The London School of Economics and Political Science

Essays in Macroeconomics and International Economics

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Abstract

This thesis is composed of three chapters exploring questions in Macroeconomics and International economics.

The first chapter studies the role of the liquidity position of households in their decision to change their sector of work after unemployment. 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 0.55 percentage points. Upon re-employment, I find that switchers initially have 10 percentage points lower earnings than stayers, but the gap reverses within two years. To rationalise these findings, I develop a quantitative framework that features incomplete markets, multiple sectors, and costly labour 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.

The second chapter studies the effect of the integration of an economy into a Global Value Chain (GVC) and its consequences on inflation dynamics. We demonstrate analytically that an increased reliance on imported intermediate goods, serving as a GVC proxy, results in a flatter Phillips curve. We find evidence indicating that UK industries with higher proportions of intermediate imports from Emerging Market Economies (EMEs) exhibit a flatter Phillips curve. This observation stems not only from the impact of the GVC integration on the slope but also from the influence of cyclical forces that shape firms' marginal costs via international relative price fluctuations.

The third chapter studies the role of transfers made by migrants to their families back home - hereafter known as remittance flows. This chapter documents five facts regarding the micro-level patterns of international remittance flows by leveraging administrative data from a large global money transfer operator (MTO). First, we find that remittance senders use their local currency as the reference currency as opposed to the recipient's local currency. Second, we find that an individual sender's remittance amount doesn't change frequently. Therefore, remittance flows are sticky in the sender's currency. Third, we find that on average, a given sender has multiple recipients, which tend to be located in one country. Fourth, we find that the recipient's local currency is the most common receiving currency, but the U.S. dollar is a prominent receiving currency in some Emerging Markets. Fifth, we find that during the pandemic, there was an increase in the number of transfers and volume of remittance flows through the MTO and this was driven in equal parts by existing and new senders to the platform.

Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

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I declare that my thesis consists of approximately 55,000 words.

Statement of conjoint work

I confirm that Chapter 2 was jointly co-authored with Tommaso Aquilante, Aydan Dogan and Melih Firat, and I contributed 30% of this work. I confirm that Chapter 3 was jointly co-authored with Maria Ludovica Ambrosino, and I contributed 50% of this work.

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Chapter 1

Liquidity and Labor Reallocation in an Uneven Economy

1.1 Introduction

Recessions are periods in which unemployment rises and labor reallocates between different sectors of the economy. Figure 1.1a 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 1.1b 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

[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`.

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.

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.

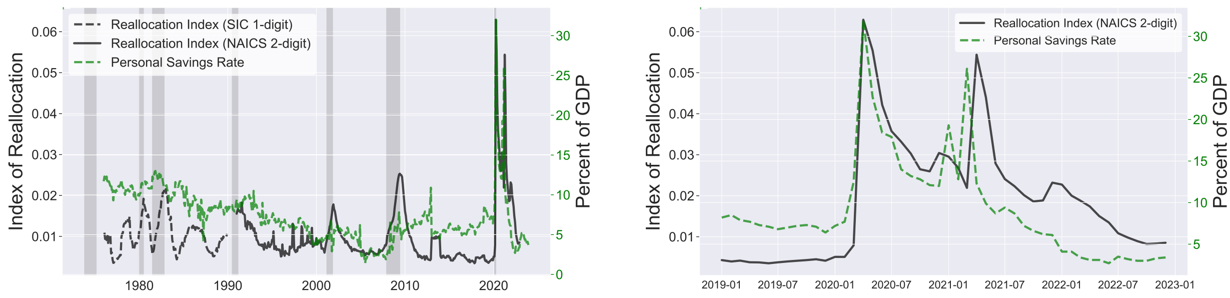
My second main finding is that displaced workers who switch industries have lower initial post-unemployment weekly earnings compared to those who do not switch industries, but the gap *reverses* over time. The initial earnings loss for switchers is around 10 percentage points larger than that of stayers 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 their search effort towards their old industry.

The model builds on the workhorse standard incomplete markets model (Bewley (1983)-Huggett

[3] Figure given in 2010 dollars.

[4] In 1982 dollars.



(a) 1975-2022

(b) 2019-2022

Figure 1.1: 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.

(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

[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.

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 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

[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.

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 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

[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).

[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).

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.

1.2 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.

1.2.1 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 1.2 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]

[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).

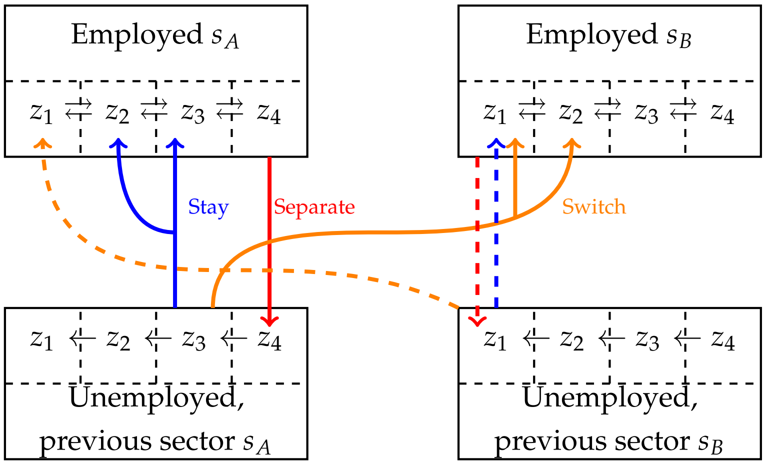


Figure 1.2: Example of Household Block for the Two-sector Case

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.

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 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.

$$\lambda_{ss'}^{zz'} = \underbrace{\lambda_{s'}}_{\text{Base Sector Arrival Rate}} \cdot \underbrace{\lambda^{z'}}_{\text{Arrival Rate of Potential Productivity}} \cdot \underbrace{\mathbb{1}(z', s' | z, s)}_{\text{Switcher Status Component}} . \tag{1.1}$$

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 indi-

[19] See figure 1.9 below.

[20] Again, I refer to figure 1.9 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.

vidual'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:

$$\begin{aligned}\rho v_t(a,z,e,s) - \partial_t v_t(a,z,e,s) = \max_{c,\ell} \mathcal{U}(c,\ell) &+ \partial_a v_t(a,z,e,s)[r_t a + (1-\tau)w_{st} z\ell - c] \\ &+ \underbrace{\zeta_s[v_t(a,z,u,s) - v_t(a,z,e,s)]}_{\text{Transition to unemployment}} \\ &+ \underbrace{\sum_{\tilde{z}} \pi_{z\tilde{z}}[v_t(a,\tilde{z},e,s) - v_t(a,z,e,s)]}_{\text{Productivity Risk}},\end{aligned} \tag{1.2}$$

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:

[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.

$$
\begin{aligned}
\rho v_t(a,z,u,s) - \partial_t v_t(a,z,u,s) = & \max_{c,\{\sigma_{s\bar{s}}\}_{\bar{s}}} \widetilde{\mathcal{U}}(c) + \partial_a v_t(a,z,u,s)[r_t a + \mathcal{T}_t(z,s) - c] \\
& + \underbrace{\xi[v_t(a,z_-,u,s) - v_t(a,z,u,s)]}_{\text{Depreciation of Productivity}} - \underbrace{\kappa}_{\text{Utility Cost of Unemployment}} \\
& + \sum_{s'=1}^{n_s}\sum_{z'=1}^{n_z} \sigma_{ss'}^{zz'} \cdot \left(\underbrace{\lambda_{ss'}^{zz'} \cdot \left[v_t(a,z',e,s') - v_t(a,z,u,s)\right]}_{\text{Gain from directing search}} \underbrace{- \frac{1}{\nu}\log \sigma_{ss'}^{zz'}}_{\text{Cost of Search}} \right),
\end{aligned} \tag{1.3}
$$

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

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 1.6. Second, this results in a tractable form

[24] The present model does not have unemployment insurance that expires after a duration of time. In Appendix 1.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 1.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).

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*

$$\sigma_{ss'}^{zz'}(a,z,u,s) = \frac{\exp\left(\nu \cdot \lambda_{ss'}^{zz'} \cdot [v(a,z',e,s') - v(a,z,u,s)]\right)}{\sum_{s'=1}^{n_s}\sum_{z'=1}^{n_z} \exp\left(\nu \cdot \lambda_{ss'}^{zz'} \cdot [v(a,z',e,s') - v(a,z,u,s)]\right)}. \tag{1.4}$$

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]

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

$$\sigma_{ss'}(a,z,u,s) \equiv \sum_{z'} \sigma_{ss'}^{zz'}. \tag{1.5}$$

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 1.3 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.

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,

[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.

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

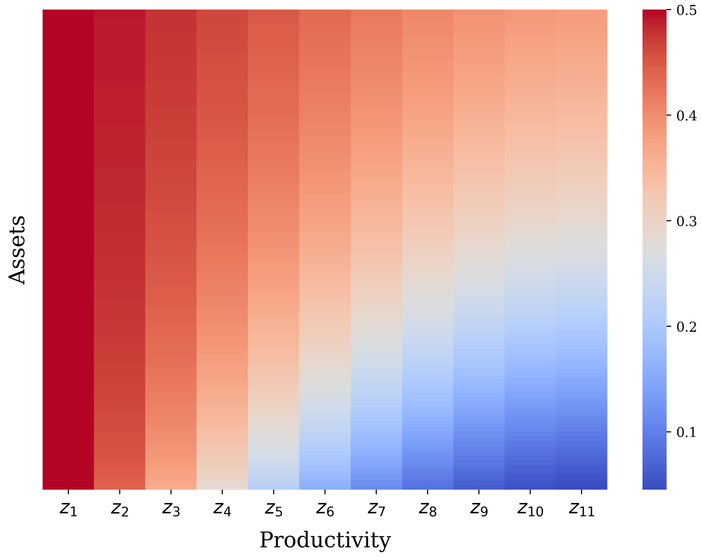


Figure 1.3: Conditional Choice Probability for Switching Sectors

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 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 1.4 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 1.3.

The solid orange line illustrates the case when the arrival rate for switching industries is relatively

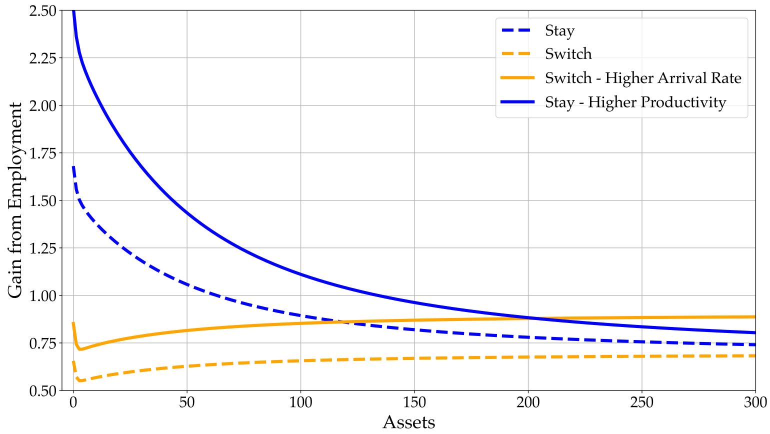


Figure 1.4: More Detail on the Conditional Choice Probability

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 $s' \neq s$.

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 1.3.

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

$$\frac{\partial \sigma_{ss'}}{\partial a}(a,z,u,s) > 0, \quad \forall z > \underline{z}, s \neq s' \tag{1.6}$$

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 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]

1.2.2 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,

$$C_t = \left[\sum_{s=1}^{n_s} \omega_s^{\frac{1}{\eta}} C_{st}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \tag{1.7}$$

where intermediate goods is a bundle of firms' goods

$$C_{st} = \left(\int_0^1 C_{jst}^{\frac{\epsilon-1}{\epsilon}} dj \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{1.8}$$

Similarly, for investment

$$I_t = \left[\sum_{s=1}^{n_s} \omega_s^{\frac{1}{\eta}} I_{st}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \tag{1.9}$$

[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 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.

where

$$I_{st} = \left(\int_0^1 I_{jst}^{\frac{\epsilon-1}{\epsilon}} dj \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{1.10}$$

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

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

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

$$\min_{K_{jst}, N_{jst}} r_t^K K_{jst} + w_{st} N_{jst} \text{ s.t. } Y_{jst} \geq \bar{Y}. \tag{1.11}$$

This results in a marginal cost

$$m_{st} = \frac{1}{Z_{st}} \left(\frac{r_t^K}{\alpha} \right)^{\alpha} \left(\frac{w_{st}}{1-\alpha} \right)^{1-\alpha}, \tag{1.12}$$

and factor demands,

$$K_{jst} = \frac{\alpha m_{st} Y_{jst}}{r_t^K}, \tag{1.13}$$

$$N_{jst} = \frac{(1-\alpha) m_{st} Y_{jst}}{w_{st}}. \tag{1.14}$$

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

$$\max_{p_{jst}, Y_{jst}} p_{jst} Y_{jst} - m_{st} Y_{jst} \text{ s.t. } Y_{jst} \leq \left(\frac{p_{jst}}{P_{st}} \right)^{-\epsilon} (C_{st} + I_{st}). \tag{1.15}$$

This results in an optimal price,

$$p_{jst} = \frac{\epsilon}{\epsilon - 1} m_{st}, \tag{1.16}$$

which is identical across firms.

1.2.3 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

[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).

[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.

as a mutual fund, which has a claim on dividends flows from firms. Thus, in any given period, the intermediary's balance sheet is

$$\mathcal{A}_t + B_t^g = K_t + p_t^Q, \tag{1.17}$$

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

$$r_t = r_t^K - \delta = r_t^b = r_t^Q. \tag{1.18}$$

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

$$\dot{K}_t = I_t - \delta K_t. \tag{1.19}$$

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,

$$\mathcal{T}_t + \dot{B}_t^g = \tau \sum_{s=1}^{n_s} w_{st} N_{st} + r_t^b B_t^g, \tag{1.20}$$

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

$$\mathcal{T}_t(z,s) = \min\{\chi w_{st} z \ell, \bar{\mathcal{T}}\}, \tag{1.21}$$

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.

1.2.4 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

$$\begin{aligned} \partial_t g_t(a,z,e,s) = &- \partial_a[\varsigma_t(a,z,e,s) g_t(a,z,e,s)] \\ &+ \sum_{\tilde{z}=1}^{n_z} \pi_{\tilde{z}z} g_t(a,\tilde{z},e,s) - \sum_{\tilde{z}=1}^{n_z} \pi_{z\tilde{z}} g_t(a,z,e,s) - \zeta_s g_t(a,z,e,s) \\ &+ \sum_{s'=1}^{n_s} \sum_{z'=1}^{n_z} \lambda_{s's}^{z'z} \sigma_{s's}^{z'z} f(x) g_t(a,z',u,s'), \end{aligned} \tag{1.22}$$

[35] $B_t^g < 0$ means that there is a positive amount of government debt.
[36] See for example McKay and Reis (2016) and Beraja and Zorzi (2023).

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

$$\begin{aligned}\partial_t g_t(a,z,u,s) = & -\partial_a[\varsigma_t(a,z,u,s)g_t(a,z,u,s)] + \xi g_t(a,z_+,u,s) - \xi g_t(a,z,u,s) \\ & + \zeta_s g_t(a,z,e,s) - \sum_{s'=1}^{n_s}\sum_{z'=1}^{n_z} \lambda_{ss'}^{zz'}\sigma_{ss'}^{zz'} f(x) g_t(a,z,u,s),\end{aligned} \tag{1.23}$$

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

$$K_t^d = K_t = \mathcal{A}_t + B_t^g - p_t^Q, \tag{1.24}$$

where $\mathcal{A}_t = \sum_{s=1}^{n_s}\sum_{\text{e}=0}^{1}\sum_{j=1}^{n_z}\int_{\underline{a}}^{\infty} a g_t(a,z_j,\text{e},s)da$ 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

$$N_{st} = L_{st} \quad \forall s, \tag{1.25}$$

where L_{st} is the effective labor employed in sector s, defined by $L_{st} = \sum_{j=1}^{n_z}\int_{a=\underline{a}}^{\infty} z_j \ell_t g_t(a,z_j,\text{e},s)da$.[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.

$$Y_{st} = C_{st} + I_{st} \quad \forall s, \tag{1.26}$$

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 $C_t = \sum_{s=1}^{n_s}\sum_{\text{e}=0}^{1}\sum_{j=1}^{n_z}\int_{\underline{a}}^{\infty} c_t(a,z_j,\text{e},s)g_t(a,z_j,\text{e},s)da$ is aggregate consumption.

1.2.5 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.

[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.

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 1.G provides the algorithm to solve for the equilibrium.

1.3 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.

1.3.1 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 1.5 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.

1.3.2 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

[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.

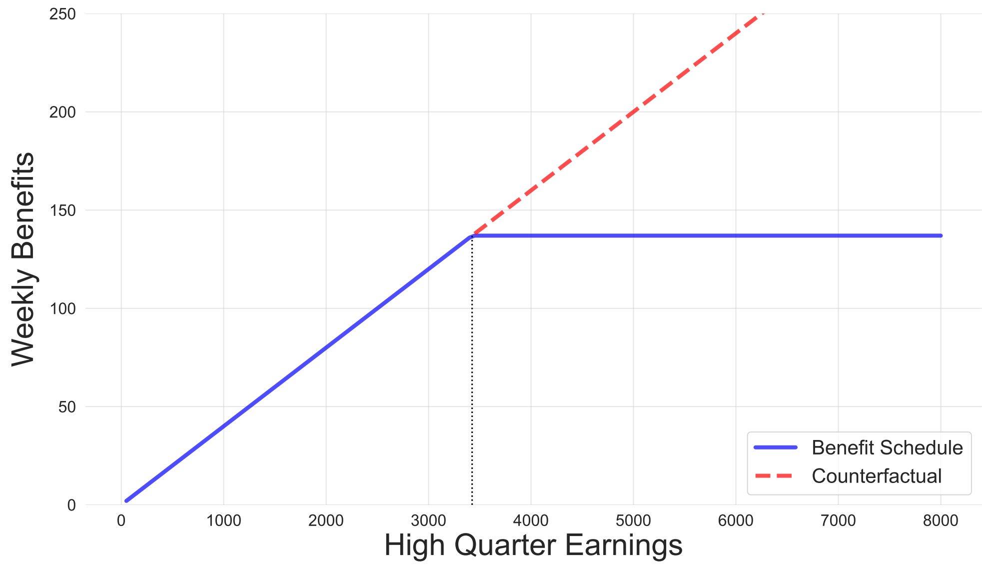


Figure 1.5: Unemployment Insurance Schedule, Washington, 1979-1980

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

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.

Summary statistics. Table 1.1 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 1.6 shows the extent of labor reallocation at the SIC 1-digit level. An interesting obser-

[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.

Table 1.1: 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

vation 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. There 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 1.17 of Appendix A, I plot the employment share of agriculture, manufacturing and 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.

