Essays on Trade Shocks and Spatial Unemployment

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Abstract

The first chapter documents how increased import competition from China affected unemployment dynamics across U.S. commuting zones. Using a shift-share empirical design, I find that regions more exposed to the China trade shock experienced persistent increases in unemployment. These effects are driven by both elevated job separation rates and sharp declines in job finding rates, with consequences that extend well beyond the initial exposure period. The empirical results highlight the need to move beyond relative effects and explore the underlying mechanisms driving the persistence and distribution of unemployment.

The second chapter develops a multi-region, multi-sector labor matching model with endogenous job creation and destruction to explain these results and capture the persistency. The calibrated model confirms that the China shock raises unemployment, decreases employment, and increases welfare inequality across many U.S. states. The China shock raises the overall U.S. unemployment rate by 0.18 percentage points 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 Hosios (1990) condition alone cannot achieve constrained socially optimal allocations in this model. A redistributive corporate tax policy could improve welfare, reduce unemployment, and restore pre-shock manufacturing employment levels.

The third chapter looks into spatial unemployment by studying how frictional labor markets contribute to spatial labor sorting and, consequently, to disparities in productivity, wages, and unemployment across regions. The model incorporates frictional labor matching with two worker types, two locations, and free labor mobility. It predicts that skilled workers tend to sort into areas with higher productivity, higher wages, and lower unemployment rates. Empirical evidence aligns with these theoretical predictions, suggesting that frictional labor markets play a crucial role in shaping spatial economic disparities.

Acknowledgements

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This dissertation could not have been completed without the love and support from Yurou He, whom I dedicate this work to.

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Chapter 1

The Anatomy of Unemployment Effects of the China Trade Shock

1.1 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. The rise in unemployment can further contribute to populism as found by Che et al. (2022) and Chen (2024). While empirical analyses have shed light on the relative effects of trade shocks across regional labor markets, they often fall short of examining the actual level 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 chapter aims to address the question: How do trade shocks influence regional labor markets and for how long, particularly in terms of unemployment and its core drivers—job finding and job separation?

This chapter 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 1.1. 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.

This chapter 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 chapter demonstrates the persistence of these labor market effects over time.[1]

By disentangling the channels through which trade exposure influences unemployment, this chapter motivates the need for an equilibrium framework that can account for regional, sectoral, and frictional heterogeneity. The next chapter builds such a model and uses it to analyze the general equilibrium and welfare consequences of trade shocks across space and sectors.

1.2 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:

$$\Delta y_{d\tau} = \beta_\tau + \beta_y \Delta IP_{d\tau} + \mathbf{X}'_{d\tau}\beta_o + \epsilon_{d\tau}, \tag{1.1}$$

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

[1] 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.

(16 - 64) population. $\Delta IP_{d\tau}$ is the local labor market exposure to import competition that is defined by:

$$\Delta IP_{d\tau} = \sum_i \frac{L_{id\tau_0}}{L_{i\tau_0}} \frac{\Delta M_{i\tau}}{L_{d\tau_0}}, \tag{1.2}$$

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 \$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 (3.11) 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:

$$\Delta IPO_{d\tau} = \sum_i \frac{L_{id\tau_{-1}}}{L_{i\tau_{-1}}} \frac{\Delta EO_{i\tau}}{L_{d\tau_{-1}}}, \tag{1.3}$$

where $\Delta EO_{i\tau}$ is the change of import values from China to eight other high-income markets during the period.[2] And the subscript -1 means the employment levels are from the prior decade.[3] 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.[4] Following ADH,

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

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

[4] 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-

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 (3.11) 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.[5]

$$\Delta y_{dT} = \beta_T + \beta_{yT} \Delta IP_{d\tau} + \mathbf{X}'_{d\tau_0} \beta_o + \epsilon_{dT}, \tag{1.4}$$

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.

1.3 Data and measurement

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 are sourced from BACI, which is based on the UN Comtrade Database.[6] Employment data by industry and commuting zone are derived from the County Business Patterns Database.[7] Labor market outcomes and control variables are obtained from the 5% sample of the Census and the American Community Survey.

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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

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

[6] 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).

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

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.[8]

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. [9] 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 Tables 1.2 - 1.5 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 Table 1.1.

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

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

1.4 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 1.7. The first stage result, which is the same as in ADH, is shown in 1.6. The coefficient of 0.258 in column 1 suggests that a $1,000 increase in a commuting zone's (CZ) import exposure per 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.

These labor market effects persist over time, as shown in Figure 1.2. 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.

1.5 Robustness

Adao et al. (2019b) argue that clustering standard errors at the state level may not be enough because regression residuals are correlated across regions with similar sectoral shares, independently of their geographic location. Moreover, they show that the way in which standard errors is clustered in ADH may shrink the confidence intervals. They derive inference methods that are valid under arbitrary cross-regional correlation in the regression residuals. As is shown in Table 1.9, the confidence intervals are enlarged. But all estimates remain statistically significant at 5% level.

Since imputation of job transition rates involves a decision of threshold on the survey answers, one might be concerned that results could change as the threshold change. In the robustness check, I apply alternative thresholds for measuring job finding and separation rates, and the results remain consistent for the period over 1990 to 2007 (see Tables 1.8 and 1.10), as well as longer periods (see Figure 1.3 and Figure 1.4). 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.

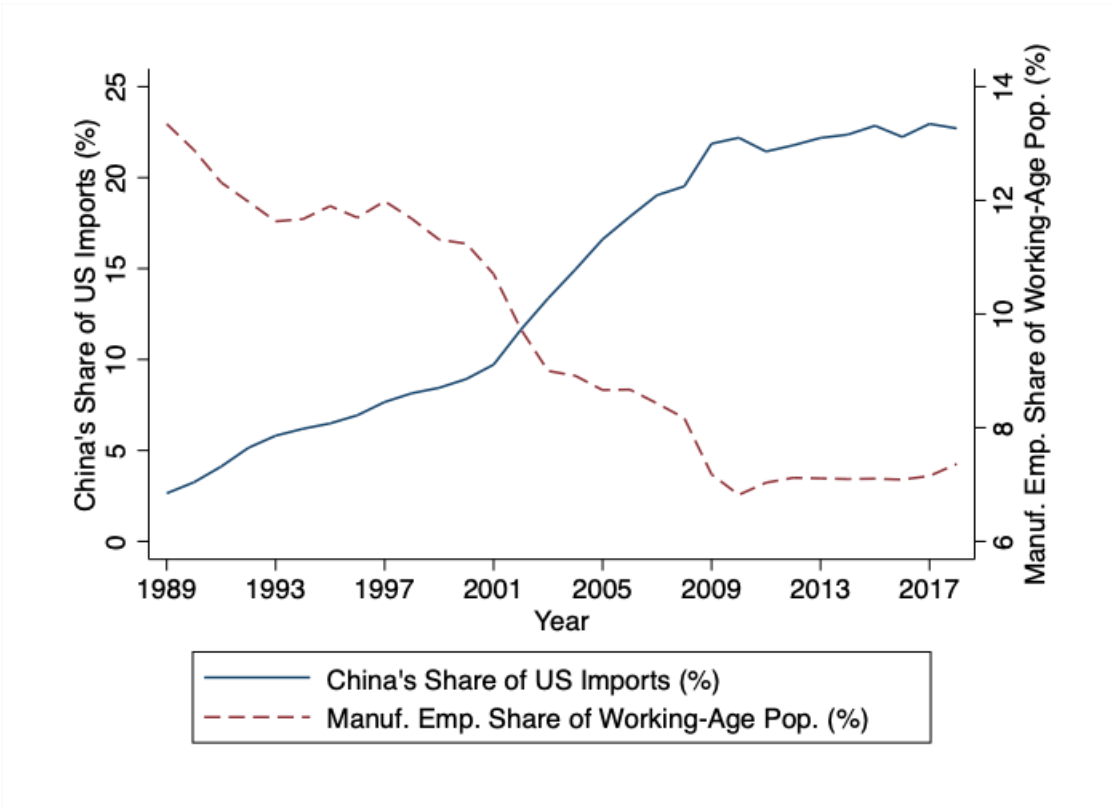
1.6 Conclusion

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 chapter, 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. I use innovative methods imputing these transition rates. 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.

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.

1.7 Figures and tables

Figure 1.1: 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.

Table 1.1: 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

Continued on next page

Table 1.1 – continued from previous page

Period	Stat	Unemp. Rate (%)	Job Find. Rate (%)	Job Sep. Rate (%)
	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

Table 1.2: 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 1.3: 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

Table 1.4: 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 1.5: 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

Table 1.6: The China trade shock outcome: first stage

	Dependent variables
	Δ Import Penetration
Δ IPO	0.746***
	(0.029)
Constant	−2.444**
	(1.235)
Observations	1,444
R^2	0.532
F Statistic	101.230*** (df = 16; 1427)

Notes: The results are from first stage estimation of regression (3.11). The samples are restricted to the working-age group (age 16 - 64). Other control variables are included but not reported here. *p<0.1; **p<0.05; ***p<0.01.

Table 1.7: The China trade shock outcome: 2SLS estimates

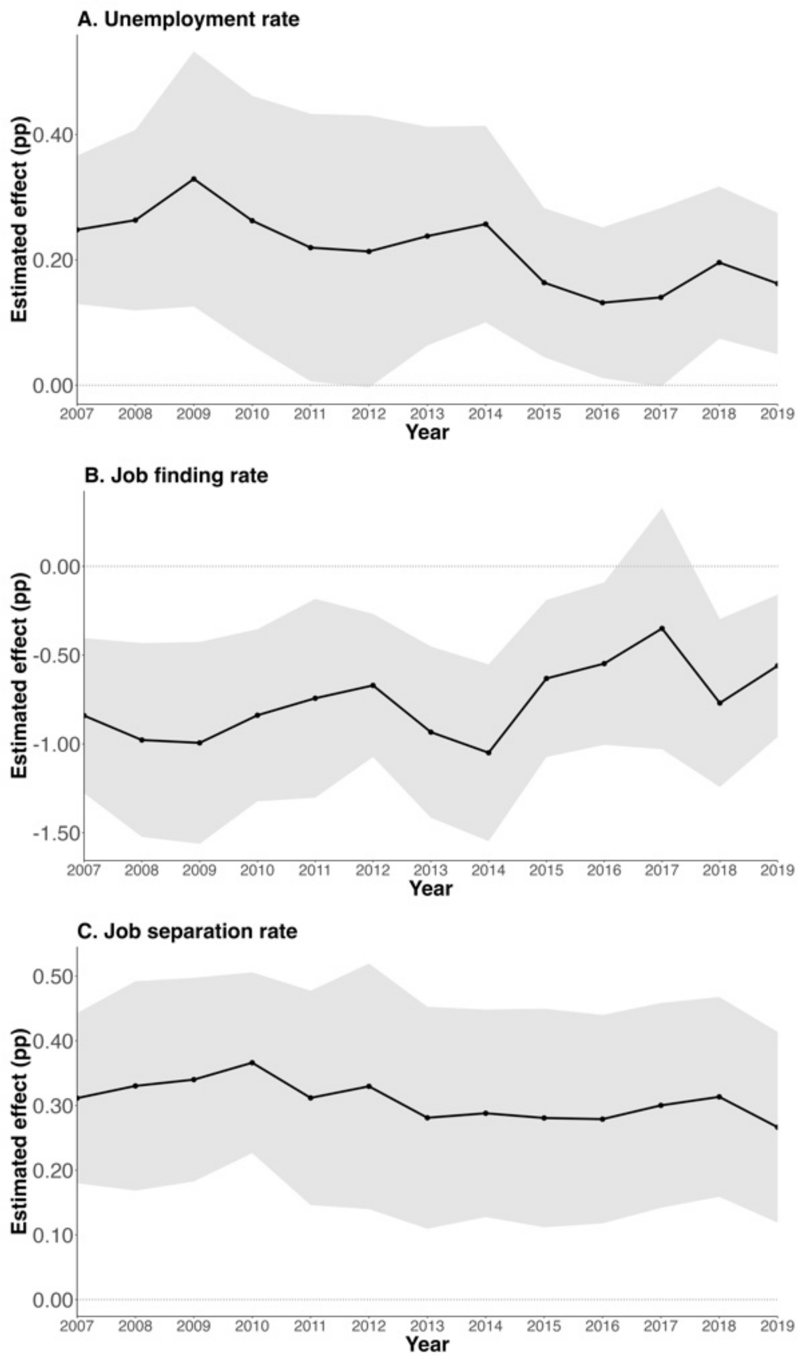
	Dependent variables		
	Δ Unemployment Rate	Δ Job Finding Rate	Δ Job Separation Rate
	(1)	(2)	(3)
ΔIP	0.248^{***}	-0.841^{***}	0.311^{***}
	(0.060)	(0.239)	(0.079)
Post 2000	0.777^{*}	-9.102^{***}	-7.458^{***}
	(0.411)	(1.055)	(0.488)
$Region_{midatl}$	0.884^{***}	-1.706	1.182
	(0.265)	(2.421)	(1.192)
$Region_{encen}$	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)

	Dependent variables (Continued)		
	Δ Unemployment Rate	Δ Job Finding Rate	Δ Job Separation Rate
	(1)	(2)	(3)
$Region_{escen}$	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^{*}
	(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. Foreign Shr.	-0.018^{***}	-0.005	-0.027

	Dependent variables (Continued)		
	Δ Unemployment Rate	Δ Job Finding Rate	Δ Job Separation Rate
	(1)	(2)	(3)
	(0.006)	(0.043)	(0.041)
Ini. Female 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 (3.11). 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 1.2: Trade shock impact, 2007 - 2019



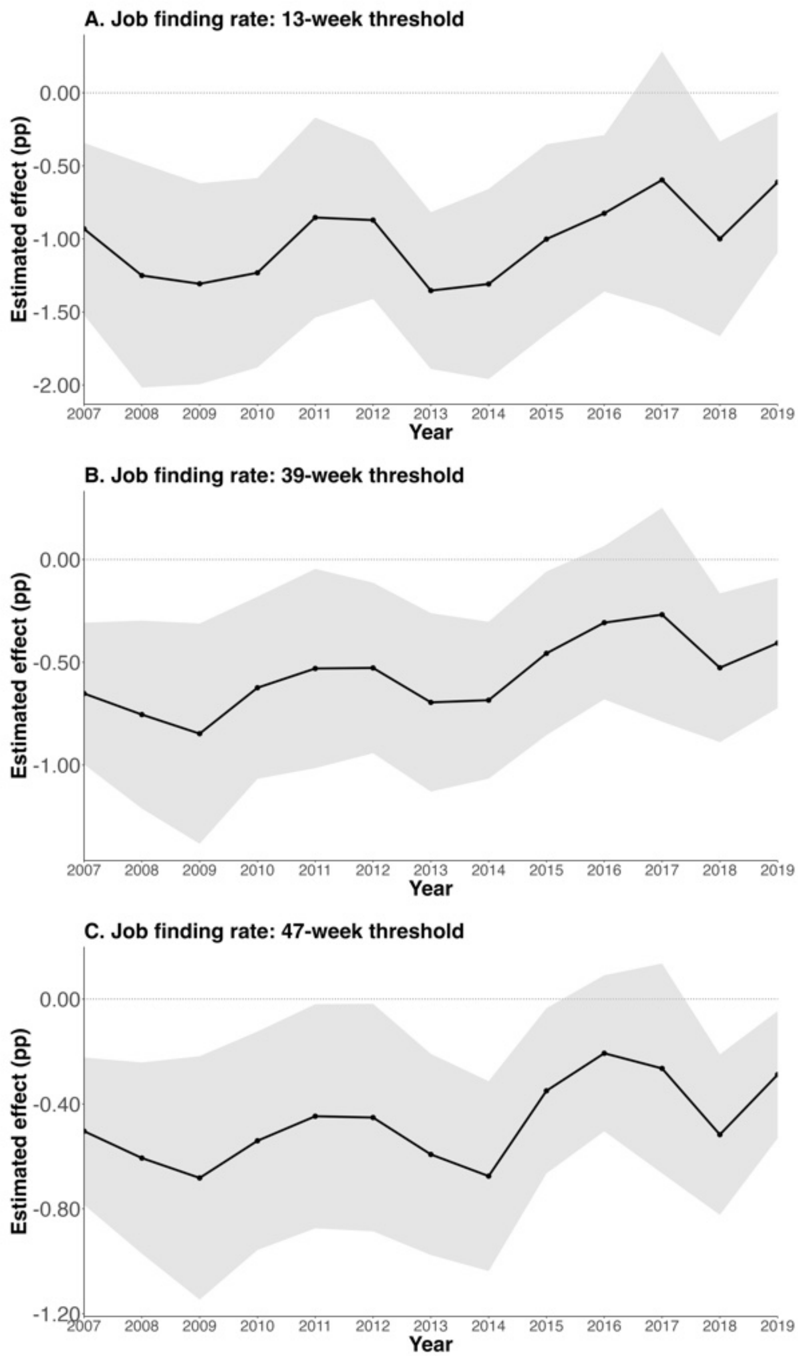
Notes: The dots are the coefficients estimated from regression (1.4) using 2SLS with successively longer first difference from period 2000 - 2007 to 2000 - 2019 on the LHS. The shaded area represents the 95% confidence interval of each coefficient. Regressions are weighted by the CZ total population in 2000; standard errors are clustered by state.

