented firms than low-skilled workers, leading to increased exposure of high-skilled workers to exchange rate shocks.

The results in column 2 suggest that wages of high-skilled workers are affected by the change in the import-weighted REER, as suggested by the statistically significant coefficient on the interaction between the change in industry's import-weighted REER and the lagged import penetration ratio. The corresponding coefficient implies an import-weighted exchange rate elasticity of -0.22 for a hypothetical worker employed in an industry with average exposure to import competition (i.e. $\overline{IP}_{k,t}$ = 0.791). This means that a 1% appreciation of the import-weighted REER index increase high-skilled wages by 0.220%, potentially channeled through reductions in the cost of imported intermediate inputs. In column 5, we can see that blue-collar workers seem also affected by swings in exchange rates. Now, both interaction terms turn significantly different from zero. For a worker employed in an industry with average export share and facing average exposure from import competition, the estimated elasticity of hourly wage to exchange rate change is 0.158. This means that the effect of a 1% currency depreciation on the hourly wage for a hypothetical blue-collar worker employed in an industry with this type of foreign exposure is a 0.158% wage expansion. This result is in line with some findings in the literature where depreciation are sometimes associated with small but significant increase in industry wage (e.g. Revenga, 1992).

Table 3.4: OLS estimates of exchange rate movements on wages for workers of different groups (1996-2008)

	Overall (1)	High-skilled (2)	Low-skilled (3)	White-collar (4)	Blue-collar (5)
$IP_{k,t-1} \times \Delta ER^M_{k,t}$	0.001	0.015***	0.137	0.000	0.981***
	(0.003)	(0.004)	(0.097)	(0.004)	(0.337)
$XS_{k,t-1} \times \Delta ER^X_{k,t}$	0.073	0.070	-0.034	0.158	-0.396*
	(0.128)	(0.278)	(0.126)	(0.230)	(0.208)
$IP_{k,t-1}$ ($\times$ 1000)	-0.002	0.316***	2.728	-0.045	2.401
	(0.000)	(0.000)	(0.002)	(0.000)	(0.004)
$XS_{k,t-1}$	0.018	-0.033**	0.020	0.027	-0.001
	(0.014)	(0.015)	(0.015)	(0.019)	(0.019)
$\Delta ER^M_{k,t}$	-0.512	-0.232	-0.640	-0.644	-0.427
	(0.394)	(0.314)	(0.444)	(0.405)	(0.656)
$\Delta ER^X_{k,t}$	-0.030	0.082	-0.045	-0.080	0.026
	(0.041)	(0.063)	(0.063)	(0.094)	(0.045)
$\Delta \overline{w}_{k,t}$	0.148***	0.176***	0.135***	0.165***	0.117*
	(0.033)	(0.054)	(0.045)	(0.041)	(0.065)
$\Delta hours_t$	-0.537***	-0.413***	-0.601***	-0.475***	-0.644***
	(0.052)	(0.061)	(0.062)	(0.076)	(0.071)
Age ($\times$ 1000)	-0.201***	-0.117***	-0.220***	-0.201***	-0.192***
	(0.020)	(0.028)	(0.022)	(0.024)	(0.029)
Age^2 ($\times$ 1000)	4.533***	2.588***	4.983***	4.536***	4.351***
	(0.462)	(0.669)	(0.518)	(0.562)	(0.679)
Age^3 ($\times$ 1000)	-0.033***	-0.019***	-0.036***	-0.033***	-0.032***
	(0.003)	(0.005)	(0.004)	(0.004)	(0.005)
Married	0.006	-0.011	0.013	-0.006	0.024*
	(0.009)	(0.010)	(0.012)	(0.008)	(0.014)
Foreign	0.010	0.018	0.006	0.011	0.006
	(0.009)	(0.013)	(0.012)	(0.011)	(0.016)
Female	0.003	-0.022	0.012	-0.007	0.010
	(0.008)	(0.016)	(0.010)	(0.010)	(0.014)
Tenure	-0.001***	-0.001	-0.001***	-0.001**	-0.002***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Firm Size	0.001	-0.005	0.013	-0.008	0.005
	(0.010)	(0.018)	(0.013)	(0.015)	(0.012)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Education FE	Yes	Yes	Yes	Yes	Yes
Sector $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.182	0.115	0.218	0.189	0.174
F	27.246	17.974	23.303	11.929	15.885
N	14,367	5,073	9,294	769	667
No. Clusters	194	169	187	185	178

Notes: The dependent variables in all columns is the growth rate of hourly wage. All regressions include a constant term. Standard errors are clustered at the industry 4-digit level. All regressions control for regional, year, education, industry 4-digit level, occupation 4-digit level and 2-digit industry$\times$year fixed effects. * p$\leq$0.10, ** p$\leq$0.05, *** p$\leq$ 0.01.

Sources: Own estimations based on merged BACII-SLFS database.

The asymmetric effect of exchange rates on wages of workers of different skills or employed in different occupations, are in line with the findings of Goldberg and Pavcnik (2003). In their paper, they also find that a currency depreciation boosts wages for blue collar workers, but lowers wages of white collar workers (something I do not find for white-collar workers, but for high-skilled workers). One potential explanation is that a currency appreciation puts pressure on costs which may push producers to invest in processes that are substitutes to blue-collar/low-skilled workers and/or complementary to white-collar/high-skilled workers (e.g. Acemoglu, 1998).

Some further evidence tend to suggest that exchange rate effects are heterogeneous across industries with different market structure. The theoretical model developed in Nucci and Pozzolo (2010, 2011) predicts that the exchange rate pass-through elasticities contribute to influence the adjustment of labor-market outcomes in response to currency shocks. A number of papers show that exchange rate pass-through elasticities depend on market structure and in particular on the extent to which products are differentiated and the substitution among different variants (Yang, 1997). Studies such as Dornbusch (1987) and Knetter (1993) show that the pass-through tends to be small if the degree of competition in the foreign market is high. The lower the pass-through elasticities, the higher is the exchange rate sensitivity of labor market outcomes.

Accordingly, the idea developed in Table 3.5 is to explore the influence of market structure on shaping the response of wages to exchange rate shocks. I use the classification of product differentiation developed in Rauch (1996, 1999), which identifies to what extent products are differentiated. The idea is that for differentiated products, connections between buyers and sellers are not formed through organized exchanges (i.e. markets) but rather through a search process which depends on proximity and preexisting ties. This kind of search process is expected to be costly, thus resulting in potentially persistent relationships once the best match is achieved. This tends to be less true for homogeneous products, because they are traded more on organized exchanges. I then expect that industries predominantly producing goods that are described as differentiated would be less affected by exchange rate movements than those producing mainly homogeneous goods, because of potentially higher pass-through elasticities.

Therefore, Table 3.5 presents regression results separately for industries according to this attribute of market structure. Panel A shows estimation results for workers employed in industries that predominately produce homogeneous goods, whereas Panel B presents results when only looking at workers employed in industries that mainly produce differentiated varieties. The distinction is made based on a modified version of the Rauch classification.[27] As shown in column 1, wages of workers employed in industries that predominantly produce homogeneous goods seem to be more responsive than those working in more differentiated industries. As suggested by the point estimates in column 1, the wage elasticity to exchange

[27] Available upon request.

rate movements is -0.162 for a hypothetical worker employed in an industry with average values of foreign exposure; a 1% currency appreciation is related to a 0.16% wage increase.

Table 3.5: OLS estimates of exchange rate movements on wages within different industry types (1996-2008)

	Homogeneous (1)	Differentiated (2)
$\text{IP}_{k,t-1} \times \Delta\text{ER}^M_{k,t}$	0.017**	0.327
	(0.007)	(0.235)
$\text{XS}_{k,t-1} \times \Delta\text{ER}^X_{k,t}$	-0.308*	-0.032
	(0.180)	(0.173)
$\text{IP}_{k,t-1}$	0.001***	0.005*
	(0.000)	(0.003)
$\text{XS}_{k,t-1}$	-0.070**	0.017
	(0.034)	(0.013)
$\Delta\text{ER}^M_{k,t}$	-0.127	-0.385
	(0.257)	(0.625)
$\Delta\text{ER}^X_{k,t}$	0.121	-0.048
	(0.129)	(0.049)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Region FE	Yes	Yes
Education FE	Yes	Yes
Sector × Year FE	Yes	Yes
Occupation FE	Yes	Yes
R-squared	0.343	0.160
F	15.828	25.684
N	2,229	12,138
No. Clusters	53	141

Notes: The dependent variables in all columns is the growth rate of hourly wage. All regressions include a constant term and all control variables that are included in Table 3.4 (not shown, but available on request). Standard errors are clustered at the industry 4-digit level. All regressions control for regional, year, education, industry 4-digit level, occupation 4-digit level and 2-digit industry × year fixed effects. Columns (1) shows results for workers employed in industries that predominantly produce homogeneous products. Column (2) shows results for workers employed in industries that predominantly produce differentiated products. The distinction is made thanks to a modified version of the classification developed in Rauch (1996, 1999). * p≤0.10, ** p≤0.05, *** p≤ 0.01.

Sources: Own estimations based on merged BACII-SLFS database.

3.7 Conclusion

This paper has explored the impact of industry-level exposure to trade and exchange rate shocks on individual-level wages of Swiss manufacturing workers over the period 1996-2008. Trade shocks are stemming from exposure to import competition or from exposure to export intensity. Exchange rate movements are considered as shocks either to the delivered price of foreign goods or to the offered price of domestic outputs sold abroad. The manner how exchange rates at the industry level are constructed reflect the geographic composition of each industry's main import competitors and export markets.

