The Effect of Trade on Unemployment: Propagation across Labor Markets*

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Abstract

I argue that trade shocks propagate to workers far beyond the directly exposed import-competing industries. By estimating the impact of rising foreign competition on the unemployment outcomes of German workers during 1990-2004, I find large effects for workers even outside the manufacturing sector. Specifically, workers in the same occupations as the most affected manufacturing workers spend more time in unemployment than those in other occupations. I next build a dynamic search model in which shock propagation is driven by displaced manufacturing workers competing for the same jobs as non-manufacturing workers, thereby prolonging their unemployment spells. Calibrated to match the pre-shock patterns of workers' transitions between sectors and occupations, the model can explain the observed trade shock's propagation. Moreover, counterfactual experiments suggest that ignoring the extensive patterns of shock propagation results in a downward bias in the reduced-form estimates of the impact of trade.

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1 Introduction

Who bears the brunt of globalization? In this one of the oldest questions in economics, it has long been assumed that losses from rising foreign competition are primarily concentrated within the group directly exposed to this shock – workers in the import-competing industries. In this paper, I show that losses are actually much more widespread and, in fact, propagate as far as to the workers from outside the manufacturing sector. This propagation happens even for arguably the most severe and yet understudied consequences of the adverse trade shocks for individual workers – job displacement and prolonged spells of unemployment.

To document the propagation of trade shocks beyond the borders of the manufacturing sector, I combine administrative data from Germany, a country where manufacturing plays a prominent role, with an episode of extraordinary increase in imports. That is I focus on the expansion of German trade with China and Eastern Europe during the 1990s and early 2000s. During this period, both China and post-communist countries in Eastern Europe were transitioning to market-oriented economies, resulting in a huge surge in their trade with the rest of the world. And thus German imports from these regions grew at a much higher rate than from any other region in the world. The detailed administrative data, in turn, allows me to measure the unemployment spells of German workers with extremely high accuracy, down to a single day, during this unprecedented expansion of foreign trade.[1]

To isolate the propagation of shocks and to separate it from the direct effect, I restrict my sample to the workers who unambiguously have no *direct* exposure to trade shocks, that is to the workers from non-manufacturing industries. For them, I construct a measure of *indirect* trade exposure, where I allow a trade shock to propagate at least within the same occupation. This occupation-specific measure is based on the share of workers from each occupation in the directly exposed import-competing industries.[2] For example, many of the locksmiths were employed in the manufacturing industries where imports have increased substantially. Thus, this measure is high for all locksmiths, even those employed in the service sector. In my estimation, their unemployment outcomes are compared with those of, for example, music teachers. Almost none of them were employed in import-competing industries, and thus their occupation has almost zero indirect exposure.

By comparing different occupations within the non-manufacturing sector I find that higher

[1]My baseline analysis stops in 2004, one year before the Hartz labor market reforms significantly affected the labor market in Germany, but I explore alternative time periods in the Appendix.

[2]To calculate this measure, I first normalize the change in imports during 1990-2004 for each industry by its pre-shock employment level. Then, for each occupation, I compute an average of these industry-specific measures, weighted by the number of workers in that occupation employed in each industry. Following seminal Autor et al. (2013), I instrument this measure with import flows from China and Eastern Europe to other developed countries, excluding Germany. This helps to extract part of the increase in trade that is related to the expanding economies of China and Eastern Europe and is not correlated with local shocks in Germany.

indirect exposure to rising import competition is associated with more time spent in unemployment. To paraphrase, consider two workers employed in the service sector in 1990, identical in all observable characteristics, but one is a locksmith and the other is a music teacher. Then, over the next 14 years, the locksmith will spend, on average, significantly more time in unemployment, than the music teacher. More precisely, the implied difference between workers with 75th and 25th percentile in indirect exposure amounts to additional 42 days without work for unemployed workers over a period of 14 years. This difference is remarkable given the fact that none of these workers were employed in the import-competing industries, and thus their jobs were not directly threatened by the rising imports from China and Eastern Europe.

This result not only reveals that the distribution of losses from trade is much less concentrated than previously assumed but also suggests that the empirical literature has likely underestimated the magnitude of these losses. Typically, reduced-form studies (e.g. Autor et al., 2014) have compared directly exposed workers with the rest. However, if many non-exposed workers have also suffered significant losses, then the reduced-form approach can only estimate the difference in losses between the two groups, and not the overall magnitude of the losses. While my empirical result documents the propagation of trade shocks within the same occupation, there could be many other channels of propagation, including within the same region, sector, through input-output structure, and so on. Consequently, the reduced-form approach appears to be limited by the challenge of finding a suitable control group that is entirely isolated from the directly exposed group.

To assess the size of such bias in my empirical result, I build a dynamic search model in which shocks to unemployment outcomes propagate in arguably the most straightforward way – through the movement of unemployed workers across various labor markets. In the model, unemployed workers can search for new jobs in any industry and occupation. However, this choice comes at the cost of acquiring new skills. Subsequently, following the trade shock, some of the displaced manufacturing workers choose to search for new jobs outside of the manufacturing sector. Most of them search for jobs within their previous occupation to avoid incurring additional costs associated with changing occupations in addition to switching industries. Therefore, these displaced workers compete for jobs with unemployed non-manufacturing workers in the same occupation, thereby prolonging their unemployment spells. Importantly, some of the displaced workers will also search for new jobs in other occupations, despite the higher costs. As a result, the model accounts for the propagation of shocks across all labor markets, rather than just within the same occupation.

Moreover, the model incorporates higher-order effects from the movement of unemployed workers. For example, consider a locksmith who moves from manufacturing to services due to increased import competition. Then, unemployment outcomes become worse for all locksmiths. As a result, some of the unemployed locksmiths in the service sector may choose to avoid spending too much time looking for a new job in the same occupation and become music teachers instead. Their reallocation is also caused by the trade shock, even though they were never directly exposed to it. Then, they will compete for jobs with other music teachers and affect their unemployment outcomes. Such second-order effects from the trade shock can, in turn, cause third-order effects and so on. Therefore, the model can capture not only the movement of displaced workers into all other labor markets but also the optimal response of all other unemployed workers to changes in labor market conditions.

Workers' expectations about the future could also amplify the propagation of trade shocks. In particular, many workers may have left the import-competing industries at the beginning of the 1990s, not necessarily because of the severity of the shock at that time, but due to their anticipation of continued trade expansion with China and Eastern Europe. This preemptive action allowed them to insulate themselves from future trade shocks by promptly changing industries. The simultaneous movement of these workers to other labor markets could congest them by more than a more gradual transition. I capture this mechanism by assuming the perfect foresight, which also helps to make the model tractable.

Next, the presence of other non-trade shocks at the time of the rising foreign competition could significantly affect the propagation of the trade shock. Notably, the boom in the German export sector in the 1990s provided an attractive destination for many displaced workers from the import-competing industries. Such boom likely influenced the direction of their reallocation and thus the pattern of propagation of the trade shock (*cf.* Dix-Carneiro et al., 2023; Dauth et al., 2021). Similarly, the trend of expanding the service sector created a comparable "pull factor" for displaced workers. Therefore, I account for the influence of these two trends by incorporating them in the model and computing a non-linear solution, which allows the response to one shock to depend on the presence of other shocks.

Finally, the rich structure of mobility costs in the model allows it to nest an economy with a single labor market where propagation is complete and uniform, an economy with isolated labor markets where there is no propagation across them, and all the options in between. For instance, certain industries and occupations could be tightly connected to each other while being completely isolated from the rest of the economy. I discipline the model by calibrating the mobility costs to match the pre-shock patterns of mobility in the data. That is I calculate the transition matrix between sectors and occupations for unemployed workers in the data and choose the structure of mobility costs so that this matrix is exactly the same in the model's initial steady state. This way I let the data determine the extent to which various labor markets are interconnected.

The ultimate goal of my counterfactual experiment of simulating the economy with and without the trade shock is to assess the full extent of its propagation. I first choose the size of the trade shock to make sure that its *direct* effect is the same in the model and in the data, that is in my reduced-form regression that compares the least and the most exposed workers *within* the manufacturing sector. Then, I evaluate the model's performance by comparing the size of the shock's *indirect* effect between the model and the data. Specifically, I check how well the model of shock propagation can explain the estimated difference between different workers *outside* of the manufacturing sector. Finally, I use the model to infer the total size of both the direct and indirect effects by comparing the outcomes of all workers not to those of the less exposed, but rather to their outcomes in the absence of the trade shock. My results suggest that even the least exposed workers are substantially impacted by the shock, and thus the reduced-form regressions underestimate the effect of the shock.

Related literature This paper contributes to and builds on several literatures. First, numerous reduced-form studies have examined the effect of trade shocks on workers' outcomes, including seminal Autor et al. (2013, 2014), as well as Acemoglu et al. (2016); Dix-Carneiro and Kovak (2017, 2019); Goldberg and Pavcnik (2005); Hummels et al. (2014); McCaig and Pavcnik (2018); Pierce and Schott (2016); Topalova (2010) among others, while the effect on the German labor market was analyzed by Dauth et al. (2014, 2017, 2021). My main contribution is to document that overall losses from trade are much less concentrated than previously believed. That is I show that trade shocks propagate well beyond the directly exposed group of workers. In addition, I also point out the bias of the reduced-form studies that this finding implies, and I use a quantitative model to evaluate its size. Finally, I also complement the literature focused on the effect of trade on workers' earnings by estimating its effect on the detailed unemployment outcomes of individual workers.

Second, there is a quantitative trade literature that uses the models of imperfect labor market mobility to estimate the adjustment to trade shocks, starting from Artuç et al. (2010) and including Artuç and McLaren (2015); Artuç et al. (2023); Caliendo et al. (2019); Dix-Carneiro (2014); Dix-Carneiro et al. (2023); Lee (2020); Traiberman (2019) among others. I extend the standard general equilibrium framework with imperfect labor mobility and international trade by adding the Diamond-Mortensen-Pissarides framework (see e.g. Pissarides, 2000) with worker heterogeneity and endogenous separation rate (as in Den Haan et al., 2000).

Third, I also complement the literature that uses occupational mobility to explain various patterns within the same occupation, e.g. wage inequality (Kambourov and Manovskii, 2009; Postel-Vinay and Sepahsalari, 2023) or the cyclicality of the value of job loss (Huckfeldt, 2022; Baley et al., 2022). Instead, I show how mobility across occupations and industries can explain the propagation of shocks between these distinct labor markets.

