Applications of search and matching to international trade and unemployment insurance

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APPLICATIONS OF SEARCH AND MATCHING TO INTERNATIONAL TRADE AND UNEMPLOYMENT INSURANCE

by

Kai You

A Dissertation
Submitted to the University at Albany, State University of New York
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the Requirements for the Degree of
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ABSTRACT

This dissertation consists of three chapters.

Chapter 1 investigates the impacts of rising Chinese import competition on US local labor markets, exploiting the role of labor market characteristics in shaping this trade effects. To identify variation of labor sub-markets we incorporate search and matching frictions and workers’ heterogeneous productivity into the otherwise standard EK [Eaton and Kortum, 2002] model. We impute equilibrium sector- and location-specific employment rates and estimate labor market frictions. We then quantify how labor market frictions impact the China trade shock within the framework of [Autor et al., 2013], and find that labor market matching efficiency reinforces the trade shock. Counterfactual analyses from the general equilibrium model reveals that incorporating unemployment rate into the general equilibrium model amplifies the distributional real income gains from the rise of China. Potential tariff retaliation policy is considered.

Chapter 2 studies how finite duration Unemployment Insurance (UI) benefit payments affect wage dispersion. It also provides a quantification of the implied re-entitlement effect. In a directed on-the-job search model, benefit duration is determined by recent employment history while benefit generosity is a function of a worker’s prior wage. As workers approach the expiry of their benefits, they lower their asking wages for two reasons: the impending drop in income makes them eager to get hired and, getting rehired puts them back on the path of benefit re-entitlement. Quantitative exercises evidence a strong interaction between the UI system and on-the-job search in generating wage dispersion. Loss of benefit plays a more important role than re-entitlement per se in the determination of the re-entitlement effect.

Chapter 3 incorporates the UI entitlement eligibility framework developed in Chapter 2 into a business cycle environment. Calibrated to U.S. real data, the results point to a greater wage dispersion and stronger re-entitlement effect in recessions. Unemployed workers with expiring UI entitlement search for low wage jobs in recessions. They spend a long period on climbing up the wage ladder compared to those hired in booms.
I would like to express my deepest gratitude to my advisor Professor Adrian Masters for continuous support of my research. Without his guidance I would have not been able to complete this dissertation.

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Chapter 1

Heterogeneous Effects of Trade with Frictional Unemployment

1.1 Introduction

Economic theories on international trade often reveal that under standard conditions the gains to winners are more than sufficient to offset any losses incurred by those suffering adverse effects from foreign competition. However, there are no consensus among economists and policy-makers about the overall benefits from trade integration. Recent literature prominently by [Autor et al., 2013] has shown that the employment implications of trade shocks in developed countries are strong and persistent. Latest research, such as [Antrás et al., 2017] and [Galle et al., 2018], is growing more concerns on inequality consequences of trade openness. Unemployment in [Heid and Larch, 2016] and [Carrère et al., 2019] has been shown significant effects on inequality. In this paper, we use a framework to evaluate trade shocks form the rise of China in 2010 - 2007, where the society cares about two inequality measures, incomes and involuntary unemployment.

In the theoretic part, we develop a multi-sector, multi-group, multi-country, general equilibrium trade model (based on [Galle et al., 2018]) with labor market frictions and equilibrium (un)employment rates. As [Galle et al., 2018] point out, there are two distributional effect and one overall effect. The reallocation effect of a trade shock leads to a decrease in employment if it reallocates labor into sectors within which workers have lower productivity and/or face higher labor market frictions. The expansion effect is a general equilibrium effect whereby an (un)favorable trade shock, may press aggregate job creation, which by allocative efficiency, in turn reduces real wages and raises employment rates in all sectors.

In the second half of the paper, we structurally estimate the parameters of the model, quantify how labor market frictions interact with China shock effects on regional- and sectoral- employment, and compute geographic real income inequality using available data. We also evaluate a counterfactual experiment that implements in the tariff retaliation policy by the Trump administration to combat the trade shock.
This chapter contributes in several aspects. First, (un)employment rate effect of trade is important: labor market participants care not only in the wages but also the probability of finding a job. By including search-and-matching labor market frictions, we find non-trivial effects of trade on equilibrium (un)employment rates. Second, our structural analysis enables us to compute the real income gains and losses caused by the China shock across groups of U.S. population, rather than only the associated relative income effects. Third, we are able to estimate local labor market efficiencies (frictions) with the imputed employment rates for local-and sectoral- labor markets. Fourth, by combining labor market frictions and labor force productivity heterogeneity, we can explicitly model occupational choice that a worker chooses an industry where he/she is more productive and more likely to secure a job. Both labor productivity dispersion and labor market matching elasticity play roles in the amplification effect, implying that ignoring either would underestimate the trade shock on employment and real income.

1.1.1 Related Literature

Our paper is related to several research areas in international trade. Since [Autor et al., 2013], a growing body of empirical work have documented substantial variation in local labor-market outcomes in response to trade shock, see for example, [Caliendo et al., 2019].

A Roy model of the allocation of workers across sectors has been introduced to offer a structural analysis of the distributional effects of trade shocks such as [Artuç et al., 2010], [Caliendo et al., 2019], and [Lee, 2018] combine a gravity model of trade with a Roy model of labor allocation, as we do, but they focus on different questions: [Caliendo et al., 2019] emphasize the dynamics of adjustment after an unexpected trade shock, and [Lee, 2018] focuses on the implications for the skill premium.

Our paper is also related with [Heid and Larch, 2016] and [Carrère et al., 2019] which include labor market frictions into the trade models. Inspired by but different from these papers, I assume Cobb-Douglas matching functions and estimate characteristics for each of local labor markets in U.S.

The rest of this paper is organized as follows. The theoretical model is described in Section 2 and its equilibrium results in Section 3. We describe data in Section 4, estimate model parameters in Section 5 and calibrate the aggregate and group-level gains from
1.2 Theoretical Model

In this section, we construct a general equilibrium model that connects workers’ occupational choice and regional labor market frictions into an otherwise standard international trade model. This model features heterogeneous workers, heterogeneous firms and a search and matching function in each labor market. Workers choose an industry to search for a job in based on their heterogeneous productivity, sectoral wage, and the probability of being hired in that industry. Firms in each sectoral competitive submarket create vacancies and hire workers until the total revenue covers workers’ wage and hiring costs.

1.2.1 Environment

Time is discrete. There are \( N \) countries indexed by \( i \in \{1, \ldots, N\} \). Each country has \( S \) industries indexed by \( s \in \{1, \ldots, S\} \). There is a continuum of differentiate goods, called varieties \( \omega_s \) within each industry \( s \).

Individual’s preference is Cobb-Douglas over all sectoral outputs and CES within-industry varieties.

\[
U_i = \prod_s C_i^{\alpha_{is}}
\]

where \( \alpha_{is} \) is individual’s expenditure share in sector \( s \) and \( C_{is} \) is consumption on final goods produced from industry \( s \), s.t., \( C_{is} = \left( \sum_{\omega_s} C_i(\omega_s)^{\frac{\alpha_s-1}{\sigma_s}} \right)^{\frac{\alpha_s}{\sigma_s-1}} \) where \( \sigma_s \) is elasticity of substitution across product varieties within sector \( s \).

1.2.2 Workers

On the labor supply side, workers in country \( i \) are classified into mutually exclusive and exhaustive \( G_i \) groups defined primarily by their geographic locations. The total number of group \( ig \) workers is exogenously given by \( L_{ig} \). A worker from group \( ig \) was born with a productivity vector \( z \). Each element of this vector is a number of efficiency...
units $z_{igs}$ in sector $s$ randomly drawn from a Fréchet distribution

$$G_{igs}(z) = \exp(-A_{igsz^{-\kappa_{ig}}}).$$

The scale parameter $A_{igs}$ of this distribution represents the absolute advantage in productivity of group $ig$ in industry $s$. The shape parameter $\kappa_{ig}$ governs the within-type dispersion of productivity. $\kappa_{ig}$ is also the elasticity of labor supply: groups with higher $\kappa$ have fewer outliers in productivity, making them more likely to adjust to changes in per-unit wages by industry. For simplicity, it is assumed that there is no correlation between industry productivity draws.

Workers are risk neutral and have full information. With the knowledge of self-productivity, per-unit wage, and the probability of being hired (employment rate) in each sector, a worker chooses the sector to search for job where she earns the highest expected income. That is, a worker chooses $s$ if her productivity draw $z$ s.t.

$$(e_{igs}w_{is})z_{igs} \geq (e_{igkw_{ik}})z_{igk} \text{ for all } k$$

where $e_{igs}$ is employment rate for the group $ig$ and $w_{is}$ is sectoral wage rate, both in industry $s$.

### 1.2.3 Labor Market

Labor market is group (location)- and industry-specific. An infinitely elastic supply of potential firms may enter the labor submarket by opening vacancies, hiring workers, and producing using labor as the only input. At the beginning of each period, firms open vacancies and hire workers, and each worker chooses a submarket to enter and search for jobs. Once a firm and a worker are matched, they bargain over the wage and produce. The worker provides her efficiency units $z_{igs}$ in production and earn wage income $w_{is}z_{igs}$ to purchase the final consumption bundle. At the end the period, the worker and the firm separate from each other and repeat search and matching in the next period.

There are matching frictions in labor markets. Let $V_{igs}$ denote the endogenous

---

1We assume everyone searches each period because for the empirical purpose, we don't have data for number of searchers and number of vacancies in highly disaggregated labor markets.
number of open vacancies, let $L_{igs}$ denote the endogenous mass of workers from group $ig$ who seek employment in sector $s$, and let $H_{igs}$ denote the subset of those workers who are actually hired. The matching technology is assumed to be Cobb-Douglas

$$H_{igs} = \tilde{\mu}_{igs} V_{igs}^{1-\lambda_{igs}} L_{igs}^{\lambda_{igs}}$$

(1.2)

where $\tilde{\mu}_{igs}$ is the total factor productivity of the matching process, and $\lambda_{igs} \in (0, 1)$ is the matching elasticity with respect to labor. By definition, labor submarket employment rate is $e_{igs} = H_{igs}/L_{igs}$. It is also the equilibrium probability of finding a job in this sector conditional on searching in it. Let the parameter $\nu_{igs}$ denote the unit vacancy cost. In our setting, this vacancy cost includes sector-specific training costs and such costs vary greatly across sectors. Vacancy cost is paid by sectoral price $P_{is}$. For each worker hired, $V_{igs}/H_{igs}$ vacancies need be created. Thus the per worker hiring cost can be expressed as

$$c_{igs}^H = P_{is} \frac{V_{igs}}{H_{igs}} = P_{is} \left( \frac{e_{igs}}{\lambda_{igs}} \right)^{\frac{1}{\lambda_{igs}}}$$

(1.3)

where

$$\mu_{igs} = \frac{\tilde{\mu}_{igs}}{\nu_{igs}}$$

is the labor submarket-specific matching total-factor productivity adjusted for vacancy costs. We can think of $\mu$ as the inverse of all labor market frictions. Thus, the cost of hiring a worker depends on the employment rate (labor market tightness in our setting) and the frictions in the labor submarket. Once matched, the firm and the worker bargain over the firm-specific wage, $w_{igs}(\omega)$, and produce.

---

2Cobb-Douglas function is the most convenient form for connecting labor market frictions to decision making for workers and firms. A difficulty of Cobb-Douglas and discrete time is that the number of hires may exceed the number of workers and firms in the market.

3Alternatively, we can understand $\nu_{igs}$ as the materials matched to a worker devoted in producing varieties. The materials cannot be produced by labor internal to firm but have to be bought on the market. All finals are divided into consumption and intermediate inputs (materials). In this sense, the labor share of production is the same as consumption share of gross output, sectorally, and nationally.
1.2.4 Wage Bargaining

The firm and the worker bargain over the wage, $w_{is}(\omega)$, to split the revenue in a cooperative fashion. They take all other prices as given. The revenue per efficiency labor unit of the firm producing $\omega$ in submarket $igs$ is

$$r_{is}(\omega) = p_{is}(\omega)T_{is}(\omega)$$

$r_{is}(\omega)$ is the rent over which the worker and the firm bargain, $p_{is}(\omega)$ is the price and $T_{is}(\omega)$ is the representative firm’s productivity for variety $\omega$. We assume that the outside option is 0 for both firms and workers, and workers’ bargaining power is $\beta_{is}$, which may vary across sectors. Note that the size of a firm is irrelevant because of constant returns to labor. It follows from independent bargaining that the wage takes $\beta_{s}$ share of firms revenue,

$$w_{is}(\omega) = \beta_{is}p_{is}(\omega)T_{is}(\omega) \quad (1.4)$$

and firms share $1 - \beta_{is}$ covers total hiring cost, and firm earns zero-profit.

$$e_{igs}^H e_{igs}^L_{igs}(\omega) = (1 - \beta_{is})p_{is}(\omega)T_{is}(\omega)e_{igs}E_{igs}(\omega) \quad (1.5)$$

The $lhs$ of $(1.5)$ is the total hiring costs for firm producing $\omega$ in submarket $igs$ and $rhs$ is firms’ share of revenue, where $e_{igs}E_{igs}(\omega)$ is the number of efficiency units used in production, supplied from group $ig$ workers.

1.2.5 Production

Within each sector, there is a continuum of varieties, and each firm produces one variety. Production technology exhibits constant returns to scale and is variety-specific. Specifically, let the output level be defined as

$$Y_{igs}(\omega) = T_{is}(\omega)E_{igs}(\omega)e_{igs}$$
where $E_{igs}(\omega)e_{igs}$ is the amount of efficiency labor units used in production supplied from worker group $L_{ig}$. The national output level for variety $\omega$ is

$$Y_{is}(\omega) = T_{is}(\omega) \sum_{g \in G_i} E_{igs}(\omega)e_{igs}$$

Firms’ productivity $z$ is drawn from a Fréchet distribution for each $\omega^s$:

$$F_{is}(z) = \exp(-T_{is}z^{-\theta_s}).$$

where the scale parameter $T_{is}$ is associated with the absolute advantage of country $i$ for industry $s$, and $\theta_s$ governs the dispersion of the productivity within sector $s$.

### 1.2.6 International Trade

Variety goods are traded internationally in the perfectly competitive market, where each country purchases each product from the lowest-cost supplier. Let $p_{is}(\omega)$ denote the price of variety good $\omega$ within sector $s$ in country $i$, and $p_{nis}(\omega)$ denote import price from country $n$ for this product, the price in country $i$ is

$$p_{is}(\omega) = \min_{n} p_{nis}(\omega).$$

The selling price of product $\omega^s$ depends on productivity $T_{is}(\omega)$, sectoral production costs $c_{is}$, which includes labor and hiring inputs, and trading costs. Iceberg trade cost $d_{ni}$ means only a fraction $1/d_{ni}$ of the goods shipped from country $n$ to country $i$ reach their destination.

### 1.3 Equilibrium

Equilibrium results are derived separately for workers’ occupational choices, production, and trade flows between countries. Each result is determined given the efficiency unit wage and product price for each country, worker group, and industry. These prices are, in turn, determined in general equilibrium.
1.3.1 Occupation Choice

The workers’ occupational choice problem is to choose an industry $s$ that maximizes expected income $e_{igs}w_{is}$, see (1.2.2). Using the Fréchet distribution of workers’ productivity, the probability that a worker from group $ig$ chooses industry $s$ is

$$\Pi_{igs} \equiv \frac{L_{igs}}{L_{ig}} = \frac{A_{igs} (e_{igs}w_{is})^{\kappa_{ig}}}{\sum_k A_{igk} (e_{igk}w_{ik})^{\kappa_{ig}}}$$

(1.6)

which is called employment share. It is obvious that workers are more likely to supply their efficiency units to the industry where they have a comparative advantage (large $A_{igs}$). In addition, the degree of within-type comparative advantage $\kappa_{ig}$ affects the responsiveness of group $ig$ workers with respect to changes in sectoral wage. The same change in wage rate may induce differential labor reallocation patterns across different worker groups.

It follows from (1.6) that the supply of efficiency units by group $ig$ to sector $s$ is given by

$$E_{igs} = \eta_{ig} \left[ \frac{\sum_k A_{igk} (e_{igk}w_{ik})^{\kappa_{ig}}}{e_{ig}w_{is}} \right]^{\frac{1}{\kappa_{ig}}} \Pi_{igs} L_{ig}$$

(1.7)

where $\eta_{ig} \equiv \Gamma\left(1 - 1/\kappa_{ig}\right)$ is a constant. One implication of this result is that expected earnings per worker (employed and unemployed) are equalized across sectors. That is, for group $ig$, we have

$$\frac{e_{igs}w_{is}E_{igs}}{\Pi_{igs}L_{ig}} = \eta_{ig} \left[ \sum_k A_{igk} (e_{igk}w_{ik})^{\kappa_{ig}} \right]^{\frac{1}{\kappa_{ig}}}.$$  

(1.8)

This is a special implication of the Fréchet distribution and it implies that the share of earnings obtained by workers of group $ig$ in sector $s$ (i.e., $e_{igs}w_{is}E_{is}/\sum_k e_{igk}w_{ik}E_{ik}$) is also given by $\Pi_{igs}$. Let $I$ denote wage income for group $ig$, earnings by workers of group $ig$ in sector $s$ can be expressed as

$$I_{igs} \equiv e_{igs}w_{is}E_{igs} = \Pi_{igs}I_{ig}$$

where total income $I_{ig} = \sum_s I_{igs}$. 

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1.3.2 Production Cost

Firm solves its problem by choosing the equilibrium demand for the efficiency units of labor through opening appropriate number of vacancies. Since firm earns zero profit, its revenue should be equal to producing cost, and it follows from (1.4) that

\[ w_{is} = \beta_{is} c_{is} \]

where \( c_{is} \) is unit cost to produce a variety in sector \( s \), country \( i \). Since wage income takes \( \beta_{is} \) share of cost and hiring cost takes the other \( 1 - \beta_{is} \) share, after combining (1.4) and (1.5) and plugging in hiring cost function (1.3), we have

\[
\frac{1}{\beta_{is}} w_{is} e_{igs} E_{igs} = \frac{1}{1 - \beta_{is}} P_{is} \left( \frac{\lambda_{igs}}{\mu_{igs}} \right)^{\frac{1}{1-\lambda_{igs}}} e_{igs} L_{igs} \tag{1.9}
\]

This is the key equation for the estimation.