Prior studies in the literature are unable to fully separate the impact of short-term trade shocks from other changes in the labor market. As an attempt to address this issue, I have proposed a gravity-type estimation strategy as a first-stage step to construct instrumental variables designed to consistently estimate the causal effect of changes in trade on wages. In addition, I have focused on individual-level data, which is particularly appropriate for studying the relationship between labor-market outcomes, trade and exchange rate as analysis relying on more aggregated data could miss heterogeneous effects in workers with different characteristics or employed in different occupations. The individual-level information at hand enables to analyze the impact of trade and exchange rates on wages of workers sharing similar characteristics in many dimensions, as well as the effect within skill groups, occupations and industry characteristics.

This study shows that industry real exchange rate movements and trade exposure influence wages of manufacturing workers of various groups differently. When averaged across all workers, the overall impact of trade on wages appears small but statistically significant: a 10% increase in import penetration leads to a drop of 0.39% in wages, while a 10% increase in the export share implies a 0.53% increase in wages. In contrast, exchange rates movements do not seem to influence average wages. However, for some specific groups, effects can be larger. The impact of import penetration ratios, export shares and exchange rates swings are concentrated among high-skilled and blue-collar workers almost exclusively. Overall, the net effect of trade shocks on wages is positive, ranging from an increase of 0.42% for high-skilled workers' wages to 0.66% for blue-collar workers' wages after a rise of 10% in import penetration ratio and export share. Concerning the effect of exchange rate fluctuations, the results imply an average exchange rate elasticity of -0.22 among high-skilled workers: the effect of a 1% currency appreciation on the hourly wage for a hypothetical high-skilled worker employed in an industry with average import exposure is a 0.220% wage expansion, potentially channeled through reductions in the cost of imported intermediate inputs. Concerning blue-collar workers, the estimated elasticity of hourly wage to exchange rate change is equal to 0.158. This means that the effect of a 1% currency depreciation on the hourly wage for a hypothetical blue-collar worker employed in an industry with average foreign exposure is a 0.158% wage rise. These results, highlighting the asymmetric effect of exchange rates on wages of workers of different skills or employed in different occupations, are in line with the findings of Goldberg and Pavcnik (2003). One potential explanation is that a currency appreciation puts pressure on costs which may push producers to invest in processes that are substitutes to blue-collar/low-skilled workers and/or complementary to white-collar/high-skilled workers (e.g. Acemoglu, 1998).

Exchange rate effects are potentially heterogeneous across industries with different market structures. Exchange rate pass-through elasticities have been shown to depend on market structure and in particular on the extent to which products are differentiated and the substitution among different variants. Preliminary evidences show that wages of workers employed in industries that predominantly produce homogeneous goods are more responsive to exchange rates movements than those working in industries that predominantly produce more differentiated varieties.

Finally, it has to be highlighted that this study has some limitations. First, I focus on changes within manufacturing industries only, therefore neglecting the impact of trade and exchange rate shocks across the broader economy, which might be larger (e.g. Ebenstein et al., 2014). Second, I am only able to capture the wage effect for workers that remain employed in the manufacturing sector. I am thus unable to gauge the wage consequence for workers switching out of manufacturing, or for those that become unemployed.

General Conclusion

International trade is typically believed to generate aggregate welfare gains for trading countries. However, it also raises considerable debate as trade is also often seen as a source of growing social disparity. As seen throughout this thesis, the combination of recent features of the global economy, the availability of new detailed data sets and new theories is a great opportunity to refine our knowledge of the labor-market consequences of international trade.

In chapter 1, through theoretical simulations and empirical estimations, pure intra-industry trade expansion is shown to be less disruptive than inter-industry trade expansion. As intra-industry shares and outward processing trade are rising over time, national economies are converging towards similar sector compositions. Even though this is mainly true for high-income economies, the opening of low- and middle-economies and the rapid convergence of technology across space could suppose an intensification of the process leading to less trade-related disruptions to the labor market.

In the second chapter, using a unique longitudinal dataset of individual worker characteristics for the UK over an extended period of time, the recent surge in Chinese exports and existing trade patterns with the EU are exploited in order to analyze how UK manufacturing workers adjust to trade competition. While trade competition from China is almost entirely driven by import growth in labor-intensive sectors, UK trade patterns with the EU is characterized by the two-way exchange of goods within similar industries. As a consequence, increased import exposure from China leads to lower cumulative earnings, wages and hours of work over the 15 year sample period for affected workers. On the contrary, increased imports from the EU are associated with positive labor-market outcomes and may have had a complementary effect to domestic production.

The third chapter is focused on the short-term impact of exposure to trade competition and real exchange rate movements on wages in Switzerland. Complementary to chapter 2, the main findings are that exposure to trade and exchange rate shocks have a mild influence on wages of Swiss workers. As expected, a rise in import competition is associated with lower wages, while an increase in exports boosts them. These impacts are especially stronger among high-skilled and blue-collar workers than among other groups. Overall, the net effect of trade shocks on wages is positive. In the same way, the impact of exposure to exchange rate fluctuations is shown to be heterogeneous across jobs types, education groups and industry with different market structures.

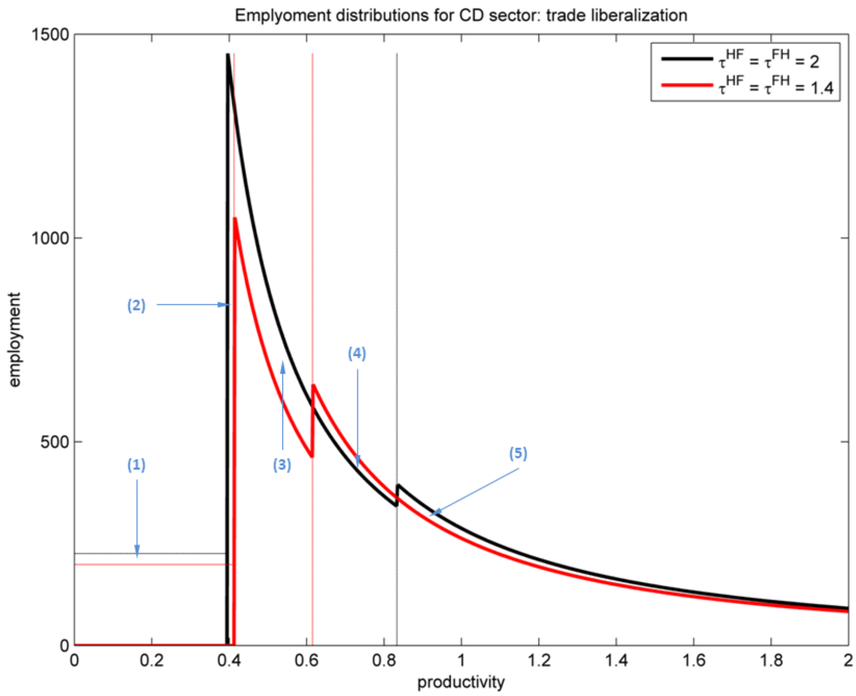
The growing importance of emerging countries, the fragmentation of modes of production, and the shift of the center of gravity of global manufacturing production networks towards the south-east of the globe is not likely to reassure exposed workers. It may indeed contribute to public ambivalence toward globalization and specific anxiety about increasing trade with countries such as China. However, some emerging economies are already specializing in more complex products, climbing the ”quality ladder”of production. With production capacities and organization becoming more and more similar to those of industrialized countries, the intensification of merchandise trade could therefore be accompanied with milder trade-related shocks to high-incomes countries’ labor market in the future. Or at least, I would presume that the rapid development of communication techniques, the automation of tasks of ever growing complexities, and the popularization of disruptive modes of production like the 3D-printer, will change the way we think the labor market in more profound ways than any other things.

Appendix A

Appendix to Chapter 1

A.1 Extra figures

Figure A.1: Simulated employment effects of trade liberalization in the comparative disadvantage industry



Source: Own simulations based on the model of Bernard, Redding, and Schott (2007).

A.2 Extra tables

Table A.1: Parameter values used in simulations

Parameters	**Name**	**Theoretically possible values**	**Values retained for comparative statics**	**Values retained for the baseline simulation**
τ_i	Variable trade cost	$[1, \infty)$	$[1, 2]$	$[1, 1.6]$
f_{ie}	Fixed entry cost	$(0, \infty)$	$[2, 4]$	2
f_i	Fixed production cost	$(0, \infty)$	$(0, f_{ix}]$	0.1
f_{ix}	Fixed exporting cost	$(0, \infty)$	$[f_i, 1.1]$	0.1
β_i	Factor intensity	$(0.5, 1)$	$(0.5, 1)$	$\beta_1 = 0.6$, $\beta_2 = 0.4$
α_i	Industry expenditure share	$[0.5, 1)$	$[0.5, 1)$	$\alpha_1 = \alpha_2 = 0.5$
k	Minimum productivity	$(0, \infty)$	$[0.2, 1.2]$	0.2
σ	Elasticity of substitution	$(1, \infty)$	$[1.85, 4.39]$ for $a = 3.4$	3.8
$a > \sigma - 1$	Firm dispersion	$a > \sigma - 1$	$[2.85, 8]$ for $\sigma = 3.8$	3.4
L_H/S_H	Relative factor endowment	$(0, 1]$	$[0.5, 1)$	0.833
$\frac{(L^F+S^F)}{(L^H+S^H)}$	Relative country size	$(0, \infty)$	$[0.44, 22]$	1

Notes: The value ranges considered are consistent with diversified equilibria (i.e. both sectors within each country produce non-zero output; no complete specialization). $\beta_2 = 1 - \beta_1$, and countries are mirror images, so varying β_1 between 0.5 and 1 captures every possible scenario. $\alpha_2 = 1 - \alpha_1$, and countries are mirror images, so varying α_1 between 0.5 and 1 captures every possible scenario. $L_H/S_H = S_F/L_F$.

