Liquidity and Labor Reallocation in an Uneven Economy

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Abstract

Do liquid savings help displaced workers change sectors when changing sectors results in short-run earnings losses but long-run gains? I provide causal evidence that displaced workers with access to liquidity are more likely to switch industries. To do so, I rely on a regression kink design approach using data from Washington state and show that a $10 increase in weekly benefits raised the propensity of switching by half a percentage point. Upon re-employment, I find that switchers initially have 10 percentage points lower earnings than stayers, but the gap reverses within two years. To rationalize these findings, I develop a quantitative framework featuring incomplete markets, multiple sectors and costly labor reallocation. More liquidity enables displaced workers to reallocate across sectors while smoothing out earnings losses and leaving unemployment faster. According to the model, more generous unemployment insurance fosters more reallocation. When shocks affect sectors unevenly, this leads to less severe recessions.

Keywords: Labor Reallocation, Liquidity, Unemployment Insurance, Asymmetric Shocks

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1 Introduction

Recessions are periods in which unemployment rises and labor reallocates between different sectors of the economy. Figure 1a shows gross sectoral labor reallocation measured as the differential growth in sectoral employment and household personal savings for the U.S. The churn of labor across broad industries is countercyclical, rising in recessions and co-moves with the personal savings rate. Perhaps, if workers could reallocate faster from contracting industries to expanding industries, unemployment would not rise as much during recessions, especially if that recession affects sectors unevenly. At the same time, recessions are periods where individuals are more likely to be liquidity-constrained.

During the pandemic recession, this was especially noticeable, as some industries experienced labor shortages.[1] Figure 1b zooms in on the period of 2019-2022. The 'spikes' in the personal savings rate roughly correspond to the three dates of the 'Economic Impact Payments' (EIP) (or 'stimulus checks') delivered by the Internal Revenue Service.[2]

This paper asks whether the liquidity position of individuals is an important determinant of labor reallocation. Since individuals who move sectors or occupations experience a temporary fall in wages, having accumulated more liquid assets allows them to smooth consumption during this transition. This paper finds that this is so empirically, and builds a model that explains it. This effect of liquidity on labor reallocation complements its effect on the duration of unemployment that the literature has focused on so far. It suggests that unemployment benefits, by providing liquidity, may lower aggregate unemployment, which the model confirms to be the case.

This paper has five main findings. First, I find that a marginal increase in liquidity leads to a higher propensity for displaced workers to switch sectors upon re-employment. An increase of $10 in weekly benefits increases the propensity to change industries by half a percentage point, based on standard industrial classification (SIC) 1-digit level, on a baseline of 36%.[3]

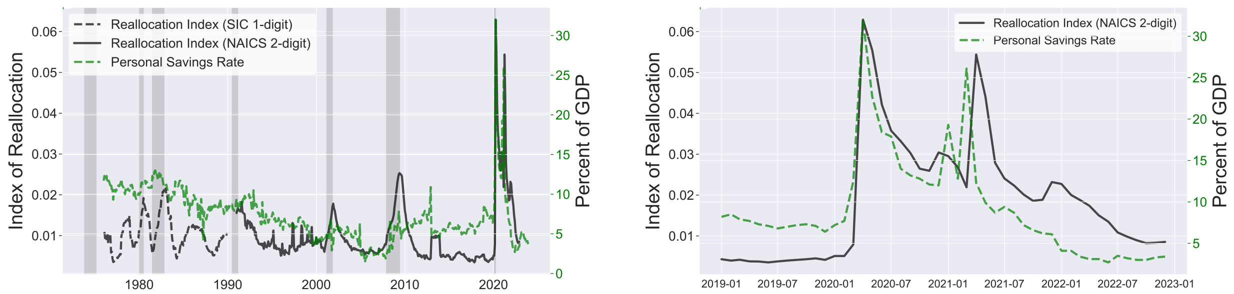
To arrive at this result, I leverage administrative data from the Continuous Wage and Benefit Histories (CWBH) Project in the United States. The CWBH collects data on unemployment spells and weekly benefits received for a collection of states. In addition, for the state of Washington, the CWBH also collects matched employer-employee data. This enables me to track the firm and industry of a worker's pre and post-unemployment job.

I implement a Regression Kink Design exploiting the 'kink' in the schedule between weekly benefits and past earnings. Workers close to the kink are quasi-exogenously allocated a weekly benefit that is either at the maximum benefit or slightly below, based on their previous earnings. For individuals below the kink, an increase in past earnings results in a marginal increase in liquidity as weekly benefits increase. This effect is absent for individuals above the kink as the weekly benefits are at the maximum. The main empirical result is valid for individuals who are local to the kink.

[1] See for example Kaplan, Moll, and Violante (2020) and Guerrieri, Lorenzoni, Straub, and Werning (2022).

[2] EIP1 was enacted in March 2020 and provided $1200 per eligible adult and $500 per qualifying child under 17. EIP2 was enacted in December 2020 and provided an additional $600 per adult and qualifying child under 17. EIP was enacted in March 2021 and provided $1400 for eligible individuals and an additional $1400 for each qualifying dependent. See `https://home.treasury.gov/policy-issues/coronavirus/assistance-for-american-families-and-workers/economic-impact-payments`.

[3] Figure given in 2010 dollars.



(a) 1975-2022

(b) 2019-2022

Figure 1: Reallocation and Savings Rates

Notes: Data from the Quarterly Census of Employment and Wages (QCEW) 1975-2022. The figure plots a measure of gross reallocation as in Chodorow-Reich and Wieland (2020), $R_{a,t,t+12} = \frac{1}{2}\sum_i^I s_{a,i,t}\left|\frac{1+g_{a,i,t,t+12}}{1+g_{a,t,t+12}} - 1\right|$. $R_{a,t,t+12}$ denotes the gross-reallocation measure for area a between months t and $t+12$, $s_{a,i,t}$ is the employment share of industry i in area a at month t, $g_{a,i,t,t+12}$ is the net employment growth rate of industry i in area a between months t and $t+12$, and $g_{a,t,t+12}$ is the net employment growth rate of area a between months t and $t+12$. The personal savings rate is from the Bureau of Economic Analysis (FRED code: PSAVERT). Shaded areas are NBER recession dates.

The headline number is significant. For comparison, Arizona has a similar unemployment insurance schedule, but with a lower maximum weekly benefits, \$115 compared to \$178 in Washington in 1982.[4] A back-of-the-envelope calculation suggests that if Washington had the same schedule as Arizona, the same individual would have had a lower propensity to reallocate by 7.81 percentage points, holding all other factors fixed. Given that the average reallocation rate in Washington is 36%, the difference in liquidity would lead to 22% lower reallocation.

My second main finding is that displaced workers who switch industries have lower initial post-unemployment weekly earnings compared to those who do not switch industries, but the gap *reverses* over time. The initial earnings loss for switchers is around 10 percentage points larger than that of stayers and the earnings of switchers catch up with those of non-switchers within 8 quarters. I do this by using the same data and implementing a cost-of-job loss regression in the spirit of Jacobson, LaLonde, and Sullivan (1993). I split the sample of the unemployed by whether they are eventual industry stayers or industry switchers.

Third, I develop a heterogeneous-agent model featuring risk aversion, multiple sectors, specific productivity, frictional labor markets, and borrowing constraints in order to study the effect of liquidity policies on labor reallocation. The main result is that conditional on a level of productivity, displaced workers with higher liquidity are more likely to change their sector of employment upon re-employment. The intuition is that due to risk aversion, individuals would like to smooth their consumption. Reallocation involves trading off lower productivity against finding a job more quickly. Productivity dynamics are such that individuals lose productivity quickly while unemployed but building productivity while employed is relatively slower. Therefore, an individual with more liquidity can afford the earnings loss that comes with the reallocation process without significantly cutting back consumption. An individual with low liquidity is less likely to switch sectors as they will be in a lower-productivity state with few assets to smooth their consumption and hence will have to cut back their consumption. Therefore, they seek to maintain their productivity by directing

[4] In 1982 dollars.

their search effort towards their old industry.

The model builds on the workhorse standard incomplete markets model (Bewley (1983)-Huggett (1993)-Imrohoroğlu (1989)-Aiyagari (1994)) by incorporating 'islands' in the spirit of Lucas and Prescott (1978) and frictional labor markets. While unemployed, the individual receives benefits from the government. However, the individual faces a risk of losing productivity over time. This captures a notion of a 'scarring' effect due to unemployment. Displaced workers direct their search effort towards jobs with different productivities and in different sectors. To capture the results from the data, displaced workers face a trade-off of finding a low-productivity job at a faster rate, or a high-productivity job at a lower rate. When displaced workers search for jobs that are different from their previous sector, they are more likely to sample lower-productivity jobs, capturing a notion of sector-specific productivity and a 'sullying effect'.[5] Though moving to a different sector is costly, individuals find it beneficial to do this for two reasons. First, it stops the loss of productivity while in unemployment, or the 'scarring' effect. Second, productivity is rebuilt while individuals are employed, mitigating the earnings losses over time.

I simulate a panel of individuals with my model and verify that the properties of the model are consistent with the data exercises by running the same regressions on the model-generated data. In particular, the model succeeds in generating the response of a marginal increase in unemployment benefits to the propensity for individuals to change their industry of work and earnings profile over time.

Fourth, I find that the model behaves differently in response to 'even' and 'uneven' shocks.[6] I shock the economy with a joint productivity and job-finding rate shock, both transitory in nature. An economy facing an uneven shock of the same size as an even shock experiences a lower peak unemployment and recovers to the steady state at a faster rate.[7] The intuition is that individuals are able to reallocate their labor units towards sectors which are *not* directly shocked. In this sense, the labor reallocation process has both a 'cleansing' and a 'sullying' effect. Given that displaced workers may partially lose their productivity compared to their previous job upon switching sectors, labor reallocation is individually costly, representing a 'sullying' effect. Simultaneously, labor reallocation redirects labor that would have otherwise been unemployed to more productive use - namely to other sectors. This represents a 'cleansing' effect in the aggregate.

Fifth, I find that a more generous fiscal policy can aid the recovery of an economy, but the mechanism differs depending on whether the shock is even or uneven. I study a targeted transfer policy where following a shock, the amount of transfers to the unemployed is temporarily increased. When faced with an even shock, the additional liquidity in the economy can be used by individuals to smooth consumption. In the process, equilibrium assets are not depleted by as much. Hence more of the asset stock can be directed to productive uses in the form of capital rented out by firms.

When the shock is uneven, the same channel is present. However, there is an additional channel through which the economy can adjust; through (net) labor reallocation. In an economy featuring more generous transfers, there is simultaneously a larger cleansing effect and sullying effect due to a higher rate of net labor reallocation away from the shocked sector. At the same time, as individuals find jobs at a faster rate, the scarring effect is weakened. The net effect of the policy is that it dampens

[5] See for example, Barlevy (2002).

[6] An even shock is one that hits all sectors symmetrically. An uneven shock hits sectors asymmetrically.

[7] I calibrate the even and uneven shocks such that they have the same impact effect on aggregate output.

the fall in aggregate output and the rise in unemployment. The liquidity provided by the policy aids labor reallocation and economic recovery.

Literature. This paper contributes to four main strands of literature. First, there is literature studying the effects of sectoral shocks on labor market outcomes such as labor market reallocation and unemployment. This starts with the seminal work of Lilien (1982) followed by Abraham and Katz (1986)), Jovanovic and Moffitt (1990) and Fallick (1993). Recent papers that study the role of sectors or industries include Kambourov (2009), Alvarez and Shimer (2011), Pilossoph (2012) and Chodorow-Reich and Wieland (2020).[8] These models typically build on the setup of Lucas and Prescott (1978) to feature 'islands' of industry or occupation with labor market frictions. Chodorow-Reich and Wieland (2020) study the role of secular labor reallocation for understanding unemployment fluctuation. They find that labor reallocation only contributes towards unemployment in recessions. There is also a parallel subset of this literature that studies the role of *occupations* instead of industries.[9] Huckfeldt (2022) studies the role of occupation switching in explaining the 'scarring effects of unemployment' and finds that it explains a large proportion of this effect.[10]

This paper contributes to this literature by bringing forward new evidence on the effect of liquidity on industry switching. On the theoretical side, the papers in this literature typically abstract from either risk-aversion or incomplete markets (or both). This paper includes both margins and innovates upon them by including an endogenous labor reallocation decision. Introducing these elements leads to a new policy conclusion whereby unemployment insurance has the additional effect of encouraging labor reallocation.

Second, there is recent literature which studies labor market outcomes in an economy featuring incomplete markets in the style of Bewley (1983)-Huggett (1993)-Imrohoroğlu (1989)-Aiyagari (1994).[11] A strand of this literature also includes nominal rigidities to study aggregate demand effects of labor market policies.[12] This paper contributes to this literature by introducing a multisector setup with imperfect skill transferability in order to study labor market reallocation.

The closest paper to this paper is Baley, Figueiredo, Mantovani, and Sepahsalari (2022). They study the risk of skill loss following involuntary layoffs, known as 'turbulence', and find that the cost of job loss is much larger for poor workers who experience turbulence. I view their paper as

[8]In the empirical literature, Jackson (2021) studies the relationship between job displacement and sectoral mobility for workers with long tenure. He finds that job displacement has a positive effect on sectoral mobility.

[9]This includes Moscarini (2001), Kambourov and Manovskii (2009), Carrillo-Tudela and Visschers (2023), Huckfeldt (2022), and Grigsby (2022).

[10]The distinction between occupation and industry is quantitatively important. Huckfeldt (2022) finds much larger *immediate* earnings losses for occupation switchers of around 42% and occupation stayers of 21%. For both groups, earnings losses persist even 10 years after job loss. One way to explain these differences is that relocating to a different occupation is more difficult than relocating to a different industry. In principle, one can switch industries without switching occupations. The analysis in this paper does not control for occupation due to data limitations. In spite of that, my results are still consistent with the idea that part of an individual's productivity is *industry* specific. Other papers in the literature that have studied industry-specific human capital include Neal (1995) and Grigsby (2022), which develop a model in which sectoral shocks may matter more than in the past due to skills becoming more specific.

[11]This includes Krusell, Mukoyama, and Şahin (2010), Herkenhoff (2019), Herkenhoff, Phillips, and Cohen-Cole (2022), Eeckhout and Sepahsalari (2023), Ifergane (2022), Beraja and Zorzi (2023), Baley, Figueiredo, Mantovani, and Sepahsalari (2022) and Huang and Qiu (2023).

[12]This includes McKay and Reis (2016), Kekre (2022), Ravn and Sterk (2020) and Den Haan, Rendahl, and Riegler (2017).

complementary to mine. Similar to their paper, I also study the role of incomplete markets, borrowing frictions for individuals and an unemployment experience. However, my paper studies a different type of labor market risk than the one studied in theirs.[13] The key difference is that my model features *endogenous* sector switching as unemployed individuals trade off their sector-specific productivity against finding employment in a new sector whereas this feature is exogenous in their model.

An alternative hypothesis is that low-liquidity individuals are more willing to engage in a precautionary job-search behaviour or precautionary mismatch, and are therefore more willing to accept lower-wage jobs.[14] In these models, earnings are *fixed* throughout the life of a job and therefore individuals use liquidity to wait for the highest-value job. In my model, individuals can *rebuild* their productivity upon re-employment and thus earnings can rise over time. Therefore, an increase in liquidity allows individuals to smooth this persistent (but still temporary) earnings change. In the data, I observe that worker's earnings increase on average over time.[15]

Third, there is a long public finance literature studying the effect of unemployment insurance on unemployment outcomes. These papers typically apply the Baily-Chetty formula in order to disentangle the moral hazard and liquidity properties of unemployment insurance.[16] In particular, Landais (2015) uses a Regression Kink Design to estimate the effect of unemployment insurance on the duration of unemployment. He finds that a 10% increase in unemployment benefits increases the duration of unemployment claims by 4% and the moral hazard and liquidity effects account for approximately 50% each. Relative to this literature, I use the same data as Landais (2015), but I study the labor market outcomes pertaining to sectoral labor reallocation. In particular, I look at whether transitions out of unemployment result in a change of industries - an outcome variable that hasn't been studied in this literature.

Roadmap. The rest of the paper is as follows. Section 2 introduces the model. The introduction of the data and implementation of the empirical exercises are contained in section 3. In section 4, I compare the stationary equilibrium of the model to that of the findings in the empirical section. Counterfactual exercises in the form of transition dynamics to symmetric and asymmetric sectoral shocks, and policy exercises will be conducted in section 5. Section 6 concludes.

[13] Their paper studies a joint unemployment and skill depreciation risk whereby individuals lose *both* their job and skill simultaneously - also known as 'turbulence' risk. In my model, these two risks are present, but independent.

[14] This channel occurs in the model of Baley, Figueiredo, Mantovani, and Sepahsalari (2022) as well as models with two-sided heterogeneity and sorting as in Eeckhout and Sepahsalari (2023) and Huang and Qiu (2023).

[15] In an extension of the model, I allow displaced workers to choose the intensive margin of search. Indeed, low-liquidity individuals search more intensely, conditional on a productivity level. However, higher productivity individuals search harder, conditional on an asset level. The intuition behind this result is that high-productivity individuals are more exposed to the risk of skill depreciation that occurs during unemployment, and therefore use search effort to reduce the risk of skill depreciation. By contrast, the lowest productivity individual is not exposed to this risk and therefore searches less intensely. In the calibrated model, the productivity effects dominate the liquidity effects.

[16] This includes Meyer (1990), Gruber (1997), Chetty (2008) and Landais (2015), Lalive, Landais, and Zweimüller (2015), Kroft and Notowidigdo (2016), Di Maggio and Kermani (2017) and Kuka (2020).

2 Model

In this section, I introduce the building blocks of the model. The model combines elements of the standard incomplete markets model (Bewley (1983)-Huggett (1993)-Imrohoroğlu (1989)-Aiyagari (1994)) with 'islands' in the spirit of Lucas and Prescott (1978) and frictional labor markets in the spirit of McCall (1970). Islands in the model refer to sector/ industry. The model is presented and solved in continuous-time, following Achdou, Han, Lasry, Lions, and Moll (2021). Throughout the model, the price of aggregate consumption is the numéraire.

2.1 Household Block

The main innovation of this model is contained in the household block. Individuals can be employed (E) or unemployed (U). There are n_s sectors in the economy where n_s is finite. Individuals are endowed with an individual productivity level of z which will vary over time.[17] Unemployed individuals search for a job, where a job is defined as a pair of potential productivity and sector (z', s').

Figure 2 illustrates the household block. The employed face productivity risk, which may go up or down. The unemployed only face a downside risk of losing productivity. When an individual becomes separated from a job, they switch their employment status and keep their productivity level (red arrow). When searching for new jobs, individuals can search for jobs in different sectors. For jobs in the same sector as their previous sector (blue arrow), individuals can draw higher productivity levels compared to jobs in a different sector than their last (orange arrow). The model endogenises how an individual's direction of search across sectors depends on their liquidity.

Next, I discuss the productivity risk. Individuals face idiosyncratic productivity risk which depends on their employment status.[18]

Transitions EE. Π captures the Poisson arrival rates for productivity transitions when the individual is employed. Its representative element is $\pi_{z\tilde{z}}$. Productivity may rise or fall when employed. This captures the notion that income may increase over time, with experience on the job and may fall due to idiosyncratic risks separate from employment risk.

Transitions EU. The parameter ζ_s captures the separation rates in each sector. This captures the sector-specific employment risk. Note that the assumption is that upon receiving a separation shock, the individual does not change their productivity.

Transitions UU. Ξ captures the transition matrix in the case that the individual is unemployed. I assume that when the individual is unemployed, productivity can only move down. This captures

[17]The assumption that productivity is a one-dimensional variable is made for tractability. There is a recent literature that has stressed the importance of a multi-dimensional notion of skill. This includes Guvenen, Kuruscu, Tanaka, and Wiczer (2020) and Lise and Postel-Vinay (2020). In these models, there is a much richer notion of misallocation in the labor market, otherwise known as 'mismatch'. My model is amenable to this extension but at the cost of more state variables.

[18]Other papers that have a similar notion of stochastic human capital or productivity include Ljungqvist and Sargent (1998), Jarosch (2023) Huckfeldt (2022) and Kehoe, Midrigan, and Pastorino (2019).

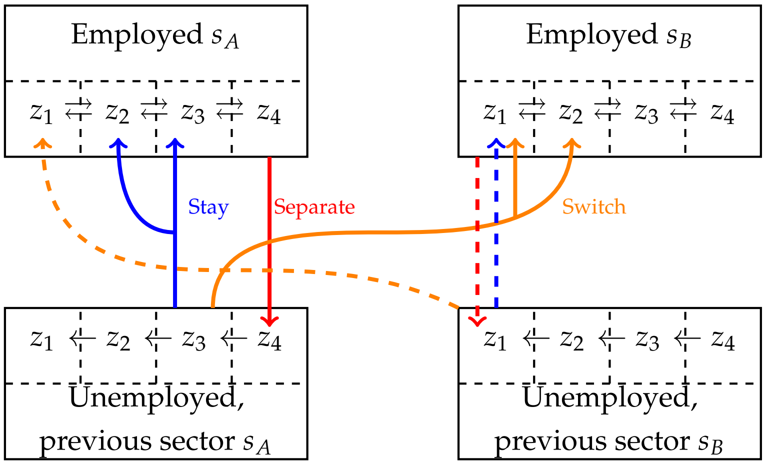


Figure 2: Example of Household Block for the Two-sector Case

Notes: The red arrow represents job separation. Blue arrows represent finding employment in the same industry as the previous. Orange arrows represent finding employment in a different industry than the previous. Arrows are illustrative and not exhaustive.

a notion of productivity loss during periods of unemployment. Furthermore, I make the restriction that the individual can only lose one level of productivity in any given time period. This enables me to parameterise the transition matrix using a single parameter ξ.

Transitions UE. Jobs arrive with an exogenous rate in the spirit of McCall (1970). Λ is a key four-dimensional array which captures the UE transition rates. The elements of Λ are $\lambda_{ss'}^{zz'}$, capturing the arrival rate of potential jobs (z', s'), which may depend on the individuals's current states (z, s). I decompose this term into three elements. A term that captures only depends on the potential sector, a term that depends only on potential productivity and a term that relates to the individual's current state.

$$\lambda_{ss'}^{zz'} = \underbrace{\lambda_{s'}}_{\text{Base Sector Arrival Rate}} \cdot \underbrace{\lambda^{z'}}_{\text{Arrival Rate of Potential Productivity}} \cdot \underbrace{\mathbb{1}(z', s'|z, s)}_{\text{Switcher Status Component}} . \tag{1}$$

The first component is termed the base sector arrival rate. It captures the sector-specific component of the arrival rates out of unemployment and how jobs in different sectors may be easier or harder to find. In section 5 ahead, I shock this component when studying transition dynamics to aggregate and asymmetric shocks.

The second component captures the potential productivity component of the arrival rates. This captures that jobs of different productivity may be easier or harder to find. The third component captures how the menu of arrival rates may differ depending on the individual's last sector and the potential new sector. $\mathbb{1}(z', s'|z, s)$ takes the value of one if given the individual's current productivity and previous sector, the job (z', s) is in their individual's choice set and zero otherwise. I collect the switcher status component into a matrix Θ^{ss} for sector stayers and $\Theta^{ss'}, s' \neq s$ for sector switchers. I make the following assumptions:

Assumption 1 *(No productivity gains through unemployment):* $\forall s, s' \quad \mathbb{1}(z', s'|z, s) = 0$ if $z' > z$.

This restricts individuals' choice sets such that they are not able to receive higher productivity offers while unemployed. That is, a costly effect of unemployment is that individuals are not able to increase their earnings potential. In particular, this assumption rules out training programs. I make this assumption given the evidence on the cost of job loss stated in the empirical section and found in the literature.[19] To capture a notion of sector-specific productivity, I will make the following assumption:

Assumption 2 *(Costly Switching): For $s' \neq s$, $\Theta^{ss'} = \Theta^{ss} \cdot L$ where L a matrix which shifts the columns of Θ^{ss} to the left.*

That is, for a job in a sector that is *different* from their last sector of employment, the individual's choice set is restricted to lower productivity jobs compared to jobs in the *same* sector as their last sector of employment.[20]

Assumption 3 *(Risk & Reward): $\lambda^{z'}$ is non-increasing in z'.*

This assumption implies that jobs with higher productivity are harder to find. Therefore, it is riskier to hold out for a higher-paying job.[21]

Given the three assumptions listed above, in the stationary equilibrium, displaced workers face a trade-off between finding jobs in which their productivity would be lower, at the gain of a higher arrival rate. The dimension of sector-switching can potentially make this trade-off even more stark, especially when the base sector arrival rates are different.

The sector dimension of the model matters for two reasons. First, the finding rate per unit of search effort can potentially differ by sector. That is, it may be easier to find a job in one sector compared to another. Second, the current sector of the individual determines the range of jobs available to search for. The assumption made in this model is that searching in a different sector as the individual's last sector results in a higher probability of working in a lower productivity job.

Savings of the employed. Individuals are risk-averse. In every period, the employed consumes and saves in a non-state contingent asset subject to a borrowing limit. They are able to work for a firm in a sector, indexed by s. The Hamilton-Jacobi-Bellman (HJB) equation of an employed individuals is given by:

$$\begin{aligned}\rho v_t(a,z,e,s) - \partial_t v_t(a,z,e,s) = \max_{c,\ell} \mathcal{U}(c,\ell) + \partial_a v_t(a,z,e,s)[r_t a + (1-\tau)w_{st} z\ell - c] \\ + \underbrace{\zeta_s[v_t(a,z,u,s) - v_t(a,z,e,s)]}_{\text{Transition to unemployment}} \\ + \underbrace{\sum_{\tilde{z}} \pi_{z\tilde{z}}[v_t(a,\tilde{z},e,s) - v_t(a,z,e,s)]}_{\text{Productivity Risk}},\end{aligned} \tag{2}$$

[19] See figure 9 below.

[20] Again, I refer to figure 9 on the cost of job loss to motivate this assumption.

[21] Note that models featuring directed search also have this feature. See for example Menzio and Shi (2011). However, as there is no vacancy posting in this model, I assume this property directly.

subject to a state constraint which ensures that $a \geq \underline{a}$,

$$\partial_a v_t(\underline{a}, z, e, s) \geq \mathcal{U}_c(r_t \underline{a} + (1-\tau) w_{st} z \ell - c).$$

Employed individuals have log preferences over consumption and isoelastic preferences on the intensive margin of labor supply

$$\mathcal{U}(c, \ell) = \log c - \psi_\ell \frac{\ell^{1+\frac{1}{\varphi_\ell}}}{1+\frac{1}{\varphi_\ell}},$$

where φ_ℓ is the Frisch elasticity.

They earn a wage w_{st} per efficiency unit and supply hours on the intensive margin ℓ. Labor income is subject to a marginal tax rate τ.[22] During employment, the individual faces two types of risk. First, individuals may become exogenously separated from their jobs and enter the unemployment state with an arrival rate ζ_s. The employment risk is sector-specific as the labor market is segmented by sectors. Note that the individual maintains his current productivity level upon entering unemployment.

Second, the idiosyncratic productivity is subject to exogenous risk both upwards and downwards. This is captured by $\pi_{z\tilde{z}}$. Productivity can move up by one step and captures the notion of increasing productivity over time and should be thought of as 'learning-by-doing'. Productivity can also fall to the previous step. This captures other idiosyncratic risks aside from employment risk. This feature is important to quantitatively match the data on the correlation between income and wealth. In contrast to the employment risk, productivity risk is *not* sector-specific. I do this such that there are no ex-ante differences in the sectors.[23]

Savings of the unemployed. Unemployed individuals have the following HJB equation:

$$\begin{aligned}\rho v_t(a,z,u,s) - \partial_t v_t(a,z,u,s) = \max_{c,\{\sigma_{s\tilde{s}}\}_{\tilde{s}}} & \widetilde{\mathcal{U}}(c) + \partial_a v_t(a,z,u,s)[r_t a + \mathcal{T}_t(z,s) - c] \\ & + \underbrace{\xi[v_t(a,z_-,u,s) - v_t(a,z,u,s)]}_{\text{Depreciation of Productivity}} - \underbrace{\kappa}_{\text{Utility Cost of Unemployment}} \\ & + \sum_{s'=1}^{n_s}\sum_{z'=1}^{n_z} \sigma_{ss'}^{zz'} \cdot \left(\underbrace{\lambda_{ss'}^{zz'} \cdot [v_t(a,z',e,s') - v_t(a,z,u,s)]}_{\text{Gain from directing search}} \underbrace{-\frac{1}{\nu}\log \sigma_{ss'}^{zz'}}_{\text{Cost of Search}} \right),\end{aligned} \tag{3}$$

subject to

$$\partial_a v_t(\underline{a}, z, u, s) \geq \widetilde{\mathcal{U}}_c(r_t \underline{a} + \mathcal{T}_t(z,s) - c), \qquad \sum_{s'=1}^{n_s}\sum_{z'=1}^{n_z} \sigma_{ss'}^{zz'} = 1,$$

where $\widetilde{\mathcal{U}}(c) = \log c$.