2 Data and Empirical Evidence

In this section, I describe the data and document the evidence that the effects of trade shocks extend beyond the borders of the manufacturing sector.

2.1 Data

Throughout the paper, I use the confidential version of the Sample of Integrated Labour Market Biographies (SIAB) from the German Institute for Employment Research (IAB). It is a random 2% sample from German administrative social security records for the years 1975 to 2014 (Antoni et al., 2016). Except for some groups of civil servants and self-employed workers, this dataset is representative of the population of workers who are subject to compulsory social insurance contributions or who collect unemployment benefits. Once an individual is drawn, he or she is followed for the rest of the sample period. This allows me to trace workers' entire labor market biographies and to evaluate the long-run effects of trade by connecting their initial trade exposure to their later outcomes, regardless of their subsequent industrial or occupational affiliation. For the same reason, I can evaluate workers' transition matrix between different industries and occupations.

The dataset includes several firm and worker characteristics, which I later use as controls in my empirical specification (3) and report in Table 1. It also includes information on the number of days worked at each job and the number of days spent in registered unemployment. This daily information on unemployment together with the fact that all unemployment spells of a particular worker are included in the sample allows me to measure unemployment outcomes extremely accurately. However, I do not observe those unemployment spells where workers do not register officially. And thus strictly speaking I can measure only the lower bound of unemployment.[3]

In my baseline analysis, I exclude from the sample all workers who have ever lived or worked in East Germany, that is I consider the effect of trade on workers from West Germany only.[4] Manufacturing trade data is taken from the United Nations Commodity Trade Statistics Database (Comtrade).[5] The original data is given at the 4-digit SITC Rev. 3 level, which I convert to the 3-digit NACE Rev. 1 level using the correspondence table from Dauth et al. (2017). I convert the original values in (current prices) US dollars to 2010 Euros using the German CPI index and the exchange rate data from the Bundesbank.[6]

2.2 Empirical Approach

The 1990s and 2000s were a time of a well-documented and extraordinary increase in globalization. The left panel of Figure 1 shows that the total volume of German manufacturing imports has almost quadrupled over 35 years (an increase over 1979-2014 has almost reached three times the level of 1979). To document the effect of this dramatic change on unemployment outcomes of workers in different occupations, I compute the following occupational measure of import exposure over the

[3]In this period, unemployed workers had strong incentives to register as most of them were entitled to short-term benefits in the amount of roughly 60% of their previous wages.

[4]I control for migration flows from East Germany as a robustness check in Appendix A.1.

[5]Available at https://comtrade.un.org/data/.

[6]Available at https://www.bundesbank.de/Navigation/EN/Statistics/statistics.html.

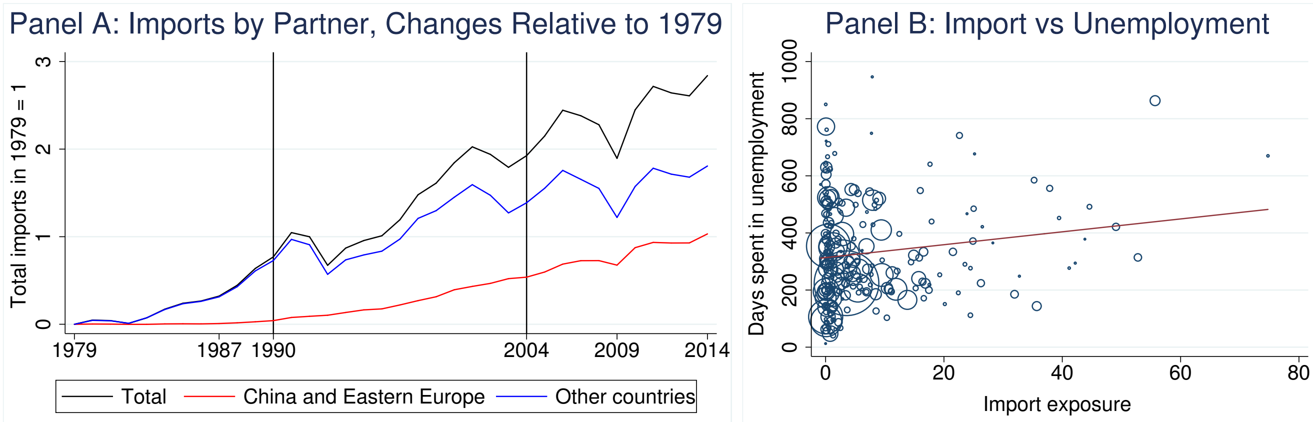

Figure 1: Manufacturing imports and time spent in unemployment for non-manufacturing workers

Notes. Panel A shows changes in German imports relative to 1979, normalized by the total imports in 1979, $\left(M_t^{G,i} - M_{1979}^{G,i}\right)/M_{1979}^{G,W}$. Here $M_t^{G,i}$ is the level of manufacturing imports in year t from region i (the world, China and Eastern Europe, all other countries) to Germany. By construction, all variables start at 0 in 1979 and the contributions of the two regions sum up to the trade with the world. The vertical lines indicate the baseline period that I consider, 1990-2004. *Panel B* plots the measures of occupational import exposure, $\triangle m_o$, versus the cumulative time spent in unemployment by workers initially employed in these occupations, y_{io}. Both variables are measured over the period of 1990-2004. Each circle represents one occupation with its size indicating the number of workers in that occupation. Only non-manufacturing workers are included in the sample.

period of 1990-2004,

$$\triangle m_o = \sum_j \frac{L_{oj,90}}{L_{o,90}} \frac{M_{j,04}^{G,W} - M_{j,90}^{G,W}}{L_{j,90}}, \tag{1}$$

where $M_{j,t}^{G,W}$ is the level of imports to Germany from the rest of the world in industry j and year t, $L_{oj,t}$ is German employment in occupation o and industry j, so that $L_{o,t} = \sum_j L_{oj,t}$ is employment in occupation o and $L_{j,t} = \sum_o L_{oj,t}$ is employment in industry j.[7] Within this measure, I first calculate the change in imports per worker in industry j. And then, to construct a measure for each occupation, I take an average across all industries weighted by their employment shares in that occupation.[8]

I then link these measures of trade exposure to unemployment outcomes of workers in different occupations over the same period. To capture not just the short-run effects, but the more prolonged effect on the substantial part of workers' careers, I focus on 15-year intervals from workers' labor market histories. Specifically, I select a sample of all workers with full-time jobs in non-manufacturing industries in 1990 with ages between 22 and 50, so that they do not hit the

[7]To measure the distribution of workers across 220 3-digit industries and 336 3-digit occupations more accurately, I pool the data over the 10 preceding years. That is I use $\sum_{t=81}^{90} L_{oj,t}/10$ instead of $L_{oj,90}$.

[8]I normalize the change in imports by employment to account for the difference in initial sizes of different industries. Autor et al. (2014) use data on firms' domestic sales to normalize trade flows by domestic absorption. But similar data in Germany are available only for larger firms, at a different level of aggregation, and from 1991. Thus I follow Autor et al. (2013) in using the employment data instead. Appendix A.1 repeats all of my analysis with weights based on the wage bill data, similar to Dauth et al. (2021).

retirement age by the end of my analysis in 2004. I then follow them for 15 years and record the total number of days they have spent in registered unemployment during 1991-2004, y_{io}, where i denotes a worker and o stands for occupation in 1990.

The right panel of Figure 1 illustrates the correlation between the exposure of occupations to trade shocks in manufacturing and unemployment outcomes of workers in non-manufacturing industries only. By construction, none of these workers are hit by the shocks directly. And yet there is a significant positive correlation between the two: non-manufacturing workers in the same occupations as the most affected manufacturing workers tend to spend more time in unemployment than workers in other occupations. This pattern suggests that the shocks to the manufacturing sector do propagate to the rest of the economy at least through occupations.

However, this correlation could also be driven by occupation-specific shocks. For example, a fall in productivity in an occupation can lead both to more time in unemployment for all workers in this occupation and to a fall in domestic output along with a rise in imports in those manufacturing industries that employ workers in this occupation more intensely. To extract a part of the increase in imports that is associated with the manufacturing sector only and has nothing to do with non-manufacturing workers, I exploit the rapid increase in trade with China and Eastern Europe.

The left panel of Figure 1 illustrates that China along with Eastern Europe was responsible for more than a third of the overall increase in imports over this period. Remarkably, German trade with these two regions was basically constant before 1990. But after 1990 it expanded at a rapid pace. And while the increase in trade with the rest of the world appears to be rather cyclical, the rise of trade with China and Eastern Europe seems to be much more stable. The previous literature, starting with Autor et al. (2013, 2014) and including Dauth et al. (2014, 2017, 2021) in the context of Germany, has tried to extract the part of this steady rise that is associated with the fundamental factors originating in these two regions. Primarily, the shift to a market economy in Eastern Europe and an increase in productivity along with the reallocation of labor to cities in China.

To extract the part of trade exposure that is driven by shocks originating in China and Eastern Europe, this literature has instrumented trade variables with trade flows of other developed countries. The instrumental variable for import exposure is thus

$$\triangle m_o^* = \sum_j \frac{L_{oj,87}}{L_{o,87}} \frac{M_{j,04}^{O,CE} - M_{j,90}^{O,CE}}{L_{j,87}}, \tag{2}$$

where $M_{j,t}^{O,CE}$ is imports from China and Eastern Europe[9] to other developed countries that include

[9]"Eastern Europe" includes post-communist European countries as well as former USSR and Czechoslovakia. Thus, it consists of Czechia, Bulgaria, Hungary, Poland, Romania, Slovakia, Russia, Armenia, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, Uzbekistan.

Australia, New Zealand, Canada, Sweden, Norway, United Kingdom, Japan, and Singapore.[10] I use employment levels in 1987, not in 1990, as weights to account for workers sorting across industries in anticipation of future shocks.[11]

The goal of instrumenting trade variables is to capture shocks in China and Eastern Europe and to eliminate domestic German shocks. Otherwise, growth in German imports may reflect an increase in German demand or a decrease in German productivity. Under the assumption that such domestic shocks are not correlated across different developed countries, growth in imports from China and Eastern Europe to other countries should reflect shocks originating in China and Eastern Europe.