Table A.2: Descriptive statistics: alternative adjustment cost measure, ISIC rev.3, four-digit

	Pooled and Fixed-Effects Samples				*First-Difference Sample*			
	mean	sd	min	max	mean	sd	min	max
Alternative AC: (ABS_{it})	0.114	0.174	0.000	1.000	0.115	0.170	0.000	1.000
$MIIT$	0.370	0.346	0.000	0.999	0.380	0.345	0.000	0.999
$MIIT \times \lvert\Delta STO\rvert$	0.030	0.570	-2.835	8.886	0.026	0.545	-2.835	8.502
ΔGL	0.001	0.056	-0.350	0.573	0.000	0.054	-0.350	0.370
$\Delta GL \times \lvert\Delta STO\rvert$	0.004	0.187	-0.656	7.229	-0.001	0.055	-0.656	0.759
$\lvert\Delta STO\rvert$	0.013	0.879	-3.271	12.627	0.015	0.811	-3.271	9.624
$\lvert\Delta AD\rvert$	0.114	0.272	0.000	4.628	0.117	0.281	0.000	4.628
Firms	360.9	698.7	3	6117	371.3	707.9	5	6117
Employment	6507.3	7389.1	25	47458	6713.6	7449.4	88	47458
$\lvert\Delta TWRER\rvert$	0.085	0.233	0.000	1.087	0.028	0.018	0.000	0.137
$\lvert\Delta TWRER\rvert \times \lvert\Delta STO\rvert$	-0.012	0.161	-3.067	0.730	0.002	0.040	-0.157	0.730
$\lvert\Delta TWRER2\rvert$	0.085	0.233	0.000	1.105	0.029	0.019	0.000	0.143
$\lvert\Delta TWRER2\rvert \times \lvert\Delta STO\rvert$	-0.013	0.162	-3.067	0.718	0.002	0.042	-0.163	0.718
Observations	1628				1470			

Source: Own calculations based on merged BACII-SLFS database.

Table A.3: Adjustment costs and MIIT (IV estimates, 1^{st} stage)

	Fixed-effects models						First-difference models					
	(1) $MIIT$	(2) $MIIT$	(3a) $MIIT$	(3b) $MIIT \times \|\Delta STO\|$	(4a) $MIIT$	(4b) $MIIT \times \|\Delta STO\|$	(5) $MIIT$	(6) $MIIT$	(7a) $MIIT$	(7b) $MIIT \times \|\Delta STO\|$	(8a) $MIIT$	(8b) $MIIT \times \|\Delta STO\|$
$\|\Delta TWRER\|$	-0.455*	-0.510*	-0.487*	-0.081	-0.521**	-0.097	-0.649**	-0.757***	-0.648**	-0.280	-0.767***	-0.283
	(0.263)	(0.261)	(0.259)	(0.311)	(0.257)	(0.314)	(0.247)	(0.253)	(0.258)	(0.246)	(0.252)	(0.244)
$\|\Delta TWRER\| \times \|\Delta STO\|$			0.158**	-0.494	0.173***	-0.490*			0.128	-0.839***	0.196***	-0.836***
			(0.069)	(0.298)	(0.059)	(0.292)			(0.093)	(0.202)	(0.074)	(0.201)
$\|\Delta STO\|$		0.044***	0.016	0.491***	0.031**	0.496***		0.066***	0.022	0.539***	0.050**	0.540***
		(0.015)	(0.015)	(0.091)	(0.015)	(0.095)		(0.018)	(0.021)	(0.032)	(0.021)	(0.033)
$\|\Delta AD\|$		-0.297***			-0.299***	-0.116		-0.336***			-0.341***	-0.011
		(0.072)			(0.073)	(0.129)		(0.079)			(0.081)	(0.052)
Firms		-0.132			-0.139	0.001		-0.688			-0.674	0.349
		(0.168)			(0.167)	(0.113)		(0.524)			(0.522)	(0.354)
Employment		0.007			0.008	0.000		0.002			0.002	-0.013
		(0.007)			(0.007)	(0.007)		(0.012)			(0.012)	(0.015)
R-squared	0.067	0.107	0.072	0.626	0.110	0.630	0.092	0.148	0.096	0.701	0.151	0.701
F	3.880***	5.641***	4.145***	71.027***	5.905***	73.630***	4.858***	5.761***	4.581***	78.368***	7.456***	75.176***
N	994	994	994	994	994	994	693	693	693	693	693	693
No. industries	100	100	100	100	100	100	84	84	84	84	84	84

Notes: Columns 1, 2, 5 and 6 show the first-stage estimates of columns 1, 2, 5 and 6 in Table 3 respectively. Columns 3a, 4a, 7a and 8a show the first-stage estimates of the instrument on *MIIT* of columns 3, 4, 7 and 8 in Table 3 respectively. Columns 3b, 4b, 7b and 8b show the first-stage estimates of the instrument on $MIIT \times |\Delta STO|$ of columns 3, 4, 7 and 8 in Table 3 respectively. All regressions include year fixed effects and a constant term (not reported). Robust standard errors reported in parentheses are clustered at the four-digit industry level. *Firms* and *Employment* are lagged one year in all regressions. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
Sources: Own estimations based on merged BACII-SLFS database.

Table A.4: Adjustment costs and 2-year interval IIT (various IV and OLS estimates)

	IV								OLS					
	(1) FE	(2) FD	(3) FE	(4) FD	(5) FE	(6) FD	(7) FE	(8) FD	(9) FE	(10) FD	(11) FE	(12) FD	(13) FE	(14) FD
$MIIT$	-15.849	-0.389	-1.964	-0.763	0.270	-1.636			0.019	0.018	0.037	0.042	-0.005	-0.000
	(936.498)	(0.525)	(9.944)	(4.641)	(0.242)	(7.089)			(0.023)	(0.015)	(0.037)	(0.026)	(0.011)	(0.008)
noalign $MIIT \times \lvert\Delta STO\rvert$	-6.464	-0.323	-3.278	1.093	-0.022	-0.716			0.016	0.005	0.020	0.022*	-0.010*	0.006
	(372.506)	(0.467)	(17.656)	(7.485)	(0.104)	(3.061)			(0.013)	(0.004)	(0.020)	(0.013)	(0.006)	(0.007)
noalign ΔGL							-0.759	-0.934						
							(2.035)	(2.926)						
noalign $\Delta GL \times \lvert\Delta STO\rvert$							0.703	-1.100						
							(1.567)	(2.670)						
noalign $\lvert\Delta STO\rvert$	3.457	0.165	1.557	-0.570	-0.002	0.324	-0.033	0.042	-0.019	-0.000	-0.020	-0.008	0.005	-0.004
	(200.236)	(0.240)	(8.356)	(4.228)	(0.047)	(1.370)	(0.042)	(0.092)	(0.013)	(0.004)	(0.015)	(0.007)	(0.003)	(0.008)
noalign $\lvert\Delta AD\rvert$	-1.216	-0.018	-0.145	-0.016	0.030	-0.151	0.004	-0.014	0.010	0.007	0.002	0.012**	0.008	0.005
	(72.957)	(0.043)	(0.734)	(0.344)	(0.029)	(0.596)	(0.039)	(0.062)	(0.022)	(0.010)	(0.011)	(0.005)	(0.011)	(0.005)
Dependent variable	BS2	BS2	BS2	BS2	BS2	BS2	BS2	BS2	BS2	BS2	BS2	BS2	ABS2	ABS2
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
N	689	533	689	533	481	404	689	533	693	533	693	533	1470	1331
No. industries	80	77	80	77	45	44	80	77	84	77	84	77	108	107
Level of disaggregation	4D	4D	4D	4D	3D	3D	4D	4D	4D	4D	4D	4D	4D	4D
Weights	None	None	Trade share	Trade share	None	None	None	None	None	None	Trade share	Trade share	Trade share	Trade share
First-Stage Statistics														
K-P LM test	0.986	0.441	0.840	0.837	0.147	0.818	0.393	0.625						
SW LM S test	0.773	0.165	0.451	0.144	0.466	0.078	0.773	0.165						
AP F-test $MIIT$	0.000	1.941	0.225	0.797	4.699	0.157	0.952	1.317						
AP F-test $MIIT \times \lvert\Delta STO\rvert$	0.001	0.667	0.045	0.032	7.923	0.100	0.368	0.226						

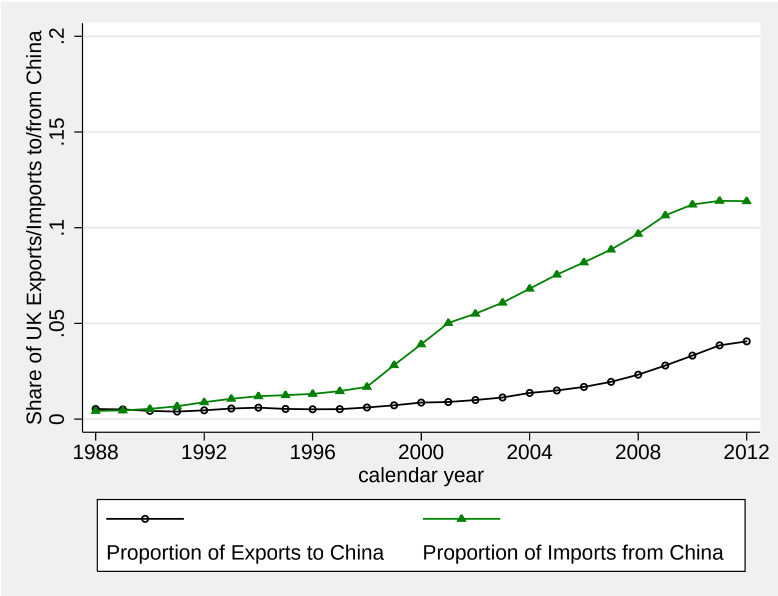
Notes: $BS2_{it}$ is the 2-average version of BS_{it}, the share of between-industry job reallocation in total job reallocation. $ABS2_{it}$ is the 2-year average version of ABS_{it}, the share of between-industry job reallocation in total job. All regressions include year fixed effects and a constant term (not reported). Robust standard errors reported in parentheses are clustered at the four-digit industry level. *Firms* and *Employment* are lagged one year in all regressions. ΔGL and $|\Delta STO|$ are computed on 2-year intervals. * p<0.10, ** p<0.05, *** p<0.01.
Sources: Own estimations based on merged BACII-SLFS database.