[22] For simplicity, I do not allow for the employed to directly switch sectors as the focus of this paper is on labor reallocation through unemployment.

[23] The model is amenable to this extension. This would capture any differences in the life-cycle earnings profile across industries.

Unemployed individuals are also able to consume and save, subject to a borrowing constraint. They receive transfers from the government $\mathcal{T}_t(z,s)$.[24] The unemployed also face a productivity risk. With an arrival rate ξ, their productivity falls one step. I denote the subsequent productivity level by z_-. This captures negative duration dependence - that is, the wages upon re-employment are often lower than the pre-employment wage, and even lower for longer unemployment duration.

Job search. Displaced workers are endowed with a unit of search effort, supplied inelastically.[25] The novel feature of this model is that displaced workers can choose the *direction* in which they exert their search effort. In particular, the individual chooses how much their search effort is spread across jobs. This is represented by the conditional choice probability $\sigma_{ss'}^{zz'}$ - the fraction of effort directed to finding jobs in sector s' at productivity level z' for an individual who was last employed in sector s with productivity level z. Thus, an individual chooses a probability distribution over the jobs in which they exert search effort. The effective job-finding rate for an individual previously employed in sector s with current productivity z and transitioning to employment in sector s' with potential productivity z' is given by $\lambda_{ss'}^{zz'} \cdot \sigma_{ss'}^{zz'}$.

The value function adds a term which captures the search costs. This captures the idea that an individual would face a utility cost from directing their search, or in other words, a cost from *not* hedging. Alternatively, it can be thought of as the information *gain* from searching in different markets.[26] I include this feature for two reasons. First, in the data, for a given pair of sectors, we see individuals reallocating in *both* directions. Refer to figure 6. Second, this results in a tractable form for the policy functions of the conditional choice probability and search effort.

Proposition 1. *The policy function for the conditional choice probability is given by*

$$\sigma_{ss'}^{zz'}(a,z,u,s) = \frac{\exp\left(\nu \cdot \lambda_{ss'}^{zz'} \cdot [v(a,z',e,s') - v(a,z,u,s)]\right)}{\sum_{s'=1}^{n_s}\sum_{z'=1}^{n_z} \exp\left(\nu \cdot \lambda_{ss'}^{zz'} \cdot [v(a,z',e,s') - v(a,z,u,s)]\right)}. \tag{4}$$

The proof directly follows from taking the first-order condition. The conditional choice probability has a multinomial logit form and as a result, this smooths out discrete choices in the model. The assumption of directing search effort across different jobs and sectors is closer to the assumption of 'semi-directed' search that is commonly used in the literature.[27]

[24]The present model does not have unemployment insurance that expires after a duration of time. In Appendix D, I run a similar regression kink design exercise for the potential duration as in Landais (2015) and I do not find any significant effects on labor reallocation. There are also no unemployment insurance benefit eligibility criteria in the model as in the real-life economy. Eligibility criteria are usually based on a minimum amount of earnings in the base period. As my model does not track past earnings, it is not possible to add this feature to the model. Additionally, there are no in-kind government transfers explicitly modelled, capturing programs such as food stamps. However, as all unemployed individuals are eligible to receive unemployment insurance, there is a minimum amount of transfers that all individuals receive.

[25]In Appendix H, I consider a model with an intensive margin of search effort.

[26]This form of entropy costs has been used in the literature on incomplete information. This term is denoted as the expected entropy cost. See for example Matějka and McKay (2015) and Flynn and Sastry (2023).

[27]The current literature relies on 'taste shocks' to achieve the same properties. Note that there is a similarity to type-I Extreme Value (Gumbel) distributed taste shocks. The parameter ν plays a similar to role to the (inverse) scale parameter. For example, see Pilossoph (2012) and Chodorow-Reich and Wieland (2020). While my model is in the same spirit as the literature, the switching mechanism in this model is entirely endogenous as it does not rely on shocks.

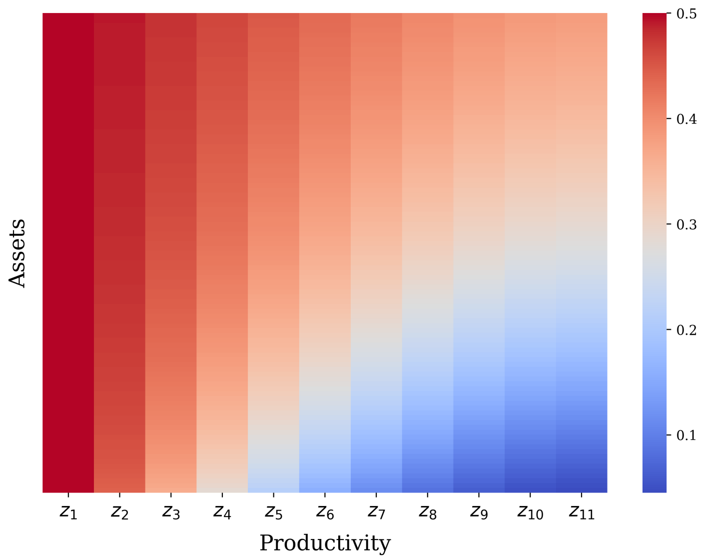


Figure 3: Conditional Choice Probability for Switching Sectors

Notes: This figure plots the policy function for switching sectors, $\sigma_{ss'} = \frac{\sum_{z'=1}^{n_z} \exp\left(\nu \cdot \lambda_{ss'}^{zz'} \cdot [v(a,z',e,s') - v(a,z,u,s)]\right)}{\sum_{s'=1}^{n_z} \sum_{z'=1}^{n_z} \exp\left(\nu \cdot \lambda_{ss'}^{zz'} \cdot [v(a,z',e,s') - v(a,z,u,s)]\right)}$ for some $s' \neq s$. z_1 denotes the lowest productivity level. Moving vertically along the figure denotes higher assets. Moving horizontally along the figure denotes higher productivity.

The intuition is that displaced workers direct their search more towards sectors with either a high finding rate per unit of search effort, or a higher expected gain from employment relative to unemployment. Summing up across jobs of different potential productivities, the probability of switching sectors is defined as

$$\sigma_{ss'}(a,z,u,s) \equiv \sum_{z'} \sigma_{ss'}^{zz'}. \tag{5}$$

The parameter ν governs how strong these forces translate to the direction of the search effort. In particular, as $\nu \to 0$, we have $\sigma_{ss'} \to \frac{1}{n_s} \forall s$. The intuition can be confirmed for the case where an individual faces no cost of switching industries.

It should be noted that once the individual receives a job offer, they do not have the option of rejecting the offer and remaining unemployed. Without this assumption, stationary equilibria in which sectors are not identical do not exist. Intuitively, if the individual always has the option of rejecting a job offer, they will remain unemployed until a job opportunity arrives from a sector that pays the highest wage. As individuals are able to choose the intensive margin of work, they are willing to accept losses in productivity as it is offset by a higher wage per efficiency unit. In aggregate, as all individuals will only work for the sector that pays the highest wage, the labor markets cannot clear. For the same reason, I do not allow for quits in the model.

Sector switching policy function. Figure 3 illustrates a heat map of sector switching policy function ($\sigma_{ss'}$) in an illustrative calibration of the model.[28] In particular, I show the extreme case where the set of potential jobs in a different sector is restricted to the lowest productivity level. Therefore a high-productivity agent loses more productivity upon switching sectors.

[28] In the calibration section below, I calibrate to a less extreme case, as documented in the data section.

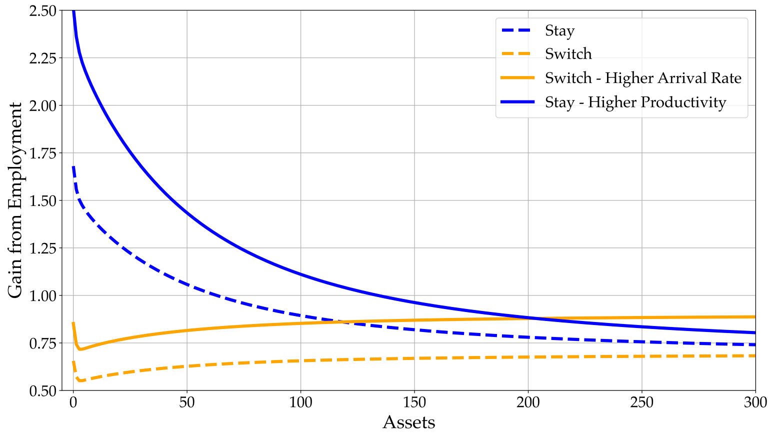


Figure 4: More Detail on the Conditional Choice Probability

Notes: This figure plots the gain from employment defined as the arrival rate multiplied by the change in the value function, $\lambda_{ss'}^{zz'} \cdot [v(a,z',e,s') - v(a,z,u,s)]$. These are components of the policy function for switching sectors, $\sigma_{ss'} = \frac{\sum_{z'=1}^{n_z} \exp\left(\nu \cdot \lambda_{ss'}^{zz'} \cdot [v(a,z',e,s') - v(a,z,u,s)]\right)}{\sum_{s'=1}^{n_z} \sum_{z'=1}^{n_z} \exp\left(\nu \cdot \lambda_{ss'}^{zz'} \cdot [v(a,z',e,s') - v(a,z,u,s)]\right)}$ for some $s' \neq s$.

Moving vertically along the plot shows how the conditional choice probability changes when assets are increased holding productivity fixed. Moving horizontally along the plot shows how the probability changes when productivity changes holding asset holdings fixed.

An individual at the lowest productivity level (z_1) has the highest effort directed to switching. This is because there is no productivity cost for switching sectors. As the productivity level increases, the individual is less likely to put effort into switching industries. Intuitively, this is due to the individual falling into a lower productivity state, thereby giving up higher wages upon re-employment. Note that the relevant comparison is the distance between the potential and current productivity levels.

As the asset level increases, an individual is more likely to direct effort towards switching. The intuition is that a high-asset individual is more able to smooth the earnings losses that occur with switching industries. In other words, the (instantaneous) marginal propensity to change sectors out of liquid wealth is positive.

Figure 4 plots the terms inside the sector switching policy function. In particular, it plots the arrival rate multiplied by the change in the value function, $\lambda_{ss'}^{zz'} \cdot [v(a,z',e,s') - v(a,z,u,s)]$, or the 'gain from employment'. Note that this is decreasing in the asset holdings of the individual. Intuitively, agents at the borrowing constraint have the highest gain from employment as they have no assets to use for consumption. As assets increase, there is a lower gain from employment as current assets can be dis-saved for consumption.

The dashed lines plot this for staying in the same sector (blue) and switching to a different sector (orange) while *holding the arrival rate fixed*. The blue dashed line is uniformly above the orange dashed line, indicating that for the same arrival rate, the gain from finding a job in the same sector as before is larger than switching to a different sector. This is because switching leads to a lower productivity job. Notice that as assets increase, the gap between the two lines narrows. The reason for this is that with enough assets, short-run changes in productivity matter less for the welfare of the individual as they can dis-save assets to smooth income fluctuations. In other words, the marginal propensity to change sectors out of liquid wealth is *positive*. This corresponds to moving vertically in Figure 3.

The solid orange line illustrates the case when the arrival rate for switching industries is relatively *higher*. This results in an upward movement relative to the orange dashed line. As a result, the gap to the blue dashed line is much smaller and the two lines intersect. For high enough assets, the individual prefers to switch. Intuitively, when the individual has enough assets, they can take the option of switching which entails finding a job quicker, but at a lower productivity. This is because the assets allow the individual to maintain consumption while building up productivity on the job and leaving unemployment much faster. Unemployment is costly due to both the lower income stream and the risk of losing productivity over time.

Finally, the blue solid line illustrates the case when the productivity for working in the same sector is *higher*. This results in an upward shift of the gain from employment due to the higher wages resulting from employment. The gap between the solid blue line and the orange dashed line is much larger, signifying that individuals with a higher level of specific productivity are less likely to switch industries, holding other factors constant. This corresponds to moving horizontally in Figure 3.

Result 1 *For individuals above the lowest level of productivity, the (instantaneous) marginal propensity to change sectors out of liquid wealth is positive.*

$$\frac{\partial \sigma_{ss'}}{\partial a}(a, z, u, s) > 0, \quad \forall z > \underline{z}, s \neq s' \tag{6}$$

Utility cost of unemployment. The fixed utility cost of unemployment should be thought of as a 'psychic cost'. It captures the notion that individuals dislike being unemployed. I include this in the model for two reasons. First, it helps offset the search cost term from the utility function. Though the name 'cost' suggests that the contribution of this term decreases utility, in practice this term is positive as the individual gains information from searching across different jobs. Second, the fixed utility cost helps ensure that enough individuals prefer employment to unemployment, even holding the potential productivity fixed.[29] In the calibration section, I set the utility cost such that the relative disutility terms when employed and unemployed are of a similar magnitude.[30]

Aspects left out of model. I abstract from endogenous search and matching frictions in the spirit of Diamond-Mortensen-Pissarides. This is for simplicity in solving for wages, which would otherwise depend on the asset holdings of individuals.[31] Instead, the model features one-sided search in the

[29] This affects how the choice probabilities change in response to changes in the arrival rates. Taking the derivative of the choice probabilities with respect to arrival rates yield

$$\frac{\partial \sigma_{s\tilde{s}}^{z\tilde{z}}}{\partial \lambda_{s\tilde{s}}^{z\tilde{z}}} \propto \nu \cdot [v(a, \tilde{z}, e, \tilde{s}) - v(a, z, u, s)]$$

and the derivative is proportional to the gain from employment. Thus, for an individual to direct their search towards a higher arrival-rate job, the gain from employment must be positive. In theory, the value of unemployment can be large as unemployment contains an option value of searching for higher productivity jobs. The fixed utility cost must be neither too small, as to discourage searching for high arrival-rate jobs, nor too large such that the individual will take any job.

[30] In particular, I set the maximum relative disutility terms between employment and unemployment states to zero across the state space.

[31] See Krusell, Mukoyama, and Şahin (2010) for a full explanation of the problem and Ifergane (2022) for a candidate

spirit of McCall (1970). As such, there is no vacancy-posting by firms nor is there any wage-posting or bargaining. Instead, wages are determined in the spot market by the equilibrium of the labor market in each sector.

I abstract from on-the-job search as the focus of the paper is on how liquidity affects the labor reallocation decision of the unemployed. However, in the model, the employed can still gain productivity while on the job. Including on-the-job search would only affect the arrival rates of moving up the productivity ladder. I leave this extension for future work.

Furthermore, this model abstracts from training and other non-pecuniary elements of jobs such as amenities (Bagga, Mann, Sahin, and Violante, 2023) and job security (Jarosch, 2023). However, including each of these elements in the model is likely to strengthen the positive effect of liquidity on labor reallocation.[32]

2.2 Firms

Final goods. There are n_s sectors in the economy. Aggregate consumption and investment goods are a nested CES over intermediate sectoral goods. In particular,

$$C_t = \left[\sum_{s=1}^{n_s} \omega_s^{\frac{1}{\eta}} C_{st}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \tag{7}$$

where intermediate goods is a bundle of firms' goods

$$C_{st} = \left(\int_0^1 C_{jst}^{\frac{\epsilon-1}{\epsilon}} dj \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{8}$$

Similarly, for investment

$$I_t = \left[\sum_{s=1}^{n_s} \omega_s^{\frac{1}{\eta}} I_{st}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \tag{9}$$

where

$$I_{st} = \left(\int_0^1 I_{jst}^{\frac{\epsilon-1}{\epsilon}} dj \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{10}$$

η is the elasticity of substitution across sectors and ϵ is the elasticity of substitution across firms. This leads to the usual constant elasticity of demand functions sectoral consumption and sectoral investment demand for firms.

Intermediate goods. There is a representative firm in each sector.[33] Firms hire labor and capital on the spot market. Their production technology takes the Cobb-Douglas form with constant returns

$$Y_{jst} = Z_{st} K_{jst}^{\alpha} N_{jst}^{1-\alpha},$$

solution.

[32]Indeed, in recent work, Figueiredo, Marie, and Markiewicz (2023) find that liquidity mitigates the medium-run cost of job loss by reducing losses in job security.

[33]I abstract from firm heterogeneity. Therefore, there is no sorting in the model. For references of models featuring incomplete markets and sorting, see Eeckhout and Sepahsalari (2023) and Huang and Qiu (2023).

where Z_{st} is the productivity level in sector s and α is the capital share of income. Firms are monopolistically competitive in the output market and perfectly competitive in input markets. First, firms choose the capital and labor inputs to minimise cost, subject to a production constraint

$$\min_{K_{jst}, N_{jst}} r_t^K K_{jst} + w_{st} N_{jst} \text{ s.t. } Y_{jst} \geq \bar{Y}. \tag{11}$$

This results in a marginal cost

$$m_{st} = \frac{1}{Z_{st}} \left(\frac{r_t^K}{\alpha}\right)^{\alpha} \left(\frac{w_{st}}{1-\alpha}\right)^{1-\alpha}, \tag{12}$$

and factor demands,

$$K_{jst} = \frac{\alpha m_{st} Y_{jst}}{r_t^K}, \tag{13}$$

$$N_{jst} = \frac{(1-\alpha) m_{st} Y_{jst}}{w_{st}}. \tag{14}$$

Then, they set prices and production to maximise profits subject to the demand constraint,

$$\max_{p_{jst}, Y_{jst}} p_{jst} Y_{jst} - m_{st} Y_{jst} \text{ s.t. } Y_{jst} \leq \left(\frac{p_{jst}}{P_{st}}\right)^{-\epsilon} (C_{st} + I_{st}). \tag{15}$$

This results in an optimal price,

$$p_{jst} = \frac{\epsilon}{\epsilon - 1} m_{st}, \tag{16}$$

which is identical across firms.

2.3 Other Blocks

Financial intermediary. There is a representative, risk-neutral financial intermediary in the economy. The intermediary has three functions. First, they take the assets of individuals and direct the funds towards different assets in the economy. This includes capital, government bonds and equity.[34] Second, they own and accumulate capital in the economy and rent it out to firms. Third, they serve as a mutual fund, which has a claim on dividends flows from firms. Thus, in any given period, the intermediary's balance sheet is

$$\mathcal{A}_t + B_t^g = K_t + p_t^Q, \tag{17}$$

where $\mathcal{A}_t$ is the total assets supplied by individuals, B_t^g is government bonds, K_t is aggregate capital and p_t^Q is the price of an asset that lays claim to aggregate dividends (mutual funds).[35] To hold a positive amount of each asset, there is a no-arbitrage condition given by

$$r_t = r_t^K - \delta = r_t^b = r_t^Q. \tag{18}$$

This simplifies the structure of the model greatly as there is only one (ex-ante) interest rate to solve for. As owners of capital, the financial intermediary accumulates capital according to the law of motion

$$\dot{K}_t = I_t - \delta K_t. \tag{19}$$

[34] The inclusion of both bonds and capital in the model is in the spirit of Aiyagari and McGrattan (1998) and more recently Kaplan, Moll, and Violante (2018) and Aguiar, Amador, and Arellano (2023). In particular, the setup of the financial intermediary is similar to the latter paper.

[35] $B_t^g < 0$ means that there is a positive amount of government debt.

Government. The government taxes labor income using proportional taxes and borrows from individuals to fund transfers to the unemployed. I assume that there is no government consumption. The government budget constraint is given by,

$$\mathcal{T}_t + \dot{B}_t^g = \tau \sum_{s=1}^{n_s} w_{st} N_{st} + r_t^b B_t^g, \tag{20}$$

where $\mathcal{T}_t$ is the sum of all transfers made to unemployed individuals. For the government's transfer policy, I have specified the following form

$$\mathcal{T}_t(z,s) = \min\{\chi w_{st} z \ell, \bar{\mathcal{T}}\}, \tag{21}$$

where χ is the replacement rate of transfers and $\bar{\mathcal{T}}$ is maximum transfers. This captures the kink in the relationship between (past) earnings and weekly benefits as in the data. To keep the model tractable, an unemployed's transfers are based on the earnings that they *would* have received had they been employed. Without this assumption, a further state variable is required in order to track down the individual's last earnings. A similar treatment has also been used in the literature. [36] In the baseline model, I assume that the tax rate is constant. The government debt adjusts such that the inter-temporal budget constraint holds.

2.4 Market Clearing and Distribution

Evolution of the distribution. The Kolmogorov Forward Equation (KFE) captures how the distribution of individuals evolves over time. The KFE for the employed is given by

$$\begin{aligned} \partial_t g_t(a,z,e,s) = &- \partial_a[\varsigma_t(a,z,e,s) g_t(a,z,e,s)] \\ &+ \sum_{\tilde{z}=1}^{n_z} \pi_{\tilde{z}z} g_t(a,\tilde{z},e,s) - \sum_{\tilde{z}=1}^{n_z} \pi_{z\tilde{z}} g_t(a,z,e,s) - \zeta_s g_t(a,z,e,s) \\ &+ \sum_{s'=1}^{n_s} \sum_{z'=1}^{n_z} \lambda_{s's}^{z'z} \sigma_{s's}^{z'z} f(x) g_t(a,z',u,s'), \end{aligned} \tag{22}$$

where $\varsigma_t(a,z,e,s) = r_t a + (1-\tau) w_{st} z \ell - c_t(a,z,e,s)$ is the savings policy of the employed. The KFE for the unemployed is given by

$$\begin{aligned} \partial_t g_t(a,z,u,s) = &- \partial_a[\varsigma_t(a,z,u,s) g_t(a,z,u,s)] + \xi g_t(a,z_+,u,s) - \xi g_t(a,z,u,s) \\ &+ \zeta_s g_t(a,z,e,s) - \sum_{s'=1}^{n_s} \sum_{z'=1}^{n_z} \lambda_{ss'}^{zz'} \sigma_{ss'}^{zz'} f(x) g_t(a,z,u,s), \end{aligned} \tag{23}$$

where $\varsigma_t(a,z,u,s) = r_t a + \mathcal{T}_t(z,s) - c_t(a,z,u,s)$ is the savings policy of the unemployed.

Market clearing. There are $2n_s + 1$ markets to clear. First, there is one capital market that clears at the aggregate level. This is because firms rent capital in every period and there are no barriers to capital mobility. The clearing condition is

$$K_t^d = K_t = \mathcal{A}_t + B_t^g - p_t^Q, \tag{24}$$

[36] See for example McKay and Reis (2016) and Beraja and Zorzi (2023).

where $\mathcal{A}_t = \sum_{s=1}^{n_s} \sum_{e=0}^{1} \sum_{j=1}^{n_z} \int_{\underline{a}}^{\infty} a g_t(a, z_j, e, s) da$ is the stock of assets of individuals. Second, there are n_s labor markets, one for each sector. This is due to the assumption that labor markets are sector-specific. The clearing condition is

$$N_{st} = L_{st} \quad \forall s, \tag{25}$$

where L_{st} is the effective labor employed in sector s, defined by $L_{st} = \sum_{j=1}^{n_z} \int_{a=\underline{a}}^{\infty} z_j \ell_t g_t(a, z_j, e, s) da$.[37] Finally, there are n_s goods markets, one for each sector. This is due to the nested-CES setup of the model, and that each sector is a differentiated good.

$$Y_{st} = C_{st} + I_{st} \quad \forall s, \tag{26}$$

where $C_{st} = \omega_s p_{st}^{-\eta} C_t$ is sectoral consumption, $I_{st} = \omega_s p_{st}^{-\eta} I_t$ is sectoral investment and $C_t = \sum_{s=1}^{n_s} \sum_{e=0}^{1} \sum_{j=1}^{n_z} \int_{\underline{a}}^{\infty} c_t(a, z_j, e, s) g_t(a, z_j, e, s) da$ is aggregate consumption.

2.5 Definition of Equilibrium

Definition An equilibrium is a sequence of solutions to the individual's problem $\{c_t, \ell_t, x_t, \sigma_t, v_t\}$, a sequence of distributions $\{g_t\}$, a sequence of solutions to the firm's problem $\{n_{jst}, k_{jst}\}$, a sequence of prices $\{w_{st}, p_{st}, p_t^Q, r_t\}$, a sequence of government fiscal policy $\{\tau, \mathcal{T}_t, B_t^g\}$ and a sequence of aggregate quantities $\{K_t, N_{st}, Y_{st}, C_{st}, I_{st}, \mathcal{A}_t\}$ such that

1. Given a sequence of prices $\{w_{st}, p_{st}, p_t^Q, r_t\}$ and government fiscal policy $\{\tau, \mathcal{T}_t, B_t^g\}$, $\{c_t, \ell_t, x_t, \sigma_t, v_t\}$ solves the individual's problem
2. Given the solution for the individual's problem $\{c_t, \ell_t, x_t, \sigma_t, v_t\}$, the sequence $\{g_t\}$ satisfies the Kolmogorov Forward Equation.
3. The aggregate quantities $\{K_t, N_{st}, Y_{st}, C_{st}, I_{st}, \mathcal{A}_t\}$ are compatible with the sequence of individual's policy functions and the sequence of distributions.
4. Given prices $\{w_{st}, r_t\}$, $\{n_{jst}, k_{jst}, p_{jst},\}$ solves the firm's problem
5. The government budget constraint is satisfied
6. The capital, goods, and labor markets clear

The model is solved using finite differences and an upwinding scheme following Achdou, Han, Lasry, Lions, and Moll (2021). Appendix G provides the algorithm to solve for the equilibrium.

[37] The assumption here is that workers of different productivity levels are perfectly substitutable. That is, a worker with twice the level of productivity of another simply can provide more units of effective labor. There is no complementarity between workers of different productivity levels.

3 Institutional Setting, Data, and Empirics

This section presents the main empirical results. First, I introduce the institutional context of the kinked Unemployment Insurance schedules across various U.S. states and introduce administrative data from Washington state. Then, I introduce the empirical setup to study the effect of liquidity on labor reallocation, appealing to a regression kink design commonly used in the Public Finance literature studying the effects of unemployment insurance. Last, I study the medium-run implications of labor reallocation by implementing a 'cost-of-job-loss' regression.

3.1 Institutional Setting

Unemployment insurance (UI) in the U.S. is administered at the state level. Each state has its own rules regarding eligibility, duration and generosity. To be eligible for UI, an unemployed person must have earned a base period wage (BPW) above some threshold. The BPW is the total earned income in some base period, usually the last five calendar months. Conditional on eligibility, the weekly benefit amount (WBA) paid out to the unemployed depends on a different notion of past earnings. In many states, the WBA is determined as a fraction of the highest quarterly wage (HQW) in the base period. That is, the HQW is the maximum of the last five quarters of earnings.[38]

In all states, there is a cap on the weekly benefits. Hence the UI schedule appears as a kink as there is some threshold of HQW above which the WBA no longer increases. This feature can be exploited to give a quasi-random experiment comparing individuals just above and just below the kink. Over time, the cap is adjusted to reflect changes in the cost of living. Figure 5 shows an example of how the unemployment benefit schedule has changed over time for the state of Washington. States change the maximum amount in response to inflation.

3.2 Data

The administrative data comes from the Continuous Wage Benefit Histories project (CWBH). The data covers the universe of unemployment spells in each of the states covered by the project.[39] The data contains information on past earnings (BPW, HQW), the weekly benefits received by unemployed individuals in each week of their unemployment spell, and some limited demographic information. For the state of Washington, there is also a matched employer-employee module. This is essential for the study of labor reallocation as it allows me to track the employer prior to, and after an unemployment spell. Furthermore, the Standard Industry Code (SIC) of the employer is also reported. Therefore, I am able to track cross-industry reallocation.[40] For the rest of the paper, I will focus on the data from Washington. The Washington data covers 1979-1983.

[38] Some states have a slightly different formula. For example, in Washington, the HQW is the average of the largest two quarters of earnings in the BPW.

[39] This includes Idaho, Louisiana, Missouri, New Mexico and Washington for the period 1979-1985.

[40] Unfortunately the occupation of a worker is only collected upon unemployment. Therefore, to track a change in occupation, I would require the worker to go through two unemployment spells. This is rare in the sample.