Table 1.8: 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 (3.11). 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 1.3: Trade shock impact, 2007 - 2019



Notes: The dots are the coefficients estimated from regression (1.4) 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.

Table 1.9: The China trade shock and job finding outcome: 2SLS estimates with AKM standard errors

	Dependent variables		
	Δ Unemployment Rate	Δ Job Finding Rate	Δ Job Separation Rate
	(1)	(2)	(3)
Δ IP	0.248***	−0.841***	0.311***
	(0.077)	(0.329)	(0.079)
Observations	1,444	1,444	1,444
R^2	0.309	0.592	0.807

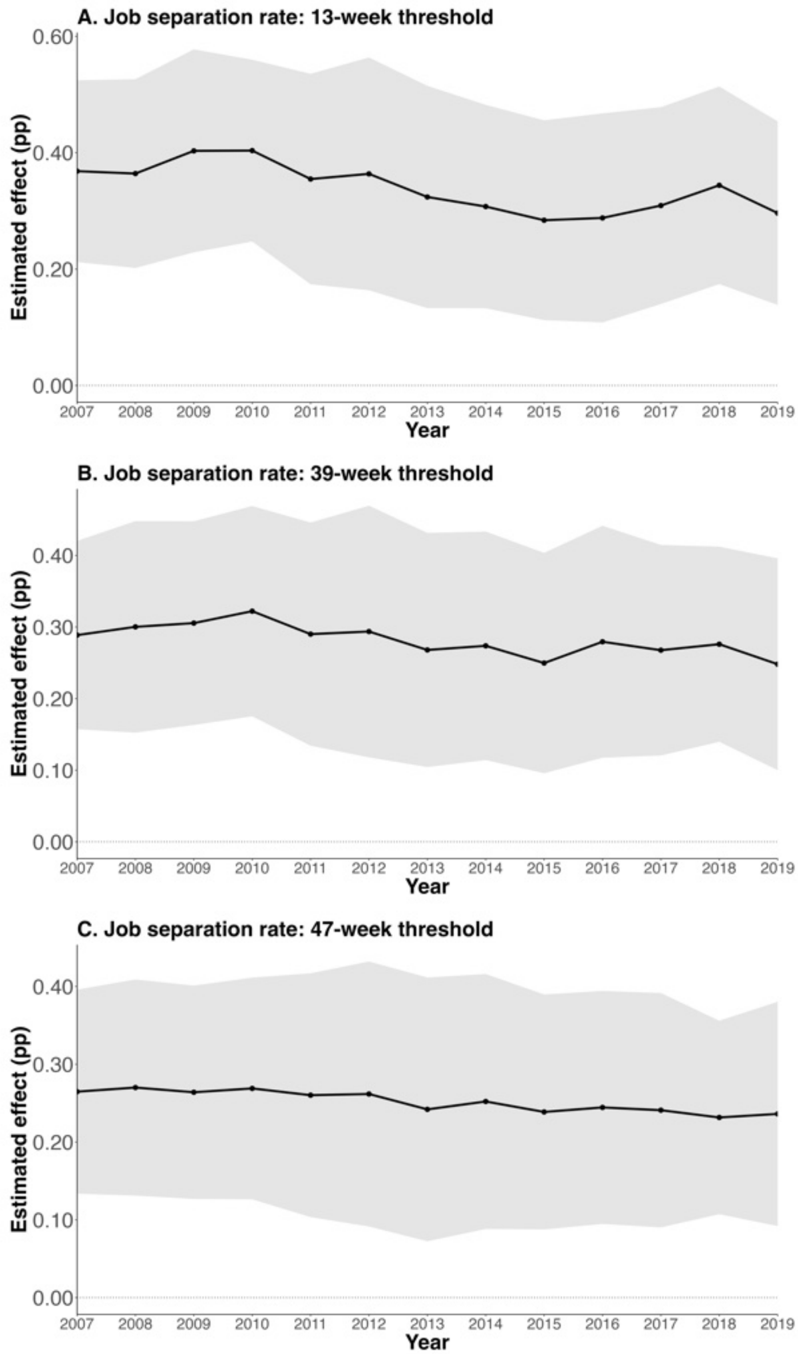
Notes: The results are from 2SLS estimation of regression (3.11) with standard errors calculated using the AKM method. The estimated results on other results are left out. The samples are restricted to the working-age group (age 16 - 64). Models are weighted by start of period CZ share of national population. *p<0.1; **p<0.05; ***p<0.01.

Table 1.10: 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 (3.11). 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 1.4: Trade shock impact, 2007 - 2019



Notes: The dots are the coefficients estimated from regression (1.4) 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.

Chapter 2

Labor Market Responses to Trade Across Sectors and Space

2.1 Introduction

The empirical evidence presented in Chapter 1 highlights the significant and persistent impact of the China trade shock on unemployment in U.S. local labor markets. These patterns are driven by both an increase in job separations and a sharp decline in job finding rates—features that cannot be captured by standard models of trade and labor mobility, which often neglect the role of labor market frictions. Moreover, because the trade shock operates at the national level and inter-regional and inter-sectoral linkages exist, the shift-share empirical approach can only identify relative effects, not absolute changes. To capture the full impact of the trade shock on unemployment and its persistence, a structural model is needed. Such a model also enables welfare analysis.

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. In addition to multiple manufacturing sectors, 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.[1] Within each frictional labor market, endogenous job destruction arises from idiosyncratic job-match productivity, following the framework of Mortensen and Pissarides (1994). Both unemployed individuals and labor non-participants, subject to idiosyncratic preference shocks, have the option to sort into different labor markets. 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 chapter. 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

[1] Since this chapter focuses exclusively on U.S. local labor markets and does not extend its analysis to other countries, the small open economy assumption can reduce computational complexity and generate necessary labor market responses. Additionally, endogenous nontradable prices allow for relative price adjustments that resemble terms-of-trade changes in an open economy.

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.[2] 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 points. On aggregate, the China trade shock raises the overall U.S. unemployment rate by 0.18 percentage points. 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.

[2] 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 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 normalized by the working-age population 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 the fraction of manufacturing employment over the working-age population, as illustrated in Figure 1.1.

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 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.

Frictional labor matching plays an important role in the propagation of trade shocks from manufacturing to non-manufacturing. Comparative advantage theories (in a neoclassic environment), such as Ricardian and Heckscher–Ohlin, tell us that for a country like the U.S., there should be employment shifts from manufacturing to non-manufacturing sectors in response to such a trade shock. And the thriving non-manufacturing sector may be able to deliver improvement in the overall labor market. But in this model, as the unemployed transition from the manufacturing to non-manufacturing, they congest one another out during job search because of frictional labor matching. The quantitative results show that there is a non-trivial amount of states having more unemployed agents searching for jobs but lower employment in the non-manufacturing sector. In other words, frictional labor matching dampens the employment shifts from manufacturing to non-manufacturing.

The model also highlights the resulting gains 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 with the Hosios condition imposed.[3] The inefficiency in a search and matching model stems from the congestion that workers and firms impose on 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 chapter introduces two additional sources of congestion: mobility 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 higher labor market tightness compared to the (constrained) social optimal level. This is because that workers do not fully internalize the benefits from their job search. To see this, an extra unemployed agent searching for non-tradable sectoral jobs can raise the chance of forming job matches for all firms. And more non-tradable output lowers the prices, benefiting all agents in that region. The agents, on the other hand, only get a fixed fraction of surpluses generated by the job. This finding motivates the following policy counterfactual analysis.

The policy counterfactual analysis in this chapter 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

[3] 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.

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 points. This chapter suggests that without waging a trade war, the US can gain more from trade while making the manufacturing great again, if that means something.

The structural approach derived in this chapter contributes to the quantitative trade literature examining the regional labor market outcomes of trade shocks (e.g., Adao et al. (2019a); 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 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 dissertation. Forward-looking assumption allows for important welfare gains from higher labor outside option values.[4] 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 chapter models frictional migration across regions, which amplifies the negative effects on local labor markets.[5]

[4] Galle et al. (2023) incorporates the static labor matching model from Kim and Vogel (2021) and find welfare losses for some groups of agents.

[5] 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

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 chapter is on unemployment, I also model labor non-participation, providing a more comprehensive view of employment effects.

This chapter 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 chapter 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 chapter, theirs abstracts from regional congestion forces, which play a significant role in migration dynamics.

This chapter 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 chapter, 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 mobility frictions, driven by idiosyncratic taste shocks. Recent

trade at the country level. Many of them are about how trade can lower unemployment, which is not consistent with the empirical facts found in this chapter. 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).

models usually rely on these taste shocks from extreme value distributions to capture mobility frictions, and I show that when combined with search externalities, they contribute to inefficiency of market equilibrium. The second source of inefficiency arises from the presence of a local non-tradable sector, which operates under frictional labor matching conditions.[6]

2.2 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.[7] 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.

2.2.1 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

[6]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.

[7]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.

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 chapter 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:

$$\mathcal{U} = \mathbb{E}\left(\sum_{t=0}^{\infty} \frac{C_t}{(1+r)^t}\right), \tag{2.1}$$

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

$$C_t = \prod_{s=1}^{S} (q_{s,t}/\alpha_s)^{\alpha_s}, \tag{2.2}$$

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 jobseeker 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 is 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. [8] 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 $(-\gamma_0\nu, \nu)$.[9] 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 jobseeker needs to pay on the job market. Allowing

[8] 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).

[9] γ_0 is the Euler constant.

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 2.1.

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 2.2. 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.

2.2.2 Equilibrium

This chapter 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 (2.2) , the final consumption price index in location d is

$$P_d^f = \prod_{s=1}^{S} p_{sd}^{\alpha_s}, \tag{2.3}$$

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:

$$\begin{aligned} U_{sd} = \frac{1}{1+r}\{ & b_d/P_d^f + \theta_{sd}\kappa(\theta_{sd})\mathbf{Pr}[x \in \mathcal{M}_{sd}]\mathbb{E}[W_{sd}(x)|x \in \mathcal{M}_{sd}] + \\ & (1-\theta_{sd}\kappa(\theta_{sd})\mathbf{Pr}[x \in \mathcal{M}_{sd}])\, \mathbb{E}\left(\max_{s' \in \{0,1,\ldots,S\},\ d' \in \{1,..,D\}} U_{s'd'} + \epsilon_{s'd'}\right)\}. \end{aligned} \tag{2.4}$$

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. [10] 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

[10] 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.

value of the nonparticipants, U_{0d}, is given by:

$$U_{0d} = \frac{1}{1+r}\left\{\omega_d/P_d^f + \lambda_0 E + (1-\lambda_0)U_{0d}\right\}. \tag{2.5}$$

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

$$\begin{aligned} W_{sd}(x) = & \frac{1}{1+r}\{w_{sd}(x)/P_d^f + (1-\delta)\mathbf{Pr}[x \in \mathcal{M}_{sd}]\mathbb{E}[W_{sd}(x)|x \in \mathcal{M}_{sd}] + \\ & (\delta + (1-\delta)\mathbf{Pr}[x \notin \mathcal{M}_{sd}])E.\} \end{aligned} \tag{2.6}$$

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:

$$J_{sd}^V = \frac{1}{1+r}\left\{-e_{sd}P_d^f + \kappa(\theta_{sd})\mathbf{Pr}[x \in \mathcal{M}_{sd}]\mathbb{E}[J_{sd}(x)|x \in \mathcal{M}_{sd}] + (1-\kappa(\theta_{sd})\mathbf{Pr}[x \in \mathcal{M}_{sd}])\, J_{sd}^V\right\}, \tag{2.7}$$

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

$$J_{sd}^V = 0 \qquad \forall s,\ d. \tag{2.8}$$

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

$$J_{sd}(x) = \frac{1}{1+r}\{p_{sd}A_{sd}x - w_{sd}(x) + (1-\delta)\mathbf{Pr}[x \in \mathcal{M}_{sd}]\mathbb{E}[J_{sd}(x)|x \in \mathcal{M}_{sd}] + \\ (\delta + (1-\delta)\mathbf{Pr}[x \notin \mathcal{M}_{sd}])J_{sd}^{V}. \tag{2.9}$$

Intra-temporal profits are $p_{sd}A_{sd}x - w_{sd}(x)$.[11] 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:

$$w_{sd}(x) = arg\max_{w}\ \left[J_{sd}(x) - J_{sd}^{V}\right]^{1-\beta}\left[P_d^f(W_{sd}(x) - E)\right]^{\beta}. \tag{2.10}$$

As discussed above, the worker's net surplus, $W_{sd}(x) - E$, is adjusted by P_d^f 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 (2.6), (2.8), and (2.9) into (2.10) gives a FOC of the Nash bargaining:

$$P_d^f\ (W_{sd}(x) - E) = \frac{\beta}{1-\beta}J_{sd}(x). \tag{2.11}$$

From (2.11), 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

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

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}:

$$P_d^f\left(W_{sd}(R_{sd}) - E\right) = \frac{\beta}{1-\beta} J_{sd}(R_{sd}) = 0. \tag{2.12}$$

The wage then is given by

$$w_{sd}(x) = \beta(p_{sd}A_{sd}x - rP_d^f E) + rP_d^f E. \tag{2.13}$$

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 (2.4) to (2.11) gives the value of being unemployed as

$$U_{sd} = \frac{1}{1+r}(b_d/P_d^f + \frac{\beta}{1-\beta} e_{sd}\theta_{sd} + E). \tag{2.14}$$

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:

$$U_{0d} = \frac{1}{\lambda_0 + r}(\omega_d/P_d^f + \lambda_0 E). \tag{2.15}$$

Both (2.14) and (2.15) 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 (2.8) generates an equation describing job creation:

$$e_{sd} = \underbrace{\kappa(\theta_{sd})(1 - F(R_{sd}))}_{\text{Prob. of a successful match}} \underbrace{\frac{1-\beta}{1+r}\rho_{sd}\mathbb{E}(x - R_{sd} \mid x > R_{sd})}_{\text{Conditional expected real returns of a filled job}}, \tag{2.16}$$

where $\rho_{sd} \equiv \frac{p_{sd}A_{sd}}{P_d^f}$ is the real marginal revenue of effective labor. Equation (2.16) 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 (2.16). 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 (2.12) gives another equation that describes job destruction:

$$\rho_{sd} \underbrace{\left[R_{sd} + \frac{1-\delta}{1+r}\mathbb{E}(x - R_{sd} \mid x > R_{sd})(1 - F(R_{sd}))\right]}_{\text{Expected present discounted product}} = rE. \tag{2.17}$$

Equation (2.17) 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.[12]

[12]This is different from Mortensen and Pissarides (1994) who derive an upward sloping job destruction condition. In fact, the quantitative exercise of this chapter produces a job destruction

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 2.3

Labor distribution

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

$$L_{sd}^{E} = L_{sd}^{U} \underbrace{\theta_{sd}\kappa(\theta_{sd})(1 - F(R_{sd}))}_{\text{Job finding rate}} / \underbrace{[\delta + (1-\delta)F(R_{sd})]}_{\text{Job separation rate}}, \tag{2.18}$$

where L_{sd}^{E} is the number of employed in sector s and region d and L_{sd}^{U} that of unemployed.[13] 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:

$$\frac{L_{sd}^{U}}{\lambda_0 \sum_{d'} L_{0d'}^{U} + \sum_{s' \neq 0,\ d'} L_{s'd'}^{U}} = \frac{\exp \frac{U_{sd}}{\nu}}{\sum_{s',\ d'} \exp \frac{U_{s'd'}}{\nu}}. \tag{2.19}$$

curve almost horizontal even without the infinitesimal labor market assumption.

[13]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 (2.18) from the dynamic environment can be found in Appendix 2.8.1.

And that of the nonparticipants:

$$\frac{\lambda_0 L^U_{0d}}{\lambda_0 \sum_{d'} L^U_{0d'} + \sum_{s' \neq 0,\ d'} L^U_{s'd'}} = \frac{\exp \frac{U_{0d}}{\nu}}{\sum_{s',\ d} \exp \frac{U_{s'd'}}{\nu}}, \tag{2.20}$$

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.[14] Again by the properties of the extreme value distribution, the expected value of moving is given by

$$E = \nu \log(\sum_{s=0}^{S} \sum_{d=1}^{D} \exp(U_{sd}/\nu)). \tag{2.21}$$

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

$$\sum_{s=1}^{S} \sum_{d=1}^{D} (L^U_{sd} + L^E_{sd}) + \sum_{d=1}^{D} L^U_{0d} = \bar{L}, \tag{2.22}$$

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

[14] 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

$$p_{1d}A_{1d}\mathbb{E}(x \mid x > R_{1d})L_{1d}^{E} = \alpha_1 I_d, \tag{2.23}$$

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 (2.14) - (2.23) hold given the exogenous tradable goods prices $\{p_s\}_{s=2}^{S}$.

2.2.3 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. 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 2.8.1. □

A trade shock, that is, a fall in the price, can affect labor market variables in the partial equilibrium shown in Figure 2.4, 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 2.4. 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.

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 (2.19). 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 2.8.1. □

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 2.8.1. □

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 chapter.