I also restrict my baseline analysis to the period of 1990-2004. I start with 1990 because it marks the end of communism in Eastern Europe and the beginning of the rapid increase in trade with China. And 2004 was the last year before the major part of the Hartz labor market reforms was implemented on January 1, 2005. As was documented by many studies (see Hartung et al., 2022; Launov and Wälde, 2013; Krause and Uhlig, 2012, among others), these reforms have significantly affected unemployment outcomes in Germany, and thus I exclude this period from my baseline analysis.[12]

The main empirical specification is

$$y_{io} = \alpha + \beta \triangle m_o + Z'_{io}\gamma + \varepsilon_{io}, \tag{3}$$

where I link the cumulative time spent in unemployment over 1991-2004 of a worker i that has an occupation o in 1990, y_{io}, with the cumulative exposure of this occupation to manufacturing import shocks over the same period, $\triangle m_o$. I instrument this measure of trade exposure with trade flows of other countries, $\triangle m^*_o$, and I control for a variety of worker- and occupation-level characteristics in 1990, Z_{io}. I also run this specification on a sample of non-manufacturing workers only to highlight the propagation of manufacturing shocks to the rest of the economy through common occupations.[13]

Since China and Eastern Europe may have a comparative advantage in certain industries, the rise of imports from these regions could be correlated with various industry and occupation characteristics. For example, China and Eastern Europe may enter industries intensive in unskilled

[10] I follow Dauth et al. (2021) and exclude the US as the large economy, the members of the Eurozone, and the German neighbors that could be affected by German domestic shocks. In Appendix A.1 I add more countries with comparable data and repeat my analysis.

[11] As before, I pool the data over 10 years to measure employment distribution more precisely, that is I use $\sum_{t=78}^{87} L_{oj,t}/10$ instead of $L_{oj,87}$.

[12] I repeat the analysis for several alternative time periods. All of them start in 1990, but several end before 2004, and several end after 2004. The results are generally similar and can be found in Appendix A.1.

[13] In Appendix A.1, I verify that the same shocks have a direct effect on manufacturing workers as well. However, the estimates from the two subsamples are not directly comparable as manufacturing workers have both direct and indirect shocks, shocks both at their occupation and industry level.

labor, and then my measure of occupational trade exposure may be correlated with occupations that involve more routine tasks. If these occupations on average exhibit different unemployment outcomes, this can bias my results. To address these concerns, I control for whether an occupation is a routine one[14], and I directly control for the pre-existing unemployment outcomes in each occupation: the average unemployment, separation, and job finding rates during 1987-1990. I also control for the initial exposure of different occupations to imports and exports in 1990.

To account for the fact that different occupations are composed of different workers and firms, I control for the workers' and firms' 1990 characteristics as well. I include the log of worker's wages in 1990 and dummies for gender, foreign-born status, 4 age groups, 3 educational groups, 11 federal states, and 4 groups for tenure as of 1990 in the worker's 1990 employer. I also include the log of the average wage at the worker's employer and dummies for 4 groups of its size. To control for pre-existing trends in occupation or firm growth, I add the growth rate of occupation's employment share over 1981-1990 and the wage growth of worker's employer over 1987-1990. Finally, in all of my regressions, I include a measure of occupational export exposure similar to (1) and I include an export measure similar to (2) to the list of instruments.[15]

I choose the main dependent variable to be the workers' *cumulative* time spent in unemployment over 1991-2004 in order to measure the *long-term* effects of shocks on workers' careers. I also want to measure not only the time they spend in unemployment in their initial occupation but all the additional time that can be attributed to the trade shock. For example, I want to include the time searching for new jobs in other occupations after the shock has induced workers to switch a profession. Finally, with a cumulative measure, I can capture the effects of both the contemporaneous and expected changes in trade. As is evident from Figure 1, 1990 marked the beginning of a long trend of a rise in trade. It is possible that a further expansion of China in certain industries was already expected in the early 1990s. Then, many firms could lay off their workers not only in response to contemporaneous changes in trade but also due to expected future changes. If instead, I measured outcomes at some point after 1990, I would miss a part of the effect of expected changes in trade.[16]

2.3 The Impact of Trade Shocks on Non-Manufacturing Workers

Table 1 shows the summary statistics for non-manufacturing workers included in the sample. First of all, there is a substantial heterogeneity in workers' outcomes as 63% of workers did not

[14] I follow Dauth et al. (2014) and use the classification of Blossfeld (1987).

[15] Specifically, $\triangle x_o = \sum_j \frac{L_{oj,90}}{L_{o,90}} \frac{X_{j,04}^{G,W} - X_{j,90}^{G,W}}{L_{j,90}}$ and $\triangle x_o^* = \sum_j \frac{L_{oj,87}}{L_{o,87}} \frac{X_{j,04}^{O,CE} - X_{j,90}^{O,CE}}{L_{j,87}}$, where $X_{j,t}^{G,W}$ is the level of exports from Germany to the rest of the world and $X_{j,t}^{O,CE}$ is the level of exports of other developed countries to China and Eastern Europe. I do not report these coefficients in the main table as they tend to be insignificant, but the results are available upon request.

[16] Also, the selection of workers into affected industries and occupations may be less of a concern in 1990 than during later periods, when expectations have been already formed.

experience a single day of (registered) unemployment during the whole period of 1991-2004.[17] And the number of days spent in unemployment between workers with 75th and 99th percentiles differs by more than a factor of 10. This drastic heterogeneity in unemployment outcomes suggests that losses from increased import competition might also be distributed extremely unevenly.

Moreover, the next two variables decompose the total number of days spent in unemployment into the number of spells and their average duration. This decomposition suggests that unemployment spells tend to be rather rare and long as opposed to frequent and short. This makes periods of unemployment more costly for workers, especially for those who are credit-constrained and risk-averse.[18]

Second, consistent with the overall trend of globalization, very few workers have experienced a decrease in import or export exposure over my baseline period. What is more surprising is that less than 1% of non-manufacturing workers in 1990 were employed in occupations with zero connection to the manufacturing sector. The vast majority of all workers in the economy are connected to the tradable sector and thus are indirectly exposed to its shocks, at least through their occupation.[19]

Lastly, the mean and the median occupational measures, such as unemployment, separation, and job-finding rates, are within some normal range, while their values for the top 1% of the workers are unusually high. This is due to the fact some occupations are very small and I get a few observations for them in my 2% random sample. Also, note the substantial variation in the pre-trend variables: some firms and occupations shrink and expand at a rapid pace, but the median growth rates are much more modest.

Table 2 shows my baseline estimates of the effect of import exposure on the time spent in unemployment for non-manufacturing workers, the coefficient β from equation (3). The first column shows the results from the ordinary least squares (OLS) with the full set of controls. Consistent with the right panel of Figure 1, the non-manufacturing workers in the more exposed occupations tend to spend more time in unemployment than workers in other occupations. This correlation has proven to be robust in controlling for pre-trends and a wide range of worker, occupation, and firm characteristics.

Columns (2)-(6) present the two-stage least squares (2SLS) results, where measures of German trade exposure as in (1) are instrumented with trade flows of other developed countries as in (2). As column (6) shows, instrumenting trade exposure increases my estimate. This is consistent with eliminating the effect of German demand shocks that increase imports along with domestic output

[17] Because the dependent variable is censored by 0 from below, I repeat my analysis using a Tobit model instead of a linear regression in Appendix A.1. I find similar results.

[18] In Appendix A.1, I also show that the import exposure has a positive and significant effect on both the number of unemployment spells and their duration.

[19] Both unemployment and trade variables exhibit rather extreme values in the top 1% of their distributions. In Appendix A.1, I remove these outliers and repeat my analysis on the resulting subsample. I find similar results.

Table 1: Summary statistics

Panel A: Continuous variables

	min	1%	25%	50%	75%	99%	max	mean	sd
Days in unemp., y_{io}	0	0	0	0	277	3197	5114	288.0	633.5
Number of unemp. spells	0	0	0	0	1	9.68	150.1	0.94	2.10
Duration of unemp. spells	0	0	0	0	146.5	1940	8622	151.3	416.2
Import exposure, Δm_o	-5.63	0.00	0.34	2.59	4.29	35.69	74.76	4.03	6.74
Export exposure, Δx_o	-5.13	0.01	0.70	4.24	8.70	81.55	188.1	8.42	15.67
Import instument, Δm_o^*	-0.04	0.00	0.12	0.58	1.61	11.25	24.48	1.36	2.10
Export instrument, Δx_o^*	0.00	0.00	0.14	0.90	1.47	11.21	28.36	1.41	2.09
Import exposure in 1990	0	0.01	0.45	3.05	4.63	40.86	79.40	4.75	7.51
Export exposure in 1990	0	0.01	0.71	4.41	7.99	78.47	176.1	8.45	15.11
Occ. unemp. rate, 1987-90	0.69	1.41	4.32	5.10	8.23	27.72	52.13	6.87	4.84
Occ. separation rate, 1987-90	0.51	1.33	3.20	3.94	6.24	18.14	44.69	5.52	4.12
Occ. job finding rate, 1987-90	0	19.9	33.9	36.5	47.9	73.6	100	40.17	10.66
Wage, 1990	1.09	9.26	39.5	55.8	71.3	127.1	157.3	58.36	27.75
Firm's average wage, 1990	1.47	20.0	52.6	63.2	74.6	149.2	564.3	65.47	23.68
Firm's wage growth, 1987-90	-88.2	-18.5	7.5	11.4	16.2	56.8	723.3	12.53	14.53
Occ. empl. growth, 1981-90	-60.0	-33.3	-3.0	8.2	19.3	79.7	500	10.03	23.47

Panel B: Dummy variables

	mean		mean
Works in Schleswig-Holstein	0.04	Age between 22 and 30	0.37
Works in Hamburg	0.04	Age between 31 and 39	0.30
Works in Niedersachsen	0.11	Age between 40 and 50	0.33
Works in Bremen	0.01	Tenure below 1 year	0.33
Works in Nordrhein-Westfalen	0.27	Tenure between 1 and 3 years	0.18
Works in Hessen	0.10	Tenure between 3 and 9 years	0.26
Works in Rheinland-Pfalz	0.05	Tenure above 9 years	0.22
Works in Baden-Wuerttemberg	0.15	Firm size below 20 workers	0.33
Works in Bayern	0.18	Firm size between 20 and 100	0.25
Works in Saarland	0.02	Firm size between 100 and 500	0.22
Works in Berlin	0.03	Firm size above 500 workers	0.20
No vocational training	0.23	German	0.93
Vocational training	0.70	Female	0.48
College degree	0.07	Works in a routine occupation	0.12

Notes. The sample includes only non-manufacturing workers. For most variables, N=197,591. The smallest number of observations is for the firm's wage growth, it's 154,533. Columns "1%", "25%", "50%", "75%", and "99%" represent workers with different quantiles. Number of days spent in unemployment, y_{io}, is computed over the period of 1991-2004. The number of unemployment spells does not have to be a natural number because it includes fractions of ongoing spells at the beginning and the end of the period, in 1991 and 2004. The average duration of unemployment spells is just a ratio of total days in unemployment to the number of unemployment spells. Tenure is calculated as the number of days worked for the 1990 employer by the start of 1990. All percentage variables such as growth rates or other rates are in percentage points.

