Labor Market Responses to Trade: Job Creation and Destruction Across Space and Sectors

Jiong Wu*

November 12, 2024

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Abstract

In an era dominated by globalization and international trade, the impact of trade shocks on employment has become a pressing concern for policymakers and the public. This paper examines the impact of the China trade shock on U.S. local labor markets, focusing on unemployment and its key drivers: job finding and job separation rates. Using a shift-share design, I find that regions exposed to the shock experience significant and persistent unemployment increases due to lower job finding and higher job separation rates. To explain these results, I develop a multi-sector, multi-region labor matching model with endogenous job creation and destruction. The calibrated model confirms that trade shocks raise unemployment, decrease employment, and increase welfare inequality across most U.S. states. The China trade shock raises the U.S. unemployment rate by 0.18 percentage point and accounts for 87% of the decline in the manufacturing employment share of working-age population from 2000 to 2007, while boosting overall productivity by 0.16% and improving welfare by 0.04%. The model shows that the Hosios (1990) condition alone cannot achieve constrained efficiency due to migration frictions and nontradable goods. A redistributive corporate tax policy subsidizing manufacturing could improve welfare, reduce unemployment, and restore pre-shock manufacturing employment levels.

*Department of Economics, University of Virginia (email: jw3tz@virginia.edu). I am grateful to Kerem Coşar, James Harrigan and John McLaren for their advice. I would like to thank Zach Bethune, Adrien Bilal, Jonathan Dingel, Peter Morrow, Eric Young for their comments. All errors are my own.

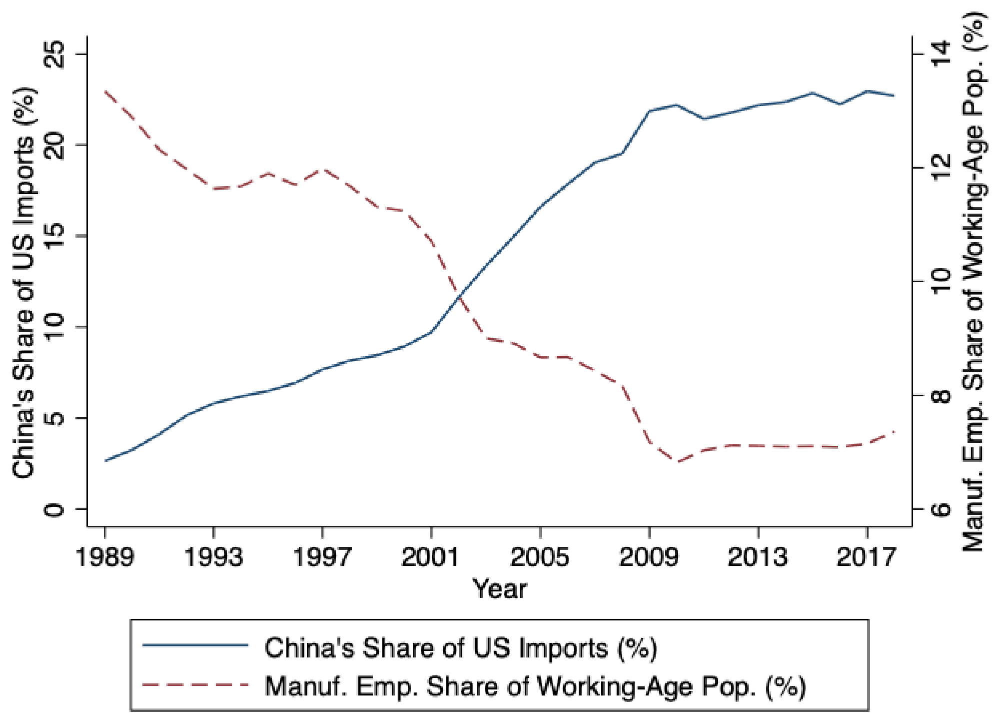
1 Introduction

In an era where globalization and international trade dominate economic discourse, concerns regarding the impact of trade shocks on employment have gained increasing attention from both the public and policymakers. The fear that trade may negatively affect domestic labor markets and exacerbate unemployment has ignited vigorous debates and prompted protectionist policies on a global scale. While empirical analyses have shed light on the relative effects of trade shocks across regional labor markets, they often fall short of examining the direct changes involved. Furthermore, key aspects of frictional labor-market dynamics, such as vacancy creation, job separation, and unemployment, are largely neglected in existing theoretical frameworks studying regional labor markets, despite the rich literature on the labor market effects of trade shocks. This paper aims to address two central questions: How do trade shocks influence regional labor markets, particularly in terms of unemployment and its core drivers—job finding and job separation? Additionally, what are the distributional welfare implications, not only across regions but also among workers with different employment statuses?

This paper examines the effects of the China trade shock on U.S. local labor markets. China's share of total U.S. imports began to rise in the 1990s, with a more pronounced and accelerated increase occurring after 2000, driven by China's rapid economic growth and its accession to the World Trade Organization (WTO). During the same period, the proportion of the U.S. working-age population employed in the manufacturing sector steadily declined. These two trends, though moving in opposite directions, exhibited a mirrored pattern, as depicted in Figure 1. Both trends plateaued after 2010, coinciding with a slowdown in China's productivity growth. To isolate the labor market effects from the Great Recession, this study focuses on the pre-2008 period.

I adapt the empirical approach developed by Autor et al. (2013) to examine the effects of the China trade shock on U.S. local labor markets, specifically focusing on unemployment and its two key margins: job finding and job separation. Regions more exposed to the China trade shock experience lower job finding rates and higher job separation rates, both of which contribute to elevated unemployment levels. The estimated effects are both statistically and economically significant: a $1,000 increase in a commuting zone's import exposure per worker is associated with a 0.3-percentage-point increase in the job separation rate and a 0.8-percentage-point decrease in the job finding rate. Moreover, these effects are found to persist from 2007 to 2019. The sustained nature of these labor market outcomes suggests that the unemployment resulting from the China trade shock is not merely a short-term, transitional phenomenon, highlighting the need for an equilibrium theory of unemployment.

Figure 1: Share of US imports from China (left scale), and share of US working-age population employed in manufacturing (right scale)



Notes: China's share of US imports is calculated using the US custom data, excluding oil and gas. The manufacturing employment share of working-age (16-64) population is calculated using CPS data.

Motivated by these facts, I propose a multi-sector, multi-region labor matching model with endogenous job creation and destruction to account for the effects of trade shocks. The model features a small open economy in which the prices of all tradable sectors are exogenous and subject to trade shocks. Each region includes a non-tradable sector, which clears locally to capture employment in non-manufacturing industries and generates differential non-participation adjustments through regional variations in the cost of living. Within each frictional labor market, endogenous job destruction arises from idiosyncratic job-match productivity, following the framework of Mortensen and Pissarides (1994). Unemployed individuals, subject to idiosyncratic preference shocks, have the option to sort into different labor markets, including non-participation. The model is sufficiently flexible to generate regional specialization patterns and predict labor market outcomes in response to exogenous trade shocks.

A stylized version of the full model, which simplifies certain complexities, generates results consistent with the empirical findings of this paper. In this simplified model, there is no non-tradable or home production sector. Unemployed workers can move freely across sectors but remain subject to idiosyncratic shocks when migrating across regions. To avoid confounding effects from exogenous variables, vacancy costs are equalized across sectors and regions. The model predicts that each region will specialize in the sector where it has the highest real marginal revenue of effective labor, facilitating a more straightforward regional analysis through complete specialization. Furthermore, the model predicts that when a labor market experiences a direct trade shock, manifested as a decline in the price of its core sector, its job separation rate will rise relative to another labor market that begins with identical labor market conditions but does not experience the shock. Additionally, its job finding rate will decrease relative to the unaffected market.

Next, I calibrate the full model to 50 U.S. states to analyze the effects of the China trade shock on U.S. labor markets.[1] All model parameters are calibrated using data from the year 2000, which serves as the initial equilibrium. The China trade shock in this small open economy model is captured by changes in tradable sector prices. These price changes are calibrated to reflect the predicted changes in U.S. net imports between 2000 and 2007, using data on China's exports to other developed economies, following the identification strategy suggested by Caliendo et al. (2019). The quantitative analysis shocks the model, calibrated to the year 2000, with price changes representing the China trade shock. This approach ensures that any changes in the variables of interest are solely attributable to the China shock, uncontaminated by other fundamental shifts that occurred between 2000 and 2007.

The quantitative analysis reveals that the China trade shock increases unemployment rates across the majority of U.S. states, driven by reduced job finding rates and heightened job separation rates. The predicted changes in unemployment rates range from -0.01 to 0.32 percentage point. On aggregate, the China trade shock raises the U.S. unemployment rate by 0.18 percentage point. States with greater exposure to the China trade shock are projected to experience higher unemployment and job separation rates, alongside lower job finding rates, which aligns with the empirical evidence.

The key variable in the model is the real marginal revenue of effective labor for each labor market, which plays a central role in both job creation and job destruction. This real marginal revenue influences job creation by balancing the expected payoff from filling a vacancy against the associated costs. It also affects job destruction by comparing the value of outside options with the payoff from maintaining a job contract. A trade shock, represented by a decline in

[1] There are four tradable sectors and one non-tradable sector. The tradable sectors are groups of Census industries based on the quantiles of industrial net import penetration. Grouping manufacturing industries in this way can not only reduce computational complexity but also lower the within-sector variation of import exposure, retaining more information that matters in the trade shock analysis.

the price of a sector's output, can reduce the real marginal revenue of effective labor in that sector, making it less profitable for firms to create new job openings. Simultaneously, firms find it more difficult to offer wages competitive with outside options, worsening job creation prospects while raising the productivity needed to sustain a job match. Higher reservation productivity increases the average productivity of surviving firms (or jobs), although it also makes layoffs more likely. This mechanism resembles the trade selection effect proposed by Melitz (2003). In the counterfactual analysis, the overall productivity of the U.S. economy improves by 0.16%, driven by higher reservation productivity across regions and sectors.

The model can predict changes in labor non-participation across regions, and consequently, shifts in employment levels. All regions experience higher non-participation rates, resulting in employment declines in most states. The manufacturing sector faces the most significant negative employment effects from the trade shock. In this quantitative exercise, the overall share of manufacturing employment decreases by 27%, accounting for a loss of approximately 3 million manufacturing jobs in the U.S. between 2000 and 2007. This decline represents 87% of the reduction in manufacturing employment relative to the working-age population, as illustrated in Figure 1.

The model also highlights the resulting changes in welfare, measured by the continuation value for each type of agent. Agents across all regions experience welfare gains from trade, primarily driven by improved expected outside option values and lower local costs of living. The overall welfare improvement for the U.S. due to the China trade shock is 0.04%. Labor non-participants, who have opted out of job searching, enjoy unambiguous welfare gains through lower costs of living. Although it becomes more difficult for unemployed individuals to find jobs, they still benefit from a higher outside option value, largely due to the increased value of non-participation. For employed individuals, the trade shock functions as a positive nominal wage shock, particularly in tradable sectors, by raising both reservation productivity and expected outside option values. Additionally, reservation productivity increases more in regions with greater exposure to the shock. As a result, welfare inequality between employed and unemployed individuals widens in the more exposed regions. The quantitative analysis shows that most regions experience a rise in welfare inequality between the employed and unemployed.

I further demonstrate that two sources of externalities in this search and matching model prevent constrained efficiency, even when the Hosios condition is imposed.[2] The inefficiency in a search and matching model stems from the congestion that workers and firms impose on

[2] Hosios (1990) shows that by equalizing worker's (Nash) bargaining power with the elasticity of matching to the number of unemployed, a one-sector one-region search and matching model can achieve constrained efficiency, with the constraint being frictional matching.

one another. The Hosios condition, derived from a one-sector, one-region model, addresses this congestion by balancing these two externalities. However, the multi-sector, multi-region model in this paper introduces two additional sources of congestion: migration frictions and the role of local non-tradable goods, both of which are crucial for analyzing the regional labor market effects of trade. These externalities cannot be neutralized by the Hosios condition alone. Consequently, there is scope for welfare-improving policies, even after the Hosios condition is applied in the quantitative exercises. Furthermore, I find that local non-tradable sectors tend to have more jobs than the socially optimal constrained level. This is because that firms do not need to consume non-tradable goods but workers do and they cannot internalize the congestion they cast on one other. Therefore, more firms than the constrained optimal level will enter the non-tradable market, which informs the subsequent policy counterfactual.

The policy counterfactual analysis in this paper examines the effects of a manufacturing subsidy policy aimed at restoring pre-shock employment levels in the manufacturing sector, an issue that has garnered significant political interest in the U.S. The subsidies are financed through corporate taxes on non-manufacturing firms. Given the substantial share of the non-manufacturing sector in the U.S. economy even prior to the trade shock, a tax rate of just 0.04% on non-manufacturing firms is sufficient to fund the subsidies required to restore manufacturing employment to pre-shock levels. This policy not only restores employment but also enhances the gains from trade and reduces the overall unemployment rate: the overall welfare gains from trade are 0.05% and unemployment rate decreases by 0.02 percentage point.

Literature

This paper contributes to the empirical literature on the regional impacts of trade shocks. While most empirical studies of trade shocks focus primarily on employment effects (e.g., Autor et al. (2013); Kovak (2013)), I provide evidence of the effects of trade shocks on regional job finding and separation rates, offering deeper insights into the dynamics of job creation and destruction. Additionally, the empirical analysis in this paper demonstrates the persistence of these labor market effects over time.[3]

The structural approach of this paper contributes to the quantitative trade literature examining the regional labor market outcomes of trade shocks (e.g., Adao et al. (2019); Caliendo et al. (2019); Lyon and Waugh (2019); Galle et al. (2023)). My work is closely related to three papers that focus on unemployment. Kim and Vogel (2021) propose a static

[3] Dix-Carneiro and Kovak (2017); Autor et al. (2021) study the long-run evolution of labor market effects of trade shocks but again focus on the employment aspect.

small open economy model with labor matching, but my model differs by incorporating endogenous job destruction and allowing for forward-looking dynamics to explain the empirical findings of this paper. Forward-looking assumption allows for important welfare gains from higher labor outside option values. Dix-Carneiro et al. (2023) also feature endogenous job destruction during dynamic transitions but not in the steady state. In contrast, my model focuses on steady-state equilibrium and includes endogenous job separation in the steady state. Moreover, while their study operates at the global level and abstracts from within-country regional migration, my paper models frictional migration across regions, which amplifies the negative effects on local labor markets.[4] Rodríguez-Clare et al. (2020) generate unemployment through nominal rigidities in their model, relying on short-run stickiness of nominal variables like exchange rates. In contrast, my model uses frictional labor market assumptions to generate long-run equilibrium unemployment effects. While the focus of this paper is on unemployment, I also model labor non-participation, providing a more comprehensive view of employment effects.

This paper contributes to the literature on spatial unemployment. Bilal (2023) shows that regional variations in unemployment are largely driven by job separation, while Kuhn et al. (2021) demonstrate that changes in the job finding rate are the primary driver of unemployment fluctuations over time. My empirical findings align with both studies. However, this paper extends the labor matching model with endogenous job destruction to include multiple sectors, enabling an analysis of sectoral shocks. Chodorow-Reich and Wieland (2020) also model multi-sectoral unemployment across multiple regions, but unlike the model in this paper, theirs abstracts from regional congestion forces, which play a significant role in migration dynamics.

This paper contributes to the literature on the efficiency of search and matching models by incorporating the complexity of multiple sectors and regions. Bilal (2023) demonstrates that, in a multi-region search and labor matching model with labor market pooling complementarities, the Hosios condition is insufficient to achieve constrained efficiency. In this paper, I identify two additional sources of externalities in labor matching across multiple labor markets that cannot be offset by the Hosios condition. The first is migration frictions, driven by idiosyncratic taste shocks. Recent models usually rely on these taste shocks from extreme value distributions to capture migration frictions, and I show that when combined with search externalities, they contribute to inefficiency of market equilibrium. The second

[4] Davidson et al. (1988, 1999); Cosar (2013); Coşar et al. (2016); Dutt et al. (2009); Hasan et al. (2012); Mitra and Ranjan (2010); Helpman et al. (2010); Davidson and Matusz (2004); Carrere et al. (2020); Lyon and Waugh (2019); Felbermayr et al. (2013) also study the unemployment effect of trade at the country level. Lyon and Waugh (2019) study the China shock effect on the aggregate US labor market using a small open economy model featuring labor market frictions that generate nonemployment as in Caliendo et al. (2019).

source of inefficiency arises from the presence of a local non-tradable sector, which operates under frictional labor matching conditions.[5]

The remainder of the article is structured as follows. Section 2 presents the motivating empirical findings. Section 3 builds a model that is motivated by the empirical facts and shows a stylized version of it that can rationalizes the facts. Section 4 discusses how the model is calibrated. Section 5 discusses the counterfactual analysis that looks into the labor market effects of the China shock. Section 6 discusses the inefficiency of market equilibrium implied by the model and a policy counterfactual. The last section concludes.

2 Motivating facts

Many studies on local economic adjustment to trade shocks focus on the China trade shock and its impact on U.S. regional labor markets. In this paper, I adopt the empirical framework developed by Autor et al. (2013)to explore additional dimensions of this shock, particularly those related to non-wage adjustments. I concentrate on two key labor market flows that largely determine unemployment: job finding and job separation. Furthermore, I examine the long-run effects of the China trade shock to demonstrate that these non-wage adjustment effects are not merely short-term disequilibrium phenomena.

2.1 Empirical approach

I adopt the same empirical approach that is proposed by Autor et al. (2013) to examine the China trade shock effects on the U.S. regional labor market between 1990 and 2007:

$$\Delta y_{d\tau} = \beta_\tau + \beta_y \Delta IP_{d\tau} + \mathbf{X}'_{d\tau}\beta_o + \epsilon_{d\tau}, \tag{1}$$

where $\Delta y_{d\tau}$ is the change in the labor market outcome of commuting zone d during period τ, which is either 1990 - 2000 or 2000 - 2007. The labor market outcomes I study include unemployment rate, job finding and separation rates of the working-age (16 - 64) population. $\Delta IP_{d\tau}$ is the local labor market exposure to import competition that is defined by:

$$\Delta IP_{d\tau} = \sum_i \frac{L_{id\tau_0}}{L_{i\tau_0}} \frac{\Delta M_{i\tau}}{L_{d\tau_0}}, \tag{2}$$

where $L_{id\tau_0}$ is the employment level in industry i (SIC 4-digit level industry) of commuting zone d at the beginning of period τ and $\Delta M_{i\tau}$ is the change in the U.S. import values (in

[5]The model in Bilal (2023) also has housing market as the local nontradable sector but it does not have a supply side that is subject to frictional labor market.

\$1000) from China in industry i between the start and end of the period τ. A concern for identifying the causal impact of import exposure on labor market outcomes in (1) is that U.S. imports may change both because of shocks to U.S. product demand and shocks to foreign product supply, where the former may be correlated with the residual. Again I follow Autor et al. (2013) to instrument for growth in Chinese imports to the United States using the contemporaneous composition and growth of Chinese imports in eight other developed countries:

$$\Delta IPO_{d\tau} = \sum_i \frac{L_{id\tau_{-1}}}{L_{i\tau_{-1}}} \frac{\Delta EO_{i\tau}}{L_{d\tau_{-1}}}, \tag{3}$$

where $\Delta EO_{i\tau}$ is the change of import values from China to eight other high-income markets during the period.[6] And the subscript -1 means the employment levels are from the prior decade.[7] I stack the first differences for the two periods: 1990 to 2000 and 2000 to 2007, and include time dummies for each period, β_τ. $\mathbf{X}_{d\tau}$ is a vector of the start-of-period controls at the commuting zone level.[8]Following ADH, standard errors are clustered at the state level to correct for spatial correlations and each commuting-zone observation is weighted by the start-of-period population.

To examine the changing effects of the China trade shock, I extend (1) to have successively longer time differences. It is done by replacing the period 2000 - 2007 with the 2000 to t (t = 2007, 2008, ..., 2019) while keeping everything else the same.[9] And now the import penetration effects β_y are estimated for years from 2007 to 2019 to see whether these effects can be persistent. Autor et al. (2021) also study the persistence of the China trade shock and use the shock period of 2000 to 2012 since the shock plateaued after 2010. I focus on 1990 to 2007 instead to avoid being confounded by the negative labor market effects cast by the 2008 financial crisis.

2.2 Data and measures

The data used to measure import penetration are standard in the literature. U.S. import data are obtained from U.S. Customs records, while data on China's exports to other countries

[6]They include Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

[7]See Autor et al. (2013) for more discussion on the IV.

[8]It contains time trends for US Census divisions and start-of-period CZ-level covariates: the manufacturing share of employment, which allows us to focus on trade exposure arising from the within manufacturing industry mix; specialization in occupations according to their routine-task intensity and offshorability (based on Autor et al. (2013)), thus accounting for exposure to automation and non-China-specific globalization; the fractions of foreign-born and non-white workers, the college-educated portion of the population, and the fraction of working-age women who are employed, which absorbs variation in outcomes related to labor-force composition

[9]The regression still includes the stack of 1990 to 2000, which is different from Autor et al. (2021)

are sourced from BACI, which is based on the UN Comtrade Database.[10] Employment data by industry and commuting zone are derived from the County Business Patterns Database.[11] Labor market outcomes and control variables are obtained from the 5% sample of the Census and the American Community Survey. The 5%-sample Census and American Community Survey contain the data on labor market outcomes and control variables. Unlike Autor et al. (2013), who examine the number of unemployed individuals and their share of the population, I focus on the unemployment rate, defined as the ratio of the unemployed to the total labor force.[12]

The job finding and separation rates for each commuting zone are measured indirectly, as neither the 5%-sample Census nor the ACS provide explicit information on individuals' lagged employment statuses. [13] However, both datasets include a question regarding the number of weeks a respondent worked in the previous year, with responses categorized into intervals such as 0, 1-13, 14-26, 27-39, 39-47, and so on. Following the approach of Dix-Carneiro et al. (2023), I classify workers as employed if they worked 26 weeks or more in the previous year. I cross-validate this measure using various data sources and find it to be highly correlated with them (see Appendix A.2 for further details). I define workers as unemployed if they worked fewer than 26 weeks in the previous year but are still participating in the labor market in the current year. Employment transition rates are calculated annually. If an individual was employed last year but becomes unemployed this year, they are counted as having experienced job separation. Conversely, if an individual was unemployed last year but is employed this year, they are counted as having found a job. I restrict the survey sample to the working-age population, defined as individuals aged 16-64, and arrange the variables for 722 commuting zones in the U.S. for the years 1990, 2000, and 2007-2019. Summary statistics for the dependent variables across all periods used in this study can be found in AppendixA.1.

2.3 Empirical results

Regions exposed to the China trade shock experience higher unemployment rates, lower job finding rates, and higher job separation rates, as shown in Table 1. The coefficient of 0.258 in column 1 suggests that a $1,000 increase in a commuting zone's (CZ) import exposure per

[10]The US Custom Data are organized and provided by Schott (2008). The concordance from HS 6-digit code to SIC 4-digit is provided by Autor et al. (2013).