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.

2.2.4 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 (2.21), 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 (2.14). 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.

2.3 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.

2.3.1 "Sectors"definitions

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 chapter 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.[15]

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.

[15] 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.

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.[16]

2.3.2 Calibration

The sources and data moments for parameter calibration are shown in Table 2.1. Among the parameters that are not calibrated in this chapter, I equalize the market tightness elasticity η to firm bargaining power $1-\beta$ to avoid search externalities (Hosios (1990)). The regions this chapter 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

[16] 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 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 chapter 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.

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 2.1.

There are 607 parameters to calibrate with the same number of data moments as shown in Table 2.1, 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

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

Since data moments are different in magnitudes with some being rates and others counts, I minimize the sum of squared percentage distances from data moments to model-generated moments as above. The calibrated results are shown in Table 2.1. The average absolute percentage distance between model-generated moments and the actual ones is about 5%.[17]

[17]More details on calibration can be found in Appendix 2.8.2.

2.3.3 Isolating the China trade shock

The counterfactual shocks studied in this chapter 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 chapter 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.

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

$$\Delta NM_i^c = \alpha_0^c + \alpha_1^c \Delta CNEX_i + u_i, \tag{2.24}$$

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 (2.24) across industries and countries, $\{\widehat{\Delta NM_i^c}\}_{i,c}$, to construct the sectoral level predicted changes as follows

$$\widehat{\Delta NM_s} = \sum_{i \in s} \sum_c \widehat{\Delta NM_i^c}. \tag{2.25}$$

The reason for running equation (2.24) 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. [18] 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 shock, for which $\Delta CNEX_i$ is a proxy. [19]

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 2.2. The price shocks are small in magnitude but large enough to generate the predicted changes in sectoral net imports.

2.4 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

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

[19] 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 Figure 2.6.

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.

2.4.1 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 2.7a 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 2.7b and 2.7c. 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 2.8, 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 2.9a. A comparison of Figures 2.9a and 2.9breveals 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.

Given that the China trade shock primarily impacts the manufacturing sector, I further examine changes in manufacturing employment rates. As shown in Figure 2.9c, 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 2.15.

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 (2.16) and (2.17) under the parameterization in calibration:

$$\widehat{\theta_{sd}} = \varepsilon^{\theta}_{\rho}(R_{sd})\widehat{\rho_{sd}} - \varepsilon^{\theta}_{E}(R_{sd})\widehat{E}, \tag{2.26}$$

$$\widehat{R_{sd}} = \varepsilon^{R}_{E}(R_{sd})\widehat{E} - \varepsilon^{R}_{\rho}(R_{sd})\widehat{\rho_{sd}}, \tag{2.27}$$

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:

$$\widehat{\rho_{sd}} = \widehat{p_{sd}} - \widehat{P^{f}_{d}} = \widehat{p_{sd}} - (\alpha_1\widehat{p_{1d}} + \alpha_2\widehat{p_2} + \alpha_3\widehat{p_3} + \alpha_4\widehat{p_4} + \alpha_5\widehat{p_5}). \tag{2.28}$$

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 2.10a 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 2.10b. 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.

With equation (2.26) and (2.27) 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 2.16). 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 2.17 and 2.18). Overall, the labor market conditions in the manufacturing sectors deteriorate, resulting in lower job finding rates, higher job separation rates, and increased unemployment.

Propagation to the nontradable sector

All states experience a reduction in nontradable prices, as shown in Figure 2.11a. 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 2.11b, 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 2.16), the nontradable sector shows better labor market outcomes compared to others (see Figures 2.17 and 2.18).In fact, a significant number of states experience higher employment in the nontradable sector following the shock, as shown in Figure 2.12.

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 2.20) and deteriorating labor market conditions, these more exposed states experience reductions in both employment and output in the nontradable sector (see Figure 2.20).

Frictional labor matching dampens sectoral labor shifts in this model. As shown in Figure 2.12, 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 (2.21):

$$\widehat{E} = \frac{1}{E}\left(\sum_{s=1,d=1}^{S,D} \frac{U_{sd}\exp(U_{sd}/\nu)}{\sum_{s=0}^{S}\sum_{d=1}^{D}\exp(U_{sd}/\nu)}\widehat{U_{sd}} + \sum_{d=1}^{D} \frac{U_{0d}\exp(U_{0d}/\nu)}{\sum_{s=0}^{S}\sum_{d=1}^{D}\exp(U_{sd}/\nu)}\widehat{U_{0d}}\right). \tag{2.29}$$

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 nonparticipation 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 (2.19) and (2.20). According to (2.29), 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 (2.15). For the unemployed, while they benefit from real income gains, they also face lower labor market tightness in most markets. According to equation (2.19), 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 (2.21c)).

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 2.10a 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):

$$TFPR = \frac{\sum_{s=1,d=1}^{S,D} L_{sd}^{E} p_{sd} A_{sd} \int_{R_{sd}}^{\infty} x d\frac{F(x)}{1-F(R_{sd})}}{\sum_{s=1,d=1}^{S,D} L_{sd}^{E}}. \tag{2.30}$$

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 exposures and labor market outcomes

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 2.19 and 2.20, 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 2.11e. 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.

2.4.2 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 (2.4) and (2.5). 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:

$$\bar{W}_{sd} = \int_{R_{sd}}^{\infty} W_{sd}(x) d\frac{F(x)}{1 - F(R_{sd})} = \frac{\beta p_{sd} A_{sd}}{(1+r) P_d^f} \left(\frac{\int_{R_{sd}}^{\infty} x dF(x)}{1 - F(R_{sd})} - R_{sd} \right) + E. \tag{2.31}$$

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 2.13a, 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 2.13b.

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 2.13c. 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.

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

$$V_d = \left(U_{0d} L_{0d}^U + \sum_{s=1} (\bar{W}_{sd} L_{sd}^E + U_{sd} L_{sd}^U) \right) / L_d. \tag{2.32}$$

There are welfare gains in all states, as shown in Figure 2.14. 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 2.21). As shown in Table 2.4, 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.

2.5 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.

2.5.1 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 2.8.3.

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:

$$\max_{\{L^E_{s,t+1}, L^U_{s,t}, \theta_{s,t}\}_{s,t}} \sum_{t=0}^{\infty} \frac{1}{(1+r)^t} \left(\sum_{s=1}^{S} (A_s L^E_{s,t} + bL^U_{s,t} - e_s \theta_{s,t} L^U_{s,t}) \right) \tag{2.33}$$

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

The steady-state constrained optimal condition derived from (2.33) above for a sector s is

$$\eta(A_s - b) - \frac{\delta + r + (1-\eta)m\theta_s^{\eta}}{m\theta_s^{\eta-1}} e_s = 0. \tag{2.34}$$

If there is free mobility across sectors, the equilibrium condition will be exactly as (2.34) 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:

$$(1-\beta)(A_s - rE) - \frac{r + \delta}{m\theta_s^{\eta-1}} e_s = 0, \tag{2.35}$$

where $E = \nu \log\left(\sum_s \exp(\frac{b + e_s\theta_s\beta/(1-\beta) + E}{\nu(1+r)})\right)$. It will not align with (2.34) 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:

$$\max_{\{L^E_{d,t+1},L^U_{d,t}\}_{d,t}} \sum_{t=0}^{\infty} \frac{1}{(1+r)^t} \left(\sum_{d=1}^{D} (AL^E_{d,t} - e_d \theta_{d,t} L^U_{d,t}) \right) \tag{2.36}$$

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

$$\bar{L} = \sum_d (L^E_{d,t} + L^U_{d,t}).\ \forall t$$

The steady-state constrained optimal condition derived from (2.36) above for a region d is

$$\eta A_d - \frac{\delta + r + (1-\eta) m\theta^{\eta}_d}{m\theta^{\eta-1}_d} e_d = 0. \tag{2.37}$$

It resembles (2.34). The benchmark equilibrium I examine here is in the environment with free mobility to avoid the externalities from the migration friction discussed above. The equilibrium condition, which is mainly from local nontradable market clearing, is given by:

$$(1-\beta)A_d - \beta\theta_d e_d = 0. \tag{2.38}$$

Again it is not equivalent to (2.34) 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. This is because that workers do not fully internalize the benefits from their job search. To see this, an extra unemployed agent searching for non- tradable sectoral jobs can raise the chance of forming job matches for all firms. And more non-tradable output lowers the prices, benefiting all agents in that region. The agents, on the other hand, only get a fixed fraction of surpluses generated by the job.

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 chapter and left for future research. This chapter experiments with the policy discussed as follows.

2.5.2 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:

$$\sum_{s=2}^{S}(1+M)p_s \sum_{d=1}^{D} \bar{y}_{sd} L_{sd}^{E} = (1-T) \sum_{d=1}^{D} p_{1d} \bar{y}_{1d} L_{1d}^{E}. \tag{2.39}$$

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.[20]

The policy can improve the overall welfare and reduce unemployment. The third column of Table 2.3 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.

2.6 Conclusion

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

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

welfare-improving policies are necessary. The policy counterfactual analysis in this chapter 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 chapter can be applied to study the labor market effects of many other sectoral shocks, such as climate change.

2.7 Figures and tables

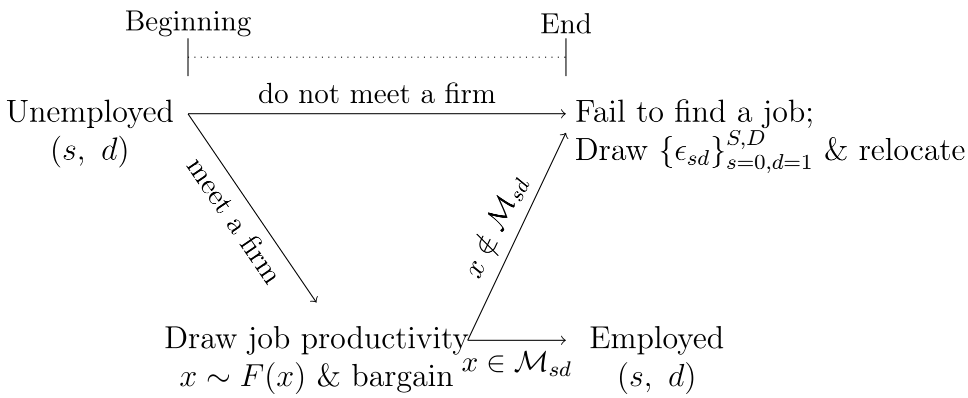


Figure 2.1: Within-Period Sequencing of Events for the Unemployed

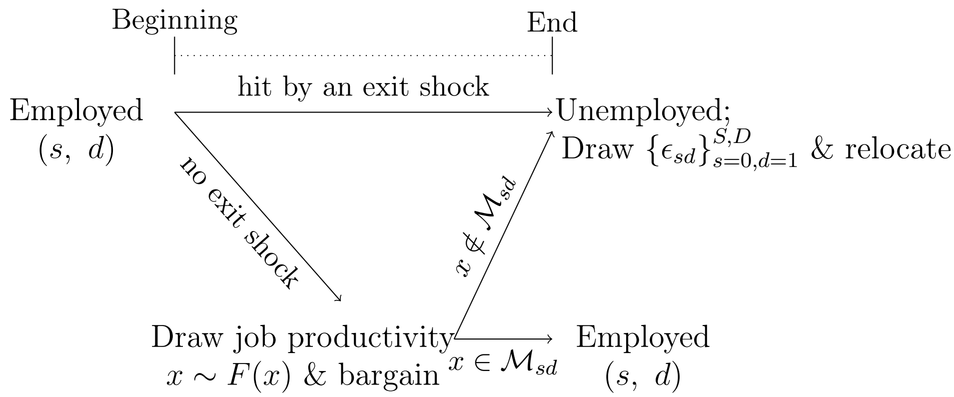


Figure 2.2: Within-Period Sequencing of Events for the Employed

Figure 2.3: Partial equilibrium reservation productivity and labor market tightness

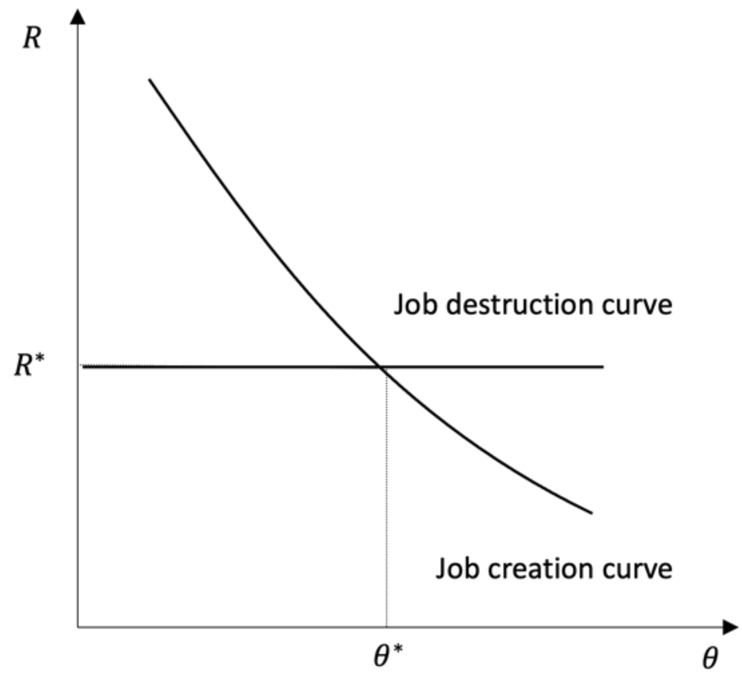
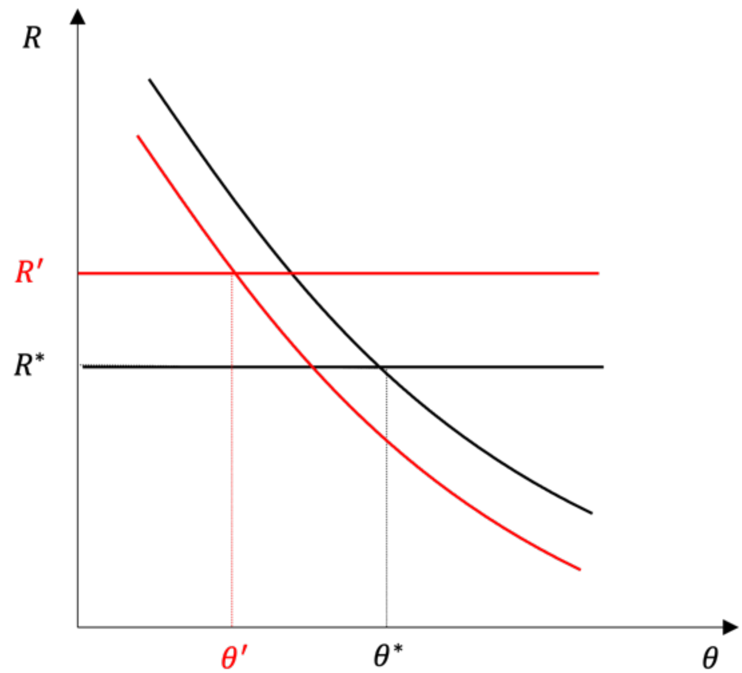


Figure 2.4: Trade shock in a partial equilibrium of a labor market



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

Table 2.1: 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.

Figure 2.5: Percentage distance

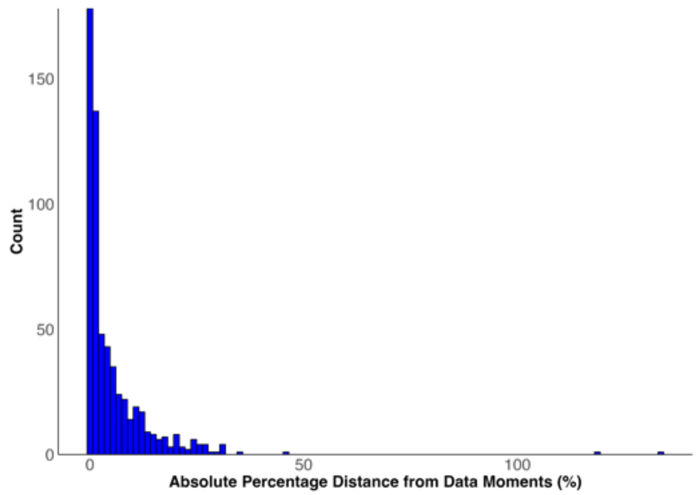
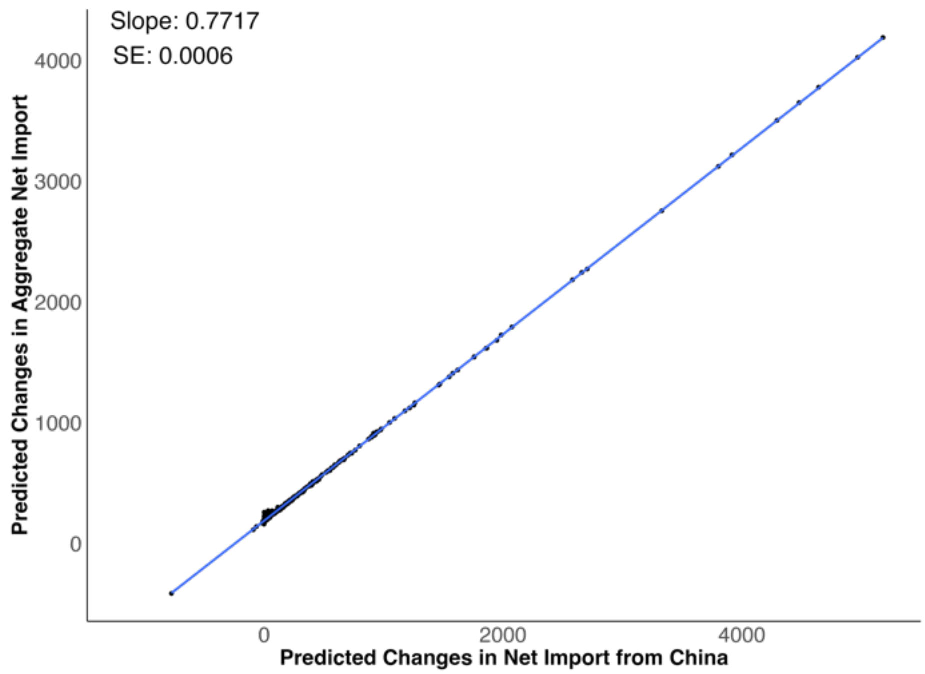


Table 2.2: Net imports and calibrated prices

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 2.24. The prices are calibrated with the first tradable sector as the numeraire.