1.3.3 International Trade

Lowest-price variety supplier wins the world market through international trade. The price of a product \( \omega \) in country \( i \), which was produced in and shipped from sector \( s \) country \( n \), is

\[ P_{nis}(\omega) = \frac{c_{is}}{T_{is}(\omega)} d_{nis}. \]

Due to perfect competition, the actual price of \( \omega \) in country \( i \) country \( n \) is given by \( P_{is}(\omega) = \min_{n} P_{nis}(\omega) \). Since firm’s productivity \( T_{is}(\omega) \) is drawn from Fréchet distribution, the probability that country \( i \) buys a good in industry \( s \) from country \( n \) is

\[
\Lambda_{nis} \equiv \frac{C_{nis}}{C_{is}} = \frac{T_{nis}(d_{nis}c_{ns})^{-\theta_{s}}}{\sum_{m} T_{ms}(d_{mis}c_{ms})^{-\theta_{s}}}. \tag{1.10}
\]

The numerator in the rhs of (1.10) is the competitiveness of country \( n \) exporting goods in sector \( s \) to country \( i \). The competitiveness increases in domestic sectoral productivity \( T_{ns} \), and decreases in production cost \( c_{ns} \) and trading cost \( d_{nis} \). In (1.10), \( \theta_{s} \) is the elasticity of imports with respect to trade costs, which is called the trade elasticity. An industry with
less dispersion of productivity across countries has a higher trade elasticity because trade flows respond more to changes in trade costs when countries are similar in productivity.

The price index $P_{is}$ for industry $s$ and country $i$ is

\[ P_{is} = \Gamma_{s} \left[ \sum_{n} T_{ns} (d_{nis} c_{ns})^{-\theta_{s}} \right]^{-\theta_{s}/\theta_{s}} \]  

(1.11)

where $\Gamma_{s} \equiv \Gamma \left( 1 - \frac{\sigma_{s}}{\theta_{s}} \right)^{1/(1-\sigma_{s})}$ is a constant. Since the preference over sectoral goods is Cobb-Douglas, the personal consumption expenditures (PCE) price level is the geometric weighted average of the sectoral prices

\[ P_{i} = \prod_{s} P_{is}^{\alpha_{is}}. \]  

(1.12)

### 1.3.4 General Equilibrium

In general equilibrium, goods markets and labor markets clear for all groups in all countries, and the trade (im)balance condition holds. Final goods markets are cleared when

\[ \beta_{is} Y_{is} = \sum_{n} \Lambda_{ins} C_{ns} \]

holds for each $i$ and $n$, where $Y_{is}$ is the value of gross output in industry $s$ in country $i$. The total expenditure is

\[ C_{is} = \alpha_{is} \left( \sum_{s} \beta_{s} Y_{is} + D_{i} \right) \]  

(1.13)

where $\beta_{s} Y_{is} = w_{is} \sum_{g \in G_{i}} E_{igs}$ is labor income from industry $s$ in country $i$, and $D_{i}$ is an aggregate trade deficit for country $i$, s.t.,

\[ D_{i} = \sum_{s} \sum_{n} \Lambda_{nis} C_{is} - \sum_{s} \sum_{n} \Lambda_{ins} C_{ns}. \]

**Definition** Given parameters $\alpha_{is}^{z}, \kappa_{is}, \theta_{s}, \lambda_{gs}, \beta_{s}$, iceberg trade costs $d_{ijs}$, firms’ productivity $T_{is}$, Workers’ productivity $A_{igs}$, labor force $L_{ig}$, labor market matching efficiency $\mu_{gs}$, hiring cost $\nu_{gs}$, an equilibrium is a wage vector $w_{is}$, sectoral prices $P_{is}$, regional employment rate $e_{igs}$, that solves firms’ problem (1.9), labor market (1.6), trade share (1.10), trade balance
1.3.5 Comparative Statics

Consider changes in some fundamentals in the equilibrium model, e.g., China’s technological progress or reduction of trade costs. We proceed using hat algebra to solve for the proportional change in the endogenous variables. A proportional change of any variable $x$ is denoted by $\hat{x} \equiv x'/x$, where $x'$ is a variable $x$ at the counterfactual equilibrium. The hat algebra generates the following intermediate results:

\begin{align*}
\hat{I}_{ig} &= \hat{P}_{is} \cdot \hat{\varepsilon}_{igs} \cdot \hat{\mu}_{igs} \tag{1.14} \\
\hat{I}_{ig} &= \hat{\varepsilon}_{igs} \cdot \hat{w}_{is} \cdot \hat{\Pi}_{igs} \tag{1.15} \\
\hat{P}_{is} &= \hat{w}_{is} \cdot \hat{\Lambda}_{iis} \tag{1.16}
\end{align*}

where country subscript $i$ is dropped since we focus on the U.S. economy. The rhs of (1.14) shows a negative relationship between sectoral price level and employment rate: facing a higher price level (higher hiring cost), the firm opens fewer vacancies and hires fewer workers, which causes lower employment rate for those searching in the submarket. The rhs of (1.15) reveals that if the expected wages are lower in industry $s$ (smaller $\hat{\varepsilon}_{igs} \cdot \hat{\varepsilon}_{is}$), fewer workers search and work in industry $s$ (smaller $\hat{\Pi}_{igs}$). Last, the rhs of (1.16) shows that if a country export more share of its output in industry $s$ (lower $\hat{\Lambda}_{iis}$), workers in this industry enjoy higher wages.

Combining (1.14), (1.15), and (1.16), and canceling out $\hat{w}_{is}$ and $\hat{P}_{is}$, we derive group- and industry-specific employment rate change expressed in observables and parameters:

\begin{align*}
\hat{\varepsilon}_{igs} &= \left( \hat{\Pi}_{igs}^{-\frac{1}{\beta_{igs}}} \cdot \hat{\Lambda}_{iis}^{-\frac{1}{\beta_{iis}}} \cdot \hat{\mu}_{igs}^{-\frac{1}{\beta_{iis}}} \right)^{1-\lambda_{igs}}. \tag{1.17}
\end{align*}

The group level employment rate change is weighted summation over $\hat{\varepsilon}_{igs}$ as in (1.17)

\begin{align*}
\hat{\varepsilon}_{ig} &= \sum_{is} \Pi_{igs} \hat{\varepsilon}_{igs} = \sum_{is} \Pi_{igs} \left( \hat{\Pi}_{igs}^{-\frac{1}{\beta_{igs}}} \cdot \hat{\Lambda}_{iis}^{-\frac{1}{\beta_{iis}}} \cdot \hat{\mu}_{igs}^{-\frac{1}{\beta_{iis}}} \right)^{1-\lambda_{igs}}. \tag{1.18}
\end{align*}
1.3.6 Counterfactuals

It is convenient to write counterfactuals using the hat algebra. Specifically, we obtain the following system of equations

\[
\sum_j \hat{\Lambda}_{ij}\Lambda_{ij} \alpha_{ij} \left( \sum_{g \in G_j} \hat{Y}_{gj} Y_{gj} + \hat{D}_j D_j \right) \beta_{is} = \sum_{g \in G_i} \hat{\Pi}_{igs} \hat{I}_g \Pi_{igs} I_{ig} \quad (1.19)
\]

with

\[
\hat{I}_g = \left[ \sum_k \Pi_{igk} \hat{A}_{igk} \left( \hat{w}_{ik} \hat{e}_{igk} \right)^{\kappa_{ig}} \right]^{1/\kappa_{ig}} \quad (1.20)
\]

\[
\hat{\Pi}_{igs} = \frac{\hat{A}_{igs} \left( \hat{w}_{is} \hat{e}_{igs} \right)^{\kappa_{ig}}}{\sum_k \Pi_{igk} \hat{A}_{igk} \left( \hat{w}_{ik} \hat{e}_{igk} \right)^{\kappa_{ig}}} \quad (1.21)
\]

\[
\hat{\Lambda}_{ijs} = \frac{\hat{\sigma}_{is} \hat{d}_{ijs} \hat{w}_{is}}{\sum_n \Lambda_{njs} \hat{\sigma}_n \hat{d}_{njs} \hat{w}_{ns}}^{-\theta_s} \quad (1.22)
\]

and (1.17). Equation (1.19) shows that the labor share of worldwide demand for sector \( s \) goods from country \( i \) is equal to total earnings of sector \( s \) in country \( i \). Given values for parameters \( \kappa_{ig}, \theta_s \) and \( \lambda_{igs} \); data on income levels, \( I_{ig} \), trade imbalances, \( D_j \), trade shares, \( \Lambda_{ijs} \), expenditure shares, \( \alpha_{is} \), labor allocation shares \( \Pi_{igs} \), and labor market participants, \( L_{ig} \); and the shocks to trade costs, \( \hat{d}_{ijs} \), trade imbalances, \( \hat{D}_j \), productivity levels, \( \hat{A}_{igs} \) and \( \hat{\sigma}_{is} \), and labor market efficiencies \( \hat{\pi}_{igs} \), we can solve for changes in wages, \( \hat{w}_{ig} \), income, \( \hat{I}_g \), labor allocations, \( \hat{\Pi}_{igs} \), trade share, \( \hat{\Lambda}_{jis} \), and local employment rates \( \hat{e}_{igs} \).
1.3.7 Grains from Trade

One of the goals is to estimate differential effects on real income of some trade shock for different groups. Group level real income is defined as

\[
\hat{W}_{ig} = \frac{\hat{f}_{ig}}{\hat{p}_{i}} \xi
\]

\[
= \prod_s \hat{\Pi}_{i gs}^{-a_{gs}} \cdot \prod_{is} \hat{\Lambda}_{iis}^{-a_{is}} \cdot \prod_{is} \mu_{i gs}^{a_{is}} \cdot \left[ \sum_{is} \prod_{i gs} \left( \hat{\Pi}_{i gs}^{-1} \cdot \hat{\Lambda}_{iis}^{-1} \cdot \hat{\mu}_{i gs}^{-1} \right)^{1-\lambda_{i gs}} \right]^{1-\lambda_{i gs}}(1.23)
\]

where \(\xi \in \mathbb{R}^+\) is a parameter governing society’s preference of employment. In the quantitative analyses below, we assume the society is not averse to unemployment. That is, we impose an equal weight (\(\xi = 0\)) to average real earnings and employment rates across groups. Then the welfare equation (1.23) can be simplified as

\[
\hat{W}_{ig} = \prod_s \hat{\Pi}_{i gs}^{-a_{gs}} \cdot \prod_{is} \hat{\Lambda}_{iis}^{-a_{is}} \cdot \prod_{is} \mu_{i gs}^{a_{is}} \cdot \left[ \sum_{is} \prod_{i gs} \left( \hat{\Pi}_{i gs}^{-1} \cdot \hat{\Lambda}_{iis}^{-1} \cdot \hat{\mu}_{i gs}^{-1} \right)^{1-\lambda_{i gs}} \right]^{1-\lambda_{i gs}}(1.24)
\]

The \(rhs\) of expressions in (1.24) has three components: \(\hat{\Pi}_{i gs}^{-1/\kappa_{ig}}\), \(\hat{\Lambda}_{iis}^{-1/\theta_{is}}\), and \(\hat{\mu}_{i gs}^{1/\lambda_{i gs}}\). The first two components (\(\hat{\Pi}_{i gs}^{-1/\kappa_{ig}}\) and \(\hat{\Lambda}_{iis}^{-1/\theta_{is}}\)) are similar to those in [Galle et al., 2018]. \(\hat{\Pi}_{i gs}^{-1/\kappa_{ig}}\) measures the labor share changes in response to the trade shock, mainly due to the change in expected wages (earnings) in each sector. The second term, \(\hat{\Lambda}_{iis}^{-1/\theta_{is}}\) reflects gains from new varieties imported from other countries. If the price of imported varieties in sector \(s\) decreases, the share of consumption of imported varieties, \(1 - \hat{\Lambda}_{iis}\), increases, while the share of consumption of domestic varieties, \(\hat{\Lambda}_{iis}\), decreases. The lower \(\hat{\Lambda}_{iis}\) contributes to the welfare gains. The last term \(\hat{\mu}_{i gs}^{1/\lambda_{i gs}}\) is new. It measures the effects of labor market frictions. As expected, a higher search and matching efficiency increases welfare because it’s easier to find a job.

Compared to [Galle et al., 2018], gains or losses from trade are amplified by a factor \(1/\lambda_{i gs} > 1\), which is decreasing in matching elasticity of labor supply. A negative trade shock, such as tremendous imports of cheap textiles, generally pushed down domestic wages in the sector producing textiles. Workers facing lower wage may transit to other sectors, and due to labor market frictions, only a portion of those switching workers could
find a job. Consequently, the average earnings for all previous textile workers experience a loss proportionally more than textiles wage drop. This magnifying effect appears in other studies modeling labor market frictions.

National income effect is defined as a CES function of group level real income:

\[
\hat{W}_i = \left( \sum_{g} \omega_{ig} \hat{W}_{is}^{1-\rho} \right)^{\frac{1}{1-\rho}}
\]

where \( \rho \geq 0 \) is society’s inequality aversion parameter, and \( \omega_g \) is a weight for group \( ig \) real income accounting for their labor force.

1.4 Data

In following sections we take our model to the data. For our quantitative analysis, we focus on U.S. workforce and define groups based on geographic location. We follow literature in using commuting zones (CZs) as geographic units to define local labor markets.

We restrict our analysis to the period 2001-2007 when the U.S. experienced historical rise in imports from China. We obtain national figures on bilateral trade flows, sectoral output and employment shares from the World Input-Output Database. For regional employment and income across U.S. groups, we rely on Local Area Personal Income data from BEA Regional Economic Accounts and Quarterly Census of Employment and Wages program from Bureau of Labor Statistics. We obtain employment shares for each industry each region using County Business Patterns (CBP). Job Openings and Labor Turnover Survey provides information on number of vacant positions opened. Unfortunately, employment rate for each industry each region is not available. We will impute the numbers using three sources: employment rate for each CZ, sectoral employment rate, and number of employments in each sector in each CZ. We also use American Community Survey to compute labor submarket employment rate. In the empirical part, we divide all US workers into four aggregate sectors: (1) construction, (2) manufacturing, (3) trade, transportation, and utility, and (4) the other sector which includes service, government and agriculture. This categorization is a compromise of consistency of data availability across
sources. The constructed world economy has 40 largest international trade participating countries and a rest-of-the-world. Each country other than U.S. is assumed to have only one group.

1.5 Estimations

We aim to quantify the employment and income consequences of any given counterfactual, e.g., a China trade shock. We expect differential consequences of trade shock because of heterogeneity in labor force and regional labor submarkets. In our model there are two variables characterizing labor market frictions: matching efficiency $\mu_{gs}$, and matching elasticity $\lambda_{gs}$. We assume $\mu_{gs}$ vary across geographic locations (CZs) and industries; and $\lambda$ is the same for all labor submarkets. Specifically, we assume that the efficiency for each labor submarket is a multiplication of efficiency for the location and for the sector: $\mu_{gs} = \mu_{g} \cdot \mu_{s}$. Workers’ bargaining power $\beta_{s}$’s are matched to data: the labor share of gross output for each industry. With these assumptions we are able to estimate these parameters and study the roles they play in the trade effects.

1.5.1 Matching Elasticity

We first estimate matching elasticity using data from the national level labor markets. Assuming the elasticity is the same across industries and groups, we can rewrite equation (1.2) as

$$H_{st} = \tilde{\mu}_{st} V_{st}^{1-\lambda} L_{st}^{\lambda}$$

(1.26)

where $H_{st}$ is number of employees, $V_{st}$ is the average number of vacancies filled and unfilled, and $L_{st}$ is the volume of labor force, all in sector $s$ time $t$. Note that sectoral labor force is the sum of number of employees and the unemployed in one sector. CPS reports the number of employees and unemployed workers in disaggregate sectors. For each unemployed respondents who is looking for jobs, CPS records her sector as the sector of her last job. It is likely that the respondent is searching in a different industry after being separated from her last position. We borrow methods and data from [Sahin et al., 2014] where they compute the number of job seekers in each sector based on their model derived
inter-industry transition rates. Taking log of (1.26), we have the reduced form

\[ \ln H_{st} = \text{const.} + \text{time} + (1 - \lambda)\ln V_{st} + \lambda \ln L_{st} + \text{error}_{st}. \]  

(1.27)

Dividing both sides of (1.26) by \( L_{st} \) and taking log, we have

\[ \ln e_{st} = \text{const.} + \text{time} + (1 - \lambda)\ln \Theta_{st} + \text{error}_{st} \]

(1.28)

where \( \Theta_{st} \) is the labor market tightness.

The number of vacancies created is endogenous, because firms’ hiring decisions are responsive to changes in matching efficiency. (See, e.g., [Borowczyk-Martins et al., 2013]) Therefore, \( V_{st} \) and \( \text{error}_{st} \) are correlated and the estimates of \( \lambda \) is biased. [Şahin et al., 2014] documents that some of the major movements in matching efficiency inducing a bias in the OLS estimator are low-frequency ones. Thus, modeling explicitly the dynamics of matching efficiency through time-varying polynomials and structural breaks could solve the problem even with the simple OLS estimator. We take this approach. Specifically, we add time trends polynomials into (1.27) and run panel regressions.

**Table 1.1: Matching Elasticity \( \lambda \) Estimation**

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Employments</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vacancy</td>
<td>0.422</td>
<td>0.383</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(16.79)</td>
<td>(13.72)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor Force</td>
<td>0.605</td>
<td>0.655</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(23.83)</td>
<td>(22.98)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Market Tightness</strong></td>
<td></td>
<td></td>
<td></td>
<td>0.413</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(16.04)</td>
</tr>
<tr>
<td><strong>Time Trend</strong></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>336</td>
<td>252</td>
<td>336</td>
<td>252</td>
</tr>
</tbody>
</table>

Columns 1 and 3 include monthly data for all four sectors from 2001 to 2007 and columns 2 and 4 exclude the service and government sector. In all specifications, time polynomials are controlled for. \( t \) statistics are reported in parentheses.

First, we run unconstrained regressions allowing for possible increasing or decreasing return of scale of the matching function. Results in Columns (1) and (2) in Table 1.1 show
that the coefficients on vacancies (around 0.4) and labor force (around 0.6) sum up to one. Therefore, we find evidence that supports a CRS matching function. Next, we regress job finding rate (employment rate) on labor submarket tightness. The elasticity on vacancy estimates is very closed to 0.4, as shown in columns (3) and (4). We therefore set our preferred value for matching elasticity w.r.t labor at $\lambda = 0.6$ from estimation using the aggregate data.