[11]I use the version provided by Eckert et al. (2020) who impute the missing values in CBP.

[12]In other words, people who are not employed and not actively searching for jobs are not counted in the denominator.

[13]CPS tracks the employment statuses of respondents but does not have geographic information at the commuting zone level.

worker—approximately the interquartile change in import penetration—is predicted to raise the unemployment rate by a quarter of a percentage point. This effect is not only statistically significant but also economically meaningful. The increase in unemployment results from both a lower job finding rate and a higher job separation rate, as shown in columns 2 and 3. In other words, workers in more exposed regions face greater difficulty in finding jobs and a higher likelihood of losing them compared to those in less exposed regions. The job separation effects are consistent with the finding in Bilal (2023) that regional variations in unemployment rates are primarily driven by job separation rates. In the robustness check, I apply alternative thresholds for measuring job finding and separation rates, and the results remain consistent (see Tables 11 and 12 in Appendix A.2).

Table 1: The China trade shock and labor market outcomes: 2SLS estimates

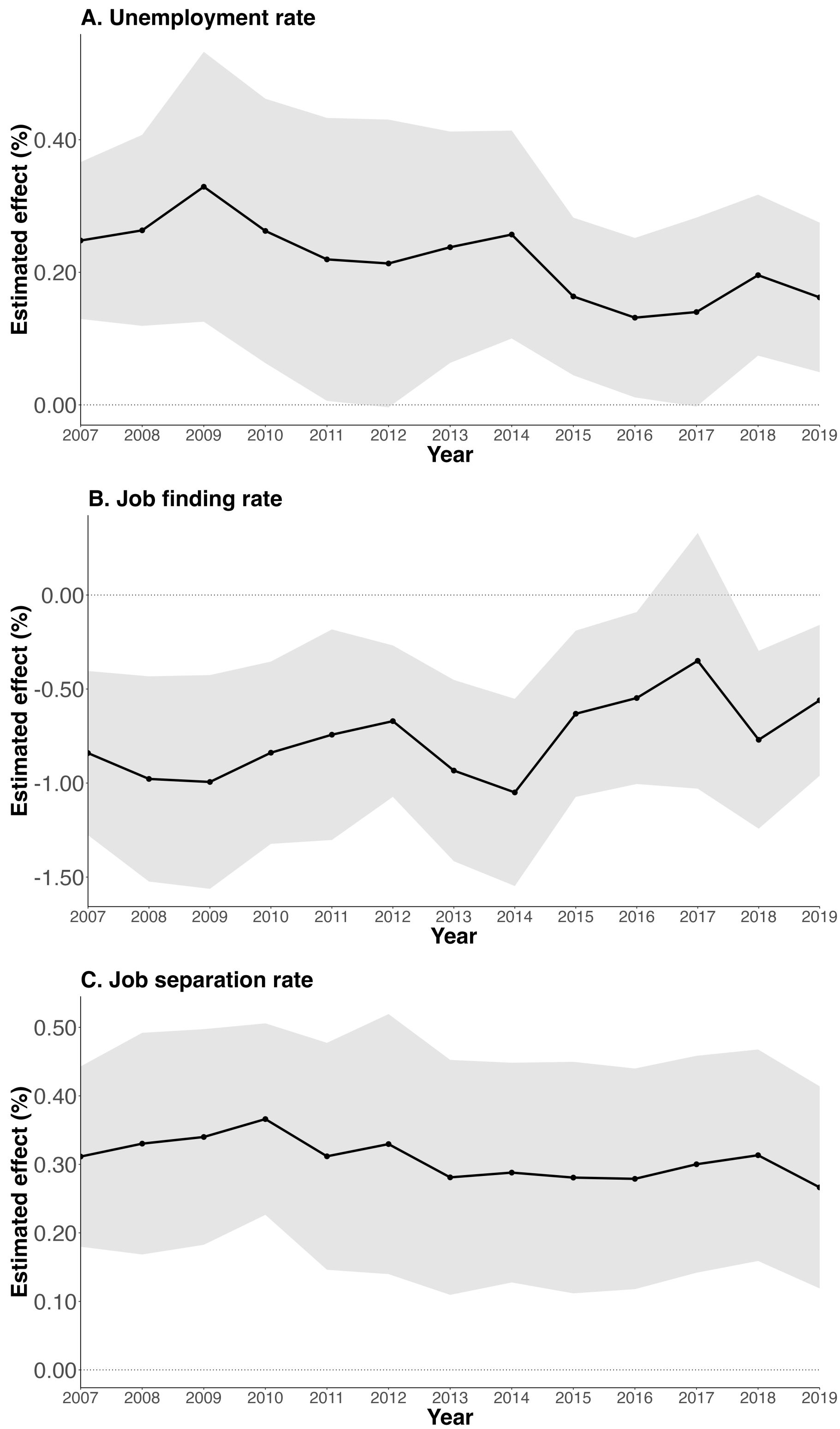
	Dependent variables		
	Δ Unemployment Rate	Δ Job Finding Rate	Δ Job Separation Rate
	(1)	(2)	(3)
Δ Import Penetration	0.248^{***}	-0.841^{***}	0.311^{***}
	(0.060)	(0.239)	(0.079)
Observations	1,444	1,444	1,444
R^2	0.309	0.592	0.807

Notes: The results are from 2SLS estimation of regression (1). The samples are restricted to the working-age group (age 16 - 64). The estimated coefficients on the controls are not reported in the table. The full results are shown in the Appendix (**??**).Robust standard errors in parentheses are clustered on state. Models are weighted by start of period CZ share of national population. *p<0.1; **p<0.05; ***p<0.01.

These labor market effects persist over time, as shown in Figure 2. Panel A illustrates that the unemployment effects fluctuate over the years but decrease by one-third by 2019. This fluctuation is driven by the impact of the trade shock on job finding rates, as shown in Panel B. The effects of the trade shock on job separation rates display a more stable and persistent trend, as depicted in Panel C. In the robustness checks, I use alternative thresholds to measure job finding and separation, and the results remain consistent (see Figure 15 and Figure 16 in the Appendix). The persistence of these labor market outcomes from the China trade shock suggests that the resulting unemployment is not merely a short-term disequilibrium phenomenon.

These facts indicate the need for a model that can generate steady-state unemployment with endogenous job creation and destruction. If unemployment were merely a temporary result of market non-clearing, such long-lasting effects would not be observed. The significant positive impact on job separation rates also motivates the inclusion of an endogenous job destruction process. Additionally, non-participation is a crucial aspect of labor market outcomes, as highlighted by ADH, and it plays a key role in understanding the full scope of employment changes. Therefore, the model presented in the following section incorporates endogenous labor non-participation to provide a more comprehensive view of labor market effects. Moreover, the analysis centers around the steady-state equilibrium which can speak to the persistent effects.

Figure 2: Trade shock impact, 2007 - 2019



Notes: The dots are the coefficients estimated from regression (1) using 2SLS with successively longer first difference from period 2000 - 2007 to 2000 - 2019 on the LHS. The shaded area represents the 95% confidence interval of each coefficient. Regressions are weighted by the CZ total population in 2000; standard errors are clustered by state.

3 Model

This section presents a multi-sector, multi-region labor matching model with endogenous job destruction and imperfect labor mobility. The model primarily extends the framework of Mortensen and Pissarides (1994) by incorporating multiple sectors and regions.[14] Section 3.1 outlines the model's original dynamic environment, while Section 3.2 focuses on the corresponding Bellman equations and the conditions for steady-state equilibrium. Section 3.3 simplifies the model and discusses some results.

3.1 Environment

Time is discrete and denoted by t. There are D regions in the economy. There are S productive sectors in each region. In each region, there is also a non-participation sector to capture the workers who opt out of labor market, denoted by 0. One can understand it as a non-productive home production sector. There is a non-tradable good sector in each region that supplies the goods locally and is indexed by 1. The rest $S-1$ sectors are tradable goods sectors. It is a small open economy: the prices of all tradable goods are exogenous and subject to trade shocks. One can think of the tradable sectors as the manufacturing sectors that are directly subject to trade shocks. Allowing for one non-tradable sector, which can cover all those non-manufacturing sectors, in each region captures the employment shares that are not directly subject to trade shocks. Since this paper focuses exclusively on U.S. local labor markets and does not extend its analysis to other countries, I adopt the small open economy assumption to reduce computational complexity. Additionally, endogenous nontradable prices allow for relative price adjustments that resemble terms-of-trade changes in an open economy.

Preferences

All the agents share the same life-time utility function:

$$\mathcal{U} = \mathbb{E}\left(\sum_{t=0}^{\infty} \frac{C_t}{(1+r)^t}\right), \tag{4}$$

[14] The key elements that I adapt from their framework are frictional labor matching, and random job-specific productivity draws that help to endogenize job destruction. The environment with multiple labor markets and imperfect inter-market mobility has different job destruction conditions from theirs as shown below.

where r is the time discount rate, and C_t the aggregator of all tradable sectoral and non-tradable goods consumption:

$$C_t = \prod_{s=1}^{S} (q_{s,t}/\alpha_s)^{\alpha_s}, \tag{5}$$

where $q_{s,t}$ is the consumption of sector s goods at time t and α_s is the expenditure share of sector s. Notice that the home production sector does not produce goods that can be sold on the market, hence excluded from final consumption. $\sum_s \alpha_s = 1$. Lending and borrowing are not allowed.

Producers

Each producer from any sectors must match with a worker to produce. For a producer-worker match with the match-specific productivity x_t in sector s and region d, the output at t is $y_{sd,t} = A_{sd} x_t$, where A_{sd} represents the sector-region-specific productivity, which does not change over time. The producers take the prices as given. All tradable sectoral goods are freely traded across the economy. The random job-specific productivity helps deliver endogenous job separation rates as shown in Mortensen and Pissarides (1994). Different from Mortensen and Pissarides (1994) who set an exogenous initial job productivity level, I allow firms and workers to draw productivity in the very first meeting. And job productivity can be redrawn each period to generate endogenous job separation rates in the steady state, which is different from Dix-Carneiro et al. (2023) who forbids it.

Labor market frictions and wage bargaining

Each sector in each region has a frictional labor market where workers meet with firms. Given the number of vacancies $N^V_{sd,t}$ and the number of unemployed individuals who have sorted into sector s and region d, $L^U_{sd,t}$, the number of matches is given by a constant-returns-to-scale matching function: $M(N^V_{sd,t}, L^U_{sd,t})$. Let $\theta \equiv N^V/L^U$ represent the labor market tightness and $\kappa(\theta) \equiv M(N^V, L^U)/N^V = M(1, 1/\theta)$ the vacancy contact rate, which is a function of θ. The probability of a job seeker meeting with a firm in sector s of region d is then $M(N^V_{sd,t}, L^U_{sd,t})/L^U_{sd,t} = \theta_{sd,t}\kappa(\theta_{sd,t})$.

Producers post vacancies to hire workers. Posting a vacancy of sector s in region d costs $e_{sd}P^f_{d,t}$ per period, where $P^f_{d,t}$ is the final consumption good price index in location d at time t. The vacancy are set up at the cost of some units of final consumption goods. There is free entry for posting vacancies in each sector and location. Producers commit to the sector and location they enter.

When an unemployed agent encounters a vacant job, they draw job-specific productivity

x from the cumulative distribution function $F(x)$ over $[0, \bar{x}]$, where $\bar{x}$ is the upper bound of domain, and engage in Nash bargaining over the joint nominal surplus. [15] The worker's bargaining power is β. A wage agreement will be reached if both parties can obtain positive net surpluses from bargaining. Let the set of productivity levels that can lead to wage agreements be $\mathcal{M}_{sd,t}$, which is endogenous to each labor market. Following this, the worker will receive a wage $w_{sd,t}(x_t)$ after they start production.

If an unemployed individual does not meet or reach an agreement with a firm, they will draw idiosyncratic value shocks $\{\epsilon_{sd,t}\}$ independently across labor markets from a Gumbel distribution $G(\epsilon)$ with parameters $(-\gamma_0\nu, \nu)$.[16] Immediately afterward, they decide which labor market to enter and stay there starting from the next period. It is important to note that each region includes a sector 0 for home production. Workers who sort into this sector become non-participants. Non-participants receive a moving chance with a probability of λ_0 each period and then make migration choices based on the value shocks drawn from the same $G(\epsilon)$. This model allows non-participants the opportunity to move back to labor markets, capturing the non-trivial flow from non-participation to employment. The unemployed in region d receive an exogenous nominal unemployment benefit of b_d each period. Non-participants in region d earn an exogenous income of ω_d each period. One can rationalize the difference between ω_d and b_d as the job searching cost a job seeker needs to pay at the job market. Allowing non-participants to earn income that can be spent on not only tradable but also non-tradable goods generates differential non-participation responses across regions, even with symmetric non-participation income. The within-period sequencing of events for the unemployed is shown in Figure 3.

A firm-worker match faces an exogenous exit shock with a probability of δ that terminates the match immediately in each period. If a job match does not receive the exit shock, the firm and worker will redraw the job-specific productivity from $F(x)$ and negotiate the wage. If no agreement is reached, the match will be destroyed. Upon the destruction of a job match, the worker will become unemployed and undergo the same migration process. The within-period sequencing of events for the employed is shown in Figure 4. The model is essentially an "island" model (Lucas Jr (1975)) with directed search over labor markets that are segmented by both sectors and regions. In this way, the model can capture inter-market worker migration while remaining tractable, preserving the frictional matching mechanism that generates unemployment.

[15] The worker's net surplus is adjusted by $P^f_{d,t}$ to become nominal values, a rationale grounded in the fact that firms do not need to consume goods. See more discussion in Bilal (2023).

[16] γ_0 is the Euler constant.

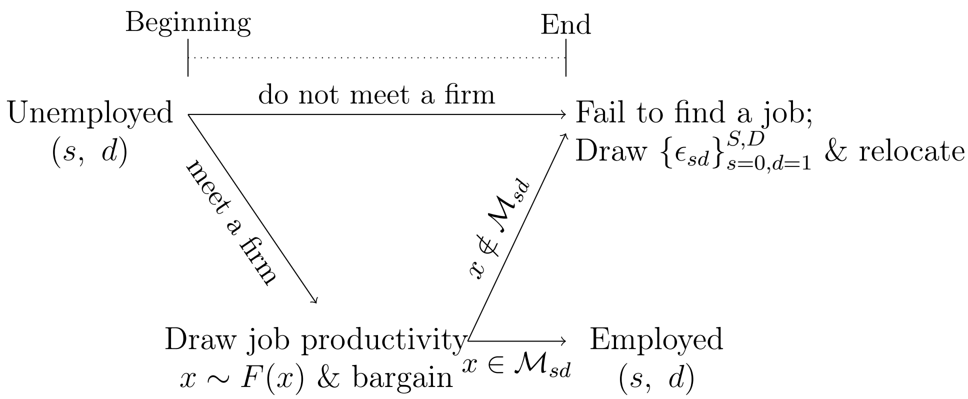


Figure 3: Within-Period Sequencing of Events for the Unemployed

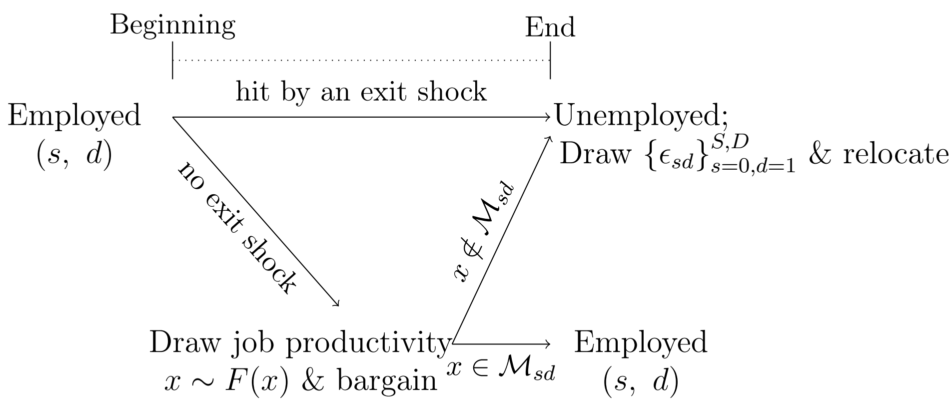


Figure 4: Within-Period Sequencing of Events for the Employed

3.2 Equilibrium

This paper focuses on a steady-state equilibrium. This subsection first presents the problems faced by agents in the economy and their corresponding value functions, followed by market clearing conditions. It concludes with the definition of the steady-state equilibrium.

Value functions

By the utility maximization of (5) , the final consumption price index in location d is

$$P_d^f = \prod_{s=1}^{S} p_{sd}^{\alpha_s}, \tag{6}$$

where p_{sd} is the price of sector s goods faced by people in location d. In this small open economy, all tradable goods are exogenous and the same across regions since there is no trade cost across regions: $p_{sd} = p_s \; \forall d, \; \forall s > 1$. The non-tradable goods prices are endogenous in each region.

The Bellman equation for the unemployed in sector s and region d is:

$$U_{sd} = \frac{1}{1+r}\{b_d/P_d^f + \theta_{sd}\kappa(\theta_{sd})\mathbf{Pr}[x \in \mathcal{M}_{sd}]\mathbb{E}[W_{sd}(x)|x \in \mathcal{M}_{sd}] + \\ (1 - \theta_{sd}\kappa(\theta_{sd})\mathbf{Pr}[x \in \mathcal{M}_{sd}])\,\mathbb{E}\left(\max_{s' \in \{0,1,\ldots,S\},\; d' \in \{1,..,D\}} U_{s'd'} + \epsilon_{s'd'}\right)\}. \tag{7}$$

Here, the unemployment benefit are discounted because they are received at the end of the period. Similarly, wages and non-participation income are also obtained at the end of the period. [17] The unemployed have a chance of $\theta_{sd}\kappa(\theta_{sd})$ to meet with a firm in sector $s$and region d and draw the job-specific productivity. $\mathbb{E}[W_{sd}(x) \mid x \in \mathcal{M}_{sd}]$ is the expected value of being employed, conditional on a match being formed. If a match is not formed, the agent will face the problem of moving as described above. Let $E \equiv \mathbb{E}\left(\max_{s',\; d'} \; U_{s'd'} + \epsilon_{s'd'}\right)$ be the expected migration value. Similarly, the value of the nonparticipants, U_{0d}, is given by:

$$U_{0d} = \frac{1}{1+r}\left\{\omega_d/P_d^f + \lambda_0 E + (1-\lambda_0)U_{0d}\right\}. \tag{8}$$

The Bellman equation for the employed in sector s and region d is:

$$W_{sd}(x) = \frac{1}{1+r}\{w_{sd}(x)/P_d^f + (1-\delta)\mathbf{Pr}[x \in \mathcal{M}_{sd}]\mathbb{E}[W_{sd}(x)|x \in \mathcal{M}_{sd}] + \\ (\delta + (1-\delta)\mathbf{Pr}[x \notin \mathcal{M}_{sd}])E.\} \tag{9}$$

A worker employed in a job with productivity x engages in production and gets paid at the end of the period. Throughout the period, they are subject to the possibility of being laid off with a probability of δ. Not experiencing the shock allows the job match to receive a new draw of productivity, resulting in a new value of employment. If the new value of being employed is lower than the expected value of outside options, the worker will opt out of the current job and make moving choices as an unemployed worker. Otherwise, they will remain in the current position.

The value of a vacant job, J_{sd}^V, is given by:

$$J_{sd}^V = \frac{1}{1+r}\left\{-e_{sd}P_d^f + \kappa(\theta_{sd})\mathbf{Pr}[x \in \mathcal{M}_{sd}]\mathbb{E}[J_{sd}(x)|x \in \mathcal{M}_{sd}] + (1-\kappa(\theta_{sd})\mathbf{Pr}[x \in \mathcal{M}_{sd}])\,J_{sd}^V\right\}, \tag{10}$$

[17] This sequencing helps render a Bellman equation that resembles the one in the continuous time version and also easy to manipulate. Not discounting the flow utility/income does not change the results. See Mortensen and Pissarides (1999) for more discussion.

where $J_{sd}(x)$ is the value of a filled job with productivity x. A vacancy will be filled when a firm meets a worker and the drawn job productivity meets the requirement for a wage agreement; otherwise, it remains vacant. Free entry of vacancies means

$$J^V_{sd} = 0 \qquad\qquad \forall s,\ d. \tag{11}$$

The value of a filled job with productivity x is as follows:

$$\begin{aligned} J_{sd}(x) = \frac{1}{1+r}\{ & p_{sd}A_{sd}x - w_{sd}(x) + (1-\delta)\mathbf{Pr}[x \in \mathcal{M}_{sd}]\mathbb{E}[J_{sd}(x)|x \in \mathcal{M}_{sd}]+ \\ & (\delta + (1-\delta)\mathbf{Pr}[x \notin \mathcal{M}_{sd}])J^V_{sd}. \end{aligned} \tag{12}$$

Intra-temporal profits are $p_{sd}A_{sd}x - w_{sd}(x)$.[18] If the job match experiences the exit shock or redraws a new productivity level that results in a filled job value lower than that of being vacant, the job match is terminated and becomes vacant again.

The wage for a job with productivity x is pinned down through the adjusted Nash bargaining:

$$w_{sd}(x) = arg\max_{w}\ \left[J_{sd}(x) - J^V_{sd}\right]^{1-\beta}\left[P^f_d(W_{sd}(x) - E)\right]^{\beta}. \tag{13}$$

As discussed above, the worker's net surplus, $W_{sd}(x) - E$, is adjusted by P^f_d to be in the nominal form. The net surplus of being employed is calculated by subtracting the value of outside options, not that of being unemployed, because when an agreement is not reached, the worker is immediately faced with the problem of moving. Taking (9), (11), and (12) into (13) gives a FOC of the Nash bargaining:

$$P^f_d\left(W_{sd}(x) - E\right) = \frac{\beta}{1-\beta}J_{sd}(x). \tag{14}$$

From (14), it is evident that there exists a productivity threshold R_{sd} below which both $W_{sd}(x) < V_{sd}$, and $J_{sd}(x) < 0$ occur simultaneously. In other words, if the drawn productivity is lower than the threshold, neither the firm nor the worker will have a positive surplus to split, resulting in the destruction of the match. Then $\mathcal{M}_{sd} = [R_{sd}, \bar{x}]$. I call R the reservation productivity following Mortensen and Pissarides (1994). It follows that at R_{sd}:

$$P^f_d\left(W_{sd}(R_{sd}) - E\right) = \frac{\beta}{1-\beta}J_{sd}(R_{sd}) = 0. \tag{15}$$

[18]Notice that the tradable sectoral prices do not vary across locations. The *sd* subscripts are used to be consistent with the non-tradable sector.

The wage then is given by

$$w_{sd}(x) = \beta(p_{sd}A_{sd}x - rP_d^f E) + rP_d^f E. \tag{16}$$

Since the expected flow return of failing to become employed, adjusted by consumption, is $rP_d^f E$, it is the minimum compensation that an unemployed agent requires to forego job search. Therefore, it can be interpreted as the reservation wage. Workers receive their nominal reservation wage, $rP_d^f E$, and a fraction β of the net surplus that they create on the job: the product revenue minus what they give up.