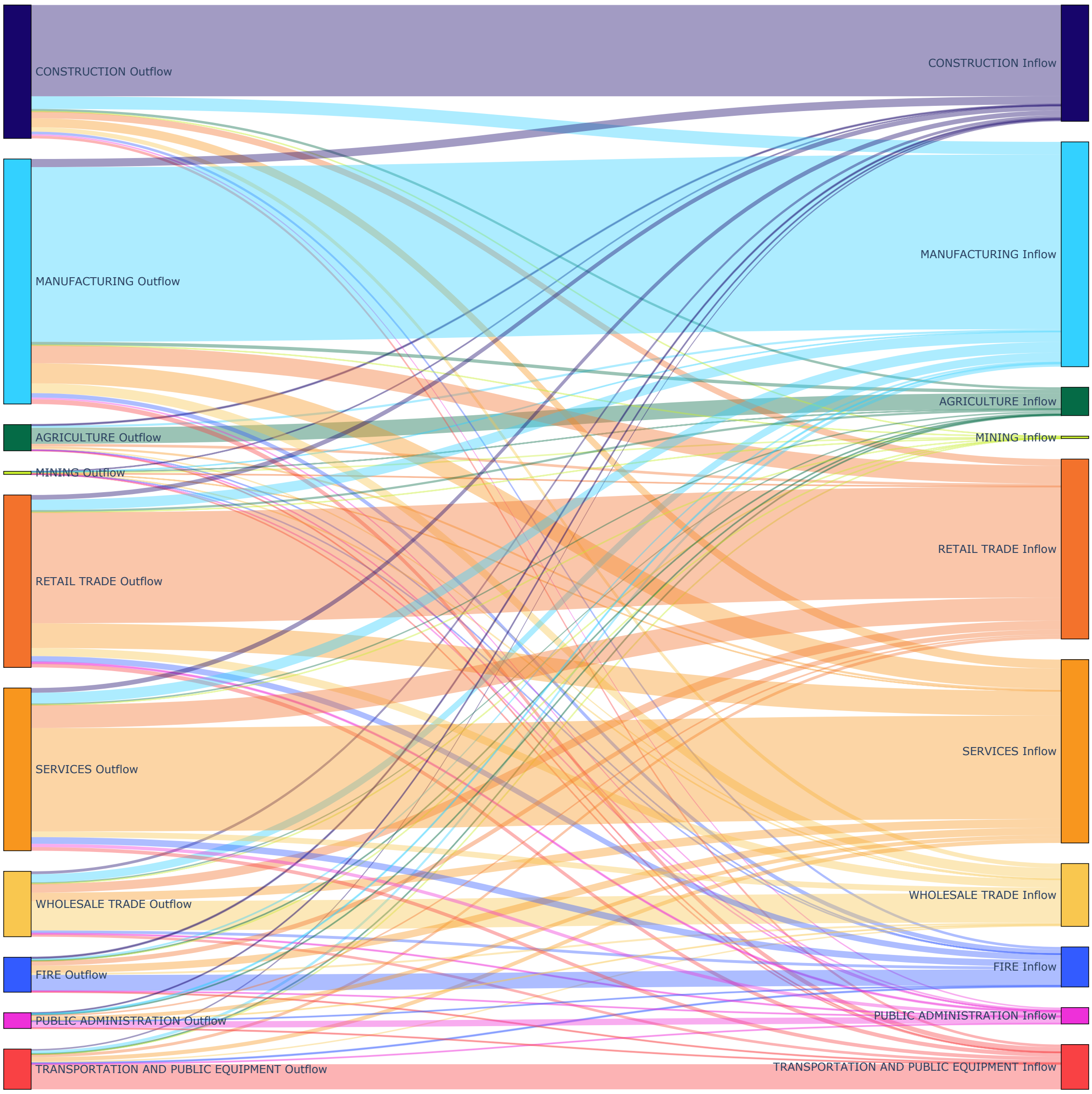


Figure 1.6: Labor Flows through Unemployment, SIC 1-digit, CWBH Washington, 1979-1983

1.3.3 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 1.7 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 1.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-

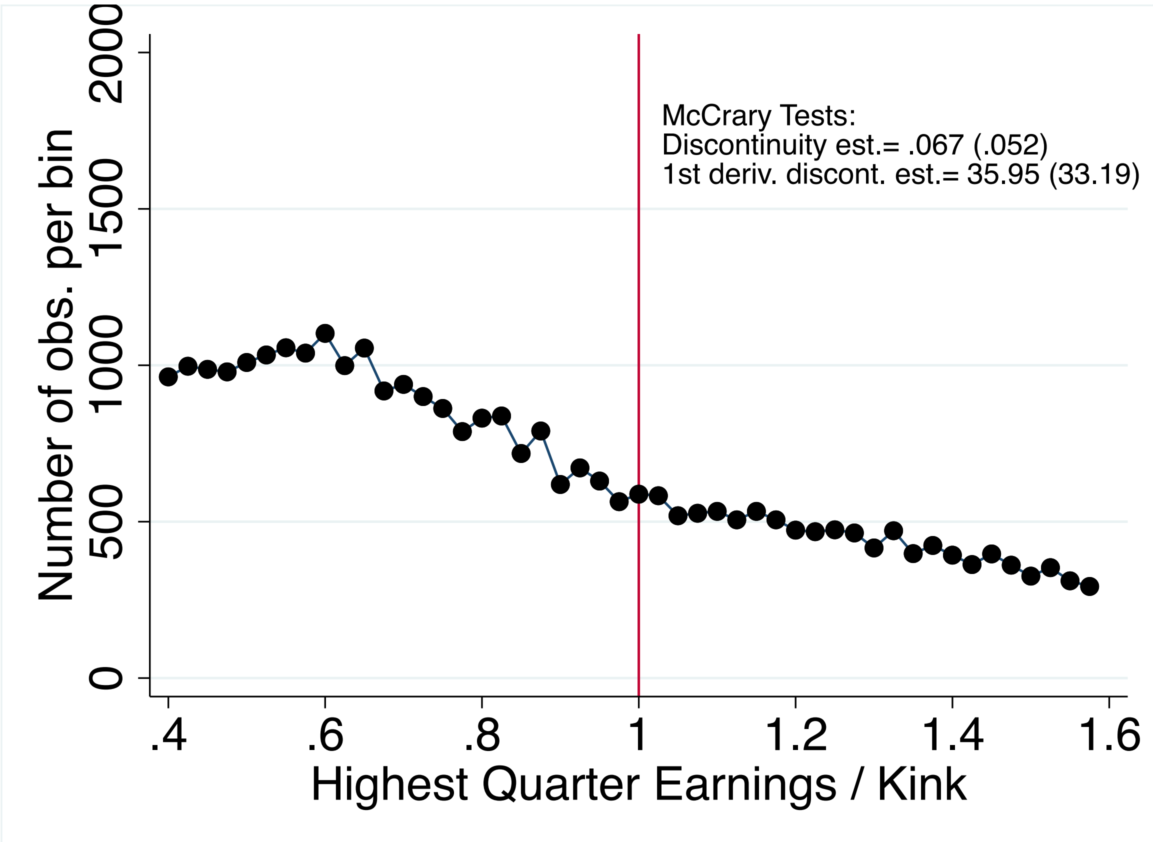


Figure 1.7: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

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

$$y_i = \mu_0 + \left[\sum_{p=1}^{\bar{p}} \gamma_p (w_i - k)^p + \nu_p (w_i - k)^p \cdot D_i \right] + \epsilon_i \tag{1.27}$$

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

$$\hat{\alpha} = \frac{\hat{\nu}_1}{\tau_1} \tag{1.28}$$

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 1.8 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 1.2 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 1.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 1.2, 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.

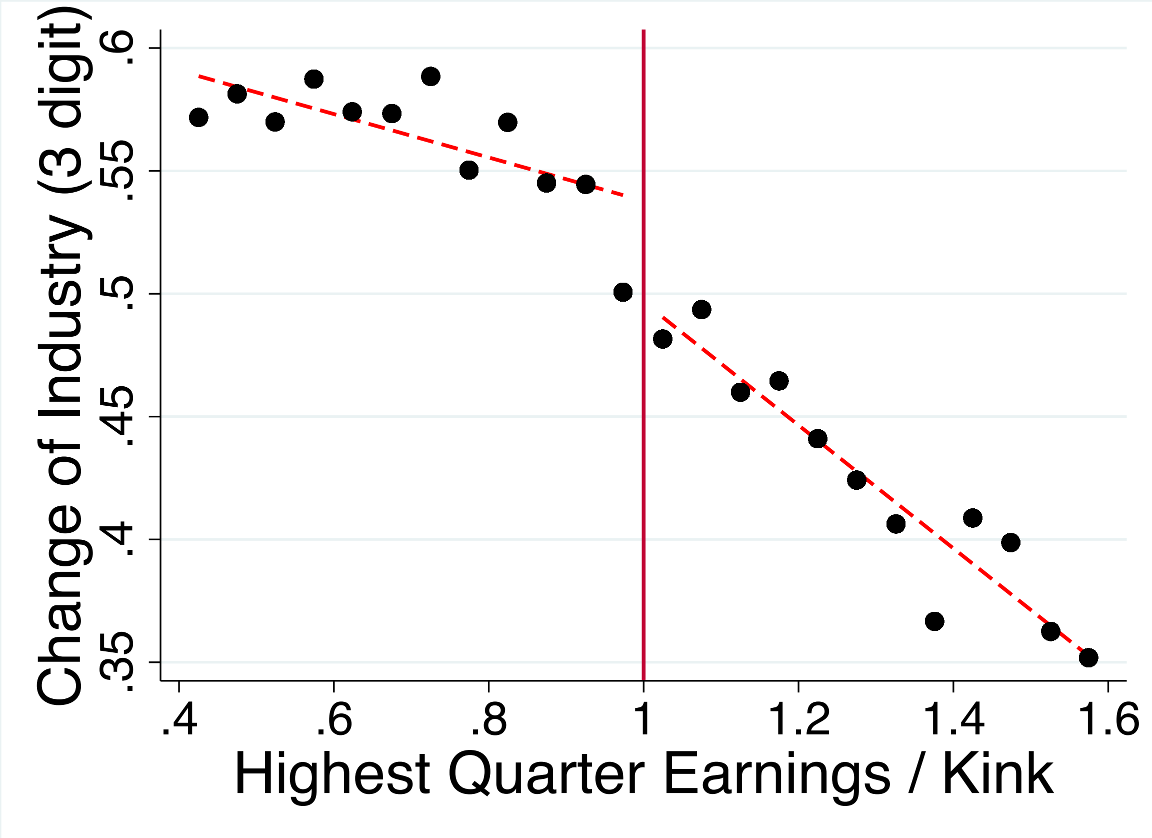


Figure 1.8: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

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 1.2, I allow for a quadratic specification. While the estimated magnitude is lower, the result remains statistically significant. Tables 1.12, 1.13, and 1.14 of Appendix 1.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 1.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 1.F for details.

Table 1.2: 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

1.3.4 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

$$y_{it} = \sum_{k=-\underline{K}}^{\bar{K}} \delta_{ns}^{k} D_{it}^{ns,k} + \varphi_{ns} F_{it}^{ns} + \sum_{k=-\underline{K}}^{\bar{K}} \delta_{sw}^{k} D_{it}^{sw,k} + \varphi_{sw} F_{it}^{sw} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{1.29}$$

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 1.9 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 noted

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

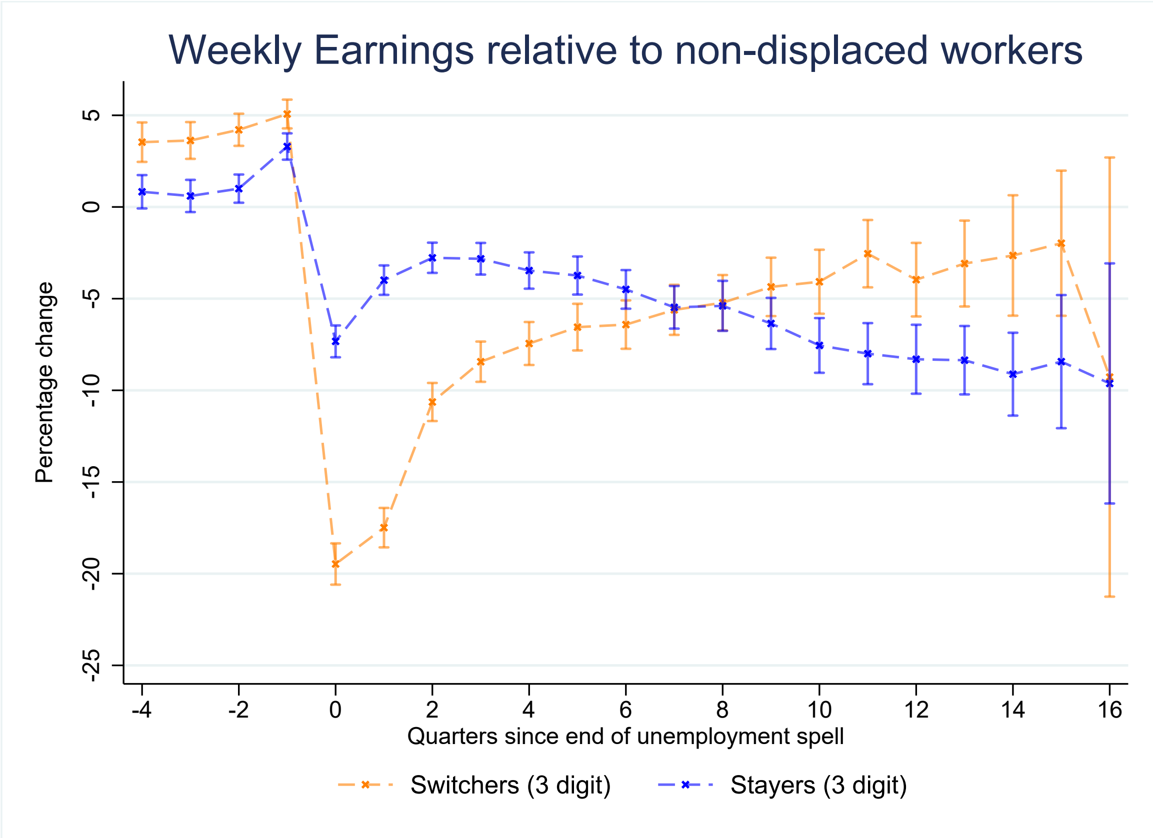


Figure 1.9: Percentage Change in Log Weekly Earnings around Displacement, CWBH Washington, 1979-1983

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.

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 1.9, 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 1.9 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 1.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.

1.4 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.

1.4.1 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 (1.30), I show productivity transition matrices.

$$\Pi = \begin{bmatrix} -\pi_+ & \pi_+ & 0 & \dots & 0 \\ \pi_- & -\pi_- - \pi_+ & \pi_+ & \dots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & \dots & \pi_- & -\pi_- - \pi_+ & \pi_+ \\ 0 & \dots & 0 & \pi_- & -\pi_- \end{bmatrix} \tag{1.30}$$

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 (1.31).

$$\Xi = \begin{bmatrix} 0 & 0 & 0 & \dots & 0 \\ \xi & -\xi & 0 & \dots & 0 \\ 0 & \xi & -\xi & \dots & \vdots \\ \vdots & \vdots & \ddots & \ddots & 0 \\ 0 & 0 & \dots & \xi & -\xi \end{bmatrix} \tag{1.31}$$

Transitions UE. I calibrate the elements of the array Λ using the decomposition in equation (1.1). 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.

$$\Theta^{ss'} = \begin{bmatrix} 1 & & & & & & & & & & \\ 1 & 0 & & & & & & & & & \\ 1 & 0 & 0 & & & & & & & & \\ 1 & 0 & 0 & 0 & & & & & & & \\ 1 & 0 & 0 & 0 & 0 & & & & & & \\ 0 & 1 & 0 & 0 & 0 & 0 & & & & & \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & & & & \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & & & \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & & \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix} \quad \forall s' \neq s \tag{1.32}$$

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 1.3 shows the externally calibrated parameter values and table 1.4 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 1.3: 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 1.4: 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 1.5.3
Government			
$\bar{\mathcal{T}}$	Maximum Transfers	0.43	Fraction of individuals with maximum benefits

1.4.2 Model Validation

Table 1.5: 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 1.5, 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.

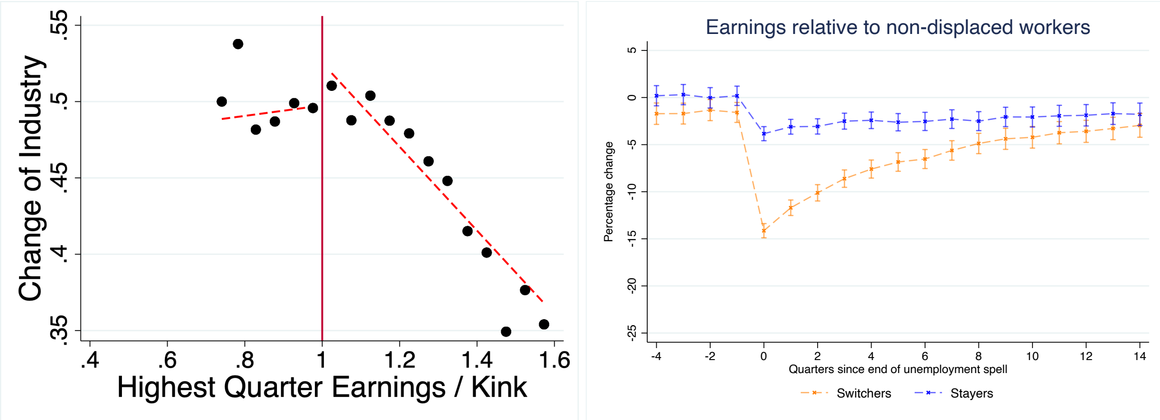
Simulation results. I simulate a panel of individuals when the economy is at the stationary equilibrium.[48] Then, I proceed with running the same regressions on the model-generated data as I do in the actual data.[49]

In panel (a) of figure 1.10, 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 1.4.1. 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 1.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 disadvantage is 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 1.10: Regressions on Model Generated Data

1.5 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.

1.5.1 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}).

$$Z_{st} = \Omega_t \cdot \vartheta_{st} \tag{1.33}$$

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

$$d\Omega_t = -\xi_\Omega(\Omega_t - \bar{\Omega})dt \tag{1.34}$$

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.

$$d\lambda_{st} = -\xi_\lambda(\lambda_{st} - \bar{\lambda}_s)dt \quad \forall s \tag{1.35}$$

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

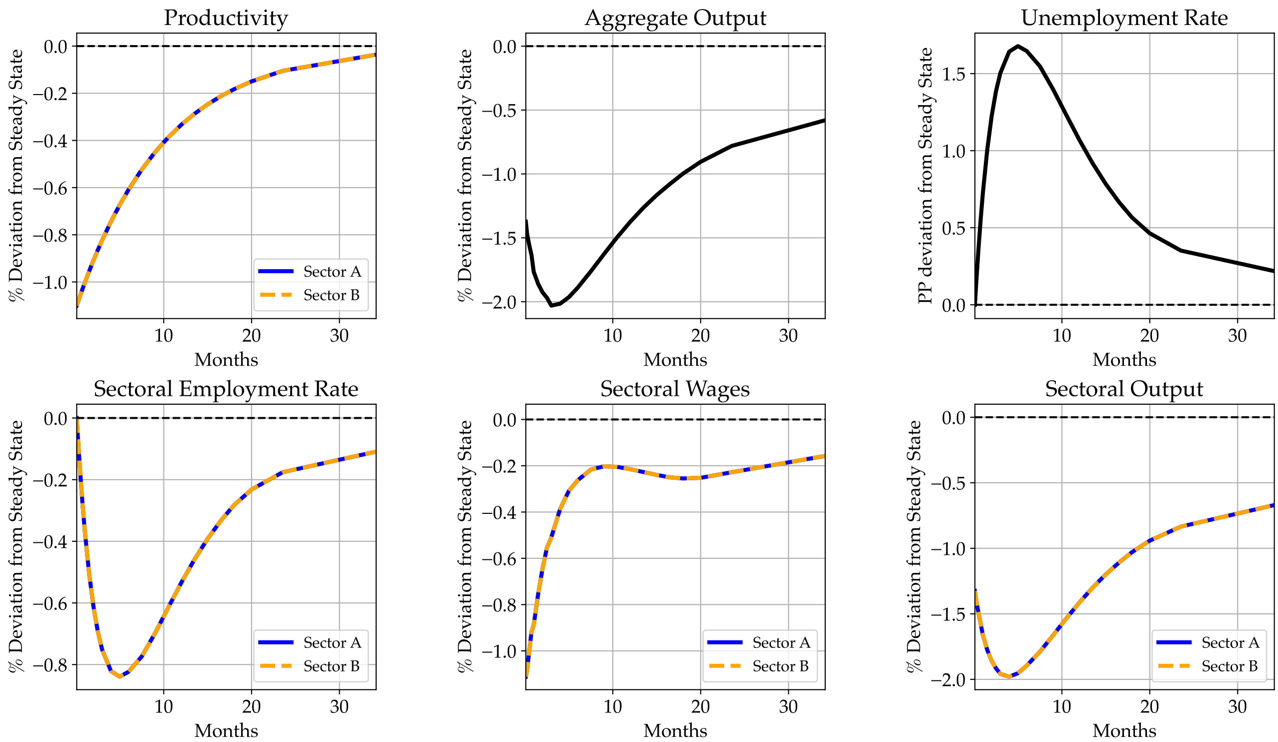


Figure 1.11: Impulse Response to a Transitory Even Shock

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 1.11 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 continues 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.