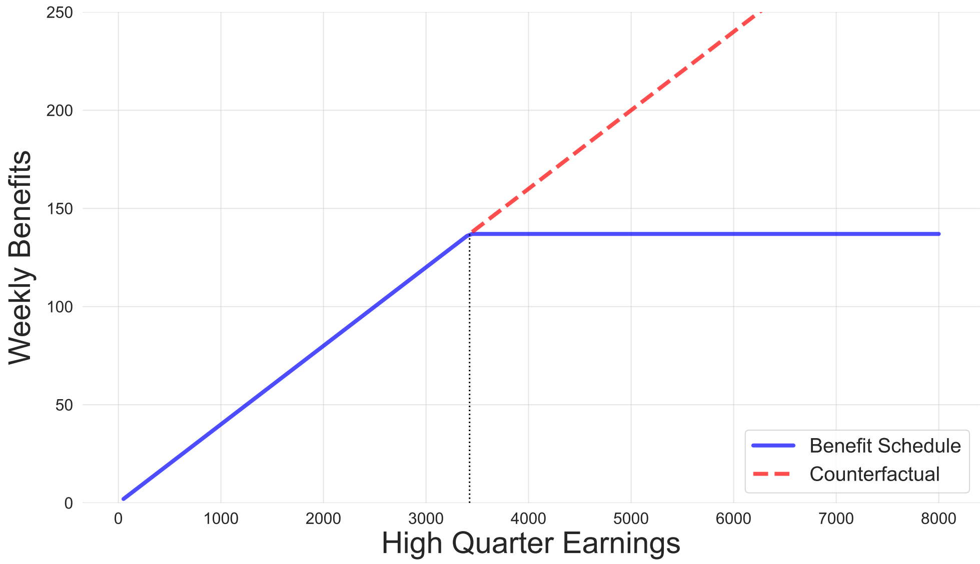


Figure 5: Unemployment Insurance Schedule, Washington, 1979-1980

NOTES: Data from U.S. Department of Labor - Employment & Training Administration. Weekly benefits and High Quarter Earnings figures are expressed in 1979 dollars.

Summary statistics. Table 1 shows the summary statistics of the CWBH sample for the state of Washington. There were 41,992 individuals who underwent a spell of unemployment in the period covering 1979 to 1983. The sample covers mostly men, with an average age of 34.2 and an average of 12.4 years of education.

The mean base period wage was $31,232 in 2010 dollars. The mean HQW was $8,982 and the mean weekly benefits were $286 in 2010 dollars. Around 37% of the sample received the maximum amount of weekly benefits. The mean duration of an unemployment spell was 17.6 weeks. Around 79% of valid responses reported that they were laid off by their previous employer.

Regarding reallocation, 27,081 individuals go on to find a job after their unemployment spell. The remainder had not found a job by the end of the sample. At the SIC 1-digit level, the fraction of individuals that found a job in a different industry is 36%. Even with a relatively large definition of a sector, there is a non-trivial rate of switching. Mechanically, the fraction that reallocates across industries increases as I use a finer definition of SIC industries. It increases to 47%, 51% and 53% for SIC 2-digit, 3-digit and 4-digit respectively. The data also contains a self-reported measure of displacement.

Figure 6 shows the extent of labor reallocation at the SIC 1-digit level. An interesting observation in this picture is that there are instances of *gross* labor reallocation between a pair of sectors. This suggests that unemployed individuals search broadly across sectors. Take for example manufacturing and retail trade sectors. The figure shows that there are flows in both directions - from manufacturing to retail trade and vice versa. Notice that the colored bars on the left and right-hand sides of the figure change size. This reflects a notion of *net* labor reallocation across sectors.

A potential concern is that structural transformation is driving the entire labor reallocation process. In Figure 17 of Appendix A, I plot the employment share of agriculture, manufacturing and

Table 1: Summary Statistics, CWBH Washington

	Mean	SD
	Earnings and Benefits ($2010)	
Base Period Wage	31,232	20,380
High Quarter Wage	8,982	5,321
Gross Weekly Benefits	286.7	94.7
	Duration Variables (Weeks)	
Duration of Spell	17.6	15.4
	Reallocation Variables	
Change Industry (1 digit)	.36	.48
Change Industry (2 digit)	.47	.5
Change Industry (3 digit)	.51	.5
Change Industry (4 digit)	.53	.5
	Covariates	
Age	34.2	11.9
Male	.63	.48
Years of Education	12.4	2.4
Number of Dependents	1.7	1.5
Percent with max benefits	.37	.48
Replacement Rate	.47	.21
Fraction Displaced	.79	.41

services in Washington over time using the Quarterly Census of Employment and Wages (QCEW). I use the classification of industries as in Herrendorf, Rogerson, and Valentinyi (2014). I find that the employment share for these three broad sectors has changed very little during the period that the CWBH covers. Therefore, it's unlikely that structural transformation explains a large portion of the labor reallocation in the CWBH.

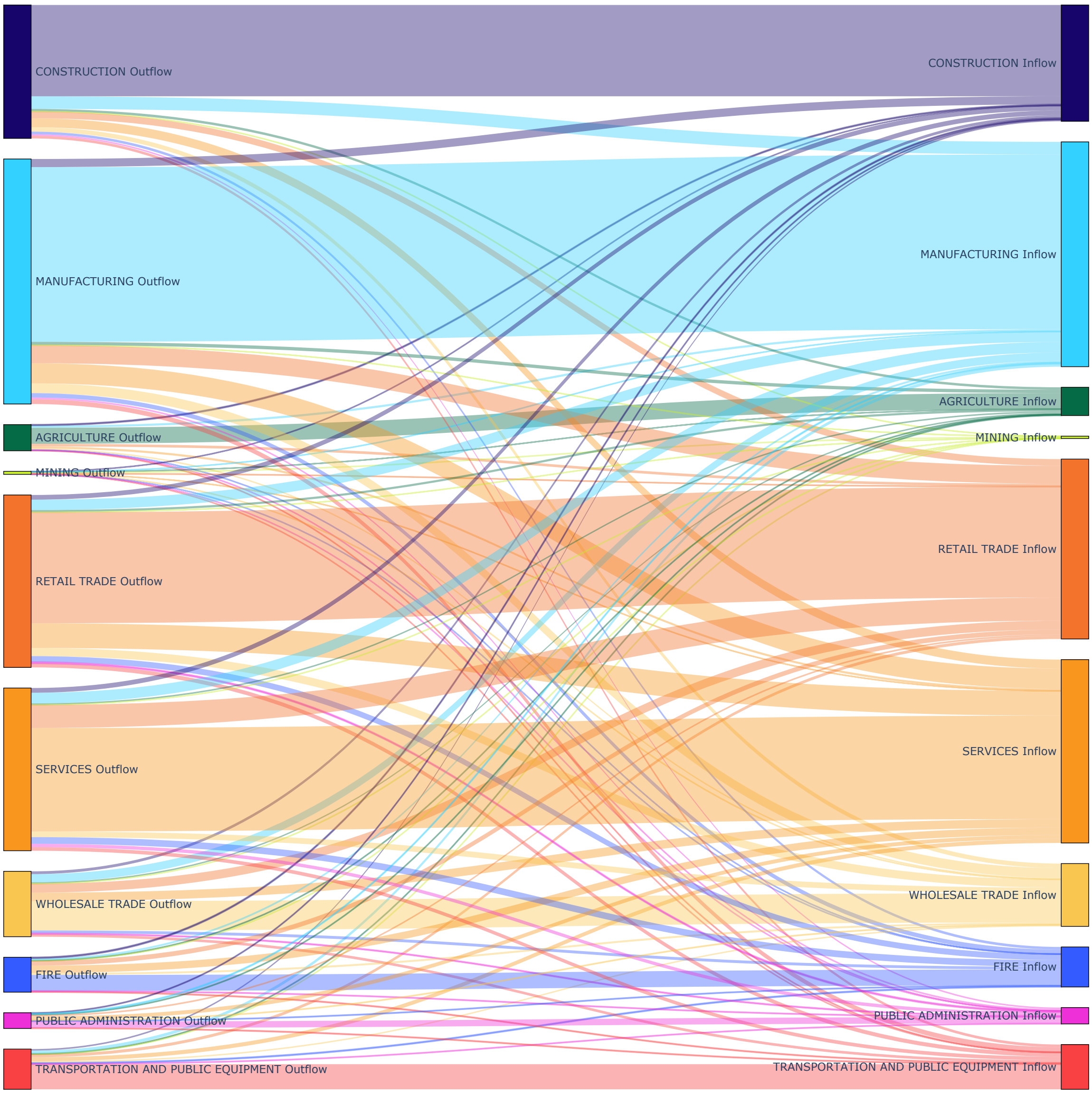


Figure 6: Labor Flows through Unemployment, SIC 1-digit, CWBH Washington, 1979-1983

3.3 Regression Kink Design

Identification. To identify the effect of liquidity on labor reallocation, I use the kinks in the UI schedule following a sharp Regression Kink Design (RKD). The main idea is that individuals just above the kink and just below the kink are similar. The location of whether they are above or below the kink is determined by their past earnings (HQW) - which is the assignment (or forcing) variable. There are two main identifying assumptions. First, the direct marginal effect of the assignment on the outcome variable should be smooth. Second, there should be a smooth density of unobserved variables at the kink. It is a reasonable assumption to assume that individuals do not have control over their past earnings and manipulate their position relative to the kink. Figure 7 shows a plot of the density (number of observations) of individuals around the kink and finds that they are smooth. In particular, there does not seem to be any bunching below the kink. In Appendix B, I show that observables are smooth around the kink.

The Regression Kink Design holds market-level factors constant. This is a benefit relative to stud-

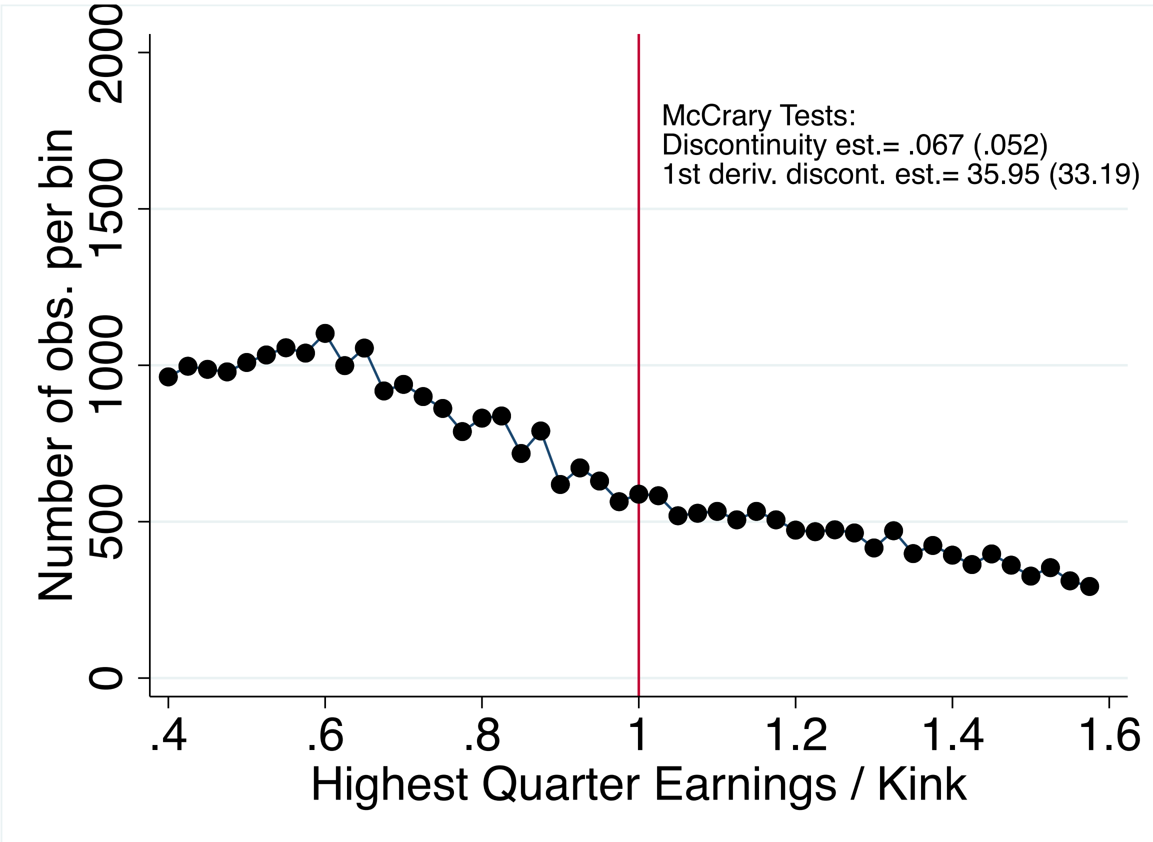


Figure 7: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

ies that exploit variation across regions or over time. Particular market-level factors include structural transformation and changes in the vacancy posting behavior of firms.

Regression. I run local polynomial regressions of the form

$$y_i = \mu_0 + \left[\sum_{p=1}^{\bar{p}} \gamma_p (w_i - k)^p + \nu_p (w_i - k)^p \cdot D_i \right] + \epsilon_i \tag{27}$$

where

$$|w - k| \leq h$$

The dependent variable is a dummy variable which takes the value of 1 if the individual switches sector upon re-employment and zero otherwise; w is the assignment variable; $D = \mathbb{1}[w \geq k]$ is an indicator variable for being above the kink threshold; h is the bandwidth size and $\bar{p}$ is the maximum polynomial order. The coefficient of interest is ν_1, which represents the change in the slope of the conditional expectation function close to the kink. The RKD estimator is

$$\hat{\alpha} = \frac{\hat{\nu}_1}{\tau_1} \tag{28}$$

where τ_1 is the change in the slope of the UI schedule at the kink. The intuition of the estimator is as follows. To the left of the kink, an increase in high quarter earnings affects three things: 1) It affects the outcome variable, 2) affects unobservables, and 3) increases weekly benefits. To the right of the kink, only the first two effects are present as weekly benefits are capped at the maximum. Thus, under the assumption that the first two effects are continuous at the kink, the regression coefficients will pick up only the third effect. Now we can proceed to the estimation results.

Result 2: *For individuals close to the kink, a marginal increase in liquidity leads to a higher propensity to switch industries.*

Figure 8 shows a binscatter of the pooled results for the SIC 3-digit industry. It shows that for individuals near the kink, a marginal increase in unemployment benefits leads to a higher propensity to switch industries. It should be noted that this picture alone states that unemployed individuals with higher past earnings have a lower propensity to switch. This is consistent with a notion of specific human capital or productivity. However, the key takeaway is that the relationship between the propensity to switch and past earnings changes significantly around the kink. That is, the slope is more negative to the right of the kink. In the absence of more benefits due to the cap, the propensity to switch industries falls.

Table 2 shows the regression coefficients. The main result is that a $10 increase in weekly benefits leads to an increase in the propensity to switch industries by 0.55 percentage points at the 1-digit SIC industry. This is relative to a mean industry switching rate of 36%. Adding controls lowers the effect to 0.47 percentage points, but remains significant. Changing the definition of industry to the SIC 3-digit level results in a slightly higher marginal effect of 0.58 percentage points.

How significant is the headline number? For comparison, Arizona has a similar unemployment insurance schedule. It has the same formula that determines weekly benefits: $\text{WBA} = 0.04 \times \text{HQW}$ but with a lower maximum weekly benefits, $115 compared to $178 in Washington in 1982. A back-of-the-envelope calculation suggests that if Washington had the same schedule as Arizona, the same individual would have had a lower propensity to reallocate by 7.81 percentage points, holding all other factors fixed. Given the average reallocation rate found in Washington of 36%, this figure is significant. [41]

Robustness. In Appendix C, I report the full set of results, broken down by each year, different levels of industry aggregation, bandwidth and polynomial orders. I also report the RKD for unemployment duration. The results in the previous section hold under different definitions of unemployment spell, and at different industry aggregations. Moreover, I also vary the polynomial degree in the local linear regression and the bandwidth parameter. [42]

Bandwidth. In general, varying the bandwidth is important as it affects the sample that is used in the estimation. Having a smaller bandwidth has the advantage of comparing observations closer to kink, but the disadvantage of using a smaller sample. In table 2, I compare the results to an estimate using a smaller bandwidth to the baseline and find that the RKD estimates are very similar in magnitude. When I compare the results to an estimate with a larger bandwidth, I find that the coefficients are much smaller, and in some cases insignificant. This is to be expected as the identification

[41] The difference in the weekly benefits were $63 in 1982 or equivalently $142 in 2010. Multiplying the headline result by 14.2 results in 7.81.

[42] The baseline specification of 2500 for the bandwidth and a polynomial was chosen to be consistent with the specification for RKD for the duration of unemployment in Landais (2015). The goal was to essentially use the sample sample, but only change the dependent variable.

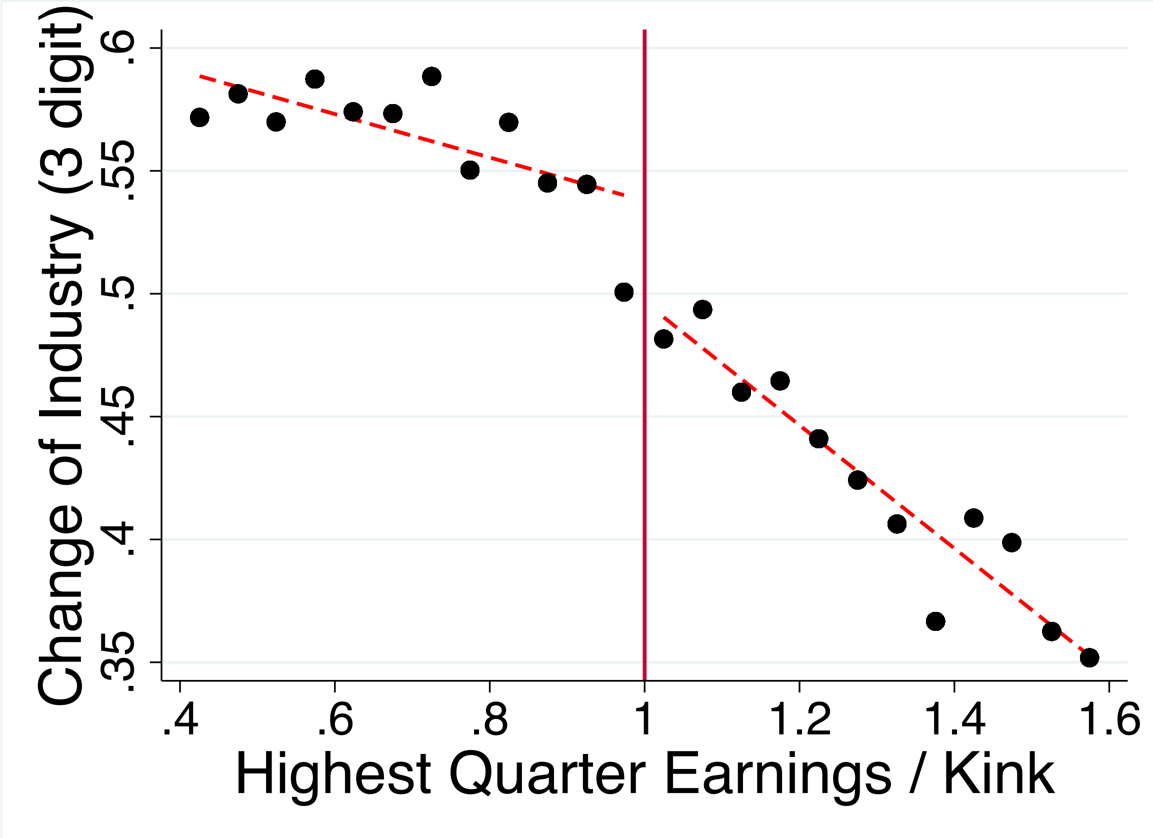


Figure 8: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

assumption becomes less plausible as individuals can be further away from the kink.

Polynomial Order. Varying the polynomial order is important as the results that I have found may be driven by the functional form of the RK estimates as opposed to true non-linearities. In table 2, I allow for a quadratic specification. While the estimated magnitude is lower, the result remains statistically significant. Tables 12, 13, and 14 of Appendix C, show further results on the sensitivity of the specification to the polynomial order when pooling the observations across years, or separating the regression year-by-year.

Other Measures of Liquidity In Appendix F, I consider the effect of severance pay on changing industries. Severance pay differs from unemployment benefits in that the transfer is usually made lump-sum towards the beginning of an unemployment spell and is funded by firms. This exercise uses the Mathematica sample collected by the Upjohn Institute and was used in Chetty (2008) to study the effect of severance pay on unemployment duration. This sample consists of two modules. The first is a representative sample of job losers in Pennsylvania in 1991. The second is a sample of unemployment durations in 25 states in 1998 and oversamples UI exhaustees.

The main takeaway from this exercise is that displaced workers who received severance pay are associated with a higher rate of across-industry reallocation. Furthermore, the effect is stronger amongst men with low levels of net liquid wealth. The result suggests that the effect of liquidity on labor reallocation is more general than unemployment insurance and the period covered by the CWBH. See appendix F for details.

Table 2: RKD for Change in Industry, Pooled 1979-1982

	Change Industry (1 digit)	Change Industry (1 digit)	Change Industry (1 digit)	Change Industry (1 digit)	Change Industry (3 digit)	Change Industry (3 digit)
α	0.55***	0.47***	0.68**	0.24*	0.58***	0.58***
	(0.14)	(0.17)	(0.33)	(0.13)	(0.15)	(0.18)
Bandwidth	2500	2500	1500	1500	2500	2500
Polynomial Order	1	1	1	2	1	1
Controls	✗	✓	✓	✓	✗	✓
Observations	11341	7525	5053	5053	11341	7525

3.4 Cost of Job Loss Regressions

In this section, I analyse the CWBH data by running a 'Cost of Job Loss' regression. The objective is to measure the medium-term costs of displacement and understand how the earnings dynamics of the unemployed vary by whether they switch or stay industries. The idea is to compare the wages or earnings of similar individuals, but one group has unexpectedly entered unemployment. Thus, by comparing to individuals who were never unemployed during the period, I can estimate the loss of earnings of an unemployed individual compared to what they would have earned had they not entered unemployment.

Regression. The regression equation is

$$y_{it} = \sum_{k=-\underline{K}}^{\bar{K}} \delta_{ns}^k D_{it}^{ns,k} + \varphi_{ns} F_{it}^{ns} + \sum_{k=-\underline{K}}^{\bar{K}} \delta_{sw}^k D_{it}^{sw,k} + \varphi_{sw} F_{it}^{sw} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{29}$$

where $j \in \{ns, sw\}$ denotes an industry stayer or switcher.[43] $D_{it}^{j,k}$ are indicator variables which take the value of one in the k-th quarter following an unemployment spell. F_{it}^{j} is an indicator variable which takes the value of one for all periods after an unemployment spell. The dependent variable is (log) weekly earnings. The coefficient of interest is $\varphi_j + \delta_j^k$.

It should be noted that the results of the regression should be taken as descriptive rather than causal. This is because the length of an unemployment spell and whether an unemployed individual chooses to stay or switch industries are endogenous outcomes. However, these moments of the data are useful to understand how long it takes for an individual who went through a period of unemployment to recover their earnings, and whether switching industries has any effect on the path of earnings. These moments will be used later as a target of the structural model.

Figure 9 plots the coefficient of interest for switchers and non-switchers for each time period relative to the end of the unemployment spell, along with a 95% confidence band. For consistency, I define an industry at the SIC 3-digit level. The blue line shows the weekly earnings of stayers relative to the base group while the orange line shows the weekly earnings of switchers. It should be

[43] The regression is similar to the one run by Huckfeldt (2022), where he splits the sample by occupation switchers and stayers.

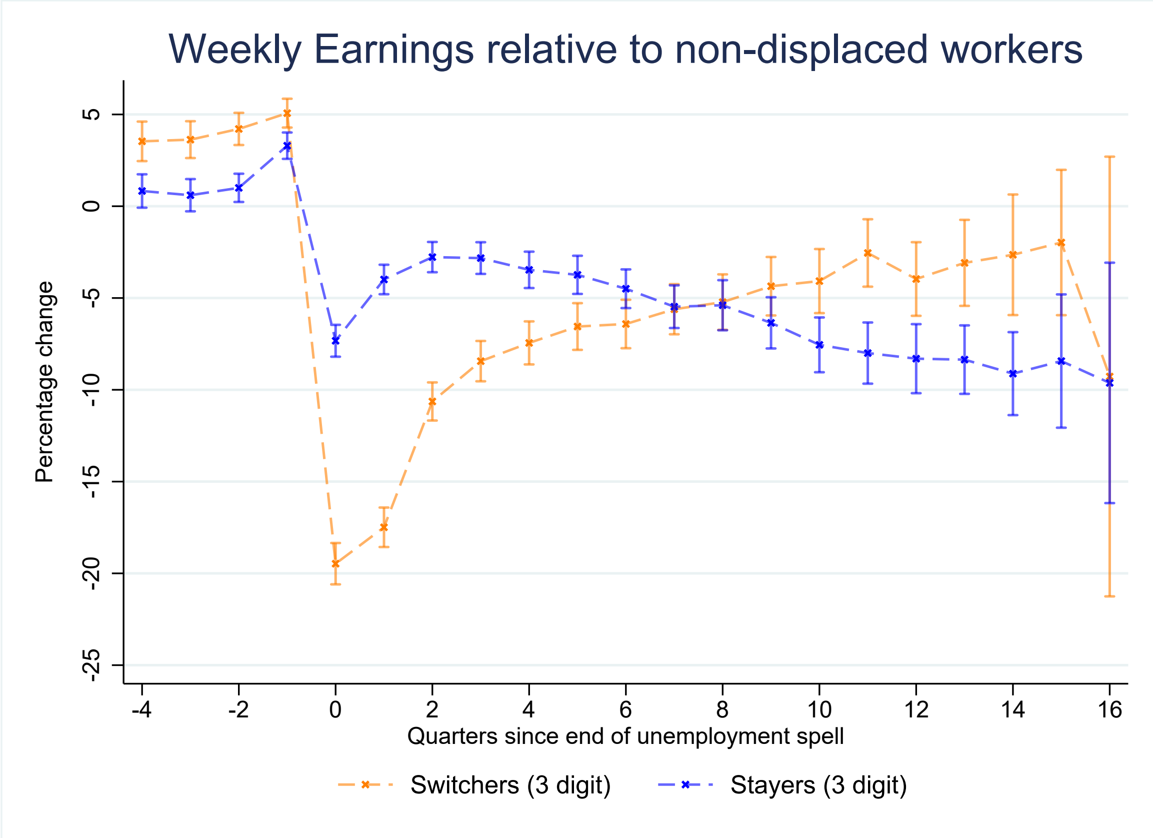


Figure 9: Percentage Change in Log Weekly Earnings around Displacement, CWBH Washington, 1979-1983

Notes: The vertical axis reports earnings differences relative to the base group of workers who did not go through a spell of unemployment during the sample. The horizontal axis plots the quarter since an individual exited unemployment. Period 0 is the first quarter in which the individual exited unemployment. Negative periods refer to the period prior to the unemployment spell.

noted that the length of the unemployment spell is collapsed within zero. [44]

Result 3: *Industry switchers have large immediate earnings losses upon re-employment compared to non-switchers, but relative earnings reverse over time*

In figure 9, the coefficient at time period 0 shows the immediate earnings losses for individuals going through a spell of unemployment. Individuals who stay in the same industry experience around an 8% loss in weekly earnings compared to the base group. For individuals who switch industries, this immediate earnings loss is closer to 21%. This shows that there is something specific to changing industries that results in lower immediate earnings. In other words, labor reallocation is costly to an individual in the near term. The variables reported in the CWBH data include the total quarterly earnings and the number of weeks worked. Unfortunately, the hours worked are not reported. Therefore, I cannot conclude whether the earnings losses are driven by wages or hours worked.

[44] This is so that we can compare weekly earnings pre and post-unemployment. During the unemployment spell itself, individuals do not have a wage but are instead receiving unemployment insurance.

Moving past the immediate earnings loss, the remainder of figure 9 shows how the (log) earnings evolve over time. Earnings losses are persistent, continuing to be lower than the base group, 12 quarters after re-employment. However, the gap in earnings between switchers and stayers reverses within 8 quarters. This shows that even though labor reallocation is costly in the very short term, after 8 quarters, industry switchers have a level of earnings that is on par with industry stayers. If anything, it appears that industry switchers are more likely to close the gap to the base group. The earnings change is insignificant from zero and precisely estimated. Towards the latter quarters, the standard errors become larger due to there being fewer observations that experienced unemployment early on in the data.