### 1.5.2 Matching Efficiencies

We estimate labor market friction parameters as follows. Dividing $e_{gs}L_{gs}$ from both sides of (1.9) and rearranging yields

$$ I_{gs} = \frac{w_s e_{gs} E_{gs}}{e_{gs} L_{gs}} = \frac{\beta_s}{1 - \beta_s} P_s \left( \frac{e_{gs}^{\lambda}}{\mu_g \mu_s} \right) \frac{1}{\lambda} $$

(1.29)

where the lhs of (1.29), $I_{gs}$, is the average wage income per employee in sector $s$. Using the fact from (1.8) that expected earnings per capita are equalized across sectors for each group, the above equation (1.29) can be rewritten as

$$ I_g = \frac{\beta_s}{1 - \beta_s} P_s \left( \frac{e_{gs}}{\mu_g \mu_s} \right) \frac{1}{\lambda} $$

(1.30)

where $I_g$ is the per capita earnings for group $g$. Note that there is an amplifying effect resulting from a shift of employment rate due to the matching elasticity $\lambda < 1$. Taking logs of (1.29) and allowing for time variation yields

$$ \ln \left( \frac{1 - \beta_s}{\beta_s} \cdot \frac{I_{gst}}{P_{st}} \right) = \frac{\lambda}{1 - \lambda} \ln e_{gst} - \frac{1}{1 - \lambda} \ln \mu_g - \frac{1}{1 - \lambda} \ln \mu_s $$

which can be estimated by running the fixed effect regression

$$ \ln \left( \frac{1 - \beta_s}{\beta_s} \cdot \frac{I_{gst}}{P_{st}} \right) = \frac{\lambda}{1 - \lambda} \ln e_{gst} + FE_g + FE_s + FE_t + error_{gst} \quad (1.31) $$

Clearly, the location-specific matching efficiency $\mu_g$'s and sectoral matching efficiency

---

4The real income term, $\ln \left( I_{gst}/P_{st} \right)$, needs to be normalized.
Table 1.2: Matching Efficiency Estimation

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment Rate</td>
<td>1.541</td>
<td>1.440</td>
<td>1.284</td>
</tr>
<tr>
<td></td>
<td>(15.04)</td>
<td>(5.08)</td>
<td>(3.83)</td>
</tr>
<tr>
<td>CZ</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Industry</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Time</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry * Time</td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>IV</td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Implied $\lambda$</td>
<td>0.606</td>
<td>0.590</td>
<td>0.562</td>
</tr>
<tr>
<td>Observations</td>
<td>17052</td>
<td>17052</td>
<td>17052</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses

$\mu$'s can be recovered using $FE_g$ and $FE_s$ along with another estimated matching elasticity $\hat{\lambda}$.

Disaggregate data on region- and sector-specific employment rate is not available. We impute these rates taking advantage of information on CZ level unemployment rates $e_g$, sectoral unemployment rates $e_s$, and number of employees for each submarket $H_{gs}$. The first step of following iterations assumes that the distribution of sectoral employment rates is the same across all regions. Then these employment rates are updated until they are consistent with CZ employment rates and with employment data from CBP.

1. Guess

$$e_{gs}^{(0)} = e_s$$

2. Update

$$e_{gs}^{(1)} = e_{gs}^{(0)} \frac{\sum_s H_{gs}/e_{gs}^{(0)}}{H/g/e_g}$$

3. Update

$$e_{gs}^{(2)} = e_{gs}^{(1)} \frac{\sum_g H_{gs}/e_{gs}^{(1)}}{H/g/e_s}$$

Repeat steps (2) and (3) until $e_{gs}$ converges.

There are endogenous issues on the specification (1.31). First, the imputed regional- and sectoral-specific employment rate $e_{gst}$ has measurement errors. Second, $e_{gst}$ is likely to
be correlated with the errors. Consider, for example, a positive local labor demand shock in construction due to infrastructural improvement causes both the employment rate and earning in local construction sector to rise in the short run. To alleviate the endogeneity, we instrument $e_{gst}$ using one period lag of local employment rate $e_{g,t-1}$ and one period lag of sectoral employment rate $e_{s,t-1}$. Lagged employment rates are observables and are not likely to correlated with current local labor market shocks.

Table 1.2 lists the fixed effects estimation on (1.31) without and with instruments. The coefficients on employment rate $e_{gst}$ are significant and closed to 1.5, implying a estimated value of $\lambda$ is closed to 0.6. It is the same the preferred value we obtained of $\lambda$ from the previous subsection. Substituting $\lambda = 0.6$ into estimated CZ fixed effects from column 2, we can recover the local labor market matching efficiencies. Figure 1.1 shows the variations of estimated matching TFPs: northeastern and western coasts and other large metros such as Chicago observe lower matching efficiencies than less populated locations. This finding reveals that it takes longer for workers to find a job match in locations with more labor supplies. Next, we bring the estimates to the trade shock quantifications.
1.5.3 China Shock

We are interested in how regional labor market characteristics moderate the effects of trade shock on employment outcomes. Specifically, we estimate the effects of proportional change of China’s manufacturing imports on regional employment share changes in the manufacturing sector:

\[ \hat{\Pi}_{gt} = \gamma_1 + \gamma_1 \hat{IPW}_{gt} + \gamma_2 \mu_g + \gamma_3 \left( \mu_g \cdot \hat{IPW}_{gt} \right) \]  (1.32)

where \( \hat{IPW}_{gt} \) is a measure of import exposure. Standard errors are clustered at the state level to account for spatial correlations across CZs. The change in manufacturing import from China in each CZ, \( \hat{IPW}_{gt} \) is endogenous because, for example, a preference shock on US consumers for manufacturing goods will affect employment and imports in manufacturing sector. Following [Autor et al., 2013], we instrument for \( \hat{IPW}_{gt} \) using China’s export change to other developed countries, \( \hat{IPW}_{ot} \).

The estimated matching efficiency \( \mu_g \) is also endogenous, because of, at least, measurement errors. We use a rich set of CZ level demographic and geographic characteristics to instrument for \( \mu_g \)’s. Labor market matching efficiency represents the productivity of job searching and recruiting activities, depending on the geographic mobility of the workforce, information and communication technologies, and unemployment benefit policies, among other factors. Local matching efficiency reflects both regional workforce factors such as search efforts, and regional matching technologies such as infrastructures and climates. Firm side factors such as recruiting intensities are captured by sectoral matching efficiencies \( \mu_s \)’s, since firms are ex-anti homogeneous and compete not locally but internationally.

Table A1 shows the first stage regression of estimated local matching efficiencies on a set of CZ characteristics. We put the predicted \( \mu_g \)’s into (1.32) and run two-stage least squares. The way of getting predicted \( \mu_g \)’s is equivalent to incorporating CZ characteristics into (1.31) and obtaining \( \mu_g \)’s through recovering the sum of fixed effects of each characteristic.

Table 1.3 displays results for 2SLS regressions of change in CZ manufacturing employment share on China trade shock and local labor market matching efficiencies.
Table 1.3: China Shock and Manufacturing Employment in CZs

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trade Shock</td>
<td>-0.746</td>
<td>-0.762</td>
<td>-0.879</td>
</tr>
<tr>
<td></td>
<td>(-10.96)</td>
<td>(-11.55)</td>
<td>(-8.21)</td>
</tr>
<tr>
<td>Matching Efficiency</td>
<td>3.161</td>
<td>5.903</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.19)</td>
<td>(3.55)</td>
<td></td>
</tr>
<tr>
<td>Matching Efficiency * Trade Shock</td>
<td>-1.452</td>
<td></td>
<td>(-2.53)</td>
</tr>
</tbody>
</table>

2SLS First Stage

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Trade Shock IV</td>
<td>0.7916</td>
<td>0.7874</td>
<td>0.8463</td>
</tr>
<tr>
<td></td>
<td>(10.14)</td>
<td>(10.11)</td>
<td>(11.19)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.5436</td>
<td>0.5457</td>
<td>0.5485</td>
</tr>
<tr>
<td>Observations</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses. Robust standard errors are clustered on state. Models are weighted by CZ share of national population. $t$ statistics are reported in parentheses.

The negative and significant coefficients on Trade Shock is almost the same as what [Autor et al., 2013] obtains: a rise in manufacturing imports from China reduces percentage of workers employed in this sector. The positive and significant estimates on $\mu_g$’s suggest that with higher matching efficiency, workers are more likely to secure a job in manufacturing firms. The negative and significant coefficients on the interaction term reveals that the China import shock has distributional effects on labor markets where frictions reinforce the impacts of trade shock; given the shock, workers in labor markets with higher matching productivity will lose relatively more jobs in the manufacturing sector. There are two channels for this effect to happen. First, in areas with fewer frictions, firms hire fast and workers find jobs fast. When firms in these areas stop hiring, local workers will lose more opportunities in manufacturing than workers in markets where search and matching take more time. The other is if domestic manufacturing firms compete by reducing prices, fewer resources are left for the costly hiring processes. From (1.3), it is clear a fall in hiring cost proportionately reduces sectoral employment rates, and the number of manufacturing workers being separated is larger in more efficient markets.
1.5.4 Robustness

We perform two robustness exercises. The first is that we obtain similar estimates for matching elasticity of labor, $\lambda$, from regressions on (1.28) using aggregate data and from model derived estimation equation (1.31) using disaggregate data.

The second robustness exercise is that we replicate the empirical work, namely, estimations on (1.31) and (1.32) using data from American Community Survey (ACS), 2005-2007. On one hand, a virtue of survey data is that we can calculate (un)employment rates directly from the dataset, thus these numbers are more accurate than those imputed. On the other, annual ACS doesn’t provide information on the county where respondents reside before 2005, so we can only construct a very short panel. Moreover, in ACS 2005-2007, only 375 counties have records of respondents surveyed, which converts to 190 CZs. Therefore, this ACS sample may not be representative. We proceed with caution to run regressions on (1.31) and (1.32). Results shown in Table A2 and A3 are very similar to what we have. Therefore, our findings are robust to different data sources.

1.5.5 Labor Supply Elasticity

We estimate the labor supply elasticity, $\kappa$ using (1.15). Moving the employment rate term $\hat{e}_{igs}$ to the left-hand side and dropping $\kappa$ as homogeneous, we obtain

\[
\ln \left( \frac{\hat{I}_{ig}}{\hat{e}_{igs}} \right) = \ln(\hat{\omega}_{is}) - \frac{1}{\kappa} \ln(\hat{\Pi}_{igs})
\]  

(1.33)

and can estimate

\[
\ln \left( \frac{\hat{I}_{ig}}{\hat{e}_{igs}} \right) = FE_{s} - \frac{1}{\kappa} \ln(\hat{\Pi}_{igs}) + \text{error}_{gs},
\]  

(1.34)

The equation boils down to the method used by [Galle et al., 2018]. The error term includes omitted variables such as trade shocks that impact both group level incomes and labor shares. Using the instrumental variable constructed by [Autor et al., 2013] satisfy the relevance restriction as the trade shock is correlated with local labor share across sectors. However, there could exist other factors that affect changes in labor-force.

\(^{5}\)ACS records county information for the year 2000. Since our econometric purpose is to run panel regressions, we use ACS 2005-2007.
such as shocks in local productivity or preferences. To alleviate the potential violation of exclusion restriction, we include CZ level characteristics in the regression as suggested by [Galle et al., 2018] and others. We exclude manufacturing and construction in the estimation. Construction is excluded because this is a very small sector and is nearly not impacted by trade shocks. The estimated $\kappa$ is 1.5, well within the range in literature.

### 1.6 Counterfactuals

Having obtained estimates for labor market characteristics, we are in a position to perform counterfactual simulations with our model to study group-level and aggregate real income implications of the “rise of China”. To this end, we need the values of five parameters in (1.23) and (1.25): matching elasticity $\lambda$, matching efficiency change $\hat{\mu}$, labor supply elasticity $\kappa$ and trade elasticity $\theta$, consumption share $\alpha$, and society’s preference of employment $\xi$ ($\xi=0$).

Following [Galle et al., 2018], we model the rise of China as manufacturing-specific technology shocks, $\hat{T}_{China, manuf}$. We calibrate this shock such that, the simulated change in US expenditure share on Chinese manufacturing goods matches the change in data. To bring our model to the data, we rewrite (1.19) as

$$
\sum_j \hat{A}_{ij}s \Lambda_{ij} \sum_{g \in G_j} \hat{Y}_{ijg} Y_{ijg} + \hat{D}_j D_j \right) i_{js} = \sum_{g \in G_i} \hat{\Pi}_{igs} \hat{I}_{ig} \Pi_{igs} I_{ig} \tag{1.35}
$$

where $Y_{ijg}$ is gross output of sector $s$ produced in location $g$ in country $j$, and $i_{js}$ is the share of value added in sector $s$. Note that for each location, the growth rate of gross output $\hat{Y}_{ijg}$ is such that $\hat{I}_{ijg} \sum_s \Pi_{igs} I_{igs} = \hat{Y}_{ijg} \sum_s \Pi_{igs} I_{igs}$. We run the counterfactual analyses in two steps: (1) we simulate an worldwide economy without trade deficits for each country ($\hat{D}_j = 0$ for all $j$), and (2) we exert the trade shock to the economy, and assume that the proportional change of trade deficit $\hat{D}_j$ is the same as that of gross output, $\hat{Y}_j$.

6Throughout the paper, we assume that workforce is constant in each labor market. Taking into account of decisions on labor force participation requires modeling unemployment insurance, income tax, etc., which is beyond the scope of this paper.

7Empirically we include all 724 CZs as geographic groups in US. It is assumed there is one geographic group in each of other countries.
Table 1.4: China Shock and Real Income Effects on CZs

<table>
<thead>
<tr>
<th>κ</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.5</td>
<td>0.295</td>
<td>0.106</td>
<td>-0.400</td>
<td>0.528</td>
</tr>
<tr>
<td>3</td>
<td>0.346</td>
<td>0.090</td>
<td>-0.243</td>
<td>0.537</td>
</tr>
<tr>
<td>6</td>
<td>0.288</td>
<td>0.058</td>
<td>-0.090</td>
<td>0.412</td>
</tr>
<tr>
<td>1.5 with full employment</td>
<td>0.219</td>
<td>0.087</td>
<td>-0.348</td>
<td>0.405</td>
</tr>
</tbody>
</table>

Observations: 724

The first column displays the weighted average income effect of the China shock for the US CZs. The second, third and fourth columns show standard deviation, the minimum and the maximum of the CZ level effects.

1.6.1 Trade effects

Figure 1.2: Geographical real income gains from China shock

This figure plots geographic distribution of \( \hat{W}_g \) for \( \theta = 5 \) and \( \kappa = 1.5 \).

The results for the U.S. labor income effects of the China shock are shown in Table 1.4 for \( \theta = 5 \) for all sectors and for different values of \( \kappa \). For the preferred value of \( \kappa = 1.5 \), results from calibration show that Aggregate (weighted average) gains from the rise of China is 0.30% (\( \xi = 0 \)), with the standard deviation across CZ as 0.11% and the range \([-0.40\%, 0.53\%]\). While 31 groups lose earnings, 25 groups gain more than 0.5%. 43% of gains in real income is contributed by trade pattern given wages and job finding rates and the other 57% comes exclusively from changes in expected wages.

8The values of trade elasticity \( \theta \) and labor elasticity \( \kappa \) are calibrated based on literature.
There is a strong geographical correlation in the gains and losses from the China shock, shown in Figure 1.2, which plots the geographical distribution of the real income effects from this shock. Many groups in eastern half of the country experienced below median gains. In Central and Southern Appalachia, there is a strong concentration of commuting zones in the bottom quartile of the gain distribution.

The distributional impact of the China shock depends on $\kappa$, the dispersion of labor ability. A larger $\kappa$ (probably due to large correlation between a worker’s ability across industries) leads to a smaller dispersion in the gains from trade as shown in Table 1.4.

We replicate the key result of [Galle et al., 2018] with a slightly different dataset and method. In Galle et al., 2018 the economy has full employment, therefore workers don’t take into account of the probability of finding a job. Table 1.4 shows that the aggregate income increase is 0.33% with $\kappa = 1.5$ and full employment. Comparing with values in the first row, it suggests that labor market frictions amplify the income gain/loss from the trade shock.

1.6.2 Decomposition

The real income changed generated by the rise the China using equation (1.24) can be decomposed into three parts. The first one is the labor market friction measured by the labor supply elasticity $\lambda$ which is responsible for by $26\%(1 - 0.219/0.295)$ of the total effects. The first term in equation (1.24), $\Pi_s \hat{\Pi}^{\alpha_s \kappa}$, measures the welfare gain from workers churning across sectors facing changes in expected wages. Calculations show that this labor market adjustment components accounts for 42% of total effects. The last part, $\Pi_s \hat{\Lambda}^{\alpha_s \theta_s}$, captures changes in real income from the adjustment of trade pattern in response to the shock given wage and employment rate. This part accounts for 32%.

1.6.3 Tariff Retaliation

This model can be easily used to analyze trade policies. To illustrate, consider the 2018 US-China trade wars mainly on manufacturing goods. According to [Caliendo and Parro, 2021], the United States raised the average tariff to China across the entire manufacturing sector by 7.67 percentage points. This retaliatory policy resulted in a sharp tariff increase from
Table 1.5: Real Income Effects on CZs with the China shock

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>0.295</td>
<td>0.106</td>
<td>-0.400</td>
<td>0.528</td>
</tr>
<tr>
<td>Retaliatory tariff</td>
<td>0.187</td>
<td>0.085</td>
<td>-0.338</td>
<td>0.374</td>
</tr>
<tr>
<td>Observations</td>
<td>724</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The first column displays the weighted average income effect of the China shock for the US CZs. The second, third and fourth columns show standard deviation, the minimum and the maximum of the CZ level effects.

3.8 percent to 12.0 percent from July through September 2018. We apply this retaliatory policy imposed by the Trump administration to the 2001-2007 the rise of China period. We aim to investigate whether the counterfactual tariff policy could combat the shock from China and protect the American consumers and manufacturing producers.