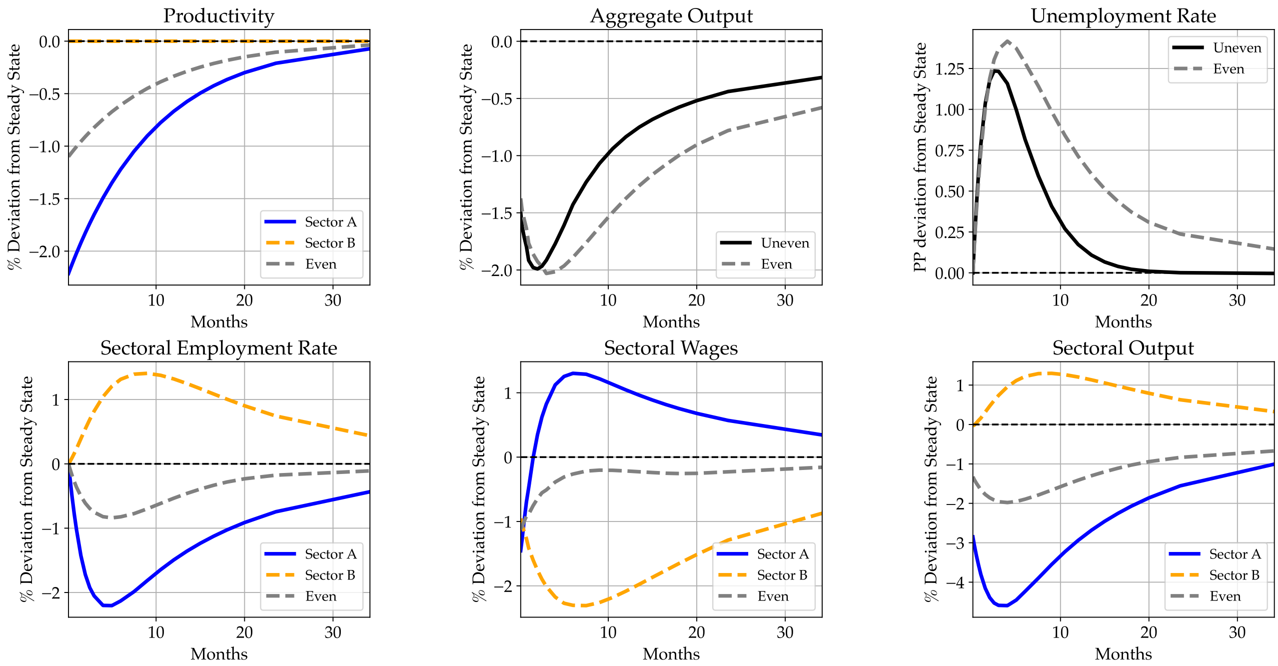


Figure 1.12: Impulse Response to a Transitory Uneven Shock

1.5.2 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.

$$d\vartheta_{At} = -\xi_{\vartheta}(\vartheta_{At} - \bar{\vartheta}_A)dt \tag{1.36}$$

$$d\lambda_{At} = -\xi_{\lambda}(\lambda_{At} - \bar{\lambda}_A)dt \tag{1.37}$$

Figure 1.12 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 1.11 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.

1.5.3 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 1.13, 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

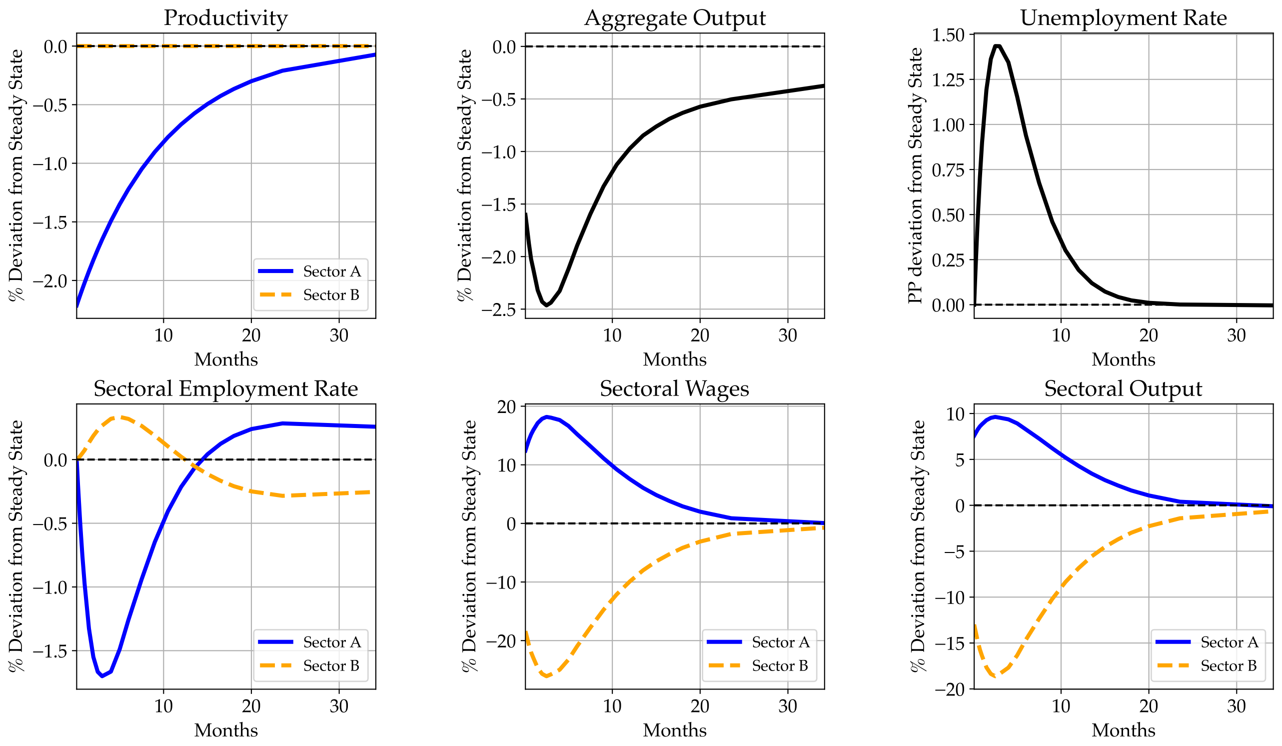


Figure 1.13: Impulse Response to a Transitory Uneven Shock - Low Elasticity of Substitution

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 1.14, 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.

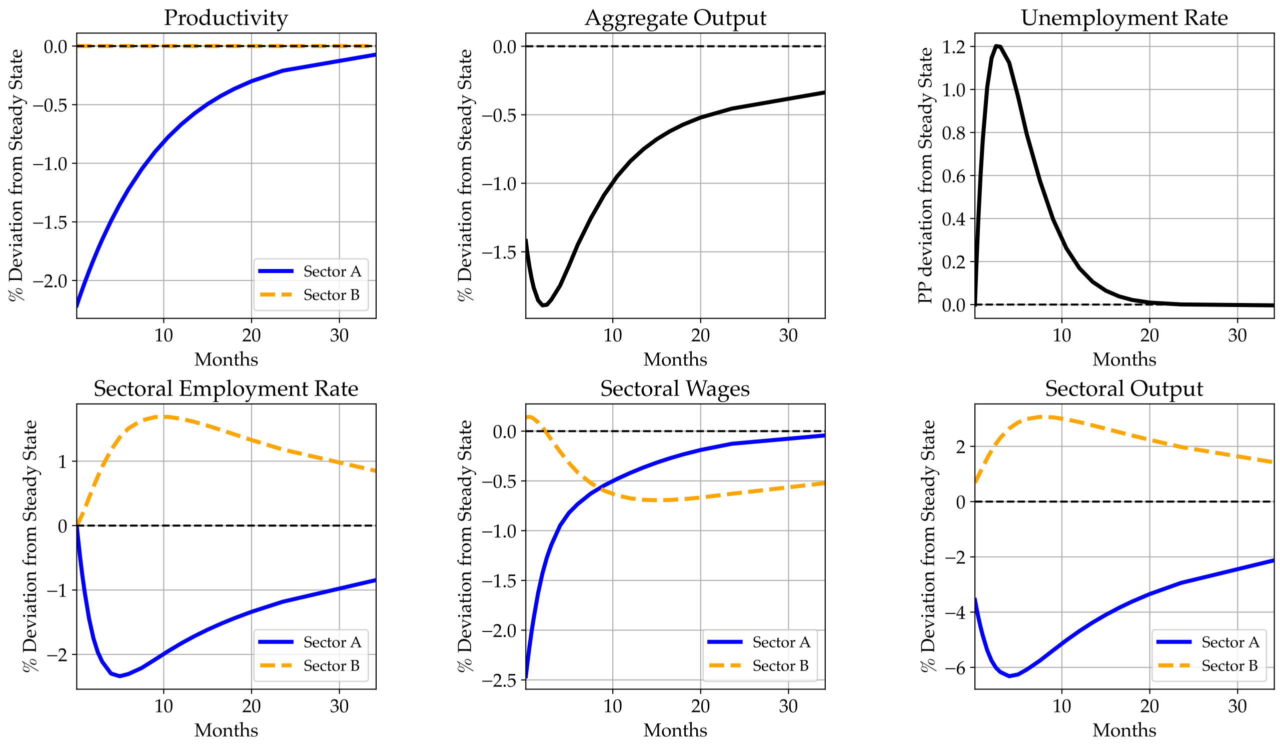


Figure 1.14: Impulse Response to a Transitory Uneven Shock - High Elasticity of Substitution

1.5.4 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 1.15 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 $t \in (0,2]$, $\mathcal{T}_t(z,s) = \min\{\chi w_{st} z\ell, \bar{\mathcal{T}}\} + \Delta\mathcal{T}$.

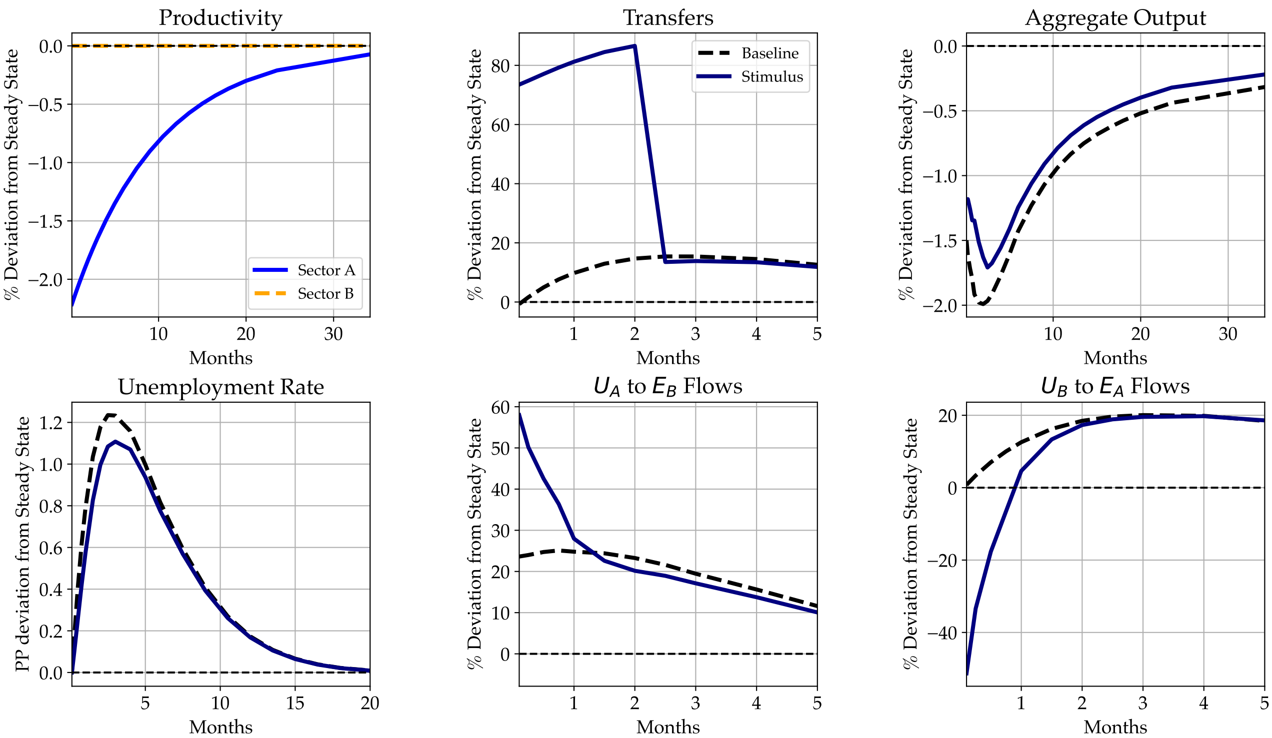


Figure 1.15: Impulse Response to a Transitory Sectoral Shock - Targeted Transfers

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.

1.6 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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Appendix to Chapter 1

1.A Additional Figures

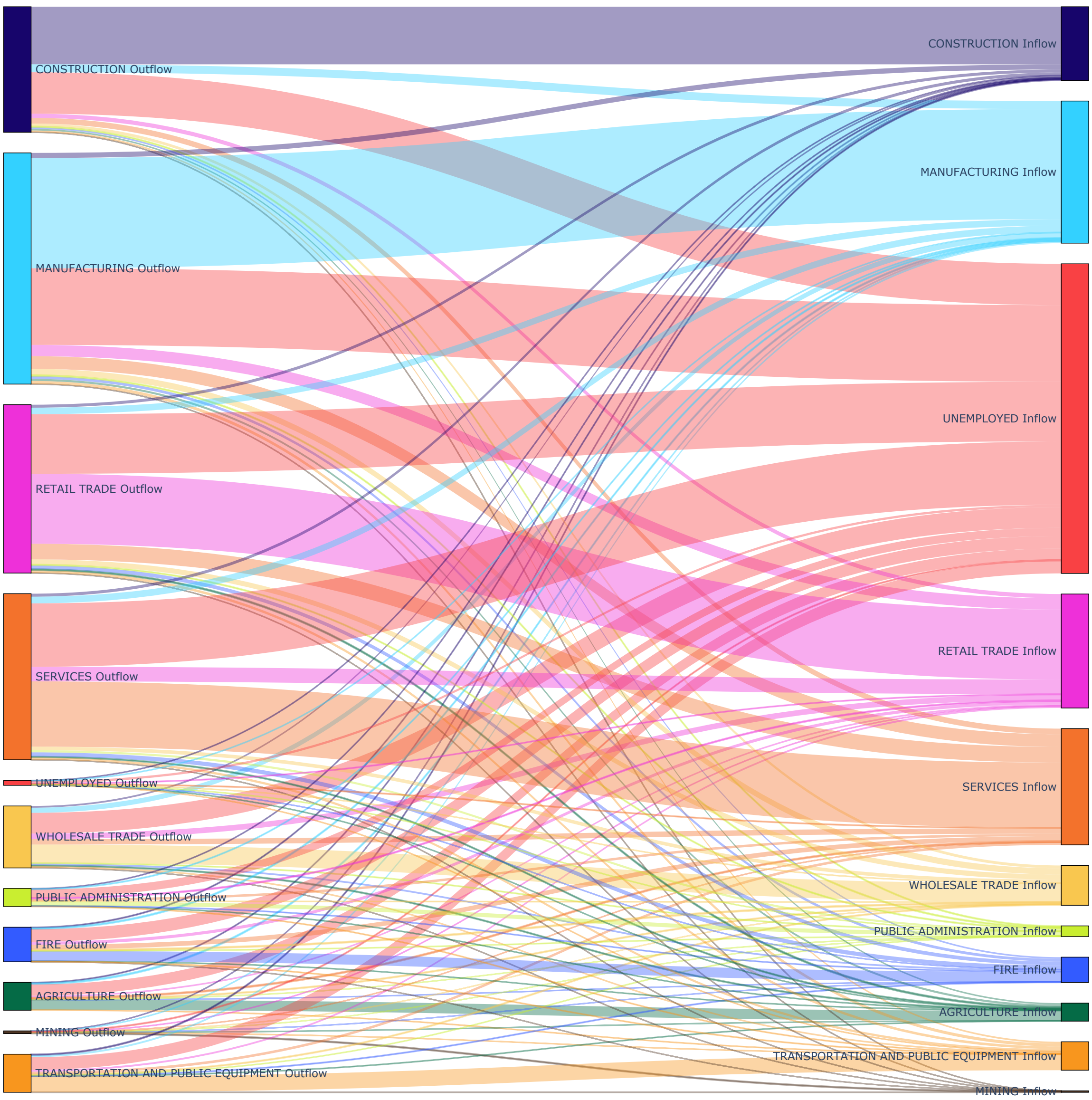


Figure 1.16: Labor Flows through Unemployment, SIC 1-digit, CWBH Washington, 1979-1983

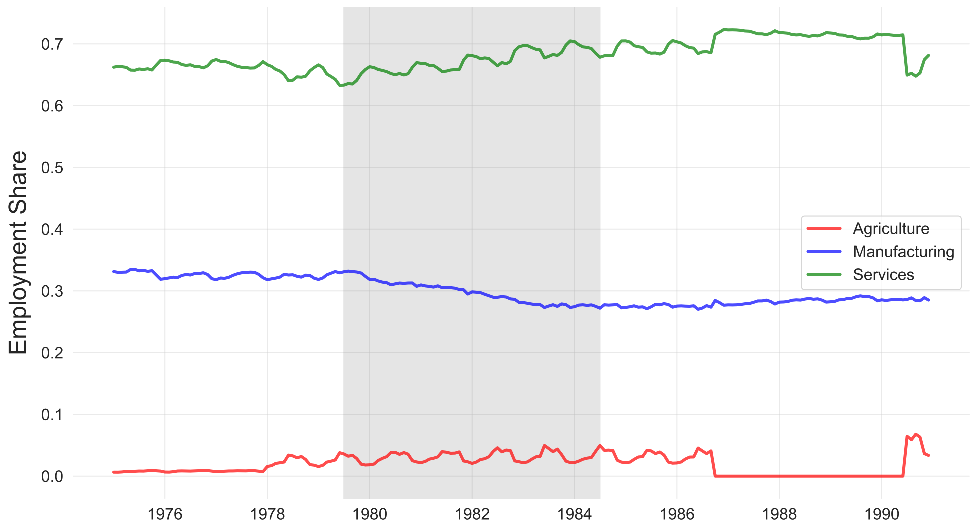


Figure 1.17: Employment Share, Quarterly Census of Employment and Wages, Washington, 1975-2022