Rearranging equations (7) to (14) gives the value of being unemployed as

$$U_{sd} = \frac{1}{1+r}(b_d/P_d^f + \frac{\beta}{1-\beta}e_{sd}\theta_{sd} + E). \tag{17}$$

Labor market tightness increases the value of being unemployed because a higher θ means that jobs arrive at a higher chance for the unemployed. Similarly, the value of non-participation is:

$$U_{0d} = \frac{1}{\lambda_0 + r}(\omega_d/P_d^f + \lambda_0 E). \tag{18}$$

Both (17) and (18) suggest that local final good price matters in determining the distribution of non-employment. Lower P_d^f means lower costs of living, which attracts people through higher indirect utility.

Free entry condition (11) generates an equation describing job creation:

$$e_{sd} = \underbrace{\kappa(\theta_{sd})(1 - F(R_{sd}))}_{\text{Prob. of a successful match}} \underbrace{\frac{1-\beta}{1+r}\rho_{sd}\mathbb{E}(x - R_{sd} \mid x > R_{sd})}_{\text{Conditional expected real returns of a filled job}}, \tag{19}$$

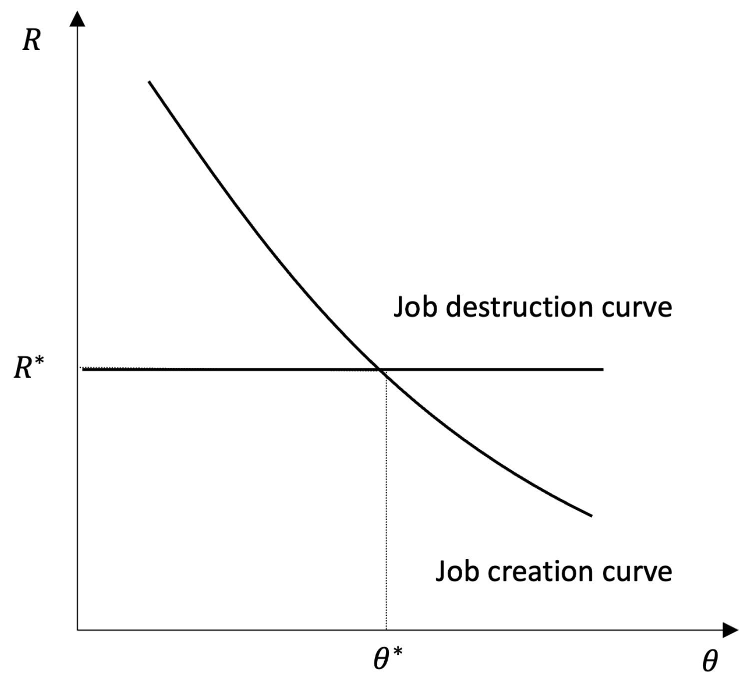
where $\rho_{sd} \equiv \frac{p_{sd}A_{sd}}{P_d^f}$ is the real marginal revenue of effective labor. Equation (19) states that the expected gain from a new job must equal the hiring cost (in real terms). Firms take $1-\beta$ share of the joint net surplus, which depends on how much the drawn productivity is larger than the reservation productivity. A negative correlation between the reservation productivity and labor market tightness is implied by (19). A higher reservation productivity R reduces the expected gain from a job by decreasing the chance of securing a successful wage agreement. Firms create fewer jobs as a result.

The threshold condition by (15) gives another equation that describes job destruction:

$$\rho_{sd}\underbrace{\left[R_{sd} + \frac{1-\delta}{1+r}\mathbb{E}(x - R_{sd} \mid x > R_{sd})(1 - F(R_{sd}))\right]}_{\text{Expected present discounted product}} = rE. \tag{20}$$

Equation (20) states that at the break-even point, the present-discounted expected sales should be equal to the flow value of outside option. In the partial equilibrium of an infinitesimal labor market, the reservation productivity does not change with labor market tightness in the same labor market since the outside option value is determined by an expectation of the tightness across all segmented labor markets.[19] Given the outside option value and real marginal revenue of effective labor, the reservation productivity for a labor market is uniquely determined. The job creation and destruction conditions together pin down the labor market tightness θ and reservation productivity R for each labor market, given the sectoral price, non-tradable price, and outside option value, as shown in Figure 5

Figure 5: Partial equilibrium reservation productivity and labor market tightness



Labor distribution

In the steady state, the relationship between the number of employed and that of unemployed is captured by

$$L_{sd}^{E} = L_{sd}^{U} \underbrace{\theta_{sd}\kappa(\theta_{sd})(1 - F(R_{sd}))}_{\text{Job finding rate}} / \underbrace{[\delta + (1-\delta)F(R_{sd})]}_{\text{Job separation rate}}, \tag{21}$$

[19]This is different from Mortensen and Pissarides (1994) who derive an upward sloping job destruction condition. In fact, the quantitative exercise of this paper produces a job destruction curve almost horizontal even without the infinitesimal labor market assumption.

where L^E_{sd} is the number of employed in sector s and region d and L^U_{sd} that of unemployed.[20] Since the productivity threshold is endogenous, the job separation rate is also endogenous here: a job match separates due to either the exit shock or drawing a low productivity level. The job finding rate in this model is also concerned with the job separation rate: higher job separation rate through higher R_{sd} lowers the job finding rate because it becomes less likely to reach a wage agreement.

According to the properties of Gumbel distribution, I express the distribution of the unemployed as follows:

$$\frac{L^U_{sd}}{\lambda_0 \sum_{d'} L^U_{0d'} + \sum_{s' \neq 0,\ d'} L^U_{s'd'}} = \frac{\exp \frac{U_{sd}}{\nu}}{\sum_{s',\ d'} \exp \frac{U_{s'd'}}{\nu}}. \tag{22}$$

And that of the nonparticipants:

$$\frac{\lambda_0 L^U_{0d}}{\lambda_0 \sum_{d'} L^U_{0d'} + \sum_{s' \neq 0,\ d'} L^U_{s'd'}} = \frac{\exp \frac{U_{0d}}{\nu}}{\sum_{s',\ d} \exp \frac{U_{s'd'}}{\nu}}, \tag{23}$$

where L^U_{0d} is the number of nonparticipants in region d. The extreme-value distributed idiosyncratic shocks drive workers to the labor markets with high values of living without clustering all in those markets. They smooth the distribution of workers and avoid corner solutions: there will not be full specialization for any regions in this model even with straight-lined production possibilities frontier.[21] Again by the properties of the extreme value distribution, the expected value of moving is given by

$$E = \nu \log\left(\sum_{s=0}^{S} \sum_{d=1}^{D} \exp(U_{sd}/\nu)\right). \tag{24}$$

It is a "weighted" average of non-employment values, which include the values of being unemployed and non-participants, across labor markets.

Labor market clears by

$$\sum_{s=1}^{S} \sum_{d=1}^{D} (L^U_{sd} + L^E_{sd}) + \sum_{d=1}^{D} L^U_{0d} = \bar{L}, \tag{25}$$

where $\bar{L}$ is the total population and normalized to 1.

[20] The steady state makes it much easier to derive the relationship between L^E and L^U, which is different from the dynamic version. Derivation of (21) from the dynamic environment can be found in Appendix A.6.2.

[21] Davidson and Matusz (2004) assume local non-tradable in production function to generate incomplete specialization.

Non-tradable market clearing

The non-tradable market clearing for region d is

$$p_{1d}A_{1d}\mathbb{E}(x \mid x > R_{1d})L_{1d}^{E} = \alpha_1 I_d, \tag{26}$$

where I_d is the total regional income and defined as:

$$I_d \equiv \sum_{s=1}^{S} \left(\mathbb{E}(w_{sd}(x) \mid x > R_{sd})L_{sd}^{E} + b_d L_{sd}^{U}\right) + \omega_d L_{0d}^{U}.$$

All agents with income spend the same fraction α_1 of their income on the non-tradable goods.

Definition 1. A steady state equilibrium consists of labor market tightness $\{\theta_{sd}\}_{s=1,d=1}^{S,D}$, reservation productivity $\{R_{sd}\}_{s=1,d=1}^{S,D}$, labor distribution $\{L_{sd}^{U}\}_{s=0,d=1}^{S,D}$, $\{L_{sd}^{E}\}_{s=1,d=1}^{S,D}$, non-tradable goods prices $\{p_{1d}\}_{d=1}^{D}$, values of non-employment $\{U_{sd}\}_{s=0,d=1}^{S,D}$, the expected value of moving E, such that equations (17) - (26) hold given the exogenous tradable goods prices $\{p_s\}_{s=2}^{S}$.

3.3 A stylized theory

This section simplifies the model described earlier to develop a stylized framework that can explain the empirical findings. In the simplified model, there is no non-tradable or home production sector. Unemployed workers can move freely across sectors but remain subject to idiosyncratic shocks when migrating between regions. In this way can the simplified model generate complete specialization for each region, as discussed below. generate Vacancy costs are equalized across sectors and regions to prevent confounding effects from exogenous variables. To create an environment with symmetric regional labor market outcomes in the initial equilibrium—resembling regression models with controls—I assume symmetric comparative advantages across regions. In other words, each region has an equal degree of comparative advantage in the sector at which it is the best. This simplification is formalized in the following assumption:

Assumption 1. *$\alpha_1 = 0$, $e_{sd} \equiv e$, and no home production sector, i.e., no non-participation. The unemployed workers can move freely across sectors but are still subject to idiosyncratic shocks when migrating across regions. Let $\rho_d \equiv \max_s \ \rho_{sd}$ equalizes across regions.*

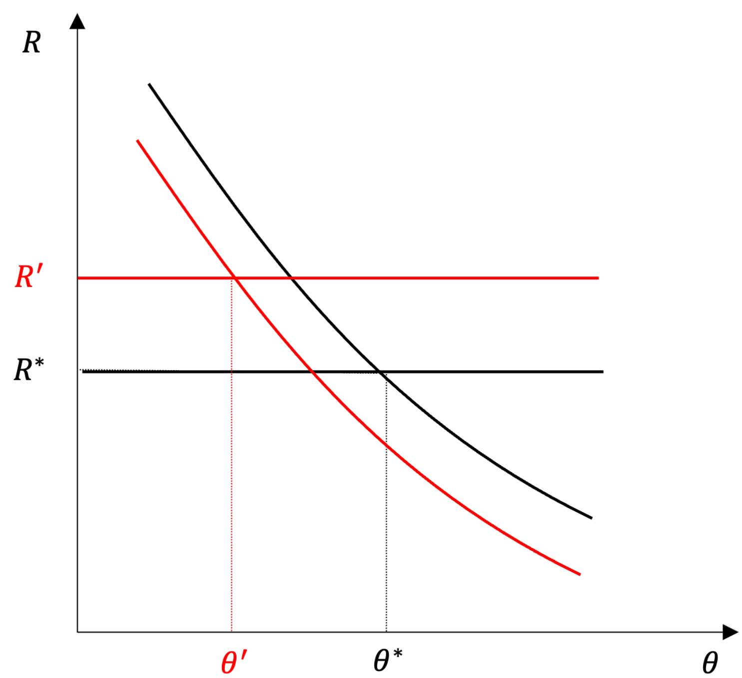
The real marginal revenue of effective labor of a sector in a region, ρ_{sd}, determines labor market tightness and reservation productivity as discussed above. The following lemma first characterizes the equilibrium of labor market variables:

Lemma 1. *In the model with Assumption 1 imposed, the marginal revenue of effective labor ρ_{sd} uniquely pins down θ_{sd} and R_{sd} for the labor market of sector s region d ($\forall s,\ d$). θ_{sd} is increasing with ρ_{sd} while R_{sd} is decreasing with ρ_{sd}.*

Proof. See Appendix A.6.3. □

A trade shock, that is, a fall in the price, can affect labor market variables in the partial equilibrium shown in Figure 6, by altering both job creation and destruction conditions. Suppose there is a fall of sectoral price. The job creation condition worsens since the expected real profits decline, deterring firms from posting vacancies. Therefore, the job condition curve moves downward to the red one as shown in Figure 6. On the other hand, declined profits makes it harder to sustain a wage agreement between employee and employer. Therefore, the job destruction curve moves upward. Altogether, a decrease in sectoral price leads to lower labor market tightness and a higher productivity threshold in the partial equilibrium: job finding rate is lower and job separation rate is higher.

Figure 6: Trade shock in a partial equilibrium of a labor market



Notes: The black curves describe the initial equilibrium while the red are for the partial equilibrium after a trade shock.

The simplified model explicitly demonstrates that real marginal revenue of effective labor determines labor shares. Lemma 1 indicates that a labor market with a higher ρ has a higher value of being unemployed, which attracts more unemployed workers, as shown in equation

(22). Consequently, the number of employed workers increases due to a larger pool of unemployed individuals, higher market tightness, and a lower productivity threshold. Intuitively, regions concentrate their labor in sectors where they have a comparative advantage. The straight-lined production possibilities frontier implies complete specialization within each region, where all unemployed agents focus on one sector for job opportunities. Each region, therefore, specializes in the sector where it has the greatest absolute advantage. Lemma 2 directly follows from Lemma 1 under Assumption 1.

Lemma 2. *In the model with Assumption 1 imposed, each region completely specializes in the sector that has the highest ρ_{sd}. All regions have the same levels of θ and R.*

Proof. See Appendix. □

Complete specialization can simplify the regional labor market outcome without the need to aggregate across all different sectors if incomplete specialization presents: the labor market outcome in a region will then be determined by only one sector in this region. Due to symmetric comparative advantage, all regions will have the same levels of θ and R, hence same employment in the beginning. The simplified model makes a prediction regarding the relative effects of a trade shock. The following proposition compares the responses of two initially symmetric labor markets to a trade shock:

Proposition 1. *In the model with Assumption 1 imposed, for any labor markets 1 and 2. When there is a trade shock such that $d \ln p_1 < 0$, labor markets will respond by $d \ln R_1 - d \ln R_2 > 0$, $d \ln \theta_1 - d \ln \theta_2 < 0$.*

Proof. See Appendix A.6.3. □

Proposition 1 states that when a labor market experiences a direct trade shock, manifested as a decline in the price of its output, its job separation rate will increase relative to another labor market that initially had the same labor market conditions but did not experience the shock. Furthermore, its job finding rate will decrease relative to the unaffected labor market. These results are consistent with the empirical findings presented in this paper.

To understand Proposition 1, it is helpful to compare the relative changes in job creation and destruction conditions. First, sectoral price changes alter final prices, which in turn affect real marginal revenues. In this stylized model, since all goods are tradable at no cost, final prices are equalized across regions. The labor market directly impacted by a price decline will have a lower real marginal revenue compared to the unaffected market. As a result, the job creation conditions are relatively worse in the market experiencing the price shock.

Second, while the direction of change in the expected outside option value is indeterminate in general equilibrium, it remains constant across all labor markets. For any given new expected migration value, the ratio of reservation wage to marginal revenue is higher in the labor market directly impacted by the price decline. Consequently, the job destruction condition is more severe in the directly shocked labor market, characterized by a higher job destruction curve than in the unaffected market. Together, these factors lead to the outcomes described in Proposition 1.

Last but not the least, imperfect mobility across regions matters in delivering regional differences in labor market outcomes. One can easily verify that if there is no idiosyncratic shocks across regions, labor market tightness responses will be equalized: $d \ln \theta_1 = d \ln \theta_2$ through equalized value of being unemployed.

3.4 Discussion

This section discusses how the full model differs from the stylized one and how additional elements can impact the results.

Expected outside option value

The simplified model predicts complete specialization, but when agents are subject to idiosyncratic shocks when moving across sectors, specialization becomes incomplete. As a result, regional labor market outcomes depend on the performance of all sectoral labor markets within a region. To capture these differential outcomes, sectoral changes for each region must be aggregated, a process that is not explicit in the current framework and is left for simulation in the following section.

Consider a scenario where each region has only one highly productive sector, perhaps due to that sector's significantly greater productivity compared to others in the region. In such a case, regional outcomes would resemble the sectoral labor market outcomes predicted by Proposition 2. Regions with a high concentration of sectors affected by trade shocks would, therefore, experience worse job finding rates and higher job separation rates compared to others.

Additionally, the change in the expected outside option value is analytically indeterminate. This value is influenced by the non-employment values across all labor markets, which in turn are affected by factors such as unemployment benefit and labor market tightness. While some markets might experience lower labor market tightness, others could see the opposite. Consequently, the change in the aggregator, as described in equation (24), remains ambiguous.

Non-tradable goods

Introducing non-tradable goods, such as housing or local services, into the model helps explain differential non-participation effects. When a region is exposed to a trade shock, out-migration occurs, and total income in the region declines. This reduction in income leads to decreased demand for regional non-tradable goods, causing their prices to fall. As a result, the cost of living in the directly impacted regions becomes relatively lower compared to other regions. Non-participants may find it more attractive to reside in these impacted regions, even if they receive the same level of income across regions. In the absence of non-tradable goods, variations in non-participant income would be necessary to account for the observed differences in non-participation rates.

Incorporating non-tradable goods markets can reduce inter-regional migration in response to a labor demand shock. Although unemployed individuals in this model receive utility flow rather than income, the cost of living still influences their decision-making, as shown in equation (17). Lower prices for non-tradable goods can offset the reduced utility from fewer job opportunities, narrowing the value differences across regions and decreasing the incentive to migrate.

4 Calibration

To quantify the effects of the China trade shock on the U.S. local economy, it is necessary to match the model parameters to the data and identify the counterfactual shock. The first step is to define the "sectors" that will be analyzed in the quantitative exercise. Next, I calibrate the model using data from the year 2000, which serves as the initial period. In this small open economy, tradable sector prices reflect the trade shock. I will outline the process of calibrating these prices before and after the shock.

4.1 Define “sectors”

This section discusses the "sectors" used for calibration and counterfactual analysis. I group all manufacturing industries into four categories based on the quantiles of industrial net import penetration from China. To do this, I calculate the changes in net imports—defined as U.S. imports from China minus exports to China—between 2000 and 2007 for each Census industry. These changes are then normalized by industrial employment in 2000 to determine the net import penetration from China for each industry. Based on these values, I categorize the industries into four sectors according to their quantile distribution. Specifically, the first tradable sector, or the least exposed sector, includes industries with net import penetration below the 25th percentile. The second sector covers those between the 25th and 50th percentiles, and so on for the subsequent sectors.

First, I select the Census industry code as the most granular level for constructing measures because it offers the most detailed industry classification with available labor transition data from the CPS and ACS. Second, I focus on net import penetration rather than import penetration to align with the framework of a small open economy. In this model, total demand and output for a sector are determined by sectoral prices. If demand exceeds output, it implies that agents in this economy will import from the rest of the world to meet the excess demand. Conversely, if demand falls below output, they will export the surplus.

Thus, net import serves as the most appropriate data counterpart for international trade in this model. Additionally, grouping industries by quantiles reduces within-sector import penetration variation and computational complexity. Existing quantitative trade research often classifies industries into sub-sectors based on product type (e.g., Caliendo et al. (2019)). However, substantial variations in import penetration can still exist within sectors defined solely by product type, potentially obscuring important insights in quantitative analysis. By grouping industries based on quantiles, the average within-sector import penetration variance can be reduced to as little as one-quarter of that observed in the 12 manufacturing sub-sector case.

This dimensionality issue is particularly significant for the model in this paper compared to those in existing literature. In models solvable by exact hat algebra methods, researchers do not need to calibrate or estimate sectoral or regional parameters, such as productivity. However, this model cannot be solved using that method. Furthermore, most data moments, such as labor shares, can only be generated after solving the full model. Therefore, reducing the number of sectors aids in making the calibration process more computationally feasible.[22]

One potential concern with this measure is that the sectors defined in this manner may not align with the conceptual framework of sectors in this model. It is possible that workers can switch jobs between sectors as easily as they can within sectors. To assess this, I calculated the job switching rates within and between sectors. The results show that, on average, 65% of workers remain in the same sector, while 35% switch to other sectors over the years. This is comparable to the case of 12 manufacturing sectors, where approximately 70% of workers stay within the same sector and 30% switch to others.[23]

[22]A reason to define manufacturing sub-sectors by the product nature is that people can speak to input-output linkage between granular industries or sectors. I do not consider input-output linkage as it does not fit well in a small open economy and I leave it to the future research.

[23]The calculation is based on the annually matched CPS data. A concern arises from such a calculation: the high within-sector switching rates might result from grouping a large number of industries together and the fact that people primarily switch jobs within industries rather than across industries in a sector. In other words, it might be difficult to switch jobs across industries within a sector. But because people switch jobs

4.2 Calibrate parameters

The sources and data moments for parameter calibration are shown in Table 2. Among the parameters that are not calibrated in this paper, I equalize the market tightness elasticity η to firm bargaining power $1-\beta$ to avoid search externalities (Hosios (1990)). The regions this paper looks into are 50 states in the U.S., excluding DC. All the data moments are measured from the data in 2000.

The tradable sectoral prices in the initial equilibrium are calibrated based on sectoral net import penetration in 2000, allowing for trade deficits. The least exposed sector (sector 2) is treated as the numeraire in the initial equilibrium, with its price set at 1. Trade deficits are incorporated into the model as an additive term to total income when purchasing tradable goods. I derive the ratio of net imports to national income for this sector from the data and calibrate the trade deficit multiplier to match this ratio. Allowing for trade deficits improves the model's alignment with net import data.

For the other tradable sectors, I calibrate the prices to reflect the ratios of net import penetration—defined as net imports normalized by sectoral employment—relative to the least exposed sector. The remaining parameters are calibrated within the context of this model. All moments are generated simultaneously by solving the full model, ensuring a match with the data counterparts, as shown in the final column of Table 2.

There are 607 parameters to calibrate with the same number of data moments as shown in Table 2, collected in the vector

$$\mathbf{\Omega} = \left(m, \sigma, \delta, \lambda_0, \{b_d\}_{d=1}^{50}, \{\omega_d\}_{d}^{50}, \{A_{sd}\}_{s=1,d=1}^{5,50}, \{e_{sd}\}_{s=1,d=1}^{5,50}, \{\alpha_s\}_{s=1}^{5}, \{p_s\}_{s=2}^{5}\right).$$

These are calibrated using the method of simulated moments. Specifically, let $\bar{\mathbf{m}}$ be a vector of data moments that the model is designed to match and $\mathbf{m}(\mathbf{\Omega})$ as the vector of model-generated counterparts to these statistics. The calibrated parameters are given by

$$\hat{\mathbf{\Omega}} = arg\min \ \left((\bar{\mathbf{m}} - \mathbf{m}(\mathbf{\Omega}))/\bar{\mathbf{m}}\right)' \left((\bar{\mathbf{m}} - \mathbf{m}(\mathbf{\Omega}))/\bar{\mathbf{m}}\right).$$

Since data moments are different in magnitudes with some being rates and others counts, I

within industries, and there are many industries within these sectors, we observe high within-sector switching rates. To address this concern, I conduct the following validation exercise. First, I randomly group industries evenly into four groups one million times. Each time, I calculate the summation of within-group off-diagonal switching rates for these groups, measuring the ease of job switching within sectors. Finally, I compare the median of the summed within-group off-diagonal switching rates from one million exercises to that obtained from the group this paper uses. The within-group off-diagonal switching rates are significantly higher than the median from the random exercise—about 7:5. This indicates that the within-sector switching rates are meaningfully high. Therefore, these two validation exercises establish the plausibility of this definition of sectors.

minimize the sum of squared percentage distances from data moments to model-generated moments as above. The calibrated results are shown in Table 2. The average absolute percentage distance between model-generated moments and the actual ones is about 5%.[24]

4.3 Identify the China trade shock

The counterfactual shocks studied in this paper are the trade shocks resulting from China's productivity increases between 2000 and 2007. However, the observed changes in U.S. net imports are not solely attributable to the China shock, despite its significance. Productivity shocks from other countries, as well as domestic demand shocks, may also contribute to the observed import changes. To accurately isolate the China trade shock, this paper first identifies the portion of net import changes specifically caused by the China shock. This is essential because the parameters that transmit the trade shocks in the model—namely, the tradable sectoral prices—are calibrated based on sectoral net imports.