Table 2: Import exposure and time spent in unemployment by non-manufacturing workers

	(1) OLS	(2)	(3)	(4) 2SLS	(5)	(6)	(7) OLS
Import exposure, $\triangle m_o$	18.06^{***}	-10.68	21.46^{*}	21.31^{**}	23.19^{**}	29.38^{***}	
	(5.56)	(12.19)	(11.38)	(9.90)	(9.19)	(10.96)	
Import instrument, $\triangle m_o^*$							10.34^{***}
							(3.03)
Occupation-level controls	✓		✓	✓	✓	✓	✓
Worker-level controls	✓			✓	✓	✓	✓
Firm-level controls	✓				✓	✓	✓
Pre-trend controls	✓					✓	✓
N	153,335	197,591	197,591	196,033	193,383	153,335	153,335

Notes. The dependent variable is the number of days spent in unemployment during 1991-2004, y_{io}. The sample includes only non-manufacturing workers. Column (1) reports the OLS results from estimating (3), columns (2)-(6) instrument the measures of trade exposure with trade flows of other countries, column (7) is the reduced-form version of (6), that is it replaces $\triangle m_o$ with $\triangle m_o^*$ in (3), but is otherwise the same. All regressions include a constant and a measure of export exposure. Column (3) adds a dummy for a routine occupation, the initial exposure of an occupation to trade in 1990, and average unemployment, separation, and job-finding rates during 1987-1990. Column (4) adds the log of worker's wages in 1990 and dummies for worker's gender, foreign-born status, 4 age groups, 3 educational groups, 11 federal states, and 4 groups for tenure as of 1990 in the worker's 1990 employer. Column (5) adds the log of the average wage at the worker's employer in 1990 and dummies for 4 groups of its employment size. Column (6) adds the 1981-1990 growth rate of occupation's employment and the 1987-1990 growth of average wage at the worker's employer. The different number of observations in different columns is because not all controls are available for all of the workers, e.g. the employer's wage growth data is available only for 154,533 workers. The first-stage results are robustly significant, e.g. the first-stage F-statistics for column (6) is 707.25. Robust standard errors in parentheses are clustered at the treatment level, that is at the level of 312 3-digit occupations. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

in some manufacturing industries and lead to less unemployment for workers connected to these industries.

The comparison between columns (2) and (3) suggests that trade shocks are correlated with occupational characteristics: an increase in imports seems to be larger for those occupations where workers used to spend less time in unemployment even before the rise in imports. Once I control for the pre-shock unemployment outcomes, greater import exposure leads to more time in unemployment. Adding more controls strengthens my results, but does not change them substantially.

To interpret the estimates, I add column (7) with the reduced-form coefficient, which shows the effect not of total import exposure, but only of the rising imports specifically from China and Eastern Europe. Comparing workers with 75th and 25th percentile in their exposure to imports from these two regions (from Table 1), the implied difference between them amounts to 15.41 $(10.34 \times (1.61 - 0.12))$ additional days in unemployment over the period of 1991-2004. Note that the regression coefficient implies the average effect for all workers in an occupation, while, in fact, 63% of workers do not experience any unemployment spells during this period. Therefore, this difference translates into 41.65 ($15.41/(1-0.63)$) additional days, or well over a month, for those workers who actually become unemployed at some point. And, of course, there is huge heterogeneity in workers' exposure to this trade shock, and thus some of the workers experience almost an order of magnitude longer time in unemployment.[20]

I do multiple robustness checks in Appendix A.1. In addition to all those already mentioned, I perform two additional checks. First, in 1990, West Germany had reunited with East Germany. As part of this process, many Germans migrated from the East to the West, found new jobs there, and thus affected labor market outcomes in West Germany. If workers from East Germany targeted the same occupations that were more exposed to international trade, the results would be biased. So in Appendix A.1, I control for migration flows from East Germany and still find significant results.

Second, in Appendix A.1 I estimate the contemporaneous effect of trade on workers' unemployment outcomes using an annual unbalanced panel of workers. This specification lacks the main advantages of my baseline approach – it fails to control for expectation of future shocks and it suffers from endogenous selection of workers into occupations. However, I still verify that the positive correlation between import exposure and time spent in unemployment is robust to more time periods and a wider range of workers.

To conclude this Section, I have shown that shocks to the manufacturing sector propagate to the rest of the economy at least through occupations of the affected workers. I have used data on trade flows of other countries to exclude the possibility of reverse causality – the direct effect of occupational shocks on trade in the manufacturing sector. Because all workers ultimately get affected by external shocks, one can not estimate the causal effect by comparing directly affected workers with the rest. It is thus necessary to take into account the propagation of trade shocks across all labor markets. In the next Section, I proceed to build a quantitative model, where shock propagation is driven by workers' mobility across sectors and occupations. Once calibrated, the model can be used to evaluate the total size of the trade shock propagation.

3 Model

In this section, I lay out the model to quantify the propagation of globalization shocks across different labor markets. Specifically, I combine elements from several models in a unified general equilibrium framework. First, I utilize the Diamond-Mortensen-Pissarides framework (see e.g.

[20]If any increase in imports had the same effect as its increase from China and Eastern Europe, then the implied difference between 75th and 25th percentile workers would be almost 8 times larger, that is 116 ($29.38\times(4.29-0.34)$) days instead of 15. However, this calculation ignores the fact that imports often increase due to positive shocks to German demand (as is suggested by the difference between columns (1) and (6)), which are likely to reduce unemployment, and not increase it. Thus, I focus on exposure to shocks that are uncorrelated with local shocks in Germany.

Pissarides, 2000) with endogenous separation rate (as in Den Haan et al., 2000) to study unemployment outcomes within each labor market. Second, I add the discrete choice problem to allow for non-trivial transitions of unemployed workers across different labor markets (see e.g. Artuç et al., 2010). Third, I use the Armington model of international trade (Armington, 1969) to model the adverse globalization shocks that reduce product demand and induce unemployment in some of the labor markets.

3.1 Worker's Problem

There are S sectors in the domestic economy and each of them has O occupations, so all occupations are sector-specific. Within each occupation, there are firms with high and low productivity z, $z \in \{h, l\}$. The value of a worker employed in occupation o in a firm with productivity z, $V_t^{o,z}$, is characterized by the following Bellman equation,

$$V_t^{o,z} = w_t^{o,z} + \tau_t + \beta\left(1 - \delta^{o,z}\right)\max\left\{V_{t+1}^{o,z}, U_{t+1}^{o}\right\} + \beta\delta^{o,z}U_{t+1}^{o}, \tag{4}$$

where $w_t^{o,z}$ is the real wage in state (o, z), τ_t is the lump-sum transfer that includes all the profits and taxes, $0 < \beta < 1$ is the discount factor, $0 < \delta^{o,z} < 1$ is the exogenous separation rate, and U_t^o is the value of an unemployed worker in occupation o. At the beginning of each period, employed workers decide whether to quit their jobs and enter an unemployment state. All agents have perfect foresight with respect to aggregate variables, but there is still uncertainty about idiosyncratic preference shocks, described later. None of the workers can save or borrow, and thus they always consume all of their disposable income.

Unemployed workers can find a new job through costly search. Workers can choose in which occupation o' to search for a job, but they can not direct their search towards a specific productivity level z. If an unemployed worker in o decides to search for a new job in o', then his or her expected (before realizing the preference shock) payoff is given by $u_t^{oo'}$,

$$\begin{aligned} u_t^{oo'} = & -C^{oo'} + b^o + \tau_t + \beta\left(1 - \phi_t^{o'}\right)U_{t+1}^{o'} \\ & + \beta\phi_t^{o'}\sum_{z=h,l}\psi^{o',z}\left[\left(1 - \delta^{o',z}\right)\max\left\{V_{t+1}^{o',z}, U_{t+1}^{o'}\right\} + \delta^{o',z}U_{t+1}^{o'}\right], \end{aligned} \tag{5}$$

where $C^{oo'}$ are the search costs that are specific to movement from o to o', b^o are the (real) unemployment benefits in occupation o,[21] $\phi_t^{o'}$ is the probability to get any job offer in o', and $\psi^{o',z}$ is the probability that a given job offer in occupation o' is made by a firm with productivity z,

[21] For most German workers in the period I consider, the size of unemployment benefits was tied to their previous wages. However, as will be evident later from (6), changing the size of the benefits in the model has no effect on the search decision of unemployed workers. Thus, I simplify the model by assuming that all workers within the same occupation o receive the same benefits.

$\psi^{o',h} + \psi^{o',l} = 1 \ \forall o'$.[22] Job-finding probabilities are common to workers from all cells after they have incurred $C^{oo'}$, which include utility-based costs of acquiring skills necessary for work in o'.

Taking the set of $\left\{u_t^{oo'}\right\}_{o,o'}$ as given, an unemployed worker makes a search decision. Specifically, the unemployment value in occupation o is given by

$$U_t^o = \mathbb{E}_\varepsilon \max_{o'} \left\{u_t^{oo'} + \nu \varepsilon_t^{o'}\right\},$$

where an unemployed worker chooses occupation o' for his or her job search and gets the expected payoff $u_t^{oo'}$ and the idiosyncratic (worker-specific) preference shock $\varepsilon_t^{o'}$, which is iid (across time, workers, occupations) Type-I Extreme Value with a zero mean.[23,24] Parameter $\nu > 0$ governs the variance of this shock, and thus $1/\nu$ can be also interpreted as the "migration elasticity". High values of ν correspond to the low mobility as workers' decisions are mostly determined by the exogenous preference shocks and do not depend on the endogenous payoffs from being employed in different occupations.