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

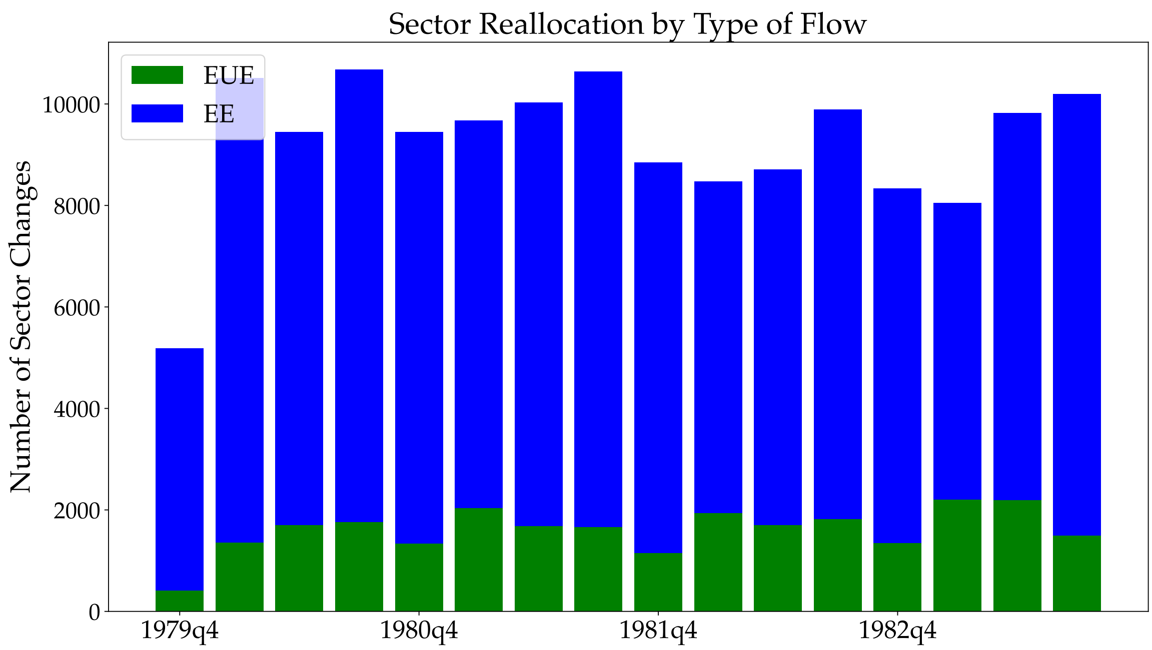


Figure 1.18: Sectoral Labor Reallocation by Type of Flow

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

1.B Additional RKD Figures

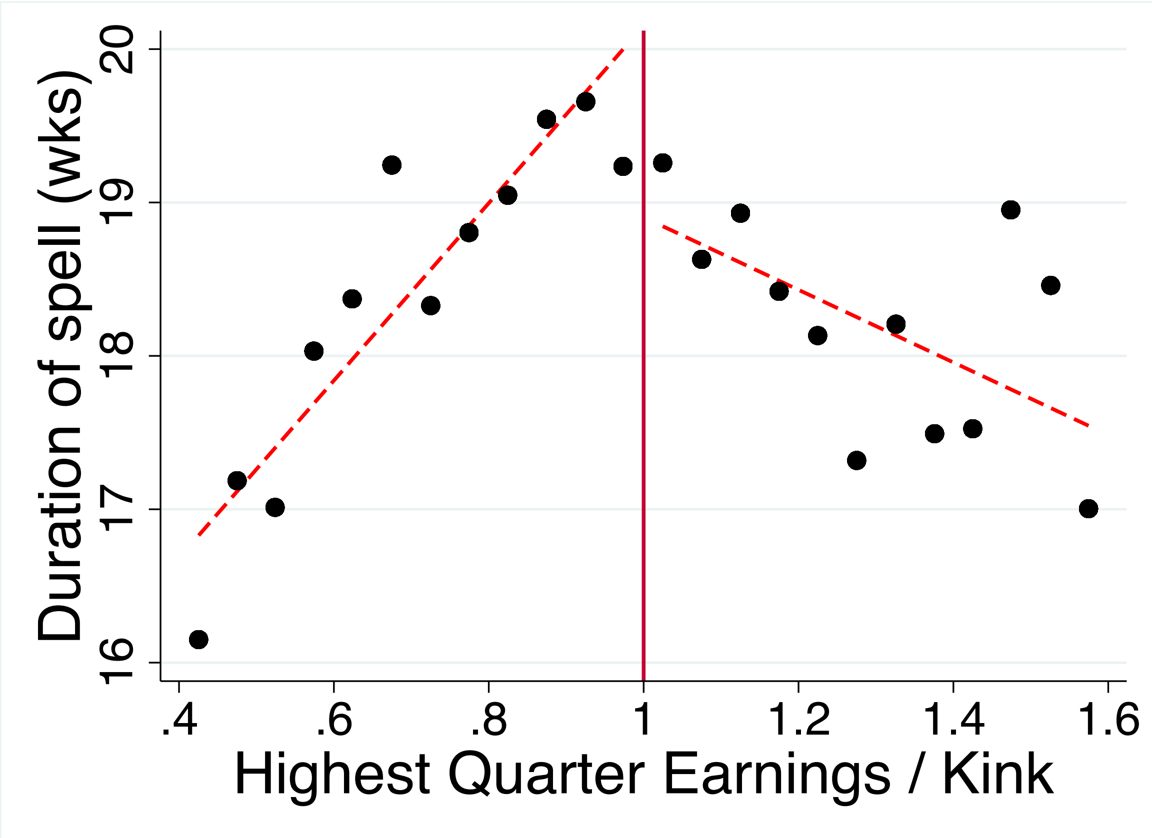


Figure 1.19: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

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 assignment variable. To the left of the kink, where weekly benefits are increasing, the duration of unemployment spell is increasing. To the right of the kink, where weekly benefits are no longer increasing due to the cap, the duration of 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.