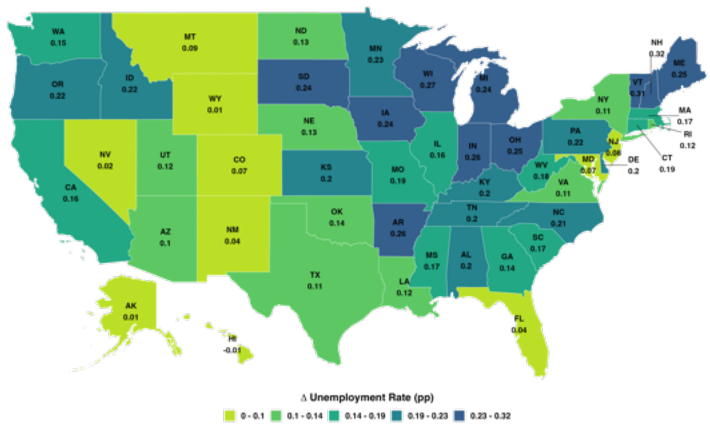
Figure 2.6: Predicted overall net import changes against predicted changes in the net imports from China



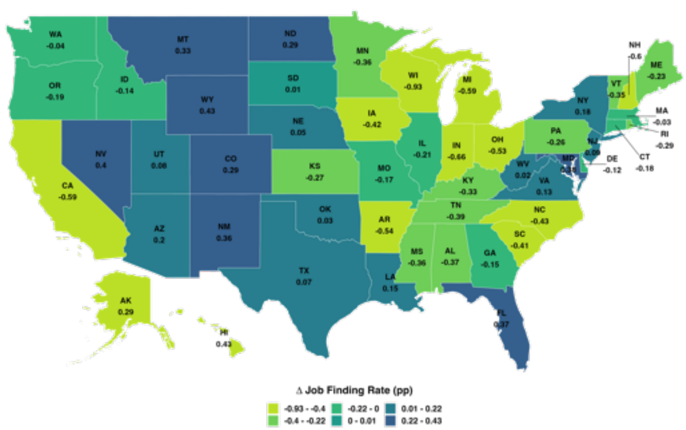
Notes: The predicted import changes are at the SIC level.

Figure 2.7: Regional labor market effects

(a) Predicted changes in unemployment rates



(b) Predicted changes in job finding rates



(c) Predicted changes in job separation rates

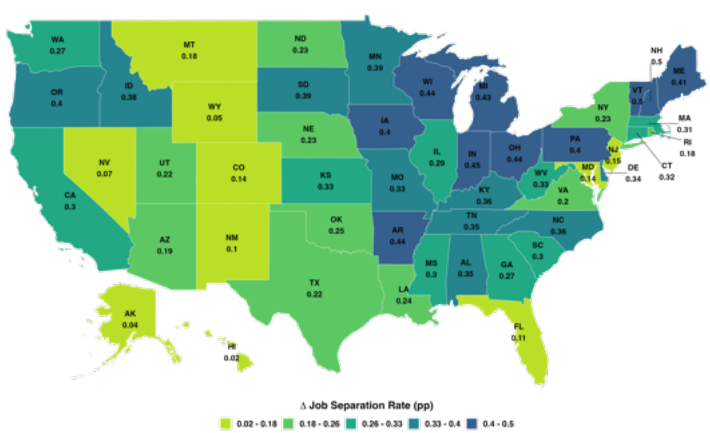
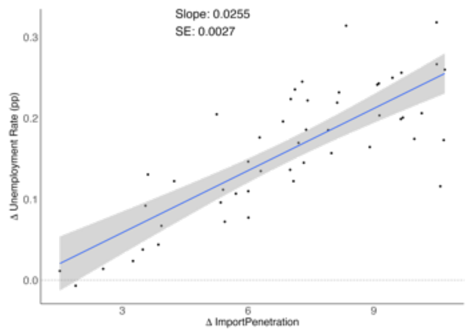
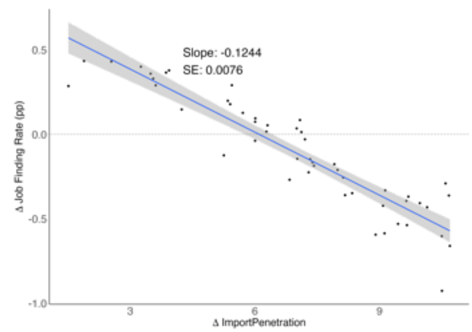


Figure 2.8: Predicted changes in labor market outcome and import penetration

(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

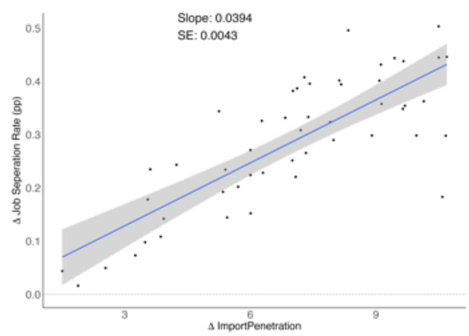
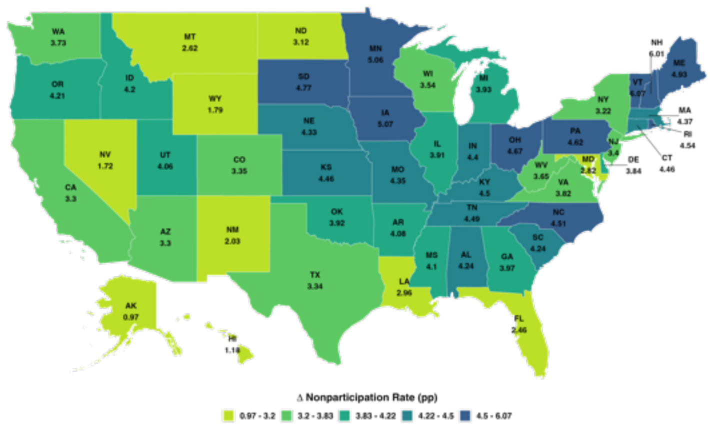
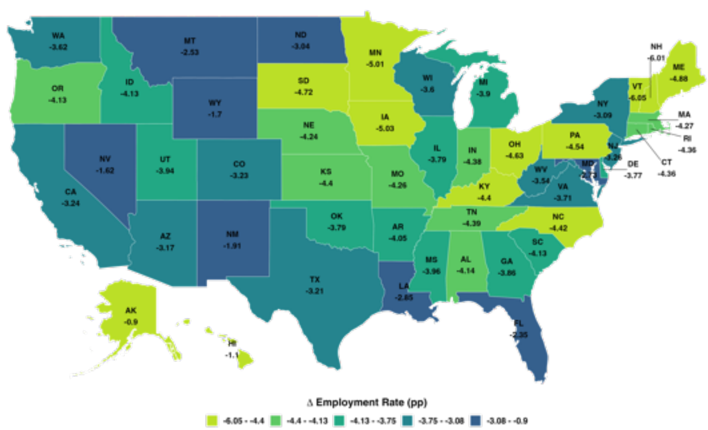


Figure 2.9: Regional labor market effects on nonparticipation and employment

(a) Predicted changes in nonparticipation rates



(b) Predicted changes in employment rates



(c) Predicted changes in manufacturing employment rates

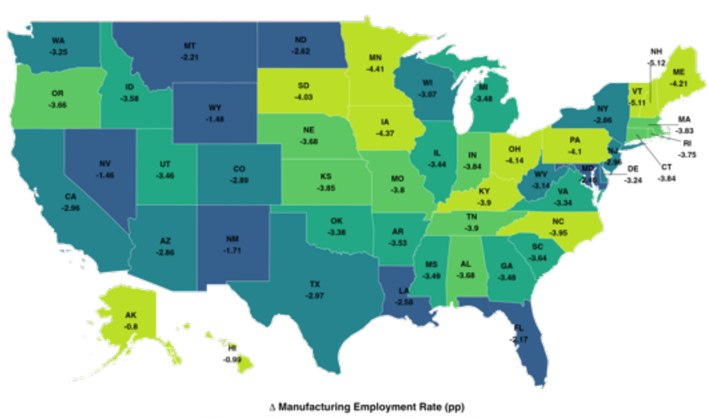
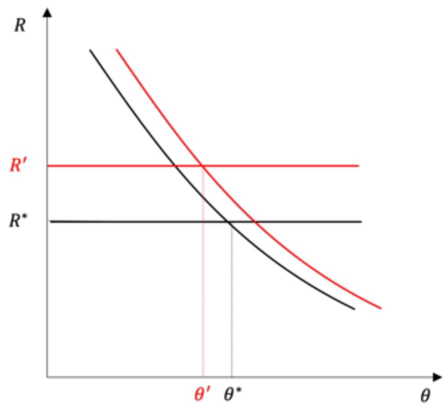


Figure 2.10: Partial equilibrium responses

(a) Small increase in real revenues per effective labor



(b) Large increase in real revenues per effective labor

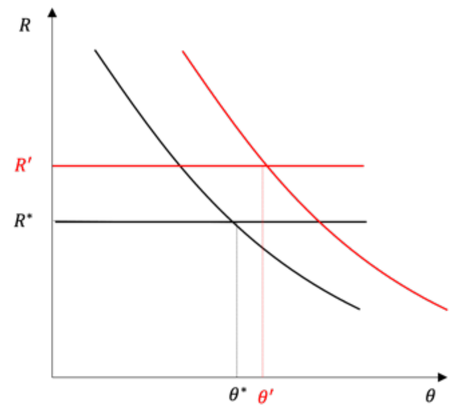
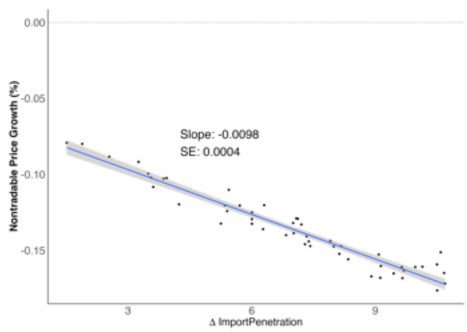
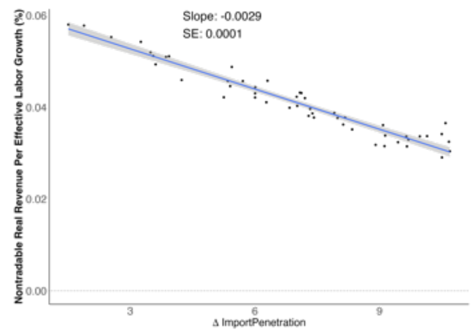


Figure 2.11: Nontradable sectoral variables and import penetration

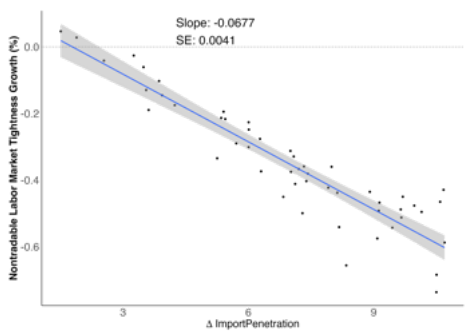
(a) Predicted changes in nontradable prices vs IP



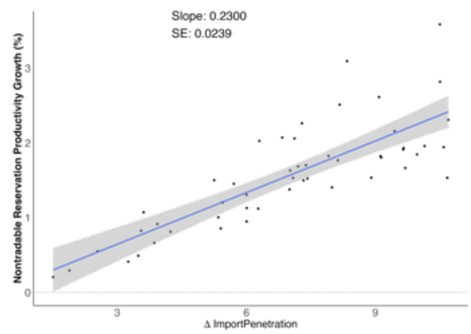
(b) Predicted changes in nontradable real revenues per effective labor vs IP



(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

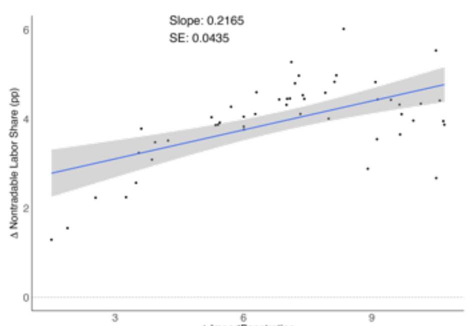


Figure 2.12: Predicted changes in nontradable employment and unemployment

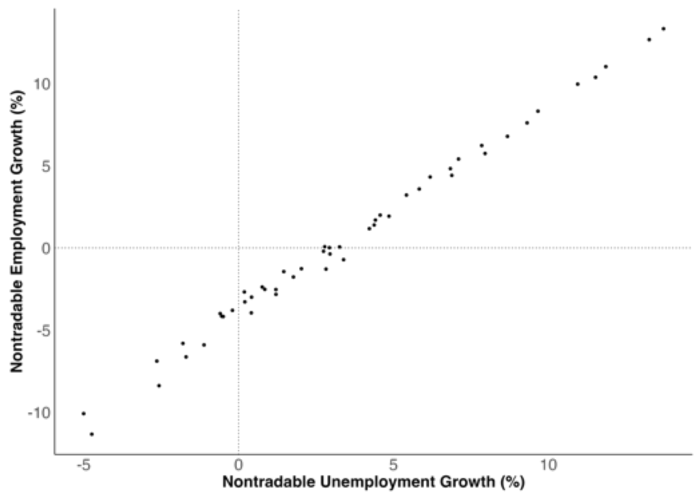
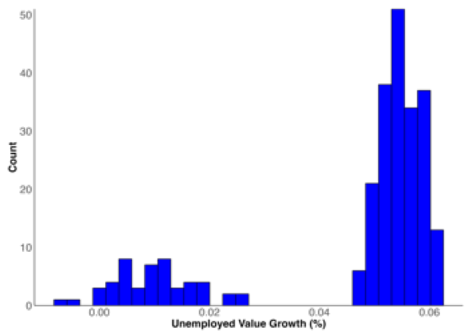
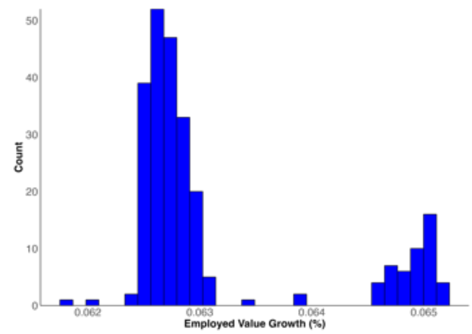


Figure 2.13: Predicted changes in welfare across sectors and regions

(a) Predicted changes in unemployed values



(b) Predicted changes in employed values



(c) Predicted changes in employed-unemployed value difference

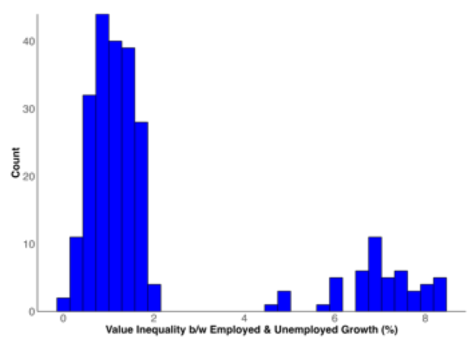


Figure 2.14: Predicted regional average welfare changes

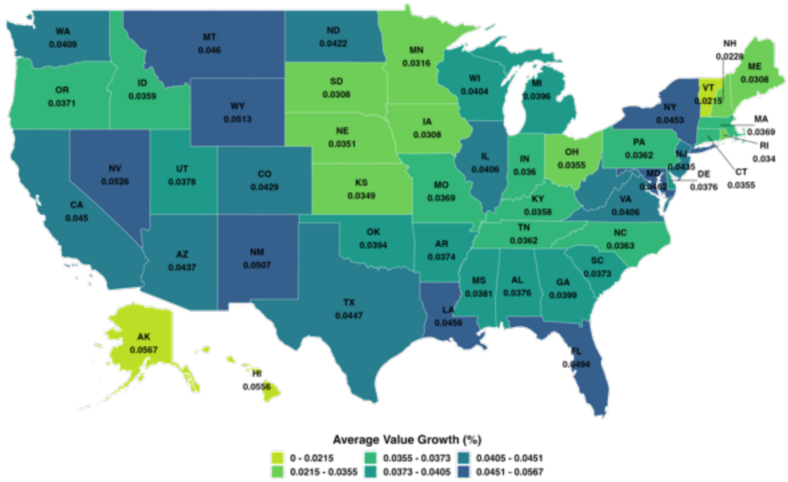


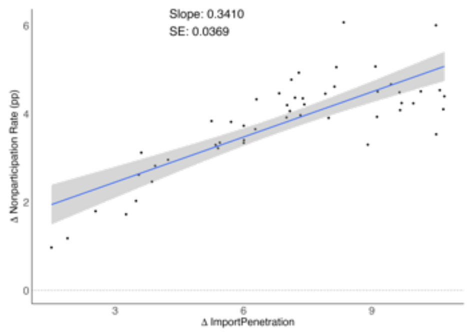
Table 2.3: Counterfactual results comparison

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

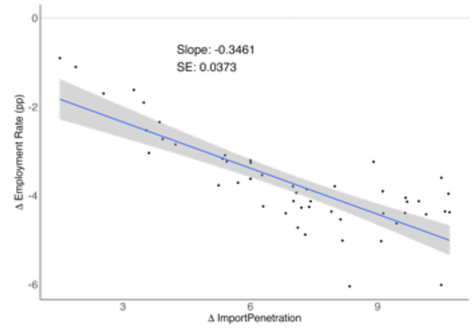
Notes: The calculation is comparing the counterfactual results with the initial equilibrium. The unemployment rate change is simple difference while the welfare change is essentially the growth rates.