After taking expectations over the idiosyncratic shock $\varepsilon_t^{o'}$ and exploiting properties of the extreme value distribution, the probability of an unemployed worker in occupation o to choose option o', $\mu_t^{oo'}$, could be expressed as

$$\mu_t^{oo'} = \frac{\exp\left(u_t^{oo'}\right)^{\frac{1}{\nu}}}{\sum_k \exp\left(u_t^{ok}\right)^{\frac{1}{\nu}}}. \tag{6}$$

Since all unemployed workers have the same probabilities to choose different options and there is a continuum of workers, these probabilities $\mu_t^{oo'}$ also represent the shares of workers, or the so-called "migration shares". Then the unemployment value U_t^o could be expressed recursively,

$$U_t^o = b^o + \tau_t + O_t^o + \beta U_{t+1}^o, \tag{7}$$

where O_t^o represents the "option value" of an unemployed worker, that is the expected value of moving to a different state (either an unemployment or employment state) relative to the value of staying in the same unemployment state,

$$O_t^o = \nu \log\left[\sum_k \exp\left(u_t^{ok} - b^o - \tau_t - \beta U_{t+1}^o\right)^{\frac{1}{\nu}}\right]. \tag{8}$$

[22] I assume that once a worker rejects a job offer from a firm in state (o', z), she moves from her current unemployment cell to the unemployment state o'. As I show later in Section 3.2.3, in equilibrium $V_t^{o,z} \geq U_t^o \ \forall o, z, t$, and thus unemployment workers never reject any job offers.

[23] Shock $\varepsilon_t^{o'}$ could also be interpreted as an idiosyncratic shock to the search costs $\left\{C^{oo'}\right\}_{io,o'}$.

[24] All unemployed workers in cell o are ex-ante identical and differ only ex-post by their realizations of shock $\varepsilon_t^{o'}$.

3.2 Consumer Demand and Firm's Problem

There are two layers of production. At the lower layer, firms are matched with workers to produce occupational tasks. At the upper layer, perfectly competitive firms combine different occupational tasks to produce final goods. These goods are then sold to consumers either domestically or abroad. Home country is a small open economy, and thus I treat all foreign variables as exogenous.

3.2.1 Demand for final goods

There is Cobb-Douglas demand for final products from different sectors defined by shares α_t^s, $\sum_{s=1}^{S} \alpha_t^s = 1 \; \forall t$.[25] Within every sector, there is CES demand between home and foreign products. The world demand for domestic products in sector s at time t, q_t^s, is given by the sum of the domestic and foreign demand,

$$q_t^s = \left(\frac{p_t^s}{P_t^s}\right)^{-\sigma} \frac{\alpha_t^s E_t}{P_t^s} + \left(\frac{p_t^s}{e_t P^{sf}}\right)^{-\sigma} \frac{\alpha^{sf} E^f}{P^{sf}}. \tag{9}$$

The first term on the right-hand side represents the domestic part of the world demand. $\sigma > 1$ is the elasticity of substitution between home and foreign goods, E_t is the aggregate expenditures of the home country, p_t^s is the price for domestic goods in sector s, and P_t^s is the sectoral price index. The second term represents the foreign part of the world demand, where e_t is the real exchange rate, and variables with subscript f are the exogenous foreign variables: Cobb-Douglas share α^{sf}, the aggregate expenditures E^f, and the sectoral price index P^{sf}.

The sectoral price index P_t^s is composed of domestic and foreign prices,

$$P_t^s = \left[(p_t^s)^{1-\sigma} + \left(e_t p_t^{sf}\right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}, \tag{10}$$

where p_t^{sf} is the exogenous price of imported goods in sector s. The real exchange rate e_t determines the price of foreign goods relative to the numeraire, the domestic aggregate bundle,

$$1 = \prod_{s=1}^{S} (\alpha_t^s)^{-\alpha_t^s} (P_t^s)^{\alpha_t^s}. \tag{11}$$

I model adverse globalization shocks as an exogenous decrease in prices of imported goods p_t^{sf} in some of the sectors. This, in turn, would lead to an endogenous decrease in demand for domestic producers in the same sectors.

[25] I allow these exogenous shares to change over time to match the trend of expanding employment in the service sector over time.

3.2.2 Final goods producers

Final goods q_t^s in sector s are produced according to a CES production function that combines tasks from different occupations q_t^o,

$$q_t^s = \left(\sum_{o \in \mathbb{O}_s} (\gamma^o)^{1-\rho} (q_t^o)^\rho \right)^{\frac{1}{\rho}}, \tag{12}$$

where $\rho < 1$ governs the degree of substitution or complementarity between occupations, $\mathbb{O}_s$ is the set of occupations used in sector s, and shares γ^o reflect different occupational intensities, $\sum_{o \in \mathbb{O}_s} (\gamma^o)^{1-\rho} = 1 \; \forall s$.

Final producers take all prices as given[26] and choose quantities to maximize their profits,

$$p_t^s q_t^s - \sum_{o \in \mathbb{O}_s} p_t^o q_t^o \to \max_{q_t^s, \{q_t^o\}_{o \in \mathbb{O}_s}},$$

subject to (12), where p_t^o is the price of a task performed by workers in occupation o. This problem results in zero profits, and the following demand for occupational tasks, as well as the equilibrium price for final goods,

$$q_t^o = \gamma^o \left(\frac{p_t^o}{p_t^s} \right)^{\frac{1}{\rho-1}} q_t^s, \quad p_t^s = \left(\sum_{o \in \mathbb{O}_s} \gamma^o (p_t^o)^{\frac{\rho}{\rho-1}} \right)^{\frac{\rho-1}{\rho}}. \tag{13}$$

3.2.3 Occupational tasks within a sector

Tasks are produced by labor with constant returns to scale, and so each sector-specific occupation o consists of single-worker firms. The value of a firm with productivity z in occupation o, $J_t^{o,z}$, is characterized by the following Bellman equation,

$$J_t^{o,z} = p_t^o a^{o,z} - w_t^{o,z} + \beta (1 - \delta^{o,z}) \max \left\{ J_{t+1}^{o,z}, 0 \right\}, \tag{14}$$

where a single worker produces $a^{o,z}$ of tasks ($a^{o,h} > a^{o,l} > 0 \; \forall o$) and earns wage $w_t^{o,z}$. At the beginning of each period, the match between a firm and a worker can be dissolved either exogenously at rate $\delta^{o,z}$ or endogenously, when a firm decides to exit.

There is a Nash bargaining between a firm and a worker that results in the following wages in equilibrium,

$$w_t^{o,z} = \lambda p_t^o a^{o,z} + (1 - \lambda) (b^o + O_t^o), \tag{15}$$

[26] Note that the domestic price is the same as the export price.

where $0 < \lambda < 1$ is the bargaining power of workers.[27] The equilibrium wage is a weighted average of the marginal revenue product of labor and the worker's outside option, which contains unemployment benefits as well as the option value of getting a new job, possibly in a different sector and occupation.

When a new firm enters occupation o, it posts a new vacancy at cost $c_v^o > 0$. Then, it randomly draws its productivity level z and has a chance to be matched with an unemployed worker. So the free entry condition is

$$-c_v^o + \beta \varphi_t^o \sum_{z=h,l} \psi^{o,z} \left(1 - \delta^{o,z}\right) \max\left\{J_{t+1}^{o,z}, 0\right\} \leq 0, \tag{16}$$

where φ_t^o is the vacancy filling probability in occupation o. This condition holds with equality whenever there is a positive entry in o, and it holds with inequality otherwise.[28]

3.3 Closing the Model

The following equilibrium conditions are required to close the model.[29]

3.3.1 Matching function

Search frictions in each labor market o are characterized by the matching function,

$$f\left(v_t^o, m_t^o\right) = \frac{v_t^o m_t^o}{\left(\left(v_t^o\right)^\zeta + \left(m_t^o\right)^\zeta\right)^{1/\zeta}},$$

where v_t^o is the mass of vacancies posted in labor market o, m_t^o is the mass of unemployed workers who search for new jobs in o. $\zeta > 0$ governs the degree of matching frictions (higher ζ implies more frictionless markets).

Because of the constant returns to scale, both the job-finding probability ϕ_t^o and the vacancy filling probability φ_t^o are functions of the market tightness v_t^o / m_t^o,

$$\phi_t^o = \frac{f\left(v_t^o, m_t^o\right)}{m_t^o} = \left(1 + \left(\frac{v_t^o}{m_t^o}\right)^{-\zeta}\right)^{-\frac{1}{\zeta}}, \quad \varphi_t^o = \frac{f\left(v_t^o, m_t^o\right)}{v_t^o} = \left(1 + \left(\frac{v_t^o}{m_t^o}\right)^{\zeta}\right)^{-\frac{1}{\zeta}}. \tag{17}$$

[27] Proof is in the Appendix A.2.1.

[28] Note that firms exit whenever $J_t^{o,z} < 0$. Therefore, in equilibrium where there are at least some active firms in each state (o, z), $J_t^{o,z} \geq 0$. This, together with a bargaining condition (24) implies, that $V_t^{o,z} \geq U_t^o \; \forall o, z, t$. Therefore, unemployed workers always accept job offers that they receive. Also, a firm's decision to exit is equivalent to a worker's decision to quit.

[29] The description of the timing within a period is in Appendix A.2.2 and the formal definition of equilibrium is in Appendix A.2.3.

In equilibrium, the mass of the job seekers is determined by the migration shares of unemployed workers and the mass of unemployed, $m_t^o = \sum_{o'} L_t^{o',U} \mu_t^{o'o}$, where $L_t^{o',U}$ is the mass of unemployed workers in occupation o'.

3.3.2 Labor balance

A movement of unemployed workers across different unemployment cells is governed by the following law of motion,

$$L_t^{o,U} = \sum_z \left(L_{t-1}^{o,z} + m_{t-1}^o \phi_{t-1}^o \psi^{o,z}\right)\left(1 - \left(1 - \delta^{o,z}\right)\left(1 - \chi_t^{o,z}\right)\right) + m_{t-1}^o \left(1 - \phi_{t-1}^o\right), \tag{18}$$

where $\chi_t^{o,z}$ is the endogenous exit/separation rate and $L_{t-1}^{o,z}$ is the total employment in state (o, z). There are two ways for a worker to get into the unemployment state o. First, an employed worker could get (exogenously or endogenously) separated from her employer in the state (o, z). This could happen both to workers who participated in production last period and to the newly hired workers. Second, an unemployed worker from occupation o could continue to stay in this state if her search effort was not successful.