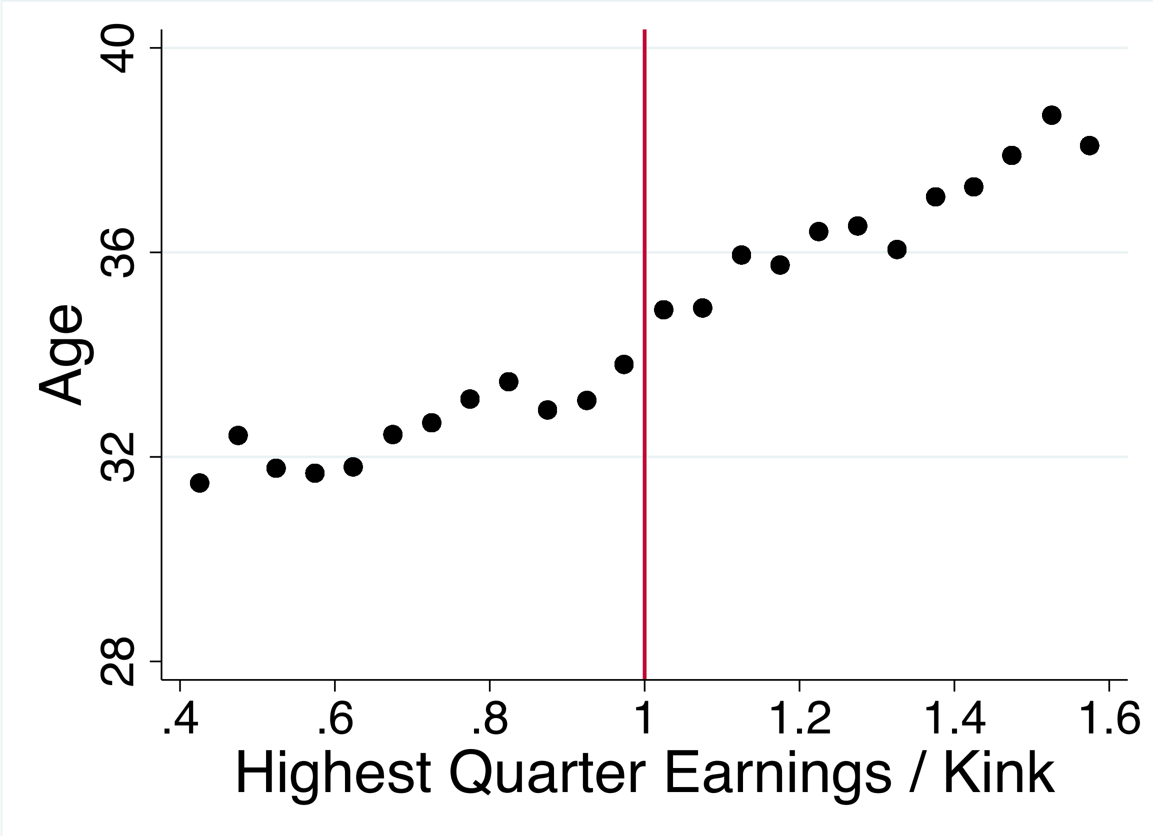


Figure 1.20: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

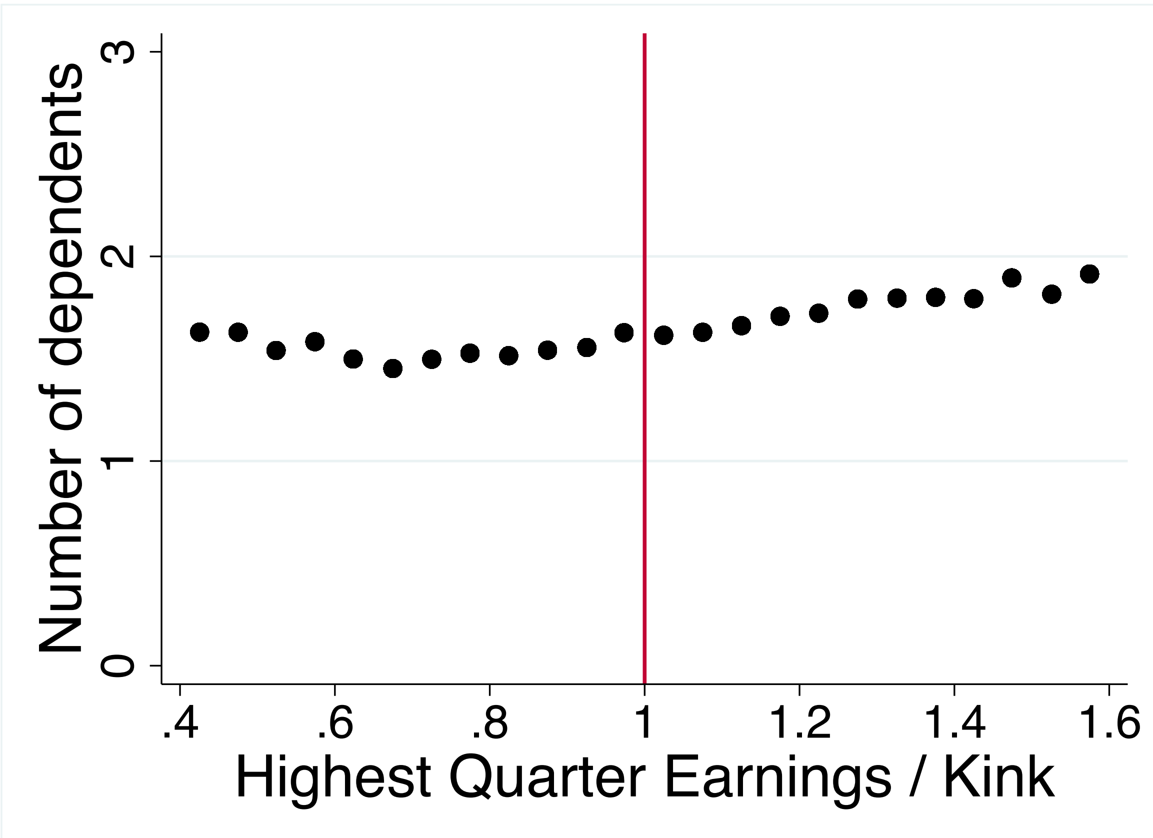


Figure 1.21: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

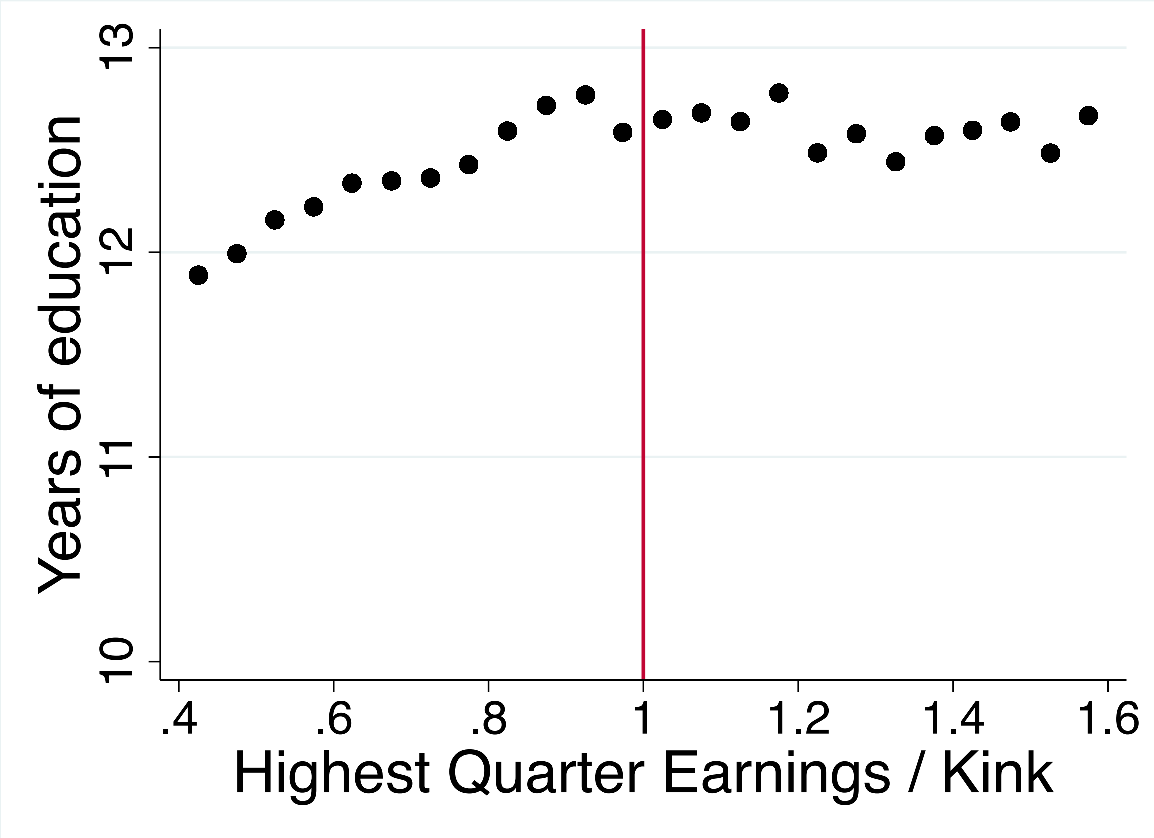


Figure 1.22: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

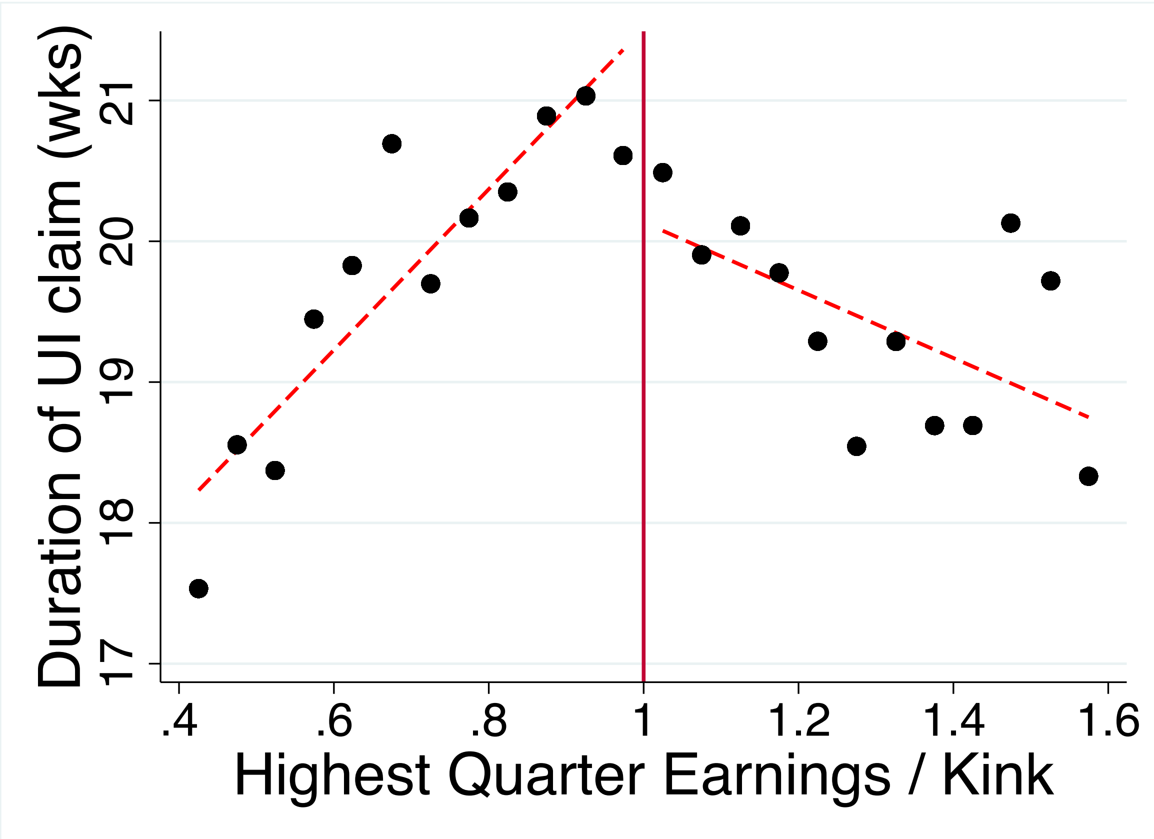


Figure 1.23: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

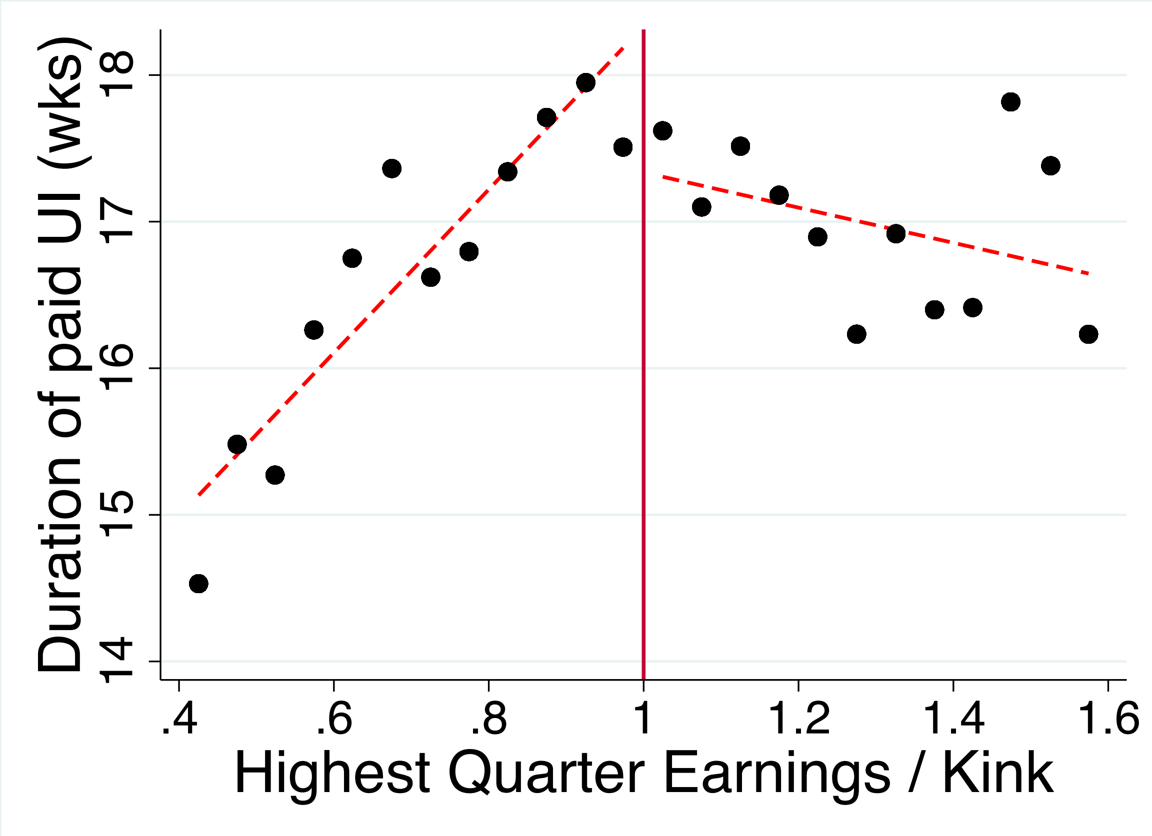


Figure 1.24: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

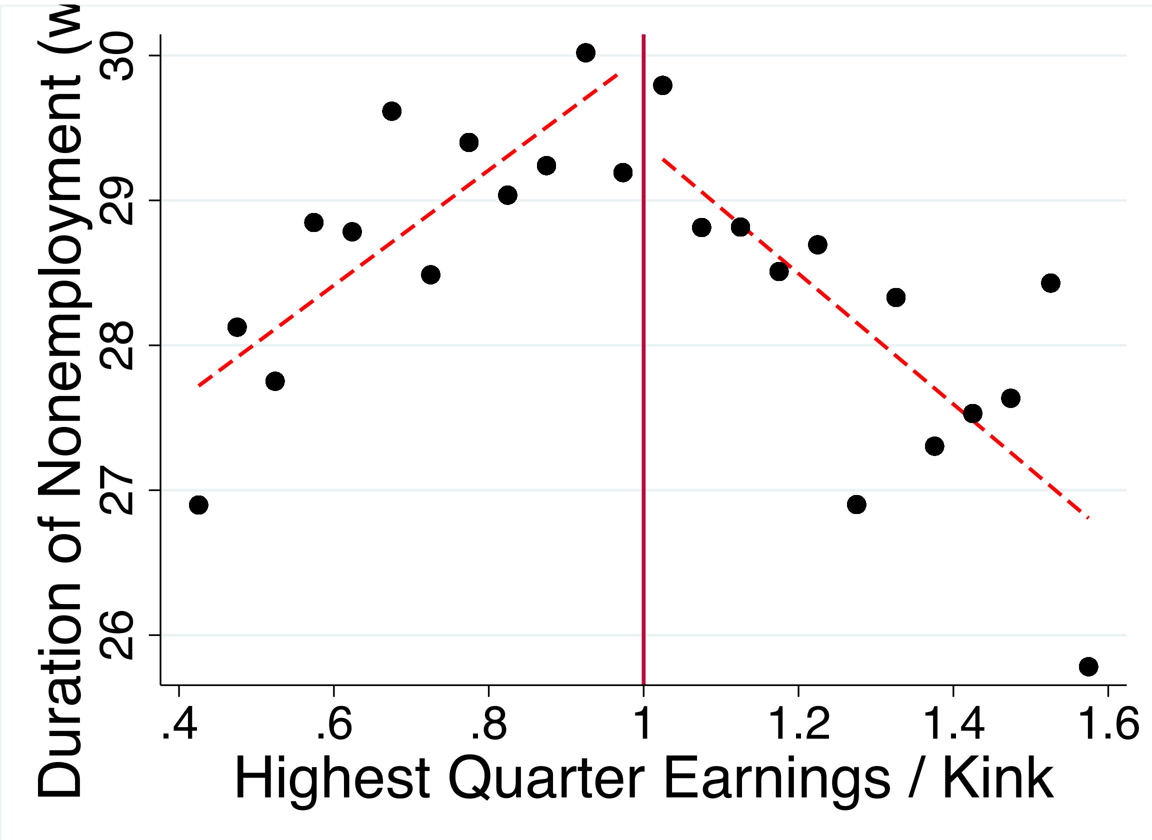


Figure 1.25: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

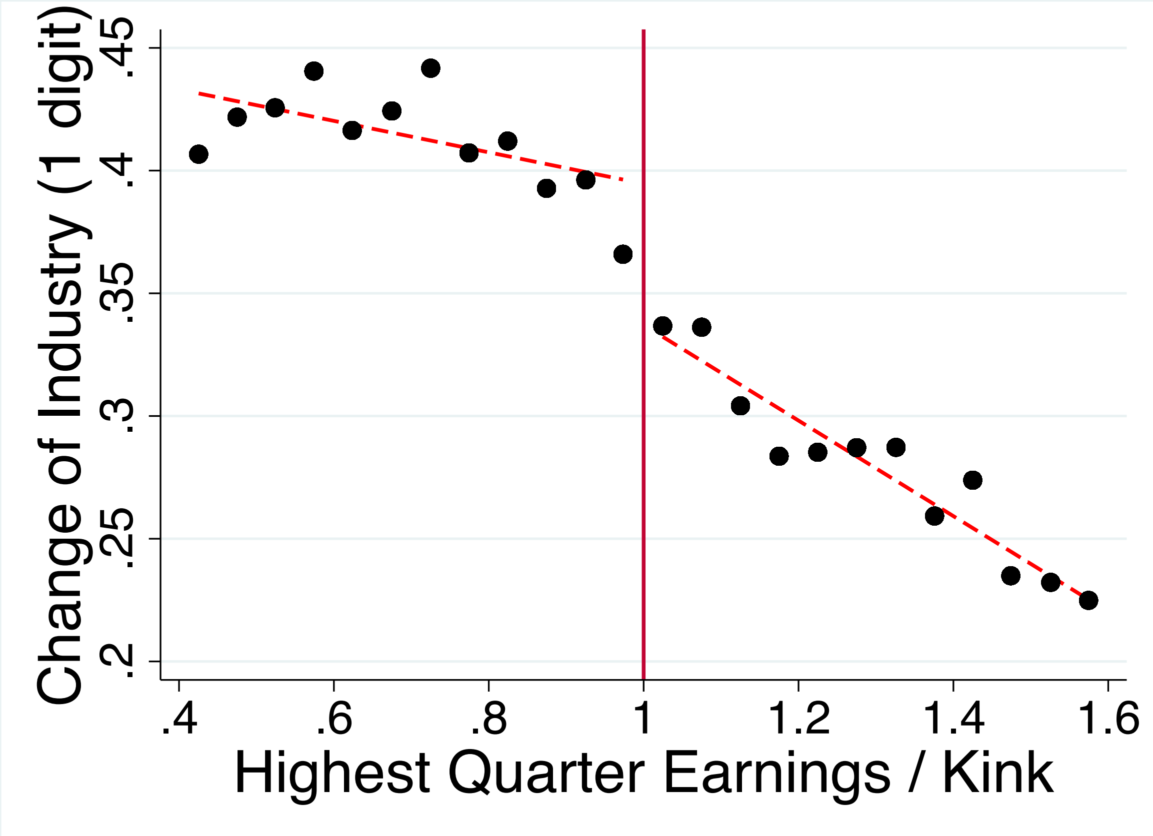


Figure 1.26: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

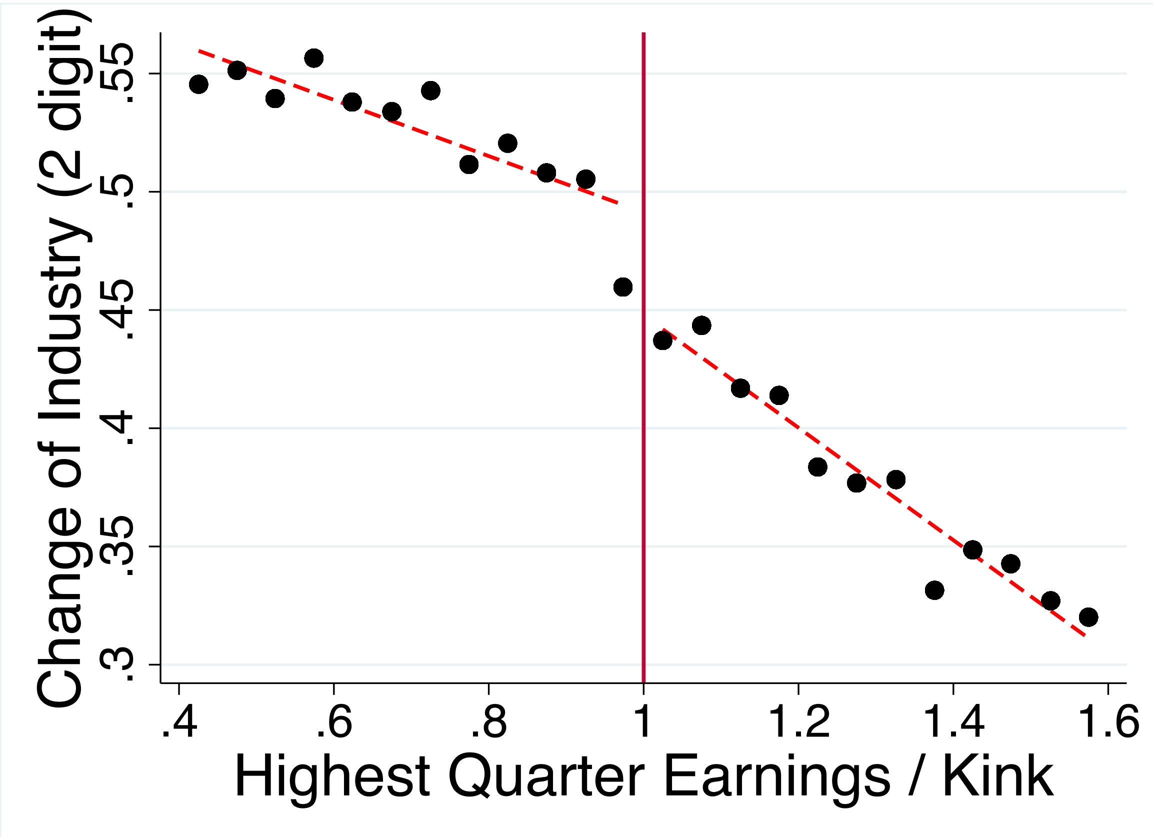


Figure 1.27: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

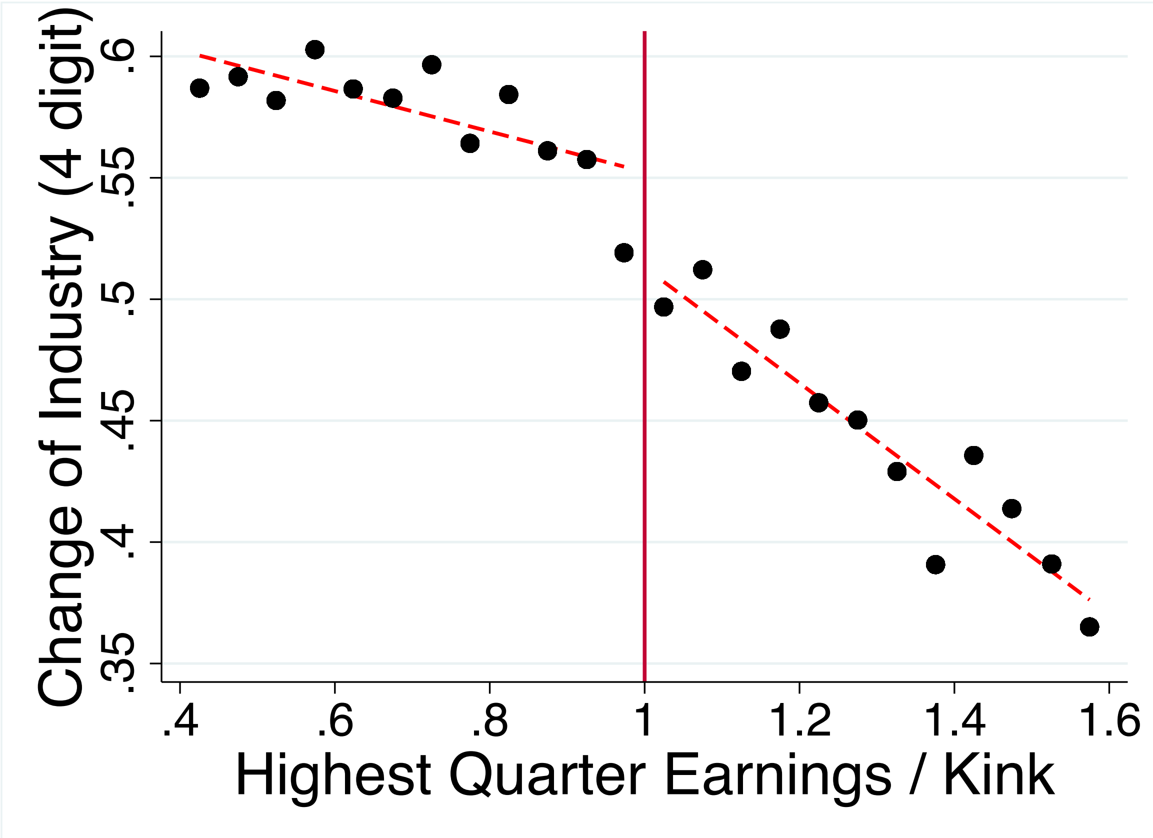


Figure 1.28: Regression Kink Design, CWBH Washington, Pooled Sample 1979-83

1.C Additional RKD Tables

Table 1.6: 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 1.7: 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 1.8: 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 1.9: 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 1.10: 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 1.11: 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 1.12: 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 1.13: 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 1.14: 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

1.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 1.15: 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 1.16: 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

1.E Additional Cost of Job-Loss Figures

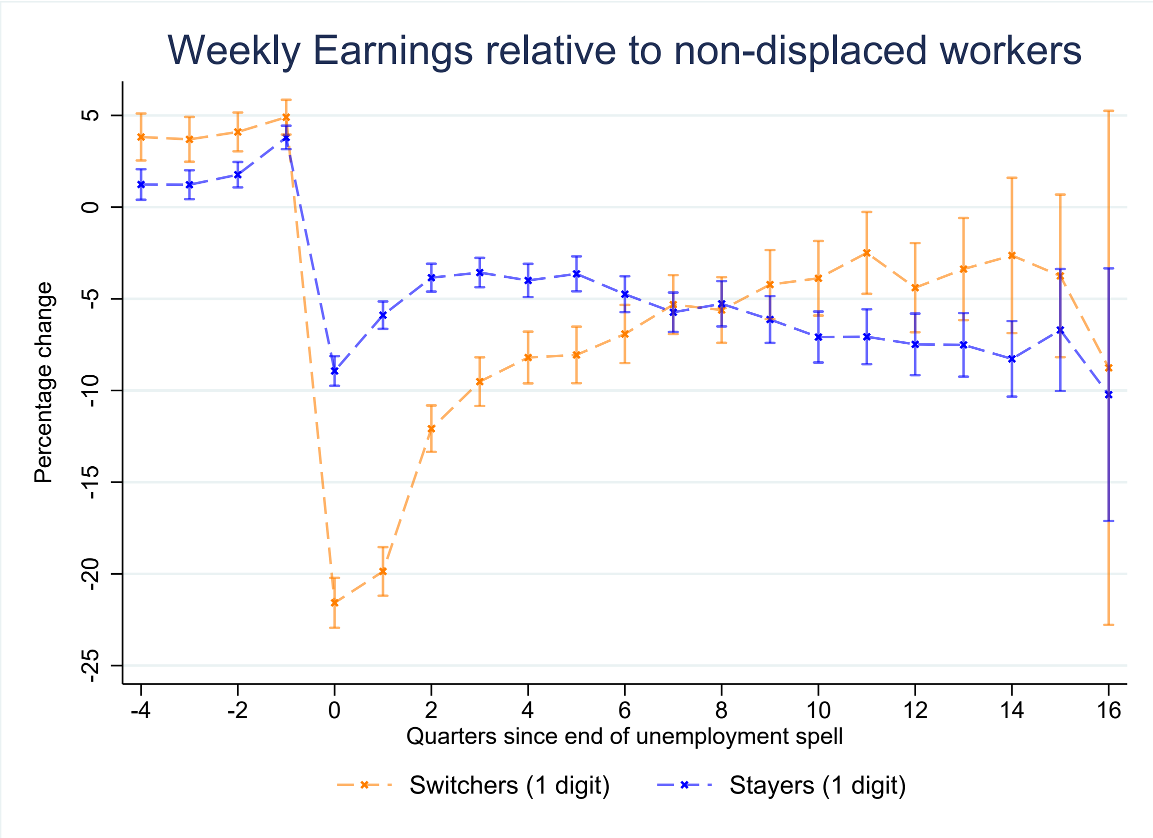


Figure 1.29: Percentage Change in Log Weekly Earnings around Displacement, CWBH Washington, 1979-1983

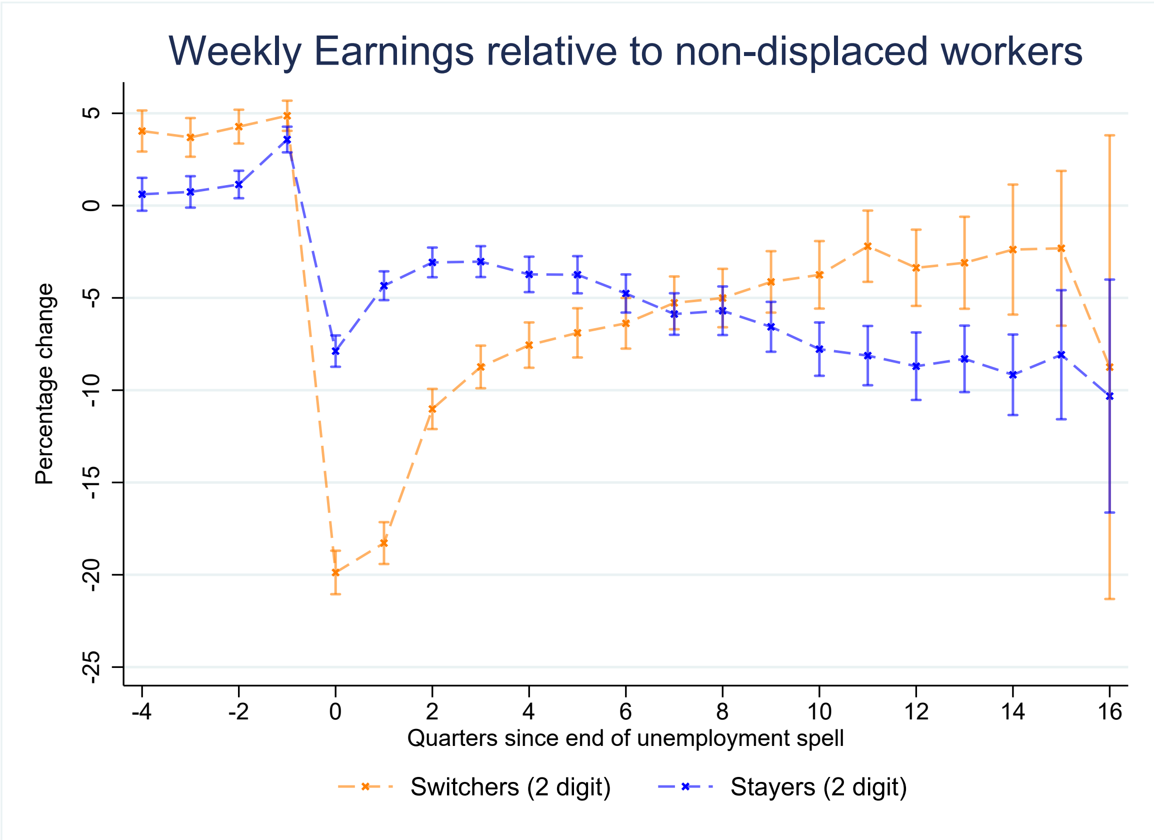


Figure 1.30: Percentage Change in Log Weekly Earnings around Displacement, CWBH Washington, 1979-1983