Robustness. In Appendix E, I carry out robustness checks by the definition of industry. I repeat the exercise for SIC 2, 3, and 4-digit industries. I find that the results are largely consistent with one another with only minor differences in magnitudes. In particular, the pattern of a larger immediate earnings loss for industry stayers and subsequent catch-up of earnings over time with industry switcher still holds.

4 Stationary Equilibrium: Taking the Model to the Data

In this section, I will go through the calibrated model and its properties. Then, I will compare the stationary equilibrium of the model to the data.

4.1 Calibration

The model is calibrated to a monthly frequency. For the baseline version, of the model, I calibrate the model to two sectors. Two sectors are sufficient to capture the features of the data as I focused only on whether displaced workers switch or stay in the same industry upon re-employment.[45] Moreover, the two sectors have an equal weight in the CES aggregator, the same separation rate and the same rate of productivity appreciation. That is, the two sectors are identical. This is a useful benchmark to assess the model before adding features that lead to the sectors becoming different.[46]

Productivity grid. The grid for productivity levels $z \in \{\underline{z}, \ldots, \overline{z}\}$ of individuals consist of $n_z = 11$ points, power spaced. Productivity levels are such that the relative gap between productivity levels is higher for lower productivity levels.

Transitions EE. I make the restriction that productivity can only move either one step upwards or downwards while employed. This allows me to parameterise the transition matrix Π using only two parameters π_+ and π_- which captures the arrival rate of upwards and downwards transitions re-

[45] It's possible to increase the number of sectors beyond two as long as it's finite. Every additional sector requires an additional two markets to clear.

[46] A different approach would be to calibrate the two sectors labelling them as 'Manufacturing' and 'Services'. Typically, manufacturing is thought of as a more risky sector. This can be captured by allowing for a higher separation rate $\lambda_{\text{manufacturing}} > \lambda_{\text{services}}$.

spectively. The productivity transition rates for the employment state have been calibrated to match annual wage changes in the CWBH data. In (30), I show productivity transition matrices.

$$\Pi = \begin{bmatrix} -\pi_+ & \pi_+ & 0 & \dots & 0 \\ \pi_- & -\pi_- - \pi_+ & \pi_+ & \dots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & \dots & \pi_- & -\pi_- - \pi_+ & \pi_+ \\ 0 & \dots & 0 & \pi_- & -\pi_- \end{bmatrix} \tag{30}$$

Transitions EU. With regard to the arrival rates in the labor market, I set the separation rate $\zeta_s = 0.033$ for both sectors, which implies a quarterly separation rate of 0.1 as used in Shimer (2005).

Transitions UU. As mentioned in section 3, I calibrate the productivity transition matrix Ξ with a constant arrival rate of losing one level of productivity. Therefore, I only need to calibrate one parameter ξ. The productivity depreciation rate in the unemployment state is set to 0.33 in line with the cost-of-job-loss regression and average duration of unemployment. This implies an average of 5% productivity loss after 3 months of unemployment. The UU transition matrix is given by (31).

$$\Xi = \begin{bmatrix} 0 & 0 & 0 & \dots & 0 \\ \xi & -\xi & 0 & \dots & 0 \\ 0 & \xi & -\xi & \dots & \vdots \\ \vdots & \vdots & \ddots & \ddots & 0 \\ 0 & 0 & \dots & \xi & -\xi \end{bmatrix} \tag{31}$$

Transitions UE. I calibrate the elements of the array Λ using the decomposition in equation (1). The relative arrival rates for each potential productivity is calibrated such that the highest productivity level is equal to 1. Then the ratio of any two consecutive productivity levels is constant at some v. That is,

$$\frac{\lambda^{z_{j-1}}}{\lambda^{z_j}} = 1 + v \quad \forall j.$$

I calibrate v and the base sector arrival rates λ_s internally to match the mean duration of unemployment and the relative unemployment duration for industry switchers compared to industry stayers in the data.

The matrix $\Theta^{ss'}$ is an $n_z \times n_z$ matrix whose (i, j)-th component consists of 1 if the individual with current productivity z_j has access to the job opportunities at productivity level z_i and 0 otherwise. Following assumption 2, these matrices are lower-triangular since unemployed individuals do not sample offers for jobs with higher potential productivity. The idea is that stayers are able to access jobs with relatively higher productivity levels than switchers, conditional on the individual's current productivity.

I calibrate these matrices to target the relative immediate cost of job loss for stayers and switchers. To do so in the simplest way, I restrict the choice set to only one potential productivity level. For jobs in the same sector as their previous sector, the matrix Θ^{ss} is calibrated to be an *identity* matrix. This implies that the unemployed can apply for jobs with the same productivity as their current level.

Note that individuals can still lose productivity while unemployed due to idiosyncratic productivity risk. For jobs in a different sector than their previous sector, I calibrate the matrices to match the immediate cost of job loss. In this case, the maximum cost of job loss is 20%, or four productivity grid points. Therefore, the matrix features ones in the fifth sub-diagonal and ones in the first columns, capturing the productivity cost for individuals with lower productivity.

$$\Theta^{ss'} = \begin{bmatrix} 1 & & & & & & & & & & \\ 1 & 0 & & & & & & & & & \\ 1 & 0 & 0 & & & & & & & & \\ 1 & 0 & 0 & 0 & & & & & & & \\ 1 & 0 & 0 & 0 & 0 & & & & & & \\ 0 & 1 & 0 & 0 & 0 & 0 & & & & & \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & & & & \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & & & \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & & \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix} \quad \forall s' \neq s \tag{32}$$

Policy parameters. Regarding government policy, I use a fixed linear tax schedule for simplicity, with a marginal tax rate of 0.25 as in Kaplan, Moll, and Violante (2018). The replacement rate of unemployment benefits is set to 0.5 to match the average replacement rate over time in Washington.

Other parameters. Table 3 shows the externally calibrated parameter values and table 4 lists the internally calibrated parameters. As standard in models featuring incomplete markets, I set the discount rate to target a moment of the wealth distribution.

A well-known problem of one-asset incomplete markets models is the inability to match both high marginal propensities to consume (MPC) and moments of the wealth distribution.[47] As mentioned in Kaplan and Violante (2022), a 'low-liquidity' calibration - where assets are interpreted as liquid wealth, matches the MPC in the data, but abstracts away from more than 98% of total wealth, and is therefore less useful for general equilibrium analyses. Therefore, I have chosen to target a wealth-to-GDP ratio of 3. This corresponds to a 'high-liquidity' or 'total wealth' calibration target of a one-asset incomplete markets model. As a result, the elasticities of policy functions such as consumption and the sector-switching probability to assets will be lower compared to the alternative 'low-liquidity' calibration.

[47] See Kaplan and Violante (2022) and Auclert, Rognlie, and Straub (2023) for papers that detail the calibration of incomplete-markets models.

Table 3: Externally Calibrated Parameters

	Parameter	Value	Target/ Source
Labor Market			
ζ_s	Separation Rate in each Sector	0.033	Shimer (2005)
π_+	Rate of productivity gain when employed	0.103	Expected annual mean wage increase for job stayers, conditional on a positive change, CWBH data
π_-	Rate of productivity loss when employed	0.06	Expected annual mean wage decrease for job stayers, conditional on a negative change, CWBH data
ξ	Rate of productivity loss when unemployed	0.33	5% productivity loss after 3 months of unemployment for industry stayers - CWBH data
Θ	Switcher status component	See text	Immediate cost of job loss
Preferences			
γ	Coefficient of Relative Risk Aversion	1	Standard calibration
ψ_h	Relative disutility of hours	6.75	Mean hours worked at 0.33
φ_h	Inverse Frisch Elasticity	0.5	Standard calibration
ν	Relative disutility of search costs	0.5	Fixed
Production			
α	Capital Share of Income	0.33	Standard calibration
δ	Depreciation Rate of Capital (p.a.)	7%	Kaplan, Moll, and Violante (2018)
ϵ	Elasticity of Substitution across Firms	10	Markup of 11%, Kaplan, Moll, and Violante (2018)
Government			
χ	Replacement rate	0.5	Average replacement rate in Washington
τ	Marginal Labor Income Tax	0.25	Kaplan, Moll, and Violante (2018)
$\underline{a}$	Borrowing Limit	0	Fixed

Table 4: Internally Calibrated Parameters

	Parameter	Value	Target/ Source
Labor Market			
λ_s	Base sector arrival rate	0.30	Average unemployment duration of 18 weeks in stationary equilibrium
υ	Ratio of finding rates between two productivity levels	0.05	Relative duration of unemployment for stayers and switchers
Preferences			
ρ	Discount Rate (p.a.)	14.4%	Wealth-to-GDP ratio of 3
κ	Utility cost of unemployment	1.75	See text
Production			
η	Elasticity of Substitution across Sectors	2.5	See section 5.3
Government			
$\bar{\mathcal{T}}$	Maximum Transfers	0.43	Fraction of individuals with maximum benefits

4.2 Model Validation

Table 5: Moments of the Stationary Distribution

Moment	Value
Unemployment Rate	6.6%
Average sector switching probability	0.40
Average marginal propensity to consume (quarterly)	3%
Average wealth to (annual) after-tax labor income	6.15
Fraction of hand-to-mouth	2.6%

Moments of the stationary distribution. In table 5, I list some key moments of the stationary equilibrium. The unemployment rate in the stationary equilibrium is 6.6%. The average sector switching probability of 0.40 is slightly higher than found for the SIC 1-digit level. Part of this is due to a composition effect. Given the arrival rates for productivity transitions, both in employment and unemployment states, there are more individuals in the lower productivity levels, which have a higher average reallocation rate. Note that the sector switching probability and conditional finding rates are *untargeted*. They result from the key ingredients of the model, which are the arrival rates and cost of switching, and the endogenous choice probabilities of the unemployed.

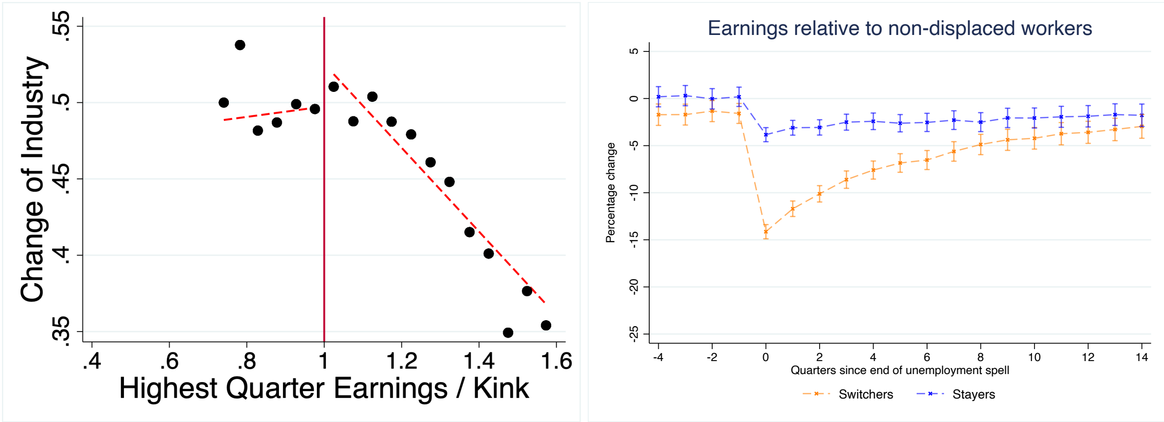
Simulation results. I simulate a panel of individuals when the economy is at the stationary equilibrium.[48] Then, I proceed with running the same regressions on the model-generated data as I do in the actual data.[49]

In panel (a) of figure 10, I compare the model and data results for the RKD on industry switching. This is an untargeted moment. The model is more successful in matching the data in this exercise. As mentioned previously, the rate of industry switching is a little higher in the model compared to the data. The relationship between the probability of changing industries and the assignment variable qualitatively changes in the same way in the model as in the data - the slope is more negative to the right of the kink point. Therefore the model captures the mechanism that an increase in liquidity is associated with a higher propensity to change industries.

Panel (b) shows the comparison of the cost of job loss regressions in the data and in the model. The model does a relatively good job of generating the correct shape of earnings profiles for switchers and stayers. The immediate earnings losses are a little smaller than those in the data. Part of the reason for this is that within the group of the unemployed, there are relatively more individuals with low productivity compared to high productivity. Subsequently, this puts a lower bound on the immediate cost of job loss as explained in section 4.1. Note that although I target the immediate loss of earnings through the Θ array, the subsequent periods are untargeted. The model performs relatively well in creating the catch-up dynamics within 8 quarters as in the data.

[48] Appendix G details a Monte-Carlo method applied to a continuous-time model.

[49] I use Monte-Carlo methods as I can use the same regression codes on the simulated panel data. The disadvantages are sampling error and computational time. For a reference on using non-stochastic simulation (histogram) methods, see Ocampo and Robinson (2022).



(a) RKD

(b) Job Loss

Figure 10: Regressions on Model Generated Data

5 Even and Uneven Shocks

In this section, I will introduce transition dynamics into the model. The goal of this section is to study the properties of labor reallocation in response to counterfactual symmetric and asymmetric sectoral shocks. I will also evaluate the properties of existing labor market policies and compare the counterfactual effects of other policies.

5.1 Even Shocks

First, I study the impulse response of the model to a symmetric, transitory shock to productivity and the finding rate per unit of search effort. This is to benchmark the model against well-known properties of business cycles to aggregate shocks. To do this, I impose that the sectoral productivity term consists of an aggregate component that affects all sectors (Ω_t), and a sector-specific component (ϑ_{st}).

$$Z_{st} = \Omega_t \cdot \vartheta_{st} \tag{33}$$

I shock the economy with a one-time unexpected shock followed by a perfect foresight transition to the stationary equilibrium, otherwise referred to as 'MIT shocks'. I feed in a path of the aggregate component Ω_t

$$d\Omega_t = -\xi_\Omega(\Omega_t - \bar{\Omega})dt \tag{34}$$

where ξ_Ω is a parameter governing the speed of mean-reversion. In the spirit of Krusell and Smith (1998) and McKay and Reis (2016), I also shock the parameter that governs the job-finding rate per unit of search effort. I referred to this component earlier as the 'Base Sector Arrival Rate'. Shocking this variable helps the model in fitting the patterns of unemployment dynamics at business-cycle frequencies.

$$d\lambda_{st} = -\xi_\lambda(\lambda_{st} - \bar{\lambda}_s)dt \quad \forall s \tag{35}$$

Regarding the government's fiscal policy, I fix the tax rate at the same level as in the stationary equilibrium but I allow for government borrowing to adjust in accordance with the government flow budget constraint. Thus the policy exercise is to study the impact of deficit-financed unemployment

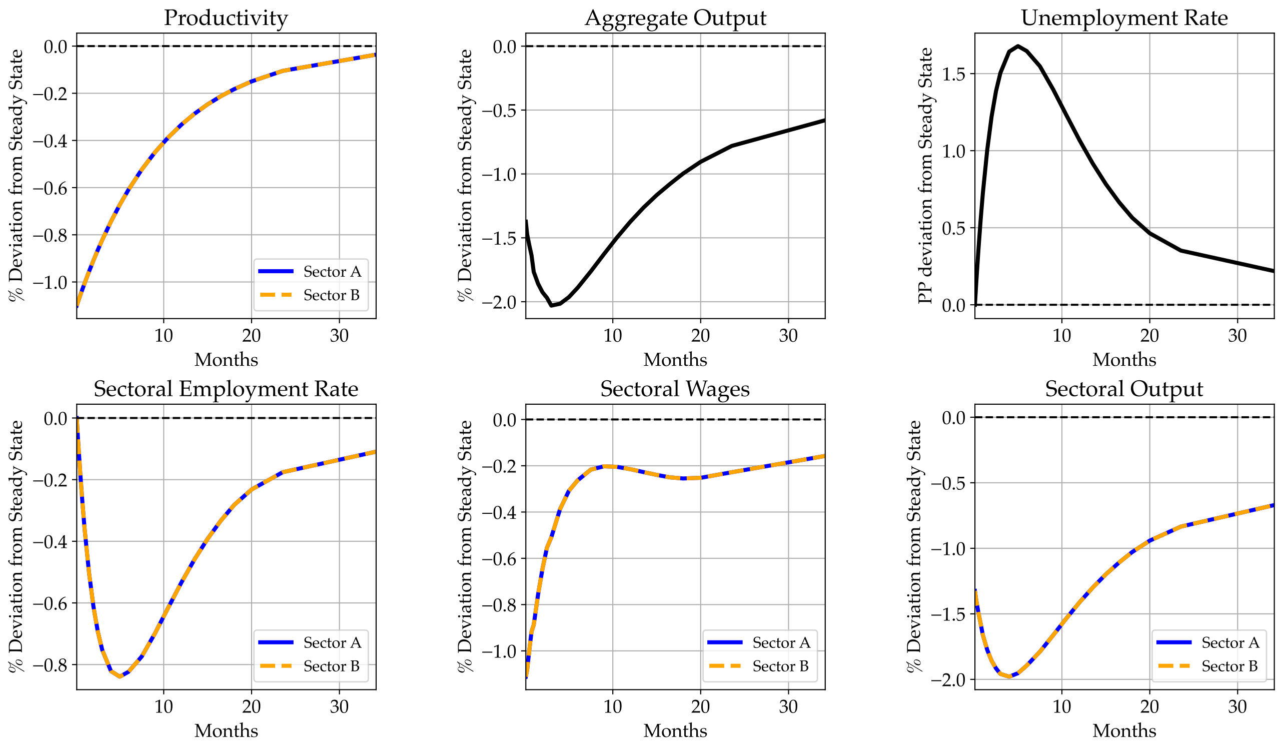


Figure 11: Impulse Response to a Transitory Even Shock

insurance policy on the labor market. In response to a negative productivity shock, the government deficit works in two ways. First, it pays for the increase in aggregate transfers as more individuals are unemployed. Second, it increases the net supply of assets in the economy, allowing for more assets for individuals to self-insure.

I calibrate the aggregate TFP shock to have a decrease of 1% of steady state on impact and with a monthly autocorrelation of 0.9. The shock to the base sector arrival rate in each sector is calibrated to have a 30% decrease on impact, with a monthly autocorrelation of 0.6.

Figure 11 shows the impulse responses. Upon impact of the shocks, the economy's output, consumption and investment fall due to the fall in aggregate productivity. As the economy moves a small time-step ahead, the unemployment rate rises due to the lower finding rate in each sector. Government debt increases as the government increases its borrowing to pay for larger aggregate transfers. Notably, the sectoral effect of the shocks is entirely symmetric. Sectoral output, prices, wages and employment change by the same amount across the two sectors. Note that there is still some gross reallocation between the sectors but the effect is cancelled in aggregate. That is, there is no *net* reallocation of labor across sector.

The main mechanism through which the economy stabilises itself is through the dis-saving of assets. Notice that equilibrium asset falls on impact due to lower equity prices and continue to fall as individuals dis-save to smooth consumption. As a result, there is less capital to be rented out to firms.[50]

[50] As equity is a jump variable, the assets of the individual can jump on the impact of a shock. I assume that before the shock, the financial intermediary invests the funds in equal proportion across the three assets.

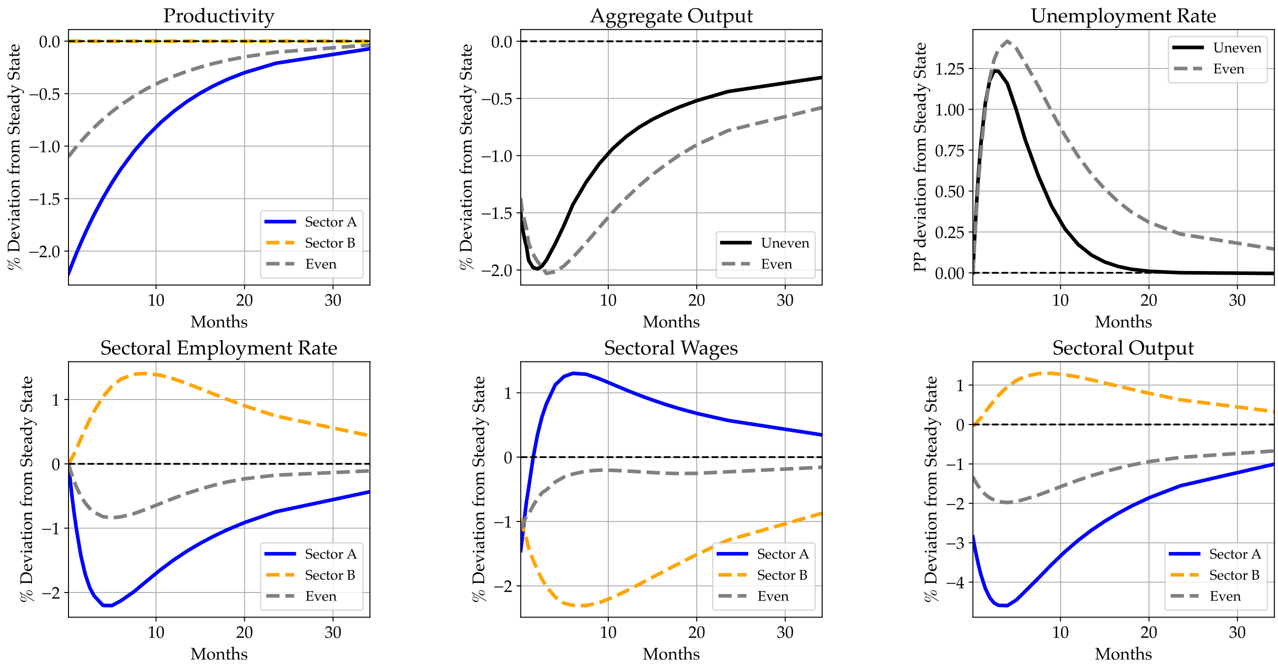


Figure 12: Impulse Response to a Transitory Uneven Shock

5.2 Uneven Shocks

In this section, I carried out a similar exercise to the previous section, focusing on a sector-specific shock. I shock one sector of the economy with a negative productivity shock and a negative shock to the base sector arrival rate.

In response to a sectoral shock, the economy may be able to adjust to the shock with net labor reallocation across sectors. Sectors that are not affected by the shock may be able to absorb some of the unemployed workers. I will detail how the reallocation process has elements of cleansing and sullying, and how it interacts with the scarring effect of unemployment.

For the purposes of comparison, the productivity shock is calibrated such that they have the same sized decrease in aggregate output on impact while keeping the persistence exactly the same. Similarly, the shock to the base sector arrival rate is calibrated to have the same proportional increase as the TFP shock, also with the same persistence as the symmetric shock.

For clarity of presentation, I label Sector A as the sector which experiences the negative shock whereas Sector B is not directly hit with a shock.

$$d\vartheta_{At} = -\xi_{\vartheta}(\vartheta_{At} - \bar{\vartheta_A})dt \tag{36}$$

$$d\lambda_{At} = -\xi_{\lambda}(\lambda_{At} - \bar{\lambda}_A)dt \tag{37}$$

Figure 12 shows the impulse responses to an uneven shock. Similar to the even shock in the previous section, aggregate output, consumption and investment fall upon impact. The responses of the even shock are plotted in grey. Compared to the effect of an even shock, unemployment rises in response, but peaks at a slightly lower level and returns to the previous steady-state level at a much faster rate. Examining the sectoral outcomes sheds light on the unemployment dynamics. A key difference with an uneven shock is that it features a change in the relative wages and prices. Upon impact, the relative wage and price in sector A *increases* and output in sector A fall due to the lower productivity. It requires more factor units to produce the same amount of output. A higher wage encourages the unemployed to direct their search towards sector A. However, the fall in the finding rate λ_A encourages the unemployed to direct their search away from sector A. In equilibrium, the employment in sector B *increases*. Therefore, reallocating labor towards sector B helps mitigate the increase in unemployment. This represents a *cleansing* effect of reallocation - resources are reallocated from a non-productive state (unemployment) to a productive state of employment in another sector.

Notably, despite the increase in employment in sector B, output also falls despite sectoral productivity remaining at its steady-state level. First, an increase in unemployment implies lower aggregate consumption and investment in *all* sectors. Second, the average productivity of workers in sector B falls. Part of the newly employed workers in sector B were last employed in sector A, and thus their productivity falls upon switching sectors. This represents a *sullying* effect of reallocation.

Third, the ability to reallocate across sectors reduces the risk of long-term unemployment and loss of productivity. Moreover, it takes time to rebuild sector-specific productivity. As labor reallocation reduces the unemployment rate, it reduces the scarring effect.

On balance, the cleaning, sullying and scarring effects of reallocation lead to the average efficiency units of labor being lower but at the same time, the labor is employed in the non-shocked sector, leading to a faster recovery from the recession compared to the symmetric shock.

I define a positive net labor reallocation as individuals flowing from sector A to sector B through unemployment. Indeed, the bottom panel of figure 11 shows that net labor reallocation increases as individuals exit unemployment towards sector B and slowly dissipates as unemployment returns to its steady state.

One more difference compared to the symmetric shock is the magnitude of the decline in equilibrium assets. It is smaller on impact and throughout. The reason for this is again the lower resulting unemployment rate. There are fewer individuals that dis-save in order to smooth consumption while in unemployment.

5.3 Elasticity of Substitution Between Sectors

In the baseline calibration, I use an elasticity of substitution $\eta = 2.5$. As a robustness exercise, I compute the impulse response changing the value of η. The main result of this exercise is that aggregate variables are qualitatively unaffected by changes in the elasticity of substitution. However, the *relative* sectoral outputs and wages do change depending on whether the elasticity is above or below 1. In the baseline specification of $\eta = 2.5$, output in sector A falls by more than output in sector B. The result is reversed for $\eta < 1$. I choose $\eta = 2.5$ as the baseline as it fits the data on *relative* sectoral output while keeping in mind that the calibration features only two sectors, and as such the elasticity of substitution ought not to be too large.

In Figure 13, I plot the impulse response to an asymmetric shock for the case of low elasticity of substitution between sectors. I set $\eta = 0.1$. This economy features large changes in sectoral wages, prices and output. In particular, although employment falls in sector A, its output increases. Most of this effect is due to higher capital usage by firms in sector A and lower capital usage by firms in sector B. Therefore, using a low elasticity of substitution generates counterfactual predictions on the

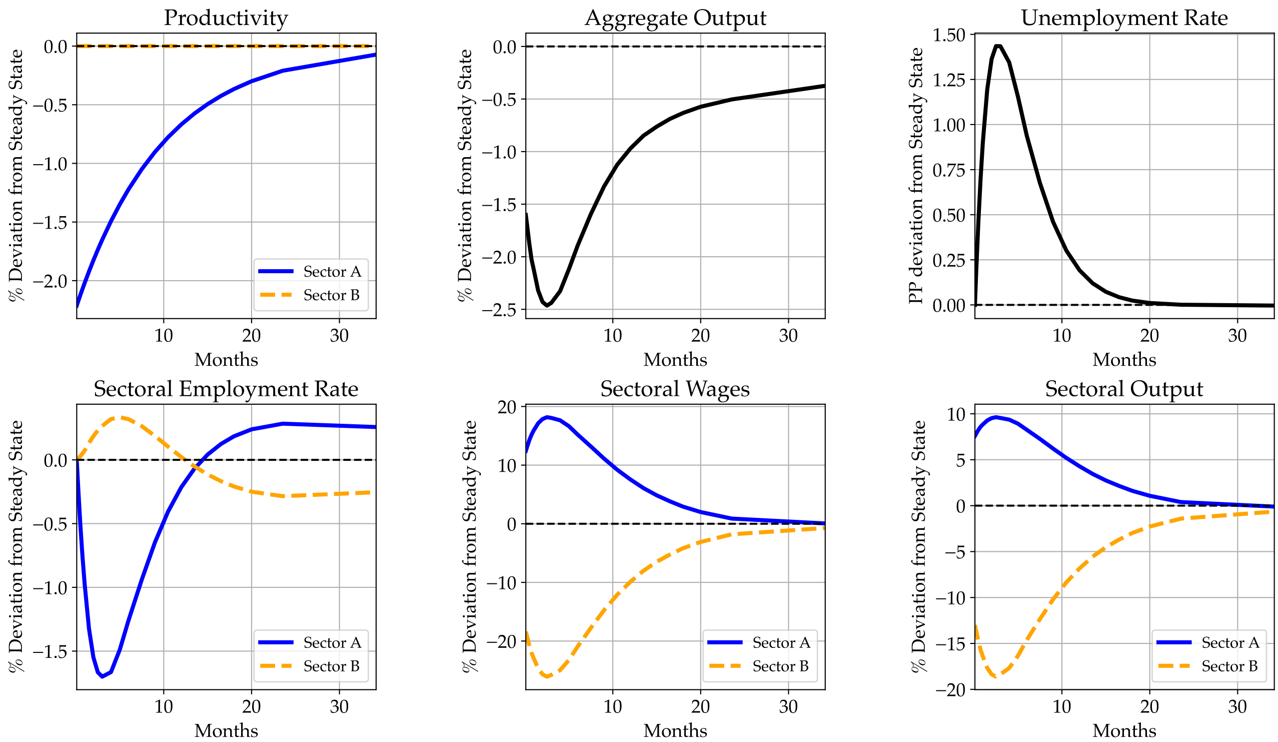


Figure 13: Impulse Response to a Transitory Uneven Shock - Low Elasticity of Substitution

co-movement of the negative shock and output.