Appendix B

Appendix to Chapter 2

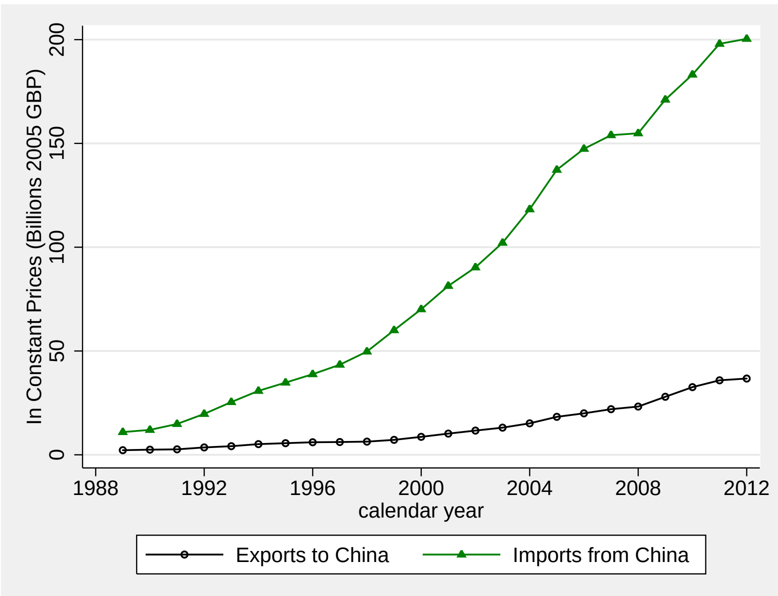
B.1 Extra figures

Figure B.1: The proportion of total trade between the UK and China, 1988-2012



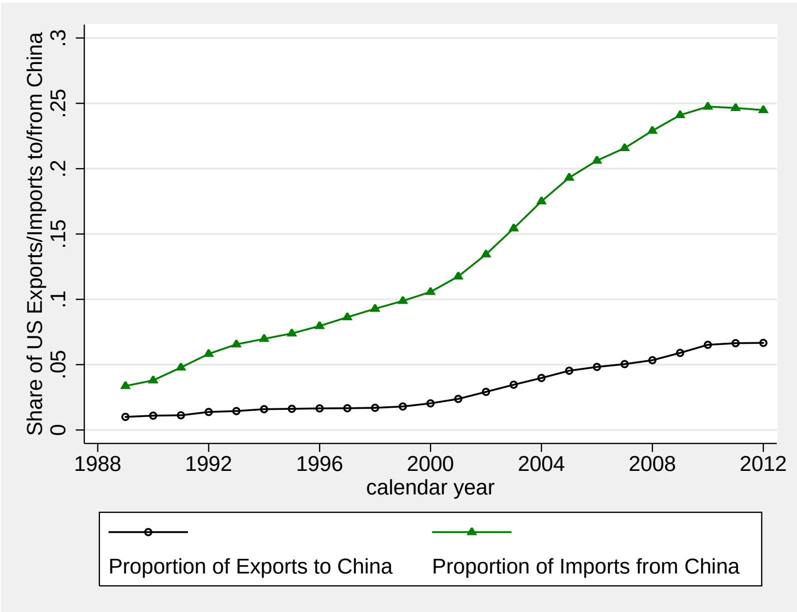
Source: Using data from UN Comtrade for 166 consistently defined manufacturing industries.

Figure B.2: Trade between the US and China, 1989-2012



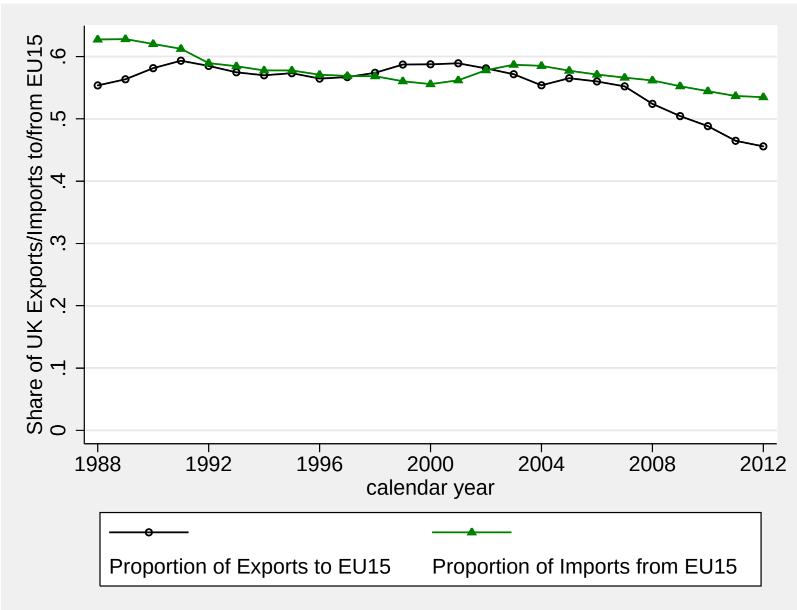
Source: Using data from UN Comtrade for 166 consistently defined manufacturing industries.

Figure B.3: The proportion of total trade between the US and China, 1989-2012



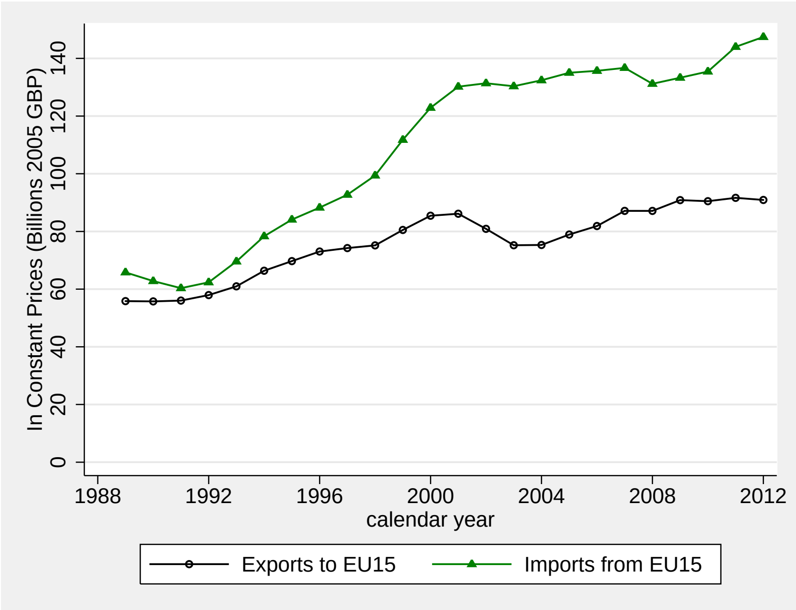
Source: Using data from UN Comtrade for 166 consistently defined manufacturing industries.

Figure B.4: The proportion of total trade between the UK and the EU, 1988-2012



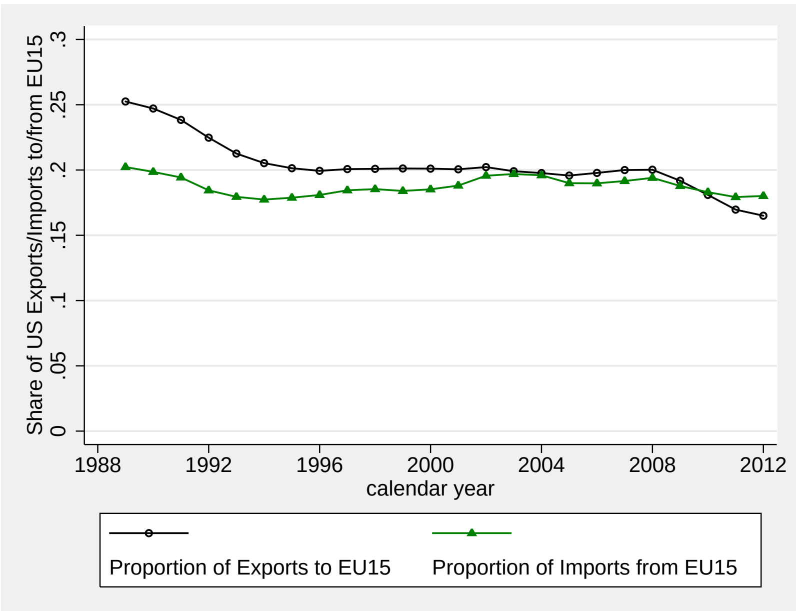
Notes: The EU consists of Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain and Sweden.
Source: Using data from UN Comtrade for 166 consistently defined manufacturing industries.