In the model the tariff is captured in the trading cost, $d$, which also contains additive shipping costs. While the data on shipping cost is not easily available, we consider two simplifying cases: shipping cost is zero or the shipping cost is proportional to tariff. The simplification translates the change in tariff to the change in trading cost, $d$. Thus we plug in $d_{China,US,manuf}$ and simulate an economy with this tariff retaliation policy.

Comparing the real income changes without and with the counterfactual US tariff policy shown in Table 1.5, retaliation reduces the average welfare gains and its variations. Aggregate welfare gain is 0.187%, a third less than the baseline without retaliation. In the baseline, there are 31 groups (CZs) suffer losses from the trade shock and this number increases to 47 if the US had retaliated using the Trump policy. Only 11 groups (CZs) who were worst hit by the shock could be protected by the rise of tariff on manufacturing goods from China, and they only account for 0.53% of US working population.

To take a closer look at whether and how the tariff policy benefits various groups we divide all CZs into two categories. The first category is CZs who incur welfare loss (31 CZs) and the second category is associated with welfare gain (693 CZs). We then compare the differential impacts across category of tariff retaliations. Figure 1.3 reveals that for losers due the China shock, the tariff policy does not rescue all of them as on average their real income decreases by 0.11% regardless of tariff retaliations. For winners from the China shock, tariff retaliation reduces their welfare gains down to 0.193% from 0.295%.

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9https://www.piie.com/research/piie-charts/us-china-trade-war-tariffs-date-chart
without tariff change. Consistent with numerous studies, tariff wars hurt most American workers.

1.7 Discussions

Our results shows that the majority of U.S. groups gain from the rise of China. After the supply shock in manufacturing, the U.S. manufacturing wage falls, inducing manufacturing worker to switch to other sectors such as construction, retail trade and services. More labor supply in non-manufacturing pulls down wages in those sectors. On the other side, with more manufacturing imports, the exports on services arise due to U.S. comparative advantage and for a stable trade deficit. The service industry expands and there is little change in U.S. wage on services. Most of the real income gains are generated from the decline on prices of both in manufacturing goods and services as a result of international trade participants being more specialized in areas they have comparative advantages.

The groups who lose earnings are those more concentrated in manufacturing. Figure A.1 shows the proportion of manufacturing workers in each CZs. After the trade
shock, manufacturing wage falls more than those of other sectors, if any, and a portion of manufacturing workers switch to other industries. Therefore, CZs with concentration on manufacturing relocate more workers but have still more workers stay in the industry and earn a lower income.

The income effects from international trade are stronger with a frictional labor market than that without; we call this an expansion effect. In the friction model, (un)employment rate contributes to the real income change. We observe in our simulation a small increase in employment rate in all sectors in all CZs, if any, and the rise in employment rates is stronger for manufacturing. An increase in the probability of finding a job raises the expected wage and earnings.

This is a simple and stylized model. It abstracts from money, government tax, frictions in changing jobs between industries, worker relocations across CZs, among others. A straightforward extension is to include intermediate goods and input-output structure for which the similar results are expected. It is also interesting to run non-tariff policy analyses using this model. Government could launch initiatives such as vocational training and job market improvement. A training program specifically for manufacturing workers could raise their productivity and incomes. Government efforts on increasing the labor market efficiencies would also raise labor income.

One of the other limitations is that (un)employment rates for local-and sectoral-labor markets are not available. We impute the values of this variable using its marginal distribution, i.e., local (en)employment rates and (un)employment rates by industry. Another limitation is that our cross-sectional static framework does not allow for modeling labor force transition between jobs in different industries over time or the dynamics of firms’ vacancy posting decisions.

1.8 Conclusion

This paper introduces local labor market matching frictions into a general equilibrium international trade model. The model features multi-sector, multi-region, and multi-country, and heterogeneity in labor abilities as well as local labor market characteristics. We estimate the TFP of matching function using imputed local and sectoral
(un)employment rates, and quantify its role in trade impacts. As expected, higher matching efficiency reinforces the trade shock, that is, manufacturing workers proportionally lose more jobs where the labor market is more efficient.

We simulate the model to quantify the real income effects of the China shocks on groups in the United States defined as commuting zones. We find a stronger average gain and a larger number (over 95%) of groups benefiting than [Galle et al., 2018], mostly because the expansionary effect of international trade reduces unemployment rates in almost all industries.

Policymakers are usually interested in both the income and employment effects of trade reforms. By explicitly allowing for equilibrium (un)employment rate, our model is able to generate more accurate predictions. We use the same framework to study the effects of tariff retaliation to the China shock implemented by the Trump Administration. The model could also be used to analyze labor market policies such as vocational training programs and efforts to reduce matching frictions.
Chapter 2
Unemployment Insurance, Wage Dispersion and the Re-entitlement Effect

2.1 Introduction

This chapter has two goals. The first is to study the role of the unemployment insurance (UI) system in generating wage dispersion. The second is to quantify the re-entitlement effect – the extent to which expiry of benefits causes workers to lower their application wages.

[Hornstein et al., 2011] (henceforth HKV) argued that models that rely on search frictions alone cannot generate the level of wage dispersion observed among homogeneous workers. Since then, a number of papers have attempted to address this shortcoming. Typically, those papers, described in more detail in Section 2.2, have relied on mechanisms that have made reemployment more desirable than is reflected in the wage alone. Here we explore the extent to which the UI system can act as one such mechanism. Meanwhile, among economists with an interest in UI, there is also a literature on the re-entitlement effect. Despite the clear connection to wage dispersion, the two literatures have remained largely separate. The distinction that we propose is that wage dispersion is a general equilibrium phenomenon while the re-entitlement effect pertains to an individual’s search behavior.

While our quantitative focus will be on UI policy in the United States, the salient features for our theoretical analysis are common throughout the OECD (see https://www.oecd.org/social/benefits-and-wages/). Those are that benefits are paid over a finite horizon and that employment (gradually) restores entitlement to future benefits. These features cause workers with longer unemployment durations to lower their wage expectations through two distinct channels. First, the reduction in income (or simply anticipation

\[\text{1For example, in 2022 the New York State UI system benefits use a replacement ratio (50\%) up to a maximum payment of around 500 per week. An unemployed person who is fully entitled to benefits receives them for 26 weeks (6 months). For workers whose benefits have expired, becoming fully re-entitled takes 12 months of continuous employment.}\]
of the impending reduction in income) sharpens a worker’s desire to find a job. Second, that re-employment sets the worker on the path to restore future benefits, makes employment more attractive than is simply reflected in the wage offer. The immediate impact of lower wage expectations is to increase both wage dispersion and the re-entitlement effect. The overall impact depends on how the policy change affects job creation which in turn depends on the specific counterfactual being considered. The goal here is to provide an environment which can simultaneously assess the contribution of existing UI policy to wage dispersion and quantify the re-entitlement effect.

We present an otherwise standard Diamond-Mortensen-Pissarides (DMP) model of directed on-the-job search. Jobs are ex ante identical as are workers. Following the typical structure of UI systems across the US, generosity of benefits is determined by the worker’s prior wage while the duration of entitlement is determined by the length of their prior employment spell. Consequently, markets are indexed by the workers’ employment status, their remaining duration of UI entitlement, and the wage payable to the worker. The equilibrium is block recursive as highlighted by [Menzio and Shi, 2011]. We calibrate the model using simulated method of moments to Survey of Income and Program Participation (SIPP) data from 1996 to 2017.

While we use various measures of wage dispersion, our main focus is on the mean to minimum ratio (MMR) as introduced by HKV. The baseline calibration generates an MMR of 1.117. This is well short of the 1.8 identified by HKV as representative of observed values for homogeneous workers. Indeed, our figure falls short of the 1.16 to 1.27 range that they obtain for a calibrated version of the one-sided on-the-job search model even though we have both on-the-job search and finite duration UI benefits. It is important to recognize, though, that the exercise in HKV is to identify the maximal wage dispersion attributable to search frictions. Our objective is to predict the actual degree of wage dispersion among homogeneous workers and ascertain the extent to which it emerges as a consequence of UI policy implementation. In any case, our figure of 1.117 is significantly larger than 1.04 that HKV argue is the maximum value consistent with sequential search. Meanwhile, we introduce a new metric of the re-entitlement effect – the average percentage drop in the application wage for each month of reduced UI entitlement. We call this the Wage-Duration Index (WDI) which is 1.44% in the baseline calibration.
Much of the subsequent focus of the paper is on the extent to which the measured MMR and WDI are attributable to the UI system. Shutting down re-entitlement by making benefits indefinite, drops the MMR to 1.043 implying an important role for the UI system\footnote{The WDI cannot be measured with indefinite benefits.}. Alternatively shutting down on-the-job search while retaining the 6 month maximum entitlement, however, generates an MMR of 1.010 (and a WDI of 0.32\%). These seemingly contradictory results point to a strong interaction between on-the-job search and the UI system. Being able to simultaneously work and look for a better paid job enables unemployed workers with little or no remaining entitlement to lower their immediate wage expectations. They do so because they expect future wage increases and because they resume accrual of UI entitlement. By conducting the same experiments on a small (measure zero) subset of workers, we are also able obtain the partial equilibrium impact of these changes.

The remainder of the paper is organized as follows. Section 2.2 reviews the related literature. Section 2.3 provides a summary of the relevant data along with a reduced form analysis of the re-entitlement effect. Section 2.4 lays out the theoretical model. Section 2.5 describes our calibration and model estimation strategy. The outcomes from the baseline model calibration are summarized in Section 2.6. The set of experiments used to quantify the impact of the UI system on wage dispersion and the re-entitlement effect are in Section 2.7. We explore the impact of various alternative policy arrangements in Section 2.8. Section 2.9 considers two possible extensions to the model: incorporating two separation rates and risk-averse workers. Section 2.10 concludes.

2.2 Literature

As mentioned above, HKV asserts that models incorporating search frictions alone cannot explain the degree of observed wage dispersion among ex ante homogeneous workers. The central intuition for their result is that a worker would not take a low wage when a much higher offer is likely to be received in the near future. Papers motivated to address this shortcoming have typically argued that either unemployment is in fact more pernicious or employment more beneficial than in the standard models. On that basis, workers are more strongly incentivized to accept low offers even when high ones are likely. Of
course, [Burdett and Mortensen, 1998], which predates HKV, falls into the second group of models. There, workers continue to receive job offers after getting hired, so accepting a low wage offer while unemployed does not carry the same opportunity cost. HKV, however, maintains that an accurate calibration of the [Burdett and Mortensen, 1998] model still generates insufficient wage dispersion. [Burdett et al., 2011] and [Ortego-Marti, 2016] enhance the baseline on-the-job search model to increase equilibrium wage dispersion. The former makes employment per se more beneficial by incorporating learning-by-doing, the latter makes unemployment more pernicious due to concomitant skill decay. By comparison (relative to a system paying benefits indefinitely), the UI system, as modelled in the current paper, lowers reservation wages through both channels. First, the impending termination of benefits reduces the present value of unemployment. Second, workers anticipate that their reemployment will (gradually) restore their entitlement to future benefits.

[Coles and Masters, 2007] identified the role of finite duration benefit payments in helping stabilize labor demand over the business cycle. Essentially, by lowering hiring wages more in recessions than in booms, the re-entitlement effect induces inter-temporal transfers from firms that hire in future booms to firms that hire in current recessions. On that basis, it is important to quantify the re-entitlement effect. However, in [Coles and Masters, 2007] workers become fully re-entitled to benefits as soon as they get hired. In fact, re-entitlement typically takes a year or more which should reduce the strength of the effect. Our quantification is carried out for a UI system that, while still stylized, is much closer to observed policy implementations.

[Ortega and Rioux, 2010] recognizes that benefits take time to accrue and provides a simple model in which workers can either be receiving UI, which is subject to termination, or a less generous unemployment assistance that can be received indefinitely. The termination of UI benefits for the unemployed and re-entitlement to UI for the employed are assumed to follow Poison processes. [Andersen et al., 2018] extends [Ortega and Rioux, 2010] to incorporate endogenous search intensity. As such it exhibits both sources of moral hazard associated with the UI system: the policy maker is unable to make benefit payments

3Indeed, in our own calibration when wage dispersion relies on on-the-job search alone, the MMR is only 1.043
4Indeed, we have consciously abstracted from certain common features of the US system such as delayed benefit collection, the implications of which are analysed in [Xie, 2019].
contingent on either the worker’s search effort or his propensity to reject job offers. In both papers, the simplicity of the UI system implies a 2-point equilibrium wage distribution which could be used to provide a simple measure of the re-entitlement effect. By comparison, our model provides for a much richer set of labor market histories from which to impute the effect.

[Andersen and Ellermann-Aarslev, 2020] considers how the rules governing re-entitlement to UI shape the distribution of employment durations. They provide a random search model in which all jobs offer the same wage but differ according to their expected duration. It is shown that when re-entitlement to UI depends on prior employment history, the labor market endogenously moves towards a “dual-market” (see e.g. [Dickens and Lang, 1985]) in which those with a weak employment history take short duration jobs and those with strong histories take longer duration jobs. A re-entitlement effect therefore emerges in the model along the employment duration dimension. As such we see this paper as complementary to our own.

The paper perhaps closest to ours in structure, is [Chaumont and Shi, 2022] they provide a directed on-the-job search model of the labor market. Workers are ex ante homogeneous but can differ ex post through accumulation of wealth. UI benefits expire stochastically as in [Ortega and Rioux, 2010] but, as wealthier workers search for higher wages, wealth provides an additional source of wage dispersion.

2.3 Data and reduced-form quantification

With reduced-form modelling we cannot provide all of the counterfactuals needed to provide a comprehensive perspective on the re-entitlement effect. Still it is helpful to identify the extent to which the effect is apparent in the data. These results will then be used to discipline the theory.

We use the Survey of Income and Program Participation (SIPP) as the main data source. In the SIPP each respondent is surveyed for up to 48 consecutive months. This longitudinal feature enables us to track labor force activities at the individual level. As our structural model will not include savings, to identify the relevant effects from the data we will need to control for wealth. Fortunately, the SIPP also includes information on
respondents’ asset holdings.

In the US the UI system is administered through the states and each state has its own eligibility rules. However, they generally have a similar structure in which the magnitude of the payments is a function of the recipient’s last wage and the duration is a function of the recipient’s recent employment history. To capture any impact of re-entitlement, then, we need both the worker’s last wage and duration of entitlement when laid-off. Data on wages is readily available in the SIPP but UI entitlement is not. We recover this value by using UI policy rules across states and time. We use this proxy as the key independent variable and control for benefit amounts, states, time, wealth and other demographic variables.

First we perform bi-variate analyses to explore correlations between monthly earnings of re-employed workers and UI benefit variables using the SIPP data. Figure 2.1 plots a positive correlation between unemployment-to-employment (UE) wages for re-employed workers and the weekly benefit payments received during their last unemployment spell. Figure 2.2 shows a slightly positive relationship between the UE earnings and the number of months of UI remaining. As benefits approach expiry, unemployed workers tend to search for jobs with lower wages.

\[
\log\text{UE wage} = \beta_1 \times (1_{\text{1st quartile of benefit}} \times 1_{\text{networth} < 0} \times \log\text{UI benefit}) \\
+ \beta_2 \times (1_{\text{higher quartile of benefit}} \times 1_{\text{networth} < 0} \times \log\text{UI benefit}) \\
+ \beta_3 \times (1_{\text{1st quartile of benefit}} \times 1_{\text{networth} > 0} \times \log\text{UI benefit}) \\
+ \beta_4 \times (1_{\text{higher quartile of benefit}} \times 1_{\text{networth} > 0} \times \log\text{UI benefit}) \\
+ \gamma_1 \times (1_{\text{1st quartile of benefit}} \times 1_{\text{networth} < 0} \times \text{MonthstoExpire}) \\
+ \gamma_2 \times (1_{\text{higher quartile of benefit}} \times 1_{\text{networth} < 0} \times \text{MonthstoExpire}) \\
+ \gamma_3 \times (1_{\text{1st quartile of benefit}} \times 1_{\text{networth} > 0} \times \text{MonthstoExpire}) \\
+ \gamma_4 \times (1_{\text{higher quartile of benefit}} \times 1_{\text{networth} > 0} \times \text{MonthstoExpire}) \\
+ \text{controls}
\]

Equation 2.1 regresses the logarithm of monthly earnings for those unemployed
workers who find a job during the month (log \textit{UEwage}) on the logarithm of benefit amounts (log \textit{UIbenefit}), number of months before UI benefits expire (\textit{MonthstoExpiry}), and other controls including individual age, education, occupation, state, months. We use 1996-2017 data, and reduce the sample using the similar strategy to [Huggett et al., 2011] to include male, unemployed workers of prime age, receiving UI benefits and not on layoff expecting a recall. We split our sample by individuals’ net worth and UI benefit in order to identify the UI entitlement impact on groups with different characteristics.

We interpret $\gamma_1$ to $\gamma_4$, the coefficients on the imputed number of months until benefit expiry\footnote{This variable is calculated as the eligible length of UI benefits minus the number of months the worker has received benefits for. The eligible UI duration is approximated by applying the UI policy to the most recent employment spell of the worker.}, as the impact of one month closer to UI benefit exhaustion on the wage unemployed workers search for. The overall effect of losing one month of benefits reduces wages the unemployed workers apply for. These estimates are not statistically significant possibly because of sample size or measurement error. However, the combined estimates of $\gamma$’s is 5% (although not statistically significant) which reveals that individuals one more month closer to UI expiration are willing to take wages more than 5% lower.
The coefficient $\beta_1$ is statistically significant and is also of interest. It shows how fast the application wages rise with the magnitude of benefits. For the poorest group, those with lowest benefit and negative wealth, the wage elasticity with respect to benefits ($\beta_1$) is 0.4. This number will be used for calibration.

2.4 Model

2.4.1 Environment

The model is set in discrete time with an infinite horizon. There is a mass 1 of workers who are ex ante identical and live forever. There is a large mass of firms that create ex ante identical individual jobs that start out as vacancies. The number of jobs will be controlled by a free entry condition. Each period, jobs are subject to destruction with probability $\lambda$. Both workers and firms are risk-neutral and discount the future at the rate $r$ per period. All unemployed workers receive $z$ units of the consumption good per period from non-market activities. Vacancies cost $c$ units of the consumption good per period to maintain.