Table 2: Calibrated Parameters

Parameters	Description	Value	Source
r	Time discount rate	0.01	4% annual interest rate
η	Market tightness elasticity	0.5	Standard
β	Worker bargaining power	0.5	Standard
ν	Gumbel distribution	5.34	Caliendo et al. (2019)
			Matched moment
m	Matching function shifter	0.629	Aggregate job market tightness 0.55
σ	Job productivity distribution	1.071	Std of wage over average wage
δ	Exit shock	0.0008	Aggregate job separation rate
λ_0	Nonparticipants moving chance	0.874	Transition rate out of nonparticipation
$\{b_d\}$	Unemployment benefit		Regional unemployment rate
$\{\omega_d\}$	Nonparticipation income		Nonparticipants distribution
$\{A_{sd}\}$	Sector-region productivity		Employment shares
$\{e_{sd}\}$	Real vacancy cost		Job separation rates
$\{\alpha_s\}$	Expenditure shares		Final use shares from IO table
$\{p_s\}$	Tradable sectoral prices		Net imports

Notes: Aggregate job market tightness 0.55 comes from JOLTS between 2000 and 2001. The transition rate from nonparticipation to unemployment is calculated from CPS from 1998 to 2000. The other labor market data moments, including the ratio of overall standard deviation of wage over average wage, are calculated based on data from Census 5% in 2000. The Cobb-Douglas preference parameters are essentially sectoral expenditure shares that are from BEA input-output table in 2000. The net import data are from the US custom data in 2000.

[24] More details on calibration can be found in Appendix A.7.

I adapt the method used in Caliendo et al. (2019). For each trading partner c of the US, I run the following regression:

$$\Delta NM_i^c = \alpha_0^c + \alpha_1^c \Delta CNEX_i + u_i, \tag{27}$$

where ΔNM_i^c is the changes in the net import of the US from country c in SIC industry i between 2000 and 2007, $\Delta CNEX_i$ the changes in the export of China to the 8 developed economies, which are the same ones in the empirical part, in SIC industry i. One can think of the changes in the export of China to 8 other developed economies as a proxy to China's productivity (or trade costs) shocks.

Next, I use the fitted left-hand-side from regression (27) across industries and countries, $\{\widehat{\Delta NM_i^c}\}_{i,c}$, to construct the sectoral level predicted changes as follows

$$\widehat{\Delta NM_s} = \sum_{i \in s} \sum_c \widehat{\Delta NM_i^c}. \tag{28}$$

The reason for running equation (27) across countries, rather than simply using total imports for each sector, is to account for trade diversion. Imports from some countries may act as substitutes, while others may complement imports from China. This regression helps capture trade diversion across countries induced by the China shock. [25] Given the nature of a small open economy, the model is not equipped to predict changes in imports from individual countries. However, the procedure outlined above allows for the estimation of changes in imports from various countries as a result of the China shockwhich is proxied by $\Delta CNEX_i$. [26]

The new sectoral prices $\{p'_s\}$ are calibrated to these predicted net import changes. These new sectoral prices capture the trade shocks that are caused by the China shock between 2000 and 2007. The calibrated prices before and after the shock are shown in Table 3. The price shocks are small in magnitude but large enough to generate the predicted changes in sectoral net imports.

[25] Therefore, the estimated α_1^c could take different signs across countries.

[26] In fact, the correlation between the predicted overall net import changes and predicted changes in the net imports from China is 0.99 and they mainly differ in magnitudes at SIC level. See the scatter plot in Appendix A.8.

Table 3: Net imports and calibrated prices

Tradable sector	Before the shock		After the shock	
	Net import	Price	Net import	Price
1	\$ 16.67 m.	1	\$ 51.13 m.	0.9983
2	\$ 116.96 m.	0.9968	\$ 182.31 m.	0.9950
3	- \$ 26.08 m.	0.9964	\$ 75.89 m.	0.9945
4	\$ 208.46 m.	0.9986	\$ 322.93 m.	0.9929

Notes: The tradable sectors are constructed as discussed in section 4.1. The net imports before the shock are calculated based on the US custom data in 2000. The net imports after the shock are predicted using regression 27. The prices are calibrated with the first tradable sector as the numeraire.

5 The effects of the China shock

This section presents the results predicted by the quantitative model on how the China trade shock affects U.S. regional labor markets, particularly at the state level. The focus is on the effects on unemployment and its two key determinants: job finding and job separation rates. Additionally, the model provides predictions on how the welfare of different types of agents is affected and how inequality evolves as a result. As previously discussed, the initial steady-state equilibrium reflects the observed conditions in 2000, and the model's parameters are calibrated accordingly. I then solve the model using updated sectoral prices that capture the China trade shock. The new steady-state equilibrium is compared to the initial one, allowing for the calculation of predicted changes in all relevant variables.

5.1 Labor market effects

The China trade shock leads to increased unemployment and job separation rates across most states, while reducing job finding rates in a majority of states. Figure 7a shows that the changes in unemployment rates due to the shock range from -0.01 to 0.32 percentage point. Hawaii, the least exposed state, is the only region where the unemployment rate slightly declines. States in the Great Lakes region experience the largest increases in unemployment rates, while the Pacific region, which is also highly exposed to the China shock, sees notable increases in unemployment. Many of these changes are substantial, especially considering that the unemployment rate was around 5% in 2000.

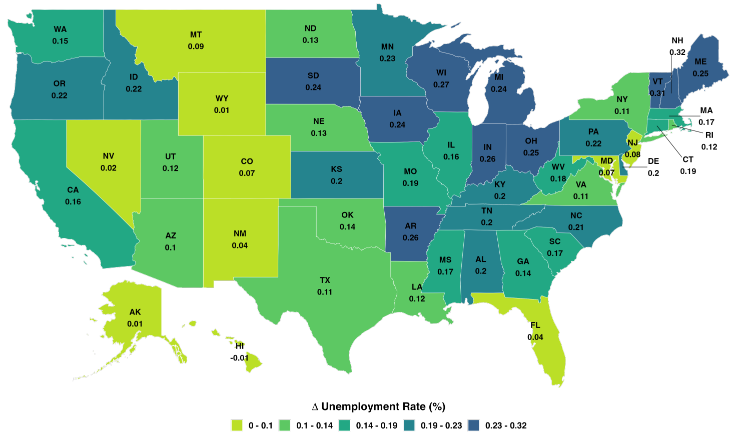
States with larger increases in unemployment rates tend to have larger increases in job separation rates and decreases in job finding rates, as illustrated in Figures 7b and 7c. In these states, it becomes more difficult for workers to find employment and easier for them to lose their jobs. A significant number of states do show higher job finding rates, but overall, the changes in unemployment rates align more closely with changes in job separation rates. On aggregate, the China trade shock raises the U.S. unemployment rate by 0.18 percentage point.

The predicted changes are consistent with the relative effects observed in the empirical analysis. In Figure 8, I plot the predicted changes in these labor market variables against import penetration levels, all generated by the model, along with fitted trend lines. The trade shock significantly increases unemployment and job separation rates in the more exposed states compared to the less exposed ones. While some states do experience higher job finding rates after the shock, the more exposed states see smaller increases or larger decreases in job finding rates compared to their less exposed counterparts.

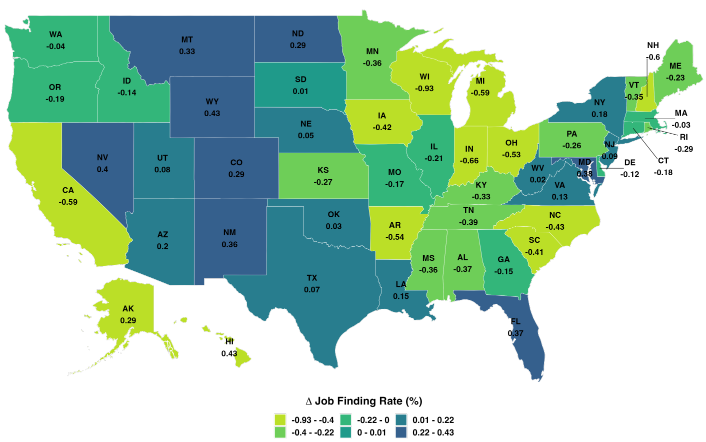
To provide a comprehensive view of the employment effects, the model also examines how labor nonparticipation responds to the trade shock. Nonparticipation rates, defined as the number of nonparticipants over the working-age population, rise universally following the shock, as shown in Figure 9a. A comparison of Figures 9a and 9breveals that these increases in nonparticipation rates largely correspond to decreases in employment rates, with the magnitudes of nonparticipation rate increases closely matching those of employment rate decreases.

Figure 7: Regional labor market effects

(a) Predicted changes in unemployment rates



(b) Predicted changes in job finding rates



(c) Predicted changes in job separation rates

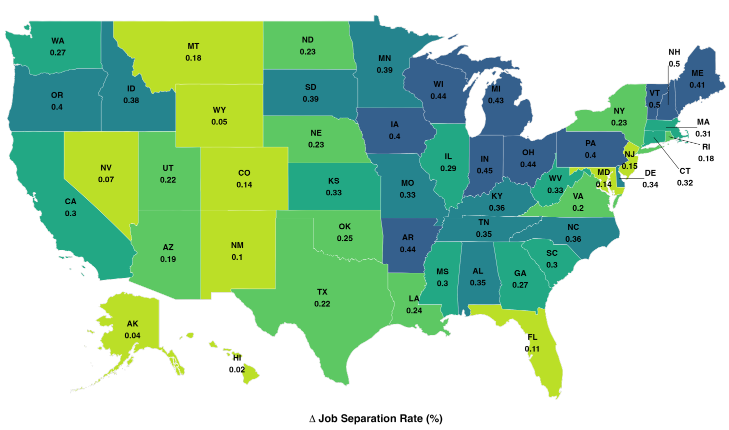
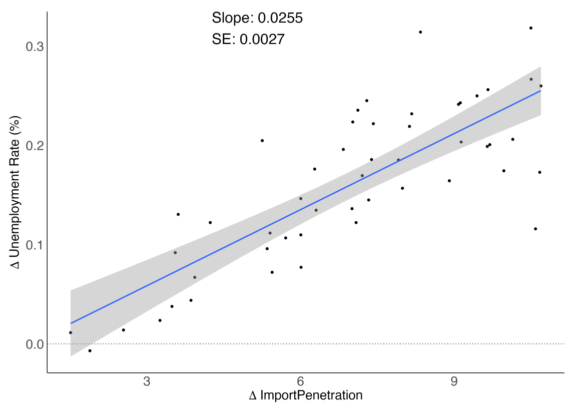
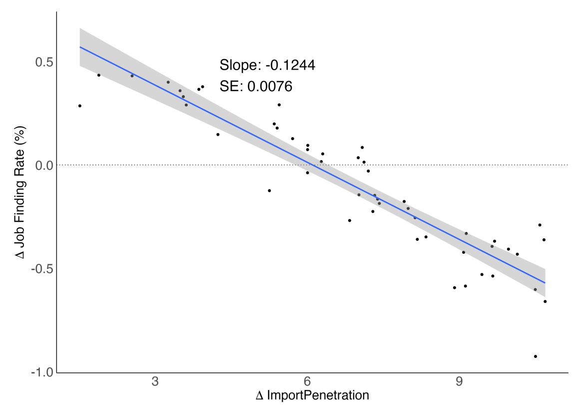


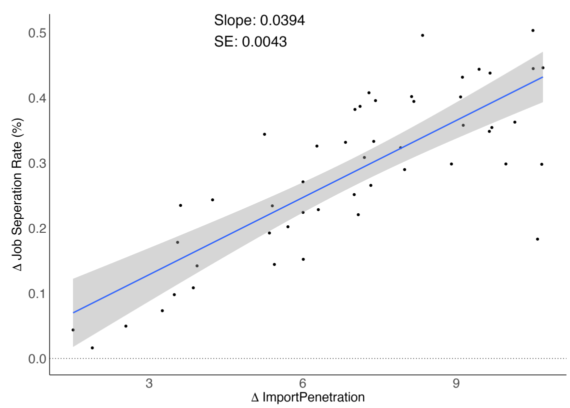
Figure 8: Predicted changes in labor market outcome and import penetration



(a) Predicted changes in unemployment rates vs IP



(b) Predicted changes in job finding rates vs IP

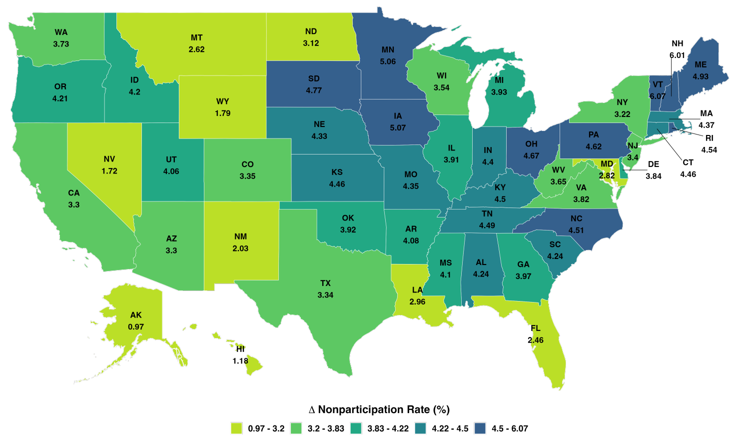


(c) Predicted changes in job separation rates vs IP

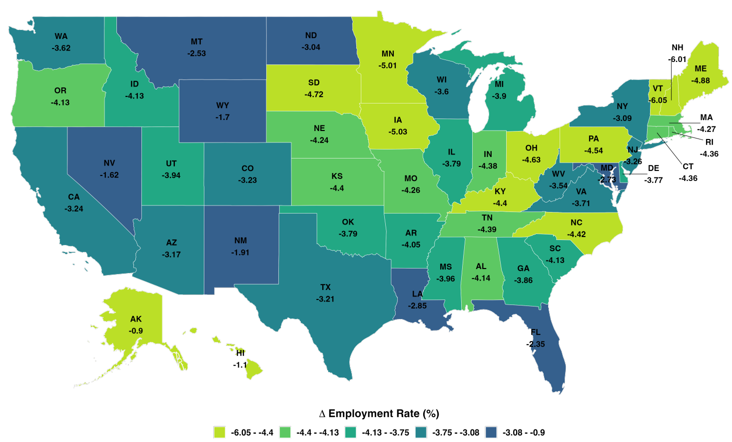
Given that the China trade shock primarily impacts the manufacturing sector, I further examine changes in manufacturing employment rates. As shown in Figure 9c, all states experience a decline in manufacturing employment relative to the working-age population as a result of the shock. These declines in manufacturing employment account for the majority of the overall employment drop, as the magnitudes are quite similar. Overall, the ratio of manufacturing employment to the working-age population falls by 27%. This accounts for 87% of the total decline in manufacturing employment observed between 2000 and 2007, covering approximately one-third of the observed decline during this period. These predicted changes are also consistent with the relative effects found by ADH: the more exposed regions have higher nonparticipation rates and lower employment and manufacturing employment rates compared to the less exposed ones. The relationship between these variables and import penetration is shown in Figure 19 in the Appendix.

Figure 9: Regional labor market effects on nonparticipation and employment

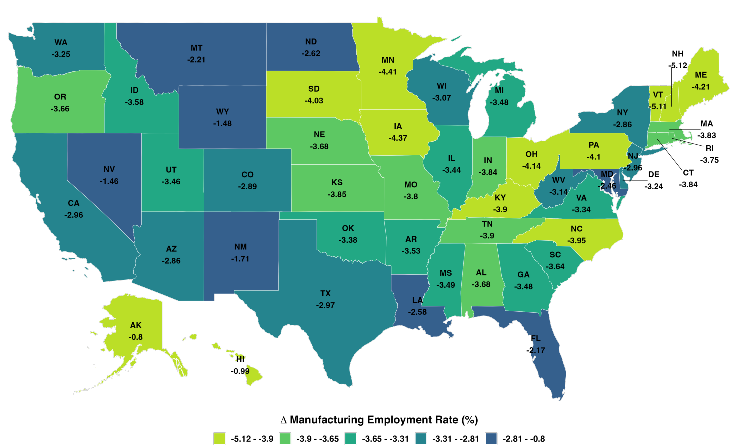
(a) Predicted changes in nonparticipation rates



(b) Predicted changes in employment rates



(c) Predicted changes in manufacturing employment rates



Labor market tightness and reservation productivity responses to trade

To understand the underlying mechanism that delivers these results, let us first turn to the two equations that determine the labor market variables for each sector and region. The following two equations are log-linearization of equation (19) and (20) under the parameterization in calibration:

$$\widehat{\theta_{sd}} = \varepsilon^{\theta}_{\rho}(R_{sd})\widehat{\rho_{sd}} - \varepsilon^{\theta}_{E}(R_{sd})\widehat{E}, \tag{29}$$

$$\widehat{R_{sd}} = \varepsilon^{R}_{E}(R_{sd})\widehat{E} - \varepsilon^{R}_{\rho}(R_{sd})\widehat{\rho_{sd}}, \tag{30}$$

where the detailed forms of those (positive) elasticities are as follows:

$$\varepsilon^{\theta}_{\rho}(R_{sd}) = \frac{1}{1-\eta}\left(1 + \frac{(1-F(R_{sd}))(R + \frac{1-\delta}{1+r}\int_{R_{sd}}^{\infty}(x-R_{sd})dF(x))}{\int_{R_{sd}}^{\infty}(x-R_{sd})dF(x)(\frac{r+\delta}{1+r} + \frac{1-\delta}{1+r}F(R_{sd}))}\right),$$

$$\varepsilon^{\theta}_{E}(R_{sd}) = \frac{1}{1-\eta}\frac{(1-F(R_{sd}))(R + \frac{1-\delta}{1+r}\int_{R_{sd}}^{\infty}(x-R_{sd})dF(x))}{\int_{R_{sd}}^{\infty}(x-R_{sd})dF(x)(\frac{r+\delta}{1+r} + \frac{1-\delta}{1+r}F(R_{sd}))},$$

$$\varepsilon^{R}_{E}(R_{sd}) = \varepsilon^{R}_{\rho}(R_{sd}) = \frac{R + \frac{1-\delta}{1+r}\int_{R_{sd}}^{\infty}(x-R_{sd})dF(x)}{R_{sd}((\frac{r+\delta}{1+r} + \frac{1-\delta}{1+r}F(R_{sd}))}.$$

The intuition of how labor market tightness and reservation productivity change with real revenues per effective labor and outside option value has been discussed in Section 3. Notice that the change in real revenues per effective labor is equivalent to the change in the relative price:

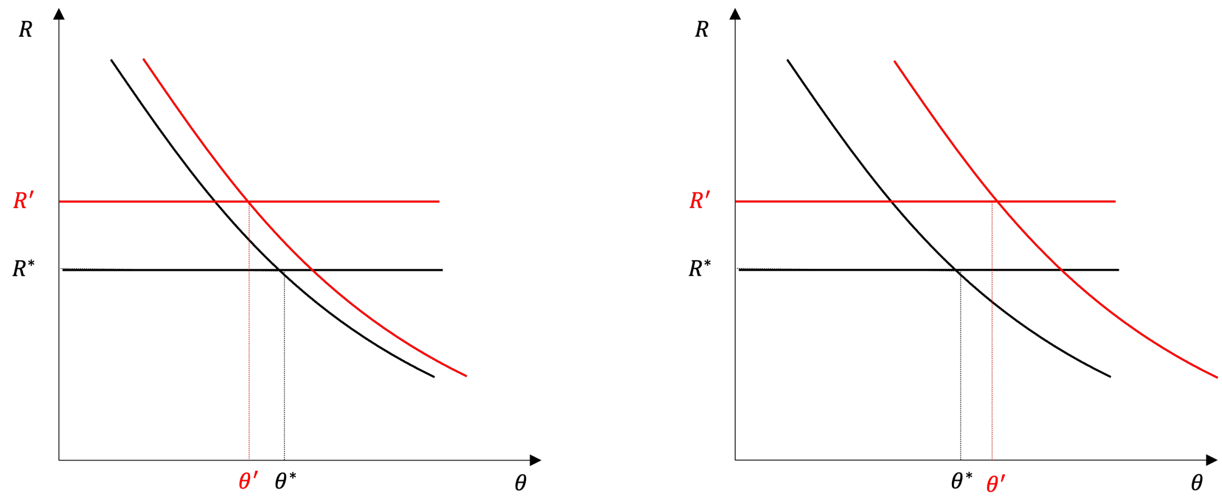
$$\widehat{\rho_{sd}} = \widehat{p_{sd}} - \widehat{P^f_d} = \widehat{p_{sd}} - \left(\alpha_1\widehat{p_{1d}} + \alpha_2\widehat{p_2} + \alpha_3\widehat{p_3} + \alpha_4\widehat{p_4} + \alpha_5\widehat{p_5}\right). \tag{31}$$

In an open economy model, an increase in the relative price usually implies terms of trade improvement. Even if there is improvement in terms of trade for a sector in a region, there can still be worse labor market outlook through the channel of outside option value. Higher outside option value makes it harder for wage bargaining to succeed, casting downward pressure on employment. Figure 10a shows a case when there is a small increase in ρ with relatively large improvement in the outside option value. There is a reduction in labor market tightness even with a better job creation condition. If the increase in ρ is large enough, there will be higher labor market tightness to counter the higher reservation productivity, as shown in Figure 10b. Then there will be higher job finding chances and job separation rates at the same time, which is what some states have experienced as shown above.

Figure 10: Partial equilibrium responses

(a) Small increase in real revenues per effective labor

(b) Large increase in real revenues per effective labor



With equation (29) and (30) in mind, one can better understand how the manufacturing sector labor markets respond to trade. In this model, all tradable sector prices decline, reflecting the trade shock. Most states experience lower relative tradable sector prices (see panels (b) - (e) of Figure 20 in the Appendix). These lower relative prices weaken job creation conditions and exacerbate job destruction in the manufacturing sectors. Consequently, labor market tightness decreases, and reservation productivity increases for the manufacturing sectors (see panels (b) - (e) of Figures 21 and 22 in the Appendix). Overall, the labor market conditions in the manufacturing sectors deteriorate, resulting in lower job finding rates, higher job separation rates, and increased unemployment.