Figure 2.15: 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

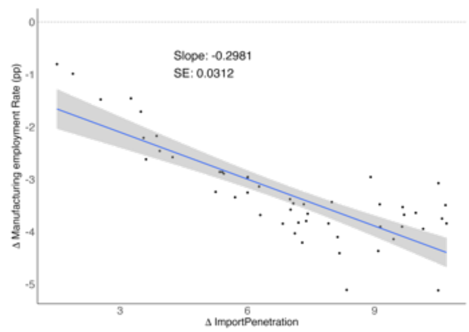
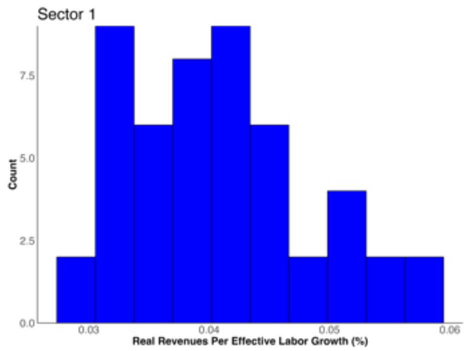
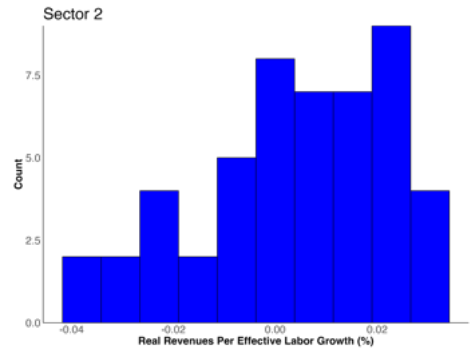


Figure 2.16: Predicted changes in sectoral real revenues per effective labor

(a)



(b)



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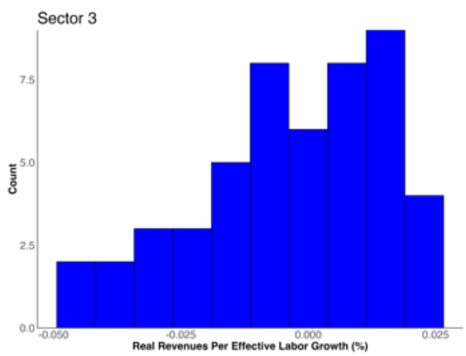

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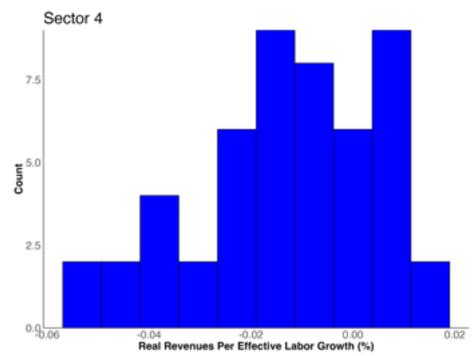

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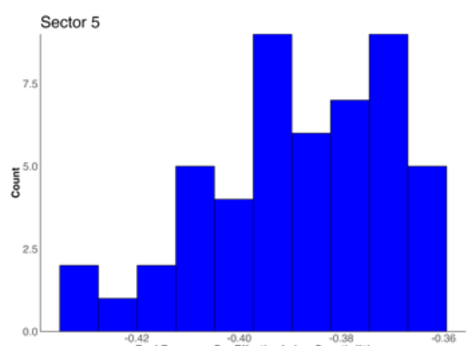


Figure 2.17: Predicted changes in sectoral labor market tightness

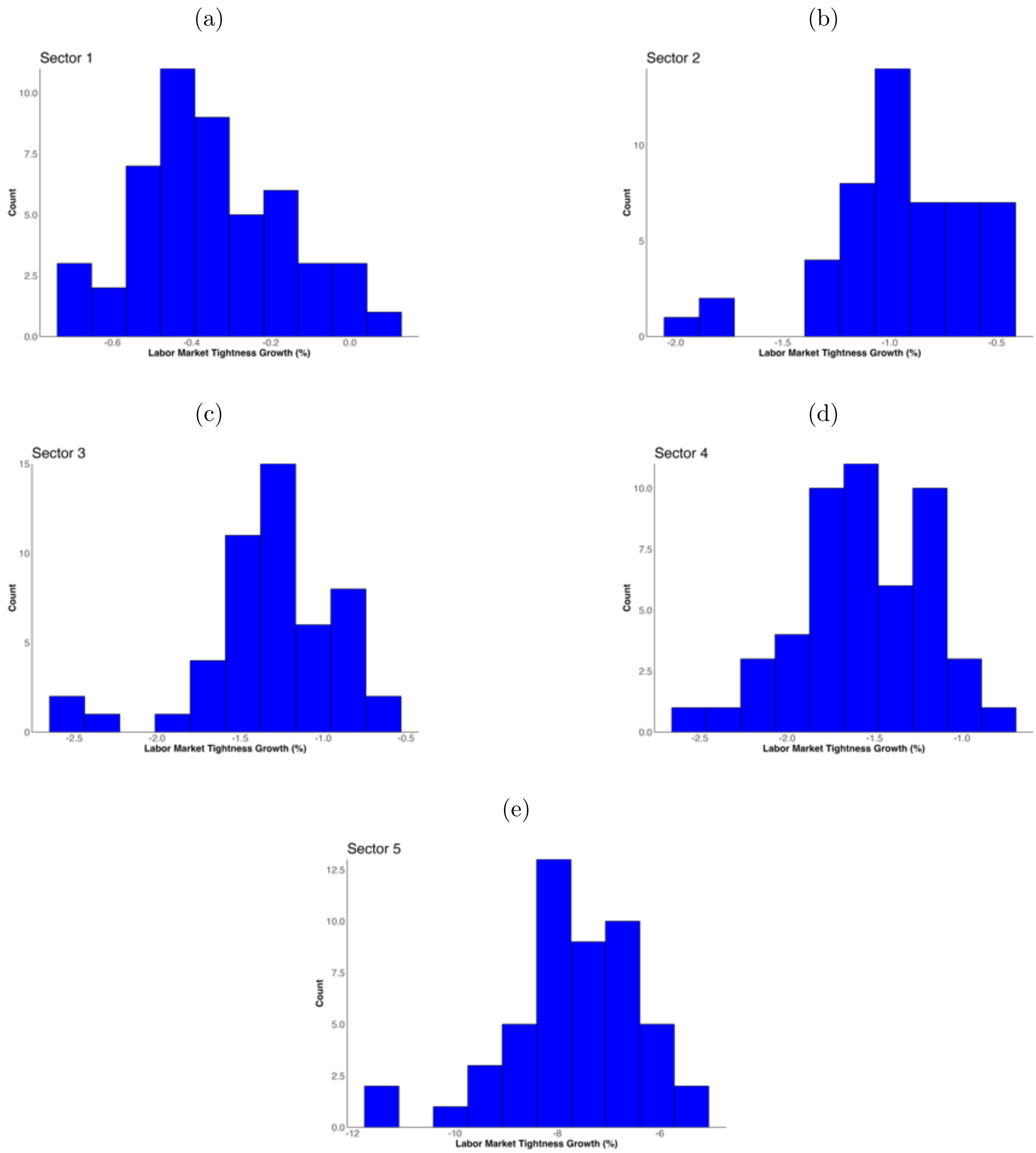


Figure 2.18: Predicted changes in sectoral reservation productivity

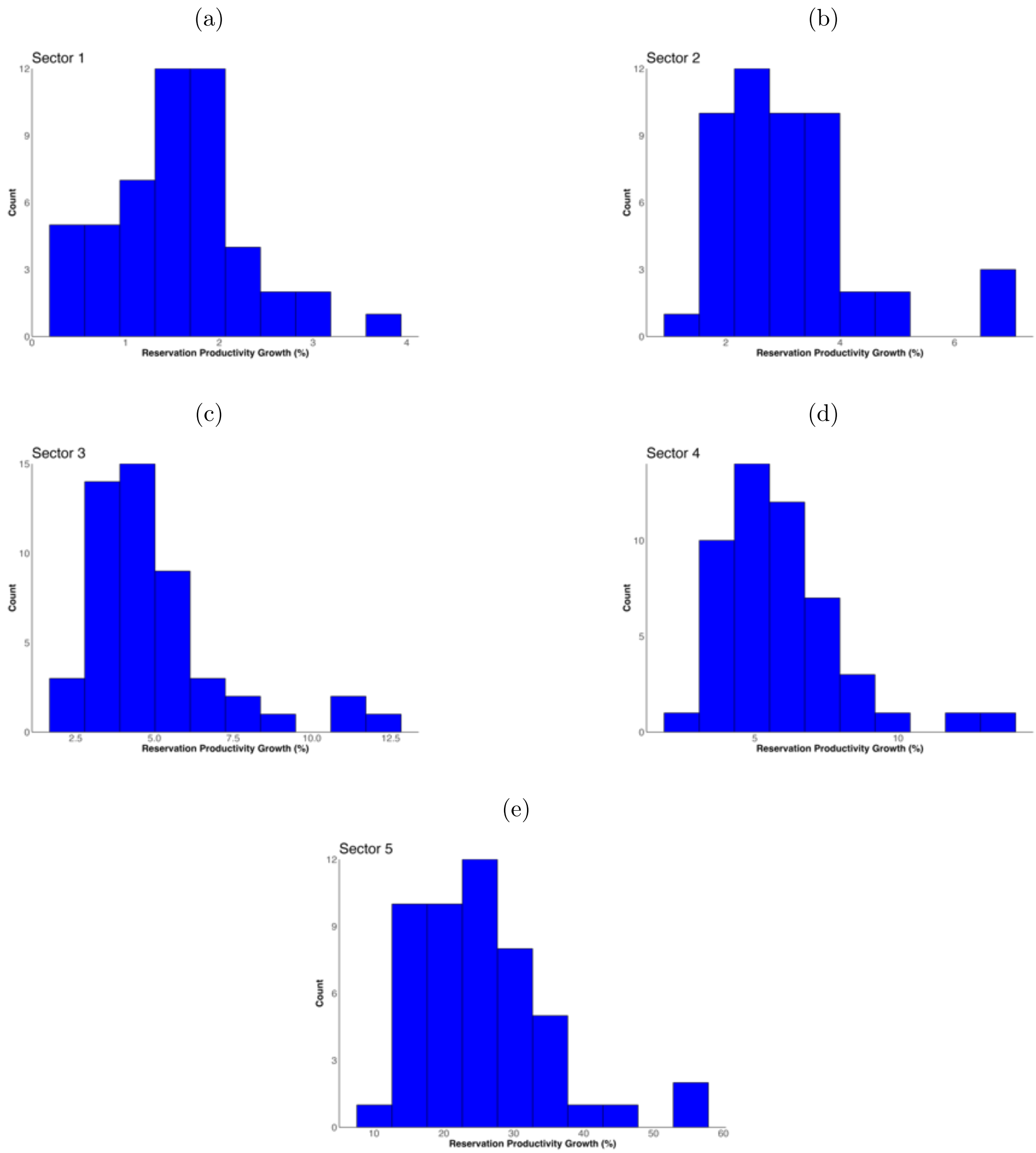
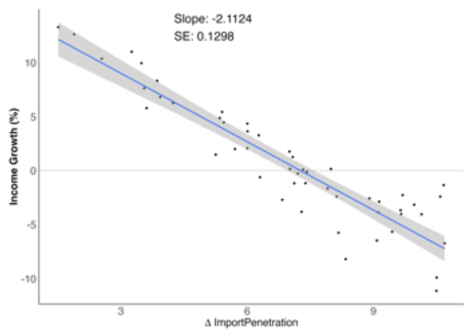


Figure 2.19: Predicted changes in income and import penetration

(a) Predicted changes in regional total income vs IP



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

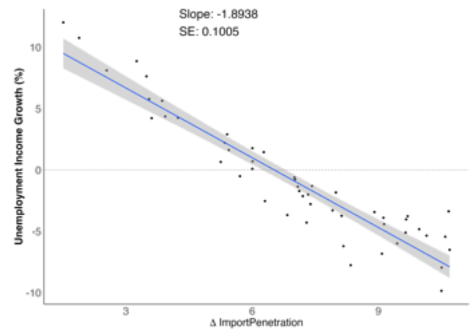
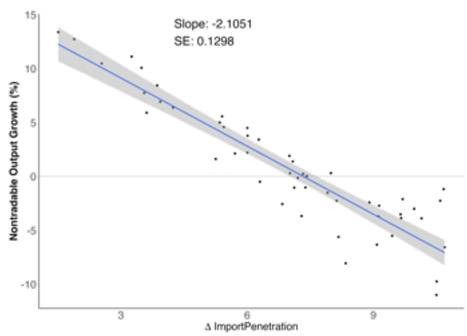
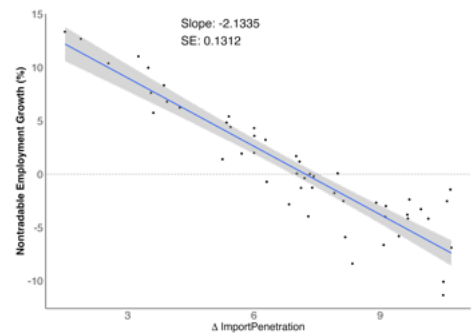


Figure 2.20: Predicted changes in nontradable output and labor and import penetration

(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

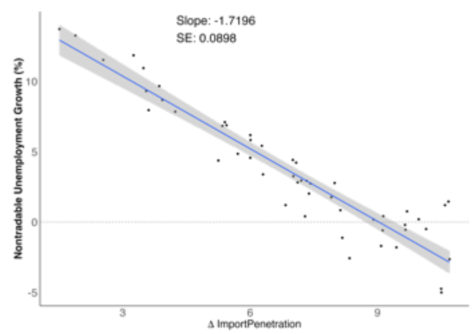
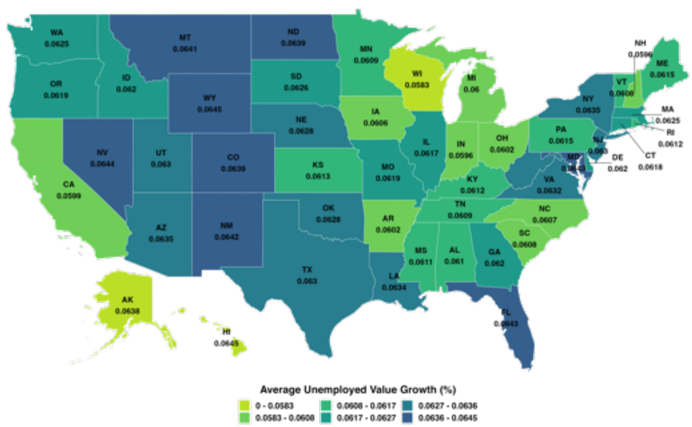
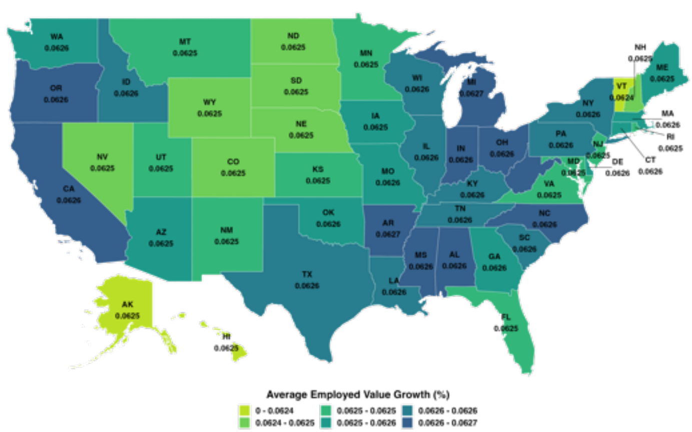