In addition to their non-market activities, unemployed workers can be entitled to UI
Table 2.1: Estimations on Out-of-Unemployment Wages

<table>
<thead>
<tr>
<th></th>
<th>Coef</th>
<th>Est.</th>
<th>Std. Dev.</th>
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</thead>
<tbody>
<tr>
<td>$1_{1st \text{ quartile of benefit}} \times 1_{\text{networth}&lt;0} \times \log UIbenefit$</td>
<td>$\beta_1$</td>
<td>0.405**</td>
<td>0.167</td>
</tr>
<tr>
<td>$1_{\text{higher quartile of benefit}} \times 1_{\text{networth}&lt;0} \times \log UIbenefit$</td>
<td>$\beta_2$</td>
<td>0.290**</td>
<td>0.119</td>
</tr>
<tr>
<td>$1_{1st \text{ quartile of benefit}} \times 1_{\text{networth}&gt;0} \times \log UIbenefit$</td>
<td>$\beta_3$</td>
<td>0.167</td>
<td>0.137</td>
</tr>
<tr>
<td>$1_{\text{higher quartile of benefit}} \times 1_{\text{networth}&gt;0} \times \log UIbenefit$</td>
<td>$\beta_4$</td>
<td>0.250*</td>
<td>0.120</td>
</tr>
<tr>
<td>$1_{1st \text{ quartile of benefit}} \times 1_{\text{networth}&lt;0} \times MonthstoExpiry$</td>
<td>$\gamma_1$</td>
<td>0.031</td>
<td>0.120</td>
</tr>
<tr>
<td>$1_{\text{higher quartile of benefit}} \times 1_{\text{networth}&lt;0} \times MonthstoExpiry$</td>
<td>$\gamma_2$</td>
<td>-0.040</td>
<td>0.089</td>
</tr>
<tr>
<td>$1_{1st \text{ quartile of benefit}} \times 1_{\text{networth}&gt;0} \times MonthstoExpiry$</td>
<td>$\gamma_3$</td>
<td>0.100</td>
<td>0.079</td>
</tr>
<tr>
<td>$1_{\text{higher quartile of benefit}} \times 1_{\text{networth}&gt;0} \times MonthstoExpiry$</td>
<td>$\gamma_4$</td>
<td>0.103*</td>
<td>0.055</td>
</tr>
</tbody>
</table>

Observations 309

Linear regression using SIPP 1996 to 2017. The sample size is small because few respondents report the amount of government UI benefits they receive.

benefits, $b(w) = \min\{\phi w, \bar{b}\}$, per period where $w$ is the worker’s prior wage. The parameter $\phi \in [0,1]$ is referred to as the replacement rate and $\bar{b}$ is the maximum benefit. The benefit is constant throughout the worker’s entitlement term. The length of the term depends on the length of the last employment spell and the amount of unused time from the previous unemployment spell.

The earlier literature (e.g., Coles and Masters, 2007) found that the non-stationary nature of the unemployed worker’s search problem had important implications for the path of their reservation wage over the unemployment spell. Consequently, we do not allow the benefits to expire according to a Poisson process. Instead, we expand the state space to incorporate the exact time to benefit expiry for the unemployed and the duration of eligibility for the employed.

Thus, we let $i \in \mathcal{I} = \{0, 1, \ldots, I\}$ represent the number of periods of a worker’s UI entitlement. Then, while unemployed,

$$i_{t+1} = \begin{cases} 
\max\{i_t - 1, 0\} & \text{with probability } q_u \in [0, 1] \\
i_t & \text{with probability } 1 - q_u 
\end{cases},$$

where $t$ represents calendar time. Analogously, while employed,

$$i_{t+1} = \begin{cases} 
\min\{i_t + 1, I\} & \text{with probability } q_e \in [0, 1] \\
i_t & \text{with probability } 1 - q_e 
\end{cases}.$$
An employed worker who loses his job becomes unemployed (or, if lucky, re-employed) next period with an entitlement of $i_{t+1} = i_t$. The introduction of the probabilistic components, $q_e$ and $q_u$, allows for re-entitlement to take longer than its expiry without having to further expand the state-space. In the typical UI system across the US, re-entitlement to benefits takes twice as long as expiry. Consequently, for the leading parameterization of the model, $q_e$ is set to 0.5 while $q_u$ is set to 1.\footnote{The only reason $q_u$ is included in the model specification is to provide the flexibility required for the policy experiments conducted below.}

The UI system is paid for by a proportional pay-roll tax, $\tau$, on wages that is nominally paid by the firms.

A matched pair of job and worker produces output $p$ per period. Vacant jobs and workers meet in a large number of submarkets indexed by the wage posted by the firm, $w$, the level of worker entitlement, $i$, and the ratio, $\theta$, of vacancies to job seekers in that submarket – the market tightness. Unemployed workers in any submarket with tightness $\theta$ contact a vacancy with probability $m(\theta)$ while employed workers in that submarket contact a vacancy with probability $\gamma m(\theta)$ where $\gamma \geq 0$\footnote{Job seeking workers are heterogeneous in terms of their "wage" (current wage for employed and former wage for unemployed), their employment status, and their current entitlement period. However, all that matters to firms, given the wage being offered, is their entitlement level.}. The function $m$ is twice continuously differentiable, increasing and concave with $m(0) = 0$, and $\lim_{\theta \to \infty} m(\theta) = 1$. Consequently, vacancies meet with workers in the market at the rate $m(\theta)/\theta$ which is assumed to be decreasing.

Each period is divided into five stages: production, entitlement, separation, search and matching (see Figure 2.3). In the production stage, all output is produced, taxes are levied and benefit payments are made. In the entitlement stage, workers’ entitlement shocks are realized. Any separations due to job destruction occur in the separation stage. In the search stage, depending on their current employment status, wage (or benefit) and benefit entitlement status, workers decide which market to enter. Unlike [Menzio and Shi, 2011], we do permit those laid-off this period to search. Of course, for such individuals, their search strategy will reflect the fact that they are destined to be unemployed next period if they do not get a job. In the matching stage, new matches for next period are realized. In the case of currently employed workers, matching means their existing employment relationships are dissolved.

We seek a block-recursive directed search equilibrium. Firms enter markets in such
numbers as to ensure that no vacancy makes positive profits ex ante. The focus throughout is on steady-state.

2.4.2 Value functions

2.4.2.1 Workers

Workers take the wages and associated levels of market tightness as given and enter the market that is optimal for them based on their current state, \((y, i, w)\) where \(y \in \{e, u\}\) is employment status, \(i \in \mathcal{I}\) is UI benefits entitlement status and \(w \in [0, p]\) is their current wage if employed or their former wage if unemployed. Let \(V^i_y(w)\) represent the value to being a worker of type \((y, i, w)\). Then, for the unemployed workers with some remaining entitlement, \(i > 0\),

\[
V^i_u(w) = \frac{1}{1 + r} \left\{ b(w) + z + q_u \max_{\bar{w}, \bar{\theta}} \left\{ m(\bar{\theta}) V^{i-1}_e(\bar{w}) + (1 - m(\bar{\theta})) V^{i-1}_u(w) \right\} 
+ (1 - q_u) \max_{\bar{w}, \bar{\theta}} \left\{ m(\bar{\theta}) V^i_e(\bar{w}) + (1 - m(\bar{\theta})) V^i_u(w) \right\} \right\} \tag{2.2}
\]
For unemployed workers with expired benefits, \( i = 0 \), any dependence on their old wage is lost. So that

\[
V_{u}^{0} = \max_{\bar{w}, \hat{\theta}} \left\{ z + m(\hat{\theta}) V_{c}^{0}(\bar{w}) + (1 - m(\hat{\theta})) V_{u}^{0} \right\}.
\] (2.3)

For employed workers with less than full entitlement, \( i = 0, \ldots, I - 1 \)

\[
V_{c}^{i}(w) = \frac{1}{1 + r} \left\{ w + q_c \left[ \lambda \max_{\bar{w}, \hat{\theta}} \left\{ m(\hat{\theta}) V_{c}^{i+1}(\bar{w}) + (1 - m(\hat{\theta})) V_{u}^{i+1}(\bar{w}) \right\} \right. \\
+ (1 - \lambda) \max_{\bar{w}, \hat{\theta}} \left\{ \gamma m(\hat{\theta}) V_{c}^{i+1}(\bar{w}) + (1 - \gamma m(\hat{\theta})) V_{c}^{i+1}(\bar{w}) \right\} \left. \\
+ (1 - q_c) \left[ \lambda \max_{\bar{w}, \hat{\theta}} \left\{ m(\hat{\theta}) V_{c}^{i}(\bar{w}) + (1 - m(\hat{\theta})) V_{u}^{i}(\bar{w}) \right\} \\
+ (1 - \lambda) \max_{\bar{w}, \hat{\theta}} \left\{ \gamma m(\hat{\theta}) V_{c}^{i}(\bar{w}) + (1 - \gamma m(\hat{\theta})) V_{c}^{i}(\bar{w}) \right\} \right\} \right\}.
\] (2.4)

For employed workers with full entitlement, \( i = I \),

\[
V_{c}^{I}(w) = \frac{1}{1 + r} \left\{ w + \lambda \max_{\bar{w}, \hat{\theta}} \left\{ m(\hat{\theta}) V_{c}^{I}(\bar{w}) + (1 - m(\hat{\theta})) V_{u}^{I}(\bar{w}) \right\} \\
+ (1 - \lambda) \max_{\bar{w}, \hat{\theta}} \left\{ \gamma m(\hat{\theta}) V_{c}^{I}(\bar{w}) + (1 - \gamma m(\hat{\theta})) V_{c}^{I}(\bar{w}) \right\} \right\}.
\] (2.5)

It will be convenient to use \((\hat{\bar{\theta}}_{c}^{i}(w), \bar{w}_{c}^{i}(w))\) as the market tightness and wage that solves the preceding problem for the employed worker with current wage \( w \). Similarly, we will use \((\hat{\bar{\theta}}_{u}^{i}(w), \bar{w}_{u}^{i}(w))\) as the market tightness and wage that solves the preceding problem for the unemployed worker with former wage \( w \).

That the unemployed search more effectively raises the possibility that workers might want to quit a low wage job once their entitlement for benefits is fully restored. These equations do not allow for that possibility because, consistent with all the UI systems we explored, people who quit are ineligible for benefits. Once they quit they face the same problem as any one who has zero entitlement to benefits. Those workers always choose the lowest wage that has positive density – quitting cannot make them better off.
2.4.2.2 Firms

Firms take the search strategies of the workers as given and create vacancies to target those workers. Because firms do not care about their current worker’s former employment status, filled jobs are characterized by the pair \((i, w)\), where \(i\) is the UI entitlement status of the worker and \(w\) is the wage paid to that worker. Let \(V^i_f(w)\) represent the present expected discounted profits accruing from such a filled job. As free-entry drives the value to holding a vacancy in every active market to zero, for the job occupied by a worker with less than full entitlement, \(i = 0..I - 1\),

\[
V^i_f(w) = \frac{1}{1+r}\left\{p - w(1 + \tau) + (1 - q_e)(1 - \lambda)(1 - \gamma m(\tilde{\theta}_e^i(w)))V^i_f(w) + q_e(1 - \gamma m(\tilde{\theta}_e^{i+1}(w)))V^{i+1}_f(w)\right\}. \tag{2.6}
\]

For a job occupied by a worker with full entitlement, \(i = I\),

\[
V^I_f(w) = \frac{1}{1+r}\left\{p - w(1 + \tau) + (1 - \lambda)(1 - \gamma m(\tilde{\theta}_e^I(w)))V^I_f(w)\right\}. \tag{2.7}
\]

Free-entry of vacancies determines the tightness in each submarket so that

\[
\frac{m(\theta)}{\theta} V^i_f(w) \leq c \text{ and } \theta \geq 0 \tag{2.8}
\]

with complementary slackness. We will focus on equilibria in which there is a unique value of the market tightness, \(\theta(i, w)\) that solves equation (2.8) for each entitlement and wage level.

Notice that while employment status, \(y \in \{e, u\}\), does matter for which market the worker enters, the market tightness function, \(\theta(i, w)\), is not indexed by \(y\). This is because the firms doing the hiring do not care about current employment status. They only care about UI entitlement and the wage they will pay. In general, for a given level of worker entitlement, \(i\), firms offering higher wages will attract employed workers while those offering low wages attract unemployed workers. That latter set of markets will have commensurately higher market tightnesses.
2.4.3 Steady State

Worker optimal search policies, \((\tilde{\theta}_i^e(w), \tilde{w}_i^e(w))\) and \((\tilde{\theta}_i^u(w), \tilde{w}_i^u(w))\), imply Markovian transition dynamics which further imply an ergodic distribution of workers across states. We denote by \(e^i(w)\) the steady state measures of employed workers whose current eligibility status is \(i\) and whose current wage is \(w\). We similarly denote by \(u^i(w)\) the steady state measures of unemployed workers whose current eligibility status is \(i\) and whose previous wage was \(w\). So that

\[
e = \sum_{i \in \mathcal{I}} \int_0^p e^i(w) dw \quad \text{and} \quad u = \sum_{i \in \mathcal{I}} \int_0^p u^i(w) dw
\]

(2.9)

are the aggregate steady state measures of employed and unemployed workers respectively. As the total population is normalized to 1, they also represent the employment and unemployment rates.

2.4.4 Government Budget constraint

Because we focus on steady states, the government budget constraint is always balanced,

\[
\sum_{i \in \mathcal{I}} \int_0^p \tau we^i(w) dw = \sum_{i \in \mathcal{I} \setminus \{0\}} \int_0^p b(w)u^i(w) dw.
\]

(2.10)

2.4.5 Equilibrium

Definition 2.1 A steady state, free-entry, directed search equilibrium consists of a pair of worker policy functions, \(\tilde{w}_i^j : \mathcal{I} \times \{e, u\} \times [0, p] \to [0, p]\) and \(\tilde{\theta}_i^j : \mathcal{I} \times \{e, u\} \times [0, p] \to \mathbb{R}_+\), a set of active submarkets, \(A \subset \mathcal{I} \times [0, p]\), a market tightness function, \(\theta : A \to \mathbb{R}_+\), the steady state population measures, \(e^i(w)\) and \(u^i(w)\), and a pay-roll tax rate, \(\tau\) such that:

1. Given the set of active markets, the market tightness function and pay-roll tax rate, the worker policy functions emerge from optimal search and matching: equations (2.2), (2.3), (2.4) and (2.5).

2. The set of active markets, \(A\), is determined where \(\frac{m(\theta)}{\theta} V_j^i(w) = c\) and \(\theta > 0\)

3. The tightness function determines \(\theta(i, w)\) from (2.8) for all \((i, w) \in A\).
Table 2.2: Parameters

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of months for eligibility</td>
<td>I</td>
</tr>
<tr>
<td>Monthly discount factor</td>
<td>1/(1 + r)</td>
</tr>
<tr>
<td>Value of leisure</td>
<td>z</td>
</tr>
<tr>
<td>Matching function TFP</td>
<td>m</td>
</tr>
<tr>
<td>Tightness elasticity</td>
<td>η</td>
</tr>
<tr>
<td>Vacancy cost</td>
<td>c</td>
</tr>
<tr>
<td>Replacement ratio</td>
<td>φ</td>
</tr>
<tr>
<td>On-the-job search efficiency</td>
<td>γ</td>
</tr>
<tr>
<td>Separation rate</td>
<td>λ</td>
</tr>
</tbody>
</table>

4. The steady state population measures, $e^i(w)$ and $u^i(w)$ represent the ergodic distribution that emerges from the worker policy functions.

5. The balanced budget condition, (2.10), holds.

This type of block-recursive equilibrium (see [Menzio and Shi, 2011]) builds on two key modeling choices. The first is the use of directed search instead of random search. In a directed search setup, firms and workers do not need to forecast wages because wages are choice variables, which do not depend on who they meet. However, in such an environment, workers and firms still need to forecast the market tightness in each market. The second modelling choice is free-entry of vacancies into any submarket. It implies that each submarket is self-contained. Since the cost of opening a vacancy is constant, the free-entry condition pins down the value of the market tightness as a function of the value of a new job independently from the distribution of firms. Therefore it is possible to construct a block-recursive equilibrium in which neither the value functions nor the market tightness depend on the distribution of firms or workers across wage levels.

2.5 Calibration

The list of parameters and their preferred values is provided in Table 2.2.
2.5.1 External parameters and functional forms

The time period is set to one month. Our only externally obtained structural model parameter is the discount rate which is based on an annual risk-free interest rate of 5% and implies \( r = 0.004 \). The matching function is chosen to be Cobb-Douglas, \( m(\theta) = \min\{m\theta^n, 1\} \). Because the parameter \( m \) moves one-to-one with the cost of holding a vacancy, \( c \), it can be chosen to avoid the matching rate hitting its upper value of 1 without otherwise impacting the results. We use \( m = 0.1 \). The match productivity, \( p \), is normalized to 1.

2.5.2 Policy parameters

While the specific details of UI policy vary across states, some features as reported by the US Department of Labor (DoL) are essentially uniform across the country. Standard UI eligibility extends to 26 weeks which implies \( I = 6 \). However, it takes a full year of working to restore full eligibility for a worker who had exhausted benefits prior to getting hired. On that basis we set \( q_u = 1 \) and \( q_e = 0.5 \). Our replacement ratio, \( \phi = 0.5 \), reflects a consensus across state rules and is common in the literature.

The benefit cap, \( \bar{b} \), varies more widely across states but here will be moot. With ex ante homogeneous workers, the wage dispersion that emerges in the model is insufficient to warrant its use. Depending on the group we are trying to capture, the cap would typically either bind on all of them or none of them. Because our focus is on lower income workers we assume \( \bar{b} > p \) so that it does not bind on anyone.

2.5.3 Calibrated parameters

The remaining targeted moments were obtained from the SIPP sample constructed in Section 2.3. The separation rate, \( \lambda = 1.5\% \), comes directly from the data. The remaining parameters are: the elasticity of the matching function, \( \eta \), the on-the-job search efficiency parameter, \( \gamma \), the value of leisure, \( z \), and the vacancy holding cost, \( c \). These were all obtained simultaneously using simulated method of moments (SMM). The target moments are reported in Table 2.3.