The mass of employed workers in state (o, z) should be equal to the mass of previously employed workers who survived separations and the mass of newly hired workers. And the mass of hired workers is a product of the job finding probability in o, all unemployed workers searching for jobs in cell o, and the share of posted vacancies by firms with productivity z. Then the labor balance can be expressed as

$$L_t^{o,z} = \left(L_{t-1}^{o,z} + m_{t-1}^o \phi_{t-1}^o \psi^{o,z}\right)\left(1 - \delta^{o,z}\right)\left(1 - \chi_t^{o,z}\right). \tag{19}$$

Finally, the demand for workers in each occupation should be equal to their supply,

$$q_t^o = a^{o,l} L_t^{o,l} + a^{o,h} L_t^{o,h}, \tag{20}$$

and the total mass of workers in the economy is fixed and given by $\bar{L} > 0$,

$$\bar{L} = \sum_o \left(\sum_z L_t^{o,z} + L_t^{o,U}\right). \tag{21}$$

3.3.3 Trade and government budget balances

In equilibrium, the price of foreign goods relative to domestic ones, that is the real exchange rate e_t, adjusts so that international trade is balanced,

$$\sum_s \left(\frac{e_t p_t^{sf}}{P_t^s}\right)^{1-\sigma} \alpha_t^s E_t + \Delta_t = \sum_s e_t \left(\frac{p_t^s}{e_t P^{sf}}\right)^{1-\sigma} \alpha^{sf} E^f, \tag{22}$$

where the left- and the right-hand sides represent the value of all imports and exports respectively. Δ_t is the exogenous trade imbalance that is financed by government expenditures. I add it to the model to match the fact that over the 1990s and 2000s Germany's exports grew faster than its imports.

To close the model, note that the government raises taxes to finance the external trade imbalance and the unemployment benefits. All firms belong to the workers, and so each worker receives her share of flows of profits from the firms. Then, the lump-sum transfers are

$$\bar{L}\tau_t = \left[\sum_{o,z} L_t^{o,z}\left(p_t^o a^{o,z} - w_t^{o,z}\right) - \sum_o v_t^o c_v^o\right] - \left[\Delta_t + \sum_o L_t^{o,U} b^o\right], \tag{23}$$

3.4 Discussion

The economy starts in the initial steady state. Then at time 0 one-time unexpected shock happens, that is agents learn about the future path of three shocks in the model: the reduction in import prices p_t^{sf}, the change in Cobb-Douglass shares α_t^s, and the increase in the trade imbalance Δ_t. Due to perfect foresight, all agents at time 0 know the future path of all aggregate variables, including these shocks. Eventually, the economy converges to the new steady state.

The key shock in the model is the exogenous reduction in import prices p_t^{sf} in some of the sectors. It leads to a shift in the demand for domestic products through the demand system (9). Then, in equilibrium both prices p_t^s and quantities q_t^s of domestic final goods are going to decrease. This, in turn, shifts down the demand for occupational tasks through the demand system (13) and results in lower occupational prices p_t^o and quantities q_t^o. So, a decrease in import prices leads to lower wages and higher unemployment in the directly affected occupations.

This local labor market shock propagates to the rest of the economy through search decisions of unemployed workers. The structure of mobility costs $C^{oo'}$ determines which other labor markets will be affected the most and the least. As there are differences in mobility between occupations, some occupations will be affected more than others. Moreover, the migration elasticity $1/\nu$ governs the change in search patterns caused by trade shocks.

Different labor markets are also connected through product markets. A change in labor demand for one occupation leads to a change in labor demand for other occupations in the same sector through the production function (12). So, once an occupation outside of the import-competing sectors is affected by the search decisions of the unemployed, this shock can further propagate to other occupations within the same sector. This channel of propagation is mostly driven by the substitutability of different occupations, captured by parameter ρ. In addition, an increase in imports has to be followed by an equal increase in exports due to the balance trade condition (22). Then a negative demand shock for import-competing sectors necessarily implies a positive shift in demand for exporting sectors.[30]

I also solve the model non-linearly. This implies that the presence of other shocks matters for the marginal effect of the shock to the import prices. In particular, during this period employment in the German service and export sectors were expanding arguably for reasons unrelated to the negative trade shock. This is likely to create additional "pull" factors for displaced unemployed workers and affect their patterns of reallocation. For this reason, I augment the model with two additional shocks. First, I allow Cobb-Douglas share α_t^s in services to rise in order to reflect the trend of growing employment in this sector. Second, I allow the trade imbalance Δ_t to grow over time to match the increase in the German current account that has put pressure on the export sector to expand.

Finally, I introduce firms with high and low productivity within the same labor market o to be able to sustain both positive hires and layoffs in this market in equilibrium. This is an important feature of the data since I don't observe interruptions in hires in any of the sector-specific occupations within my time period. In the model, the free entry condition (16) determines the value only of the *average* firm in labor market o, $\sum_{z=h,l} \psi^{o,z} (1 - \delta^{o,z}) \max\{J_t^{o,z}, 0\}$, not the values of all firms in the market. Then, after a large enough negative demand shock, the value of the firms with low productivity drops to 0, $J_t^{o,l} = 0$, and this induces positive a exit rate in market o, $\chi_t^{o,z} > 0$. But the free entry condition (16) can still be satisfied as an equality due to high productive firms having a high enough positive value, $J_t^{o,h} > 0$, and thus the simultaneous entry and exit in the same labor market can be supported in equilibrium.[31]

[30] Dauth et al. (2021, 2014) find that in contrast to other countries, there are not only losses for German workers from rising import competition from China and Eastern Europe but also gains from expanded export opportunities from trade with these regions.

[31] The solution to the model has the following properties. In the steady state, all firms' values are non-negative, $J^{o,z} \geq 0$, and thus there is no endogenous exit, $\chi^{o,z} = 0$. There is a positive mass of new entrants to replace matches lost to exogenous separations. Outside of the steady state, as the size of the negative demand shock increases, the firms' values decrease along with the mass of new entrants. As the size of the shock increases even more, the value of the firms with low productivity is going to hit 0, $J^{o,l} = 0$, at which point there will be the positive endogenous exit, $\chi^{o,l} > 0$. When the size of the shock is even larger, the value of the firms with high productivity is also reduced to 0, $J^{o,h} = 0$, and then the labor market o features positive exit by both types of firms and no entry.

4 Quantitative Analysis

In this section, I start by calibrating the model. I set the values of parameters to match the pre-shock data and I adjust the size of the trade shock to match the reduced-form estimates of the direct effect of trade shocks on manufacturing workers. Then I evaluate how much of the observed shock propagation from Section 2 can be explained by my model of workers' mobility. Finally, I perform counterfactual experiments to assess the total magnitude of shock propagation and the bias it implies for the reduced-form estimates from Section 2.

4.1 Calibration

The model parameters are either calibrated to the pre-1990 quarterly data or taken from the previous literature. Roughly speaking, I take elasticities from the literature but calibrate all levels to the pre-shock data. The size of shocks is calibrated to match some moments based on the 1991-2004 data. Table 3 provides an overall summary.

Calibrated parameters I choose values of all calibrated parameters to simultaneously match several moments from the pre-shock data, which I interpret as the initial steady state. In particular, I pool data over 1981-1990 to achieve a higher accuracy when I compute these moments.[32] Panel A of Table 3 summarizes the list of calibrated parameters and targeted moments (which I match exactly), with only a rough correspondence between each parameter and the moment that drives its identification.

Generally, I match all key characteristics of different labor markets from an unemployed worker's perspective: wages, separation rates, and the size of unemployment benefits.[33] The central parameter in the model is the matrix of mobility costs $C^{oo'}$. I choose it to match the unemployed workers' transition matrix across sectors and occupations, thereby allowing the data to determine the degree to which different labor markets were connected before the shock. Because of the limited sample sizes, I have to aggregate all 3-digit industries into 3 sectors and all 3-digit occupations into 4 occupational groups to get non-trivial number of observations for the transition matrix.[34] Specifically, one sector includes all non-manufacturing industries, I call this sector "services" and later calibrate its parameters so that its goods are not traded internationally. All manufacturing industries are aggregated into two roughly similar-sized sectors based on their

[32]All of my targeted moments remain roughly constant during this period. Remarkably, this includes the share of workers employed in manufacturing, even though it has been declining before and after this decade.

[33]In Germany at that time the size of the benefits was linked to the worker's previous wage and the length of the current unemployment spell. As explained in Section 3.1, the size of the unemployed worker's benefits does not affect her search decision, and thus I simplify the model by assuming the same benefits for all workers within a sector and an occupation.

[34]Due to the data use agreement, I can not report any numbers based on fewer than 20 individual observations.

Table 3: Calibration of model parameters and shocks

Parameter/Shock		Moment/Source
Panel A: Parameters calibrated to the 1981-1990 data		
b^o	Unemployment benefits	Replacement rates
$C^{oo'}$	Mobility costs	U-to-E transitions
c_v^o	Vacancy posting costs	
$\delta^{o,z}$	Exogenous separation rates	Separation rates
$\psi^{o,z}$	Share of high/low prod. entrants	
γ^o	Occupational intensities	Wage distribution
$a^{o,z}$	Workers' productivity	
α^s	Cobb-Douglas demand shares	
E^f	Aggregate expenditures abroad	Imp./exp.-to-revenue ratios
α^{sf}	Cobb-Douglas demand shares abroad	
p^{sf}	Prices of imported goods	
Δ	Trade imbalance	
Panel B: Parameters from the literature		
σ	Final demand elasticity	Simonovska and Waugh (2014)
ρ	Elasticity for occupational tasks	Goos et al. (2014)
ν	Migration elasticity	Traiberman (2019)
λ	Nash bargaining share	Coşar et al. (2016)
ζ	Matching elasticity	
Panel C: Shocks calibrated to the 1991-2004 data		
p_t^{sf}	Prices of imported goods	Unemp. time for imp. and exp. workers
α_t^s	Cobb-Douglas demand shares	Share of workers employed in services
Δ_t	Trade imbalance	Trade surplus

measures of exposure to rising imports from China and Eastern Europe during the subsequent 1991-2004. The more exposed half of the manufacturing sector is called the "import" sector, while the other half is called the "export" sector.

Similarly, I aggregate all occupations into four groups of roughly similar size in the same way, by their exposure to rising imports from China and Eastern Europe during 1991-2004. Then, only about 1% of workers in the import sector are employed in the least exposed occupational group. The sample size of this sector/occupation group is too small for me to calibrate its parameters, and thus I round down the size of this group to 0. In the end, after dividing the economy into 3 sectors and 4 occupations and omitting one of the groups, I am left with 11 groups in total.