Moreover, although there is net labor reallocation from sector A to sector B, its magnitude is much smaller and reverses much quicker compared to the baseline case - 13 months relative to 40 months.

In Figure 14, I repeat the exercise using a high elasticity of substitution $\eta = 10$. This economy features employment and output that co-move in the same direction, but the magnitude of the response sectoral output is large relative to the shock. In addition, the wage in sector A falls relative to sector B. However, the relative sectoral prices do not deviate very much from their steady-state level of 1. Thus, an economy with a high elasticity of substitution features a higher relative wage change compared to a relative price change.

Note that in this economy, as the wage of Sector A falls relative to that of Sector B, this leads to even more reallocation away from Sector A towards Sector B. As such, the baseline calibration of 2.5 is a case where net labor reallocation from sector A to B rises, but the magnitude is in between these two cases.

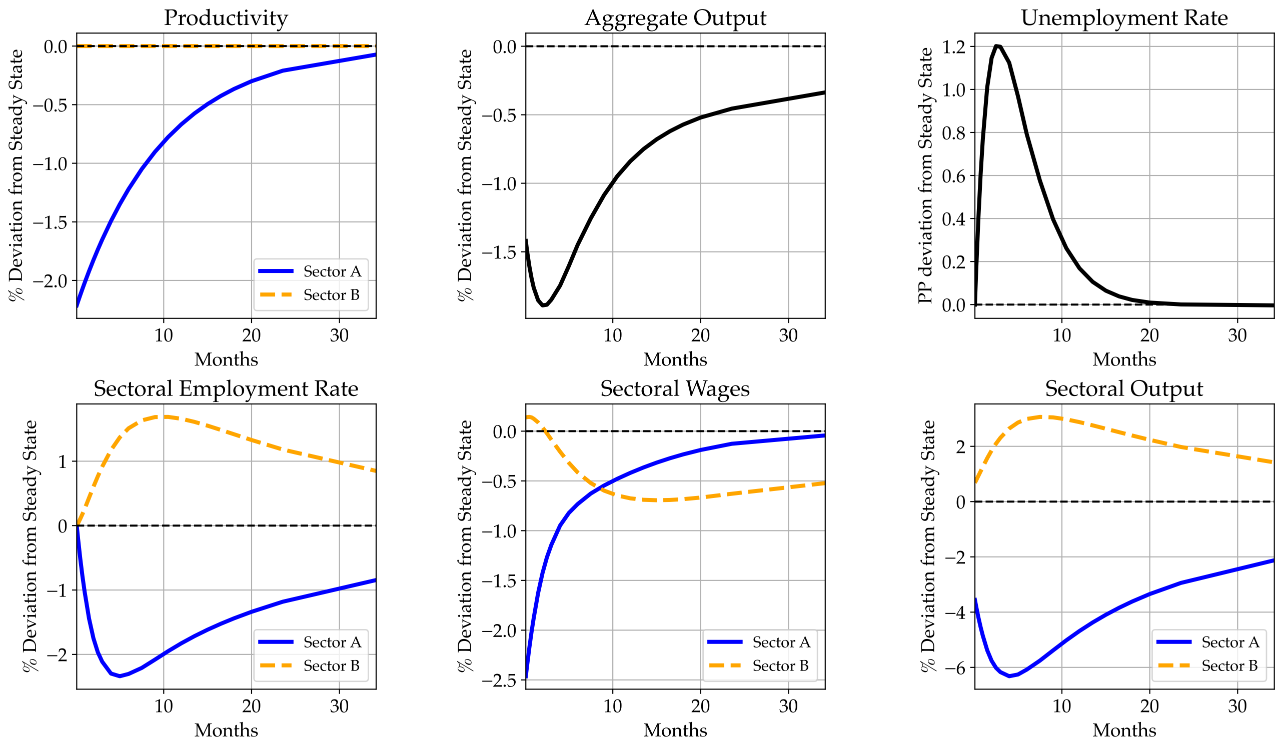


Figure 14: Impulse Response to a Transitory Uneven Shock - High Elasticity of Substitution

5.4 Targeted Transfers

In this section, I study how liquidity affects the cleansing, sullying and scarring effects of reallocation. I study a policy exercise of a stimulus in the form of targeted transfers. Specifically, transfers to the unemployed increase by an amount $\Delta\mathcal{T}$ for a limited amount of time after the initial shock.[51] The policy increases the liquidity provision to unemployed individuals, which will affect their labor reallocation decision.

I set $\Delta\mathcal{T} = \bar{\mathcal{T}}$, effectively doubling the maximum benefits, and this policy remains in place for only 2 months, after which the transfer policy reverts to the steady-state level. This is a relatively large policy change, but only for a short amount of time. Note that as individuals have perfect foresight, the policy exercise is fully anticipated.

Figure 15 plots the results from the policy exercise. In the top row, I plot the difference in transfers, aggregate output, and unemployment rate due to the policy. In the bottom panels, I plot equilibrium assets and flows from unemployed individuals whose last sector is A (U_A) to employment in sector B (E_B) and vice-versa. Specifically, I multiply the average switching probability from sector A to B by the mass of unemployed, whose last job was in sector A, similarly for sector B.

The exercise shows that in the case of the stimulus, the recession is less severe. Aggregate output does not fall by as much and unemployment peaks at a lower rate. Part of the output stabilisation is due to the lower drop in equilibrium assets, but part of the stabilisation also occurs from the lower unemployment rate.

On the impact of the shock, the U_A to E_B flow increases on impact due to a higher average switch-

[51] That is, for $t \in (0, 2]$, $\mathcal{T}_t(z, s) = \min\{\chi w_{st} z \ell, \bar{\mathcal{T}}\} + \Delta\mathcal{T}$.

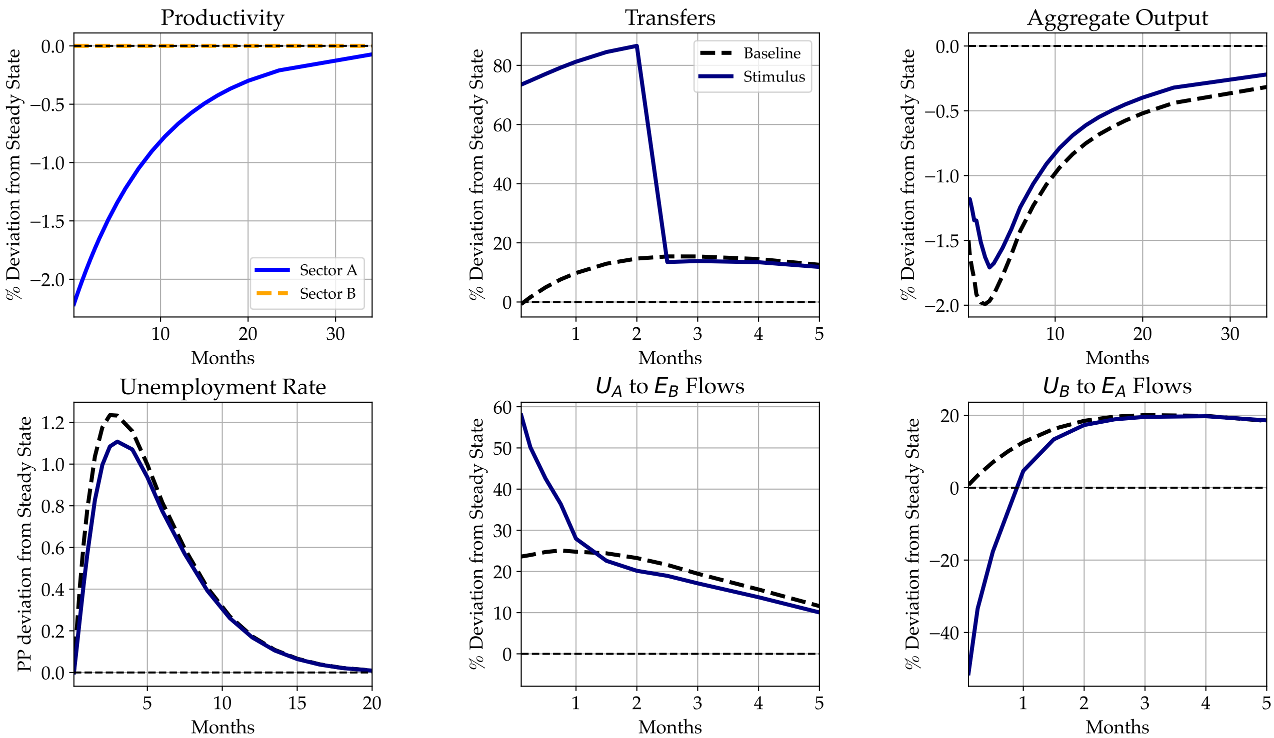


Figure 15: Impulse Response to a Transitory Sectoral Shock - Targeted Transfers

ing probability. At the same time, the U_B to E_A flow decreases. This implies that individuals are reallocating towards sector B at a higher rate. The aggregate effect of these flows is a lower unemployment rate.

As the relative wage begins to increase in Sector A, the net reallocation from Sector A to Sector B starts to slow down. This is reflected in the decrease of the U_A to E_B flow and an increase in the U_B to E_A flow. As the shocks dissipate, the direction of labor reallocation reverses such that the economy returns to its steady state.

The additional liquidity speeds up both the cleansing and sullying effect, as well as reducing the scarring effect. The lower peak unemployment rate in periods following the targeted transfers implies both a speeding up cleansing effect and a reduction in the scarring effect. The targeted transfers increase the incidence of individuals who were previously employed in sector A to switch to sector B and therefore finding a job at a faster rate. However, as the reallocation process is costly and happens at a faster rate, the sullying effect is also increased. In aggregate, the positive effects of reallocation outweigh the negative effects as the effect of the recession on both the aggregate output and unemployment are dampened.

6 Conclusion

In this paper, I studied the implications of individuals' liquidity on labor reallocation through unemployment. Empirically, I find that a marginal increase in liquidity increases the propensity of individuals to reallocate across industries. I develop a quantitative heterogeneous-agent model featuring risk aversion, multiple sectors, specific productivity, frictional labor markets and endogenous labor reallocation. I use the model in order to study the implications of the economy in response to symmetric and asymmetric shocks. I also use the model as a laboratory in order to study policy counterfactuals.

There are a couple of interesting avenues to follow up. First, it would be interesting to study a version of this model that features price and/or wage rigidities in a 'HANK'. Additional aggregate demand channels may be present due to the labor reallocation decision. In an economy facing an uneven shock, labor reallocation in the economy is additionally affected by aggregate demand effects. In particular, as newly reallocated workers have lower productivity, this increases their (intertemporal) marginal propensity to consume. As a result, the transmission of transfers to aggregate demand may be stronger. In addition, it would be interesting to understand the implications of labor reallocation on sectoral inflation and vice versa through its impact on real wages.

Second, there is a question of what is the optimal unemployment insurance policy taking labor reallocation into account. A model featuring the key ingredients of the present paper may be needed, along with endogenous search and matching frictions. In particular, providing liquidity has the effect of increasing the rate of labor reallocation across sectors. However, due to the "cleansing" and "sullying" effects of reallocation, there is a trade-off in the optimal rate of labor reallocation. A utilitarian social planner weighs up the net present value of switching an individual's sector against keeping them unemployed for a longer period of time but re-employed at potentially higher productivity. The optimal rate of labor reallocation may depend on the persistence of the negative shock. Intuitively, if the shock is short-lived, the optimal policy induces a low rate of labor reallocation, thereby maintaining specific productivity. If the shock is more persistent, the optimal policy should induce a higher rate of labor reallocation to lower unemployment.

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A Additional Figures

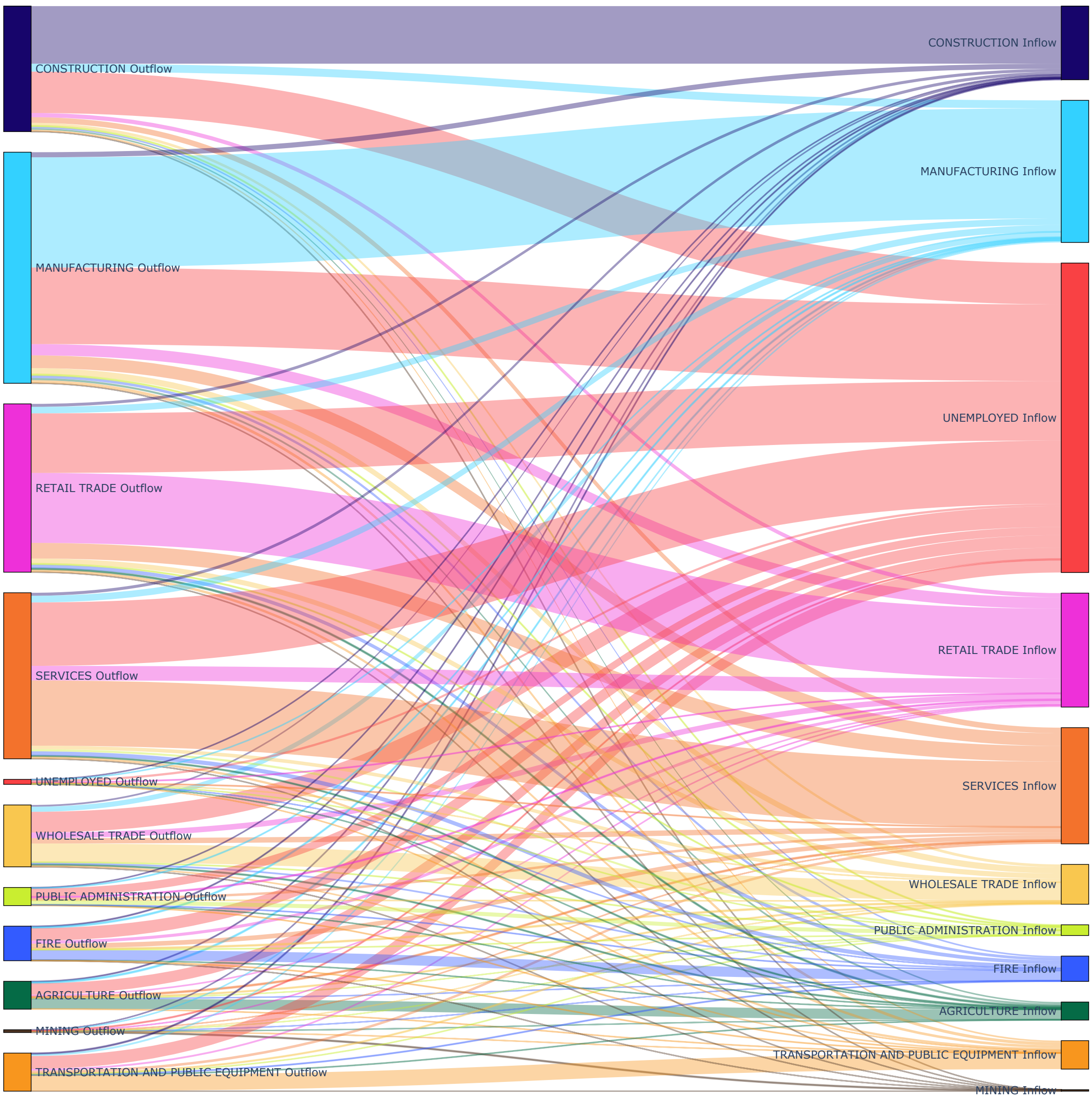


Figure 16: Labor Flows through Unemployment, SIC 1-digit, CWBH Washington, 1979-1983

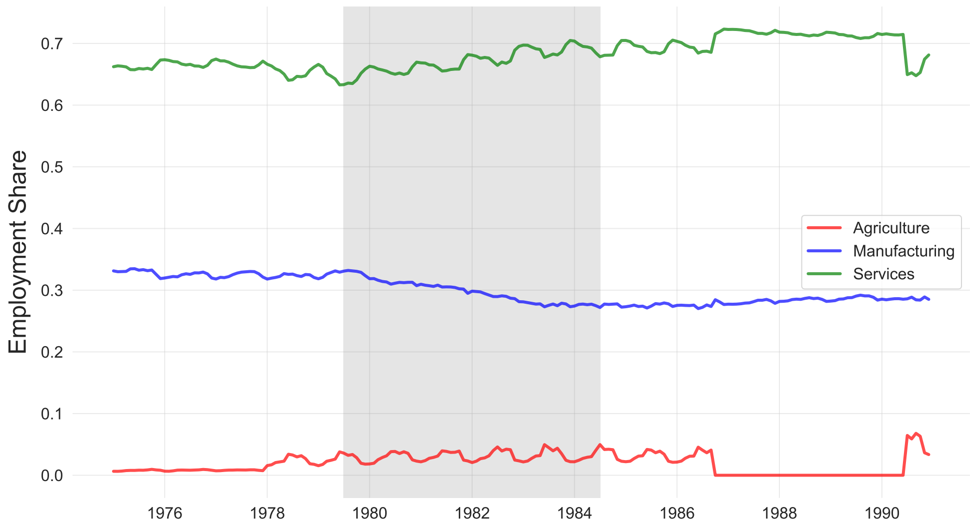


Figure 17: Employment Share, Quarterly Census of Employment and Wages, Washington, 1975-2022

Notes: Grey area indicates the period of coverage of the Continuous Wage and Benefit History Program.

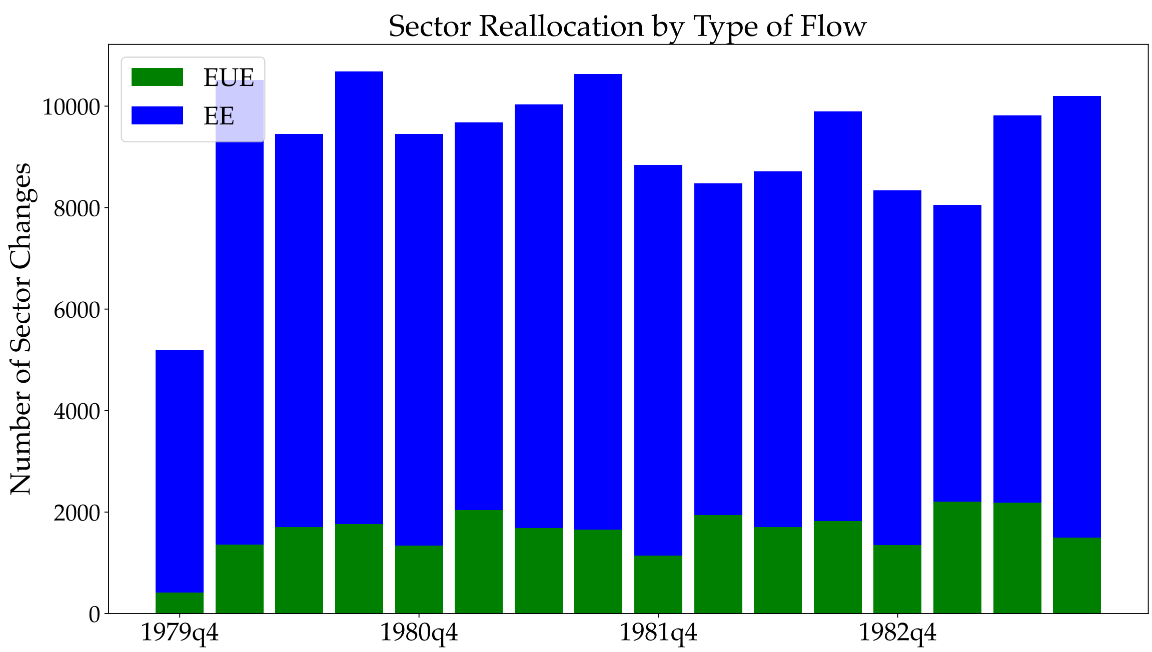


Figure 18: Sectoral Labor Reallocation by Type of Flow

Notes: SIC 1-digit, CWBH Washington, 1979-1983

B Additional RKD Figures

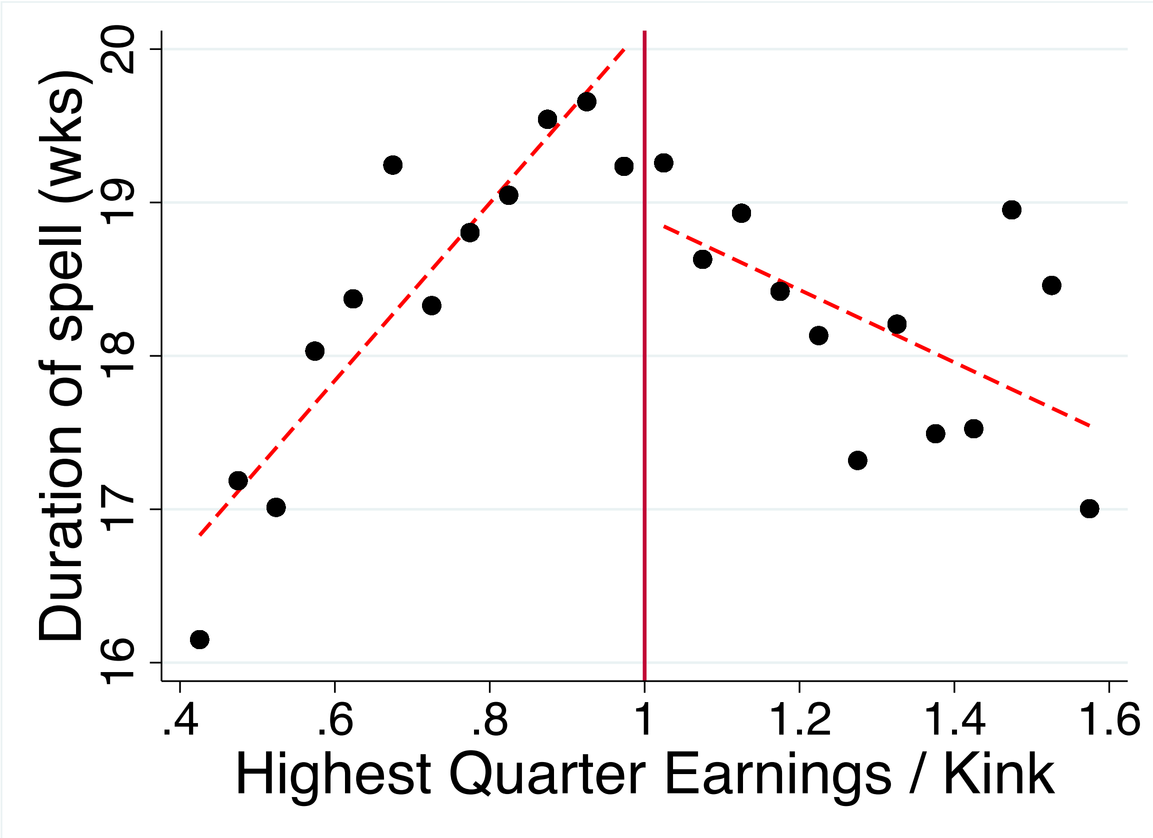


Figure 19: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

First, I replicate the result in Landais (2015). In his paper, he shows that a marginal increase in liquidity leads to a longer unemployment duration. This result is robust for various states in the CWBH. I show the results for Washington. This is an important result that my model will have to match. Figure 5 shows a binscatter of the duration of unemployment (dependent variable) on the HQW (assignment variable). This is the numerator of the RKD estimator. The figure shows that in a bandwidth around the kink, there is a change in the relationship between the dependent variable and the assignment variable. To the left of the kink, where weekly benefits are increasing, the duration of the unemployment spell is increasing. To the right of the kink, where weekly benefits are no longer increasing due to the cap, the duration of the unemployment spell is no longer increasing. Under the identifying assumptions underpinning the RKD, this shows that a marginal increase in benefits at the kink leads to an increase in the duration of unemployment spells. It should be noted that this is a result that is local to the kink and is not the average treatment effect of the population.

Table 2 shows the results of the regression. The regression is run separately by year to account for a stable unemployment insurance schedule. In the table, I report the RKD coefficient (α), the elasticity of the outcome variable to benefits (ε), and the polynomial order. Estimates are done using nominal schedules, with $\hat{\alpha}$ rescaled to 2010 dollars. The baseline bandwidth used is 2500, which is the same as that used in Landais (2015). The main result is that a \$1 increase in weekly benefits leads to an increase in unemployment duration by 0.02-0.03 weeks for individuals close to the kink. In Appendix B, I do not find significant changes in the slope of other covariates around the kink.