Figure 2.21: Regional average welfare for different types of agents

(a) Predicted changes in average unemployed values



(b) Predicted changes in average employed values



(c) Predicted changes in nonparticipation values

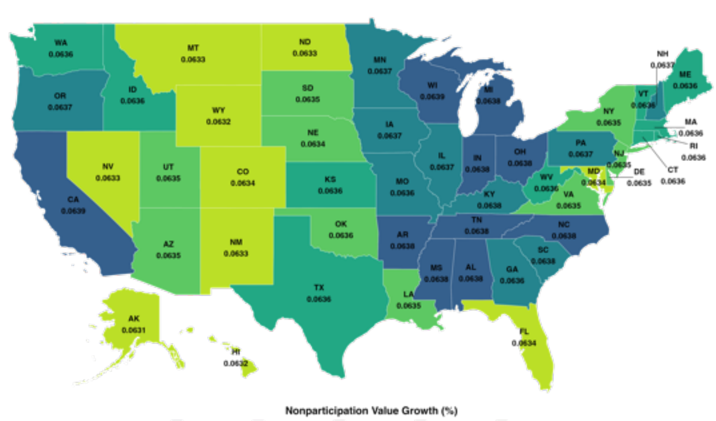


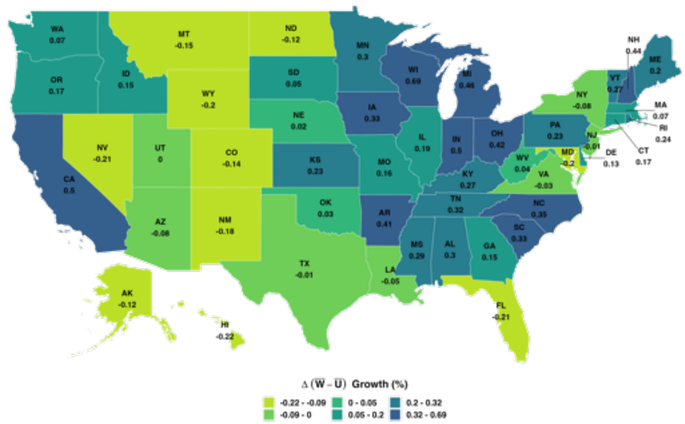
Table 2.4: The China trade shock and regional welfare outcome

	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

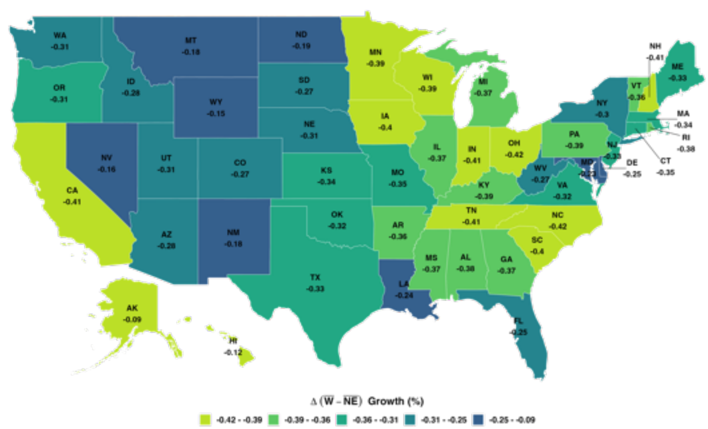
Notes: All data for the regressions are generated by the model. *p<0.1; **p<0.05; ***p<0.01.

Figure 2.22: 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



2.8 Appendix

2.8.1 Derivation and proofs

Derivation of equilibrium conditions

Let $E_{sd}^W \equiv \int_{R_{sd}}^{\bar{x}} W_{sd}(x)dF(x)$ and $E_{sd}^J \equiv \int_{R_{sd}}^{\bar{x}} J_{sd}(x)dF(x)$. Integrating (2.11) by $F(x)$ over $[R_{sd},\ \bar{x}]$ gives:

$$P_d^f E_{sd}^W - P_d^f(1 - F(R_{sd}))E = \frac{\beta}{1-\beta} E_{sd}^J. \tag{2.40}$$

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

$$W_{sd}(x) = \frac{1}{1+r} \left\{ \frac{w_{sd}(x)}{P_d^f} + (\delta + (1-\delta)F(R_{sd}))\, E + (1-\delta)E_{sd}^W \right\}, \tag{2.41}$$

and

$$J_{sd}(x) = \frac{1}{1+r} \left\{ p_{sd}A_{sd}x - w_{sd}(x) + (1-\delta)E_{sd}^J \right\}. \tag{2.42}$$

Take (2.41), (2.42) along with (2.40) into (2.11) to get the bargained wage:

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

Evaluate the wage equation and (2.42) at the reservation productivity and take them into (2.12) to get:

$$(1-\delta)E_{sd}^J = (1-\beta)(rP_d^f E - p_{sd}A_{sd}R_{sd}).$$

Then I can express the value of a filled job as

$$J_{sd}(x) = \frac{1-\beta}{1+r} p_{sd} A_{sd}(x - R_{sd}). \tag{2.43}$$

Take (2.43) into the free entry condition along with the value of a vacant job to get the job creation condition (an expanded version of (2.16)):

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

Take (2.43) into the threshold condition (2.12) to get the job destruction condition (an expanded version of (2.17)):

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

Taking (2.40) into (2.4) renders (2.14). And labor distribution equations (2.19) and (2.20) follow according to the properties of the Gumbel distribution.

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 (2.18).

Proofs

Proof of Lemma 1

Rearranging (2.17) 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 (2.17) and we can express the reservation productivity as a function of ρ_{sd}: $R_{sd} = R(\rho_{sd})$. Then I rearrange (2.16) 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 (2.16) and (2.17) for labor market i gives:

$$\frac{\theta_i\kappa'(\theta_i)}{\kappa(\theta_i)}\widehat{\theta_i} + \widehat{\rho_i} = \frac{R_i(1-F(R_i))}{\int_{R_i}^{\bar{x}}(x-R_i)dF(x)}\widehat{R_i}. \tag{2.44}$$

$$\frac{R_i(\frac{r+\delta}{1+r} + \frac{1-\delta}{1+r}F(R_{sd}))}{rE/\rho_i}\widehat{R_i} + \widehat{\rho_i} = 0. \tag{2.45}$$

When $\widehat{p_1} < 0$, it is easy to see that $\widehat{\rho_1} < \widehat{\rho_2}$. By (2.45), $\widehat{R_1} > \widehat{R_2}$. Taking $\widehat{R_1} > \widehat{R_2}$ into (2.44) we have $\widehat{\theta_1} < \widehat{\theta_2}$.[21]

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

2.8.2 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

$$\frac{rE}{\rho_{sd}} - \frac{1-\delta}{1+r}\int_{R_{sd}}^{\infty}(x - R_{sd})dF(x) - R_{sd} = 0. \tag{2.46}$$

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:

$$\frac{1+r}{r}\nu \ln\left(\sum_{s=0,d=1}^{S,D}\exp(\tilde{U}_{sd}/\nu)\right) - E = 0. \tag{2.47}$$

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^U_{SD}:

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

for $s \neq 0$ and

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

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

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

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:

$$\alpha_1 I_d - p_{1d} L_{1d}^E A_{1d} \int_{R_{1d}}^{\infty} xd \frac{F(x)}{1 - F(R_{1d})} = 0. \tag{2.48}$$

Equations (2.46), (2.47), (2.48) form a system of equations for the equilibrium denoted as $\mathcal{F}(\mathbf{x})$:

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

The solution is $\mathbf{x} = \left(E, \{p_{1d}\}_{d=1}^{D}, \{R_{sd}\}_{s=1,d=1}^{S,D} \right)$ 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:

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

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

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

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:

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

I use genetic algorithm to solve the following minimization problem:

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

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

Moment Estimation) algorithm to solve the minimization problem of

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

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 2.1.

2.8.3 Inefficiency

Mobility 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 (2.33) in a dynamic setup. But the outcome will be finally evaluated in the steady state for comparison and relevancy. FOCs of (2.33) for sector i are as follows:

$$\frac{\partial \mathcal{L}}{\partial L^E_{i,t+1}} = \frac{1}{(1+r)^{t+1}} A_s + \lambda_{i,t+1}(1-\delta) - \lambda_{i,t} - \lambda_{0,t+1} = 0, \tag{2.49}$$

$$\frac{\partial \mathcal{L}}{\partial L^U_{i,t}} = \frac{1}{(1+r)^t}(b - e_i\theta_{i,t}) + \lambda_{i,t} m\theta^{\eta}_{i,t} - \lambda_{0,t} = 0, \tag{2.50}$$

$$\frac{\partial \mathcal{L}}{\partial \theta_{i,t}} = -\frac{1}{(1+r)^t} e_i L^U_{i,t} + \lambda_{i,t}\eta m\theta^{\eta-1}_{i,t} = 0. \tag{2.51}$$

FOC (2.51) is evaluated in the steady state to identify $\lambda_{i,t}$ as follows:

$$\frac{e_i}{\eta m}\theta^{1-\eta}_{i,t} = \lambda_{i,t}(1+r)^t = \lambda_{i,t+1}(1+r)^{t+1}. \tag{2.52}$$

Subtracting (2.49) by (2.50) with (2.52) in the steady state renders equation (2.34) that captures the constrained optimal result.

The equilibrium conditions with idiosyncratic shocks affecting cross-sectoral migration choices can be derived as Appendix (2.8.1). Firstly, I derive the wage equation in the equilibrium:

$$w_i = \beta A_i + (1-\beta) rE. \tag{2.53}$$

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

$$w_i = \beta A_i + (1-\beta)(b + \frac{\beta}{1-\beta} e_i\theta_i), \tag{2.54}$$

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 (2.53) 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

$$e_i = m\theta_i^{\eta-1}\frac{1-\beta}{r+\delta}(A_i - rE). \tag{2.55}$$

Rearranging (2.55) can get the equilibrium condition (2.35).

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 (2.49) - (2.52), 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:

$$p_d A_d L_d^E = \underbrace{(\beta p_d A_d + \beta p_d e_d \theta_d)}_{wage} L_d^E, \tag{2.56}$$

which is rearranged to get (2.38).

Chapter 3

Frictional Labor Markets, Spatial Sorting and Disparities

3.1 Introduction

Spatial disparities in key economic variables like productivity, wage, and unemployment are of great policy concern and academic interest (e.g., Ehrlich and Overman (2020)). Beneath the spatial disparities could lie spatial sorting. It is an important factor in explaining not just the distributions of those economic variables but also the city size. This chapter links spatial sorting with spatial differentials in productivity, wage, and unemployment through a new channel, frictional labor markets, to answer the question: how can frictional labor market explain spatial sorting, hence disparities?

To address this question, I first present a static search model, based on an extension of Acemoglu (1999), with two locations and free labor mobility. The model considers two types of workers—skilled and unskilled—and firms that make ex-ante capital investment decisions before hiring. In a frictional labor market, firms and workers cannot freely change partners after meeting, bargaining, and forming a match. Firms increase investment only when the human capital difference between skilled and unskilled workers is sufficiently large and there is a high probability of encountering a skilled worker. Skilled workers then sort into locations offering higher wages due to increased firm investment, which further encourages firms to hire only skilled workers, deterring unskilled workers from entering. Unskilled workers, consequently, settle in the other location, accepting lower wages. The chapter also identifies conditions under which a symmetric allocation of workers across locations can exist as an equilibrium.

The model is then extended to a dynamic setting, incorporating more general features of search models that address unemployment differences. The core insights from the static model persist, with the dynamic model predicting lower unemployment rates in areas with a higher concentration of skilled workers. This is because these areas attract more firms, increasing job-finding rates and reducing unemployment. Spatial sorting is usually explained by city size due to urban agglomeration, making it challenging to separate the two both theoretically and empirically (Combes and Gobillon (2015)). However, the theory presented here predicts sorting independently of total city size. The resulting equilibrium suggests that observed firm sorting may arise from variations in regional human capital levels rather than inherent differences in firm productivity.

I test the prediction at the commuting zone level using Census/ACS data. The results indicate that a higher fraction of skilled workers is positively associated with regional average wages and job-finding rates, and negatively associated with unemployment rates. The job finding 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. I exploit the answers to a question from these survey data to obtain proxies for the individuals' lagged employment statuses.

This chapter contributes to the literature on spatial labor sorting. In the empirical literature, Andersson et al. (2007) found that larger urban labor markets exhibit more assortative matching between workers and firms, using U.S. data. This finding aligns with the predictions of my model, assuming a constant-return-to-scale matching function. Mion and Naticchioni (2009) employed matched employer-employee data from Italy to demonstrate that skills are geographically sorted, accounting for a significant share of spatial wage variation. Similarly, Matano and Naticchioni (2012), using the same dataset, showed that spatial sorting is not uniform across sectors. This finding supports my model's prediction that differences in production structures can lead to varying levels of sorting. Combes et al. (2008), using French panel data, concluded that skill-based spatial sorting explains a substantial portion of wage inequality and that differences in worker human capital across cities account for 40-50% of the size-productivity relationship. These empirical results inform the model developed in this chapter, which further introduces the novel insight that production structure plays a key role in generating sorting. To the best of my knowledge, no prior studies have highlighted this mechanism.

The theoretical foundations of spatial sorting are often linked to urban agglomeration, making it challenging to separate sorting effects from agglomeration both theoretically and empirically (Combes and Gobillon (2015)). Behrens and Behrens and Robert-Nicoud (2015) empirically demonstrated that the proportion of skilled workers in a metropolitan statistical area (MSA) is positively correlated with the area's size and density. They extended Henderson's (1974) model to explain sorting through agglomeration externalities. Similarly, the theoretical frameworks of Davis and Dingel (2019, 2020) attribute spatial sorting of talent to agglomeration driven by costly idea exchanges within cities, once again linking sorting to city size. In contrast, my model predicts sorting without relying on agglomeration or city size. Diamond (2016) documented the spatial sorting of skilled workers in the U.S., noting that college graduates tend to cluster in high-wage, high-rent cities. She attributed this sorting to local labor productivity shocks. The increased skill sorting, driven by changes in labor demand, was further reinforced by endogenous improvements in amenities in these cities. Tabuchi et al. (2018) also used productivity shocks to explain regional disparities. Behrens et al. (2014) integrated sorting, selection, and agglomeration into a unified model, where sorting is driven by selection—tougher competition in larger cities results in more talented individuals remaining there. This concentration of talent, in turn, intensifies selection, leading firms to offer higher wages. The resulting wage premium from sorting and selection attracts more individuals, further reinforcing agglomeration economies. Eeckhout et al. (2014) found that average skill levels remain constant across cities of different sizes, as large cities disproportionately attract both high- and low-skilled workers. This finding challenges the theories that consistently link agglomeration to skill sorting: how can sorting occur if average skill levels do not vary with city size? The authors argued that complementarities between high- and low-skilled workers shape the distribution of skills within a city and influence how it varies by size. While my model does not address this "thicker tails" phenomenon, as it does not assume complementarities between different worker types, it does incorporate unemployment—an aspect that few spatial sorting models address.

This chapter contributes to the literature on wage inequality. Extensive research documents a significant rise in wage inequality in the United States, attributing it primarily to skill-biased technological change (see Acemoglu and Autor (2011)). Autor and Dorn (2013) observed faster growth at both ends of the wage distribution between 1980 and 2005, attributing the rise in wage inequality to the declining costs of automating middle-skill jobs. In contrast, Moretti (2013) provided evidence that real wage inequality has grown less significantly than nominal wage differences. However, real wages may not fully capture well-being, as local amenities vary considerably across cities. Moretti argued that well-being inequality depends largely on why college graduates choose to reside in expensive metropolitan areas, with relative labor demand shocks playing a more critical role than labor supply factors. The model in this chapter explains skilled-unskilled wage inequality through sorting. In the absence of sorting, firms would pool jobs and wages, leading skilled and unskilled workers to have similar job opportunities and wages, thereby eliminating inequality.

This chapter contributes to the literature on spatial unemployment. Several studies have examined spatial unemployment differentials. OECD (2005) documented that these differentials are significant and persistent. Kline and Moretti (2013) and Marinescu and Rathelot (2018) focused on the role of the job-finding rate while abstracting from job-loss rate differentials. In contrast, Bilal (2023) found that gaps in job-loss rates are the key empirical determinant of spatial unemployment differentials, based on detailed data from France. This distinction has important policy implications. Kline and Moretti (2013) argued that subsidies to high-unemployment areas reduce welfare, while Bilal found that such subsidies can increase welfare, thereby reconciling theoretical models with real-world place-based policies. Although Bilal's analysis provides valuable insights into regional unemployment differences, the approach to modeling endogenous job separation lacks sufficient empirical support. The key feature of Bilal's model is a stochastic decay in firm productivity, which allows for the possibility of firm exit and varies across firms due to its stochastic nature. However, assuming such a decaying process for firm productivity is not entirely convincing, as other studies suggest that productivity may increase over time, such as through learning by exporting. This chapter aligns with the literature that emphasizes the job-finding rate as a driver of unemployment differences. It also predicts that areas with lower unemployment rates are those where firms sort and have higher productivity, consistent with Bilal's findings.