Figure B.5: Trade between the US and the EU, 1989-2012



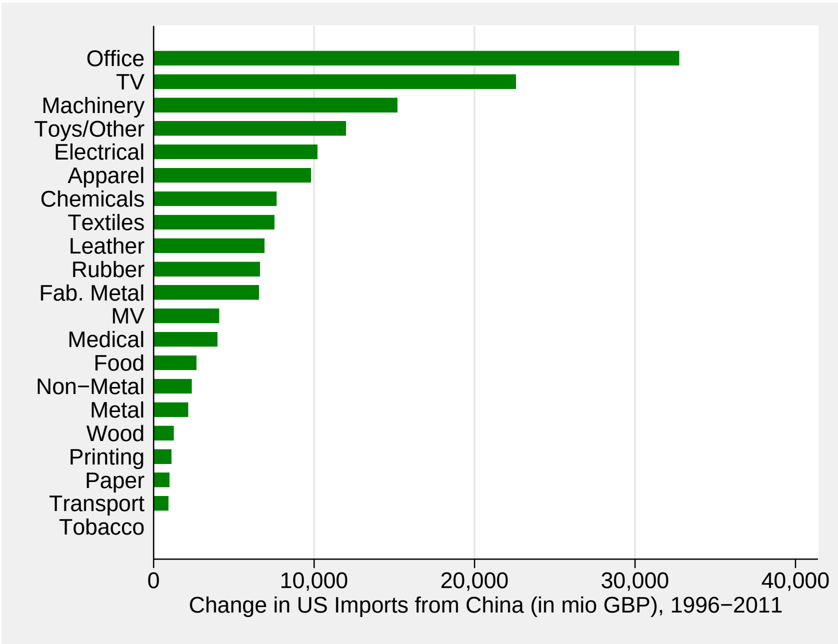
Source: Using data from UN Comtrade for 166 consistently defined manufacturing industries. The EU contains the UK.

Figure B.6: The proportion of total trade between the US and the EU, 1989-2012



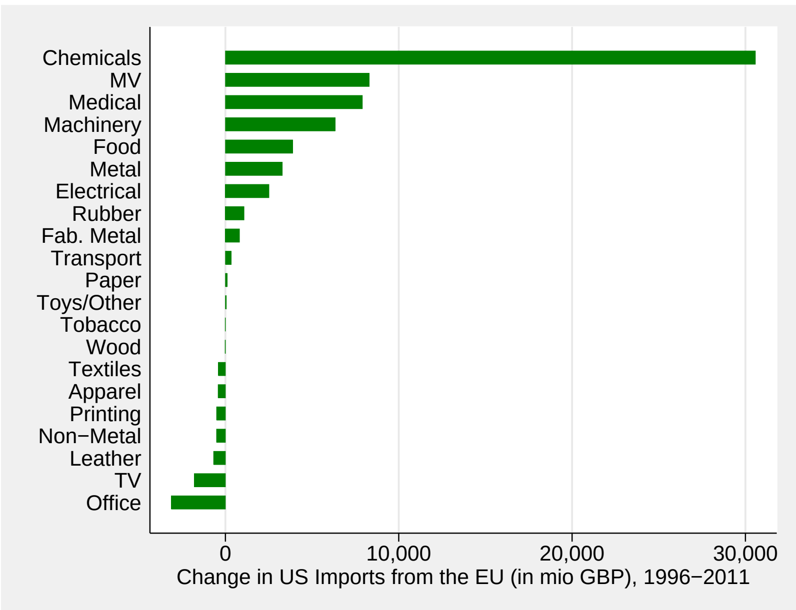
Source: Using data from UN Comtrade for 166 consistently defined manufacturing industries. The EU contains the UK.

Figure B.7: The change in imports from China to the US, 1996-2011



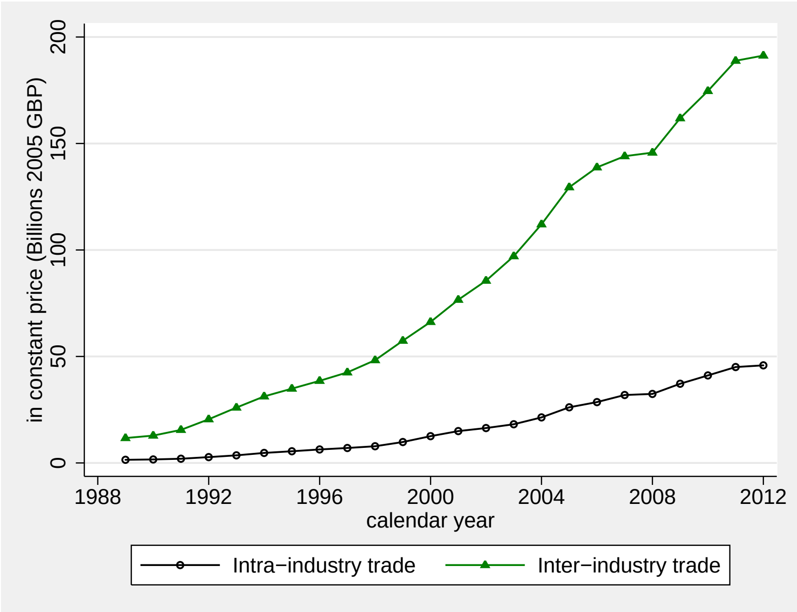
Source: Using data from UN Comtrade for 166 consistently defined manufacturing industries.

Figure B.8: The change in imports from the EU to the US, 1996-2011



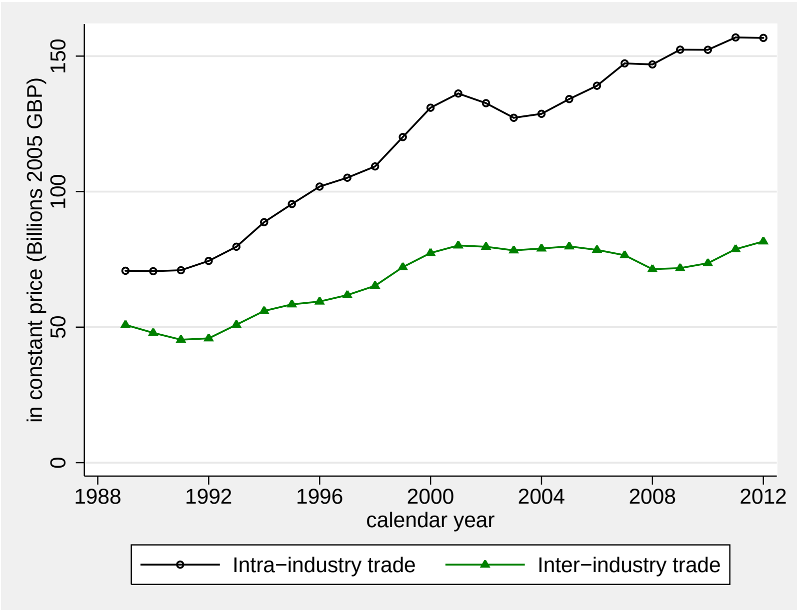
Source: Using data from UN Comtrade for 166 consistently defined manufacturing industries. The EU contains the UK.

Figure B.9: The nature of trade between the US and China, 1989-2012



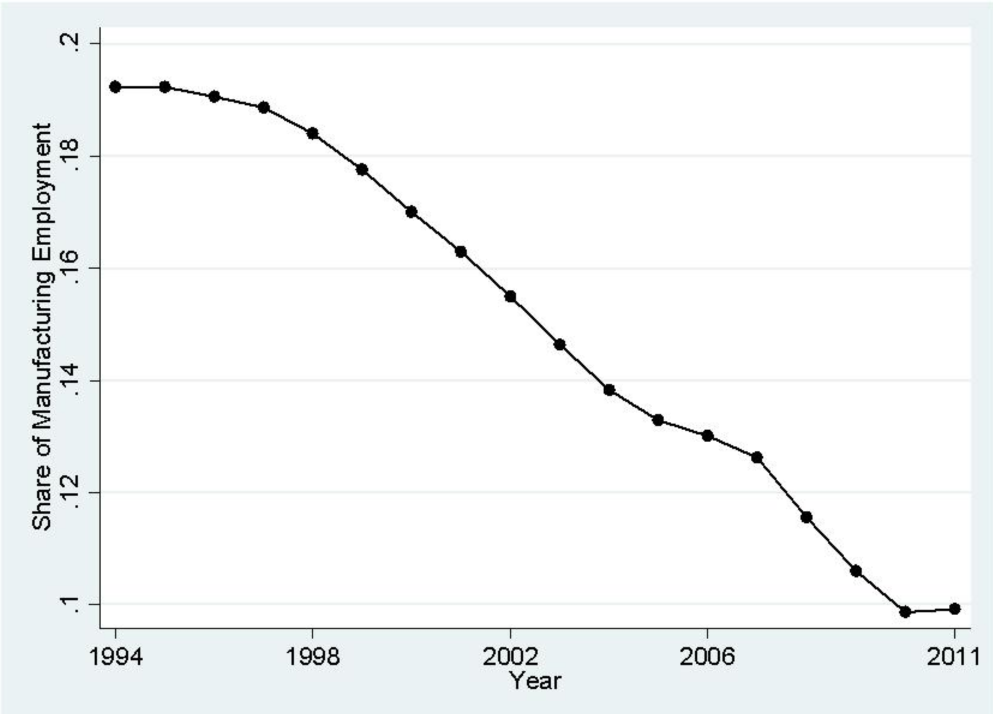
Source: Using data from UN Comtrade for 166 consistently defined manufacturing industries. The EU contains the UK.

Figure B.10: The nature of trade between the US and the EU, 1989-2012



Source: Using data from UN Comtrade for 166 consistently defined manufacturing industries. The EU contains the UK.