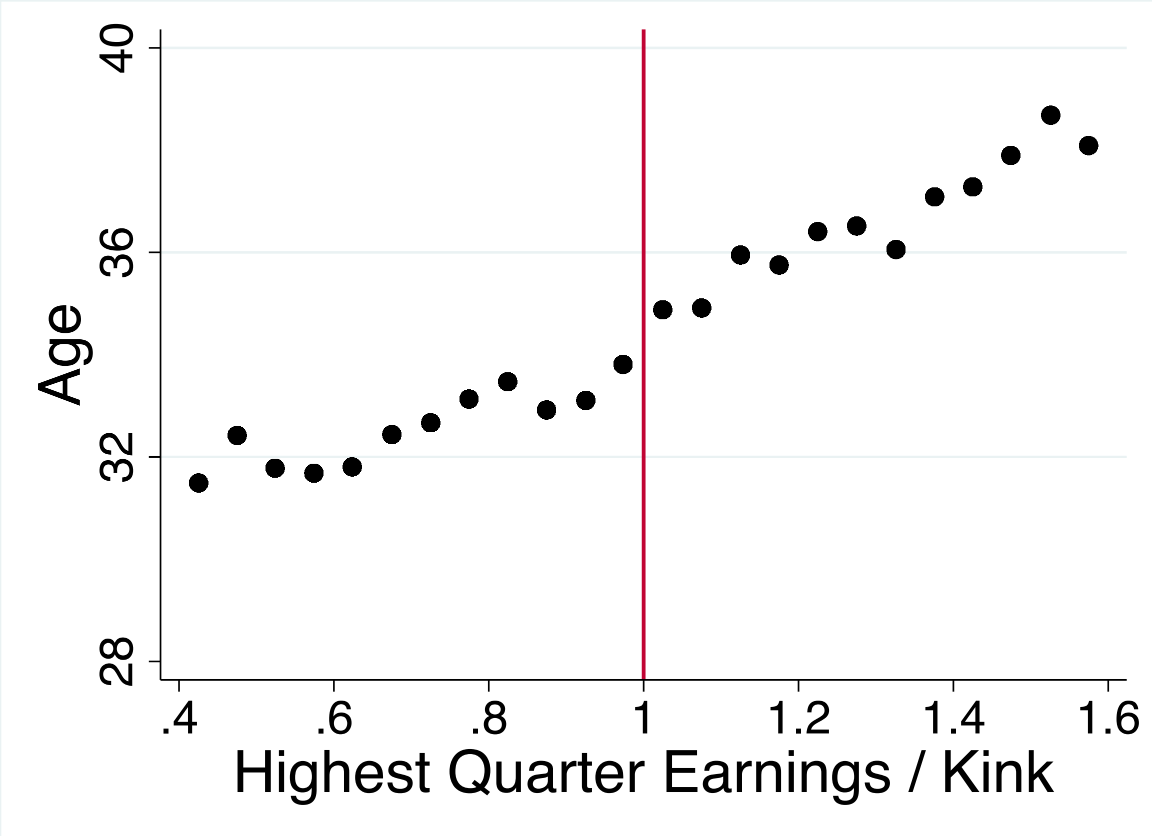


Figure 20: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

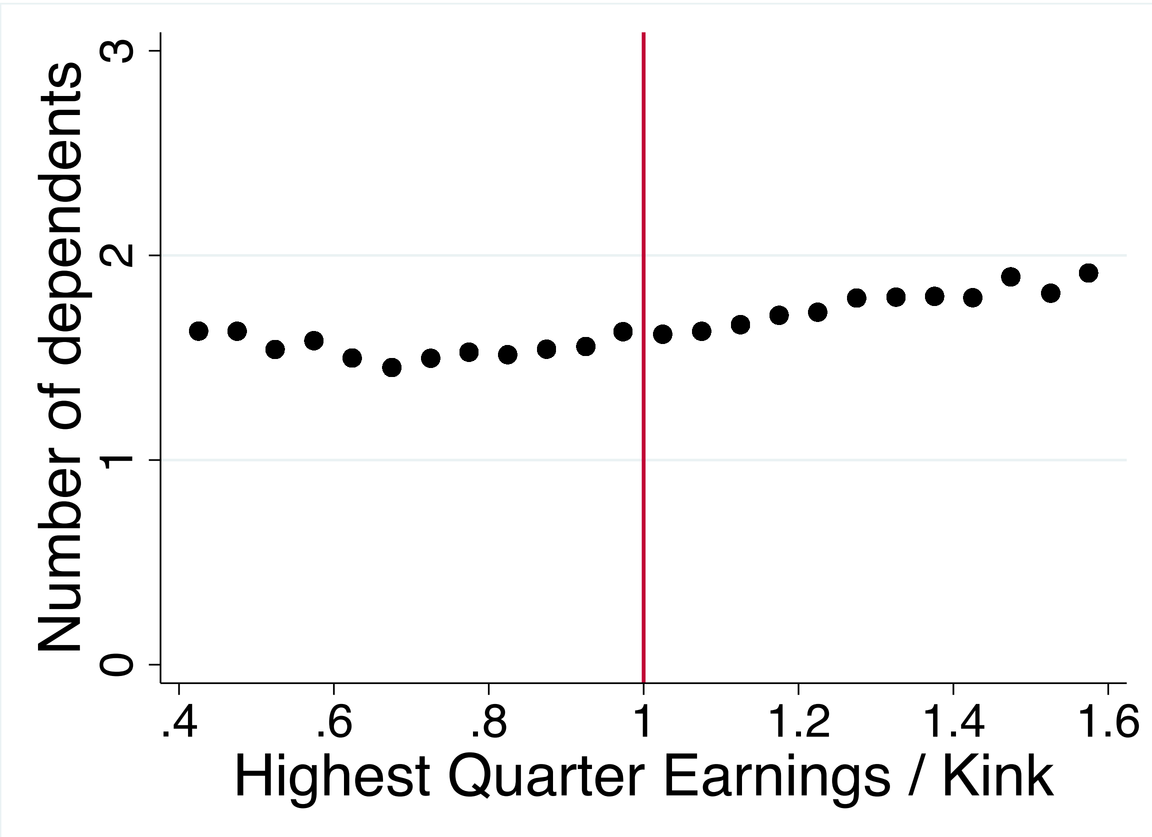


Figure 21: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

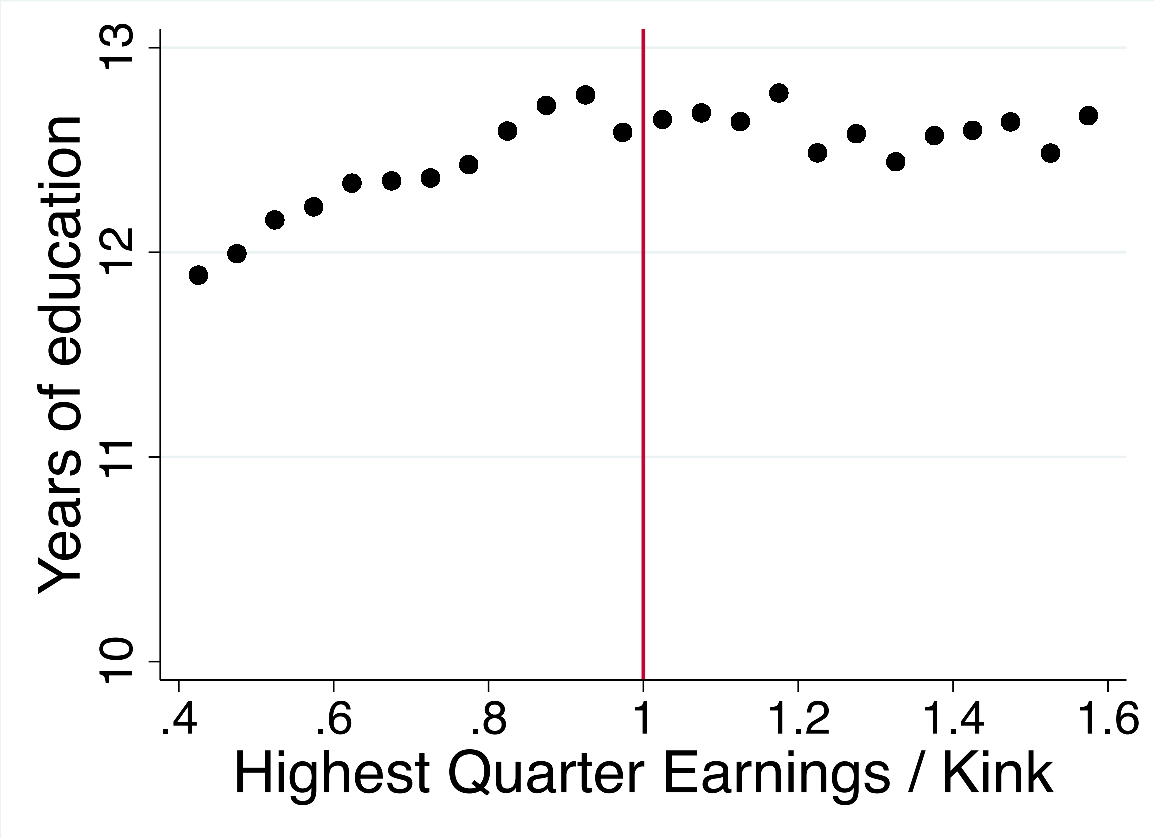


Figure 22: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

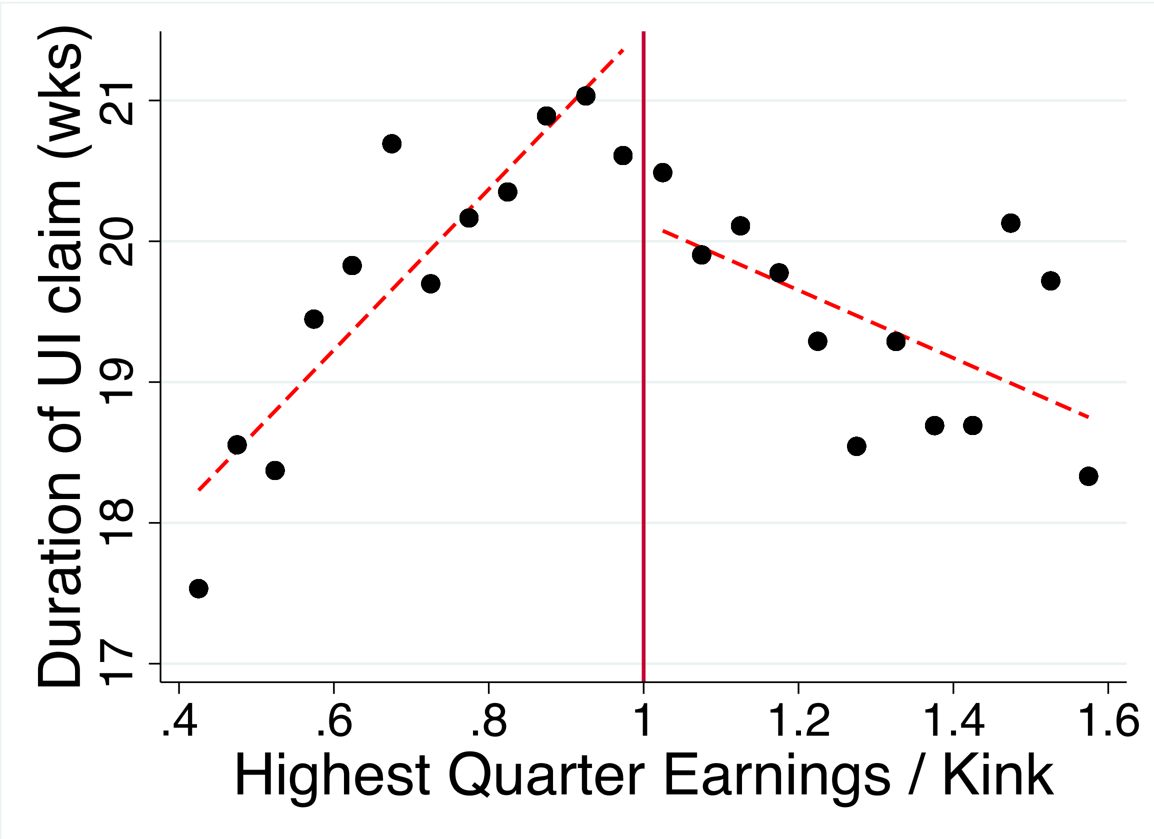


Figure 23: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

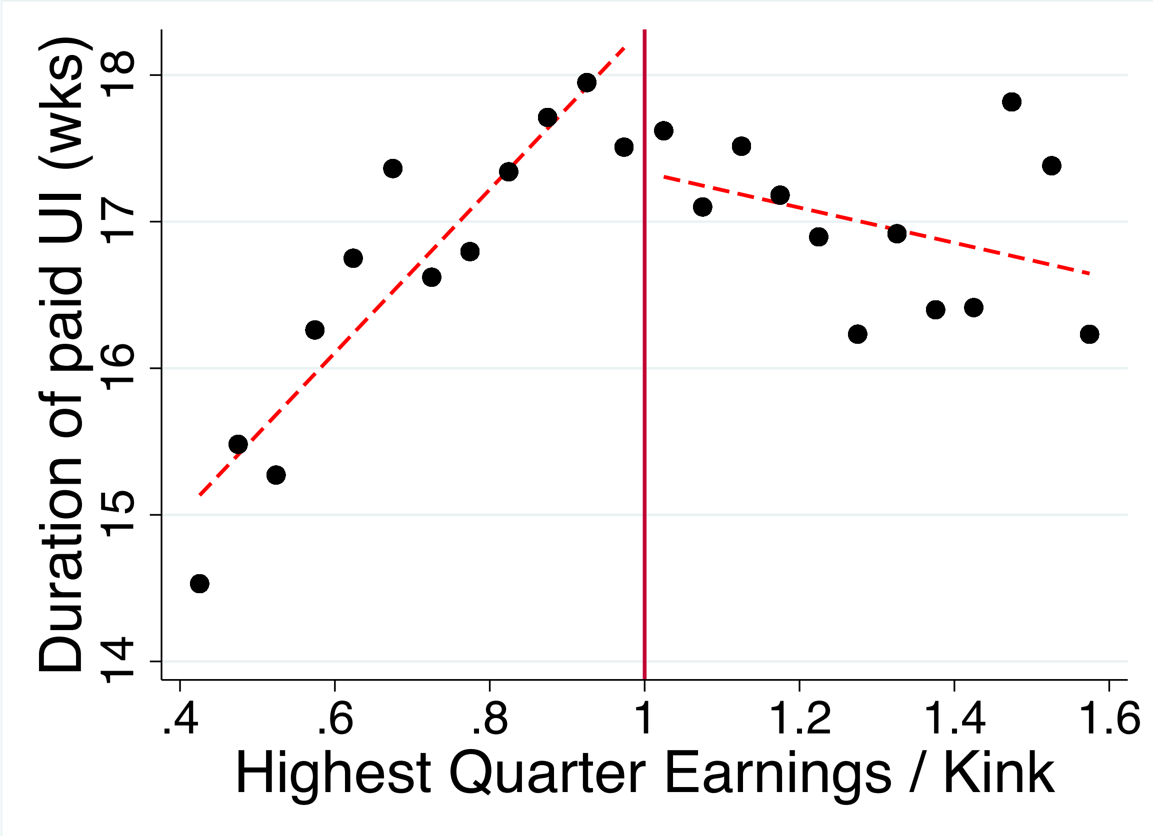


Figure 24: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

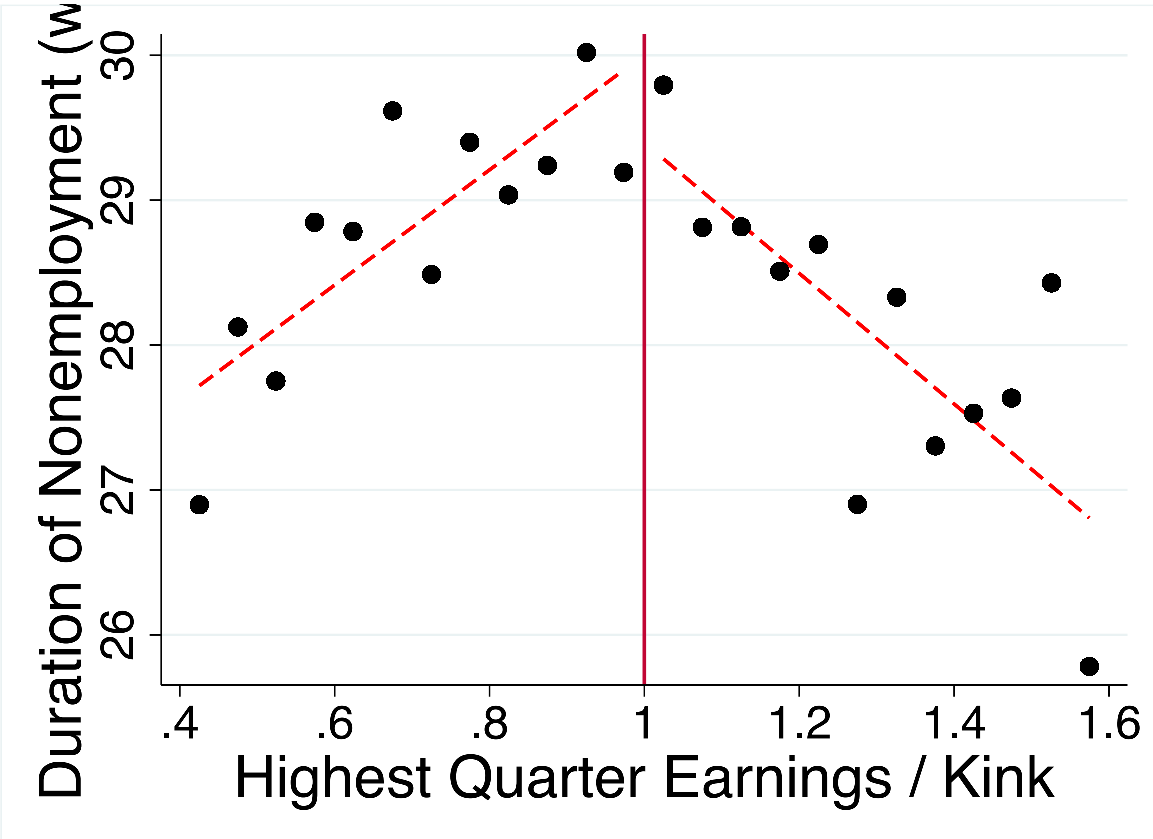


Figure 25: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

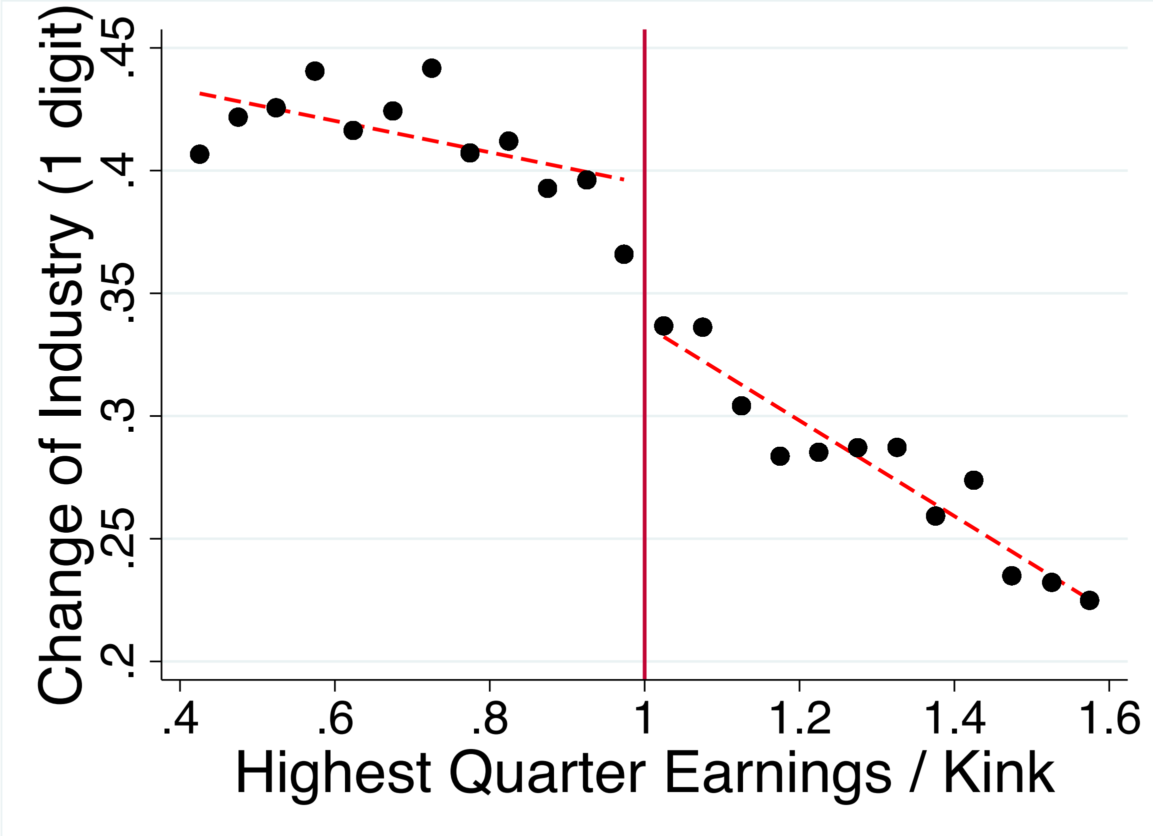


Figure 26: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

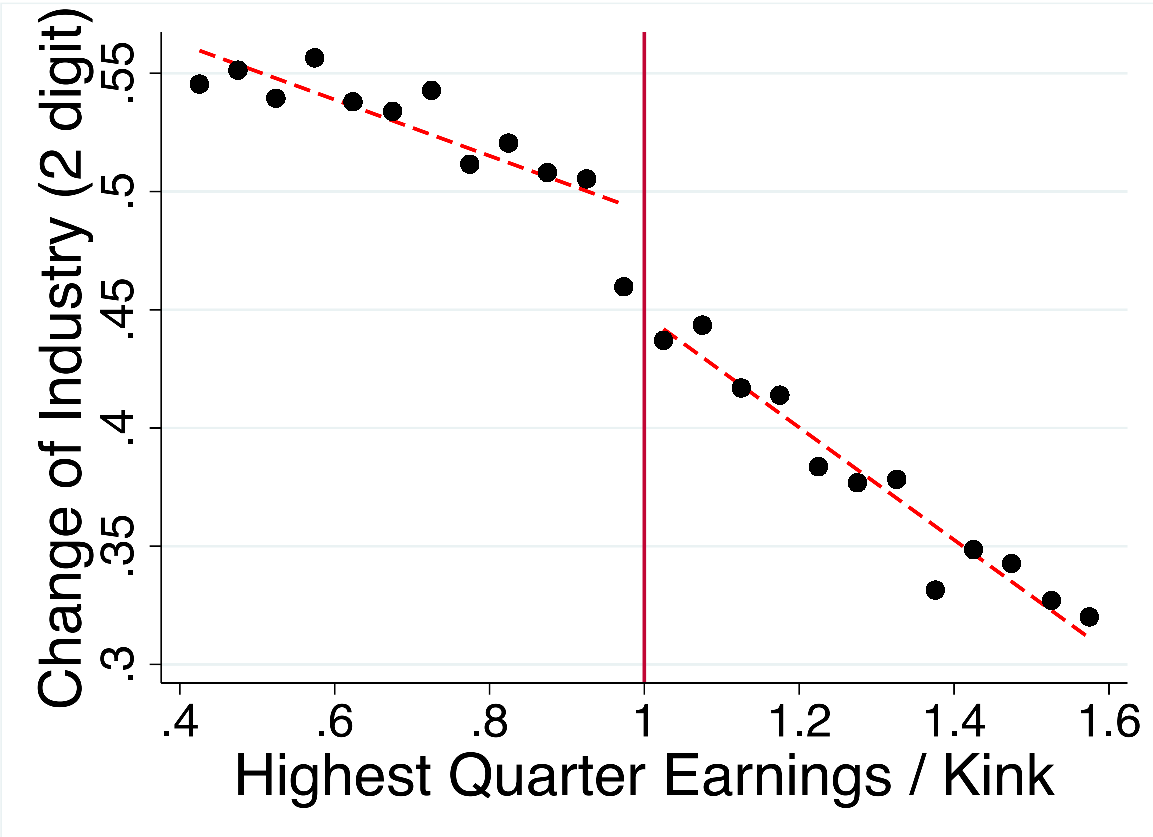


Figure 27: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

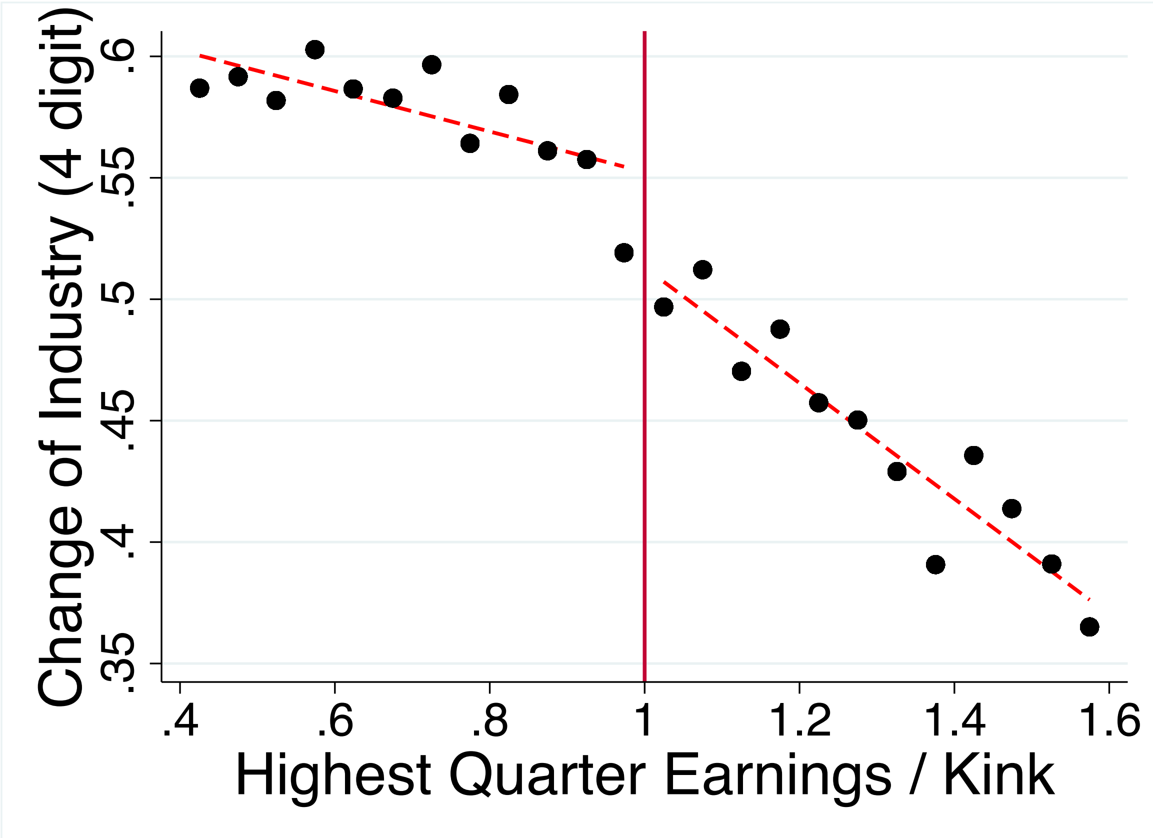


Figure 28: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

C Additional RKD Tables

Table 6: RKD Estimates of the Effect of the Benefit Level

	Duration of Initial Spell	Duration of UI Paid	Duration of UI Claimed	Change Industry (4 digit)	Change Industry (3 digit)	Change Industry (2 digit)	Change Industry (1 digit)
			July 1979 - June 1980				
α	.031	.028	.031	.00034	.00034	.00016	.00058
	(.007)	(.006)	(.007)	(.00027)	(.00027)	(.00027)	(.00025)
$\varepsilon_b = \frac{dY}{db} \cdot \frac{b}{Y}$	.677	.682	.647	.23	.233	.119	.574
	(.147)	(.152)	(.136)	(.179)	(.183)	(.203)	(.249)
Polynomial Order	1	1	1	1	1	1	1
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	3493	3493	3493	3010	3010	3010	3010
			July 1980 - June 1981				
α	.028	.024	.031	.00098	.00101	.00079	.00069
	(.007)	(.006)	(.007)	(.00027)	(.00027)	(.00027)	(.00026)
$\varepsilon_b = \frac{dY}{db} \cdot \frac{b}{Y}$	.58	.543	.588	.588	.618	.516	.576
	(.138)	(.146)	(.128)	(.163)	(.166)	(.178)	(.22)
Polynomial Order	1	1	1	1	1	1	1
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	3603	3603	3603	2898	2898	2898	2898
			July 1981 - June 1982				
α	.024	.015	.024	.00051	.00057	.00062	.00051
	(.009)	(.009)	(.009)	(.00028)	(.00028)	(.00028)	(.00027)
$\varepsilon_b = \frac{dY}{db} \cdot \frac{b}{Y}$	.371	.263	.352	.326	.376	.43	.437
	(.146)	(.153)	(.137)	(.182)	(.188)	(.198)	(.235)
Polynomial Order	1	1	1	1	1	1	1
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	4278	4278	4278	3143	3143	3143	3143
			July 1982 - June 1983				
α	-.015	-.013	-.018	.00025	.00007	-.00015	.00018
	(.009)	(.009)	(.009)	(.00035)	(.00034)	(.00034)	(.00031)
$\varepsilon_b = \frac{dY}{db} \cdot \frac{b}{Y}$	-.278	-.264	-.312	.256	.079	-.193	.275
	(.168)	(.179)	(.159)	(.352)	(.367)	(.42)	(.474)
Polynomial Order	1	1	1	1	1	1	1
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	3908	3908	3908	2173	2173	2173	2173

Table 7: RKD Estimates of the Effect of the Benefit Level, with Controls

	Duration of Initial Spell	Duration of UI Paid	Duration of UI Claimed	Change Industry (4 digit)	Change Industry (3 digit)	Change Industry (2 digit)	Change Industry (1 digit)
July 1979 - June 1980							
α	.026	.023	.029	.00032	.00029	.00013	.0005
	(.008)	(.008)	(.008)	(.00033)	(.00033)	(.00033)	(.00031)
$\varepsilon_b = \frac{dY}{db} \cdot \frac{b}{Y}$	.58	.545	.598	.212	.202	.098	.5
	(.182)	(.189)	(.169)	(.219)	(.223)	(.249)	(.311)
Polynomial Order	1	1	1	1	1	1	1
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	2421	2421	2421	2073	2073	2073	2073
July 1980 - June 1981							
α	.026	.023	.029	.00093	.00099	.0007	.00075
	(.008)	(.008)	(.008)	(.00033)	(.00033)	(.00033)	(.00032)
$\varepsilon_b = \frac{dY}{db} \cdot \frac{b}{Y}$	.532	.529	.558	.558	.607	.462	.623
	(.173)	(.182)	(.16)	(.199)	(.202)	(.217)	(.271)
Polynomial Order	1	1	1	1	1	1	1
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	2457	2457	2457	1972	1972	1972	1972
July 1981 - June 1982							
α	.018	.011	.019	.00045	.00052	.00041	.00022
	(.011)	(.011)	(.011)	(.00034)	(.00034)	(.00034)	(.00033)
$\varepsilon_b = \frac{dY}{db} \cdot \frac{b}{Y}$	.286	.187	.274	.293	.348	.29	.186
	(.178)	(.187)	(.166)	(.22)	(.227)	(.238)	(.286)
Polynomial Order	1	1	1	1	1	1	1
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	3012	3012	3012	2177	2177	2177	2177
July 1982 - June 1983							
α	-.016	-.015	-.018	.00038	.00014	-.00019	.0002
	(.011)	(.01)	(.011)	(.00042)	(.00042)	(.00041)	(.00039)
$\varepsilon_b = \frac{dY}{db} \cdot \frac{b}{Y}$	-.301	-.304	-.314	.387	.147	-.237	.3
	(.198)	(.213)	(.187)	(.427)	(.446)	(.516)	(.592)
Polynomial Order	1	1	1	1	1	1	1
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	2739	2739	2739	1505	1505	1505	1505

Table 8: RKD Estimates, Benefit Level, Displaced Workers

	Duration of Initial Spell	Duration of UI Paid	Duration of UI Claimed	Change Industry (4 digit)	Change Industry (3 digit)	Change Industry (2 digit)	Change Industry (1 digit)
				July 1979 - June 1980			
α	.027	.024	.03	.00039	.00036	.00022	.00056
	(.008)	(.008)	(.008)	(.00033)	(.00033)	(.00033)	(.00031)
$\varepsilon_b = \frac{dY}{db} \cdot \frac{b}{Y}$	.602	.566	.621	.26	.25	.172	.557
	(.184)	(.192)	(.171)	(.219)	(.224)	(.249)	(.312)
Polynomial Order	1	1	1	1	1	1	1
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	2395	2395	2395	2052	2052	2052	2052
				July 1980 - June 1981			
α	.026	.023	.029	.00083	.0009	.00061	.00066
	(.008)	(.008)	(.008)	(.00033)	(.00033)	(.00033)	(.00032)
$\varepsilon_b = \frac{dY}{db} \cdot \frac{b}{Y}$	.532	.52	.543	.496	.546	.399	.554
	(.173)	(.183)	(.16)	(.197)	(.201)	(.216)	(.269)
Polynomial Order	1	1	1	1	1	1	1
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	2437	2437	2437	1957	1957	1957	1957
				July 1981 - June 1982			
α	.018	.01	.018	.00045	.00052	.00041	.00023
	(.012)	(.011)	(.011)	(.00034)	(.00034)	(.00034)	(.00033)
$\varepsilon_b = \frac{dY}{db} \cdot \frac{b}{Y}$	.275	.172	.265	.287	.343	.285	.198
	(.179)	(.188)	(.167)	(.22)	(.227)	(.238)	(.286)
Polynomial Order	1	1	1	1	1	1	1
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	2991	2991	2991	2164	2164	2164	2164
				July 1982 - June 1983			
α	-.015	-.013	-.016	.00039	.00014	-.0002	.00018
	(.011)	(.011)	(.011)	(.00042)	(.00041)	(.00041)	(.00039)
$\varepsilon_b = \frac{dY}{db} \cdot \frac{b}{Y}$	-.281	-.274	-.29	.395	.152	-.255	.266
	(.199)	(.213)	(.186)	(.424)	(.443)	(.515)	(.592)
Polynomial Order	1	1	1	1	1	1	1
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	2722	2722	2722	1494	1494	1494	1494

Notes: This version controls for a dummy variable on whether the individual perceived the separation as a displacement.