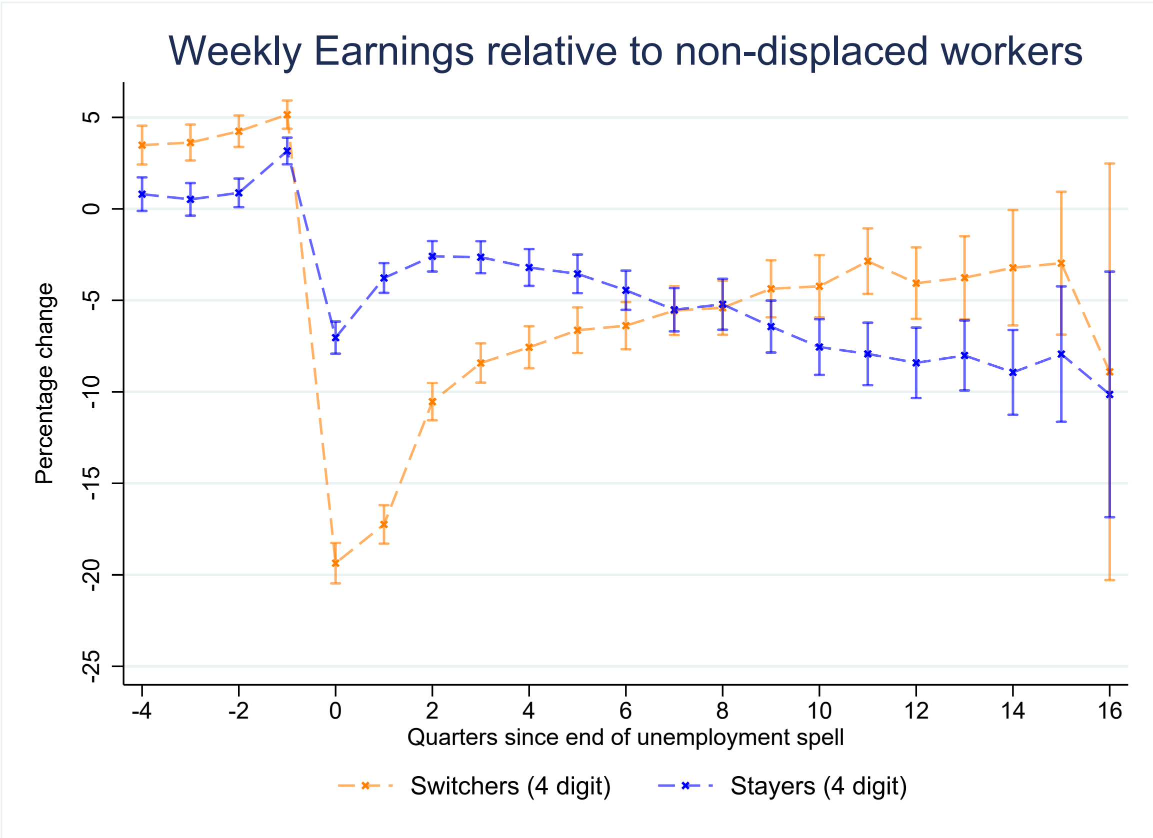


Figure 1.31: Percentage Change in Log Weekly Earnings around Displacement, CWBH Washington, 1979-1983

1.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 1.17 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

$$y_i = \alpha + \beta_1 \mathbb{1}(\text{severance pay})_i + \beta_2 \text{tenure}_i + \gamma' X_i + \varepsilon_i, \tag{1.38}$$

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 1.18 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

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

Table 1.17: 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.

(2008). 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.

$$\begin{aligned} y_i = \alpha &+ \beta_1 \mathbb{1}(\text{severance pay})_i \times \mathbb{1}(\text{above median net liquid wealth})_i \\ &+ \beta_2 \mathbb{1}(\text{severance pay})_i + \beta_3 \mathbb{1}(\text{above median net liquid wealth})_i \\ &+ \beta_4 \text{tenure}_i + \gamma' X_i + \varepsilon_i \end{aligned} \tag{1.39}$$

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 1.18 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.

$$\begin{aligned} y_i = \alpha &+ \beta_1 \mathbb{1}(\text{severance pay})_i \times \mathbb{1}(\text{above median tenure})_i \\ &+ \beta_2 \mathbb{1}(\text{severance pay})_i + \beta_3 \mathbb{1}(\text{above median tenure})_i + \gamma' X_i + \varepsilon_i \end{aligned} \tag{1.40}$$

Table 1.18: 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: 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 1.19: 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.

1.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

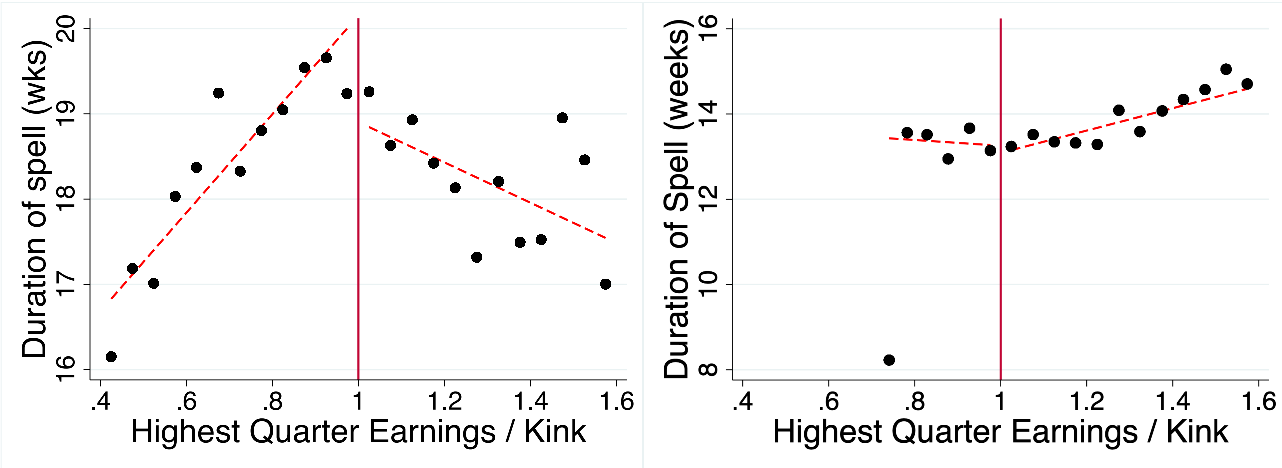
1. Let $\mathbf{x}$ denote a vector $\{x_1, ..., x_T\}$. Guess price vectors $\mathbf{r}$, $\{\mathbf{p_s}, \mathbf{N_s}\}_{s\in\mathcal{S}}$
2. Get $\mathbf{r^K} = \mathbf{r} + \delta$ from the no-arbitrage condition
3. Given $\mathbf{p_s}$, calculate marginal cost $\mathbf{m_s} = \frac{\epsilon-1}{\epsilon}\mathbf{p_s}$
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

1.H Model Appendix

1.H.1 Additional Simulation Results



(a) Data

(b) Model

Figure 1.32: 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.

1.H.2 Calibration - Additional Figures

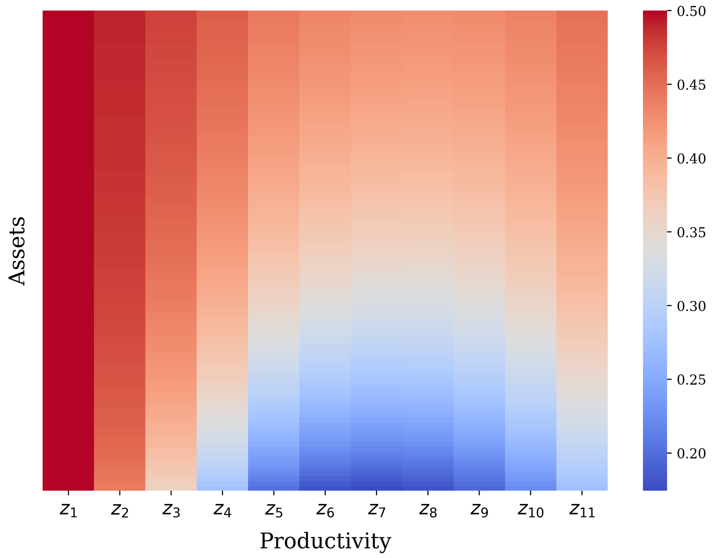


Figure 1.33: Conditional Choice Probability for Switching Sectors

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

1.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:

$$\begin{aligned}\rho v_t(a,z,u,s) = \max_{c,x,\{\sigma_{s\tilde{s}}\}_{\tilde{s}}} & \widetilde{U}(c,x) + \partial_a v_t(a,z,u,s)[r_t a + \mathcal{T}_t(z,s) - c] \\ & + \underbrace{\lambda_z^u [v_t(a,z_-,u,s) - v_t(a,z,u,s)]}_{\text{Depreciation of Productivity}} - \underbrace{\kappa}_{\text{Utility Cost of Unemployment}} \\ & + \left\{ \sum_{\tilde{s}=1}^{n_s} \sum_{\tilde{z}=1}^{n_z} \lambda_{s\tilde{s}}^{z\tilde{z}} \cdot \sigma_{s\tilde{s}}^{z\tilde{z}} \cdot \underbrace{f(x)}_{\text{Search Effort}} \cdot [v_t(a,\tilde{z},e,\tilde{s}) - v_t(a,z,u,s)] \right\} - \frac{1}{\nu} \cdot f(x) \cdot \underbrace{\sum_{\tilde{s}=1}^{n_s} \sum_{\tilde{z}=1}^{n_z} \sigma_{s\tilde{s}}^{z\tilde{z}} \log \sigma_{s\tilde{s}}^{z\tilde{z}}}_{\text{Expected Entropy Costs}}\end{aligned} \tag{1.41}$$

subject to

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

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]

$$\sigma_{s\tilde{s}}^{z\tilde{z}}(a,z,u,s) = \frac{\exp\left(\nu \cdot \lambda_{s\tilde{s}}^{z\tilde{z}} \cdot [v(a,\tilde{z},e,\tilde{s}) - v(a,z,u,s)]\right)}{\sum_{s'} \sum_{z'} \exp\left(\nu \cdot \lambda_{ss'}^{zz'} \cdot [v(a,z',e,s') - v(a,z,u,s)]\right)}. \tag{1.42}$$

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

$$x(a,z,u,s) = \left[\frac{1}{\psi_x} \sum_{\tilde{s}=1}^{n_s} \sum_{\tilde{z}=1}^{n_z} \sigma_{s\tilde{s}}^{z\tilde{z}} \left(\lambda_{s\tilde{s}}^{z\tilde{z}} [v_t(a,\tilde{z},e,\tilde{s}) - v_t(a,z,u,s)] - \frac{1}{\nu} \log \sigma_{s\tilde{s}}^{z\tilde{z}} \right) \right]^{\frac{1}{\varphi_x}}. \tag{1.43}$$

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).

Chapter 2

Global Value Chains and the Dynamics of UK Inflation

This chapter is jointly co-authored with Tommaso Aquilante, Aydan Dogan, and Melih Firat.

2.1 Introduction

Over the last few decades, the rise in global value chains (GVCs) has led to increasingly interlinked production processes across countries and sectors, making firms' pricing decisions much more dependent on foreign factors. The implications of globalisation of production for inflation dynamics have become even more central after the supply-chain disruptions following the COVID-19 crisis.

In this paper, we investigate whether the integration of the UK economy into GVCs has affected the link between domestic output and inflation. Most of the existing literature exploring the impact of globalisation on shaping domestic inflation dynamics primarily concentrates on the U.S. Here, our focus shifts to the UK, due to its high degree of openness and substantial integration into GVCs.

Figure 2.1 illustrates the growing dependence of UK production on imported inputs. The red line shows a slight increase in imported intermediate goods dependence at the aggregate level. However, aggregate series mask the heterogeneity in trends between manufacturing and service sectors. The manufacturing sector imported intermediate goods share (blue line) increased from 31% to 61% between 2000 and 2012 whereas this share has been stable in the service sector (green line) during this period.[1] Digging deeper into the data, we show that the increase in the UK's manufacturing sector imported intermediate goods share is almost entirely attributable to Emerging Market Economies (EMEs), with the share of the European Union (EU) and Advanced Economies (AEs) remaining relatively stable between 2000 and 2014 (Figure 2.1b). Motivated by this fact, we investigate the relationship between the increased involvement of the UK economy in GVCs and its implications for the UK's inflation dynamics.

First, we demonstrate analytically that a rise in the share of imported intermediate goods flattens the Phillips curve. We build a static two-country New Keynesian model that incorporates trade

[1] The UK has experienced a relatively higher rate of integration into GVCs compared to other advanced countries. This can be seen in Appendix 2.A Figure 2.3, which shows the comparison in "the change" in imported intermediate goods share from 2000 across four selected advanced countries.

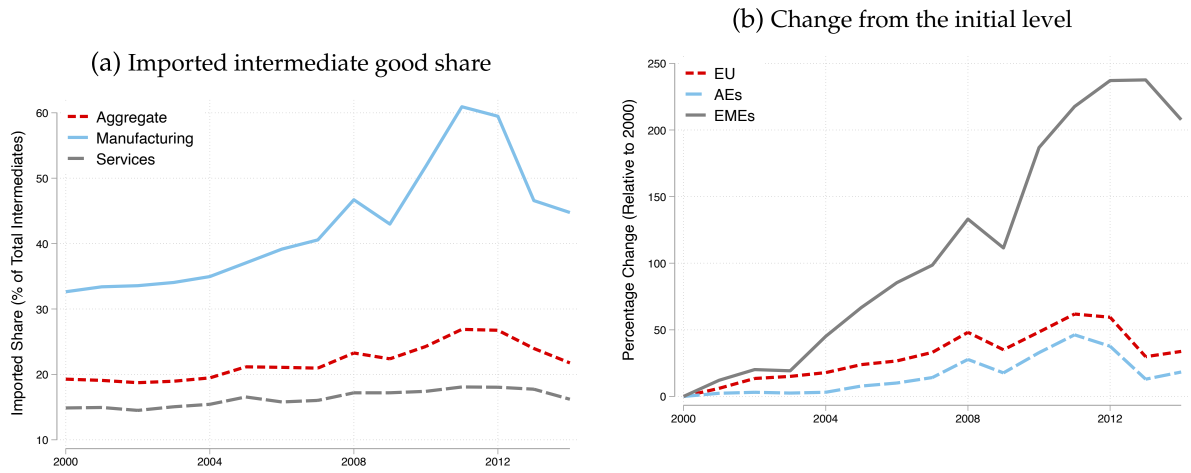


Figure 2.1: UK's integration in the global economy

Note: Source - World Input-Output Database (WIOD). Panel (a) presents the imported intermediate goods share as a proportion of total intermediate goods. Panel (b) displays the aggregate imported intermediate good shares from different regions which are weighted averages of sectoral imported intermediate good shares. Country classifications follow IMF.

in both intermediate and final goods. This model allows us to delve into the theoretical connection between GVC integration and the slope of the Phillips curve. GVC integration results in firms employing a higher amount of imported intermediate inputs in their production, thereby reducing the sensitivity of their marginal cost to domestic wage pressures. Consequently, domestic inflation becomes increasingly linked to the foreign output gap in the presence of integration to GVCs.

Second, we discover that UK industries with higher proportions of intermediate imports from EMEs exhibit flatter sectoral Phillips curves. We employ industry-level data to examine the impact of an increased proportion of imported intermediate inputs on the response of the sectoral Producer Price Index (PPI) to the sectoral output gap over the 2000-2014 period. Our findings indicate that greater integration into GVCs is not consistently associated with flatter Phillips curves. Rather, it is the *interaction* between the sectoral and source-country dimensions that drives this flattening effect.

While integration with China constitutes an influential factor, this phenomenon is not exclusive to China alone. Integration with other EMEs also significantly weakens the response of UK inflation to the output gap. Importantly, this result withstands various specifications, including the use of an instrumental variable approach inspired by Autor, Dorn, and Hanson (2013).

Third, we investigate why the previous result holds only for EMEs but not advanced economies. We find that GVCs affect the relationship between inflation and real economic activity through two channels: i) the slope channel; for given prices abroad, the higher the imported input share, the lower the response of inflation to an increase in domestic demand ii) the terms of trade channel; for a given slope, the lower the relative price of imported inputs, the lower the response of inflation to an increase in domestic demand. The latter channel is especially important for small open economies like the UK as they cannot alter the world prices.

To do this, we extend our static two-country New Keynesian model to a multi-sector DSGE model to fully account for the determinants of the GVCs measure we use in our empirical analysis. According to our model, the measure we use is not only a function of imported intermediate inputs *share* but also a function of international relative prices. Terms of trade fluctuations affect the empirical measure of GVCs through their impact on marginal cost. When firms use imported intermediates in their production, marginal cost does not only move with the fluctuations in wages (or cost of value added) but also moves with domestic and imported intermediate input prices. The relative price of imported to domestic intermediate inputs, i.e. the terms of trade, allows firms to switch between domestic and foreign inputs in response to shocks reducing the pass-through from wages to prices.

It is well-known in international macroeconomics literature that business cycles are highly correlated across developed economies. Put differently, when demand increases in the UK, it also increases in other AEs. This limits the degree of fluctuations in the terms of trade, a fact that is visible in our sample period over which the business cycle correlation of the UK economy is lower with EMEs than AEs. Specifically, we show that, in our sample period, the correlation of the UK's output with AEs is on average 74% while with EMEs is 40%.

Finally, we test the importance of these medium-term forces for our benchmark results and find that a rising imported intermediate goods share from countries with low business cycle correlation with the UK leads to a fall in response of inflation to real economic activity. We do not find a significant role for imported intermediates from countries with high business cycle correlations with the UK. We argue that this relative price channel may be an important driver of our results.

Literature. The positive relationship between inflation and the output gap lies at the centre of New Keynesian DSGE models. Changes in this relationship have important implications for the transmission of monetary policy. Therefore, academics and policymakers have extensively explored the importance of globalisation for the degree to which inflation responds to fluctuations in real economic activity.[2]. Our empirical strategy is similar to Gilchrist and Zakrajsek (2019). By using industry-level data, they show that increased integration of the US economy to trade is important in explaining the fall in the response of inflation to the domestic output gap. We also rely on industry-level data but instead of looking at trade integration, which includes both trade in final and intermediate goods, we investigate the role of imported intermediate goods only.

In this respect, our paper is more related to studies that focus on the trade in intermediate inputs aspect of globalisation such as Auer, Borio, and Filardo (2017) and Auer, Levchenko, and Sauré (2019). We differ from this empirical literature in two dimensions: First, the literature tends to be focused primarily on the US, but our paper examines the UK which is a relatively more open economy. Second, the literature does not consider the importance of the integration of EMEs into the GVCs. In this paper, we show that investigating this channel both empirically and theoretically is crucial to shed light on the inflation dynamics of a *small open economy* like the UK.

On the modelling side, our contribution is to study the role of input-output linkages in understanding inflation dynamics in an *open economy* setting. In a closed economy setting, by building a multi-sector New Keynesian model with input-output linkages, Rubbo (2023) shows that the use of intermediate inputs lowers the slope of the Phillips curve. By using a similar framework in an open economy setting, we instead show how trade in intermediate inputs leads to a fall in the slope of the Phillips curve.