Shock propagation to the nontradable sector

All states experience a reduction in nontradable prices, as shown in Figure 11a. Trade-induced sectoral shifts increase nontradable output more than nominal income, particularly given that the trade shock in this model functions as a negative nominal shock. Consequently, nontradable goods prices fall. However, the relative prices of nontradable goods rise, as shown in Figure 11b, due to the relatively small magnitude of the price decreases. Despite this, most states still face lower labor market tightness and higher reservation productivity. This outcome relates to the earlier discussion on how a higher outside option value can offset the positive effects of relative price improvements on the labor market. The quantitative results show that the outside option value increases by 0.06%.

Before delving into the reasons behind this rise in the outside option value, it is important to compare the predicted changes in labor market tightness and reservation productivity across sectors. As the sector with larger and more frequent increases in real revenues per unit of effective labor (see Figure 20 in the Appendix), the nontradable sector shows better labor market outcomes compared to others (see Figures 21 and 22 in the Appendix).In fact, a significant number of states experience higher employment in the nontradable sector following the shock, as shown in Figure 12.

However, the nontradable sector labor markets are not strong enough to improve overall local labor market conditions. In fact, some states experience declines in nontradable employment. States with higher import penetration tend to have less productive nontradable sectors to begin with. As a result, these sectors fail to attract sufficient workers. Following the shock, given the small number of unemployed workers searching in these markets (see panel (c) of Figure 24 in the Appendix) and deteriorating labor market conditions, these more exposed states experience reductions in both employment and output in the nontradable sector (see Figure 24 in the Appendix).

Frictional labor matching dampens sectoral labor shifts in this model. As shown in Figure 12, an increased number of unemployed agents are searching for nontradable jobs in most states, leading to greater congestion in the local nontradable job markets. This congestion results in lower labor market tightness. In some states, despite the increased number of unemployed agents in the nontradable sector, the actual number of employed workers decreases due to the effects of congestion.

Higher outside option value, along lower labor participation, also negatively impacts the employment. To understand how the outside option responses to trade, let us first look at the log-linearization of E from (24):

$$\widehat{E} = \frac{1}{E}\left(\sum_{s=1,d=1}^{S,D} \frac{U_{sd}\exp(U_{sd}/\nu)}{\sum_{s=0}^{S}\sum_{d=1}^{D}\exp(U_{sd}/\nu)}\widehat{U_{sd}} + \sum_{d=1}^{D} \frac{U_{0d}\exp(U_{0d}/\nu)}{\sum_{s=0}^{S}\sum_{d=1}^{D}\exp(U_{sd}/\nu)}\widehat{U_{0d}}\right). \tag{32}$$

Higher initial value for a market makes the value change from this market more important to the overall outside option value change. Given the fact that U.S. had a fairly high non-participation rates compared to unemployment rates, one can tell that the nonparticipation values, $\{U_{0d}\}$, are generally larger than the unemployed values, $\{U_{sd}\}_{s\neq 1}$, from (22) and (23). According to (32), the outside option value change is expected to be more affected by how the nonparticipation values change.

As discussed earlier, declining tradable sector prices further reduce nontradable prices, primarily through the supply channel. This leads to a reduction in final good prices across all regions. Consequently, the intra-temporal (indirect) utility for nonparticipants improves in every region, as shown in equation (18). For the unemployed, while they benefit from real income gains, they also face lower labor market tightness in most markets. According to equation (22), the direction of changes in the unemployed's value remains ambiguous. However, the outside option value increases primarily due to higher nonparticipation values (see Figure (25c) in the Appendix).

Even with rising relative prices in the nontradable sector across regions, the higher outside option value still leads to reduced labor market tightness and increased reservation productivity in most nontradable labor markets, as previously discussed (see Figure 10a for a graphic illustration). Alongside worsened job destruction conditions, the number of agents participating in labor markets decreases as a result of higher nonparticipation values.

Higher reservation productivity acts as a double-edged sword: it increases the likelihood of job loss for workers, but it also raises the productivity of surviving job matches (firms). I measure overall productivity as revenue per worker, essentially Total Factor Productivity Revenue (TFPR):

$$TFPR = \frac{\sum_{s=1,d=1}^{S,D} L_{sd}^{E} p_{sd} A_{sd} \int_{R_{sd}}^{\infty} x d\frac{F(x)}{1-F(R_{sd})}}{\sum_{s=1,d=1}^{S,D} L_{sd}^{E}}. \tag{33}$$

It increases by 0.16% after the shock, despite the decline in prices across most sectors and regions.

In a model without productivity improvements, such as R&D, firm entry thresholds govern overall market productivity. Lower real revenues per unit of effective labor and higher outside option values make it more difficult for job matches to form or endure. As a result, higher job output is required to sustain joint surpluses. This prediction aligns with the trade selection effect described by Melitz (2003).

Differential regional trade shock exposure and labor market outcome

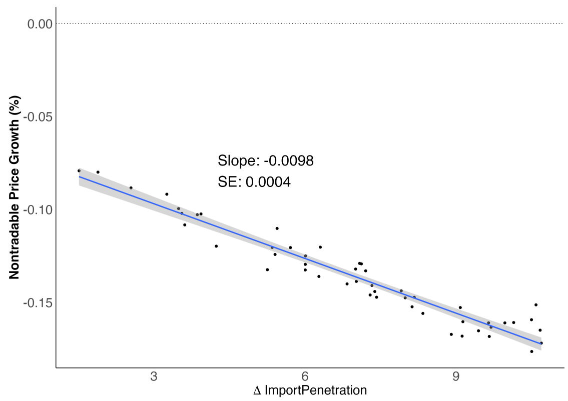
Differential regional exposure to the trade shock arises from the varying sectoral comparative advantages across regions. In this model, both sector-region productivity and vacancy costs contribute to comparative advantages. Regions tend to have larger employment shares in sectors where their productivity is higher and vacancy costs are lower. Since there are no internal trade costs in this model, the sectoral employment composition determines the degree of exposure to trade for each region. Regions with higher levels of import penetration typically have relatively lower productivity in the nontradable sectors.

The fact that income is more sensitive to trade than nontradable output, as shown by comparing panels (a) of Figures 23 and 24, helps explain the relationship between decreases in nontradable prices and trade exposure. This can be understood through the trade-induced sectoral shifts. Within each region, the nontradable sector becomes relatively more attractive than others. In regions with higher import penetration or lower initial nontradable labor shares, these sectoral labor composition shifts are more pronounced, as illustrated in Figure 11e. This shift serves as a buffer against the decline in nontradable output in the more exposed regions, making nontradable output less sensitive to trade shocks.

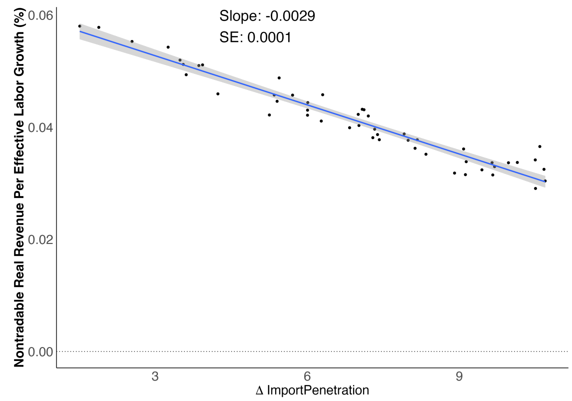
With smaller increases in real revenues per unit of effective labor and larger increases in the nontradable labor share, the nontradable sectors in the more exposed states were not only weaker initially but also experience smaller gains after the shock. Since nontradable sector labor markets are the primary source of potential employment improvements following the shock, the more exposed states exhibit worse overall labor market outcomes.

Figure 11: Nontradable sectoral variables and import penetration

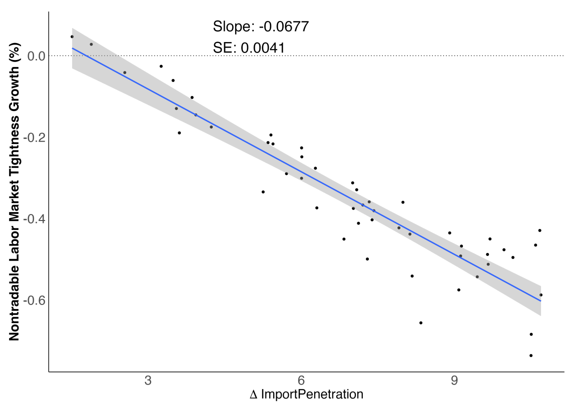
(a) Predicted changes in nontradable prices vs IP



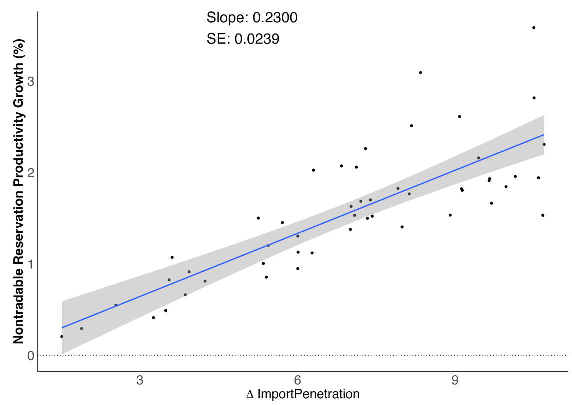
(b) Predicted changes in nontradable real revenues per effective labor vs IP



(c) Predicted changes in nontradable labor market tightness vs IP



(d) Predicted changes in nontradable reservation productivity vs IP



(e) Predicted changes in nontradable labor share vs IP

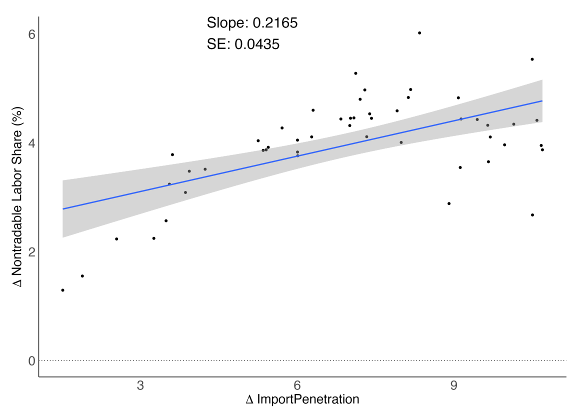
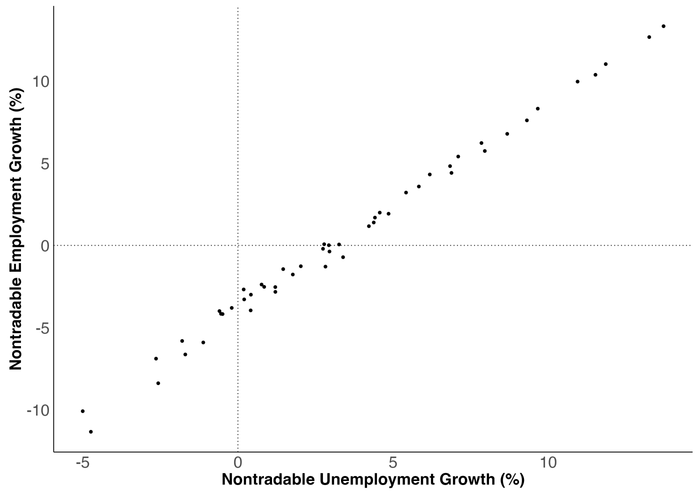


Figure 12: Predicted changes in nontradable employment and unemployment



5.2 Welfare effects

Regardless of worse labor market outlook, the China trade shock leads to welfare gains. The values of being unemployed across sectors and regions are calculated according to (7) and (8). There is, however, not an explicit measure of values of being employed since they depend on drawn productivity. I turn to the average value of being employed in a sector s and a region d for the measure of employed worker welfare:

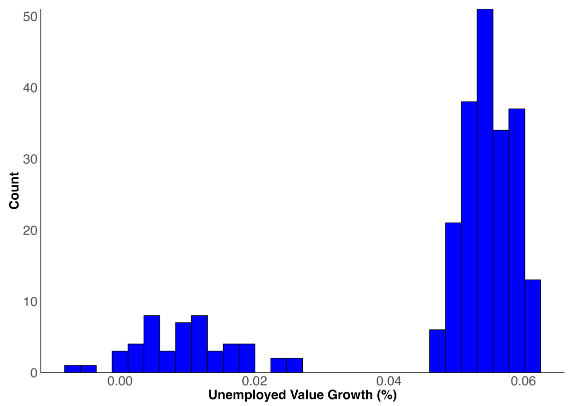
$$\bar{W}_{sd} = \int_{R_{sd}}^{\infty} W_{sd}(x) d\frac{F(x)}{1-F(R_{sd})} = \frac{\beta p_{sd} A_{sd}}{(1+r)P_d^f}\left(\frac{\int_{R_{sd}}^{\infty} x dF(x)}{1-F(R_{sd})} - R_{sd}\right) + E. \qquad (34)$$

Higher reservation productivity increases the average value of being employed in a sector-region mainly through higher expected wage. I first calculate the growth rate of being unemployed and employed in each sector and region. As shown in Figure 13a, being unemployed gets higher values in almost all sectors and regions after the shock. The gains mainly come from the improved outside option value: the growth rates of U_{sd} are mostly smaller than 0.06% which is the growth rate of E. The importance of outside option value in welfare gains has been argued in Artuç et al. (2010). Being employed, on the other hand, is universally better now, as shown in Figure 13b.

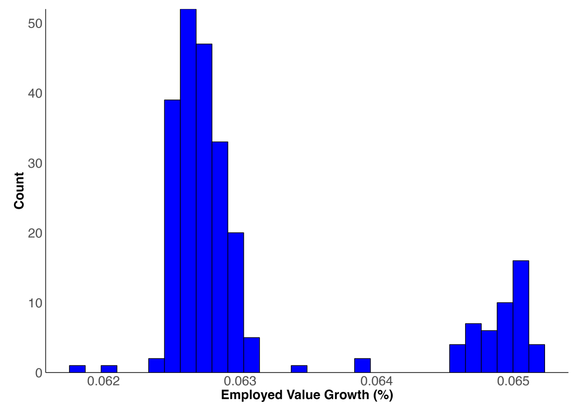
The welfare inequality between the employed and unemployed, measured by $(\bar{W}_{sd} - U_{sd})$, is higher in all sectors and regions as shown in Figure 13c. This is mainly because most labor markets have lower labor market tightness and higher reservation productivity at the same time. The former depresses the value of being unemployed while the latter improves the average value of being employed, hence enlarged gap between the two.

Figure 13: Predicted changes in welfare across sectors and regions

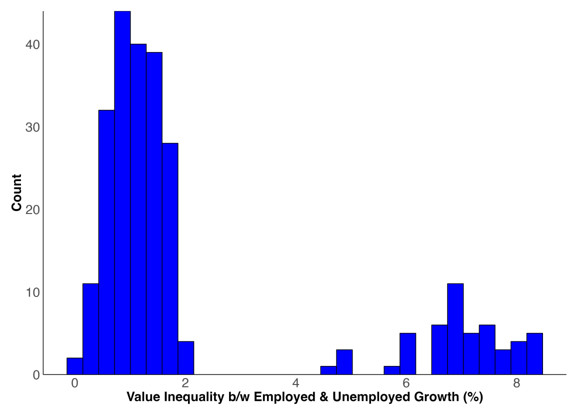
(a) Predicted changes in unemployed values



(b) Predicted changes in employed values



(c) Predicted changes in employed-unemployed value difference

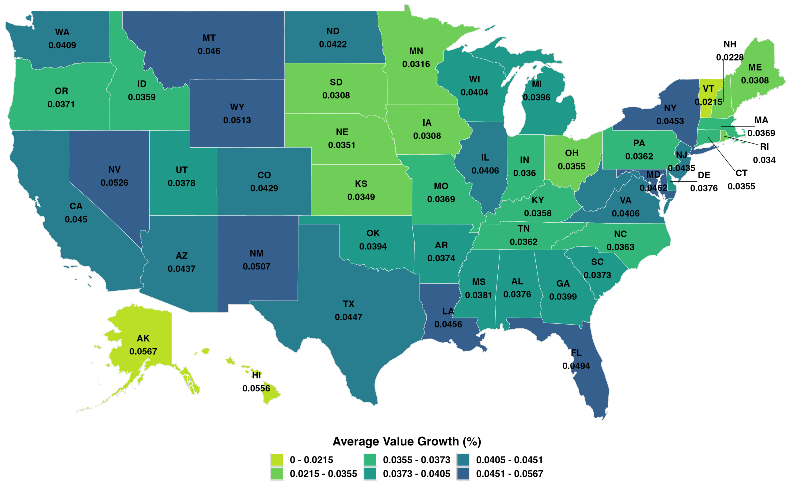


Regional welfare is the average values of agents who live in the region:

$$V_d = \left(U_{0d} L_{0d}^U + \sum_{s=1} (\bar{W}_{sd} L_{sd}^E + U_{sd} L_{sd}^U) \right) / L_d. \tag{35}$$

There are welfare gains in all states, as shown in Figure 14. Overall, the average welfare improvement for the US is around 0.04%. The regional average welfare for the unemployed, employed and nonparticipants all improves due to the shock (see Figure 25 in the Appendix). As shown in Table 13, the states that are more exposed to the China shock enjoy fewer gains in the average welfare. The increases in the average unemployed welfare are also smaller in these states. This is mainly driven by larger decreases in employment rates in these regions. The average employed and nonpartcipation values, on the other hand, increase more in the more exposed states. As discussed above, it is because of larger increase in reservation productivity across sectors and bigger falls in nontradable prices.

Figure 14: Predicted regional average welfare changes



6 Policy counterfactual: subsidizing the manufacturing sectors

This section first shows that the constrained optimal cannot be achieved even with Hosios condition imposed, hence room for policies. Next, I implement a counterfactual analysis of a redistribution tax policy: subsidizing the manufacturing sectors using taxes imposed on the nontradable sector after the shock. The policy aims to restore the pre-shock manufacturing employment level. The results show welfare improvement in addition to lower unemployment compared to the scenario with the trade shock only.

6.1 Inefficiency of the equilibrium

After imposing Hoisios condition, there are still two sources of inefficiency to keep the equilibrium from achieving the constrained efficiency. One is the sector-region migration friction cast by idiosyncratic shocks, and the other is the nontradable sector. I use two simplified models as examples to illustrate how the constrained efficiency can be different from the equilibrium. Detailed description and derivation of models can be found in Appendix A.10.

Migration friction

I simplify the model to one region and leave out the nonparticipation "sector" and nontradable sector. I also abstract from random job-match productivity, hence no endogenous job separation. Local final good price is normalized to 1 in this case. The constrained efficiency is what social planner can achieve subject to frictional matching. The social planner's problem is to choose the distribution of labor and market tightness across sectors in order to maximize the life-time total social output:

$$\max_{\{L^E_{s,t+1}, L^U_{s,t}, \theta_{s,t}\}_{s,t}} \sum_{t=0}^{\infty} \frac{1}{(1+r)^t} \left(\sum_{s=1}^{S} (A_s L^E_{s,t} + b L^U_{s,t} - e_s \theta_{s,t} L^U_{s,t}) \right) \tag{36}$$

$$\begin{gathered} s.t.\ L^E_{s,t+1} = m\theta^{\eta}_{s,t} L^U_{s,t} + L^E_{s,t}(1-\delta),\ \forall s,\ t \\ \bar{L} = \sum_s (L^E_{s,t} + L^U_{s,t}).\ \forall t \end{gathered}$$

The steady-state constrained optimal condition derived from (36) above for a sector s is

$$\eta(A_s - b) - \frac{\delta + r + (1-\eta) m\theta_s^{\eta}}{m\theta_s^{\eta-1}} e_s = 0. \tag{37}$$

If there is free mobility across sectors, the equilibrium condition will be exactly as (37) when the Hosios condition is imposed, that is, $\beta = 1 - \eta$. However, when there are migration frictions caused by idiosyncratic taste shocks, the equilibrium condition will be:

$$(1-\beta)(A_s - rE) - \frac{r+\delta}{m\theta_s^{\eta-1}} e_s = 0, \tag{38}$$

where $E = \nu \log \left(\sum_s \exp\left(\frac{b + e_s\theta_s\beta/(1-\beta) + E}{\nu(1+r)}\right)\right)$. It will not align with (37) even with $\beta = 1-\eta$.

The inefficiency of a search and matching model centers around the congestion that workers and firms cause to each other. The idiosyncratic shocks act as an additional congestion force to the model. Therefore, Hosios condition that was originally derived in an environment without such a friction falls short of delivering the constrained optimal in this model. One might argue that the constraint on the social optimal analysis can be extended to include the idiosyncratic-shock-driven migration frictions. But there is another congestion force at play in this model as discussed below.

Nontradable sector

I simplify the model to multiple regions with only one nontradable sector in each region. Again there is no nonparticipation "sector" nor endogenous job separation. Moreover, the unemployed receive zero unemployment benefit to simplify the demand side. The social planner's problem is as follows:

$$\max_{\{L^E_{d,t+1}, L^U_{d,t}\}_{d,t}} \sum_{t=0}^{\infty} \frac{1}{(1+r)^t} \left(\sum_{d=1}^{D} (AL^E_{d,t} - e_d \theta_{d,t} L^U_{d,t}) \right) \tag{39}$$

$$\begin{aligned} s.t.\ L^E_{d,t+1} &= m\theta^\eta_{d,t} L^U_{d,t} + L^E_{d,t}(1-\delta),\ \forall d,\ t \\ \bar{L} &= \sum_d (L^E_{d,t} + L^U_{d,t}).\ \forall t \end{aligned}$$

The steady-state constrained optimal condition derived from (39) above for a region d is

$$\eta A_d - \frac{\delta + r + (1-\eta)m\theta^\eta_d}{m\theta^{\eta-1}_d} e_d = 0. \tag{40}$$

It resembles (37). The benchmark equilibrium I examine here is in the environment with free mobility so as to avoid the externalities from the migration friction discussed above. The equilibrium condition, which is mainly from local nontradable market clearing, is given by:

$$(1-\beta)A_d - \beta\theta_d e_d = 0. \tag{41}$$

Again it is not equivalent to (37) even with $\beta = 1-\eta$. Under Hosios condition, the equilibrium θ is larger than that in the constrained optimal result. In other words, the nontradable sector has more jobs than necessary. This result will help to rationalize the policy counterfactual analysis results shown below. Since firms (the filled jobs) do not need to consume nontradable goods but workers do, more firms will enter the market.

Given that the constrained efficiency cannot be achieved with the Hosios condition which has been imposed in calibration, there can be welfare-improving policies. The optimal policy design is beyond the scope of this paper and left for future research. This paper experiments with the policy discussed as follows.