3.2 Theory

I extend Acemoglu (1999) model to include two locations with free mobility, allowing for the endogenization of the proportions of skilled workers. This approach demonstrates how sorting among different types of workers can arise from a frictional labor market. I begin with a static version of the model to illustrate the core mechanism. The dynamic version introduces greater complexity, incorporating general features of a search model that addresses unemployment, including endogenous job-finding and vacancy contact rates, which were treated as exogenous in Acemoglu's original model.

3.2.1 Static model

There is exogenous heterogeneity in worker skill levels: some workers are unskilled with human capital normalized to 1, while others are skilled with a human capital level of η. By distinguishing between different types of workers, agglomeration is characterized by the concentration of each worker type. Let $\bar{\phi}$ represent the exogenous fraction of skilled workers in the total labor force, which is inherent in the economy. The labor market clearing conditions are as follows:

$$L_1^H + L_2^H = \bar{\phi}L,$$

$$L_1^L + L_2^L = (1 - \bar{\phi})L,$$

where H and L denote the skilled and unskilled workers. I further denote ϕ_i as the fraction of skilled workers in location i: $\phi_i = L_i^H/(L_i^H + L_i^L)$, which is the key variable as shown below. Notice that ϕ_1 and ϕ_2 are endogenously determined.

The timeline of the static model begins with a firm deciding on the level of physical capital to allocate to a potential worker. However, the firm must make this decision before meeting the worker and knowing their type. In a frictional labor market, it is assumed that each worker meets only one firm, and each firm meets only one worker, randomly. However, a match does not form immediately upon meeting; both parties must agree to work together for the match to be established. Once a firm matches with a worker, production takes place. The production function for a match is:

$$y(k, h) = k^{1-\alpha}h^{\alpha},$$

where h is the human capital level and k the physical capital or capacity for this specific match. The firm also needs to incur sunk costs c per unit of capital when the match is formed. But it does not need to pay this cost if the match is not formed. To reach the agreement, both parties need to negotiate the wage paid to the worker and I assume it to be a fraction β of the output. Thus, the firm will get the rest $1 - \beta$. Again, this β can be understood as the bargaining power of worker side. In this static environment which is just like one period of game, both parties will get zero pay-off if they do not agree to form the match.

The expected value of a firm deciding on k in location i is then:

$$
\begin{aligned}
V_i(k, x^H, x^L) &= \phi_i x^H \left[(1-\beta)k^{1-\alpha}\eta^\alpha - ck\right] + (1-\phi_i)x^L \left[(1-\beta)k^{1-\alpha} - ck\right] \\
&= \phi_i x^H (1-\beta)[k^{1-\alpha}\eta^\alpha - k] + (1-\phi_i)x^L(1-\beta)[k^{1-\alpha} - k], \qquad (3.1)
\end{aligned}
$$

where c is set to be $1-\beta$ for simplicity and x^j $(j = H,\ L)$ is the equilibrium probability that the firm hires the worker of j type.[1] I do not consider any mixed strategies, hence x^j being 0 or 1 and decided by the firm. The firms are not allowed to moved across locations. In each location, the firms decide on k, x^j to maximize (3.1) given the fraction of skilled workers, which partially determines the probability for them to meet one.

An equilibrium in this two location model contains the fractions of skilled workers ϕ_1 and ϕ_2 at which no workers will be better off by moving to other places, distribution of capital choices $F_i(k)$ over endogenously determined support K_i, and decision functions $x_i^H(k)$ and $x_i^L(k)$ such that for all $k \in K_i$, $(k, x_i^H(k), x_i^L(k)) \in arg\max\ V_i(k, x^H, x^L)$ for location i $(i = 1, 2)$.

In a partial equilibrium where ϕ_i is given, if $\eta < \left(\frac{1-\phi_i}{\phi_i^\alpha - \phi_i}\right)^{1/\alpha}$,all firms there will accept both types of workers, i.e., $x_i^H = x_i^L = 1$, and set capital $k_i^P = a[\phi_i\eta^\alpha + (1-\phi_i)]^{1/\alpha}$, where $a \equiv (1-\alpha)^{1/\alpha}$ for both types of workers. This is a pooling result. On the other hand, if $\eta \geq \left(\frac{1-\phi_i}{\phi_i^\alpha - \phi_i}\right)^{1/\alpha}$, the firms in location i will only hire skilled workers, i.e., $x_i^H = 1,\ x_i^L = 0$, and $k_i^H = a\eta$.[2]

[1] To understand (3.1), since a firm meets one worker randomly, with probability of ϕ_i it will meet a skilled worker. Multiplying with the hiring probability x^H gives the probability of matching with a skilled worker $\phi_i x^H$. Then the firm will get $1-\beta$ of the total output while the capital cost has already been sunk.

[2] To derive this partial equilibrium, one can take F.O.C. of (1) with respect to k given ϕ_i, x_i^H and x_i^L. Then replace x_i^H and x_i^L with different values to calculate k and the values of $V_i(k)$ under different decision rules. Do the comparison and the conditions above will be obtained.

To move from the partial equilibrium to general equilibrium for two locations, the main job is to endogenize the fractions of skilled workers in these two places under the assumption of free labor mobility. First, I denote a function for the threshold

$$\eta^T(\phi) = \left(\frac{1-\phi}{\phi^\alpha - \phi}\right)^{1/\alpha}.$$

As was discussed above, when the exogenous human capital difference is lower than this threshold, there will be pooling results. It is easy to verify that η^T decreases with ϕ monotonically from 0 to 1. Moreover, $\eta^T \to \infty$ as $\phi \to 0$ and $\eta^T \to (1-\alpha)^{-1/\alpha}$ as $\phi \to 1$.

Different initial allocations of skilled workers, denoted as ϕ_1^o and ϕ_2^o , and the level of η will render different equilibrium results. In fact, there are multiple equilibria in many cases. Without specifying any rules or orders of workers moving, I just focus on two types of equilibrium: one for sorting of skilled workers in one place (the unskilled ones then agglomerate in the other) and the other for symmetric allocations. Before analyzing the general equilibrium, we still to define a way of how moving of a marginal worker can affect the fraction of skilled workers ϕ:

Definition 2. A large population economy is such that moving of one worker will not change the fractions of skilled workers in both places. In other words, a worker is of zero mass. And a small population economy is such that moving of one worker will change the fractions of skilled workers in both places.

The proposition below summarizes when these equilibria appear.

Proposition 2. *In this static model, if $\eta > (1-\alpha)^{-1/\alpha}$:*

a) The sorting of skilled workers to one place is always an equilibrium regardless of initial allocations of skilled workers.

b) The symmetric distribution can be an equilibrium only when i) $\eta > \max\{\eta^T(\phi_1^o),\ \eta^T(\phi_2^o)\}$ *in a small population economy, and ii)* $\eta > \min\{\eta^T(\phi_1^o),\ \eta^T(\phi_2^o)\}$ *and* $\eta < \max\{\eta^T(\phi_1^o),\ \eta^T(\phi_2^o)\}$ *in a large population economy.*

If $1 < \eta \leq (1-\alpha)^{-1/\alpha}$:

c) The sorting will not be an equilibrium regardless of initial allocations of skilled workers.

d) The symmetric allocation can be an equilibrium only when $\phi_1^o = \phi_2^o$ *in a large population economy.*

Proof. a) If $\phi_i = 0$ and $\phi_j = 1$, $\eta^T(\phi_i) = \infty > \eta$ and $\eta^T(\phi_j) = (1-\alpha)^{-1/\alpha} < \eta$. Then firms in place i will hire both types of workers and set the pooling capital as $k_i = a$ (setting ϕ_i to 0 for k_i^P as mentioned above) and pay $w_i^L = \beta a/(1-\alpha)$ to the unskilled and $w_i^H = \beta a\eta/(1-\alpha)$ to the skilled. And firms in place j will only hire the skilled and set $k_j = a\eta$ and pay $w_j^H = \beta a\eta/(1-\alpha)$ to them. The skilled and unskilled will only live in j and i respectively then. Since if a marginal skilled worker move to i in a small population economy, they will get a pooling wage at $\beta a[\phi_i\eta^\alpha + (1-\phi_i)]^{\frac{1-\alpha}{\alpha}}\eta^\alpha/(1-\alpha)$ for a small ϕ_i. And it is easy to verify that this wage level is lower than $\beta a\eta/(1-\alpha)$ when $\phi_i < 1$. Then no skilled workers will move. Neither do the low skilled workers since they will not even get hired. As for the case of large population economy, the skilled workers will get the unskilled pay-off by moving to the other place, hence no moving. Thus, this allocation is an equilibrium. And it does not depend on the initial worker allocations.

The rest of the proof is shown in Appendix 3.6. □

Before discussing more on this result, let's look at the equilibrium in an otherwise Walrasian environment. The Walrasian allocation of this economy is such that firms and workers can switch partners without cost when bargaining over wage, and wage is the marginal product for each worker. It is easy to verify that the allocation of two types of workers is indeterminate while the skilled worker get $\alpha a\eta/[(1-\alpha)c^{\frac{1-\alpha}{\alpha}}]$ and the unskilled workers get $\alpha a/[(1-\alpha)c^{\frac{1-\alpha}{\alpha}}]$ in any place. The sorting will not necessarily happen.

Without any labor market frictions, the equilibrium outcome is simply symmetric, while agglomeration always emerges as an equilibrium when frictional labor markets are present in this setting. When firms cannot switch their worker partners at no cost and must make job capacity decisions before meeting workers, they face the risk of establishing a capital level without being able to find suitable matches for it. This risk is higher in locations where the proportion of skilled workers is small. In such places, firms are less inclined to invest in job positions and offer high wages. Conversely, if there are many skilled workers, firms become more willing to invest and even hire skilled workers exclusively. Meanwhile, workers can relocate to alter this proportion. Skilled workers can improve their income by increasing the proportion to a level at which firms will hire only them (wages for them in the separating equilibrium are always higher than in the pooling equilibrium). This creates a barrier for unskilled workers, leading to sorting. In contrast, the Walrasian market allocates skilled workers to high-capacity firms, maximizes output, and does not create barriers for unskilled workers.

Let's also examine the symmetric equilibria and their conditions. In the two symmetric equilibria that arise under different conditions, all firms hire only skilled workers. As a result, unskilled workers have no better options, as they are not paid anywhere. Skilled workers have no incentive to move since the wages in the separating equilibria are identical. Note that a large human capital difference, η, is necessary to achieve these results. The intuition is that when the skill gap between the two types of workers is large enough, all firms will take the risk of creating skilled job positions, as having a skilled worker makes a significant difference. In this case, the entire market effectively becomes homogeneous, leading to symmetry.

To summarize the intuition: in a frictional labor market, firms' hiring and investment decisions depend on the likelihood of meeting high-quality workers. A greater number of skilled workers in a location will increase firms' expected value of investing in jobs for those workers and hiring more of them instead of unskilled workers. These hiring decisions will then deter unskilled workers from entering areas where skilled workers agglomerate.

3.2.2 Dynamic model

The main results and intuition of the static model still hold in the dynamic version. To understand why a dynamic model is needed: in the agglomeration equilibrium of the static model, there are no unemployed workers, as they all move to locations that welcome them. Unemployment occurs only in the symmetric equilibria, where all unskilled workers are unemployed. These results are not sufficiently informative or helpful. Introducing labor matching frictions can help explain unemployment, and it is more effective in a dynamic setting. I extend the static model to include more general characteristics in a dynamic search model, such as endogenous job-finding and vacancy contact rates.

In a dynamic version, the timeline of the game should be specified in more detail. A firm enters the market and rents a site at an exogenous cost of γ. As in the static model, the firm decides on job capacity k and opens a job vacancy at that site before meeting a worker. A vacancy meets an unemployed worker at a rate of f_i, and an unemployed worker finds a vacancy at a rate of q_i with both rates endogenously determined by the unemployment and vacancy rates in the local market, as in the standard search model setting.[3] These rates are assumed to be negatively correlated, which becomes apparent when assuming a constant-returns-to-scale matching function. Once they meet and the worker's type is revealed, the firm decides whether to hire the worker. If the firm hires the worker, it incurs a sunk cost of ck, which does not apply to any other workers. If the firm and the worker reach an agreement during wage negotiation after the sunk cost has already been paid, they produce according to the output function specified in the previous section; otherwise, they continue searching for new partners. At a rate of s, the match dissolves, the worker becomes unemployed, the capital and site for the job become obsolete, and the firm exits.[4]

The value of a vacancy for the job of capital k, $J_i^V(k)$, satisfies

$$rJ_i^V(k, x^H, x^L) = -\gamma + q_i \left[\lambda_i x^H \left(J_i^H(k) - ck - J_i^V(k)\right) + (1-\lambda_i)x^L \left(J_i^L(k) - ck - J_i^V(k)\right)\right], \tag{3.2}$$

where λ_i is the equilibrium fraction of skilled ones among the unemployed workers in location i and r is the time discount rate. It says that the flow value of a vacancy equals to the expected pay-off from matching with a worker, who could be skilled and unskilled, after subtracting the site rental. The firms choose k, x^H and x^L to

[3]Notice that f_i and q_i are the same to different types of workers. Mortensen and Pissarides (1999) assume separating labor search market for different types of workers, hence different job finding and vacancy contact rates. I did not follow this since the separating labor market does not necessarily hold and it is clearer to illustrate the congestion through multiplying these location level terms with the fractions of skilled workers.

[4]A vacancy can be understood as a firm when the total output of a firm is of constant returns to scale, which means the size of firm does not matter.

maximize $J_i^V(k)$ given q_i and λ_i. The asset value for a matched firm with capital k:

$$rJ_i^j(k) = k^{1-\alpha}h_j^\alpha - w_i^j(k) + s\left(J_i^V(k) - J_i^j(k)\right), \quad (j = H, L) \tag{3.3}$$

It says that the flow value of matching with a type j worker equals to the profits this match could generate and possibly getting separate next period.

The life-time utility is

$$\int_0^\infty e^{-rt} c_t \, dt,$$

where c_t is the consumption level at time t. The asset value for a matched worker of type j is then

$$rW_i^j(k) = w_i^j(k) + s\left(N_i^j - W_i^j(k)\right), \quad (j = H, L) \tag{3.4}$$

where the unemployed value of type-j worker in location i, N_i^j, satisfies

$$rN_i^j = b + f_i \int_{K_i} x_j(k)\left(W_i^j(k) - N_i^j\right) dF_i(k). \tag{3.5}$$

This equation says that the flow value of being unemployed equals to the unemployment benefits plus the expected gains from matching with a firm. With the distribution of firm investment choice $F_i(k)$, and the corresponding hiring decision $x^j(k)$ for type j worker, the expected gains are calculated as in the second term on the RHS of (3.5).

Following Acemoglu (1999), I let the wages be determined by bargaining with alternating offers rather than Nash bargaining which is usually used in the search literature. By doing so, the wages can simply be a fraction of output while the wages from Nash bargaining contain other terms like meeting rate and the separation rate. The wage setting is then:

$$w_i^j(k) = \max\left\{rN_i^j, \min\left[\beta k^{1-\alpha}h_j^\alpha, k^{1-\alpha}h_j^\alpha - rJ_i^j(k)\right]\right\}. \tag{3.6}$$

The steady state market clearing conditions:

$$u_i^j = \frac{s}{s + f_i \int_{K_i} x_i^j(k)\, dF_i(k)}, \tag{3.7}$$

$$\lambda_i = \frac{\phi_i u_i^H}{\phi_i u_i^H + (1-\phi_i)u_i^L}. \tag{3.8}$$

Free entry of firms:

$$J_i^V(k, x^H, x^L) = 0. \tag{3.9}$$

Free labor mobility says that the workers can go to any places they want. But that does not necessarily mean $N_1^j = N_2^j$ hold in the equilibrium. For example, if firms in one place only hire the skilled workers, it will be equivalent to restricting the mobility of unskilled workers. As was discussed in the first model section, that will give agglomeration.

The equilibrium contains functions $\{F_i(k), x_i^H(k), x_i^L(k)\}_{i=1,2}$, rates $\{\lambda_i, u_i^H, u_i^L, f_i, q_i, \phi_i\}_{i=1,2}$ such that market clearing conditions (3.3) to (3.9) are satisfied with (3.2) maximized and no workers will be better off by migration.

To solve for the equilibrium, the first step is to find the optimal capital level for different acceptance rules. Suppose bargaining does not result in corner solutions which is true after solving all the variables in the equilibrium. Then the value of a firm matching with a skill level j worker is:

$$J_i^j(k) = \frac{(1-\beta)k^{1-\alpha}h_j^\alpha}{r+s}.$$

Substitute it back to (3.2) and derive the F.O.C:

$$\lambda_i x^H[(1-\alpha)k^{-\alpha}\eta^\alpha - 1] + (1-\lambda_i)x^L[(1-\alpha)k^{-\alpha} - 1] = 0. \tag{3.10}$$

Next, take different values of x^H and x^L into (3.10) to get the optimal capital under different acceptance rules along with the vacancy value.