Clearly, \( \gamma \), is readily identified from the overall employment-to-employment move-
Table 2.3: Moments Calibration results

<table>
<thead>
<tr>
<th>Model</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment rate</td>
<td>6.37%</td>
</tr>
<tr>
<td>( \varepsilon_{w,b} ) for low benefit recipients</td>
<td>0.365</td>
</tr>
<tr>
<td>On-the-job transition rate (all)</td>
<td>1.72%</td>
</tr>
<tr>
<td>On-the-job transition rate ratio (upper half vs lower half)</td>
<td>4.09%</td>
</tr>
</tbody>
</table>

...ment rate. Then, \( \eta \) is identified from differential matching rates between workers searching for higher and lower wages. In all active submarkets, firms have to expect the same return from creating vacancies. Because they will earn lower expected profits in high wage submarkets, they have to be compensated by higher matching rates. Consequently, workers will have lower matching rates in those markets and that is something we can observe. As higher values of \( \eta \) generate higher differential matching rates between workers searching for high and low wages, identification comes from the relative matching rates across submarkets.

Identification of \( z \) comes from the impact it has on the elasticity of the wages unemployed workers apply for with respect to their current benefit receipt, \( \varepsilon_{w,b} \). To a worker in the model, the value of leisure and UI benefits are interchangeable. Because \( p \) represents an upper bound on wages, the higher is \( z \) the lower is the impact of any given change in benefits on the wage that worker will apply for. This is depicted in Figure 2.4. Value of leisure level \( z_1 \) (left panel) is lower than \( z_2 \). The application wage is less responsive to changes in \( b \) when \( z = z_2 \). Finally, as the cost of maintaining a vacancy, \( c \), is the main variable that determines market tightness, it is pinned down by the overall unemployment rate.

2.6 Baseline model outcomes

Figure 2.5 superimposes the match values for firms on the equilibrium wage distribution. An implication of directed search is that wages emerge in blocks. The unemployed generally apply for the jobs in the lowest wage block centered around 0.85. Its wide

\textsuperscript{8}See [Delacroix and Shi, 2006]
\textsuperscript{9}See [Griffy, 2021]
dispersion reflects the importance of UI entitlement to the unemployed. As will become clear below, once they get a job, duration of entitlement is not as important to them so the subsequent blocks of wages in the ladder are increasingly concentrated. While firms are indifferent across which of the active markets to enter, their realized profits from hiring a worker decrease in the wage. This is offset for the newly created vacancies by the increased matching rates in higher wage markets.

For both employed and unemployed workers, Figure 2.6 plots worker values against
the wage for each level of entitlement. The match values of employed workers increase noticeably with the wage but cluster close together with respect to UI entitlement. This is because the chance of being made unemployed is relatively low and what matters to them most is their current wage and its implications for future wage increases. It is apparent from the cluster of curves near the bottom of the figure that for the unemployed, entitlement is relatively more important than their former wage. This is driven by the immediacy of the impending loss of benefits to them. As identified by Coles and Masters, 2007, termination of relatively generous benefits after a fixed period of time allows for income maintenance while still incentivizing job search.

Figure 2.6: Values of workers with different entitlements versus the wage

Figure 2.7 plots the wage search strategies for unemployed workers across entitlement levels. Again the general implication is that entitlement matters more than does former earnings. Here we see, though, that this effect itself does depend on entitlement. Workers with a lot of remaining UI entitlement and whose last wage was high will apply for high wages. As UI entitlement declines, the former wage becomes less important in

10One concern here might be that in equilibrium anyone earning the highest wage cannot be ineligible for benefits. To earn that highest wage the worker must have ascended the wage ladder which takes several months even if the worker receives an offer at every possible occasion. However, from the model we can still identify the wage such an hypothetical worker would apply for.
Figure 2.7: Application wages for unemployed workers

![Figure 2.7](image)

Figure 2.8: Application wages for employed workers

![Figure 2.8](image)
determining application wages. Ultimately, for workers who have exhausted their benefits, their former wage has no impact on the jobs they apply for. On average, one-month closer to UI expiration causes unemployed workers to search for wages 1.44% lower. This is our central measure of the re-entitlement effect which we will call the Wage-Duration Index (WDI). This is considerably lower than the 5% reported in Section 2.3 which likely reflects our inability to fully control for individual characteristics in that exercise.

Figure 2.8 shows the wage ladder for employed workers. For example, a worker starting (regardless of UI entitlement) with a wage lower than 0.94 will search for a wage of 0.945, then 0.962, then 0.967, and finally settling in at 0.968. The 0.968 wage is the highest across all active submarkets. Meanwhile the ladders for each entitlement level lie on top of each other because there is no impact of UI entitlement on the employed workers’ search strategy. It could matter, but it does not due to the relatively low probability of losing a job in any given month.

2.7 Wage dispersion and re-entitlement effects

The baseline calibration generates an MMR of 1.1169 and a WDI of 1.44%. The objective here is to assess the contribution of the UI system to wage dispersion and to the re-entitlement effect. To do so we consider various counterfactual scenarios in both general and partial equilibrium contexts.

2.7.1 General equilibrium exercises

The general equilibrium exercises compare outcomes across scenarios when vacancy creation is endogenous.

2.7.1.1 Indefinite benefits

Here the baseline model is compared with a version in which UI eligibility never expires. Wage dispersion still arises because of on-the-job search (see [Delacroix and Shi, 2006]). UI can still interact with the distribution of wages because benefit payments depend on

\[11\] Regardless of their matching probability, firms will not pay more than 0.968 because above that level they cannot recover their vacancy posting costs.
the worker’s last wage. Entitlement type is moot so submarkets are indexed by wage alone. After dropping the \(i\) superscript from the previous notation, we have

\[
V_u(w) = \max_{\tilde{w}, \tilde{\theta}} \left\{ b(w) + z + m(\tilde{\theta}) V_e(\tilde{w}) + (1 - m(\tilde{\theta})) V_u(w) \right\},
\]

(2.11)

\[
V_e(w) = \frac{1}{1 + r} \left\{ w + \lambda \max_{\tilde{w}, \tilde{\theta}} \left\{ m(\tilde{\theta}) V_e(\tilde{w}) + (1 - m(\tilde{\theta})) V_u(w) \right\} \right\},
\]

(2.12)

\[
+ (1 - \lambda) \max_{\tilde{w}, \tilde{\theta}} \left\{ \gamma m(\tilde{\theta}) V_e(\tilde{w}) + (1 - \gamma m(\tilde{\theta})) V_e(w) \right\}, \text{ and}
\]

(2.13)

\[
V_f(w) = \frac{1}{1 + r} \left\{ p - w(1 + \tau) + (1 - \lambda)(1 - \gamma m(\tilde{\theta}, \tilde{w})) V_f(w) \right\}.
\]

(2.14)

And, the free-entry condition becomes,

\[
\frac{m(\theta)}{\theta} V_f(w) \leq c \text{ and } \theta \geq 0
\]

(2.15)

with complementary slackness.

An issue with any of these policy variations is making the correct comparisons. If we simply keep the benefit payment profile, \(b(w)\), unchanged and impose an indefinite payment scheme, the present value of benefits will increase and push all wages up towards \(p\). We have therefore chosen to make the change revenue neutral by adjusting the replacement rate, \(\phi\), downwards. The new values are reported along with the baseline calibration results in Table 2.4. The remaining wage dispersion in the counter-factual model comes entirely from on-the-job search. The Wage-Duration Index is not reported here because it has no relevance when benefits are paid indefinitely.

Imposing indefinite benefit payments significantly reduces wage dispersion even though workers are free to look for jobs while employed and the benefit level still depends on the worker’s last wage. Absent the impending loss of benefit payments, the unemployed look for higher wage jobs which reduces job creation and increases unemployment. Given the need to balance the UI budget, this forces government to lower the replacement rate. The resulting (balanced budget) equilibrium still exhibits higher application wages for the unemployed which drives the reduction in wage dispersion. Also, notice that under indefinite benefit payments, workers’ average present value of being in the market is lower.
Table 2.4: Re-entitlement effects

<table>
<thead>
<tr>
<th></th>
<th>Baseline model</th>
<th>Indefinite benefits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Replacement ratio</td>
<td>50%</td>
<td>26.5%</td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>6.37%</td>
<td>9.28%</td>
</tr>
<tr>
<td>Tax rate</td>
<td>2.88%</td>
<td>2.74%</td>
</tr>
<tr>
<td>Mean wage</td>
<td>0.9301</td>
<td>0.9382</td>
</tr>
<tr>
<td>Minimum wage</td>
<td>0.8327</td>
<td>0.8992</td>
</tr>
<tr>
<td>Wage Mean-Min ratio</td>
<td>1.1169</td>
<td>1.0434</td>
</tr>
<tr>
<td>Wage standard deviation</td>
<td>0.0444</td>
<td>0.0260</td>
</tr>
<tr>
<td>Wage Gini coefficient</td>
<td>0.0228</td>
<td>0.0146</td>
</tr>
<tr>
<td>Mean value for workers</td>
<td>222.4389</td>
<td>220.7633</td>
</tr>
</tbody>
</table>

This comes from the higher level of unemployment – there is simply not as much output to go around.

2.7.1.2 Fixed and indefinite benefits

Here we replace the benefit payment profile, $b(w)$, with a wage invariant and indefinite payment, $b = 0.3109$. Again, the value is chosen to maintain revenue neutrality. The results are provided in the second column in Table 2.5 alongside those of the baseline calibration.

Comparison of these results with those in Table 2.4 points to the role of wage dependent benefits in exacerbating wage dispersion. The results are very similar but, contrary to what might have been expected, the degree of wage dispersion across all measures is slightly higher when benefits are invariant to the prior wage. This comes from the impact on the lowest wage in the economy. When benefits are invariant to the prior wage, workers with exhausted benefits have a reduced incentive to hold out for a high wage.

Column 3 of Table 2.5 shows the outcomes for a wage invariant benefit which expires in 6 months. The experiment harks back to the earlier literature on UI (see e.g. [Coles and Masters, 2007]) by incorporating immediate re-entitlement upon reemployment. The results are very close to the baseline calibration in which full re-entitlement is expected to take 12 months. This suggests that the re-entitlement effect is driven more by
Table 2.5: Fixed and indefinite benefits on re-entitlement effects

<table>
<thead>
<tr>
<th></th>
<th>Baseline model</th>
<th>Fixed and indefinite benefit</th>
<th>Immediate re-entitlement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benefit</td>
<td>50% of wage</td>
<td>0.3109</td>
<td>0.44</td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>6.37%</td>
<td>7.93%</td>
<td>6.17%</td>
</tr>
<tr>
<td>Tax rate</td>
<td>2.88%</td>
<td>3.01%</td>
<td>2.65%</td>
</tr>
<tr>
<td>Mean wage</td>
<td>0.9301</td>
<td>0.9354</td>
<td>0.9321</td>
</tr>
<tr>
<td>Minimum wage</td>
<td>0.8327</td>
<td>0.8915</td>
<td>0.8342</td>
</tr>
<tr>
<td>Wage Mean-Min ratio</td>
<td>1.1169</td>
<td>1.0492</td>
<td>1.1173</td>
</tr>
<tr>
<td>Wage standard deviation</td>
<td>0.0444</td>
<td>0.0287</td>
<td>0.0438</td>
</tr>
<tr>
<td>Wage Gini coefficient</td>
<td>0.0228</td>
<td>0.0157</td>
<td>0.0227</td>
</tr>
<tr>
<td>Wage-Duration Index</td>
<td>1.44%</td>
<td>0%</td>
<td>1.48%</td>
</tr>
<tr>
<td>Mean value for workers</td>
<td>222.4389</td>
<td>221.8833</td>
<td>222.58</td>
</tr>
</tbody>
</table>

the expiry of current benefits than by the rapidity of re-entitlement per se.

2.7.1.3 Sequential search

In this model there are two basic engines of wage dispersion: the UI scheme and on-the-job search. It was shown above that shutting down benefit expiry had a significant impact. The question here is what happens when, instead, we shut down on-the-job search. To achieve that we simply set $\gamma$, the effectiveness of search while employed, to zero.

The second column in Table 2.6 shows that the elimination of on-the-job search almost entirely eliminates wage dispersion: the mean-min wage ratio drops to 1.01 and the wage variation is extremely small. Without the wage ladder, all unemployed workers with some remaining UI entitlement search for the same relatively high wage. The mean wage at 0.94, however, is not much higher than in the baseline model at 0.93 but there is no wage ladder.

Recall, though, that wage dispersion was also much diminished when benefits were set to be fixed and indefinite (see Table 2.5). What the results point to, therefore, is an interaction between these two sources of wage dispersion – each reinforces the other. In the full model, unemployed workers with low or zero entitlement are prepared to accept low reemployment wages because being employed makes them eligible for both future pay raises and restoration of their UI entitlement. As workers move up the wage ladder,
Table 2.6: On-the-job search on re-entitlement effects

<table>
<thead>
<tr>
<th></th>
<th>OTJ search (baseline)</th>
<th>No OTJ search</th>
</tr>
</thead>
<tbody>
<tr>
<td>Replacement ratio</td>
<td>50%</td>
<td>53.86%</td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>6.37%</td>
<td>5.67%</td>
</tr>
<tr>
<td>Tax rate</td>
<td>2.88%</td>
<td>2.71%</td>
</tr>
<tr>
<td>Mean wage</td>
<td>0.9301</td>
<td>0.9388</td>
</tr>
<tr>
<td>Minimum wage</td>
<td>0.8327</td>
<td>0.9293</td>
</tr>
<tr>
<td>Wage Mean-Min ratio</td>
<td>1.1169</td>
<td>1.0102</td>
</tr>
<tr>
<td>Wage standard deviation</td>
<td>0.0444</td>
<td>0.0074</td>
</tr>
<tr>
<td>Wage Gini coefficient</td>
<td>0.0228</td>
<td>0.0045</td>
</tr>
<tr>
<td>Wage-Duration Index</td>
<td>1.44%</td>
<td>0.32%</td>
</tr>
<tr>
<td>Mean value for workers</td>
<td>222.44</td>
<td>225.09</td>
</tr>
</tbody>
</table>

The generosity and expected duration of future benefits increase in unison.

2.7.2 Partial equilibrium exercises

As we alter the UI system (even under the constraint of revenue neutrality) it has feedback effects through the unemployment rate that is determined in general equilibrium. The idea here is to understand how important those feedback effects can be for the impact of UI on the wage structure. We introduce a small (measure zero) group of artificial workers into our model whose behavior does not affect the rest of the economy.

Mirroring the work above, our first partial equilibrium experiment is to have benefits extend indefinitely for the small group of workers and look at how it affects their wage choices. For comparability we use the benefit profile reported in Table 2.4 for those workers. They have the same meeting rates with vacancies but value those meetings differently to the other workers. Despite the fact that their indefinite benefits still depend on their former wages through the replacement ratio, when unemployed, they all apply for the same wage of 0.968. That is, they all hold out for the highest wage in the market and experience no wage dispersion even from on-the-job search. What happens here is that workers receive a fixed share of their prior wage as benefits. When we make those benefits indefinite, it pushes up the wages they apply for which then pushes up the benefit payments they receive after losing their job and so on. This mechanism is present in the general equilibrium exercise but it is tempered in that case by the impact...
on unemployment. By making the prospect of continued unemployment less attractive, the general equilibrium effect, therefore, works against the direct effect of eliminating the termination of benefits on wage dispersion.

Our next experiment is to create a measure zero group of workers who receive fixed but indefinite benefits when unemployed. The benefit amount is set at the calibrated value 0.3109 from Table 2.5. This group of workers has wage mean-min ratio 1.064, and search for a lowest wage of 0.878 while unemployed. They subsequently move to 0.945, 0.9622 and finally 0.968. Consistent with the earlier comparison under general equilibrium, these workers experience higher wage dispersion than those whose benefits depend on their prior wage. Fixing the benefit level ex ante breaks the feedback loop that pushes benefits higher as wages rise which, in turn, push up wages. Instead, their application decisions simply reflect the availability of on-the-job search.

As an alternative, we also looked at a one-time indefinite extension of UI benefit for a small group of unemployed workers. Specifically, the government announces unexpectedly that these unemployed workers can receive endless benefits of the same amount as they do during the current unemployment spell, and they will not lose or gain entitlement until they find a new job. This experiment is designed to measure the short term effect of removal of the termination of benefits. Here there is some narrow dispersion in their application wages between 0.950 and 0.968. The feedback loop that pushes up wages and then pushes up benefits does not occur in this scenario either because the workers go back to their old entitlement levels on getting a job. Still, they are reluctant to take a job at low wages because they are not subject to the impending termination of their current benefits.

Another experiment is to assume that a measure zero group of workers are not able to search on the job but still face entitlement expiry. This group has wage mean-min ratio 1.0204. Unemployed workers without benefits apply for a wage of 0.8803. All other unemployed workers with unexpired UI search for wage = 0.9451 jobs. Wage dispersion among this group is therefore much lower than among the general population. Deprived of the opportunity to search on the job, these workers hold out for higher wages while unemployed. The wage dispersion among them is, however, still higher than when on-the-job search is unavailable to everyone (see Table 2.6). In the latter scenario, vacancy creation is higher because of the reduced possibility of losing a worker. This pushes up
the lowest wage acceptable to the unemployed.

2.8 Alternative UI policy design

Here we consider some alternative policy arrangements. First, we look at changing the maximum number of months of benefit entitlement, $I$. We set $q_e = I/12$ to ensure that anyone who has expired benefits needs to work for about 12 months to recover full entitlement. The other parameters are kept unchanged. Table 2.7 shows what happens as the maximum entitlement increases from 4 to 7 months. All else equal, a longer, but still finite benefit period might be expected to increase wage dispersion. With a longer entitlement period, the newly unemployed are more incentivized to search for high-wage jobs with low finding probabilities. Meanwhile, a worker whose benefits have expired, recognizing the higher reward associated with the potential for re-entitlement, lowers their reservation wage. Indeed, this effect does show up in the MMR measure of wage dispersion but the effects are small. This is because as we extend the benefit period, the tax rate rises which stems vacancy creation. The ensuing higher level of unemployment tempers the optimism of the fully entitled. Of course, as we have seen above, the MMR will be lower when benefits are paid indefinitely. In that scenario, there are no workers with expired benefits and so no one will apply for very low wages.

The Wage-Duration Index peaks at 5 months of maximum entitlement. This is where the benefit expiry scheme has the strongest impact in terms of incentivizing workers to lower their wage expectations while still providing some income to the unemployed. With risk-neutral workers, however, shorter benefits always give higher levels of welfare (Total Values) to the workers because of the fiscal externality coming from the pay-roll tax.\footnote{When they create a vacancy, firms do not internalize the benefit to other firms of a lower expected tax rate.} We consider risk-aversion in Section 2.9.2.