6.2 Manufacturing subsidy policy

The policy counterfactual analysis is essentially about subsidizing the manufacturing sector to restore the pre-shock manufacturing employment level, which has also been of great political interest in the US. The funding source for the subsidies comes from corporate taxes on the nontradable sector. The rationale for this setup mainly comes from the theoretical results above: there are more jobs than the (constrained) optimal level in the nontradable sector. The policy is illustrated in the following budget constraint:

$$\sum_{s=2}^{S}(1+M)p_s\sum_{d=1}^{D}\bar{y}_{sd}L_{sd}^{E}=(1-T)\sum_{d=1}^{D}p_{1d}\bar{y}_{1d}L_{1d}^{E}. \tag{42}$$

There is a universal tax rate T on firms in the nontradable sector. The tax revenues collected will be distributed to all manufacturing firms as subsidies per dollar of sales, M. The nontradable tax rate T is chosen to achieve an equilibrium with total manufacturing employment being the same as that before the shock. It turns to be small: 0.04% sales tax on all nontradable firms can fund the manufacturing subsidies to achieve the goal. This is mainly due to the large labor share of non-manufacturing sector even before the trade shock.[27]

The policy can improve the overall welfare and reduce unemployment. The third column of Table 4 tells that the unemployment rate in the counterfactual result with the subsidy policy is even lower than the pre-shock level. Moreover, the welfare improves by 0.05%, which is even higher than the counterfactual with the trade shock only. That means the subsidy policy can improve the gains from trade even more while restoring the manufacturing employment.

Table 4: Counterfactual results comparison

Variable	Trade shock	Trade shock + subsidies
Unemployment rate	+0.18%	-0.02%
Welfare	+0.04%	+0.05%

Notes: The calculation is comparing the counterfactual results with the initial equilibrium. The unemployment rate change is simple difference while the welfare change is essentially the growth rates.

7 Conclusion

This paper provides a comprehensive analysis of the China trade shock's impact on U.S. regional labor markets, with a particular focus on unemployment, job finding, and job separation rates. By adopting the empirical framework of Autor et al. (2013), I find that regions more exposed to the China trade shock face higher unemployment, driven by reduced job finding rates and increased job separations. These effects are persistent, indicating that the unemployment resulting from the China trade shock is not merely a short-term disequilibrium but a structural shift requiring further theoretical and policy exploration.

I propose a dynamic multi-sector, multi-region labor matching model with endogenous

[27] About 83% of total employment is in the non-manufacturing sector before the shock.

job creation and destruction to account for the effects of trade shocks. The model highlights the role of trade-induced sectoral shifts, particularly in the non-tradable sector, which buffers the employment declines to some extent but does not offset the overall negative labor market outcomes in more exposed regions. Overall, the China trade shock raises the U.S. unemployment rate by 0.18 percentage point and accounts for about 87% of the observed decline in the share of manufacturing employment over working-age population from 2000 to 2007. Despite worsening labor markets, the China shock boosts the overall productivity of the U.S. by 0.16% and improves the overall welfare by 0.04%. Moreover, the quantitative analysis shows that most regions experience a rise in welfare inequality between the employed and unemployed.

Furthermore, the analysis identifies two sources of externalities—migration frictions and the role of local non-tradable goods—that prevent the constrained efficiency of the labor market, even under the Hosios condition. These externalities suggest that welfare-improving policies are necessary. The policy counterfactual analysis in this paper evaluates a manufacturing subsidy aimed at restoring pre-shock employment levels in the sector, a topic of significant political interest in the U.S. Financed by a modest 0.04% tax on non-manufacturing firms, this subsidy effectively restores manufacturing employment to pre-shock levels. In addition to boosting employment, the policy enhances gains from trade and reduces the overall unemployment rate: the overall welfare gains from trade are 0.05% and unemployment rate decreases by 0.02 percentage point under the policy.

Future work can bring in more nuances in terms of production input-output network. It is also meaningful to study the optimal labor market policies that can channel more benefits of trade. The quantitative framework developed by this paper can be applied to study the labor market effects of many other sectoral shocks, such as climate change.

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A Appendix

A.1 Summary statistics

Table 5: Means and standard deviations of CZ level labor market outcome

Period	Stat	Unemp. Rate (%)	Job Find. Rate (%)	Job Sep. Rate (%)
1990-2000	mean	-0.63	0.15	1.98
	sd	1.44	4.75	1.82
2000-2007	mean	0.33	-8.32	-3.64
	sd	1.76	8.08	1.98
2000-2008	mean	-0.09	-11.88	-4.44
	sd	2.12	10.85	1.94
2000-2009	mean	3.01	-25.33	-3.44
	sd	2.67	10.48	2.01
2000-2010	mean	3.73	-26.64	-4.16
	sd	2.95	10.34	2.03
2000- 2011	mean	3.29	-25.92	-4.27
	sd	2.88	10.90	2.05
2000-2012	mean	2.60	-23.85	-4.58
	sd	2.51	10.14	1.95
2000- 2013	mean	1.89	-21.04	-4.63
	sd	2.30	10.27	1.88
2000-2014	mean	0.82	-17.62	-4.96
	sd	2.17	9.82	1.93
2000-2015	mean	0.13	-15.99	-5.06
	sd	1.75	9.27	1.99
2000-2016	mean	-0.02	-15.00	-5.01
	sd	1.58	7.68	2.00
2000-2017	mean	-0.72	-13.54	-5.31
	sd	1.68	8.43	2.06
2000-2018	mean	-1.09	-12.44	-5.51
	sd	1.62	7.91	1.90
2000-2019	mean	-1.52	-8.62	-6.01
	sd	1.63	7.98	2.06

A.2 Cross-validation of job transition measures

The employment status for an agent in the previous year is identified according to the answer to a question asking how many weeks the agent worked for last year. The answers are categorized into the following intervals (see WKSWORK2 in the IPUMS ACS): N/A or missing, 1-13 weeks, 14-26 weeks, 27-39 weeks, 40-47 weeks, 48-49 weeks, 50-52 weeks. Denote a threshold of weeks to be T ($T = 13, 26, 39, 47$). I define an agent to be unemployed last year if they worked for fewer than T weeks and they are in the labor force this year. I assume people who are in the labor force this year were also in the labor force last year. And an agent is counted as being employed last year if they worked for more than T weeks.

The first cross-validation is to use ACS dataset itself and do the commuting-zone level calculation and validation. For each commuting zone, I can calculate the employment and unemployment in year $t-1$ using ACS data of year t. Meanwhile, I can obtain the employment and unemployment in year $t-1$ directly using the employment status information in ACS data of year $t-1$. Since ACS has continuous samples with puma code (a code that can be used to identify CZ) from 2006 and onward, I do the validation for all CZ across 2006 to 2018, which covers the whole period used in the empirical part. It turns out that all these four thresholds offer high correlations.The following two tables summarize the correlation between the data moments measured using different thresholds and the actual data moments.

Table 6: Correlation between the CZ unemployment calculated using different thresholds and those from ACS

Variable	L^U_{13wks}	L^U_{26wks}	L^U_{39wks}	L^U_{47wks}
Corr.	0.9487	0.9521	0.9543	0.9545

Table 7: Correlation between the CZ employment calculated using different thresholds and those from ACS

Variable	L^E_{13wks}	L^E_{26wks}	L^E_{26wks}	L^E_{26wks}
Corr.	0.9736	0.9741	0.9747	0.9747

Next, I use CPS data to do the cross-validation. CPS is essentially a short panel dataset, tracking agents for about one year. However, it only has accurate records of geographic information at the state level[28]. Another concern is that there were many respondents who dropped out of sample and could not be tracked. Therefore, I calculate the job transition rates using gross flow ratios at the state level. For example, I obtain the total number

[28] It has metropolitan information but there are too many missing observations to be used.

of the unemployed who became employed after a year UE_t, and the total number of the unemployed at the beginning of the year U_t. The job finding rate is then UE_t/U_t. I compare the state-level job transition rates I construct using those four thresholds in ACS data with the job transition rates calculated using CPS data. The correlations for job finding rates increase with the threshold while the correlations for job separation rates decrease with it. The results are shown in the following two tables:

Table 8: Correlation between the state-level job finding rates calculated using different thresholds and those calculated from CPS

Year	JF_{13wks}	JF_{26wks}	JF_{39wks}	JF_{47wks}
1990	0.78	0.79	0.82	0.80
2000	0.71	0.71	0.72	0.74
2007	0.81	0.82	0.83	0.87

Table 9: Correlation between the state-level job separation rates calculated using different thresholds and those calculated from CPS

Year	JS_{13wks}	JS_{26wks}	JS_{39wks}	JS_{47wks}
1990	0.74	0.69	0.61	0.56
2000	0.66	0.56	0.50	0.45
2007	0.59	0.57	0.56	0.48

According to all these results, I choose 26 weeks as the threshold.

A.3 Full regression results

Table 10: The China trade shock outcome: 2SLS estimates

	Dependent variables		
	Δ Unemployment Rate	Δ Job Finding Rate	Δ Job Separation Rate
	(1)	(2)	(3)
ΔIP	0.248^{***}	-0.841^{***}	0.311^{***}
	(0.060)	(0.239)	(0.079)
Post 2000	0.777^{*}	-9.102^{***}	-7.458^{***}
	(0.411)	(1.055)	(0.488)
$Region_{midatl}$	0.884^{***}	-1.706	1.182
	(0.265)	(2.421)	(1.192)
$Region_{encen}$	1.033^{***}	-1.421	1.218
	(0.333)	(1.218)	(1.068)
$Region_{wncen}$	0.463^{*}	-0.385	0.438
	(0.268)	(1.076)	(1.294)
$Region_{satl}$	1.350^{***}	-3.189^{***}	1.332
	(0.261)	(1.034)	(1.090)
$Region_{escen}$	0.953^{***}	-1.231	1.355
	(0.311)	(1.298)	(1.197)
$Region_{wscen}$	0.686^{**}	-0.469	1.552
	(0.280)	(1.365)	(1.103)
$Region_{mount}$	0.490^{*}	0.174	1.101
	(0.269)	(1.257)	(1.122)
$Region_{pacif}$	1.368^{***}	-2.466^{*}	1.986^{*}

	Dependent variables (Continued)		
	Δ Unemployment Rate	Δ Job Finding Rate	Δ Job Separation Rate
	(1)	(2)	(3)
	(0.314)	(1.348)	(1.102)
Ini. Manuf. Shr.	−0.017	0.055	−0.048***
	(0.011)	(0.050)	(0.016)
Ini. Skilled Rate	−0.006	0.076	−0.037
	(0.008)	(0.058)	(0.037)
Ini. F.B. Shr.	−0.018***	−0.005	−0.027
	(0.006)	(0.043)	(0.041)
Ini. F.E. Shr.	0.092***	−0.295**	0.135***
	(0.019)	(0.117)	(0.045)
Ini. Routine Shr.	0.048	−0.102	0.070
	(0.033)	(0.136)	(0.092)
Ini. Sourcing	−0.046	−0.416	−0.128
	(0.195)	(0.844)	(0.644)
Constant	−8.319***	19.887***	−6.588
	(1.286)	(6.830)	(4.744)
Observations	1,444	1,444	1,444
R^2	0.309	0.592	0.807

Notes: The results are from 2SLS estimation of regression (1). The samples are restricted to the working-age group (age 16 - 64). Robust standard errors in parentheses are clustered on state. Models are weighted by start of period CZ share of national population. *p<0.1; **p<0.05; ***p<0.01.

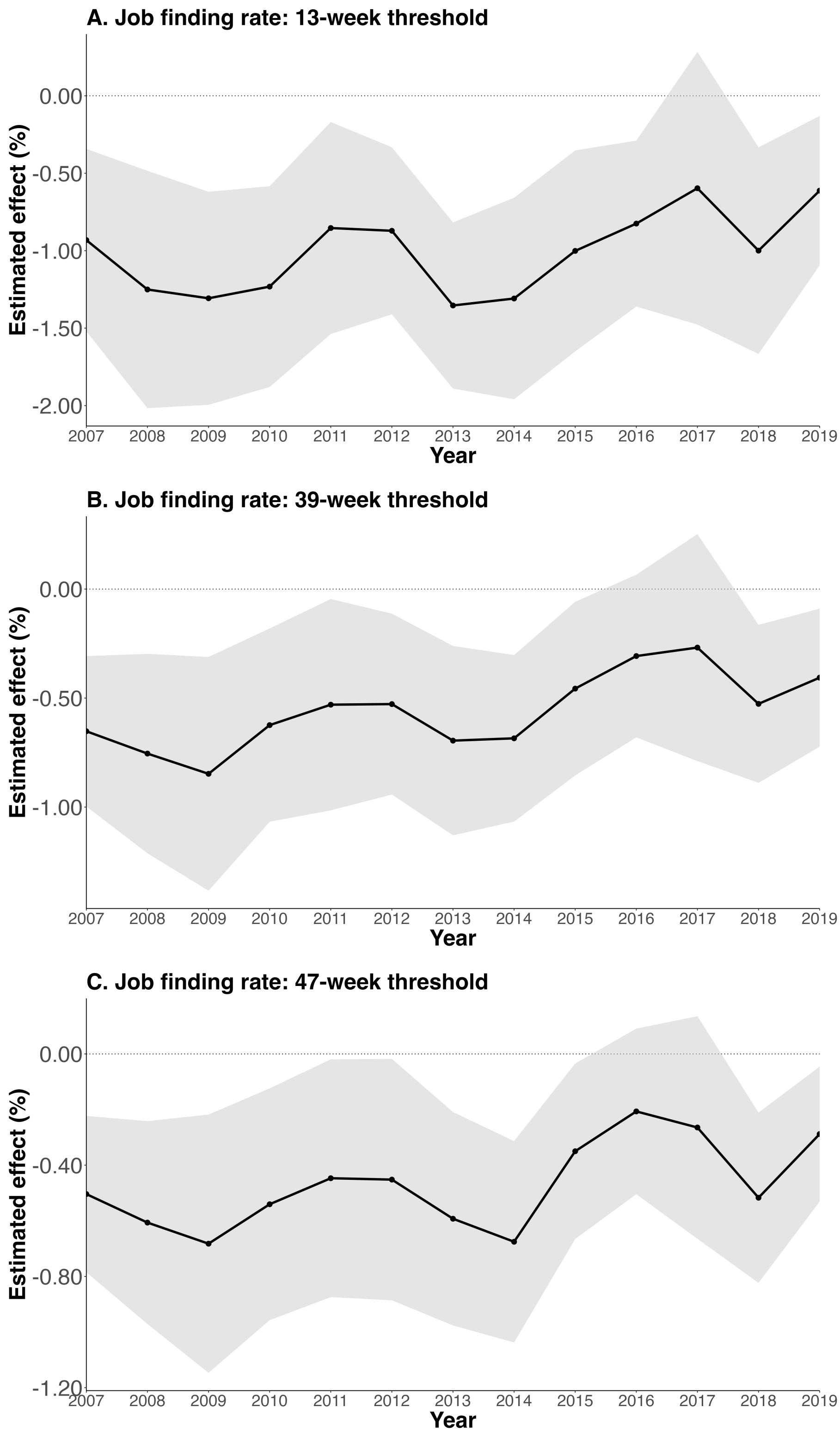
A.4 Job finding effects with different measures

Table 11: The China trade shock and job finding outcome: 2SLS estimates

	Dependent variables			
	ΔJFR_{13wks}	ΔJFR_{26wks}	ΔJFR_{39wks}	ΔJFR_{47wks}
	(1)	(2)	(3)	(4)
Δ Import Penetration	-0.931^{***}	-0.841^{***}	-0.652^{***}	-0.504^{***}
	(0.300)	(0.223)	(0.176)	(0.143)
Constant	27.606^{***}	19.887^{***}	16.970^{***}	15.275^{***}
	(6.053)	(4.612)	(3.796)	(3.219)
Observations	1,444	1,444	1,444	1,444
R^2	0.638	0.592	0.580	0.584

Notes: The results are from 2SLS estimation of regression (1). The samples are restricted to the working-age group (age 16 - 64). Robust standard errors in parentheses are clustered on state. Models are weighted by start of period CZ share of national population. *p<0.1; **p<0.05; ***p<0.01.

Figure 15: Trade shock impact, 2007 - 2019



Notes: The dots are the coefficients estimated from regression (1) using 2SLS with successively longer first difference from period 2000 - 2007 to 2000 - 2019 on the LHS. The shaded area represents the 95% confidence interval of each coefficient. Regressions are weighted by the CZ total population in 2000; standard errors are clustered by state.

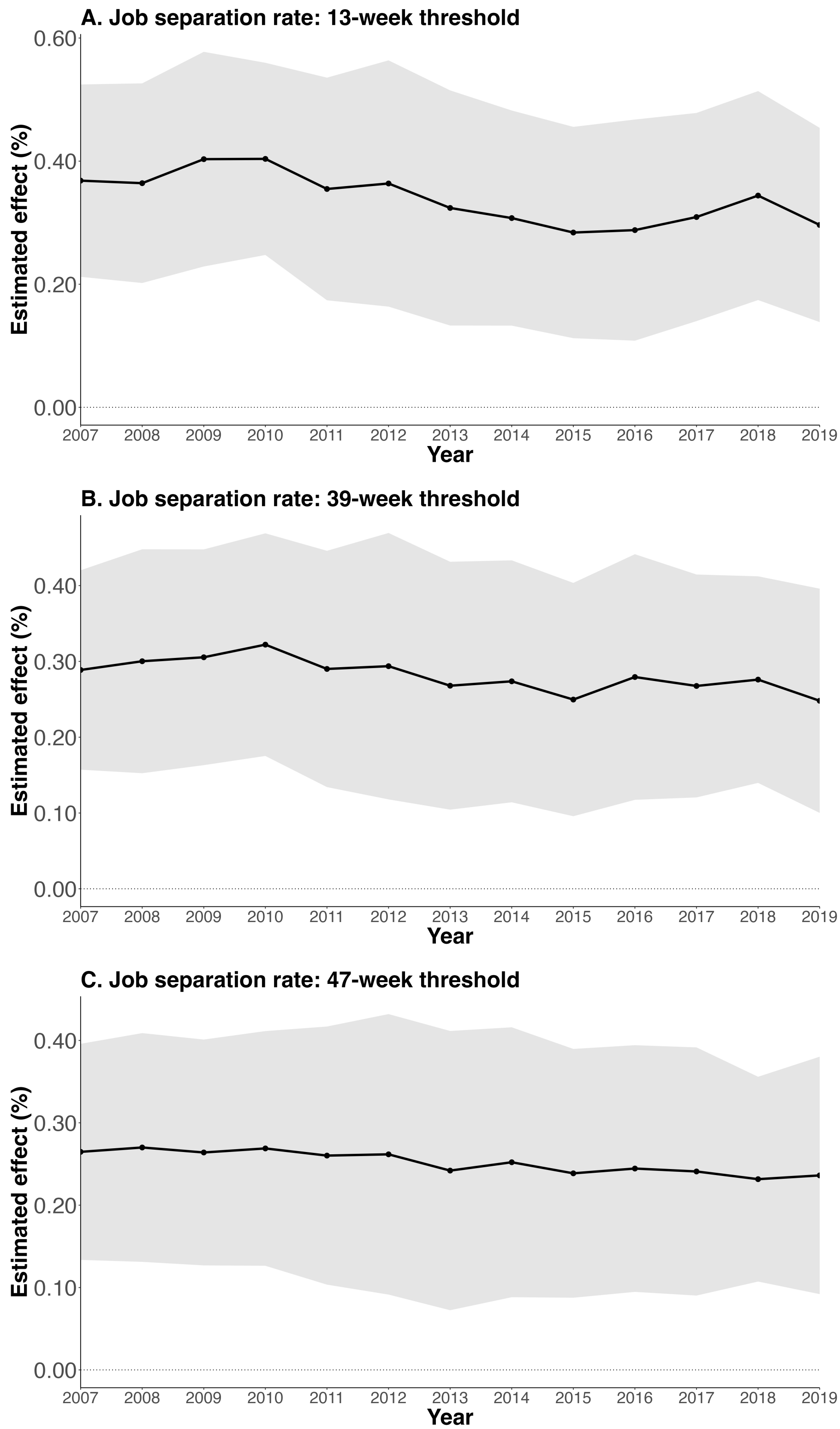
A.5 Job separation effects with different measures

Table 12: The China trade shock and job separation outcome: 2SLS estimates

	Dependent variables			
	ΔJSR_{13wks}	ΔJSR_{26wks}	ΔJSR_{39wks}	ΔJSR_{47wks}
	(1)	(2)	(3)	(4)
Δ Import Penetration	0.368***	0.311***	0.289***	0.265***
	(0.080)	(0.067)	(0.067)	(0.067)
Constant	−8.742***	−6.588**	−5.520*	−4.919*
	(3.015)	(3.026)	(2.877)	(2.766)
Observations	1,444	1,444	1,444	1,444
R^2	0.744	0.807	0.847	0.877

Notes: The results are from 2SLS estimation of regression (1). The samples are restricted to the working-age group (age 16 - 64). Robust standard errors in parentheses are clustered on state. Models are weighted by start of period CZ share of national population. *p<0.1; **p<0.05; ***p<0.01.

Figure 16: Trade shock impact, 2007 - 2019



Notes: The dots are the coefficients estimated from regression (1) using 2SLS with successively longer first difference from period 2000 - 2007 to 2000 - 2019 on the LHS. The shaded area represents the 95% confidence interval of each coefficient. Regressions are weighted by the CZ total population in 2000; standard errors are clustered by state.

A.6 Derivation and proofs

A.6.1 Derivation of equilibrium conditions

Let $E^W_{sd} \equiv \int_{R_{sd}}^{\bar{x}} W_{sd}(x)dF(x)$ and $E^J_{sd} \equiv \int_{R_{sd}}^{\bar{x}} J_{sd}(x)dF(x)$. Integrating (14) by $F(x)$ over $[R_{sd},\ \bar{x}]$ gives:

$$P^f_d E^W_{sd} - P^f_d(1 - F(R_{sd}))E = \frac{\beta}{1-\beta}E^J_{sd}. \tag{43}$$

I rewrite the value functions for the employed and filled job as

$$W_{sd}(x) = \frac{1}{1+r}\left\{\frac{w_{sd}(x)}{P^f_d} + (\delta + (1-\delta)F(R_{sd}))\,E + (1-\delta)E^W_{sd}\right\}, \tag{44}$$

and

$$J_{sd}(x) = \frac{1}{1+r}\left\{p_{sd}A_{sd}x - w_{sd}(x) + (1-\delta)E^J_{sd}\right\}. \tag{45}$$

Take (44), (45) along with (43) into (14) to get the bargained wage:

$$w_{sd}(x) = \beta p_{sd}A_{sd}x + (1-\beta)rP^f_d E.$$

Evaluate the wage equation and (45) at the reservation productivity and take them into (15) to get:

$$(1-\delta)E^J_{sd} = (1-\beta)(rP^f_d E - p_{sd}A_{sd}R_{sd}).$$

Then I can express the value of a filled job as

$$J_{sd}(x) = \frac{1-\beta}{1+r}p_{sd}A_{sd}(x - R_{sd}). \tag{46}$$

Take (46) into the free entry condition along with the value of a vacant job to get the job creation condition (an expanded version of (19)):

$$e_{sd} = \kappa(\theta_{sd})\frac{1-\beta}{1+r}\rho_{sd}\int_{R_{sd}}^{\bar{x}}(x - R_{sd})dF(x).$$

Take (46) into the threshold condition (15) to get the job destruction condition (an expanded version of (20)):

$$R_{sd} - \frac{rE}{\rho_{sd}} + \frac{1-\delta}{1+r}\int_{R_{sd}}^{\bar{x}}(x - R_{sd})dF(x) = 0.$$

Taking (43) into (7) renders (17). And labor distribution equations (22) and (23) follow according to the properties of the Gumbel distribution.