Under $x^H = x^L = 1$, a firm accepts both types of workers and posts a pooling job position with capacity $k_i^P = a(\lambda_i\eta^\alpha + 1 - \lambda_i)^{1/\alpha}$. The associated value of vacancy is

$$J_i^V(k^P) = \frac{1}{r+q_i}\left[-\gamma + \frac{q_i(1-\beta)\alpha a}{(r+s)(1-\alpha)}(\lambda_i\eta^\alpha + 1 - \lambda_i)^{1/\alpha}\right].$$

For $x^H = 1$ and $x^L = 0$, the firm only hires the skilled and posts the job position with capacity $k_i^H = a\eta$. The value of vacancy under this acceptance rule is:

$$J_i^V(k^H) = \frac{1}{r+q_i\lambda_i}\left[-\gamma + \frac{q_i(1-\beta)\alpha a\eta}{(r+s)(1-\alpha)}\right].$$

And it can be verified that if the firm only hire the unskilled ones, its vacancy value will be strictly less than the one of posting pooling job. Therefore, this strictly dominated strategy can be eliminated. I move on to compare the above two values.

The free entry condition implies that the maximum value of $J_i^V(k)$ is zero. Therefore, it will either be $J_i^V(k^P) = 0 > J_i^V(k^H)$ or $J_i^V(k^H) = 0 > J_i^V(k^P)$. Given q_i and λ_i, it can be verified that if $\eta > \eta^T(\lambda_i) = \left(\frac{1-\lambda_i}{\lambda_i^\alpha - \lambda_i}\right)^{1/\alpha}$, there will be $J_i^V(k^H) = 0 >$

$J_i^V(k^P)$. And $J_i^V(k^P) = 0 > J_i^V(k^H)$ if $\eta \leq \eta^T(\lambda_i)$. The threshold function is the same as the one in the static model. But the argument becomes the fraction of the skilled ones among the unemployed workers. Since the initial allocation again might matter in determining the equilibrium, I assume that in the beginning, $\lambda_i = \phi_i^o$, that is, all workers are unemployed.

The proposition on the symmetric equilibrium with sorting is stated as below:

Proposition 3. *In this dynamic model, if $\eta > (1-\alpha)^{-1/\alpha}$:*

a) The sorting of skilled workers to one place is always an equilibrium regardless of initial allocations of skilled workers.

b) The symmetric distribution can be an equilibrium only when i) $\eta > \max\{\eta^T(\phi_1^o),\ \eta^T(\phi_2^o)\}$ in a small population economy, and ii) $\eta > \min\{\eta^T(\phi_1^o),\ \eta^T(\phi_2^o)\}$ and $\eta < \max\{\eta^T(\phi_1^o),\ \eta^T(\phi_2^o)\}$ in a large population economy.

If $1 < \eta \leq (1-\alpha)^{-1/\alpha}$:

c) The sorting will not be an equilibrium regardless of initial distribution of skilled workers.

d) The symmetric allocation can be an equilibrium only when $\phi_1^o = \phi_2^o$ in a large population economy.

Proof. The proof of a), b), d) and e) is similar as that in Proposition 1. To see the unemployment rate differentials, one needs to use (3.3) and (3.9) to pin down the vacancy contact rate in two places. The vacancy contact rate in the highly skilled place is

$$q_H = \frac{\gamma(r+s)(1-\alpha)}{(1-\beta)\alpha a\eta},$$

and smaller than that in the unskilled area,

$$q_L = \frac{\gamma(r+s)(1-\alpha)}{(1-\beta)\alpha a}$$

Since the higher the vacancy contact rate, the lower job finding rate will be, i.e., $f_H > f_L$. The unemployment rate in the skilled area is then

$$u = u^H = \frac{s}{s+f_H},$$

which is smaller than

$$u_L = \frac{s}{s+f_L}.$$

□

The results and intuitions from the static model still apply here. In terms of unemployment rate differences within the sorting equilibrium, the mechanism remains centered around sorting. The value of matching with a worker is higher in areas where skilled workers are concentrated. As a result, firms move to those areas to open vacancies, which drives down the vacancy contact rate while increasing the job-finding rate. Consequently, these areas experience lower unemployment rates, as finding a job there becomes easier.

3.2.3 Prediction to be tested

Areas concentrated with skilled workers tend to have higher productivity and lower unemployment rates. According to the model, as different workers sort into different areas, the firms entering those areas also adjust their hiring and investment decisions accordingly. In regions with more skilled workers, firms invest more in each job, leading to higher productivity (output per worker). Wages in this model are proportional to output, resulting in higher average wages as well. The high output or return attracts more firms to areas with skilled workers, further increasing the job-finding rate and reducing the unemployment rate. This prediction captures the correlations among these variables rather than implying causal relationships, offering new insights into spatial differences in skilled worker distributions and unemployment rates.

3.2.4 Discussion

A weakness of the model stems from its strength: the simplicity of the equilibrium wage form, which results from bargaining with alternating offers. Under this bargaining rule, wages are proportional to match output. In contrast, if Nash bargaining were used, the wage form would include additional terms related to labor market tightness. By not using Nash bargaining, as many other search models do, my model cannot capture the congestion within skill groups. As more skilled workers move into one area, the effects of changes in market tightness on wages are not accounted for in the model.

In addition to the absence of the congestion effect from market tightness on wages, this model does not account for other forms of congestion, such as the classic housing rental costs discussed in urban economics literature. Incorporating congestion forces is essential to establish a unique equilibrium (see Allen and Arkolakis (2014)).

The producer side requires more structure. First, complementarity between different skill groups can be added to production, which could help capture the relationship between skill sorting and city size observed by Eeckhout et al. (2014). The purpose of linking sorting with size is to introduce agglomeration, a crucial factor in determining the size and activities across locations. Second, incorporating multiple industries is necessary to better model the relationship between the production structure and sorting. As I will explain below, there are empirical challenges in testing the second prediction, as the model does not address spillovers across industries. Finally, with a more complete producer-side structure, the model could incorporate trade, which is also essential for modeling economic geography.

3.3 Empirical evidence

I mainly use 5%-sample Census data in 1990 and 2000 and American Community Survey (ACS) data from 2006 to 2019 to test the prediction. The empirical analysis focuses on the working-age group (16 - 64) and is conducted using commuting-zone level observations.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. [5] As mentioned above, 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. I classify workers as employed if they worked 26 weeks or more in the previous year as in the previous chapter. I restrict the survey sample to the working-age population, defined as individuals aged 16-64, and arrange the variables for 741 commuting zones in the U.S. for the years 1990, 2000, and 2006-2019.

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

3.3.1 Regional employment patterns

The first empirical exercise tests the predicted regional employment patterns: regions with a higher fraction of skilled workers are expected to have higher labor productivity, lower unemployment rates, and higher job-finding rates. Since these variables are determined in equilibrium, my goal is not to establish causal identification but to examine the correlations among them in the data. To clarify the measurement, I define a skilled worker as anyone currently in the labor force, whether employed or not, who has completed at least four years of college education (e.g., a master's degree). While this is not an explanatory variable in a causal analysis, I use it as the main independent variable to illustrate the correlation. I calculate the fraction of skilled workers in a commuting zone using 5%-sample Census data in 1990 and 2000, along with ACS data from 2006 to 2019, applying the weights assigned to each survey participant by the Census.

The average wage and salary income in a region serves as a proxy for productivity in that region. The rationale is that labor productivity in the model represents the output produced by a worker-firm match, and the wage is proportional to this output. Similarly, the average wage and unemployment rate are calculated using Census/ACS data. Job finding rates are calculated according to the method described above. I regress the regional unemployment rate, average wage and job finding rate on the fraction of skilled workers in the regional labor force to test the prediction:

$$y_{rt} = \alpha_0 + \alpha_1 SkilledRate_{rt} + \lambda_t + \lambda_r + \epsilon_{rt}, \tag{3.11}$$

where y_{rt} is the outcome variables in CZ r in year t, and λ_t and λ_r are year and CZ fixed effects. Region and time fixed effects are controlled to exclude any region-specific shocks or aggregate national shocks that can help generate regional disparities.

I test the prediction using the year 2000 samples first. As is shown in Table 3.1, empirical results support the prediction. Higher skilled worker fraction is positively associated with regional average wage and job finding rate, and negatively with unemployment rate. In the data, increasing the skilled worker fraction from 25th to 75th percentile is found to be equivalent to increasing the skilled worker fraction by around 6% in each year. According to the table, that suggests moving from an area at 25th percentile of skilled worker fraction to 75th percentile is associated with a decrease of about 1 percentage point in unemployment, which is of a large magnitude given that CZ unemployment rate is averagely 5%. It is also associated with 0.1% increase in average wage and 2 percentage points increase in job finding rate.

Although some of these patterns can be explained by other existing models, there are still valuable empirical facts that enhance our understanding of employment. The positive correlation between a higher fraction of skilled workers and average wages can be attributed to the skill wage premium, while the finding that it also raises the job-finding rate and lowers the unemployment rate is novel. According to the model, firms will relocate to areas where skilled workers agglomerate, resulting in more job opportunities and, consequently, a higher job-finding rate. Without this firm sorting, the crowding of skilled workers in one place would not lead to a higher job-finding rate.

I further test the prediction using samples from all years that I obtain, with CZ and year fixed effects controlled. The results are robust as shown in Table 3.2. I also use different measures of job finding rates to test the prediction and find them to be robust, as shown in Table 3.3.

3.4 Conclusion

This chapter aims to link spatial sorting with spatial differences in productivity, wages, and unemployment through a new channel: the frictional labor market. It seeks to answer the question: how can the frictional labor market explain spatial sorting and, consequently, disparities?

I first demonstrated the main mechanism by which a frictional labor market generates spatial labor sorting through a static search model with two locations and free labor mobility. Spatial sorting, characterized by the segregation of skilled and unskilled workers, occurs when the human capital difference between these two types of workers is sufficiently large. The intuition is that in a frictional labor market, firms' hiring and investment decisions depend on the likelihood of meeting high-quality workers. An increase in skilled workers in a given area raises firms' expected value of investing in jobs for those workers and hiring more skilled rather than unskilled workers. As a result, hiring decisions discourage unskilled workers from entering areas where skilled workers agglomerate.

I extended the static model to a dynamic one to incorporate more general features of a search model that can address unemployment. The main results and intuitions from the static model still hold, with the dynamic model predicting that areas where skilled workers sort will have lower unemployment rates. This is because, according to the model, these areas attract more firms seeking higher profits, which increases the job-finding rate and, consequently, lowers the unemployment rate.

The model further predicts that the places concentrated with skilled workers tend to have higher productivity and lower unemployment rate. I test the prediction at the commuting zone level using Census/ACS data. The results indicate that a higher fraction of skilled workers is positively associated with regional average wages and job-finding rates, and negatively associated with unemployment rates. The job finding 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. I exploit the answers to a question from these survey data to obtain proxies for the individuals' lagged employment statuses.

Future research will focus on extending the model to: i) incorporate the congestion effect by using Nash bargaining, allowing market tightness to influence wages, as well as other forms of congestion, such as housing rental costs; ii) add complementarity between different skill groups in production, linking sorting to city size in line with empirical patterns found in existing literature; iii) include multiple industries to understand inter-industry spillovers from changes in the production structure, leading to more precise empirical implications; and iv) introduce trade between firms and locations to better model economic activities across space.

3.5 Figures and tables

Table 3.1: CZ-level regression results in 2000

	(1) Unemp. Rate	(2) log(Wage)	(3) Job Find. Rate
Skilled Rate	-0.154***	0.016***	0.346***
	(0.013)	(0.001)	(0.035)
Constant	8.613***	9.947***	69.797***
	(0.252)	(0.014)	(0.661)
Observations	741	741	741

Notes: Results are estimated using regression 3.11, excluding the fixed effects. Data are from 5% Census in 2000 with working-age (16-64) population only. Robust standard errors clustered at the region-year level in parentheses. Significance: *p<0.1; **p<0.05; ***p<0.01.

Table 3.2: CZ-level regression results across years

	(1) Unemp. Rate	(2) log(Wage)	(3) Job Find. Rate
Skilled Rate	-0.079***	0.009***	0.248***
	(0.009)	(0.000)	(0.043)
Constant	8.394***	10.306***	56.121***
	(0.181)	(0.006)	(0.815)
Fixed effect	CZ, Year	CZ, Year	CZ, Year

Notes: Results are estimated using regression 3.11. Data are from 5% Census in 1990, 2000 and ACS from 2006 to 2019 with working-age (16-64) population only. Robust standard errors clustered at the region-year level in parentheses. Significance: *p<0.1; **p<0.05; ***p<0.01.

Table 3.3: Different thresholds for job finding rates

	(1) JF_13wks	(2) JF_39wks	(3) JF_47wks
Skilled Rate	0.152***	0.288***	0.321***
	(0.053)	(0.035)	(0.030)
Constant	47.791***	62.613***	67.114***
	(1.016)	(0.663)	(0.573)
Fixed effect	CZ, Year	CZ, Year	CZ, Year

Notes: Results are estimated using regression 3.11. Data are from 5% Census in 1990, 2000 and ACS from 2006 to 2019 with working-age (16-64) population only. Robust standard errors clustered at the region-year level in parentheses. Significance: *p<0.1; **p<0.05; ***p<0.01.

3.6 Appendix

Proof i) $\eta > (1-\alpha)^{-1/\alpha}$:

When $\phi_i = 0 and \phi_j = 1, \eta^T(\phi_i) = \infty > \eta$ and $\eta^T(\phi_j) = (1-\alpha)^{-1/\alpha} < \eta$. Then the firms in place i will hire both types of workers, set the pooling capital as $k_i = a$ (setting ϕ_i to 0 for k_i^P mentioned above), and pay $w_i^L = \frac{\beta a}{1-\alpha}$ to the unskilled workers, and $w_i^H = \frac{\beta a \eta}{1-\alpha}$ to the skilled workers. The firms in place j will only hire skilled workers, set $k_j = a\eta$, and pay $w_j^H = \frac{\beta a \eta}{1-\alpha}$ to them. Thus, skilled workers will only live in j, while unskilled workers will live in i. If a marginal skilled worker moves to i in a small population economy, they will receive a pooling wage at:

$$\beta a \left[\varphi_i \eta^\alpha + (1-\varphi_i)\right]^{\frac{1-\alpha}{\alpha}} \frac{\eta^\alpha}{1-\alpha}$$

for a tiny ϕ_i. It is easy to verify that this wage level is lower than $\frac{\beta a \eta}{1-\alpha}$ if $\phi_i < 1$. Therefore, no skilled workers will move. The unskilled workers will not move either, since they will not be hired. In the case of a large population economy, the skilled workers would receive the unskilled payoff by moving to the other place, hence no movement occurs. Thus, this allocation is an equilibrium and does not depend on the initial worker allocations. To determine when a symmetric allocation appears, we need to consider different situations:

Small population economy:

1. $\eta > \max\{\eta_T(\phi_1^o), \eta_T(\phi_2^o)\}$: Firms in both places will hire only skilled workers, resulting in a symmetric allocation of both worker types. Skilled workers receive the same wages in both places, while unskilled workers receive zero pay regardless of location.

2. $\min\{\eta_T(\phi_1^o), \eta_T(\phi_2^o)\} \leq \eta \leq \max\{\eta_T(\phi_1^o), \eta_T(\phi_2^o)\}$: Assume $\eta_T(\phi_1^o) = \min\{\eta_T(\phi_1^o), \eta_T(\phi_2^o)\}$ and $\eta_T(\phi_2^o) = \max\{\eta_T(\phi_1^o), \eta_T(\phi_2^o)\}$. The symmetric allocation will not hold, as skilled workers will move to place 1, where only skilled workers are hired, and unskilled workers will remain in place 2.

3. $\eta < \min\{\eta_T(\phi_1^o), \eta_T(\phi_2^o)\}$: Firms in both places will offer pooling positions and pay pooling wages. Since pooling wages increase with the fraction of skilled workers, symmetric allocation will not hold in equilibrium; people will move to alter the skilled fraction and improve their income.

Large population economy: the first two are exactly the same as the small population economy. For the last point, since now the skilled fraction will not be changed by moving of a worker, the symmetric allocation can hold as an equilibrium.

ii) $1 < \eta \leq (1-\alpha)^{-1/\alpha}$:

When $\phi_i = 0$ and $\phi_j = 1$, $\eta^T(\phi_i) = \infty > \eta$ and $\eta^T(\phi_j) = (1-\alpha)^{-1/\alpha} \geq \eta$. Firms in both places offer pooling jobs and wages. Workers in the area with $\phi_i = 0$ would benefit by moving to the other area, as pooling wages increase with ϕ. This behavior is independent of the initial allocations.

In a small population economy, workers will always move, even if both places start with the same skilled worker allocation, as they can change the fraction to affect wages. In a large population economy, when two places start with the same initial fraction of skilled workers, workers will not move, as they cannot change the fractions. They will stay put and accept the same wage in both places.

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