Table 2.8 demonstrates the impact of changing the replacement ratio between 0.43 and 0.57. A more generous replacement ratio does not alter the wage MMR but does reduce employment and consumption. As we saw above, when benefits are made proportional to wages, there is a feedback effect that raises all wages thereby reducing wage dispersion. The higher is the replacement ratio, the stronger is this effect. The implied reduction
Table 2.7: Re-entitlement effects across lengths of UI benefit in months

<table>
<thead>
<tr>
<th>Maximum benefit</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment rate</td>
<td>4.66%</td>
<td>5.51%</td>
<td>6.37%</td>
<td>7.23%</td>
<td>8.07%</td>
</tr>
<tr>
<td>Tax rate</td>
<td>1.83%</td>
<td>2.31%</td>
<td>2.88%</td>
<td>3.31%</td>
<td>3.79%</td>
</tr>
<tr>
<td>Mean wage</td>
<td>0.9369</td>
<td>0.9339</td>
<td>0.9301</td>
<td>0.9275</td>
<td>0.9245</td>
</tr>
<tr>
<td>Min wage</td>
<td>0.8398</td>
<td>0.8366</td>
<td>0.8327</td>
<td>0.8298</td>
<td>0.8285</td>
</tr>
<tr>
<td>Wage MMR</td>
<td>1.1156</td>
<td>1.1163</td>
<td>1.1169</td>
<td>1.1177</td>
<td>1.1159</td>
</tr>
<tr>
<td>Wage-Duration Index</td>
<td>1.14%</td>
<td>2.00%</td>
<td>1.44%</td>
<td>1.39%</td>
<td>1.20%</td>
</tr>
<tr>
<td>Mean value for workers</td>
<td>223.65</td>
<td>223.13</td>
<td>222.44</td>
<td>221.94</td>
<td>221.35</td>
</tr>
</tbody>
</table>

Table 2.8: Re-entitlement effects across replacement rate, $\phi$

<table>
<thead>
<tr>
<th>$\phi = 0.43$</th>
<th>$\phi = 0.47$</th>
<th>$\phi = 0.50$</th>
<th>$\phi = 0.53$</th>
<th>$\phi = 0.57$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment rate</td>
<td>5.24%</td>
<td>5.85%</td>
<td>6.37%</td>
<td>6.54%</td>
</tr>
<tr>
<td>Tax rate</td>
<td>2.05%</td>
<td>2.47%</td>
<td>2.88%</td>
<td>3.00%</td>
</tr>
<tr>
<td>Mean wage</td>
<td>0.9363</td>
<td>0.9332</td>
<td>0.9301</td>
<td>0.9292</td>
</tr>
<tr>
<td>Min wage</td>
<td>0.8383</td>
<td>0.8354</td>
<td>0.8327</td>
<td>0.8319</td>
</tr>
<tr>
<td>Wage MMR</td>
<td>1.1169</td>
<td>1.1170</td>
<td>1.1169</td>
<td>1.1170</td>
</tr>
<tr>
<td>Wage-Duration Index</td>
<td>0.78%</td>
<td>1.75%</td>
<td>1.44%</td>
<td>1.60%</td>
</tr>
<tr>
<td>Mean value for workers</td>
<td>223.38</td>
<td>222.91</td>
<td>222.44</td>
<td>222.53</td>
</tr>
</tbody>
</table>

in wage dispersion is, however, offset here by the increase in unemployment that makes workers with expired benefits more inclined to accept low wages. For the same reason, there is also no discernible pattern to the Wage-Duration Index across replacement ratios (above 0.47). For the lowest value of $\phi = 0.43$, the Wage-Duration Index is notably lower. This because the range of wages unemployed workers apply for is narrower so the decline in their application wages is not so responsive to the duration of UI entitlement.\(^\text{13}\)

### 2.9 Extensions

#### 2.9.1 Two separation rates

In our baseline calibration the fraction of workers who are ineligible for UI (Type 0) is 17.6%. Meanwhile, [Auray et al., 2019](#) find that in US data this figure is closer to 50%. To improve our model in this respect we introduce two separations rates: a high rate $\lambda_h$ for

\(^{13}\)For $\phi = 0.45$, WDI = 1.21%. For $\phi = 0.40$, WDI = 0.70%
Table 2.9: Parameters for the two separation rates model

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tightness elasticity</td>
<td>η</td>
</tr>
<tr>
<td>Vacancy cost</td>
<td>c</td>
</tr>
<tr>
<td>On-the-job search efficiency</td>
<td>γ</td>
</tr>
<tr>
<td>Value of leisure</td>
<td>z</td>
</tr>
<tr>
<td>Separation rate switch rate</td>
<td>qλ</td>
</tr>
<tr>
<td>High Separation rate</td>
<td>λ_h</td>
</tr>
<tr>
<td>Low Separation rate</td>
<td>λ_l</td>
</tr>
<tr>
<td>Combined Separation rate</td>
<td>λ</td>
</tr>
</tbody>
</table>

Table 2.10: Two separation rates

<table>
<thead>
<tr>
<th>基线 vs 两λ</th>
<th>17.6%</th>
<th>35.4%</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of U pop with exhausted UI</td>
<td>50%</td>
<td>50%</td>
</tr>
<tr>
<td>Replacement ratio</td>
<td>6.37%</td>
<td>6.80%</td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>2.88%</td>
<td>2.31%</td>
</tr>
<tr>
<td>Mean wage</td>
<td>0.9301</td>
<td>0.8919</td>
</tr>
<tr>
<td>Minimum wage</td>
<td>0.8327</td>
<td>0.7777</td>
</tr>
<tr>
<td>Wage Mean-Min ratio</td>
<td>1.1169</td>
<td>1.1469</td>
</tr>
<tr>
<td>Wage standard deviation</td>
<td>0.0444</td>
<td>0.0743</td>
</tr>
<tr>
<td>Wage Gini coefficient</td>
<td>0.0228</td>
<td>0.0414</td>
</tr>
<tr>
<td>Wage-Duration Index</td>
<td>1.44%</td>
<td>0.90%</td>
</tr>
<tr>
<td>Mean value for workers</td>
<td>222.44</td>
<td>209.65</td>
</tr>
</tbody>
</table>

all workers starting new jobs, and a low rate λ_l switching from λ_h with probability q_λ as long as workers don’t change jobs. This shock on separation rates occurs at the same stage in the time period as the entitlement eligibility shock. The model is detailed in Appendix B.1.

To calibrate the model with two separation rates, λ_h is set to the empirical separation rate for workers in their first month of employment, λ_l is set to the empirical rate for those who work more than 12 months (stable job), and q_λ is calibrated to let the overall separation rate in the model match the data. Other parameters are obtained using the same procedure as for the baseline calibration. The parameter values are shown in Table 2.9.
The outcomes appear in Table 2.10. As shown there, the introduction of heterogeneous separation rates increases the share of UI ineligible unemployed workers from 17.6% to 35.4%. Overall wage dispersion by all measures is higher with two separation rates while the Wage-Duration Index is lower. This apparent contradiction emerges because the range of wages that the unemployed apply for is much smaller with two separation rates. Even those with high prior wages and full entitlement just need to find a job that they can keep for long enough to establish a stable match. This tends to both lower and compress the range of wages the unemployed apply for.

Figure 2.9 plots expected present values of workers for each state against the current wage (employed workers) or previous wage (unemployed workers). The flatter but more separated set of curves near the bottom of the figure represents the unemployed workers. Again, duration of remaining benefits matters relatively more to them than does their former wage. There are two other groups of curves in Figure 2.9. The lower and more separated of the two corresponds to the high separation rate employed workers while the other group corresponds to the low separation rate employed workers. Despite a ten fold difference in their separation rates, worker values are quite similar at low wages (i.e. close to the lowest acceptance wage of 0.7777). This comes from the well known result in search theory that at the reservation wage, workers are indifferent to the separation rate since they are equally well off in employment as unemployment. Consequently, at low wages both the high and low separation rate workers climb the wage ladder quickly. At higher wages, however, because what matters to the worker is the present value of the employment relationship, low separation workers will only apply for new jobs with considerably higher wages. The horizontal distance between the corresponding low and high separation rate curves in Figure 2.9 represents the amount of current income a high separation rate worker would be prepared to give up in order to become a low separation rate worker. As they give up their low separation rate status to take a new job, that distance also represents a lower bound on the wage increase sought by low separation rate workers as they search on the job.
2.9.2 Risk aversion

Up to this point, a maintained assumption has been worker risk-neutrality so that UI has no actual insurance role. To see how risk aversion impacts the behavior of the model we introduce CRRA utility with the coefficient of relative risk aversion set to 2. The calibration procedure is the same as above but with one exception. Here, we target the empirical wage volatility (standard deviation of the logarithm of the wage) rather than the elasticity of application wages with respect to current benefits.\footnote{It is not feasible to match $\varepsilon_{w,b}$ as a large block of unemployed workers search for the lowest wage and $\varepsilon_{w,b} = 0$.}

Table 2.11 compares the results for risk averse workers with those of the baseline model. The outcomes are qualitatively similar. Risk aversion exaggerates the degree of wage dispersion and increases the Wage-Duration index.\footnote{The different calibration strategies between the risk aversion and risk neutrality models may be causing some of the increase in wage dispersion. However, various experiments with different calibration strategies and parameters values produce the similar results.} Risk averse workers are eager to avoid the drop in consumption that occurs when benefits expire and so target low wages to improve their prospects of re-employment. By assuming risk-neutrality the foregoing analysis, therefore, underestimates the degree of wage dispersion that is
Table 2.11: Re-entitlement effects with risk aversion and neutrality

<table>
<thead>
<tr>
<th></th>
<th>CRRA=2</th>
<th>Linear Utility(Baseline)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment rate</td>
<td>9.35%</td>
<td>6.37%</td>
</tr>
<tr>
<td>Tax rate</td>
<td>3.14%</td>
<td>2.88%</td>
</tr>
<tr>
<td>Mean wage</td>
<td>0.6863</td>
<td>0.9301</td>
</tr>
<tr>
<td>Minimum wage</td>
<td>0.4904</td>
<td>0.8327</td>
</tr>
<tr>
<td>Wage Mean-Min ratio</td>
<td>1.3893</td>
<td>1.1169</td>
</tr>
<tr>
<td>Log of Wage standard deviation</td>
<td>0.1945</td>
<td>0.0444</td>
</tr>
<tr>
<td>Wage-Duration Index</td>
<td>2.53%</td>
<td>1.44%</td>
</tr>
<tr>
<td>Wage Gini coefficient</td>
<td>0.1006</td>
<td>0.0228</td>
</tr>
</tbody>
</table>

Attributable the UI system. Allowing workers to self-insure through saving would mitigate the impact of risk aversion somewhat and bring the economy back closer to the risk neutral version. Incorporating savings, however, goes beyond the scope of this paper and is left for future work.

2.10 Conclusion

This paper has provided a framework for simultaneously assessing the role of the UI structure in the determination of the wage distribution and quantifying the re-entitlement effect. Our baseline calibration of the directed on-the-job search and matching model generates an MMR of 1.117. The analysis points to a high degree of interaction between the termination of benefits and on-the-job search in the determination of wage dispersion. Shutting down each source lowers the MMR to 1.043 and 1.010 respectively. Because they recognize that moving up the wage ladder simultaneously increases the generosity and expected duration of future benefits, workers are especially eager to get back onto it.

Our metric of the re-entitlement effect is the Wage-Duration Index (WDI), the extent to which workers lower their asking wage for each month of reduced entitlement. Our main calibration yields a WDI of 1.44%. Essentially, the re-entitlement effect represents the component of wage dispersion attributable to the search behavior of the unemployed. As such the WDI generally moves in lockstep with the MMR. The one exception to that pattern occurs when the model was extended to incorporate two separation rates. New matches were assumed to separate at 10 times the rate of older ones. While overall wage dispersion
increased (MMR=1.147), the re-entitlement effect fell (WDI=0.9%). What matters to the unemployed workers here, almost independently of their current UI eligibility status, is getting any job. We also saw that allowing for immediate re-entitlement, rather than the baseline policy in which full re-entitlement is expected to take a full calendar year, did not have much impact on the re-entitlement effect (WDI=1.48%). This tells us that it is the expiry of benefits rather than re-entitlement per se that is the most powerful driver of wage dispersion emerging from the UI system.

While we do briefly consider risk-aversion among workers in this model, we do not allow them to self-insure through savings. While access to savings might allow workers to smooth their consumption, the impending loss of benefits has a more powerful impact on risk-averse workers. Incorporating savings along with risk-aversion is left for future work.
Chapter 3  

Dynamics of the Unemployment Insurance Re-entitlement Effect

3.1 Introduction

This chapter extends the framework of unemployment insurance (UI) re-entitlement effect from Chapter 2 to a dynamic setting. We aim to ask two questions. First, are there differential wage dispersion and re-entitlement effects of UI over the business cycle? Second, what are the implications for the labor market and welfare?

A strand of literature investigate the income and redistribution effects of UI with frictions in the labor market. [Golosov et al., 2013] studies optimal income redistribution in a directed search model. In their model without on-the-job (OTJ) search, the optimal UI entails a positive benefit and a regressive payroll tax which compensates for workers who search for high wage jobs. [Gervais et al., 2022] instead investigates optimal UI benefit policy in response to aggregate and idiosyncratic volatility in a directed search model with OTJ search.

Another literature study the scarring effect of recessions. For example, [Huckfeldt, 2022] discovers that unemployed workers in recessions optimally search for lower-skill jobs, resulting in more time spent on climbing the skill-job ladders.

There are few papers that focus on the dynamic features of the UI re-entitlement effect with uncertainty. We know little about how strong the wage dispersion and re-entitlement effect are and how different they are across recessions and booms. To answer these questions, we create a stylized business cycle environment where the output/productivity is low in recessions and high in booms. To closely reflect the features of the U.S. economy, a cycle is set to take 70 months ([Gervais et al., 2022]). The output of a worker-firm match is low in the first 11 months and high in the rest of the cycle. The values of the outputs are set so such that the average productivity over the cycle is 1. There is no aggregate uncertainty in each period, but workers and firms are uncertain about the future (idiosyncratic subjective uncertainty). Workers and firms perceive the transition
probabilities of the economy states but don’t know exactly when the economy states change.

We embed the framework developed in Chapter 2 into this dynamic setting and calibrate the model with both first and second order statistics of the U.S. economy. We observe greater wage dispersion (Wage Mean-Min Ratio (MMR) = 1.16) and stronger re-entitlement effects (Wage-Duration Index (WDI) > 1.5%) in recessions than in booms (MMR = 1.017 and WDI is essentially 0). Unemployed workers hired in recessions with low UI entitlements spend on average 10 more months to pick up the wage if they were hired in booms. There is no scarring effect for employed workers who search on the job.

3.2 Model

3.2.1 Environment

Building on the environment setup in Chapter 2, we assume the period output per work-firm match is not constant. Specifically, the productivity has two values (states): 0.9676 and 1.0072. It is assumed a business cycle takes 70 months. In the first 11 months, it’s in trough and \( p = 0.9676 \). In the last 59 months each cycle, \( p = 1.0072 \). This set up is such that the average productivity over the cycle is 1. These numbers are calibrated to volatility and correlation of detrended real GDP per capita.\(^1\) Workers and firms perceive the productivity \( p \) follows Markovian movement with transition rate:

\[
M = \begin{bmatrix}
0.9091 & 0.0909 \\
0.0169 & 0.9831
\end{bmatrix}.
\]

(3.1)

That is, for example, they believe \( p \) stays low next month with the probability \( M_{1,1} = 0.9091 \) if \( p = 0.9676 \), and \( p \) moves up with the probability \( M_{1,2} = 0.0909 \). The productivity realizes at the beginning of each period. After observing the realized \( p \), workers and firms then follow the timeline outlined in Figure 2.3.

\(^1\)See, for example, [Gervais et al., 2022].
3.2.2 Value functions

Workers select the submarket to search for jobs based on their expectations of the next period. Firms behave in the similar way. Therefore we can adapt the values functions in section 2.4.2 by replacing $V^i_u(w)$, $V^i_e(w)$, and $V^i_f(w)$ on the right-hand side of those equations with their respective expectations. We use $s = h$ or $l$ to denote the economy is in high or low state. The value of the unemployed workers in the high state ($p = 1.0072$) with unexpired entitlement, $i > 0$, can be expressed as

$$V^{i,h}_u(w) = \frac{1}{1 + r} \left\{ b(w) + z + q_u \max_{w, \tilde{\theta}} \left\{ m(\tilde{\theta}) V^{i-1,h}_{e,\text{expec}}(\tilde{w}) + (1 - m(\tilde{\theta})) V^{i-1,h}_{u,\text{expec}}(w) \right\} \right. + \left. (1 - q_u) \max_{w, \tilde{\theta}} \left\{ m(\tilde{\theta}) V^{i,h}_{e,\text{expec}}(\tilde{w}) + (1 - m(\tilde{\theta})) V^{i,h}_{u,\text{expec}}(w) \right\} \right\}$$

(3.2)

where $V^{i,h}_{e,\text{expec}}(w)$ and $V^{i,h}_{u,\text{expec}}(w)$ represent workers' expected values of being employed and unemployed next period, respectively. When the economy is in boom, these two expectations can be expressed as

$$V^{i,h}_{e,\text{expec}}(w) = M_{2,1} * V^{i,l}_{e}(w) + M_{2,2} * V^{i,h}_{e}(w)$$

(3.3)

$$V^{i,h}_{u,\text{expec}}(w) = M_{2,1} * V^{i,l}_{u}(w) + M_{2,2} * V^{i,h}_{u}(w).$$

(3.4)

All other value functions and the free-entry condition can be adapted from section 2.4.2 in the same manner.

3.2.3 Government Budget constraint

The government budget is balanced in the long run:

$$\sum_{t} \sum_{i \in I} \int_{0}^{p} \left( \frac{1}{1 + r} \right) t \tau w_{i}^{e}(w) dw = \sum_{t} \sum_{i \in I \setminus \{0\}} \int_{0}^{p} \left( \frac{1}{1 + r} \right) t b(w) u_{i}^{e}(w) dw.$$  

(3.5)

3.2.4 Equilibrium

**Definition 3.1** A Block Recursive Equilibrium consists of a pair of worker policy functions, $\tilde{w}_{i}^{j} : I \times \{e,u\} \times [h,l] \times [0,p] \rightarrow [0,p]$ and $\tilde{\theta}_{i}^{j} : I \times \{e,u\} \times [h,l] \times [0,p] \rightarrow \mathbb{R}_{+}$ a set of active submarkets, $A \subset I \times [h,l] \times [0,p]$, a market tightness function, $\theta : A \rightarrow \mathbb{R}_{+}$, the steady state...
population measures, \( e^i_t(w) \) and \( u^i_t(w) \), and a pay-roll tax rate, \( \tau \) such that:

1. Given the set of active markets, the market tightness function and pay-roll tax rate, the worker policy functions emerge from optimal search and matching.