A.6.2 Derivation of labor transition rates

Start with dynamic transitions of employed workers:

$$L^E_{sd,t+1} = (1-\delta)(1-F(R_{sd,t}))L^E_{sd,t} + \theta_{sd,t}\kappa(\theta_{sd,t})(1-F(R_{sd,t}))L^U_{sd,t}.$$

In the steady state, $x_{t+1} = x_t$. We can rewrite the equation above as

$$L^E_{sd} = (1-\delta)(1-F(R_{sd}))L^E_{sd} + \theta_{sd}\kappa(\theta_{sd})(1-F(R_{sd}))L^U_{sd},$$

which gives (21).

A.6.3 Proofs

Proof of Lemma 1

Rearranging (20) gives:

$$F(R_{sd}, \rho_{sd}) \equiv R_{sd} + \frac{1-\delta}{1+r}\int_{R_{sd}}^{\bar{x}}(x - R_{sd})dF(x) - \frac{rE}{\rho_{sd}} = 0.$$

By the Implicit Function Theorem:

$$\frac{dR_{sd}}{d\rho_{sd}} = -\frac{rE/\rho_{sd}^2}{\frac{r+\delta}{1+r} + \frac{1-\delta}{1+r}F(R_{sd})} < 0.$$

It further suggests that ρ_{sd} can uniquely pin down R_{sd} using (20) and we can express the reservation productivity as a function of ρ_{sd}: $R_{sd} = R(\rho_{sd})$. Then I rearrange (19) to be

$$G(\theta_{sd}, \rho_{sd}) \equiv \rho_{sd}\frac{1-\delta}{e(1+r)}\int_{R(\rho_{sd})}^{\bar{x}}(x - R(\rho_{sd}))dF(x) - \kappa(\theta_{sd})^{-1} = 0.$$

By the Implicit Function Theorem:

$$\frac{d\theta_{sd}}{d\rho_{sd}} = -\frac{\frac{1-\delta}{e(1+r)}\int_{R(\rho_{sd})}^{\bar{x}}(x - R(\rho_{sd}))dF(x) - R'(\rho_{sd})\rho_{sd}\frac{1-\delta}{e(1+r)}(1-F(R(\rho_{sd})))}{\kappa(\theta_{sd})^{-2}\kappa'(\theta_{sd})} > 0.$$

It also suggests a unique mapping between θ_{sd} and ρ_{sd}. Therefore, ρ_{sd} uniquely pins down R_{sd} and θ_{sd} and $R'(\theta_{sd}) < 0$ and $\theta(\rho_{sd}) > 0$.

Proof of Lemma 2

It suffices to show that the unemployed will not move away from the sector s with the highest ρ_{sd} in a region d. The value of being unemployed in a sector s of region d is

$$U(\rho_{sd}) = \frac{1}{1+r}(b + \frac{\beta}{1-\beta}e\theta(\rho_{sd}) + E).$$

According to Lemma 1, $\theta()$ is an monotonically increasing function. Therefore, $U(\max_s\ \rho_{sd}) \geq U(\rho_{sd})$ with the equality held at $s' = arg\max_s\ \rho_{sd}$. The unemployed in region d all sort to s' given the free mobility within the region.

Proof of Proposition 1

Log-linearizing (19) and (20) for labor market i gives:

$$\frac{\theta_i\kappa'(\theta_i)}{\kappa(\theta_i)}\widehat{\theta_i} + \widehat{\rho_i} = \frac{R_i(1-F(R_i))}{\int_{R_i}^{\bar{x}}(x-R_i)dF(x)}\widehat{R_i}. \tag{47}$$

$$\frac{R_i(\frac{r+\delta}{1+r} + \frac{1-\delta}{1+r}F(R_{sd}))}{rE/\rho_i}\widehat{R_i} + \widehat{\rho_i} = 0. \tag{48}$$

When $\widehat{p_1} < 0$, it is easy to see that $\widehat{\rho_1} < \widehat{\rho_2}$. By (48), $\widehat{R_1} > \widehat{R_2}$. Taking $\widehat{R_1} > \widehat{R_2}$ into (47) we have $\widehat{\theta_1} < \widehat{\theta_2}$.[29]

[29] Notice that $\frac{\theta_i\kappa'(\theta_i)}{\kappa(\theta_i)} < 0$.

A.7 Calibration

Solve the model

The number of unknowns to be solved can be reduced to: $E, \{p_{1d}\}_{d=1}^{D}, \{R_{sd}\}_{s=1,d=1}^{S,D}$. Given $\{p_{1d}\}_{d=1}^{D}$ and tradable prices $\{p_s\}_{s=2}^{S}$, the final prices $\{P_d^f\}_{d=1}^{D}$ and real revenues per effective labor $\{\rho_{sd}\}_{s=1,d=1}^{S,D}$ can be immediately obtained. The equilibrium equations for $\{R_{sd}\}_{s=1,d=1}^{S,D}$ are as follows

$$\frac{rE}{\rho_{sd}} - \frac{1-\delta}{1+r}\int_{R_{sd}}^{\infty}(x - R_{sd})dF(x) - R_{sd} = 0. \tag{49}$$

Then labor market tightness is derived as:

$$\theta_{sd} = \left(m(1-\beta)\rho_{sd}A_{sd}\int_{R_{sd}}^{\infty}(x - R_{sd})dF(x)/(1+r)\right),$$

which can be used to derive the following adjusted non-employed values:

$$\tilde{U}_{sd} = \frac{1}{1+r}\left(\frac{b_d}{P_d^f} + \frac{\beta e_{sd}\theta_{sd}}{1-\beta}\right),$$

and

$$\tilde{U}_{0d} = \frac{\omega_d}{(\lambda_0 + r)P_d^f} - \frac{(1-\lambda_0)r}{(1+r)(\lambda_0+r)}E.$$

They are the non-employed values divided by $E/(1+r)$. By using this form, the equation of E can converge more easily:

$$\frac{1+r}{r}\nu \ln\left(\sum_{s=0,d=1}^{S,D}\exp(\tilde{U}_{sd}/\nu)\right) - E = 0. \tag{50}$$

To back out the labor distribution, I first calculate the ratio of the non-employed number for each sector and region over the number of unemployed in a specific labor market, L_{SD}^U:

$$L_{sd}^U/L_{SD}^U = \frac{\exp(\tilde{U}_{sd}/\nu)}{\exp(\tilde{U}_{SD}/\nu)}$$

for $s \neq 0$ and

$$L_{0d}^U/L_{SD}^U = \frac{\exp(\tilde{U}_{0d}/\nu)}{\lambda_0\exp(\tilde{U}_{SD}/\nu)}.$$

The ratios of the number of employed over the number of unemployed in this specific labor market are

$$L^E_{sd}/L^U_{SD} = \frac{m\theta^\eta_{sd}(1-F(R_{sd}))}{\delta+(1-\delta)F(R_{sd})} L^U_{sd}/L^U_{SD}.$$

Then the number of unemployed in the specific labor market can be backed out:

$$L^U_{SD} = \frac{\bar{L}}{\sum_{s\neq 0,d}(L^E_{sd}/L^U_{SD} + L^U_{sd}/L^U_{SD}) + \sum_d L^U_{0d}/L^U_{SD}}.$$

The whole labor distribution $\{L^E_{sd}\}^{S,D}_{s=1,d=1}$, $\{L^U_{sd}\}^{S,D}_{s=0,d=1}$ can be obtained by multiplying L^U_{SD} with those ratios.

The average wage of a sector and region is

$$\bar{w}_{sd} = (1-\beta)rP^f_d E + \beta p_{sd} A_{sd} \int_{R_{sd}}^{\infty} x d\frac{F(x)}{1-F(R_{sd})}.$$

Then the total nominal demand for nontradable goods in a region is:

$$\alpha_1 I_d = \sum_{s=1}^{S} \bar{w}_{sd} L^E_{sd} + b_d \sum_{s=1}^{S} L^U_{sd} + \omega_d L^U_{0d}.$$

Market clearing conditions are used to pin down nontradable prices:

$$\alpha_1 I_d - p_{1d} L^E_{1d} A_{1d} \int_{R_{1d}}^{\infty} x d\frac{F(x)}{1-F(R_{1d})} = 0. \tag{51}$$

Equations (49), (50), (51) form a system of equations for the equilibrium denoted as $\mathcal{F}(\mathbf{x})$:

$$\mathcal{F} = \begin{pmatrix} \frac{rE}{\rho_{sd}} - \frac{1-\delta}{1+r}\int_{R_{sd}}^{\infty}(x-R_{sd})dF(x) - R_{sd}, & \forall s,d \\ \frac{1+r}{r}\nu \ln\left(\sum_{s=0,d=1}^{S,D} \exp(\tilde{U}_{sd}/\nu)\right), & \\ \alpha_1 I_d - p_{1d}L^E_{1d}A_{1d}\int_{R_{1d}}^{\infty} xd\frac{F(x)}{1-F(R_{sd})}, & \forall d \end{pmatrix}$$

The solution is $\mathbf{x} = \left(E, \{p_{1d}\}^D_{d=1}, \{R_{sd}\}^{S,D}_{s=1,d=1}\right)$ such that $\mathcal{F}=0$.

Calibrate tradable prices

Before introducing the computation process of calibration, I discuss how tradable prices are calibrated. Firstly, there are no other well-defined countries in this small open economy. Imports are the gap between total demand and output and it is likely that output exceeds the demand, leading to net exports. Therefore, the relevant moments to calibrate tradable prices are net imports for each sector. The (net) imports derived from the model is:

$$NetImports_s = \alpha_s(\sum_d I_d + TD) - p_s \sum_d L^E_{sd} A_{sd} \int_{R_{sd}}^{\infty} xd\frac{F(x)}{1 - F(R_{sd})}.$$

To fit the data better, I allow aggregate trade deficits TD. It is an additive term to total income when purchasing tradable goods. TD being positive means net trade deficits while negative trade surpluses. I can back out TD while normalizing the first tradable sector as the numeraire in the beginning. To do this, I obtain the ratio of the net imports of sector 2 which is the first tradable sector over total income from data. Following the equation above, the model equation to back out TD is

$$TD = \frac{1}{\alpha_2}\left(\frac{p_2 \sum_d L^E_{2d} A_{2d} \int_{R_{2d}}^{\infty} xd\frac{F(x)}{1-F(R_{2d})}}{\sum_d I_d} + \left(\frac{NetImports_2}{TotalIncome}\right)^{data}\right).$$

Next, I use the ratios of net imports of sector 3, 4, 5 over net imports of sector 2 respectively to calibrate these tradable sectoral prices. TD is kept fixed when calibrating the new tradable prices. In other words, trade deficits are assumed to be the same after the trade shock.

Calibration process

Step 1 All data moments can only be generated after solving the model. Therefore, I start with a minimization problem stacking the model system with the data matching equations:

$$\mathcal{G}\left(\mathcal{F}\left(\mathbf{x}|\mathbf{\Omega}\right), \mathbf{\Omega}\right) = \begin{pmatrix} \mathcal{F}\left(E, \{p_{1d}\}_{d=1}^{D}, \{R_{sd}\}_{s=1,d=1}^{S,D}\right) \\ (\bar{\mathbf{m}} - \mathbf{m}(\mathbf{\Omega}))/\bar{\mathbf{m}} \end{pmatrix}.$$

I use genetic algorithm to solve the following minimization problem:

$$(\mathbf{x_{-1}}, \mathbf{\Omega_0}) = \arg min\ \mathcal{G}\left(\mathcal{F}\left(\mathbf{x}|\mathbf{\Omega}\right), \mathbf{\Omega}\right)' \mathcal{G}\left(\mathcal{F}\left(\mathbf{x}|\mathbf{\Omega}\right), \mathbf{\Omega}\right).$$

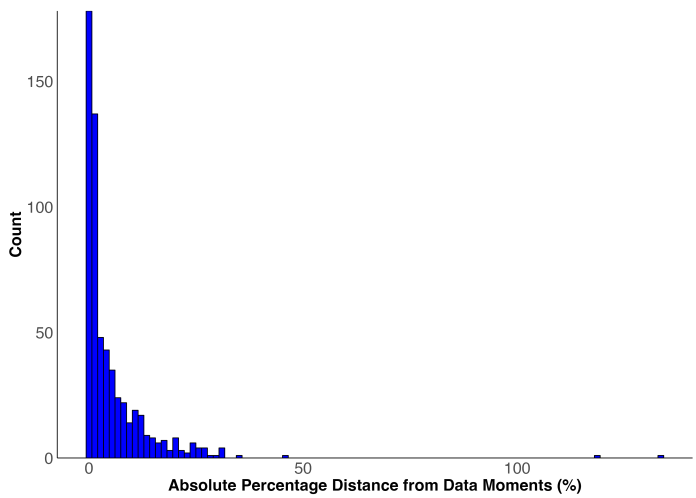
Step 2 $(\mathbf{x_{-1}}, \mathbf{\Omega_0})$ from the first step serve as the initial guess for the parameters and model solutions. The initial solution $\mathbf{x}_0$ given parameters $\mathbf{\Omega_0}$ is from $\mathcal{F}\left(\mathbf{x_0}|\mathbf{\Omega_0}\right) = 0$. Due to model system and calibration being highly nonlinear, I use ADAM (Adaptive Moment Estimation) algorithm to solve the minimization problem of

$$\hat{\mathbf{\Omega}} = arg \min\ \left((\bar{\mathbf{m}} - \mathbf{m}(\mathbf{\Omega}))/\bar{\mathbf{m}}\right)' \left((\bar{\mathbf{m}} - \mathbf{m}(\mathbf{\Omega}))/\bar{\mathbf{m}}\right).$$

ADAM algorithm converges better with small changes of $\mathbf{\Omega}$. At nth iteration, I can use the model solution from the previous iteration $\mathbf{x_{n-1}}$as the initial guess to solve $\mathcal{F}\left(\mathbf{x_n}|\mathbf{\Omega_n}\right)=0$.

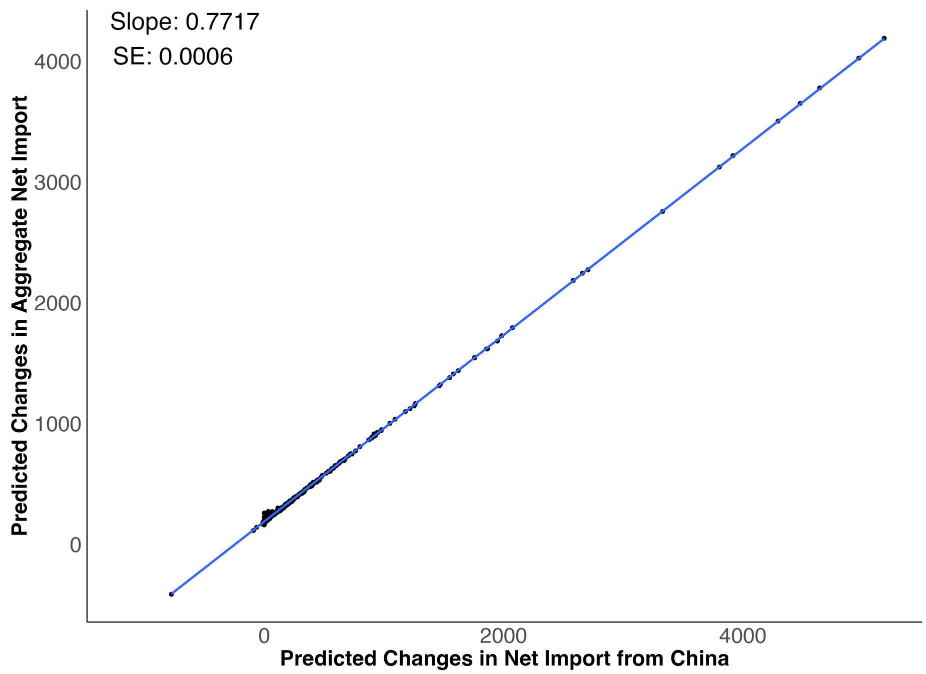
The following graph summarizes the absolute percentage distance between the model-generated moments and actual data moments shown in Table 2.

Figure 17: Percentage distance



A.8 Predicted overall net import changes and predicted changes in the net imports from China

Figure 18: Predicted overall net import changes against predicted changes in the net imports from China

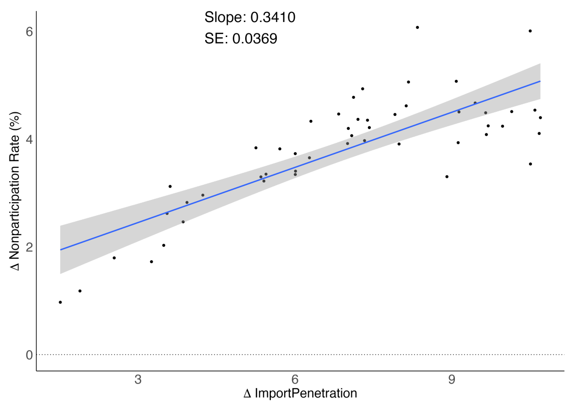


Notes: The predicted import changes are at the SIC level.