Figure B.11: The share of manufacturing employment in the UK, 1994-2011



Source: Quarterly Labour Force Survey, 1994-2011

B.2 Extra tables

Table B.1: Descriptive statistics

	Main Earnings Sample	Main Earnings Sample for China and EU Imports
	Trade Exposure 1997-2011	
(ΔChina Imports)/UK Consumption$_{96}$	0.0593 (0.0942)	0.0592 (0.0939)
P10-P90 Interval	[0.0007, 0.1910]	[0.0007, 0.1910]
P25-P75 Interval	[0.0026, 0.0597]	[0.0026, 0.0597]
(ΔEU Imports)/UK Consumption$_{96}$		0.0492 (0.2052)
P10-P90 Interval		[-0.0600, 0.1683]
P25-P75 Interval		[-0.0004, 0.0877]
(China Imports$_{96}$)/UK Consumption$_{96}$	0.0064 (0.0659)	0.0064 (0.0659)
(EU Imports$_{96}$)/UK Consumption$_{96}$		0.1923 (0.2944)
(Non-China Imports$_{96}$)/UK Consumption$_{96}$	0.3443 (0.4847)	0.3442 (0.4847)
	Instruments 1992-2011	
Import penetration from China to High Income Countries	0.3979 (0.5140)	0.3978 (0.5140)
P10-P90 Interval	[0.0094, 1.1374]	[0.0094, 1.1374]
P25-P75 Interval	[0.0225, 0.5769]	[0.0225, 0.5769]
Import penetration from the EU to rest of OECD		0.2735 (0.8407)
P10-P90 Interval		[-0.1579, 0.8478]
P25-P75 Interval		[-0.0001, 0.4095]
	Dependent Variables	
Cumulative Annual Earnings	14.687 (25.336)	14.687 (25.337)
Years of Non-Zero Earnings	6.311 (4.627)	6.311 (4.627)
Cumulative Annual Earnings/Year	3.495 (5.176)	3.795 (5.176)
Cumulative Hourly Pay	17.392 (26.106)	17.392 (26.107)
Cumulative Hours of Work	10.297 (11.616)	10.296 (11.616)
	Worker Characteristics	
Female	0.255 (0.436)	0.255 (0.436)
Age	34.902 (8.174)	34.902 (8.175)
Employees in Firm 1-99	0.263 (0.440)	0.263 (0.440)
Employees in Firm 100-499	0.270 (0.444)	0.270 (0.444)
Employees in Firm 500-999	0.123 (0.328)	0.123 (0.328)
Employees in Firm $\geq$ 1000	0.343 (0.475)	0.343 (0.475)
Job Tenure 0-1 Year	0.149 (0.356)	0.149 (0.356)
Job Tenure 2-5 Years	0.318 (0.466)	0.318 (0.466)
Job Tenure 6-10 Years	0.499 (0.500)	0.499 (0.500)
Job Tenure $\geq$ 11 Years	0.034 (0.182)	0.034 (0.182)
Average Log Wages 1990-1996	7.529 (2.477)	7.528 (2.477)
Number of Observations	19,949	19,946

Notes: As per Table 2.3. The table provides the mean (standard deviation) and [percentile interval].

B.3 Mapping trade products to industries: from SITC revison 3 to UKSIC 1992 revision

The aim is to carry out extensive analysis using trade data classified by the UK Standard Industrial Classification, revised in 1992 (UKSIC(92)) at the finest, five-digit level of disaggregation. The original trade data are classified according to the Standard International Trade Classification, revision 3 (SITC rev3).

To perform such a correspondence, we used one existing official (administrative) concordance table that matches 8-digit Combined Nomenclature 2002 codes (CN 2002) with 6-digit Classification of Products by Activity 2002 codes (CPA 2002), with 6-digit Harmonized System 2002 (HS 2002) and also with 5-digit SITC rev3 (SITC3) codes. Therefore, CN 2002, and at a lesser extend HS 2002, serve as "proxy" classifications that linked SITC3 to UKSIC(92). Indeed, CPA 2002 is identical to NACE 1.0, on which UKSIC(92) is built. Therefore, CPA 2002 and UKSIC(92) are identical up to the 4-digit level (with some exceptions).

This CN-HS-CPA-SITC concordance table was built by EuroStat by putting in correspondence several existing official tables. The concordances were created by electronic means and have not been thoroughly checked or validated by any organization or working party. As a consequence no guarantee can be given as to their full reliability. However, it is a valuable starting point and it serves as an input file which forms the skeleton of the SITC3-UKSIC(92) concordance.

The strategy is then based on two steps. The first step is to build a correspondence table going from SITC3, at five-digit, to CPA 2002, at 6-digit using information from CN-SITC3, CN-CPA, HS-SITC3 and HS-CPA tables. Some SITC3 products couldn't be fairly allocated to a single 6-digit CPA code, so some SITC3 products are matched to a 5-digit CPA code. In cases where it was needed to improve the appropriateness and precision of the allocation, we also used an additional table that linked 8-digit (and not 6-digit as before) HS 2002 codes to 6-digit CPA codes.

The second step involves converting those 6-digit CPA codes to 5-digit UKSIC(92) activities. With few exceptions, CPA 2002 and UKSIC(92) are identical up to the fourth digit. As a consequence, and again with few exceptions, 6-digit CPA codes within any fourth digit, are embedded, by construction, within the corresponding UKSIC(92) 4-digit activity. From that, we can allocate the vast majority of 6-digit CPA codes to 5-digit UKSIC(92) activities (see below for the list of exceptions).

The result gives 3121 SITC Rev.3 codes each with a given 5-digit UKSIC(92) match; 283 sectors in total (251 are manufacturing sectors; the remaining 32 sectors are mainly comprised into "Mining and Quarrying").

B.3.1 Limitations

No SITC products are left unmatched but two exceptions; SITC codes 91100 (postal packages not classified according to kind) and 93100 (special transactions and commodities not classified according to kind) have no corresponding codes with CPA 2002 or even with different revisions of HS and CN classifications. Therefore, those codes have a corresponding UKSIC missing code represented by "." in the concordance table.

Unfortunately, not every UKSIC(92) manufacturing sectors are matched. Indeed, the list below shows the ones that are not:

- 17.13: preparation and spinning of worsted-type fibres;
- 17.23: worsted-type weaving;
- 22.21: printing of newspaper;
- 22.23: bookbinding and finishing;
- 22.25: Other activities related to printing;
- 22.3: reproduction of recorded media;
- 27.35: Other first processing of iron and steel not elsewhere classified; production of non-ECSC ferro-alloys;
- 27.5: casting of metals;
- 28.4: forging, pressing, stamping and roll forming of metal; powder metallurgy;
- 28.5: treatment and coating of metals; general mechanical engineering;
- 33.3: industrial process control equipment;
- 37: recycling.

The main reason for the non-matching (except for codes 17.13, 17.23 and 27.35) is that the corresponding CPA codes (thus identical to UKSIC(92)) have been found to have no match at all with any HS or CN classification, since they mainly consist of related services linked to the corresponding activities (see the CPA 2002 structure). For codes 17.13 and 17.23, the reason is that the SITC3 classification does not distinguish between worsted-type fibres and other fibres made with other techniques. For code 27.35, we decided to allocate those to code 27.10; we did that as a matter of consistency across the different correspondence and correlation tables built. To be more precise, 27.35 no longer exists in UKSIC(2003), it is allocated into 27.10. Therefore in the correspondence table matching sectors from UKSIC(2003) to UKSIC(1992), 27.35 cannot be matched since it is incorporated into 27.10 in UKSIC(2003).

Moreover, 10 4-digit UKSIC(92) manufacturing sectors could not be broken further down into their fifth digit because of the SITC3 classification nature. Those sectors are:

- 15.13: production of meat and poultry meat products;
- 15.93: manufacture of wines;
- 15.94: manufacture of cider and other fruit wines;
- 23.20: manufacture of refined petroleum products;
- 24.30: manufacture of paints, varnishes and similar coatings, printing ink and mastics;
- 25.23: manufacture of builders' ware of plastic;
- 29.12: manufacture of pumps and compressors;
- 33.20: manufacture of instruments and appliances for measuring, checking, testing, navigating and other purposes, except industrial process control equipment;
- 33.30: industrial process control equipment;
- 36.50: games and toys.

Finally, two pairs of 4-digit UKSIC(92) sectors have to be grouped together, again because of the SITC3 classification nature, it was impossible to distinguish them one from the other. Those sectors are:

- 15.81 and 15.82 grouped together into code number 15.81 in the table;
- 26.63 and 26.64 grouped together into code number 26.63 in the table.

B.4 Mapping industries consistently: from UKSIC 2007 revision to UKSIC 1992 revision

Because the UKSIC classification has been updated twice since the 1992 version, we need to work with one consistent industry classification for all available years. The aim is to concord industries classified according to the 2007 or 2003 UKSIC versions into the 1992 UKSIC version. The classification has been revised in 2003 and 2007 (and one minor revision in 1997). The 2003 revision was not a full-scale change, so its structure is still tightly linked to the 1992 revision. In 2007, however, the structure of the classification has been revised in depth leading to major changes. So, we proceed first by mapping UKSIC 2007 industry codes to UKSIC 2003 ones and then we map UKSIC 2003 industry codes to corresponding UKSIC 1992 codes.

B.4.1 From UKSIC 2007 to UKSIC 2003

The crosswalk table is heavily built on the one provided by the Inter-Departmental Business Register (IDBR) from ONS. The ONS last update was done in December 2009 and no further updates are expected.

The table is a weighted correlation table that maps any UKSIC(2007) code to at least one corresponding UKSIC(2003) code at the 5-digit level. The weighted correlation table shows the level of change that might be expected at UKSIC level in employment data, turnover data (see the section ”limitations”) and the number of business in percentage format following implementation of UKSIC(2007).

The table is based on data taken from the IDBR, which contains information on VAT traders and PAYE employers in a statistical register comprising of over 2 million enterprises. This dataset relates to a snapshot of VAT and/or PAYE registered businesses on the IDBR, taken in December 2009.