To compute the transition matrix across these 11 groups, I identify all unemployment spells in the data from 1981-1990. To be consistent with the quarterly model, I calculate the share of spells that resulted in employment within the first 90 days of the spell. This way I can record both the old and the new sectoral/occupational groups of each unemployment-to-employment transition.[35] Once calculated, this unemployment-to-employment transition matrix also implies the share of unemployment spells that did not result in employment within their first quarter. Thus, it implies the job-finding rates in each sectoral/occupational group, which help to identify the vacancy posting costs c_v^o, as there is a one-to-one relationship between job-finding and vacancy-filling probabilities from (17).

As explained in Section 3.4, I add firm/worker heterogeneity within sectoral/occupational groups to make sure that job-finding probabilities don't fall to zero during the transition to the new steady state in any of these groups. Since in equilibrium, the service sector is always expanding, I don't divide firms in this sector into high- and low-productivity. Every other group in the economy I split into two equally sized parts based on workers' wages. I then compute and match exactly both average wages and separation rates for the high- and low-productivity halves in each group.

Parameters taken from the previous literature Key elasticities of the model are difficult to identify based on the pre-shock data that approximate the steady state. I also choose not to set their values based on the outcomes of the model during its transition to the new steady state. This way I limit the degrees of freedom with which the key mechanism of the model, the mobility of unemployed workers, can explain the size of the trade shock propagation documented in Section 2. Thus, I take the values for key elasticities from related studies.

I take the value of demand elasticity $\sigma = 5$ from Simonovska and Waugh (2014). This corresponds to the trade elasticity of 4, the value they have estimated. Next, I take the CES elasticity of substitution between occupations of 0.9 from Goos et al. (2014), which implies $\rho = -0.11$ and complementarity rather than substitutability of different occupations. And I set the quarterly discount factor β to 0.99.

The migration elasticity ($\nu = 0.7$) is taken from Traiberman (2019), who also uses a logit function to characterize worker migration across occupations. Finally, I take the Nash bargaining parameter ($\lambda = 0.44$) and the matching parameter ($\zeta = 1.84$) from Coşar et al. (2016), who also study firm-worker matching in a dynamic trade model. Since there are significant differences between our frameworks, I perform robustness checks to explore the sensitivity of the results to these parameters.

Calibration of shocks As discussed in Section 3.4, I include additional shocks in the model to take into account major "pull" factors for the displaced manufacturing workers at the time of the rising import competition. In particular, I set the increase in the Cobb-Douglas share α_t^s in the

[35] Note that according to the model, once mobility costs $C^{oo'}$ are paid, worker's occupation changes to o', even if the search did not result in employment in the same quarter. Suppose that in the next quarter, this worker finds a new job in occupation k. Then, this data is informative about the size of $C^{o'k}$, not C^{ok}. Since I observe only workers' transitions and not their search decisions, that is I observe o and k, but not o', I can use the data from only the first 90 days of their unemployment spells to calibrate mobility costs.

service sector (while the other two shares decrease so that $\sum_{s=1}^{S} \alpha_t^s = 1$) to match the path of the rising share of workers employed in non-manufacturing industries during 1991-2004. Similarly, I measure the increase in German trade surplus over the same 14 years and make sure that the trade imbalance Δ_t grows at the same rate. This creates incentives for job creation and wage raises in the export sector and makes it a relatively more attractive destination than the import sector.

The main shock of my analysis is, of course, the decrease in import prices p_t^{sf}. Since ultimately I want to use the model to evaluate the magnitude of the trade shock propagation, I choose the size of this shock to make sure that its direct effect is the same in the model and the data. In the data, I go back to my regression based on the comparison of different industries within manufacturing (see (5) in Section A.1). I use this estimate to predict how much more time in unemployment over 1991-2004 workers in the calibrated import sector would have to spend relative to workers from the calibrated export sector. This difference amounts to 12.54 days.

In the model, I simulate individual workers' career trajectories with and without the shock to import prices p_t^{sf}. Then, similar to my regression, I calculate the average time spent in unemployment over the first 56 quarters of this simulation. To evaluate the effect of the shock, I compare these numbers between simulations with and without it. I then take a difference between workers initially employed in the import and export sectors. I choose the size of the increase in import prices p_t^{sf} so that this difference is also 12.54 days.[36]

[36]Note that I can not literally run the same regression in the model as I did in the data. I compare only 2 aggregated industries in the model, while in the data my regression was based on 98 manufacturing industries. This is why I can't include the same controls in the model-based regression and instead choose to use a counterfactual to calibrate the shock's direct effect.

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A Appendix

A.1 Robustness checks from Section 2

In this section I describe multiple robustness checks of my main result from Section 2, namely the estimate from column (6) in Table 2.

1) East Germany The year 1990 marked not only the beginning of a rapid increase in trade with China and Eastern Europe but also the reunification of East and West Germany. As many workers fled from the East to the West, they had affected labor market outcomes in the West. If they targeted the same occupations that had seen a rise in import exposure from China and Eastern Europe, the results would be biased.

To explicitly control for the effect of the reunification, I calculate the migration flows of workers from East Germany. Specifically, I compute the following occupational measure of exposure to labor flows from East Germany,

$$\triangle eg_o = \frac{L^{EG\to WG}_{o,91-04}}{\sum_{o'} L^{EG\to WG}_{o',91-04}},$$

where $L^{EG\to WG}_{o,91-04}$ is the number of workers who moved from East Germany to West Germany at some point during 1991-2004 and found a job in occupation o there.[37]

I then add this measure as a control to my main specification of (3) and report results in line (1) in Table 4, where for convenience I also duplicate my baseline estimate in line (0). The results are very similar.

2) Wage-bill weights I repeat my baseline analysis using data on the total wage bill by industry and occupation instead of employment weights. Specifically, I replace measures (1) and (2) with

$$\triangle m_o = \sum_j \frac{WB_{oj,90}}{WB_{o,90}} \frac{M^{G,W}_{j,04} - M^{G,W}_{j,90}}{WB_{j,90}}, \quad \triangle m^*_o = \sum_j \frac{WB_{oj,87}}{WB_{o,87}} \frac{M^{O,CE}_{j,04} - M^{O,CE}_{j,90}}{WB_{j,87}},$$

where $WB_{oj,90}$ is the total wage bill in occupation o and industry j in 1990. As before, $WB_{o,t} = \sum_j WB_{oj,t}$, $WB_{j,t} = \sum_o WB_{oj,t}$, and I pool the data over 10 preceding years to improve the accuracy of my measurement, that is I use $\sum_{k=t-9}^{t} WB_{oj,k}/10$ instead of $WB_{oj,t}$. I report the results in line (2) in Table 4. Note that these results are not directly comparable with those in Table 2 as I changed the units of the import exposure. But as before, I can compare workers with the 75th and 25th percentile in the new measure of import exposure. Then my estimates imply a difference of 103 ($0.84 \times (137.05 - 14.35)$) additional days in unemployment over the period of 1991-2004, which is roughly comparable to 116 additional days from Table 2.

[37] This measure is calculated based on the total of 95,163 job transitions, $\sum_{o'} L^{EG\to WG}_{o',91-04}$.

Table 4: Robustness checks

	Model	Estimate	St.Er.	N
(0)	Baseline model	29.38***	(10.96)	153,335
(1)	Control for migration from East Germany	29.26***	(10.96)	153,335
(2)	Use wage-bill weights	0.84**	(0.35)	153,335
(3)	Use more countries for instruments:			
	st. err. clustered at occupation	15.85	(11.57)	153,335
	st. err. clustered at occupation and region	15.85**	(6.47)	153,335
(4)	Use the period of:			
	1990-2002	23.79***	(6.24)	153,335
	1990-2003	29.75***	(10.96)	153,335
	1990-2005	24.15**	(11.40)	153,335
	1990-2006	24.90	(20.58)	153,335
(5)	The effect on manufacturing workers:			
	based on comparing industries	2.69**	(1.33)	96,092
	based on comparing occupations	21.50**	(9.69)	96,092
(6)	Tobit model:			
	Tobit estimate	93.89**	(36.87)	153,335
	Probit for spending any time in unemp.	0.078**	(0.035)	153,335
	linear regression for those with $y_{io} > 0$	25.98**	(13.17)	51,472
(7)	Intensive and extensive margins of y_{io}:			
	number of unemp. spells, n_{io}	0.08***	(0.02)	153,335
	duration of unemp. spells, d_{io}	19.04**	(7.91)	153,335
(8)	Without outliers	23.28**	(9.90)	150,187
(9)	Annual panel	34.57***	(3.25)	3,980,462

Notes. Line (0) reproduces the baseline estimate from column (6) in Table 2. All other lines report results from various robustness checks, but the specification in all of them is as close to the baseline as possible. Controls from the baseline specification (0) are included in all other specifications when possible. Most standard errors (if not stated otherwise) are clustered at the level of 312 occupations. For Tobit and Probit models from line (7), the standard errors are bootstrapped and clustered. For the specification for manufacturing workers in line (5) based on industries, the standard errors are clustered at the treatment level of 98 industries, and the controls are similar to the baseline controls, but include industry- instead of occupation-level controls. The standard errors in the annual panel in line (9) are not clustered. I also use trade measures that are based on trade with China and Eastern Europe in lines (5) and (9). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ The last column reports the number of observations.

3) Instrumental variables In my baseline analysis of Section 2, I follow Dauth et al. (2021) and exclude data on several developed countries from my instrumental variables. Out of all developed countries with available trade data with similar product classification, I exclude the US because it is a large economy and its domestic shocks can have a direct effect on Germany. Then such an instrument may be correlated with German labor market outcomes not just through the imports from China and Eastern Europe, but through other channels as well, and thus this instrument may be endogenous. I exclude Denmark and Switzerland because they are small German neighbors, so their trade patterns could reflect domestic German shocks and not shocks originating in China and Eastern Europe. And I exclude Finland and Spain as members of the Eurozone, that is members of the same currency union as Germany. Because of that, their exchange rate fluctuations and thus the short-run trade patterns may also reflect German shocks and not just shocks originating in China and Eastern Europe.

In this Section, I add all of these countries (the US, Denmark, Switzerland, Finland, Spain) to my original list (Australia, New Zealand, Canada, Sweden, Norway, United Kingdom, Japan, Singapore) and recalculate the instrumental variables as in (2). The results from estimating equation (3) are in line (3) in Table 4. The main estimate is smaller but still positive, which is consistent with the endogeneity concerns. The estimate is insignificant, but there I cluster standard errors at the level of 312 3-digit occupations. (The first stage is still significant with the F-statistics of 615.98.) If I increase the number of clusters, the estimate becomes significant. As an example, I also report standard errors clustered at the regional and occupational level with 2,721 clusters.