Table 9: Robustness of RKD Estimates in Weekly Benefits, Bandwidth, Pooled

	Duration of Initial Spell	Duration of UI Paid	Duration of UI Claimed	Change Industry (4 digit)	Change Industry (3 digit)	Change Industry (2 digit)	Change Industry (1 digit)
α	.017	.013	.016	.00051	.00062	.00059	.00043
	(.008)	(.007)	(.008)	(.00028)	(.00028)	(.00028)	(.00027)
Bandwidth	1500	1500	1500	1500	1500	1500	1500
AIC	93553.218	92699.484	93558.886	10714.33	10704.174	10644.551	10076.181
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	11146	11146	11146	7536	7536	7536	7536
α	.016	.013	.016	.00058	.00058	.00042	.00055
	(.004)	(.004)	(.004)	(.00015)	(.00015)	(.00014)	(.00014)
Bandwidth	2500	2500	2500	2500	2500	2500	2500
AIC	143935.599	142639.271	143909.26	16088.482	16059.151	15920.061	14891.918
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	17129	17129	17129	11341	11341	11341	11341
α	.018	.016	.018	-.00002	.00001	-.0001	.00011
	(.002)	(.002)	(.002)	(.0001)	(.0001)	(.0001)	(.00009)
Bandwidth	4500	4500	4500	4500	4500	4500	4500
AIC	178413.132	176856.24	178376.529	19793.77	19719.438	19449.069	17902.524
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	21265	21265	21265	13930	13930	13930	13930

Table 10: Robustness of RKD Estimates in Weekly Benefits, Bandwidth, Pooled with Controls

	Duration of Initial Spell	Duration of UI Paid	Duration of UI Claimed	Change Industry (4 digit)	Change Industry (3 digit)	Change Industry (2 digit)	Change Industry (1 digit)
α	.02	.016	.02	.00073	.00089	.00074	.00068
	(.009)	(.009)	(.009)	(.00034)	(.00034)	(.00034)	(.00033)
Bandwidth	1500	1500	1500	1500	1500	1500	1500
AIC	65814.46	65255.525	65798.992	7141.136	7126.085	7095.711	6795.812
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	7830	7830	7830	5053	5053	5053	5053
α	.013	.011	.014	.00058	.00058	.00033	.00047
	(.005)	(.005)	(.005)	(.00018)	(.00018)	(.00018)	(.00017)
Bandwidth	2500	2500	2500	2500	2500	2500	2500
AIC	99799.174	98972.799	99749.229	10617.341	10587.277	10521.999	9967.47
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	11861	11861	11861	7525	7525	7525	7525
α	.019	.016	.019	.00003	.00007	-.00009	.00013
	(.003)	(.003)	(.003)	(.00012)	(.00012)	(.00012)	(.00012)
Bandwidth	4500	4500	4500	4500	4500	4500	4500
AIC	122783.764	121794.031	122728.359	12971.87	12919.255	12773.164	11922.529
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	14608	14608	14608	9178	9178	9178	9178

Table 11: Robustness of RKD Estimates in Weekly Benefits by Bandwidth

	Duration of Initial Spell	Duration of UI Paid	Duration of UI Claimed	Change Industry (4 digit)	Change Industry (3 digit)	Change Industry (2 digit)	Change Industry (1 digit)
			July 1979 - June 1980				
α	.035	.032	.037	.00006	.00014	.00012	-.00013
	(.012)	(.011)	(.012)	(.00046)	(.00046)	(.00046)	(.00045)
Bandwidth	1500	1500	1500	1500	1500	1500	1500
AIC	20758.268	20515.938	20761.463	3137.075	3135.722	3128.866	2983.296
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	2573	2573	2573	2210	2210	2210	2210
α	.031	.028	.031	.00034	.00034	.00016	.00058
	(.007)	(.006)	(.007)	(.00027)	(.00027)	(.00027)	(.00025)
Bandwidth	2500	2500	2500	2500	2500	2500	2500
AIC	28108.238	27735.891	28071.837	4283.977	4275.32	4267.445	3972.737
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	3493	3493	3493	3010	3010	3010	3010
α	.019	.017	.018	-.00015	-.00016	-.00024	.00013
	(.005)	(.005)	(.005)	(.0002)	(.0002)	(.0002)	(.00019)
Bandwidth	4500	4500	4500	4500	4500	4500	4500
AIC	32561.721	32165.223	32530.544	5023.009	4996.441	4953.326	4512.15
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	4068	4068	4068	3519	3519	3519	3519
			July 1980 - June 1981				
α	.035	.033	.034	.00126	.00134	.00114	.00087
	(.014)	(.013)	(.014)	(.00054)	(.00054)	(.00055)	(.00053)
Bandwidth	1500	1500	1500	1500	1500	1500	1500
AIC	18764.586	18514.397	18791.823	2708.965	2720.726	2738.587	2636.744
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	2315	2315	2315	1897	1897	1897	1897
α	.028	.024	.031	.00098	.00101	.00079	.00069
	(.007)	(.006)	(.007)	(.00027)	(.00027)	(.00027)	(.00026)
Bandwidth	2500	2500	2500	2500	2500	2500	2500
AIC	29091.166	28707.877	29113.717	4123.28	4132.102	4127.151	3960.313
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	3603	3603	3603	2898	2898	2898	2898
α	.03	.027	.032	.00026	.00032	.0001	.00018

	(.005)	(.004)	(.005)	(.00019)	(.00019)	(.00019)	(.00018)
Bandwidth	4500	4500	4500	4500	4500	4500	4500
AIC	34184.511	33717.066	34201.256	4903.308	4901.695	4877.892	4604.241
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	4248	4248	4248	3435	3435	3435	3435
				July 1981 - June 1982			
α	.018	.011	.018	.00016	.00039	.00078	.00038
	(.02)	(.019)	(.02)	(.00058)	(.00058)	(.00058)	(.00057)
Bandwidth	1500	1500	1500	1500	1500	1500	1500
AIC	23144.496	22913.227	23110.439	2797.377	2801.613	2798.893	2667.954
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	2652	2652	2652	1960	1960	1960	1960
α	.024	.015	.024	.00051	.00057	.00062	.00051
	(.009)	(.009)	(.009)	(.00028)	(.00028)	(.00028)	(.00027)
Bandwidth	2500	2500	2500	2500	2500	2500	2500
AIC	37374.193	37006.313	37337.256	4474.997	4472.69	4454.637	4220.571
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	4278	4278	4278	3143	3143	3143	3143
α	.032	.026	.031	-.00011	-.00009	-.00009	.00011
	(.006)	(.005)	(.006)	(.00018)	(.00018)	(.00018)	(.00018)
Bandwidth	4500	4500	4500	4500	4500	4500	4500
AIC	46690.139	46227.859	46660.466	5669.383	5667.353	5618.932	5261.697
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	5365	5365	5365	3979	3979	3979	3979
				July 1982 - June 1983			
α	-.017	-.017	-.02	.00027	.0003	-.00001	.00058
	(.019)	(.018)	(.018)	(.00069)	(.00068)	(.00067)	(.00062)
Bandwidth	1500	1500	1500	1500	1500	1500	1500
AIC	20881.813	20761.88	20883.841	1965.196	1940.907	1874.233	1687.63
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	2451	2451	2451	1389	1389	1389	1389
α	-.015	-.013	-.018	.00025	.00007	-.00015	.00018
	(.009)	(.009)	(.009)	(.00035)	(.00034)	(.00034)	(.00031)
Bandwidth	2500	2500	2500	2500	2500	2500	2500
AIC	33310.255	33136.333	33313.252	3053.267	3023.595	2920.29	2599.385
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	3908	3908	3908	2173	2173	2173	2173

α	0	.002	-.001	-.00023	-.00023	-.00036	-.00018
	(.006)	(.005)	(.006)	(.00022)	(.00022)	(.00021)	(.0002)
Bandwidth	4500	4500	4500	4500	4500	4500	4500
AIC	43880.443	43656.511	43885.134	3997.551	3948.688	3798.298	3341.612
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	5147	5147	5147	2845	2845	2845	2845

Table 12: Robustness of RKD Estimates in Weekly Benefits, Polynomial Order, Pooled

	Duration of Initial Spell	Duration of UI Paid	Duration of UI Claimed	Change Industry (4 digit)	Change Industry (3 digit)	Change Industry (2 digit)	Change Industry (1 digit)
α	.016	.013	.016	.00058	.00058	.00042	.00055
	(.004)	(.004)	(.004)	(.00015)	(.00015)	(.00014)	(.00014)
Polynomial Order	1	1	1	1	1	1	1
AIC	143935.599	142639.271	143909.26	16088.482	16059.151	15920.061	14891.918
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	17129	17129	17129	11341	11341	11341	11341
α	.009	.004	.007	.00034	.00055	.00063	.00026
	(.015)	(.014)	(.015)	(.00055)	(.00055)	(.00055)	(.00053)
Polynomial Order	2	2	2	2	2	2	2
AIC	143915.199	142622.751	143883.547	16076.45	16044.267	15903.544	14881.466
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	17129	17129	17129	11341	11341	11341	11341
α	.063	.057	.064	-.00126	-.00113	-.00068	.0008
	(.037)	(.036)	(.037)	(.00137)	(.00137)	(.00137)	(.00132)
Polynomial Order	3	3	3	3	3	3	3
AIC	143910.603	142618.533	143878.884	16071.883	16040.403	15899.882	14876.426
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	17129	17129	17129	11341	11341	11341	11341

Table 13: Robustness of RKD Estimates in Weekly Benefits, Polynomial Order, Pooled with Controls

	Duration of Initial Spell	Duration of UI Paid	Duration of UI Claimed	Change Industry (4 digit)	Change Industry (3 digit)	Change Industry (2 digit)	Change Industry (1 digit)
α	.013	.011	.014	.00058	.00058	.00033	.00047
	(.005)	(.005)	(.005)	(.00018)	(.00018)	(.00018)	(.00017)
Polynomial Order	1	1	1	1	1	1	1
AIC	99799.174	98972.799	99749.229	10617.341	10587.277	10521.999	9967.470
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	11861	11861	11861	7525	7525	7525	7525
α	.017	.012	.016	.00068	.00092	.00088	.0009
	(.018)	(.017)	(.018)	(.00067)	(.00067)	(.00067)	(.00065)
Polynomial Order	2	2	2	2	2	2	2
AIC	99787.28	98961.175	99735.943	10611.633	10580.213	10512.324	9963.891
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	11861	11861	11861	7525	7525	7525	7525
α	.091	.083	.094	-.00007	.00017	.00066	.00248
	(.044)	(.043)	(.044)	(.00165)	(.00165)	(.00165)	(.00161)
Polynomial Order	3	3	3	3	3	3	3
AIC	99783.679	98957.596	99732.059	10610.415	10579.462	10510.844	9961.597
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	11861	11861	11861	7525	7525	7525	7525

Table 14: Robustness of RKD Estimates in Weekly Benefits by Polynomial Order, Year-by-Year

	Duration of Initial Spell	Duration of UI Paid	Duration of UI Claimed	Change Industry (4 digit)	Change Industry (3 digit)	Change Industry (2 digit)	Change Industry (1 digit)
			July 1979 - June 1980				
α	.031	.028	.031	.00034	.00034	.00016	.00058
	(.007)	(.006)	(.007)	(.00027)	(.00027)	(.00027)	(.00025)
Polynomial Order	1	1	1	1	1	1	1
AIC	28108.238	27735.891	28071.837	4283.977	4275.32	4267.445	3972.737
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	3493	3493	3493	3010	3010	3010	3010
α	.032	.031	.035	-.00113	-.001	-.00073	-.00137
	(.025)	(.023)	(.025)	(.00097)	(.00097)	(.00097)	(.00092)
Polynomial Order	2	2	2	2	2	2	2
AIC	28109.121	27737.353	28071.712	4274.772	4265.142	4257.358	3962.987
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	3493	3493	3493	3010	3010	3010	3010
α	.102	.099	.109	.00086	.00157	.00005	.00045
	(.061)	(.058)	(.061)	(.0024)	(.0024)	(.0024)	(.00229)
Polynomial Order	3	3	3	3	3	3	3
AIC	28104.717	27732.852	28066.652	4273.826	4263.736	4256.934	3962.076
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	3493	3493	3493	3010	3010	3010	3010
			July 1980 - June 1981				
α	.028	.024	.031	.00098	.00101	.00079	.00069
	(.007)	(.006)	(.007)	(.00027)	(.00027)	(.00027)	(.00026)
Polynomial Order	1	1	1	1	1	1	1
AIC	29091.166	28707.877	29113.717	4123.28	4132.102	4127.151	3960.313
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	3603	3603	3603	2898	2898	2898	2898
α	.037	.036	.031	.0021	.00231	.00207	.00092
	(.027)	(.025)	(.027)	(.00105)	(.00105)	(.00105)	(.00103)
Polynomial Order	2	2	2	2	2	2	2
AIC	29095.037	28711.56	29117.611	4125.054	4133.829	4128.821	3964.2
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	3603	3603	3603	2898	2898	2898	2898
α	.005	-.001	-.009	-.00046	-.00037	.00047	.00247

	(.065)	(.062)	(.065)	(.00256)	(.00257)	(.00259)	(.00256)
Polynomial Order	3	3	3	3	3	3	3
AIC	29094.745	28710.996	29117.127	4122.03	4131.555	4124.945	3957.281
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	3603	3603	3603	2898	2898	2898	2898
				July 1981 - June 1982			
α	.024	.015	.024	.00051	.00057	.00062	.00051
	(.009)	(.009)	(.009)	(.00028)	(.00028)	(.00028)	(.00027)
Polynomial Order	1	1	1	1	1	1	1
AIC	37374.193	37006.313	37337.256	4474.997	4472.69	4454.637	4220.571
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	4278	4278	4278	3143	3143	3143	3143
α	-.012	-.019	-.013	-.00042	-.00005	.00056	.0004
	(.037)	(.036)	(.037)	(.00111)	(.00111)	(.00111)	(.00109)
Polynomial Order	2	2	2	2	2	2	2
AIC	37360.768	36997.585	37322.735	4470.298	4468.372	4448.447	4217.918
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	4278	4278	4278	3143	3143	3143	3143
α	.2	.229	.237	.0008	.00003	.00271	.00397
	(.093)	(.089)	(.093)	(.00276)	(.00277)	(.00277)	(.0027)
Polynomial Order	3	3	3	3	3	3	3
AIC	37353.617	36986.818	37313.22	4468.794	4467.652	4447.147	4212.727
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	4278	4278	4278	3143	3143	3143	3143
				July 1982 - June 1983			
α	-.015	-.013	-.018	.00025	.00007	-.00015	.00018
	(.009)	(.009)	(.009)	(.00035)	(.00034)	(.00034)	(.00031)
Polynomial Order	1	1	1	1	1	1	1
AIC	33310.255	33136.333	33313.252	3053.267	3023.595	2920.29	2599.385
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	3908	3908	3908	2173	2173	2173	2173
α	-.02	-.024	-.023	-.00006	.00009	-.00013	.00048
	(.035)	(.034)	(.035)	(.00131)	(.0013)	(.00126)	(.00118)
Polynomial Order	2	2	2	2	2	2	2
AIC	33308.037	33132.832	33309.807	3050.807	3020.375	2917.781	2599.152
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	3908	3908	3908	2173	2173	2173	2173
α	.052	.029	.045	-.00752	-.00701	-.00683	-.00265

	(.087)	(.086)	(.087)	(.00321)	(.00318)	(.0031)	(.00294)
Polynomial Order	3	3	3	3	3	3	3
AIC	33302.959	33128.195	33305.472	3044.063	3014.366	2912.018	2597.399
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	3908	3908	3908	2173	2173	2173	2173

D Regression Kink Design - Potential Duration

In this section, I consider the effect of changes in the potential duration of unemployment benefits on the re-employment sector.

Table 15: RKD Estimates of the Effect of the Potential Duration

	Duration of Initial Spell	Duration of UI Paid	Duration of UI Claimed	Change Industry (4 digit)	Change Industry (3 digit)	Change Industry (2 digit)	Change Industry (1 digit)
				July 1979 - June 1980			
β	-.336	-.361	-.472	-.0204	-.024	-.0163	-.0241
	(.379)	(.353)	(.374)	(.0154)	(.0155)	(.0161)	(.0166)
ε_B	-.659	-.808	-.87	-.852	-1.021	-.739	-1.385
	(.742)	(.791)	(.689)	(.642)	(.661)	(.727)	(.955)
Polynomial Order	1	1	1	1	1	1	1
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	2037	2037	2037	1726	1726	1726	1726
				July 1980 - June 1981			
β	-.074	-.151	-.018	-.0032	-.0023	-.006	-.0128
	(.14)	(.134)	(.141)	(.0061)	(.0062)	(.0062)	(.0063)
ε_B	-.172	-.39	-.037	-.187	-.141	-.384	-1.106
	(.323)	(.345)	(.296)	(.36)	(.371)	(.397)	(.544)
Polynomial Order	1	1	1	1	1	1	1
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	4493	4493	4493	3620	3620	3620	3620
				July 1981 - March 1982			
β	-.133	-.305	-.14	-.0353	-.0314	-.0313	-.025
	(.221)	(.21)	(.22)	(.0074)	(.0075)	(.0076)	(.0075)
ε_B	-.248	-.645	-.245	-2.525	-2.297	-2.442	-2.498
	(.413)	(.443)	(.384)	(.526)	(.549)	(.592)	(.75)
Polynomial Order	1	1	1	1	1	1	1
Controls	✗	✗	✗	✗	✗	✗	✗
Observations	3738	3738	3738	2801	2801	2801	2801

Table 16: RKD Estimates of the Effect of the Potential Duration, with Controls

	Duration of Initial Spell	Duration of UI Paid	Duration of UI Claimed	Change Industry (4 digit)	Change Industry (3 digit)	Change Industry (2 digit)	Change Industry (1 digit)
				July 1979 - June 1980			
β	.092	-.014	-.062	-.0296	-.0322	-.0271	-.0441
	(.459)	(.432)	(.453)	(.0184)	(.0185)	(.0192)	(.0199)
ε_B	.18	-.032	-.115	-1.235	-1.367	-1.227	-2.536
	(.899)	(.968)	(.835)	(.767)	(.789)	(.872)	(1.144)
Polynomial Order	1	1	1	1	1	1	1
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	1366	1366	1366	1170	1170	1170	1170
				July 1980 - June 1981			
β	-.029	-.072	.04	.0015	.0035	-.0005	-.0097
	(.181)	(.173)	(.182)	(.0077)	(.0077)	(.0078)	(.008)
ε_B	-.067	-.187	.085	.088	.213	-.03	-.839
	(.417)	(.448)	(.382)	(.452)	(.464)	(.499)	(.688)
Polynomial Order	1	1	1	1	1	1	1
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	2921	2921	2921	2350	2350	2350	2350
				July 1981 - March 1982			
β	-.369	-.551	-.385	-.0461	-.0412	-.0424	-.0264
	(.276)	(.261)	(.273)	(.0089)	(.0091)	(.0093)	(.0093)
ε_B	-.687	-1.166	-.672	-3.293	-3.015	-3.312	-2.637
	(.515)	(.552)	(.477)	(.634)	(.669)	(.729)	(.932)
Polynomial Order	1	1	1	1	1	1	1
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	2540	2540	2540	1874	1874	1874	1874

E Additional Cost of Job-Loss Figures

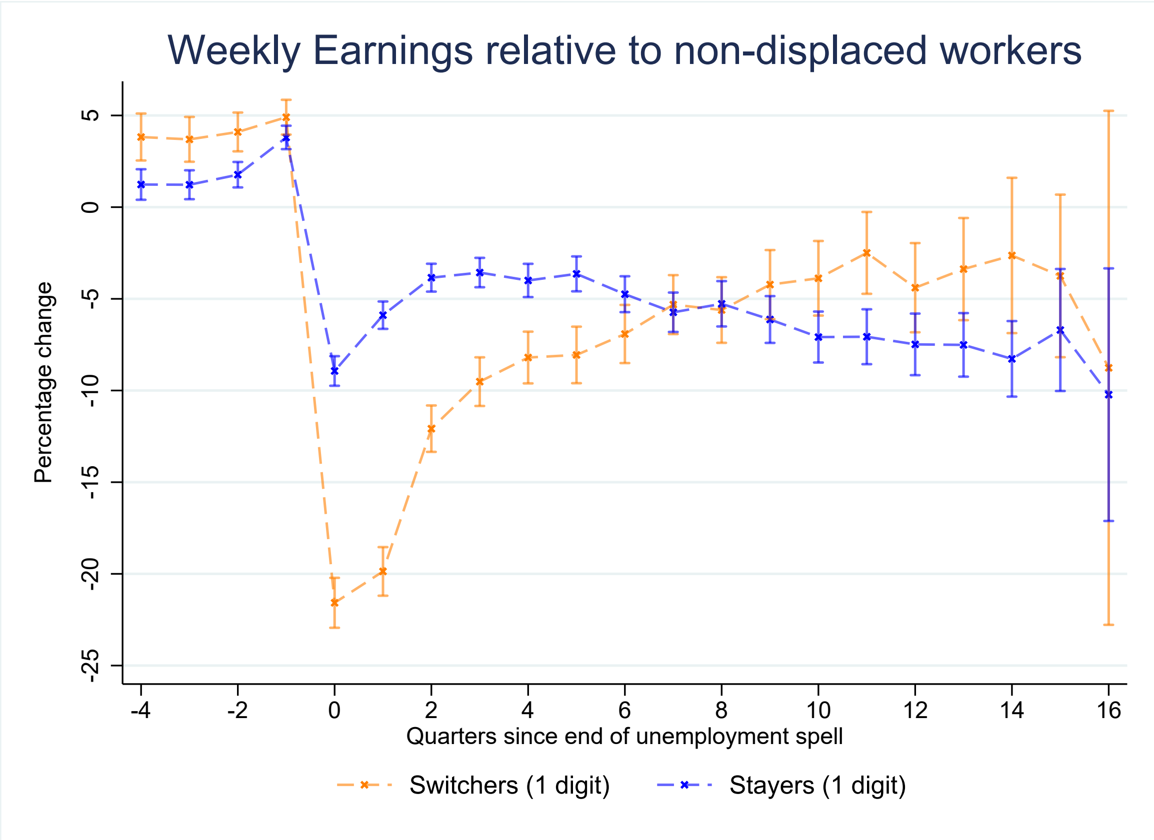


Figure 29: Percentage Change in Log Weekly Earnings around Displacement, CWBH Washington, 1979-1983

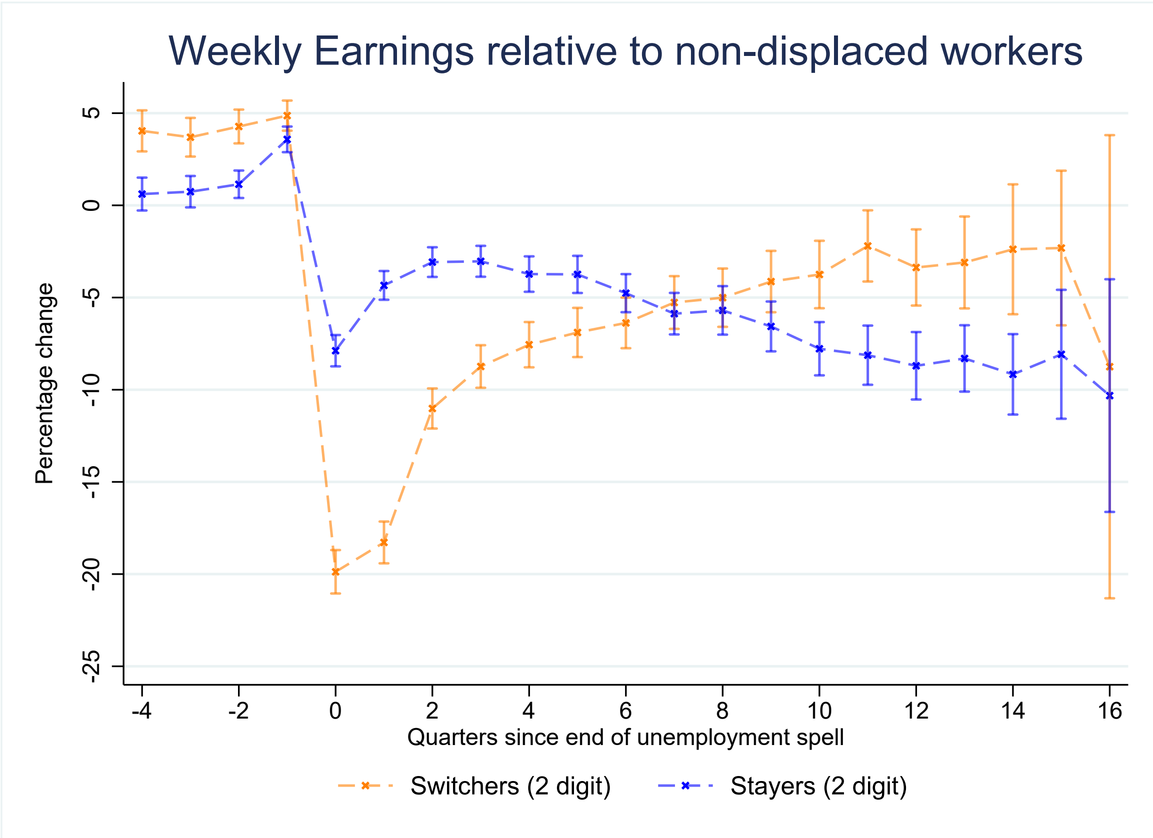


Figure 30: Percentage Change in Log Weekly Earnings around Displacement, CWBH Washington, 1979-1983

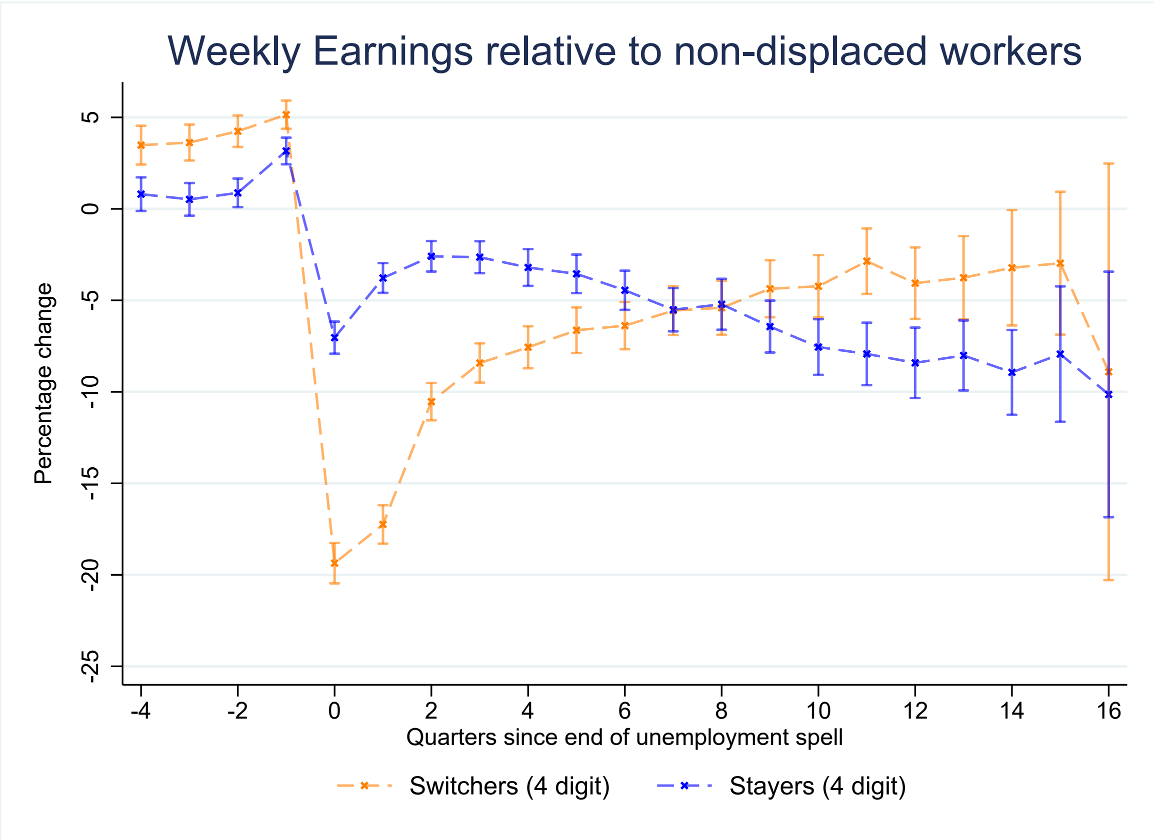


Figure 31: Percentage Change in Log Weekly Earnings around Displacement, CWBH Washington, 1979-1983

F Severance Pay in Mathematica Sample

In this section, I carry out an empirical exercise based on a different method of increasing liquidity - whether a displaced worker received severance pay. The exercise is similar in spirit to Chetty (2008), but looks at whether a displaced worker has changed their industry upon re-employment.