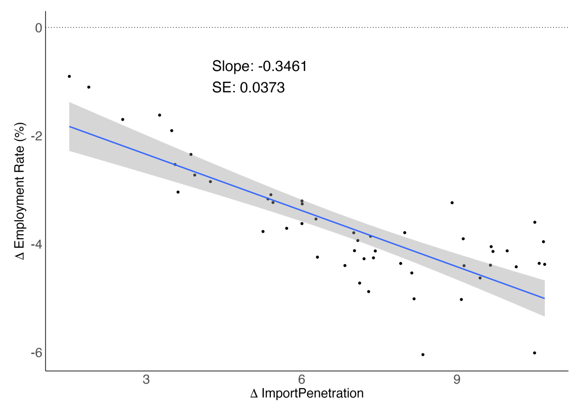
A.9 Counterfactual analysis results

Figure 19: Predicted changes in labor market outcome and import penetration

(a) Predicted changes in nonparticipation rates vs IP



(b) Predicted changes in employment rates vs IP



(c) Predicted changes in manufacturing employment rates vs IP

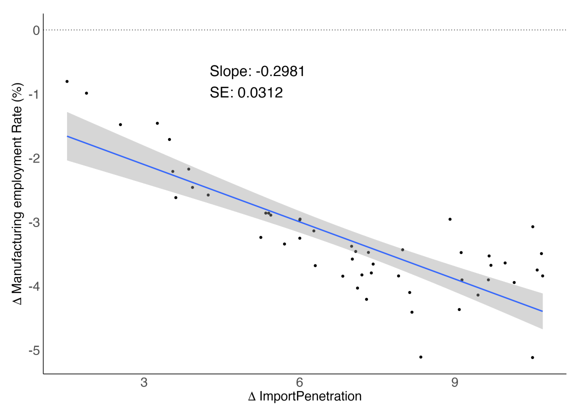


Figure 20: Predicted changes in sectoral real revenues per effective labor

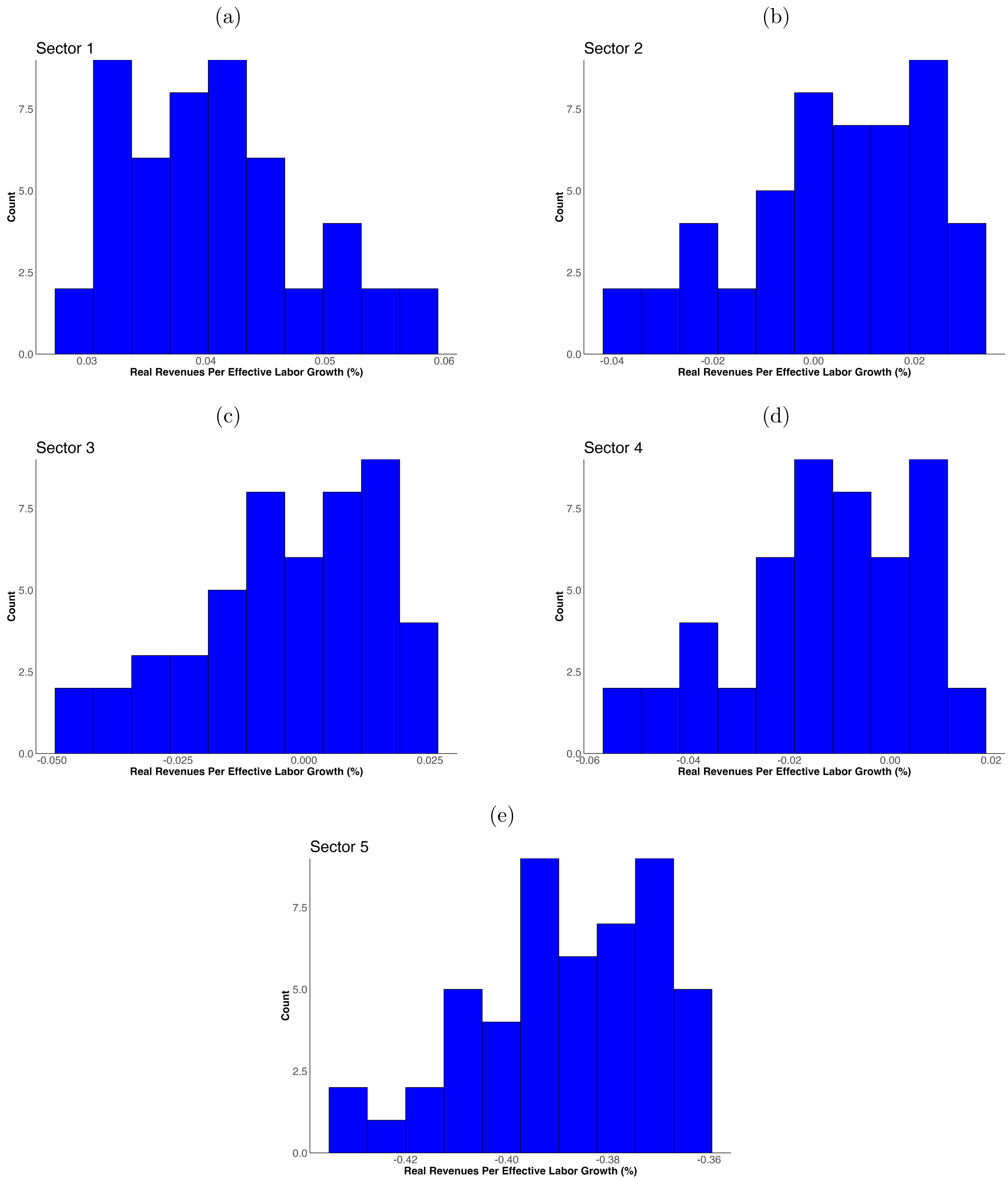


Figure 21: Predicted changes in sectoral labor market tightness

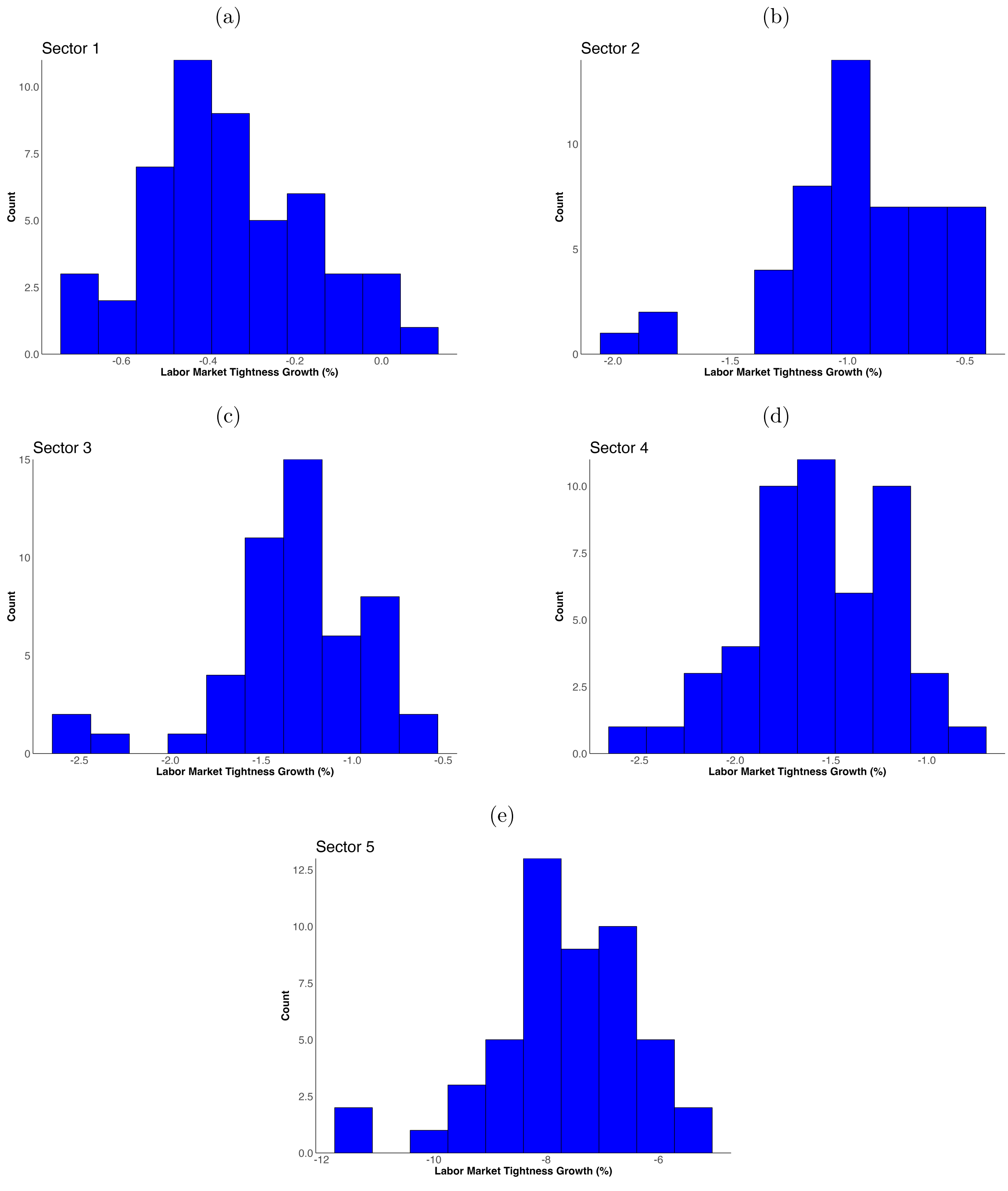


Figure 22: Predicted changes in sectoral reservation productivity

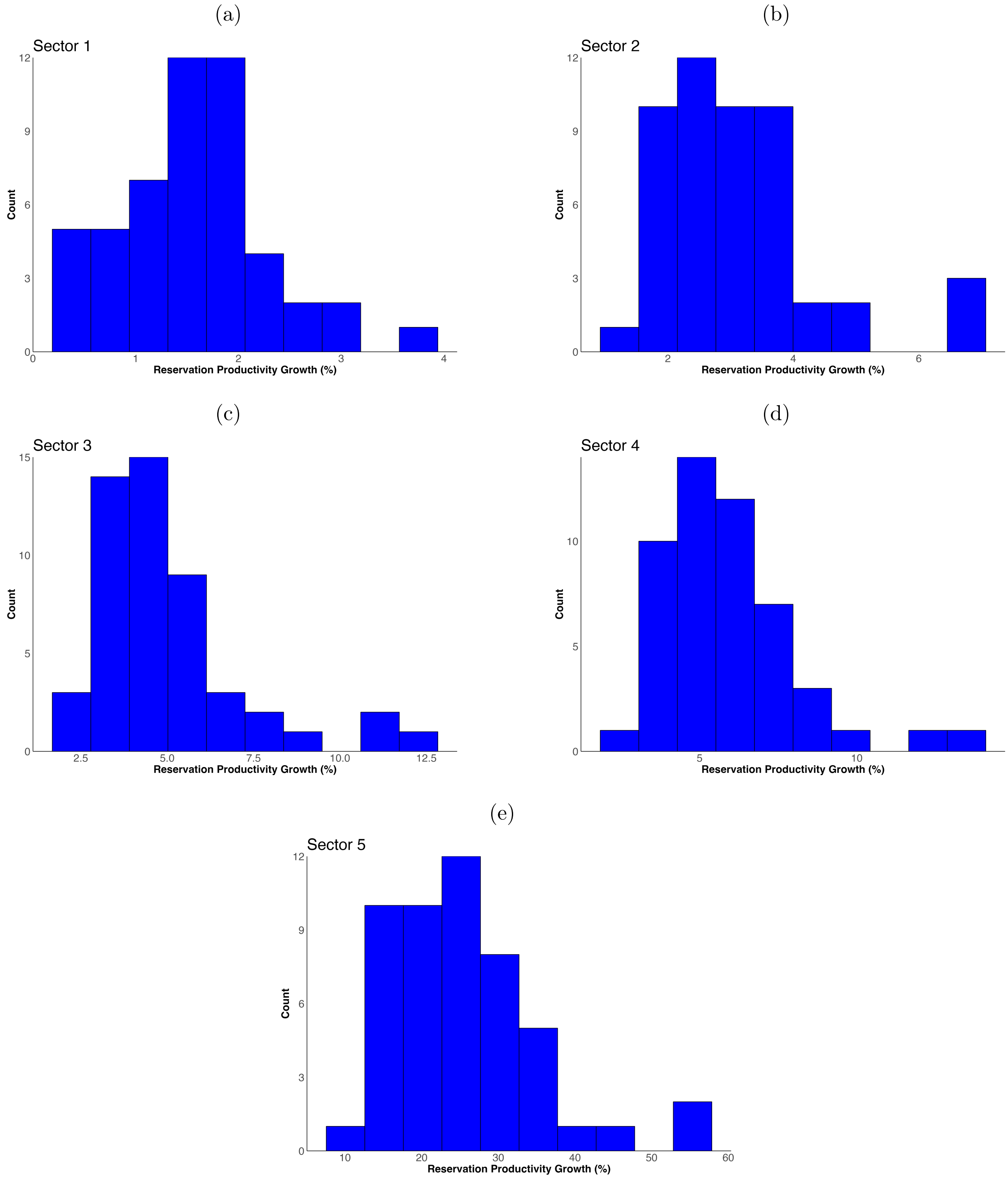
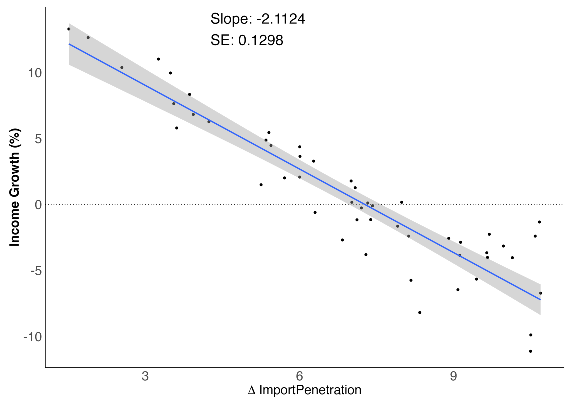


Figure 23: Predicted changes in income and import penetration

(a) Predicted changes in regional total income vs IP



(b) Predicted changes in regional total unemployment income vs IP

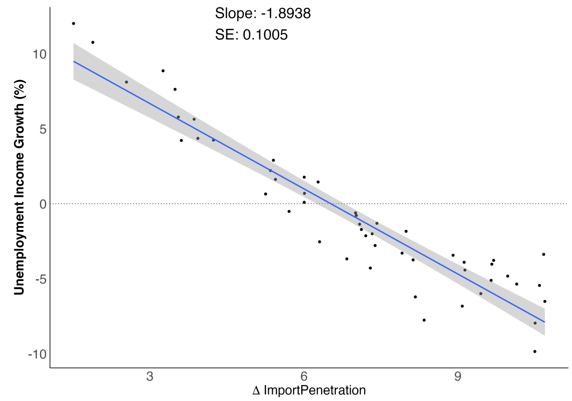
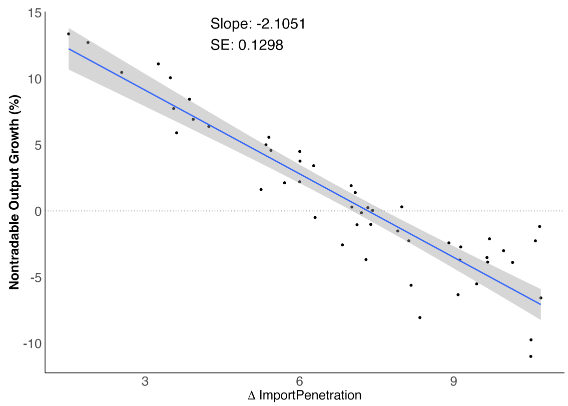
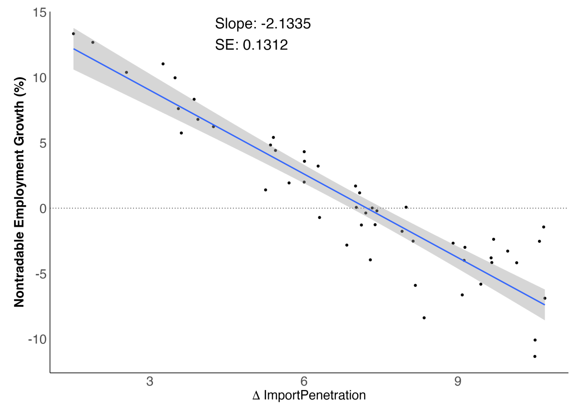


Figure 24: Predicted changes in nontradable output and labor and import penetration

(a) Predicted changes in regional nontradable output vs IP



(b) Predicted changes in nontradable employment vs IP



(c) Predicted changes in nontradable unemployment vs IP

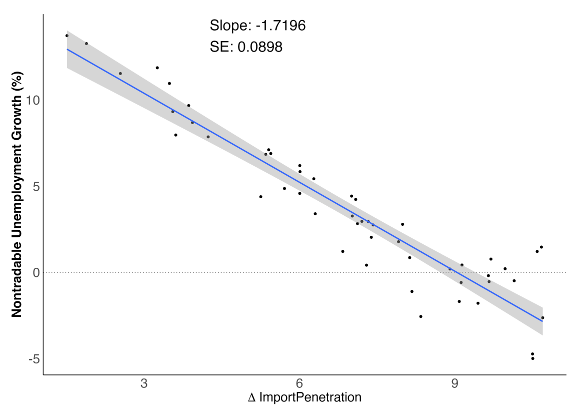
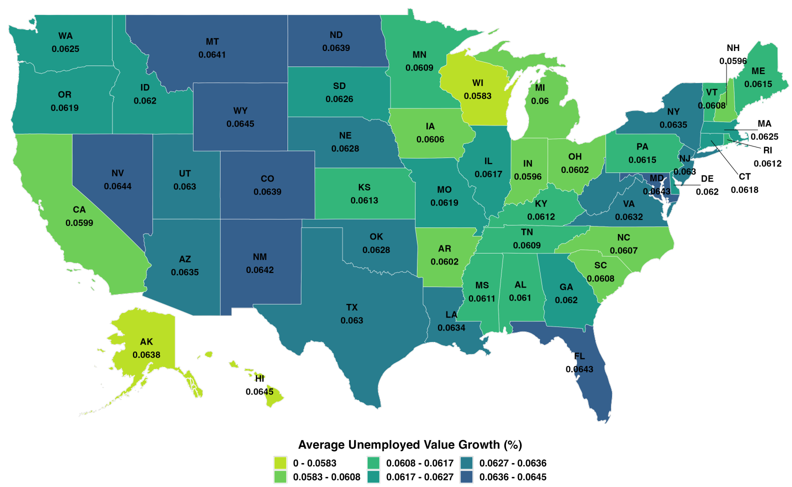
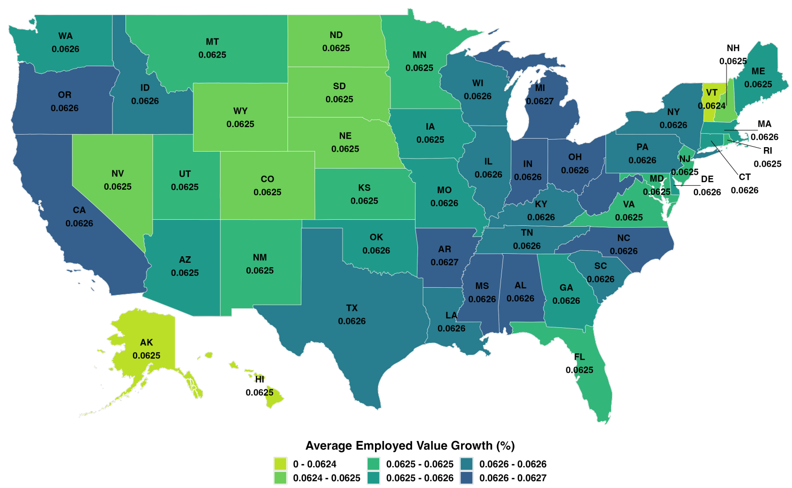


Figure 25: Regional average welfare for different types of agents

(a) Predicted changes in average unemployed values



(b) Predicted changes in average employed values



(c) Predicted changes in nonparticipation values

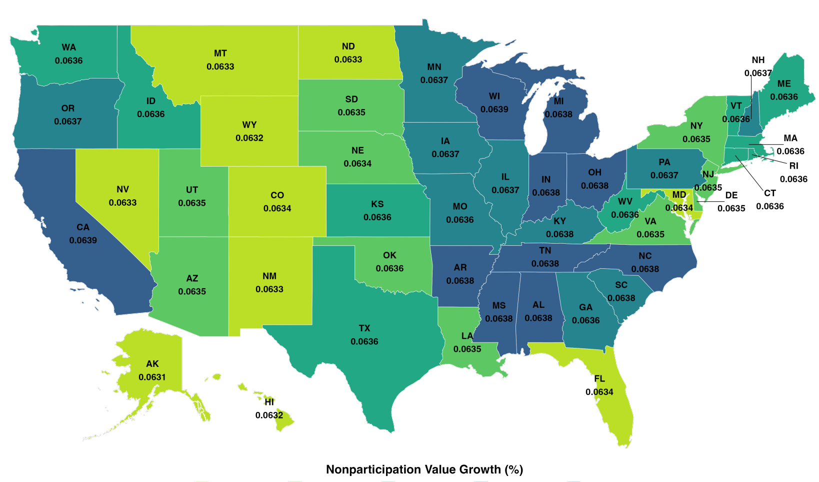


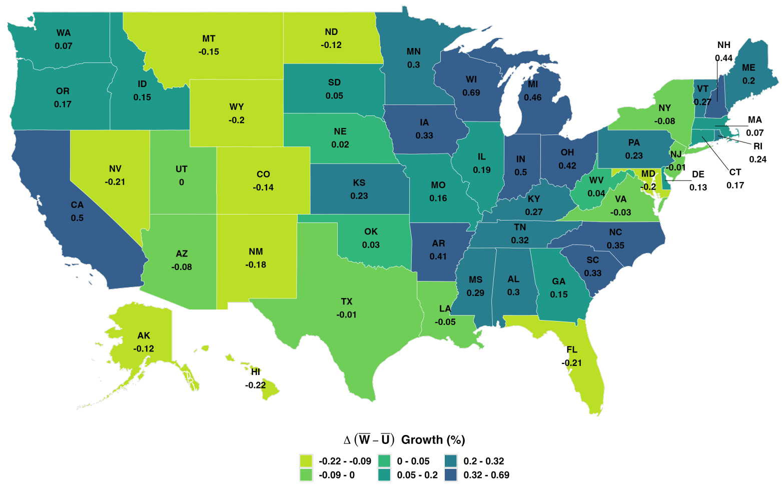
Table 13: The China trade shock and regional welfare outcome

	Dependent variables			
	$\bar{V}$ gr.	$\bar{U}$ gr.	$\bar{W}$ gr.	U_0 gr.
	(1)	(2)	(3)	(4)
Δ IP	-0.002^{***}	-0.001^{***}	0.00001^{***}	0.0001^{***}
	(0.0003)	(0.00004)	(0.00000)	(0.00000)
Observations	50	50	50	50
R^2	0.554	0.839	0.339	0.875

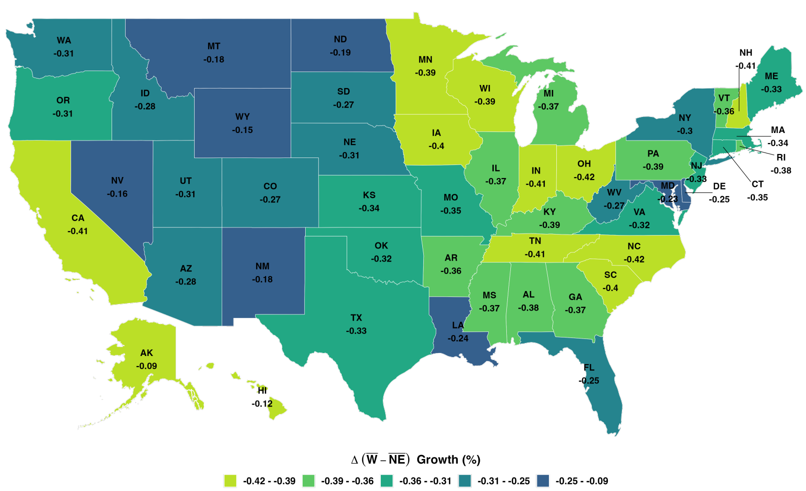
Notes: All data for the regressions are generated by the model. *p<0.1; **p<0.05; ***p<0.01.

Figure 26: Average welfare differences

(a) Predicted changes in the average value difference b/w employed and unemployed



(b) Predicted changes in the average value difference b/w employed and nonemployed



A.10 Inefficiency

Migration friction

Idiosyncratic shocks act as migration frictions across sectors and regions. For illustrative purpose, I simplify the model to have S sectors but only one region. These sectors are all tradable sectors, hence exogenous prices. The revenues per job in sector s is denoted as A_s. The simplified model also abstracts from random job-match productivity draws. Other notations and parameters are exactly the same as the main model.

I start with a social planner's problem of (36) in a dynamic setup. But the outcome will be finally evaluated in the steady state for comparison and relevancy. FOCs of (36) for sector i are as follows:

$$\frac{\partial \mathcal{L}}{\partial L^E_{i,t+1}} = \frac{1}{(1+r)^{t+1}} A_s + \lambda_{i,t+1}(1-\delta) - \lambda_{i,t} - \lambda_{0,t+1} = 0, \tag{52}$$

$$\frac{\partial \mathcal{L}}{\partial L^U_{i,t}} = \frac{1}{(1+r)^{t}}(b - e_i\theta_{i,t}) + \lambda_{i,t} m \theta^{\eta}_{i,t} - \lambda_{0,t} = 0, \tag{53}$$

$$\frac{\partial \mathcal{L}}{\partial \theta_{i,t}} = -\frac{1}{(1+r)^{t}} e_i L^U_{i,t} + \lambda_{i,t}\eta m \theta^{\eta-1}_{i,t} = 0. \tag{54}$$

FOC (54) is evaluated in the steady state to identify $\lambda_{i,t}$ as follows:

$$\frac{e_i}{\eta m}\theta^{1-\eta}_{i,t} = \lambda_{i,t}(1+r)^t = \lambda_{i,t+1}(1+r)^{t+1}. \tag{55}$$

Subtracting (52) by (53) with (55) in the steady state renders equation (37) that captures the constrained optimal result.

The equilibrium conditions with idiosyncratic shocks affecting cross-sectoral migration choices can be derived as Appendix (A.6.1). Firstly, I derive the wage equation in the equilibrium:

$$w_i = \beta A_i + (1-\beta) r E. \tag{56}$$

It is different from the wage equation in a model with perfect mobility:

$$w_i = \beta A_i + (1-\beta)(b + \frac{\beta}{1-\beta} e_i \theta_i), \tag{57}$$

derivation of which comes directly from [Pissarides 2000]. They are different because of different outside option values. With perfect mobility of the unemployed, the value of being unemployed equalizes across labor markets. The flow outside option value rE can be replaced by any rU_i, whose form is $b + \frac{\beta}{1-\beta} e_i \theta_i$. But with idiosyncratic shocks, $rE = r\nu \log \left(\sum_s \exp(\frac{b + e_s \theta_s \beta/(1-\beta) + E}{\nu(1+r)}) \right)$.

Taking (56) into the value function of a filled job gives the value of a job being filled as

$$J_i = \frac{1-\beta}{r+\delta}(A_i - rE),$$

which can be taken into the free entry condition of vacancies to get

$$e_i = m\theta_i^{\eta-1} \frac{1-\beta}{r+\delta}(A_i - rE). \tag{58}$$

Rearranging (58) can get the equilibrium condition (38).

Nontradable

For illustrative purpose, I simplify the model to have D sectors but only one sector, which is the nontradable sector. The job productivity of nontradable sector in region d is denoted as A_d. To single out the inefficiency caused by nontradable sector, I abstract from migration frictions in this model. Meanwhile, the unemployed benefit are set to be zero so as to simplify the nontradable goods market clearing. The derivation of constrained social optimal result is essentially the same as (52) - (55), except that b is left out.

The key equilibrium condition of this model is the market clearing condition for nontradable goods: local nontradable output equal to total local demand. There is just one good. All income of the employed is spent on the nontradable goods:

$$p_d A_d L_d^E = \underbrace{(\beta p_d A_d + \beta p_d e_d \theta_d)}_{wage} L_d^E, \tag{59}$$

which is rearranged to get (41).