[2]See Erceg, Gust, and Lopez-Salido (2007), Forbes (2019), Obstfeld (2020), Guilloux-Nefussi (2020), Borio and Filardo (2007), Auer and Fischer (2010), and Heise, Karahan, and Şahin (2022).

There is also a relatively large literature that studies the transmission of shocks within frameworks that include production networks (Galesi and Rachedi (2019), Pasten, Schoenle, and Weber (2020) etc.). We contribute to this literature by emphasising the importance of terms of trade movements for the pass-through from wages to inflation in response to shocks. Our paper is closely related to two studies in this literature. First, Comin and Johnson (2020) build an open economy New Keynesian framework with trade in both intermediate inputs and final goods and analyse the impact of an input trade shock on US inflation. They focus on the impact of a permanent shock on trade openness and show that this shock does not lead to a fall in inflation. We do not focus on a shock that increases the imported inputs share in production but instead, we analyse whether intermediate input trade lowers the response of domestic inflation to domestic slack. We show that this is indeed the case both through the slope and also through terms of trade movements. Second, Amiti, Heise, Karahan, and Şahin (2023) examine how supply chain disruptions, coupled with labor supply constraints, have contributed to the surge in inflation since 2021. They explore the interaction of these forces with an expansionary monetary policy and a demand shift from services to goods. They build a two-sector New Keynesian model with input-output linkages and augment it with shocks to the price of imports, the price of competitors abroad, and labor supply and show that this framework can account for the observed rise in inflation in the US. While our model does not explicitly incorporate the foreign competition channel, it would yield similar results in response to labor supply and terms of trade shocks.

Roadmap. The remainder of the paper is structured as follows. Section 2.2 describes the theoretical framework for the relationship between input trade and the slope of the Phillips curve. Sections 2.3 and 2.4 present the main empirical results and their robustness checks, respectively. In section 2.5, we extend our model to a dynamic setting and discuss the importance of medium-term forces. Section 2.6 concludes.

2.2 A Model of Global Value Chains

How does GVC integration affect the Phillips curve? In this section, we develop a two-country, New-Keynesian model with trade in intermediate and final goods. We build on the work of Rubbo (2023) to derive a theoretical relationship between GVC integration and the Phillips curve.

2.2.1 Outline of Model

Households. The global economy consists of a home (H) and foreign (F) economy, each producing a differentiated good in the spirit of Armington (1969). The two countries, home and foreign, are populated by a continuum of infinitely lived households with a fraction of (n) and (1-n) of the total world population, respectively. Throughout the paper, we use the notation " $*$ " to capture variables in the foreign economy. To start with, we abstract from multiple sectors for simplicity.[3] Households

[3]Extending to a multi-sector setup would allow for an additional dimension of heterogeneity in the price-stickiness across sectors, and the centrality of sectors in the production network. We abstract from a multi-sector setup in this static model for simplicity. We focus on the importance of the multi-sector dimension, in Section 2.5 where we extend our model to a dynamic setting.

in the home economy consume and supply labor and have preferences

$$U = \frac{C^{1-\sigma}}{1-\sigma} - \Xi \frac{L^{1+\varphi}}{1+\varphi},$$

where σ and φ denote the inverse of the intertemporal elasticity of substitution and Frisch elasticity of labor supply, respectively. The consumption bundle in turn consists of home and foreign goods

$$C = C_H^{\alpha} C_F^{1-\alpha},$$

where α represents the expenditure share of home goods. As in De Paoli (2009), the share of imported goods in each country is a function of relative country size, $1-n$, and the degree of openness in final demand, v_C: $1-\alpha = (1-n)\, v_C$. When $\alpha > 0.5$, there is home bias in preferences. A similar expression holds for households in the foreign economy.

Production. Firms in each economy are identical and use labor (L) and intermediate inputs (M) to produce a unit of output. The production function has the following constant-returns-to-scale functional form

$$Y_H(i) = AL(i)^{\delta} M(i)^{1-\delta},$$

where Y_H denotes firm i's gross-output of home goods, A is the aggregate productivity and δ denotes the share of labor in production. Intermediate goods used by the firms are a CES aggregate of home and foreign-produced intermediate inputs

$$M(i) = \left[\mu^{\frac{1}{\phi}} (M_H(i))^{\frac{\phi-1}{\phi}} + (1-\mu)^{\frac{1}{\phi}} (M_F(i))^{\frac{\phi-1}{\phi}} \right]^{\frac{\phi}{\phi-1}}.$$

where $M_H(i)$ and $M_F(i)$ denote the demand for domestically and foreign-produced intermediate goods, respectively and ϕ denotes the elasticity of substitution between home and foreign-produced intermediate goods. The parameter $(1-\mu)$ captures the share of intermediate goods that are imported from abroad. Similar to the consumption preference structure, we assume that the share of imported intermediate goods is a function of relative country size, $(1-n)$, and the degree of openness in intermediate goods in a sector, v_M: $1-\mu = (1-n)\, v_M$.

Pricing. To introduce a Phillips Curve into the model, we allow for nominal rigidities in the form of sticky information as in Mankiw and Reis (2002). The timing within the period is as follows:

1. All firms pre-set their price as a markup over the expected marginal cost.
2. A fraction 1-θ of firms are able to observe aggregate shocks in the economy.
3. Firms who observe aggregate shocks are able to change their price.

We assume that all firms price goods according to producer currency pricing, therefore there is a perfect exchange rate pass-through.[4] Thus, home and foreign firms pre-set their price to

$$P_H^{\#}(i) = \frac{\epsilon}{\epsilon - 1} \mathbb{E}[MC], \tag{2.1}$$

$$P_F^{*\#}(i) = \frac{\epsilon}{\epsilon - 1} \mathbb{E}[MC^*], \tag{2.2}$$

[4] We acknowledge that imperfect exchange rate pass-through can be important to understand the fluctuations in international relative prices as explored by Devereux and Engel (2002). Nevertheless, we follow Galí and Monacelli (2005) and focus on producer currency pricing to single out the mechanism at play.

where the expectation is taken over aggregate states. A fraction 1-θ of home (1-θ^* of foreign) firms are able to observe aggregate shocks and hence update their price. These firms change their prices to

$$\widetilde{P}_H(i) = \frac{\epsilon}{\epsilon - 1} MC, \tag{2.3}$$
$$\widetilde{P}_F^*(i) = \frac{\epsilon}{\epsilon - 1} MC^*, \tag{2.4}$$

The aggregate price level at the end of the period is given by

$$P_H^{1-\epsilon} = \theta P_H^{\#1-\epsilon} + (1-\theta)\tilde{P}_H^{1-\epsilon},$$

and inflation is given by

$$\Pi_H^{1-\epsilon} = \theta + (1-\theta)\left(\frac{MC}{\mathbb{E}[MC]}\right)^{1-\epsilon},$$

where $\Pi_H \equiv \frac{P_H}{P_H^\#}$. Thus inflation is defined as the change in prices relative to the pre-set price before any shocks hit the economy. Inflation occurs when the actual marginal cost rises above the expected marginal cost. We can linearise this equation as

$$\log \Pi_H \equiv d\log P_H = (1-\theta) d\log MC,$$

where

$$d\log P_H \equiv \log P_H - \log P_H^\#,$$
$$d\log MC \equiv \log MC - \log \mathbb{E}[MC].$$

A symmetric expression holds for the foreign economy.

Trade. Trade of both final goods and intermediate goods arises in the economy. We assume financial autarky such that there is balanced trade in both final and intermediate goods in equilibrium.

$$nP_F(C_F + M_F) = (1-n)P_H(C_H^* + M_H^*). \tag{2.5}$$

2.2.2 The Global Phillips Curve

We define the following notation:

$$\log \mathbf{p} = \begin{pmatrix} \log P_H \\ \log P_F^* \end{pmatrix}, \quad \log \mathbf{W} = \begin{pmatrix} \log W \\ \log W^* \end{pmatrix}, \quad \log \mathbf{A} = \begin{pmatrix} \log A \\ \log A^* \end{pmatrix}, \quad \delta = \begin{pmatrix} \delta \\ \delta^* \end{pmatrix}, \quad 1 = \begin{pmatrix} 1 \\ 1 \end{pmatrix},$$

$$\Phi = \begin{pmatrix} \alpha & 1-\alpha \\ 1-\alpha^* & \alpha^* \end{pmatrix}, \qquad \Omega = \begin{pmatrix} 1-\delta & 0 \\ 0 & 1-\delta^* \end{pmatrix} \begin{pmatrix} \mu & 1-\mu \\ 1-\mu^* & \mu^* \end{pmatrix},$$

where Ω represents the global input-output matrix, taking into account the degree of price stickiness. Let $\log \boldsymbol{P} = \Phi \log \boldsymbol{p}$ denote the vector of (log) CPI inflation

Lemma 1. *The Global Phillips Curve can be written as*

$$d\log \mathbf{P} = \mathcal{K}\widetilde{y} + \mathcal{G} d\log \mathbf{A} + \mathcal{H} d\log \mathcal{E}, \tag{2.6}$$

where $\mathcal{K} = \Phi\Theta(I - \Omega\Theta)^{-1}\delta[I - ((1 + \sigma\Phi - \sigma I)\Theta(I - \Omega\Theta)^{-1}\delta]^{-1}(\sigma + \varphi)$ and $\mathcal{E}$ is the nominal exchange rate (units of foreign currency in home currency).

The proof and expressions for the $\mathcal{G}, \mathcal{H}$ matrices are shown in Appendix 2.D. This expression shows that inflation dynamics are driven by: (i) domestic and foreign output gap, (ii) cross-country, relative productivity, and (iii) exchange rates. The main diagonal of $\mathcal{K}$ represents the *slope* of the Phillips Curve – the dependence of CPI inflation on the domestic output gap. The off-diagonal elements of $\mathcal{K}$ capture the dependence of domestic inflation on the foreign output gap. This leads us to the following proposition.

Proposition 1. *The higher the imported intermediate good share, the flatter the Phillips curve. That is,*

$$\frac{d\mathcal{K}_{ii}}{d(1 - \mu_i)} < 0.$$

The proof follows directly from taking the derivative. Intuitively, as firms depend more on intermediate inputs imported from abroad, their marginal costs are less exposed to the domestic output and more exposed to foreign output. As a result, inflation depends less on the domestic output gap and more on the foreign output gap. Given that the share of imported goods (both final demand and intermediate) is proportional to the country size as in De Paoli (2009), the relative country size will matter for the slope through α and μ. Smaller countries like the UK are more open, so all else equal should have a flatter Phillips Curve. In addition, unsurprisingly, the Phillips Curve become steeper as labor share increases, consistently with the standard three-equation closed-economy New Keynesian model.

In addition, the price-stickiness of domestic and foreign goods captured by $\Theta = diag(1 - \theta, 1 - \theta^*)$, is also amplified along the production network. The price stickiness of foreign goods implies that the cost of imported intermediate goods, and hence the marginal costs for home firms do not rise by as much as in the flexible-price case. This then implies that domestic prices do not rise by as much.

Note that this channel also interacts with the degree of exchange rate pass-through. Under producer currency pricing, the price of goods is sticky in the currency of the producer. Therefore, the changes in import prices transmit through the nominal exchange rate which is captured in the $\mathcal{H}$ matrix. International relative prices are very volatile in the data and in the presence of GVCs, relative prices affect the firm's marginal cost directly as some inputs are sourced from abroad. The following section will introduce a dynamic, multi-sector version of our model exploring the importance of international relative price fluctuations for inflation dynamics.

2.3 Global Value Chains and the Phillips Curve

Can the use of imported inputs in production, affect the inflation dynamics in the UK? This section analyzes the role of rising imported intermediate goods share on the UK Phillips curve using a sectoral Phillips curve.[5]

[5]We also look at whether aggregate trade openness can be related to the weakened relationship between the UK's inflation and the output gap. We find supporting evidence that rising trade openness in the UK led to a flattening in the

2.3.1 Data

Sectoral Data. Sectoral price indices data are from the Office of National Statistics (ONS). Sectoral inflation is calculated as a four-quarter percent change in Producer Price Index (PPI) and Service Producer Price Index (SPPI). Data has been available at a quarterly frequency since 1997. The sectoral output series, Index of Production (IoP), and Index of Services (IoS) are also from ONS. Data has been available at a quarterly frequency since 1995 (1997 for the service sectors). Sectoral output gap series is calculated as the deviation indexes from their HP-filtered trends separately.

World Input-Output Database (WIOD). We use the last version (2016) of the WIOD to calculate imports, exports, and imported intermediate good values for 56 sectors at an annual frequency from 2000 to 2014. However, the sectoral aggregation from WIOD does not match the aggregation level of sectoral price and output data from ONS. Therefore, we use many-to-many matching using the weights from the Blue Book GDP Source Catalogue.

Country Classification. We use the IMF's classification for Advanced Economies and Emerging Market Economies.[6]

2.3.2 Estimation

We combine quarterly ONS inflation and output data with the annual WIOD for 40 UK industries between 2000Q1 and 2014Q4.[7]Interacting the imported intermediate good dependence series with the sectoral output gap, we examine the role of GVCs and in particular GVC integration to the EMEs on the inflation and output gap relationship in reduced-form.[8]

To investigate the relation between GVCs and inflation, we estimate the following specification for the period 2000Q1-2014Q4

$$\begin{aligned}\pi_{j,t} = \beta_1 \left(y_{j,t} - y^*_{j,t}\right) + \beta_2 IIS_{j,t} + \beta_3 \left(y_{j,t} - y^*_{j,t}\right) \times IIS_{j,t} \\ + \beta_4 \left(\frac{1}{4}\sum_{k=1}^{4} \pi_{j,t-k}\right) + \delta_j + \delta_t + \varepsilon_{j,t},\end{aligned} \tag{2.7}$$

where $IIS_{j,t}$ is defined above as the ratio of imported intermediate goods in total intermediate goods in sector j at time t. To provide clarity in interpretation, $IIS_{j,t}$ is standardized (around the mean). Sectoral inflation series $\pi_{j,t}$ are calculated as the four-quarter percentage change in PPI and SPPI, and sectoral output gap $\left(y_{j,t} - y^*_{j,t}\right)$ is the deviation of production index series (IoP and IoS) from

Phillips curve. However, given that the estimations at the aggregate level are subject to identification issues and that our focus is trade in intermediate inputs, we do not report the results in the main text. See, Appendix 2.B for details.

[6]We consider Brazil, Hungary, China, India, Indonesia, Mexico, Poland, Romania, Russia and Turkey as EMEs. Austria, Belgium, Czech Republic, Cyprus, Germany, Denmark, Spain, Estonia, Finland, France, Greece, Croatia, Hungary, Ireland, Italy, Lithuania, Latvia, Luxembourg, Malta, the Netherlands, Norway, Poland, Romania, Slovakia, Slovenia and Sweden as the EU and Australia, Canada, South Korea, Japan, US, Switzerland and the EU excluding Poland, Hungary and Romania as AEs.

[7]We can merge trade, price, and output data for 40 out of 56 WIOD sectors with a balanced panel, and they comprise 70% of total output in the UK.

[8]Inflation and output data are always winsorized at 1st and 99th percentiles. Results are qualitatively unchanged if we do not winsorize the data.

their HP filtered trends.[9] The rich panel data allow us to control for time-invariant sector-specific factors using sector fixed-effects (δ_j) as well as time-varying aggregate factors affecting inflation such as monetary policy (McLeay and Tenreyro (2020)) and inflation expectations (Ball and Mazumder (2019)) using time fixed-effect (δ_t).[10]

We assess the role of the integration into the GVCs on the flattening of the UK Phillips curve by estimating the coefficient of the interaction term (β_3). A negative interaction term would imply that more GVC integration is associated with lower responsiveness of inflation to the output gap.

Table 2.1 presents the results from estimating equation (2.7). Column (1) shows the positive and significant relationship between sectoral inflation and the output gap. This provides evidence that the UK Phillips curve can be precisely estimated using sectoral data. This is in line with the McLeay and Tenreyro (2020) critique that a successful monetary policy might have caused a flattening in the Phillips curve by reacting to inflation at the right time and muting its response following demand-side shocks at the aggregate level. However, exploiting the rich panel structure in inflation and output gap and after controlling for aggregate level time-varying trends with time fixed-effects, we find a positive and significant Phillips curve coefficient in the UK within our sample period.

Moving to our main argument that increasing input trade might be an important cause of the flattening of the UK Phillips curve, we present the results from the interaction of the sectoral output gap with the imported intermediate goods share in column (2). The coefficient of the interaction term (the third row) is negative, pointing to a role for GVCs in explaining the heterogeneity in inflation and output gap relationship across sectors. However, the coefficient is insignificant, implying an insufficient heterogeneity in $IIS_{j,t}$ to precisely estimate the role of GVCs on the flattening of the UK Phillips curve. Next, we will examine the sources of heterogeneity in integration to the GVCs in terms of the sources of imports. Figure 2.1b shows that the UK manufacturing sector has integrated into the EMEs since the 2000s. Here we further demonstrate that there is considerable heterogeneity in dependence on EME inputs within the manufacturing sector. Figure 2.2 compares the change in the share of AEs and EMEs in intermediate inputs used by each sector in the UK. The figure displays the widespread rise in integration to the EMEs compared to the stable levels of dependence on the AE imports between 2000 and 2014. The integration is more striking in sectors such as "Computer Electronics", "Electrical equipment" and "Transport equipment", reaching up to six times higher share in intermediate goods used in these sectors. By decomposing the $IIS_{j,t}$ variable into regional sources of imports, we observe the heterogeneity comes from the EMEs rather than AEs or EU countries Note that the level of imported intermediate goods is much higher from AEs than EMEs. However, the change in our sample, which is our focus, can be attributable to the increased importance of EMEs in world trade. We present the level of imported intermediate goods share in Appendix 2.A, Figure 2.2.

To formally differentiate the roles of integration of the UK sectors to different regions, we estimate Equation (2.7) distinguishing between different source-region in variable $IIS_{j,t}$ such that

$$IIS^{AEs}_{j,t} = \frac{\text{Imported Intermediate Goods}^{AEs}_{j,t}}{\text{Total Intermediate Goods}_{j,t}}, \quad IIS^{EMEs}_{j,t} = \frac{\text{Imported Intermediate Goods}^{EMEs}_{j,t}}{\text{Total Intermediate Goods}_{j,t}},$$

and using the same equation, we can measure the impact of imported intermediate goods share for

[9] Both sectoral inflation and output series are at a quarterly frequency and $IIS_{j,t}$ is available at the annual frequency.

[10] We use *year* fixed-effects in our benchmark analysis, however, our results are robust to using *quarterly* fixed effects. Results from these estimations are available upon request from the authors.

Table 2.1: GVCs and the UK Phillips Curve

2000Q1-2014Q4	(1)	(2)
Dep Var: $\pi_{j,t}$	Only Output Gap	Role of GVCs
$(y_{j,t} - y^*_{j,t})$	0.0430***	0.0419***
	(0.0138)	(0.0118)
$IIS_{j,t}$		0.616
		(0.533)
$(y_{j,t} - y^*_{j,t}) \times IIS_{j,t}$		-0.0164
		(0.0197)
Average of Lags	0.376***	0.373***
	(0.0429)	(0.0449)
Industry FE	Y	Y
Time FE	Y	Y
No of Obs.	2158	2158
R^2	0.251	0.255

Note: Results are from Equation (2.7). Column (1) uses the equation without $IIS_{j,t}$ term. Column (2) estimates the full equation. Driscoll-Kraay standard errors are in parenthesis with a lag of 8.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

each country/region. Since we aim to compare the relative flattening effects of imports from each region, we standardize each variable around their mean before adding in regressions (leaving out the scaling effects).