Mathematica Sample. The data consists of two modules. The first is a representative sample of job losers in Pennsylvania in 1991. The second is a sample of unemployment durations in 25 states in 1998 and oversamples UI exhaustees. The dataset includes demographic information, the status of the receipt of severance pay and characteristics of jobs, both prior to unemployment and post-unemployment. In particular, I observe the industry, occupation and tenure in the previous job, as well as the industry and occupation of post-unemployment jobs. A limitation of the data is that I do not observe the amount of severance pay.

The Mathematica sample does not contain measures of the liquidity position of households. To address this, I follow Chetty (2008) in using a predicted measure of net liquid wealth using data from the Survey of Income and Program Participation (SIPP).[52] See Chetty (2008) for a full discussion of the procedure. In terms of sample selection, I exclude individuals who expected a recall at the time of layoff, those above the age of 65, and those who have missing data on job tenure, industry and occupation. In particular, those who have not been re-employed by the end of the sample are also dropped. This is consistent with the earlier sample selection in the CWBH.

Summary Statistics. Table 17 shows the summary statistics from the full sample, and broken by severance payment receipt status. Notice that the sample of those who receive and do not receive severance pay are different on observables. In particular receivers of severance pay are older, slightly more educated (more college graduates, fewer high-school dropouts), and have much longer tenure in their last job. In terms of post-unemployment outcomes, those receiving severance pay have a higher rate of cross-industry reallocation. Notice that the duration of unemployment differs by 1.5 weeks across the two groups.

Regression Equation. The goal of the exercise is to understand how the receipt of severance pay affects whether an unemployed worker changes their industry or occupation. The first specification looks only at whether conditional on job tenure, the receipt of severance pay affects the industry or occupation of the unemployed worker's next job. The idea is that once tenure has been controlled for, any variation in severance pay is due to firm-specific policies. In particular, the regression equation is

$$y_i = \alpha + \beta_1 \mathbb{1}(\text{severance pay})_i + \beta_2 \text{tenure}_i + \gamma' X_i + \varepsilon_i, \tag{38}$$

where the dependent variable is a dummy variable that takes the value of 1 when the new job is in a different 1-digit SIC industry to the previous job and X_i is a vector of controls. The first 3 columns of Table 18 show the results of this regression. Column (2) runs the regression with controls and column (3) runs the regression on a subsample of only prime-aged males - the sample used in Chetty (2008).

[52] Net liquid wealth is measured as total wealth less housing equity, vehicles and unsecured debt.

Table 17: Summary Statistics - Mathematica Sample

	Full Sample	Sev. Pay = 0	Sev. Pay = 1
Change Industry (1-digit)	0.54	0.53	0.57
Change Industry (2-digit)	0.67	0.67	0.71
Change Occupation (1-digit)	0.39	0.40	0.35
Change Occupation (2-digit)	0.55	0.56	0.54
Duration (Weeks)	20.06	19.75	21.30
Age (Years)	35.49	34.70	38.76
Male	0.56	0.56	0.55
Married	0.55	0.53	0.64
High School Dropout	0.10	0.11	0.03
College Graduate	0.17	0.13	0.31
Weekly Benefits ($ 1990)	198.72	187.80	243.71
Tenure (Years)	4.12	3.40	7.11
N	3660	2945	715

Notes: Reported numbers are means in each sample.

In particular, the receipt of severance pay is associated with an increase in the probability of changing industries by around 5 percentage points.

Next, I look at whether the effect of severance pay on industry switching is larger for those with little net liquid wealth.

$$\begin{aligned} y_i = \alpha &+ \beta_1 \mathbb{1}(\text{severance pay})_i \times \mathbb{1}(\text{above median net liquid wealth})_i \\ &+ \beta_2 \mathbb{1}(\text{severance pay})_i + \beta_3 \mathbb{1}(\text{above median net liquid wealth})_i \\ &+ \beta_4 \text{tenure}_i + \gamma' X_i + \varepsilon_i \end{aligned} \tag{39}$$

In particular, the coefficient of interest is an interaction term between a dummy variable for the receipt of severance pay and a dummy variable for whether an unemployed worker is above the median net liquid wealth. If liquidity constraints are important, the effect of severance pay on industry switching should be weaker for those with high liquidity and therefore the sign of the interaction term should be negative.

Columns (4)-(6) of Table 18 presents the results. In particular, the coefficient of interest is negative in the regression without controls and with controls. However, it is statistically insignificant. Digging deeper into the results, column (6) shows the result for the subsample of males. In this specification, the coefficient is more negative and statistically significant. Therefore, the effect of severance pay on industry switching is stronger for males with low liquid net worth.

Last, I look at whether the effect is stronger for the unemployed who receive more severance pay. As severance pay is a non-decreasing function of tenure in the previous job, I look at the interaction between severance pay and an indicator of whether the tenure at the previous job is greater than the median.

$$\begin{aligned} y_i = \alpha &+ \beta_1 \mathbb{1}(\text{severance pay})_i \times \mathbb{1}(\text{above median tenure})_i \\ &+ \beta_2 \mathbb{1}(\text{severance pay})_i + \beta_3 \mathbb{1}(\text{above median tenure})_i + \gamma' X_i + \varepsilon_i \end{aligned} \tag{40}$$

Table 18: OLS Estimates - Mathematica Sample

	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Severance Pay)	0.06***	0.08***	0.05**			
	(0.02)	(0.02)	(0.02)			
$\mathbb{1}$(Severance Pay) $\times$ $\mathbb{1}$(Net Liq. Wealth $\geq$ Median)				-0.05	-0.05	-0.13**
				(0.04)	(0.04)	(0.06)
Controls	✗	✓	✓	✗	✓	✓
Males only	✗	✗	✓	✗	✗	✓
Observations	3,660	3,659	2,045	3,660	3,659	2,045

Notes: The dependent variable is an indicator variable which takes the value of one if an unemployed worker changes their industry of work at the SIC 1-digit level.

Table 19: Change of Industry by Tenure

	(1)	(2)	(3)
$\mathbb{1}$(Severance Pay) $\times$ $\mathbb{1}$(Tenure $\geq$ Median)	0.06*	0.05	0.07*
	(0.03)	(0.03)	(0.04)
$\mathbb{1}$(Tenure $\geq$ Median)	-0.06***	-0.04**	-0.01
	(0.02)	(0.02)	(0.02)
$\mathbb{1}$(Severance Pay)	0.04*	0.06**	0.01
	(0.02)	(0.02)	(0.03)
Observations	3,660	3,659	2,045
Controls	✗	✓	✓
Males only	✗	✗	✓

Notes: The dependent variable is an indicator variable which takes the value of one if an unemployed worker changes their industry of work at the SIC 1-digit level.

G Computational Appendix

Definition A stationary equilibrium is a solution to the individual's problem $\{c, \ell, x, \sigma, v\}$, a stationary distribution $\{g\}$, a solution to the firm's problem $\{n_{js}, k_{js}\}$, prices $\{w_s, p_s, p^Q, r\}$, government fiscal policy $\{\tau, \mathcal{T}, B^g\}$ and aggregate quantities $\{K, N_s, Y_s, C_s, I_s, \mathcal{A}\}$ such that

1. Given prices $\{w_s, p_s, r\}$, and government fiscal policy $\{B^g\}$, $\{c, \ell, x, \sigma, v\}$ solves the individual's problem
2. Given the solution for the individual's problem $\{c, \ell, x, \sigma, v\}$, $\{g\}$ satisfies the Kolmogorov Forward Equation
3. The aggregate quantities $\{K, N_s, Y_s, C_s, I_s, \mathcal{A}\}$ are compatible with individual's policy functions and stationary distribution
4. Given prices $\{w_s, r\}$, $\{n_{js}, k_{js}, p_{js}, \}$ solves the firm's problem
5. The government budget constraint is satisfied
6. The capital, goods and labor markets clear

Algorithm for Solving the Stationary Equilibrium

1. Guess $r, \{p_s, N_s\}_{s\in\mathcal{S}}$
2. Get $r^K = r + \delta$ from the no-arbitrage condition
3. Given p_s, calculate marginal cost $m_s = \frac{\epsilon-1}{\epsilon} p_s$
4. Given r, m_s, N_s, calculate capital demand $K_s^d = \left(\frac{\alpha m_s \Theta_s}{r^K}\right)^{\frac{1}{1-\alpha}} N_s$
5. Given K_s^d, N_s get output $Y_s = \Theta_s (K_s^d)^\alpha N_s^{1-\alpha}$
6. Given K_s^d, get aggregate capital demand $K^d = \sum_{s\in\mathcal{S}} K_s^d$
7. Given K^d, get investment $I = \delta K^d$
8. Given m_s, Y_s, N_s, get wages $w_s = \frac{(1-\alpha) m_s Y_s}{N_s}$
9. Given p_s, m_s, Y_s, calculate dividends $d_s = (p_s - m_s) Y_s$
10. Given d_s, r calculate equity price $p^Q = \frac{\sum_{s\in\mathcal{S}} d_s}{r}$ where the return is pinned down by the no-arbitrage equation of the financial intermediary
11. Given r, p_s, w_s, solve individual's HJB marching backwards. Calculate policy functions
12. Given savings policy, solve KFE marching forward to get the distribution g
13. Given g, get asset supply $\mathcal{A} = \int\int\int\int a g(a, z, e, s) dadzdeds$,
    aggregate consumption $\mathcal{C} = \int\int\int\int c g(a, z, e, s) dadzdeds$,
    sectoral labor supply $\mathcal{L}_s = \int\int\int z \ell g(a, z, e, s) dadzde$
    and total transfer payments $\mathcal{T} = \int\int\int\int \min\{\chi w_s z, \bar{T}\} g(a, z, e, s) dadzdeds$
14. Given $r, \mathcal{T}, N_s$, get government debt from the government's budget constraint $B^g = \frac{\mathcal{T} - \tau \sum_{s\in\mathcal{S}} N_s}{r}$ (bonds are adjusting)
15. Given $B^g, \mathcal{A}, p^Q$ get capital supply $K = \mathcal{A} + B^g - p^Q$
16. Given $p_s, \mathcal{C}, I$ get sectoral consumption $\mathcal{C}_s = \omega_s p_s^{-\eta} \mathcal{C}$ and sectoral investment $I_s = \omega_s^I (\frac{p_s}{p_I})^{-\eta_I} I$
17. Check market clearing in the capital, sectoral labor and sectoral goods markets
    $\Lambda = \frac{|K^d - K|}{K^d} + \sum_{s\in\mathcal{S}} \left(\frac{|N_s - \mathcal{L}_s|}{N_s} + \frac{|\mathcal{C}_s + I_s - Y_s|}{Y_s}\right)$
18. If Λ is close enough to zero, the equilibrium has been found. Otherwise, update the guess and go back to step 2.

Algorithm for Solving the Transition Dynamics

1. Let $\mathbf{x}$ denote a vector $\{x_1, ..., x_T\}$. Guess price vectors $\mathbf{r}$, $\{\mathbf{p_s}, \mathbf{N_s}\}_{s\in\mathcal{S}}$
2. Get $\mathbf{r^K} = \mathbf{r} + \delta$ from the no-arbitrage condition
3. Given $\mathbf{p_s}$, calculate marginal cost $\mathbf{m_s} = \frac{\epsilon-1}{\epsilon}\mathbf{p_s}$
4. Given $\mathbf{r}, \mathbf{m_s}, \mathbf{N_s}$, calculate capital demand $\mathbf{K_s^d} = \left(\frac{\alpha \mathbf{m_s}\Theta_s}{\mathbf{r^K}}\right)^{\frac{1}{1-\alpha}} \mathbf{N_s}$
5. Given $\mathbf{K_s^d}, \mathbf{N_s}$ get output $\mathbf{Y_s} = \Theta_s(\mathbf{K_s^d})^{\alpha}\mathbf{N_s}^{1-\alpha}$
6. Given $\mathbf{K_s^d}$, get aggregate capital demand $\mathbf{K^d} = \sum_{s\in\mathcal{S}} \mathbf{K_s^d}$
7. Given $\mathbf{K^d}$, get investment $\mathbf{I} = \dot{\mathbf{K}}^{\mathbf{d}} + \delta\mathbf{K^d}$
8. Given $\mathbf{m_s}, \mathbf{Y_s}, \mathbf{N_s}$, get wages $\mathbf{w_s} = \frac{(1-\alpha)\mathbf{m_s}\mathbf{Y_s}}{\mathbf{N_s}}$
9. Given $\mathbf{p_s}, \mathbf{m_s}, \mathbf{Y_s}$, calculate dividends $\mathbf{d_s} = (\mathbf{p_s} - \mathbf{m_s})\mathbf{Y_s}$
10. Given $\mathbf{d_s}, \mathbf{r}$ calculate equity price by solving the following differential equation $p_t^Q = \frac{\dot{p_t}^Q + \sum_{s\in\mathcal{S}} d_{st}}{r_t}$ using the terminal conditional $p_T^Q = p^Q$
11. Given $\mathbf{r}, \mathbf{p_s}, \mathbf{w_s}$, solve individual's HJB marching backwards from the terminal stationary value function to get a sequence of value functions $\mathbf{V}$. Calculate policy functions
12. Given savings policy, solve KFE marching forwards to get a sequence of distributions $\mathbf{g}$
13. Given $\mathbf{g}$, get asset supply $\boldsymbol{\mathcal{A}}$, aggregate consumption $\boldsymbol{\mathcal{C}}$, sectoral labor supply $\boldsymbol{\mathcal{L}_s}$ and total transfer payments $\boldsymbol{\mathcal{T}}$
14. Given $\mathbf{r}, \boldsymbol{\mathcal{T}}, \mathbf{N_s}$, get government debt from solving the differential equation $\dot{B}_t^g - r_t \cdot B_t^g = \tau \sum_{s\in\mathcal{S}} w_{st}\mathcal{L}_{st} - \mathcal{T}_t$ with the terminal condition $B_T^g = B^g$ (bonds are adjusting)
15. Given $\mathbf{B^g}, \boldsymbol{\mathcal{A}}, \mathbf{p^Q}$ get capital supply $\mathbf{K} = \boldsymbol{\mathcal{A}} + \mathbf{B^g} - \mathbf{p^Q}$
16. Given $\mathbf{p_s}, \boldsymbol{\mathcal{C}}, \mathbf{I}$ get sectoral consumption $\boldsymbol{\mathcal{C}_s} = \omega_s \mathbf{p_s}^{-\eta}\boldsymbol{\mathcal{C}}$ and sectoral investment $\mathbf{I_s} = \omega_s^I(\frac{\mathbf{p_s}}{\mathbf{p_I}})^{-\eta_I}\mathbf{I}$
17. Check market clearing in the capital, sectoral labor and sectoral goods markets
$\Lambda = \frac{|\mathbf{K^d} - \mathbf{K}|}{\mathbf{K^d}} + \sum_{s\in\mathcal{S}}\left(\frac{|\mathbf{N_s} - \boldsymbol{\mathcal{L}_s}|}{\mathbf{N_s}} + \frac{|\boldsymbol{\mathcal{C}_s} + \mathbf{I_s} - \mathbf{Y_s}|}{\mathbf{Y_s}}\right)$
18. If Λ is close enough to zero, the equilibrium has been found. Otherwise, update the guess and go back to step 2.

Algorithm for Monte-Carlo Simulation. The following algorithm simulates a panel of N individuals for T periods. Individuals are moving only along the stationary distribution and can only move to a finite number of states. The key is to track only the index of individuals in the vector of the distribution. The method is simple and fast and only requires the intensity matrix and the stationary distribution.

1. Draw an initial point of the state-space from the stationary distribution

2. Use the time-dependent KFE to get the matrix that updates the distribution. If using the explicit method, then

$$g_{t+dt} = B^* g_t \text{ where } B^* = I + A^* dt$$

   If using the implicit method, then

$$g_{t+dt} = B^* g_t \text{ where } B^* = (I - A^* dt)^{-1}$$

   In practice, the implicit method is more accurate at the cost of computational time as B^* is a dense matrix.

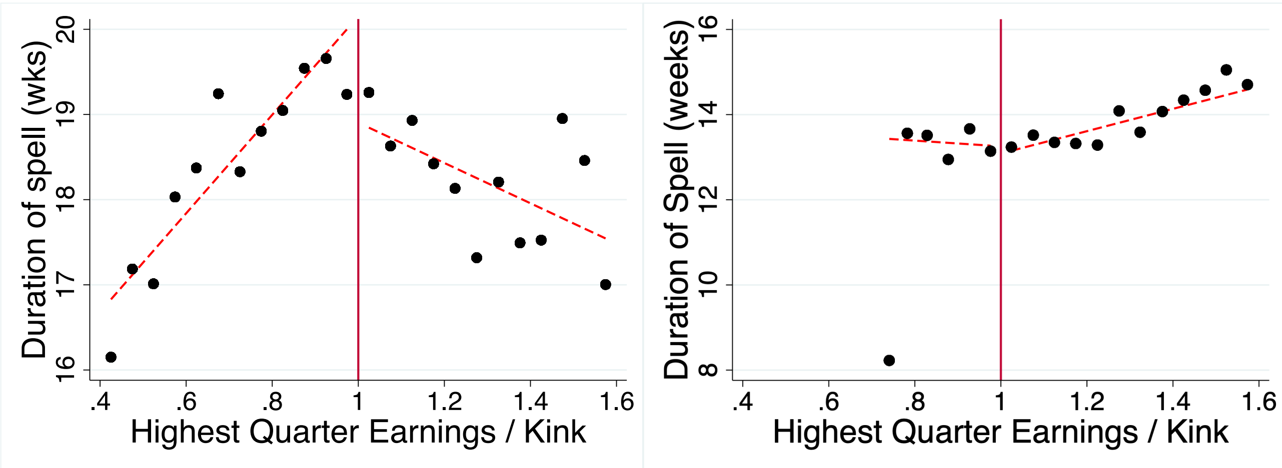
3. Draw an $N \times T$ matrix from a standard uniform distribution. Call it U.

4. For an individual at a given point of the state-space (index), extract the non-zero values and indices of the corresponding column of B^*. Each column of B^* should sum to 1.

5. Create a vector containing the cumulative sum of the non-zero values of the corresponding column of B^*, call it $F_{n,t}$. Compare to the (n, t) realisation of the matrix of standard uniform distribution and find the smallest index such that $F_{n,t} > U_{n,t}$. The smallest index is then the index of the next state variable for the individual

H Model Appendix

H.1 Additional Simulation Results



(a) Data

(b) Model

Figure 32: Regression Kink Design for Unemployment Duration

In Figure 10, I show the results from running the regression kink design for the duration of unemployment, comparing the model and the data. In general, the model slightly underestimates the duration of unemployment, and the effect of liquidity on the duration is insignificant compared to the data. The reason for this result is that individuals above the kink are more likely to have higher productivity. However, high-productivity individuals are more likely to search in their previous industry, conditional on their liquidity. As individuals near the kink point have similar liquidity, the productivity channel offsets the liquidity channel.

H.2 Calibration - Additional Figures

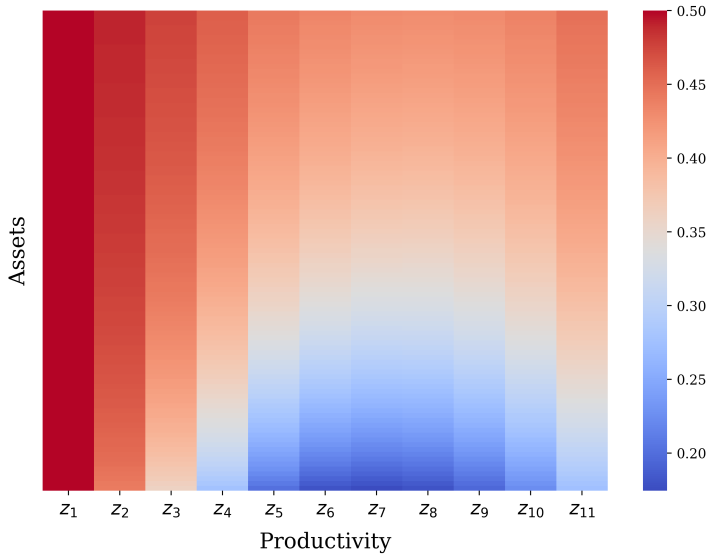


Figure 33: Conditional Choice Probability for Switching Sectors

Notes: This figure plots the policy function for switching sectors, $\sigma_{ss'} = \frac{\sum_{z'=1}^{n_z} \exp\left(\nu \cdot \lambda_{ss'}^{zz'} \cdot [v(a,z',e,s') - v(a,z,u,s)]\right)}{\sum_{s'=1}^{n_z} \sum_{z'=1}^{n_z} \exp\left(\nu \cdot \lambda_{ss'}^{zz'} \cdot [v(a,z',e,s') - v(a,z,u,s)]\right)}$ for the baseline calibration. z_1 denotes the lowest productivity level. Moving vertically along the figure denotes higher assets.

H.3 Model with Endogenous Search Effort

I amend the model to include endogenous search effort in the unemployment state. The unemployed choose how much search effort x to exert. Exerting search effort and its direction incurs a disutility, which is captured in $\widetilde{U}(c, x, \sigma)$. The HJB equation for the unemployed is:

$$\begin{aligned}\rho v_t(a,z,u,s) = \max_{c,x,\{\sigma_{s\tilde{s}}\}_{\tilde{s}}} & \widetilde{U}(c,x) + \partial_a v_t(a,z,u,s)[r_t a + \mathcal{T}_t(z,s) - c] \\ & + \underbrace{\lambda^u_z[v_t(a,z_-,u,s) - v_t(a,z,u,s)]}_{\text{Depreciation of Productivity}} - \underbrace{\kappa}_{\text{Utility Cost of Unemployment}} \\ & + \left\{\sum_{\tilde{s}=1}^{n_s}\sum_{\tilde{z}=1}^{n_z} \lambda^{z\tilde{z}}_{s\tilde{s}} \cdot \sigma^{z\tilde{z}}_{s\tilde{s}} \cdot \underbrace{f(x)}_{\text{Search Effort}} \cdot [v_t(a,\tilde{z},e,\tilde{s}) - v_t(a,z,u,s)]\right\} - \frac{1}{\nu} \cdot f(x) \cdot \underbrace{\sum_{\tilde{s}=1}^{n_s}\sum_{\tilde{z}=1}^{n_z} \sigma^{z\tilde{z}}_{s\tilde{s}} \log \sigma^{z\tilde{z}}_{s\tilde{s}}}_{\text{Expected Entropy Costs}}\end{aligned} \tag{41}$$

subject to

$$\partial_a v_t(\underline{a}, z, u, s) \geq \widetilde{U}_c(r_t \underline{a} + \mathcal{T}_t(z,s) - c), \qquad \sum_{\tilde{s}=1}^{n_s}\sum_{\tilde{z}=1}^{n_z} \sigma^{z\tilde{z}}_{s\tilde{s}} = 1$$

The utility function for the unemployed is given by

$$\widetilde{U}(c,x) = \log c - \psi_x \frac{x^{1+\varphi_x}}{1+\varphi_x}$$

and the linear form for $f(x) = x$.

The expression for the choice probabilities is given by [53]

$$\sigma^{z\tilde{z}}_{s\tilde{s}}(a,z,u,s) = \frac{\exp\left(\nu \cdot \lambda^{z\tilde{z}}_{s\tilde{s}} \cdot [v(a,\tilde{z},e,\tilde{s}) - v(a,z,u,s)]\right)}{\sum_{s'}\sum_{z'} \exp\left(\nu \cdot \lambda^{zz'}_{ss'} \cdot [v(a,z',e,s') - v(a,z,u,s)]\right)}. \tag{42}$$

The expression for the policy function of search effort is given by

$$x(a,z,u,s) = \left[\frac{1}{\psi_x}\sum_{\tilde{s}=1}^{n_s}\sum_{\tilde{z}=1}^{n_z} \sigma^{z\tilde{z}}_{s\tilde{s}} \left(\lambda^{z\tilde{z}}_{s\tilde{s}}[v_t(a,\tilde{z},e,\tilde{s}) - v_t(a,z,u,s)] - \frac{1}{\nu}\log \sigma^{z\tilde{z}}_{s\tilde{s}}\right)\right]^{\frac{1}{\varphi_x}}. \tag{43}$$

Two things are of note. First, as standard in models featuring search effort and assets, the average search effort and elasticity with respect to assets depend on the parameters ψ_x and φ_x.[54] Second, what matters for the aggregate search effort is a weighted sum of the *expected* utility gains from employment across all potential jobs.

[53] Had I specified the utility function without scaling the expected entropy costs with $f(x)$, the model would be identical to one with taste shocks. However, this results in a less tractable form for the CCP, which requires solving a *nonlinear* equation at all points in the state-space as the CCP and the search effort would depend on each other. In particular, the CCP would be $\sigma_{s\tilde{s}}(a,z,u,s) = \frac{\exp(\nu \cdot f(x) \cdot \lambda_{\tilde{s}} \cdot [v_t(a,\tilde{z},e,\tilde{s}) - v_t(a,z,u,s)])}{\sum_{s'=1}^{n_s} \exp(\nu \cdot f(x) \cdot \lambda_{s'} \cdot [v_t(a,z',e,s') - v_t(a,z,u,s)])}$

[54] See also Chetty (2008) and Ifergane (2022).