Some minor modifications have been made to the original IDBR table. Indeed, some UKSIC(2007) industries are absent from the original table and, thus, have been included in the current table for a matter of completeness. Those industries are:

- 01150: Growing of tobacco;
- 01230: Growing of citrus fruits;
- 01260: Growing of oleaginous fruits;
- 01280: Growing of spices, aromatic, drug and pharmaceutical crops;
- 05200: Mining of lignite;
- 07210: Mining of uranium and thorium ores;
- 10810: Manufacture of sugar;

- 17110: Manufacture of pulp;
- 24460: Processing of nuclear fuel;
- 64110: Central banking;
- 84210: Foreign affairs;
- 84230: Justice and judicial activities;
- 84240: Public order and safety activities;
- 84300: Compulsory social security activities;
- 97000: Activities of households as employers of domestic personnel;
- 98100: Undifferentiated goods-producing activities of private households for own use;
- 98200: Undifferentiated service-producing activities of private households for own use;
- 99000: Activities of extraterritorial organisations and bodies.

Part of those sectors include some in which UK does not produce anything (i.e. mining of uranium and thorium ores, growing of oleaginous fruits) and some that were apparently protected by ONS (so the weights were not computed). In order to find at least one corresponding UKSIC(2003) match, we double-checked our priors with a raw correspondence table provided by Eurostat and a UKSIC(2007) detailed alphabetical index, provided by ONS, for which corresponding UKSIC(2003) codes were provided (without weights, so it is a m-to-m correspondence table).

For example, for 16 out of the 18 above-mentioned industries, we could identify a 1-to-1 match, therefore having a 100% weight in the table. For the other two (codes 01260 and 01280), there is more than 1 plausible match, thus we had to weight them according to their corresponding UKSIC(2003) ”frequency” matches. To be more specific, let us introduce an example on how the correspondence is presented in the alphabetical index. The example is for UKSIC(2007) code number 01280 (Growing of spices, aromatic, drug and pharmaceutical crops):

UKSIC(2007) code: source	**UKSIC(2003) code: target**
01280	01110: Pharmaceutical crops growing
01280	01110: Plants used chiefly in pharmacy or for insecticidal, fungicidal or similar purposes
01280	01110: Drug and narcotic crops growing
01280	01110: Hop cones growing
01280	01120: Pepper growing
01280	01139: Spice crops growing

01280	01139: Vanilla growing
01280	01139: Anise growing
01280	01139: Aromatic crops growing
01280	01139: Badian growing
01280	01139: Basil growing
01280	01139: Bay growing
01280	01139: Chilli growing
01280	01139: Chillies and peppers capsicum sop. growing
01280	01139: Cinnamon growing
01280	01139: Clove growing
01280	01139: Coriander growing
01280	01139: Ginger growing
01280	01139: Nutmeg, mace and cardamoms growing

So, UKSIC(2007) code number 01280 matches 14 times with UKSIC(2003) code number 01139, 4 times with 01110 and once with 01120. Accordingly, the weights are respectively 14/19, 4/19 and 1/19 in the table.

Turnover data weights for some industries were not provided by IDBR. Those industries are UKSIC(2007) codes 64201, 64202, 64203 and 64204. Since those industries are not from manufacturing and account for a small fraction of the industry total in many respects, I've taken the arithmetic mean of the two other weights to approximate them. Noteworthy, correlations between any two weighting scheme are more than 98%.

B.4.2 From UKSIC 2003 to UKSIC 1992

The 2003 revision was not a major change; accordingly both classification structures at each level of disaggregation are tightly linked. The changes and modifications made to the 2003 revision are listed and available in an ONS PDF-format file.[1] Therefore, we directly applied those changes without any further modification except one. UKSIC(1992) code number 27350 no longer exists in the UKSIC(2003) revision; this code is included into code number 27100. Therefore, it should be noted that 27350 is absent from the UKSIC(1992) classification in the table and integrated into code number 27100 as in the 2003 revision.

[1] File available on the ONS website.

Appendix C

Appendix to Chapter 3

C.1 Extra tables

Table C.1: Descriptive statistics

	mean	sd	p25	p50	p75	min	max
Continuous variables: sample when estimating trade effect (22,633 observations)							
Hourly Rate of Pay	40.97	32.52	30.12	37.00	46.71	5	2,188.0
Number of hours of work	39.56	8.907	40	41	42	2	95
Number of hours of work	1,860.4	418.9	1,880	1,927	1,980	90	4,465
Gross Annual Earnings	75362	46,300	55,890	70,440	89,790	200	1,922,461
Import Penetration	0.791	12.63	0.161	0.385	0.658	0.0004	92.19
Export Share	0.549	0.740	0.0967	0.420	0.813	0.0007	17.68
Export-weighted REER Index	106.8	3.887	104.2	106.4	108.9	33.79	119.6
Import-weighted REER Index	106.7	6.117	104.4	106.8	109.3	1.279	131.2
Industry average hourly wage	41.89	9.195	36.24	40.54	45.88	11.12	132.4
Age	40.56	11.61	31	40	50	16	64
Tenure (in years)	10.42	9.960	2.519	7.250	15.37	0.02	50
Dummy variables: (22,633 observations)							
Married	0.590	0.492	.	.	.	0	1
Foreign	0.315	0.464	.	.	.	0	1
Women	0.284	0.451	.	.	.	0	1
Workers in Firm $\geq$ 20 empl.	0.747	0.435	.	.	.	0	1
Continuous variables: sample when estimating exchange rate movements effect (14.367 observations)							
$\Delta \text{ER}^{M}_{k,t}$	0.0040	0.0205	-0.0095	0.0092	0.0173	-0.197	0.317
$\Delta \text{ER}^{X}_{k,t}$	0.0040	0.0648	-0.0092	0.0090	0.0189	-1.545	2.504
Δw_t	0.0398	0.366	-0.0421	0.0146	0.0896	-5.419	4.994
Δhours_t	0.0042	0.234	-0.0030	0	0.0030	-3.689	3.689

Source: Own calculations based on BACII-SLFS database.

Table C.2: First-stage IV estimates of wage determinants (1996-2008): various groups of workers

	ln(IP) (1)	ln(XS) (2)	ln(IP) (3)	ln(XS) (4)	ln(IP) (5)	ln(XS) (6)	ln(IP) (7)	ln(XS) (8)	ln(IP) (9)	ln(XS) (10)
$\ln(\text{IP})^{IV}_{k,t-1}$	0.917***	0.145**	0.936***	0.107**	0.903***	0.167**	0.916***	0.123**	0.926***	0.223***
	(0.044)	(0.058)	(0.029)	(0.044)	(0.060)	(0.068)	(0.044)	(0.054)	(0.059)	(0.073)
$\ln(\text{XS})^{IV}_{k,t-1}$	-0.056	0.672***	-0.113	0.673***	-0.023	0.674***	-0.050	0.663***	-0.104	0.631***
	(0.086)	(0.100)	(0.100)	(0.112)	(0.093)	(0.103)	(0.105)	(0.106)	(0.092)	(0.125)
$\overline{\text{w}}_{k,t}$	0.046	0.115***	0.087	0.175***	0.029	0.090**	0.054	0.130**	0.040	0.086*
	(0.039)	(0.043)	(0.055)	(0.059)	(0.038)	(0.043)	(0.047)	(0.051)	(0.040)	(0.050)
$\overline{\text{w}}_{k,t-1}$	-0.018	0.031	-0.019	0.006	-0.023	0.045	0.002	0.028	-0.036	0.026
	(0.030)	(0.043)	(0.042)	(0.065)	(0.028)	(0.038)	(0.039)	(0.055)	(0.029)	(0.040)
$\overline{\text{w}}_{k,t-2}$	-0.008	0.046	-0.021	-0.015	-0.010	0.064*	0.007	0.038	-0.016	0.049
	(0.031)	(0.036)	(0.048)	(0.045)	(0.027)	(0.035)	(0.042)	(0.046)	(0.025)	(0.032)
ln(hours)	-0.015***	-0.005	0.000	-0.004	-0.019***	-0.003	-0.011*	-0.006	-0.016**	0.004
	(0.004)	(0.006)	(0.008)	(0.007)	(0.005)	(0.008)	(0.006)	(0.008)	(0.007)	(0.010)
Age	0.004	-0.004	-0.004	-0.000	0.006	-0.005	0.001	0.002	0.007	-0.011
	(0.007)	(0.007)	(0.011)	(0.012)	(0.007)	(0.007)	(0.009)	(0.008)	(0.007)	(0.009)
Age^2 ($\times$ 1000)	-0.087	0.093	0.108	0.008	-0.162	0.122	-0.014	-0.033	-0.195	0.257
	(0.162)	(0.160)	(0.276)	(0.295)	(0.165)	(0.176)	(0.210)	(0.199)	(0.171)	(0.222)
Age^3 ($\times$ 1000)	0.001	-0.001	-0.001	-0.000	0.001	-0.001	-0.000	0.000	0.002	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Married	0.002	0.003	0.007	-0.001	-0.003	0.004	0.006	0.008	-0.002	-0.003
	(0.003)	(0.004)	(0.006)	(0.007)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)
Foreign	0.003	0.009	0.008	0.010	0.004	0.008	0.011	0.012*	-0.004	0.012
	(0.005)	(0.005)	(0.007)	(0.009)	(0.005)	(0.006)	(0.007)	(0.007)	(0.005)	(0.007)
Female	-0.005	0.000	0.000	0.000	-0.003	0.002	-0.003	-0.006	-0.012*	0.008
	(0.004)	(0.005)	(0.007)	(0.009)	(0.005)	(0.006)	(0.004)	(0.006)	(0.006)	(0.008)
Tenure	-0.000	-0.000	0.000	0.000	-0.000	-0.000*	-0.000	-0.001**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Size	0.005	-0.007	-0.011	-0.018**	0.010**	-0.001	-0.003	-0.005	0.009*	-0.006
	(0.004)	(0.005)	(0.009)	(0.009)	(0.005)	(0.005)	(0.008)	(0.008)	(0.004)	(0.005)
Education	All	All	HS	HS	LS	LS	All	All	All	All
Occupation	All	All	All	All	All	All	WC	WC	BC	BC
R-squared	0.749	0.486	0.768	0.475	0.738	0.495	0.774	0.501	0.679	0.428
F	82.699***	18.928***	106.845***	12.555***	62.677***	20.651***	89.885***	15.714***	75.121***	16.114***
N	22,633	22,633	7,979	7,979	14,654	14,654	11,864	11,864	10,761	10,761
No. Clusters	193	193	173	173	186	186	181	181	182	182