2. The set of active markets, \( A \), is determined by the free entry condition.

3. The tightness function determines \( \theta(i,s,w) \) for all \((i,s,w) \in A\).

4. The steady state population measures, \( e^i_t(w) \) and \( u^i_t(w) \) represent the ergodic distribution that emerges from the worker policy functions.

5. The balanced budget condition, (3.5) holds.

### 3.3 Calibration

Same as in Chapter 2, there are 4 parameters to calibrate: the elasticity of the matching function, \( \eta \), the on-the-job search efficiency parameter, \( \gamma \), the value of leisure, \( z \), and the vacancy holding cost, \( c \). These were all obtained simultaneously using simulated method of moments (SMM). The target moments are reported in Table 3.1.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Moment Target</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( c ) (vacancy cost)</td>
<td>Long run average unemployment rate</td>
<td>0.1267</td>
</tr>
<tr>
<td>( \eta ) (tightness elasticity)</td>
<td>Standard deviation of unemployment rate</td>
<td>0.8750</td>
</tr>
<tr>
<td>( \gamma ) (OTJS efficiency)</td>
<td>Overall Job-to-job (EE) movement rates</td>
<td>0.8887</td>
</tr>
<tr>
<td>( z ) (value of home production)</td>
<td>EE rates ratio between high/low wage workers</td>
<td>0.6653</td>
</tr>
</tbody>
</table>

In the dynamic setting, we can use first order and second order statistics of the U.S. economy. For example, the mean and standard deviation of unemployment rate to identify the vacancy cost \( (c) \) and matching function elasticity \( (\eta) \) simultaneously since these are the two main parameters in employment creation and matching technology determining the size and distributions of (un)employment. The values of all other parameters are obtained in the same way as in section 2.5. In the next section, we report one version of calibrated results. In this version, the UI benefit replacement ratio is muted because all benefits are capped at maximum 0.35.
Figure 3.1: Average wage and Lowest wage over the business cycle.

Figure 3.2: Density of workers earning the lowest wage over the business cycle.
3.4 Results

Figure 3.1 shows the average wage and lowest wage over the cycle. The period average wage is between 0.935 and 0.945. The lowest wage is 0.806, a constant in all months. However, the worker density at the lowest wage, 0.806, varies substantially across time. For example, it is show in Figure 3.2 that, in month 70, there are only fewer than 1e-6 workers earning that wage. The measure of this worker group with lowest wage increases rapidly in recessions. We will return to this group later.

Since the lowest wage is of special interest, I calculate two MMRs using the lowest wage and the wage at the 1st percentile each month. The MMR using the 1st percentile wage is high (1.14 - 1.17) in months 1 to 23 and low (1.02) in other boom months (see the red line in Figure 3.3). While the MMR with lowest wage (blue line in Figure 3.3) is stable because the mean wage and lowest wage are stable (Figure 3.1). This difference between two MMRs is consistent with the very small amount (< 1%) of workers who earn the lowest wage from month 24 to 70.

The wage dispersion for selected months are shown in Appendix C. It’s interesting to compare the height of the lowest wage, 0.806, and two spikes, 0.928 and 0.956 over the cycle. Consistent with discussed above, the height of 0.806 rises in bust, peaks at the ending month of the recession, shown in Figure C.1 and C.2 and decreases thereafter until another recession (See Figure C.3 and C.4). On the opposite, the heights of two other spikes (wage = 0.928 and wage = 0.956) decrease in recession and increase in booms, respectively. Figure C.5 and Figure C.6 show that these three spikes are steps in the wage-job ladder. This is a block-wise equilibrium of directed search where the sizes of steady state blocks change slightly across the cycle.

The UI re-entitlement effect is measured by the the Wage-Duration Index (WDI), which is defined as drops in application wage one month closer to the UI benefit expiry. It is displayed in Figure 3.4 that the WDI is between 1.48% (in month 1) and 1.94% in months 1-11, but it is essentially 0 in all months in booms. To investigate this difference in WDI across the cycle, I depict the application wages for the unemployed workers in recessions (Figure 3.5) and in booms (Figure 3.6). The search strategies are constant in recessions and in booms, respectively. In months 1 to 11, unemployed workers without any UI entitlement (Type 0 workers) search for the lowest wage in the market, 0.806; Type 1
Figure 3.3: Mean-Min Wage ratios over the business cycle.

Figure 3.4: Wage-Duration Index over the business cycle.
Figure 3.5: Application wages for Unemployed workers in recessions

Figure 3.6: Application wages for Unemployed workers in booms
unemployed workers search for wage 0.822, and the unemployed of all other types search for 0.928. With low productivity in recessions, it is not profitable for firms to post as many vacancies as in booms. The unemployed workers with expiring entitlement who are eager to find jobs reduce application wages to increase the probability of a successful match. While in booms, productivity is higher and vacancy supply is more abundant. Thus, all unemployed workers regardless of entitlement search for 0.928, and the WDI is 0. Note that UI benefit is fixed at 0.35. The previous wage of the unemployed does not play roles in the search strategies, and the re-entitlement effect.

Next, we investigate the scarring effect of the recession due to UI entitlement eligibility using this version of calibrated results. We ask this question: What happens to the workers who are hired during the recession and how long does their average wage stay below that of the rest of the economy? To quantify the scarring effect, we perform back-of-the-envelope calculation on how much slower the re-employed workers hired in recessions climb up the job-wage ladder compared to those hired in booms.

The wage search strategies are constant across all periods in recessions (month 1 to month 11 in the model) and in booms (month 12 to month 70 in the model), respectively. Figure 3.5 shows that regardless of the wage of last employment, unemployed workers with expired UI entitlement search for wage 0.806. After getting the job, the worker earning the lowest wage in the model economy search for 0.928 on the job. The probability of successful on-the-job movement for this worker is 3.38% in recessions (Figure 3.7) and 17.45% in booms (Figure 3.8). While in booms, the search wage for every unemployed worker is 0.928 (See Figure 3.6). Therefore, back-of-the-envelope calculation shows it takes about 10 months to catch up the wages of who are hired in booms.

The UI re-entitlement scarring effects for employed workers who search on the job collapse to 0, because, in each period, the search strategies are functions of current wage, not the entitlement eligibility of the employed. See Figure C.5 and Figure C.6.

3.5 Discussions

We incorporate the UI entitlement eligibility framework developed in Chapter 2 into a dynamic setting featuring the business cycles in U.S.. The calibrated results point to
Figure 3.7: The job finding rates for employed workers in recessions

![Graph showing EE Movement probabilities in Month 1](image)

Figure 3.8: The job finding rates for employed workers in booms

![Graph showing EE Movement probabilities in Month 12](image)
a greater wage dispersion and stronger re-entitlement effect in recessions. The fixed UI benefit isolates any effect from previous wages. To quantify these findings, it remains to separate out the effect of on-the-job search. This work is left for future.
Chapter 4

Conclusion

Search and matching has been proved to play a key role in more and more empirical research in various areas. By incorporating labor market frictions, we investigate the welfare implications of international trade in the rise of China in 2000-2007, and wage dispersion and re-entitlement effects of the unemployment insurance policy in U.S.. We hope to better understand search and matching mechanisms and bring them to more topics in the future.
## Appendix A

### Appendix for Chapter 1

### A.1 Tables

Table A1: Matching Efficiency Determinants

<table>
<thead>
<tr>
<th></th>
<th>Matching Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage of college-educated population</td>
<td>-0.000420 (-0.87)</td>
</tr>
<tr>
<td>Percentage of foreign-born population</td>
<td>0.000695 (1.80)</td>
</tr>
<tr>
<td>Percentage of employment among women</td>
<td>0.00127 (1.61)</td>
</tr>
<tr>
<td>Maximum January temperature</td>
<td>0.0143 (0.35)</td>
</tr>
<tr>
<td>Maximum July temperature</td>
<td>0.0832 (1.73)</td>
</tr>
<tr>
<td>Mean July relative humidity</td>
<td>0.00352 (0.09)</td>
</tr>
<tr>
<td>Log population density 1900</td>
<td>-0.0187 (-6.52)</td>
</tr>
<tr>
<td>Maximum monthly AFDC/TANF benefit</td>
<td>-0.00000133 (-0.04)</td>
</tr>
<tr>
<td>Residulized rent index</td>
<td>-0.384 (-9.37)</td>
</tr>
<tr>
<td>Residulized house price index</td>
<td>0.0561 (2.75)</td>
</tr>
<tr>
<td>Feature</td>
<td>Coefficient</td>
</tr>
<tr>
<td>-----------------------------------------------------</td>
<td>-------------</td>
</tr>
<tr>
<td>Below 37th parallel</td>
<td>-0.0149</td>
</tr>
<tr>
<td>CZ with coastline (ocean or Great Lakes)</td>
<td>0.00149</td>
</tr>
<tr>
<td>Log distance to closest CZ (between weighted centroids)</td>
<td>-0.0164</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.160</td>
</tr>
<tr>
<td>Observations</td>
<td>722</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.884</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses
A.2 Figures

Figure A.1: Manufacturing workers share of each CZ labor force
Table A2: Matching Efficiency Estimation

<table>
<thead>
<tr>
<th>Real labor income</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment Rate</td>
<td>0.967</td>
<td>0.972</td>
</tr>
<tr>
<td></td>
<td>(2.52)</td>
<td>(2.55)</td>
</tr>
<tr>
<td>CZ</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Industry</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Time</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Industry * Time</td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>IV</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Observations</td>
<td>2992</td>
<td>2992</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.6473</td>
<td>0.6493</td>
</tr>
</tbody>
</table>

Data is extracted from ACS 2005-2007. $t$ statistics in parentheses.

Table A3: China Shock and Manufacturing Employment in CZs

<table>
<thead>
<tr>
<th>Δ manufacturing employment share</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trade Shock</td>
<td>-0.929</td>
<td>-0.937</td>
<td>-0.958</td>
</tr>
<tr>
<td></td>
<td>(-6.11)</td>
<td>(-6.19)</td>
<td>(-6.18)</td>
</tr>
<tr>
<td>Matching Efficiency</td>
<td>2.856</td>
<td>7.323</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.80)</td>
<td>(3.42)</td>
<td></td>
</tr>
<tr>
<td>Matching Efficiency*Trade Shock</td>
<td></td>
<td></td>
<td>-2.551</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-2.45)</td>
</tr>
<tr>
<td>Observations</td>
<td>188</td>
<td>188</td>
<td>188</td>
</tr>
</tbody>
</table>

Data is extracted from ACS 2005-2007. Robust standard errors in parentheses are clustered on state. Models are weighted by CZ share of national population. $t$ statistics are reported in parentheses.
Appendix B

Appendix for Chapter 2

B.1 The model for two separation rates

In this environment, the problem for unemployed workers is not affected. For employed workers with less than full entitlement, \( i = 0, \ldots, I - 1 \), and with long tenure (low separation rate), \( \lambda_l \)

\[
V_{e,l}^i (w) = \frac{1}{1 + r} \left\{ w + \lambda_l \max_{\tilde{w}, \tilde{\theta}} \left\{ m(\tilde{\theta}) V_{e,s}^{i+1} (\tilde{w}) + (1 - m(\tilde{\theta})) V_{u}^{i+1} (w) \right\} \\
+ (1 - \lambda_l) \max_{\tilde{w}, \tilde{\theta}} \left\{ \gamma m(\tilde{\theta}) V_{e,s}^{i+1} (\tilde{w}) + (1 - \gamma m(\tilde{\theta})) V_{e,l}^{i+1} (w) \right\} \\
+ (1 - q_e) \left[ \lambda_l \max_{\tilde{w}, \tilde{\theta}} \left\{ m(\tilde{\theta}) V_{e,s}^i (\tilde{w}) + (1 - m(\tilde{\theta})) V_{e,l}^i (w) \right\} \\
+ (1 - \lambda_l) \max_{\tilde{w}, \tilde{\theta}} \left\{ \gamma m(\tilde{\theta}) V_{e,s}^i (\tilde{w}) + (1 - \gamma m(\tilde{\theta})) V_{e,l}^i (w) \right\} \right\} \right\}. \tag{B.1}
\]

For employed workers with full entitlement, \( i = I \), and with long tenure (low separation rate), \( \lambda_l \), the value of being employed is

\[
V_{e,l}^i (w) = (1 - q_{\lambda}) \frac{1}{1 + r} \left\{ w + q_e \left\{ \lambda_l \max_{\tilde{w}, \tilde{\theta}} \left\{ m(\tilde{\theta}) V_{e,s}^{i+1} (\tilde{w}) + (1 - m(\tilde{\theta})) V_{u}^{i+1} (w) \right\} \\
+ (1 - \lambda_l) \max_{\tilde{w}, \tilde{\theta}} \left\{ \gamma m(\tilde{\theta}) V_{e,s}^{i+1} (\tilde{w}) + (1 - \gamma m(\tilde{\theta})) V_{e,l}^{i+1} (w) \right\} \\
+ (1 - q_e) \left[ \lambda_l \max_{\tilde{w}, \tilde{\theta}} \left\{ m(\tilde{\theta}) V_{e,s}^i (\tilde{w}) + (1 - m(\tilde{\theta})) V_{e,l}^i (w) \right\} \\
+ (1 - \lambda_l) \max_{\tilde{w}, \tilde{\theta}} \left\{ \gamma m(\tilde{\theta}) V_{e,s}^i (\tilde{w}) + (1 - \gamma m(\tilde{\theta})) V_{e,l}^i (w) \right\} \right\} \right\} + q_{\lambda} V_{e,l}^i (w). \tag{B.2}
\]

For employed workers with less than full entitlement, \( i = 0, \ldots, I - 1 \), and with short tenure (high separation rate), \( \lambda_h \)
rate), $\lambda_l$,

$$V_{c,l}^I(w) = \frac{1}{1 + r} \left\{ w + \lambda_l \max_{\tilde{w}, \tilde{\theta}} \left\{ m(\bar{\theta})V_{c,s}^I(\tilde{w}) + (1 - m(\bar{\theta}))V_{u}^I(w) \right\} + (1 - \lambda_l) \max_{\tilde{w}, \tilde{\theta}} \left\{ \gamma m(\bar{\theta})V_{c,s}^I(\tilde{w}) + (1 - \gamma m(\bar{\theta}))V_{c,l}^I(w) \right\} \right\}. \quad (B.3)$$

For employed workers with full entitlement, $i = I$, and with short tenure (high separation rate), $\lambda_h$,

$$V_{c,s}^I(w) = (1 - q_\lambda) \frac{1}{1 + r} \left\{ w + \lambda_h \max_{\tilde{w}, \tilde{\theta}} \left\{ m(\bar{\theta})V_{c,s}^I(\tilde{w}) + (1 - m(\bar{\theta}))V_{u}^I(w) \right\} + (1 - \lambda_h) \max_{\tilde{w}, \tilde{\theta}} \left\{ \gamma m(\bar{\theta})V_{c,s}^I(\tilde{w}) + (1 - \gamma m(\bar{\theta}))V_{c,s}^I(w) \right\} + q_\lambda V_{c,l}^I(w). \quad (B.4)$$

For the job occupied by a worker with less than full entitlement, $i = 0..I - 1$, and long tenure (low separation rate), $\lambda_l$,

$$V_{f,l}^i(w) = \frac{1}{1 + r} \left\{ p - w(1 + \tau) + (1 - q_e)(1 - \lambda_l) \left[ (1 - \gamma m(\bar{\theta}_c^i(w, \theta)))V_{f,l}^i(w) \right] + q_e(1 - \lambda_l) \left[ (1 - \gamma m(\bar{\theta}_c^{i+1}(w, \theta)))V_{f,l}^{i+1}(w) \right] \right\} \quad (B.5)$$

where $\bar{\theta}_c^i(w, \theta)$ is the tightness of the market that the worker currently employed in this job will search in. For the job occupied by a worker with less than full entitlement, $i = 0..I - 1$, and short tenure (high separation rate), $\lambda_h$,

$$V_{f,s}^i(w) = (1 - q_\lambda) \frac{1}{1 + r} \left\{ p - w(1 + \tau) + (1 - q_e)(1 - \lambda_h) \left[ (1 - \gamma m(\bar{\theta}_c^i(w, \theta)))V_{f,s}^i(w) \right] + q_e(1 - \lambda_h) \left[ (1 - \gamma m(\bar{\theta}_c^{i+1}(w, \theta)))V_{f,s}^{i+1}(w) \right] \right\} + q_\lambda V_{f,l}^i(w). \quad (B.6)$$

For a job occupied by a worker with full entitlement, $i = I$, and long tenure (low separation rate), $\lambda_l$,

$$V_{f,l}^I(w) = \frac{1}{1 + r} \left\{ p - w(1 + \tau) + (1 - \lambda_l) \left[ (1 - \gamma m(\bar{\theta}_c^I(w, \theta)))V_{f,l}^I(w) \right] \right\}. \quad (B.7)$$
For a job occupied by a worker with full entitlement, $i = I$, and short tenure (high separation rate), $\lambda_h$,

$$V^I_{f,s}(w) = (1 - q_\lambda) \frac{1}{1 + r} \left\{ p - w(1 + \tau) + (1 - \lambda_h) \left[ (1 - \gamma m(\theta^I_e(w, \Theta))) V^I_{f,s}(w) \right] \right\} + q_\lambda V^I_{f,l}(w). \quad (B.8)$$

The free-entry condition is the same as before.
Appendix C

Appendix for Chapter 3

C.1 Figures

Figure C.1: Worker Densities across Wages at the Start of Recession
Figure C.2: Worker Densities across Wages at the End of Recession

Figure C.3: Worker Densities across Wages at the Start of Recession
Figure C.4: Worker Densities across Wages at the Start of Recession

Figure C.5: Application wages for Employed workers in recessions
Figure C.6: Application wages for Employed workers in booms
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