4) Baseline period I explore the sensitivity of my results to the choice of the end date for my period of analysis. In the baseline period of 1990-2004, I chose 2004 as the last year before the major part of the Hartz labor market reforms was enacted. In line (4) in Table 4, I report the estimates for some end dates before and after 2004. Throughout all of the regressions, I don't change the sample to keep constant the composition of workers. But because of that some workers may retire after 2004, and this may bias the estimates.

5) Manufacturing workers Here I verify that the same manufacturing shock that was shown to have an indirect effect on non-manufacturing workers in Section 2 has a direct effect on manufacturing workers as well. This is straightforward to show by comparing workers in industries with different exposure to trade with China and Eastern Europe, as I do in line (5) in Table 4. When I repeat the same analysis for occupations instead of industries, as specification (3) implies, the results are much harder to interpret as each manufacturing worker is exposed both directly to shocks in his or her industry and indirectly to shocks in other industries through his or her occupation. Fully controlling for all of the shocks is outside of the scope of this reduced-form analysis and is performed through counterfactuals in Section 4. Yet line (5) in Table 4 shows that there is a positive and significant association between trade exposure of occupations and unemployment outcomes of manufacturing workers.

6) Tobit model Since my main dependent variable is censored by 0 from below, I repeat my analysis by estimating the following Tobit model instead of the linear model (3),

$$y_{io} = \max\left(0, \alpha + \beta \triangle m_o + Z'_{io}\gamma + \varepsilon_{io}\right), \quad \triangle m_o = Z'_{io}\delta_1 + \delta_2 \triangle m^*_o + u_{io},$$

where $(\varepsilon_{io}, u_{io})$ are zero-mean normally distributed and independent of (Z_{io}, m^*_o). As before, I instrument trade exposure measures with trade flows of other developed countries.[38] Line (6) in Table 4 shows that the effect of import exposure is positive and significant.

The Tobit model assumes that the import exposure affects both the probability of spending any days in unemployment and the number of such days conditional on having an unemployment spell. I check both of these assumptions. To check the first one, I estimate a Probit model where the dependent variable is a dummy for the positive number of days spent in unemployment throughout 1991-2004. To check the second assumption, I repeat the linear regression (3) on a subsample of workers with positive time in unemployment. Line (6) in Table 4 shows that indeed the import exposure has a positive and significant effect on both the extensive and intensive margins of unemployment outcomes.

7) Intensive and extensive margins To look further into the extensive and intensive margins of adjustment, I decompose my main dependent variable of interest, the total number of days spent in unemployment during 1991-2004, into the number of unemployment spells and the average duration of each spell, $y_{io} = n_{io} \times d_{io}$. The summary statistics of this decomposition are presented in Table 1. I then repeat my analysis using the same empirical specification (3) where I replace the dependent variable y_{io} with n_{io} and d_{io}. As line (7) from Table 4 shows, the import exposure has a positive and significant effect on both the average number of unemployment spells and their average duration.

8) Outliers As can be seen from Table 1, the dependent variable y_{io} and the main trade variables $\triangle m_o$ and $\triangle x_o$ have rather extreme values in the top 1% of their distributions. To check that my results are not driven by these outliers, I re-estimate my main empirical specification (3) on a subsample where I remove observations with top 1% of values for y_{io}, $\triangle m_o$, and $\triangle x_o$. The results are shown in line (8) in Table 4 and are pretty similar to my baseline estimate.

9) Annual panel I verify that a positive association between import exposure and unemployment outcomes is robust to a wider set of workers and to variation of trade exposure across time as well as across occupations. To do that, I build an unbalanced panel of 534,590 non-manufacturing

[38] For simplicity of exposition, I omit export variables from the model above. But in the actual regression, I add export exposure measure $\triangle x_o$ to the list of endogenous variables and export exposure instrument $\triangle x^*_o$ to the list of instruments.

workers over 1991-2004 and estimate

$$y_{iot} = \alpha_i + \beta \triangle m_{ot} + X'_{iot}\gamma + \delta_t + \varepsilon_{iot},$$

where t denotes a year, y_{iot} is time spent in unemployment in that year by worker i who started this year in occupation o, $\triangle m_{ot}$ is the change in import exposure over this year, and X_{iot} are the time-varying worker characteristics. Importantly, I can control for workers' fixed effects α_i and thus I can control for unobserved time-invariant workers' characteristics. Then I leave only time-varying controls in X_{iot} such as squared and linear terms of age and tenure at the worker's employer, the logs of worker's and employer's wages relative to the average in the economy in that year, the employer's employment size. And I also include years' fixed effects δ_t.

The estimate of the effect of import exposure β is reported in line (9) in Table 4, but it can not be directly compared with my baseline estimate at least because this panel approach can measure only the effect of contemporaneous changes in trade without controlling for the expected future changes in trade. In addition, this approach also suffers from the endogenous sorting of workers into occupations in response to the expectation of future shocks. Yet, as the estimate suggests, there is still a positive and significant relationship between import exposure and time spent in unemployment.

A.2 Proofs

In this section, I derive the equilibrium wage function, specify the timing within a period, and provide a formal definition of equilibrium.

A.2.1 The wage function

Let's derive the wage function (15).

Nash bargaining between a firm and a worker implies the following division of surplus

$$\lambda J_t^{o,z} = (1-\lambda)\left(V_t^{o,z} - U_t^o\right), \tag{24}$$

which holds for all states (o, z) and time periods t. Iterated one period forward, this condition implies that $J_{t+1}^{o,z} \geq 0$ whenever $V_{t+1}^{o,z} \geq U_{t+1}^o$. Thus, it also implies that

$$\lambda \max\left\{J_{t+1}^{o,z}, 0\right\} = (1-\lambda)\max\left\{V_{t+1}^{o,z} - U_{t+1}^o, 0\right\}. \tag{25}$$

By combining the Bellman equations for the employed and unemployed workers, (4) and (7), I get

$$V_t^{o,z} - U_t^o = w_t^{o,z} - b^o - O_t^o + \beta\left(1-\delta^{o,z}\right)\max\left\{V_{t+1}^{o,z} - U_{t+1}^o, 0\right\}. \tag{26}$$

Plug this equation along with the firm's Bellman equation (14) into (24) to get

$$\frac{\lambda}{1-\lambda}\left[p_t^o a^{o,z} - w_t^{o,z} + \beta\left(1-\delta^{o,z}\right)\max\left\{J_{t+1}^{o,z},0\right\}\right] = w_t^{o,z} - b^o - O_t^o + \beta\left(1-\delta^{o,z}\right)\max\left\{V_{t+1}^{o,z} - U_{t+1}^o,0\right\}.$$

Finally, use (25) to arrive at (15).

A.2.2 Timing within a period

Within each period t, the sequence of events is as follows:

1. Unexpected (zero-probability) aggregate shocks realize. The only sources of aggregate shocks in the model are the import prices p_t^{sf}, sectoral Cobb-Douglas shares α_t^s, and the trade imbalance Δ_t.
2. Matches separate exogenously at rate $\delta^{o,z}$.
3. Firms decide whether to dissolve a match endogenously. This is equivalent to the worker's decision on whether to quit.
4. Production takes place. Firms that are about to enter during this period pay vacancy costs c_v^o. Employed workers receive wages, unemployed workers receive benefits. All workers receive lump-sum transfers of taxes and flow of profits.
5. Idiosyncratic preference shocks $\varepsilon_t^{o'}$ are realized. Unemployed workers decide where to search for a new job. New matches are formed.

A.2.3 Definition of equilibrium

I treat constant exogenous variables such as E^f as parameters. For a given sequence of exogenous variables $\left\{\alpha_t^s, p_t^{sf}, \Delta_t\right\}_{t,s}$, an equilibrium is a sequence of endogenous variables $\{J_t^{o,z}$, $V_t^{o,z}$, U_t^o, O_t^o, $w_t^{o,z}$, τ_t, φ_t^o, ϕ_t^o, $u_t^{oo'}$, $\mu_t^{oo'}$, q_t^s, q_t^o, p_t^s, p_t^o, P_t^s, E_t, e_t, v_t^o, m_t^o, $L_t^{o,z}$, $L_t^{o,U}$, $\chi_t^{o,z}\}_{t,o,o',s}$ that satisfy equilibrium conditions (4)-(23). Specifically:

1. Unemployed workers make their search decisions according to (6), where $u_t^{oo'}$ are given by (5), O_t^o is given by (8), and the Bellman equations (7) and (4) hold.
2. Consumers at home and abroad demand domestic final goods according to (9). The sectoral price index is given by (10), and the domestic aggregate bundle is the numeraire, (11).
3. Demand of final producers for occupational tasks and the prices for final goods are given by (13). The sectoral production function is given by (12) and the production function for occupational tasks is given by (20).

4. The value of a firm $J_t^{o,z}$ satisfies (14). The free entry condition is (16), which holds as equality whenever there is a positive entry and as an inequality otherwise. Firms exit when $J_t^{o,z} < 0$, and the share of firms that exit in state (o, z) is denoted by $\chi_t^{o,z}$.

5. Equilibrium wage function is given by (15).

6. The job finding probability ϕ_t^o and the vacancy filling probability φ_t^o are given by (17), where $m_t^o = \sum_{o'} L_t^{o',U} \mu_t^{o'o}$ and $v_t^o = m_t^o \phi_t^o / \varphi_t^o$.

7. Employment levels in each state evolve according to (18) and (19). The total mass of workers in the economy is fixed at $\bar{L}$, (21).

8. The country's budget constraint is given by (22).

9. Firms' flows of profits and government taxes are rebated to consumers according to (23).

Domestic consumers spend all of their income on the final aggregate bundle. Vacancy posting costs c_v^o are also paid in units of the final output.[39] Then the aggregate domestic demand for final goods, E_t, is equal to the sum of workers' income and the expenditures on posting vacancies,

$$E_t = \sum_{o,z} L_t^{o,z} \left(w_t^{o,z} + \tau_t\right) + \sum_{o} L_t^{o,U} \left(b^o + \tau_t\right) + \sum_{o} v_t^o c_v^o.$$

Due to Walras' law, this condition follows from the rest of the equilibrium conditions, (4)-(23).

[39]Note that the search costs $C^{oo'}$ are assumed to be utility costs, and thus they do not enter any of the market clearing conditions.