Notes: All regressions include a constant term. Standard errors are clustered at the industry 4-digit level. All regressions control for regional, year, education, industry 4-digit level, occupation 4-digit level and 2-digit industry $\times$ year fixed effects. Columns (1) and (2) show first-stage estimates of column (1) in Table 3.2. Columns (3) and (4) show first-stage estimates of column (2), Panel A, in Table 3.3. Columns (5) and (6) show first-stage estimates of column (4), Panel A, in Table 3.3. Columns (7) and (8) show first-stage estimates of column (2), Panel B, in Table 3.3. Columns (9) and (10) show first-stage estimates of column (4), Panel B, in Table 3.3. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.
Source: Own estimations based on BACII-SLFS database.

C.2 Conceptual base of the structural gravity model

This section follows similar developments done by Anderson and Yotov (2012), Anderson and Yotov (2010a) and Anderson and Yotov (2010b). The structural gravity model follows Anderson (1979) because it uses the assumptions of a CES demand specification with product differentiation by place of origin (i.e. Armington type). Further assumptions are the inclusion of budget constraints (one for each destination in each sector) and market clearance equations (one for each origin in each sector). I abstract from the time subscript *t* to ease notation. Let:

- $T_{o,d,k}$ be the value of shipments at destination prices from origin o to destination *d* in sector *k*;
- $t_{o,d,k} \geq 1$ be the variable trade cost factor on shipment of goods from origin *o* to destination *d* in sector *k*;
- $p^*_{o,k}$ be the factor gate price. Hence, destination prices are $p^*_{o,k} \times t_{o,d,k}$;
- $E_{d,k}$ be the expenditure at destination *d* on goods in sector *k* from all origins;
- $Y_{o,k}$ be sales of goods at destination prices from origin o in sector *k* to all destinations.

Then, the demand function (for either final or intermediate goods) is given by:

$$T_{o,d,k} = \left(\beta_{o,k} p^*_{o,k} t_{o,d,k} / P_{d,k}\right)^{1-\sigma_k} E_{d,k} \tag{C.1}$$

where $\beta_{o,k}$ is a share parameter at origin *o* in sector k, σ_k is the elasticity of substitution parameter for sector *k*; and $P_{d,k}$ is the CES sectoral price index defined as:

$$P_{d,k} = \left[\sum_o (\beta_{o,k} p^*_{o,k} t_{o,d,k})^{1-\sigma_k}\right]^{\frac{1}{1-\sigma_k}}. \tag{C.2}$$

Market clearance implies, for each sector *k*:

$$Y_{o,k} = \sum_d (\beta_{o,k} p^*_{o,k})^{1-\sigma_k} (t_{o,d,k}/P_{d,k})^{1-\sigma_k} E_{d,k} \tag{C.3}$$

Thus, defining $Y_k \equiv \sum_o Y_{o,k}$, "world expenditure shares" at the sectoral level are generated by:

$$(\beta_{o,k} p^*_{o,k} \Pi_{o,k})^{1-\sigma_k} = Y_{o,k}/Y_k \tag{C.4}$$

where

$$\Pi_{o,k} \equiv \sum_d (t_{o,d,k}/P_{d,k})^{1-\sigma_k} E_{d,k}/Y_k \tag{C.5}$$

and the CES "world" price index is equal to 1, because summing (C.4) yields:

$$\sum_o (\beta_{o,k} p^*_{o,k} \Pi_{o,k})^{1-\sigma_k} = 1. \tag{C.6}$$

Next, use (C.4) to substitute for $\beta_{o,k}p^*_{o,k}$ in (C.1), the market clearance in (C.3) and the CES price index in (C.6). This yields the structural gravity model for each time period *t* at the sectoral level *k* (Anderson and Van Wincoop, 2004):

$$T_{o,d,k} = \frac{E_{d,k}Y_{o,k}}{Y_k}\left(\frac{t_{o,d,k}}{\Pi_{o,k}P_{d,k}}\right)^{1-\sigma_k} \tag{C.7}$$

$$(\Pi_{o,k})^{1-\sigma_k} = \sum_d \left(\frac{t_{o,d,k}}{P_{d,k}}\right)^{1-\sigma_k}\frac{E_{d,k}}{Y_k} \tag{C.8}$$

$$(P_{d,k})^{1-\sigma_k} = \sum_o \left(\frac{t_{o,d,k}}{\Pi_{o,k}}\right)^{1-\sigma_k}\frac{Y_{o,k}}{Y_k} \tag{C.9}$$

where $\Pi_{o,k}$ represents outward multilateral resistance and $P_{d,k}$ represents inward multilateral resistance (and is also the CES sectoral price index for the demand system)[1].

C.3 Mapping trade products to industries: from SITC revison 3 to NACE revision 1.0

The aim is to carry out extensive analysis using trade data classified by the industrial classification of the European Union (Nomenclature générale des activités économiques dans les communautés européennes), first revision, NACE Rev. 1 (NACE1) at the highest, fourth-digit level of disaggregation. The original trade data are classified according to the Standard International Trade Classification, revision 3 (SITC rev3).

To perform such a correspondence, I used one existing official (administrative) concordance table that matches 8-digit Combined Nomenclature 2002 codes (CN 2002) with 6-digit Classification of Products by Activity 2002 codes (CPA 2002), with 6-digit Harmonized System 2002 (HS 2002) and also with 5-digit SITC rev3 (SITC3) codes. Therefore, CN 2002, and at a lesser extend HS 2002, serve as “proxy” classifications that linked SITC3 to NACE1. Indeed, CPA 2002 is identical to NACE 1.0 up to the fourth-digit level (with some exceptions).

This CN-HS-CPA-SITC concordance table was built by EuroStat by putting in correspondence several existing official tables. The concordances were created by electronic means and have not been thoroughly checked or validated by any organization or working party. As a consequence no guarantee can be given as to their full reliability. However, it is a valuable starting point and it serves as an input file which forms the skeleton of the SITC3-NACE1 concordance.

The strategy is then based on two steps. The first step is to build a correspondence table going from SITC3, at five-digit, to CPA 2002, at 6-digit using information from CN-SITC3, CN-CPA, HS-SITC3 and HS-CPA tables. Some SITC3

[1] See Anderson and Van Wincoop (2003).

products couldn't be fairly allocated to a single 6-digit CPA code, so some SITC3 products are matched to a 5-digit CPA code. In cases where it was needed to improve the appropriateness and precision of the allocation, I also used an additional table that linked 8-digit (and not 6-digit as before) HS 2002 codes to 6-digit CPA codes.

The second step involves converting those 6-digit CPA codes to 4-digit NACE1 economic activities. With some exceptions, CPA 2002 and NACE1 are identical up to the fourth digit. From that, I can allocate the vast majority of 6-digit CPA codes to 4-digit NACE1 activities (see below for the list of exceptions).

The result gives us 3121 SITC Rev 3 codes each with a given 4-digit NACE1 code; 253 sectors in total, among which 221 are manufacturing sectors. The remaining 32 sectors are mainly comprised into "Mining and Quarrying".

C.3.1 Limitations

No SITC products are left unmatched but two exceptions; SITC codes 91100 (postal packages not classified according to kind) and 93100 (special transactions and commodities not classified according to kind) have no corresponding codes with CPA 2002 or even with different revisions of HS and CN classifications. Therefore, those codes have a corresponding NACE missing code represented by "." in the concordance table.

Unfortunately, not every NACE1 manufacturing sectors are matched. Indeed, the list below shows the ones that are not:

- 17.13: preparation and spinning of worsted-type fibres;
- 17.23: worsted-type weaving;
- 22.21: printing of newspaper;
- 22.23: bookbinding and finishing;
- 22.25: Other activities related to printing;
- 22.3: reproduction of recorded media;
- 27.35: Other first processing of iron and steel not elsewhere classified; production of non-ECSC ferro-alloys;
- 27.5: casting of metals;
- 28.4: forging, pressing, stamping and roll forming of metal; powder metallurgy;
- 28.5: treatment and coating of metals; general mechanical engineering;
- 33.3: industrial process control equipment;

- 37: recycling.

The main reason for the non-matching (except for codes 17.13 and 17.23) is that the corresponding CPA codes (thus identical to NACE1) have been found to have no match at all with any HS or CN classification, since they mainly consist of related services linked to the corresponding activities (see the CPA 2002 structure for more details). For codes 17.13 and 17.23, the reason is that the SITC3 classification does not distinguish between worsted-type fibres and other fibres built with other techniques.

Finally, two pairs of 4-digit NACE1 sectors have to be grouped together, again because of the SITC3 classification nature, it was impossible to distinguish them one from the other. Those sectors are:

- 15.81 and 15.82 grouped together into code number 15.81 in the table;
- 26.63 and 26.64 grouped together into code number 26.63 in the table.

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