Table 2.2 presents the results. The previous estimation result from total imported intermediate goods shares is shown in column (1). The estimated coefficients from columns (2), (3), and (4) provide the striking difference in the role of integration to the EU, AEs, and EMEs on the UK Phillips curve, respectively. Column (4) shows that the coefficient of the interaction term is negative and statistically significant, implying a role for imported intermediate goods shares from EMEs. To state differently, we find that increased integration of the UK sectors to the EMEs led to a diminished response of UK inflation to the output gap between 2000 and 2014. On the other hand, columns (2) and (3) suggest that we cannot precisely estimate the role of integration to the EU or AEs on the UK Phillips curve.

To report the economic significance of the results, recall that $IIS^{EME}_{j,t}$ is standardized; thus, the coefficient for the output gap (0.0433) denotes the Phillips curve coefficient for the mean level of integration to the EMEs. The coefficient of the interaction term (-0.0426) implies that one standard deviation increase in the share of imported intermediate goods from EMEs in UK sectors reduces the slope of the Phillips curve near 0. Furthermore, we apply back-of-the-envelope calculations to understand the importance of rising imported intermediate goods dependence on the EMEs on the value of the UK Phillips curve slope. Using the coefficients from column (4), we find that the Phillips curve coefficient reduced by 64% between 2000 and 2014 due to rising $IIS^{EME}_{j,t}$, after controlling for aggregate time-varying sector-specific time-invariant effects.

Our findings provide new evidence on the reasons behind the fall in response of inflation to the fluctuations in domestic demand in the UK. Different from previous studies that emphasise the importance of trade integration on inflation dynamics, here we argue that the regional direction of the integration affects inflation and economic activity relationships. Comparing the role of integration

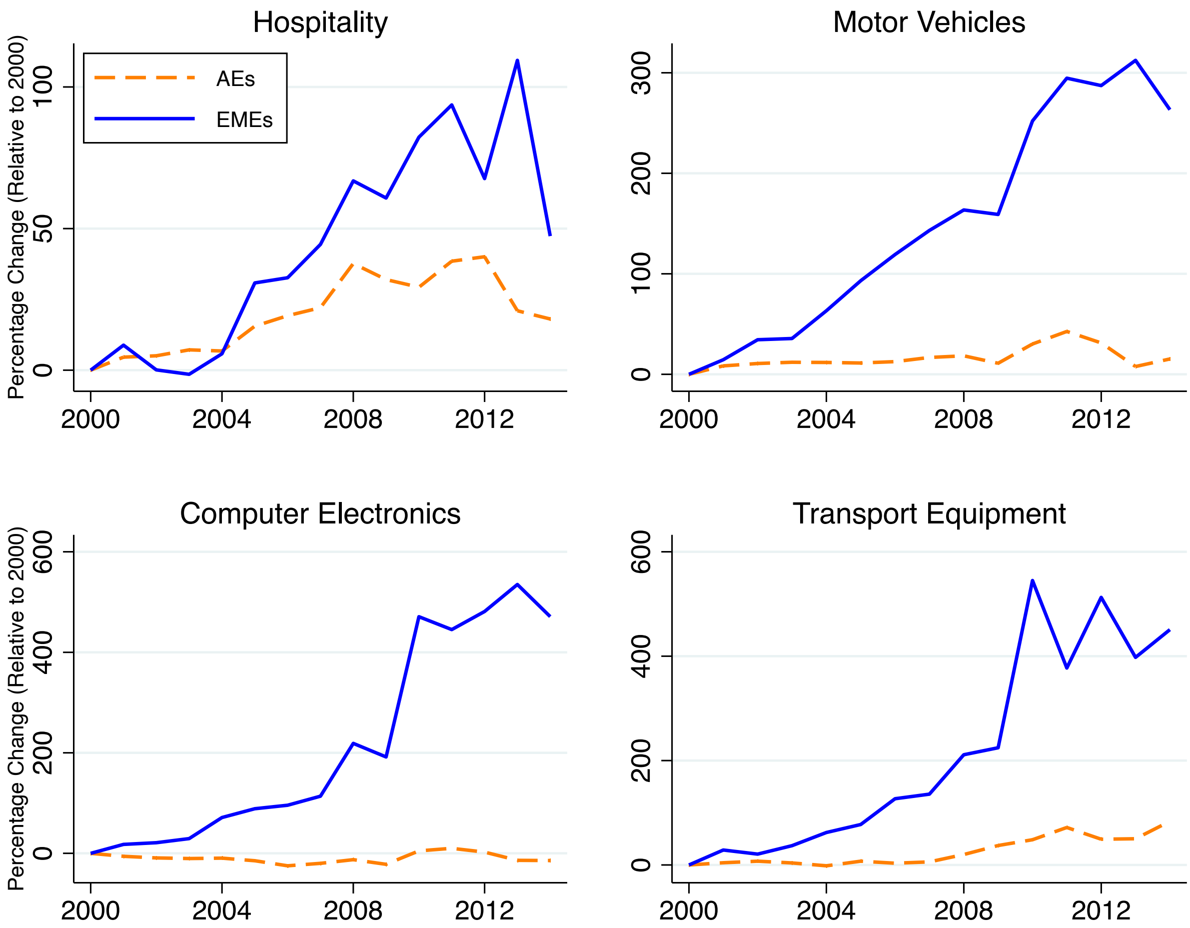


Figure 2.2: The Share of Regions in Total Inputs - Selected Sectors

Note: Figure plots the change in the shares of imported intermediate goods for selected sectors. Country classifications follow IMF and details are provided in section 2.3.1.

towards EMEs and other regions, we show that the sources of imports are extremely important to provide a claim on the role of imported intermediate goods dependence on the UK inflation dynamics.

2.4 Robustness

Here we examine the sensitivity of our estimation results to (a) the role of China in EMEs; (b) the instrumental variable approach; (c) the impact of medium-term forces. We show that our findings are robust.[11]

[11] We also examine the role of indirect effects of the rising imported intermediate goods dependence on the UK Phillips curve. We find that taking indirect effects into account does not matter for our results both qualitatively and quantitatively. Details of this exercise can be found in Appendix 2.C.

Table 2.2: GVCs and the UK Phillips Curve: Source Matters

Dep Var: $\pi_{j,t}$	(1) Total	(2) EU	(3) AEs	(4) EMEs	(5) EMEs vs. AEs
$(y_{j,t} - y^*_{j,t})$	0.0419***	0.0406***	0.0412***	0.0433***	0.0384***
	(0.0118)	(0.0123)	(0.0124)	(0.00965)	(0.0107)
$IIS_{j,t}$	0.616				
	(0.533)				
$(y_{j,t} - y^*_{j,t}) \times IIS_{j,t}$	-0.0164				
	(0.0197)				
$IIS^{EU}_{j,t}$		0.768			
		(0.668)			
$(y_{j,t} - y^*_{j,t}) \times IIS^{EU}_{j,t}$		-0.00256			
		(0.0169)			
$IIS^{AE}_{j,t}$			0.533		0.353
			(0.603)		(0.619)
$(y_{j,t} - y^*_{j,t}) \times IIS^{AE}_{j,t}$			-0.00746		0.0417*
			(0.0178)		(0.0222)
$IIS^{EME}_{j,t}$				0.445**	0.348
				(0.213)	(0.212)
$(y_{j,t} - y^*_{j,t}) \times IIS^{EME}_{j,t}$				-0.0426***	-0.0735***
				(0.0149)	(0.0202)
Average of Lags	0.373***	0.369***	0.374***	0.365***	0.364***
	(0.0449)	(0.0484)	(0.0453)	(0.0448)	(0.0447)
Industry FE	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y
No of Obs.	2158	2158	2158	2158	2158
R^2	0.255	0.256	0.254	0.259	0.261

Note: Results are from Equation (2.7). Columns (1)-(4) use $IIS_{j,t}$, $IIS^{EU}_{j,t}$, $IIS^{AEs}_{j,t}$, $IIS^{EMEs}_{j,t}$, respectively. Column (5) includes both $IIS^{AEs}_{j,t}$ and $IIS^{EMEs}_{j,t}$ in the regression. Driscoll-Kraay standard errors are in parenthesis with a lag of 8. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.4.1 Integration to the EMEs: With and Without China

Table 2.2 has shown that the integration of the UK to the EMEs resulted in a diminished response of UK inflation to the output gap. We now ask whether this result can be attributed to imports from a single EME such as China. To answer this question, we calculate the $IIS^{CH}_{j,t}$ variable using imported intermediate goods from only China for 40 sectors. We also calculate the share of imported intermediate goods from EMEs excluding China as $IIS^{exCH}_{j,t}$.

Estimating Equation (2.7) using these variables, we present the results in Table 2.3. Column (1) shows the previous result pointing to the role of integration in the EMEs. Columns (2) and (3) compare the role of rising imported intermediate goods share from China and excluding China on the UK Phillips curve, respectively. The coefficients of interaction terms are close to each other, implying a significant role for both groups. Therefore, we can not claim that the effects of integration of the EMEs are only due to rising dependence on Chinese goods in the UK.

Furthermore, we control for the imported intermediate goods prices (from ONS) to isolate the role

Table 2.3: EMEs vs China

	Full Sample			Manufacturing Sector		
	(1)	(2)	(3)	(4)	(5)	(6)
	EME	CH	exCH	EME	CH	exCH
$(y_{j,t} - y^*_{j,t})$	0.0433***	0.0438***	0.0449***	0.0961***	0.0796**	0.0929***
	(0.00965)	(0.00980)	(0.0114)	(0.0331)	(0.0384)	(0.0295)
$IIS^{EM}_{j,t}$	0.445**			-0.152		
	(0.213)			(0.272)		
$(y_{j,t} - y^*_{j,t}) \times IIS^{EM}_{j,t}$	-0.0426***			-0.0467***		
	(0.0149)			(0.0143)		
$IIS^{CH}_{j,t}$		0.462***			0.375	
		(0.131)			(0.279)	
$(y_{j,t} - y^*_{j,t}) \times IIS^{CH}_{j,t}$		-0.0415***			-0.0374**	
		(0.0108)			(0.0153)	
$IIS^{exCH}_{j,t}$			-0.0752			-0.272
			(0.276)			(0.323)
$(y_{j,t} - y^*_{j,t}) \times IIS^{exCH}_{j,t}$			-0.0445**			-0.0449
			(0.0221)			(0.0272)
$\pi^M_{j,t}$				0.0226**	0.0220**	0.0222**
				(0.00894)	(0.00892)	(0.00887)
Average of Lags	0.365***	0.360***	0.378***	0.232***	0.230***	0.236***
	(0.0448)	(0.0444)	(0.0427)	(0.0625)	(0.0627)	(0.0629)
Industry FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
No of Obs.	2158	2158	2158	802	802	802
R^2	0.259	0.261	0.255	0.266	0.267	0.267

Note: Driscoll-Kraay standard errors are in parenthesis with a lag of 8. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

of greater imported input dependence on the slope of the Phillips curve rather than the direct effects on inflation. However, due to data availability, we can focus only on the 18 manufacturing sectors. The results are presented in columns (4-6). The flattening effect of the integration to the EMEs and China is robust to controlling for imported intermediate goods prices, whereas the coefficient of interaction is borderline insignificant for the imports from EMEs excluding China. Since the coefficient (-0.0449) is higher for this group (exCH) compared to the other two groups (-0.0467 for EME and -0.0374 for CH), the insignificance can be due to lower variation in $IIS^{exCH}_{j,t}$ within manufacturing sectors.

2.4.2 Instrumental Variable Analysis

Following the trade literature, we assess the potential endogeneity problem due to including the $IIS_{j,t}$ variable in Equation (2.7) which can affect the interpretation of its role on the flattening of the Phillips curve. In particular, we follow Autor, Dorn, and Hanson (2013) and argue that import increases might not be due to the increased competitiveness or higher productivity in the source country but also be caused by increasing demand in the importer country. Since higher import demand is

Table 2.4: Instrumental Variable Analysis

	(EMEs)		(China)	
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
$(y_{j,t} - y^*_{j,t})$	0.0433***	0.0428***	0.0438***	0.0432***
	(0.00965)	(0.0103)	(0.00980)	(0.00948)
$IIS^{EM}_{j,t}$	0.445**	1.125		
	(0.213)	(0.694)		
$(y_{j,t} - y^*_{j,t}) \times IIS^{EM}_{j,t}$	-0.0426***	-0.0498***		
	(0.0149)	(0.0170)		
$IIS^{CH}_{j,t}$			0.462***	0.771***
			(0.131)	(0.199)
$(y_{j,t} - y^*_{j,t}) \times IIS^{CH}_{j,t}$			-0.0415***	-0.0463***
			(0.0108)	(0.0133)
Average of Lags	0.365***	0.358***	0.360***	0.355***
	(0.0448)	(0.0496)	(0.0444)	(0.0465)
First-stage Fstat		1048.6		520.7
Industry FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
No of Obs.	2158	2158	2158	2158
R^2	0.259	0.268	0.261	0.266

Note: Driscoll-Kraay standard errors are in parenthesis with a lag of 8.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

correlated with higher inflation, estimations would suffer from endogeneity, and an OLS estimation would understate the actual impact.

We follow Autor, Dorn, and Hanson (2013) and estimate the following structural equation and the first stage of the IV specification

$$\pi_{j,t} = \beta_1(y_{j,t} - y^*_{j,t}) + \beta_2 IIS_{j,t} + \beta_3(y_{j,t} - y^*_{j,t}) \times IIS_{j,t} + \beta_4\left(\frac{1}{4}\sum_{j=1}^{4}\pi_{t-j}\right) + \delta_j + \delta_t + \epsilon_{j,t},$$

$$IIS_{j,t} = \alpha IIS^{Others}_{j,t} + \delta_j + \delta_t + \eta_{j,t},$$

where we use the imports of 8 other developed countries from EMEs and China separately to calculate $IIS^{Others}_{j,t} = \frac{\text{Imported Intermediate Goods}^{Others}_{j,t}}{\text{Total Intermediate Goods}_{j,t}}$.[12][13] Here, the identification assumption is that the import demand shocks at the sector level between the UK and 8 other developed countries are independent.[14]

Table 2.4 shows that the flattening effect of integration with both EMEs (columns (1) and (2)) and China (columns (1) and (2)) are robust to IV estimation. The coefficients on interaction terms are slightly higher (in absolute terms) and statistically significant at 5%.

[12]Australia, Denmark, Finland, Germany, Japan, Spain, Switzerland, United States.

[13]The correlation between the instrument and the endogenous regressor is 0.85.

[14]The results are robust to using G7 countries or only the US for instrumenting the UK's imports.

Table 2.5: Further Controls on Medium-term Impacts

	(1) Baseline	(2) Lag Variable	(3) Two-Year Moving Average	(4) Three-Year Moving Average
$(y_{j,t} - y^*_{j,t})$	0.0483**	0.0429**	0.0432**	0.0363*
	(0.02130)	(0.02024)	(0.02061)	(0.02080)
$IIS^{EM}_{j,t}$	0.216	0.146	0.158	-0.0672
	(0.2993)	(0.3043)	(0.3326)	(0.3108)
$(y_{j,t} - y^*_{j,t}) \times IIS^{EM}_{j,t}$	-0.0429**	-0.0382**	-0.0402**	-0.0376*
	(0.0163)	(0.0174)	(0.0168)	(0.0201)
Average of Lags	0.379***	0.382***	0.381***	0.426***
	(0.1093)	(0.1121)	(0.1125)	(0.1069)
Industry FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
No of Obs.	2158	2030	2030	1877
R^2	0.537	0.536	0.537	0.549

Note: Driscoll-Kraay standard errors are in parenthesis with a lag of 8. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.4.3 Further Controls on Medium-term Impacts

Finally, we provide another control on the role of GVC integration following the arguments from Comin and Johnson (2020). They argue that long-lived shocks' impact on trade openness provides a long phase-in dynamics. They also note that a shift in steady states, from a less open to a more open world, would slowly occur over time.

However, our GVC integration measurement is defined at the annual level. To address the potential concern that the role of GVCs from previous periods would also matter for the recent period on inflation dynamics, we use lags of our GVC measurement in our regressions. Furthermore, we calculate the two- and three-year moving average in $IIS^{EM}_{j,t}$ to take into account the medium-term impacts of GVC integration on the Phillips curve relationship.

Table 2.5 presents the results with a baseline specification (column (1)), using the lag of our GVC measurement $IIS^{EM}_{j,t-1}$ (column (2)), two-year moving average $\frac{IIS^{EM}_{j,t}+IIS^{EM}_{j,t-1}}{2}$, and three-year moving average $\frac{IIS^{EM}_{j,t}+IIS^{EM}_{j,t-1}+IIS^{EM}_{j,t-2}}{3}$. The interaction terms from each column suggest that our results are robust to taking into account the medium-term phase in effects of GVC integration with the EMEs and integration to the EMEs flattens the slope of the UK's Phillips curve.

2.5 The Role of Medium-Term Forces

While our findings consistently demonstrate the significance of the slope effect of GVCs integration to EMEs on the UK's Phillips curve, it is important to acknowledge that our benchmark results may not be driven only by the slope effect, but also influenced by cyclical forces acting as an additional channel. This can provide insights into why our results are specifically applicable to EMEs but not AEs. To understand the importance of the source dimension of GVCs integration, we use a more general version of the model presented in Section 2.2.

In particular, the static model we have presented in Section 2.2 does not discuss why our results hold only when the source of GVCs integration is EMEs. According to this model, sectors with higher GVCs integration should have a flatter Phillips Curve. However, our empirical results show that the source of GVC integration also matters. This requires a more general model.

To address this, we extend our static model in two ways. First, we introduce dynamics into our model. This allows us to move away from the financial autarky assumption. Second, we introduce multiple sectors in each economy. This framework is much closer to our empirical framework so can shed results on the importance of source dimension. We outline the details of this model in Appendix 2.E.

GVCs in our Model: Why EMEs? In our framework, GVC integration affects the link between inflation and domestic slack through two distinct channels: Firstly, it exerts a direct impact on the slope, thereby influencing the response of inflation to fluctuations in real economic activity. Secondly, our GVC measure is influenced by movements in terms of trade. Differential prices across countries enable firms to switch between domestic and imported inputs, thereby creating a disconnect between domestic prices and marginal costs.

In our empirical analysis, we use the sum of the nominal value of imported goods from all sectors divided by the value of intermediate goods as our GVC measure. In our model, this corresponds to

$$GVC_{st} = \frac{n\sum_{s'}^{S} P_{Fs't} M_{Fss't}}{(1-n)\, P_{st}^{M} M_{st}} = \frac{\sum_{s'}^{S} P_{Fs't}(1-\mu_{ss'})\left(\frac{P_{Fs't}}{P_{ss't}^{M}}\right)^{-\phi_M} \omega_{ss'}\left(\frac{P_{ss't}^{M}}{P_{st}^{M}}\right)^{-\theta_M} M_{st}}{P_{st}^{M} M_{st}},$$

where $M_{Fss't}$ is the imported intermediate good demand of sector s from sector s' at time t, and M_{st} is total intermediate goods demand in sector s. The intermediate input price index is P_{st}^{M} and sectoral intermediates price index, $P_{ss't}^{M}$ is a weighted average of home, $P_{Hs't}$, and foreign, $P_{Fs't}$, sectoral output prices. $\omega_{ss'}$ is the share of sector s' in total intermediate good expenditure of sector s with $\sum_{s'=1}^{S} \omega_{ss'} = 1$. The elasticity of substitution across sectoral intermediate goods is denoted by θ_M. The share of foreign-produced goods at the intermediate level is denoted by $1-\mu_{ss'}$, and ϕ_M denotes the elasticity of substitution between home and foreign-produced intermediate goods.

In our benchmark model, we discussed how imported intermediate goods share, $1-\mu$ can make the slope of the Phillips curve flatter. Indeed our GVC measure is a function of μ and increases as the share of imported intermediates increases. However, our measure is also affected by relative prices. We discussed briefly how the exchange rate can affect inflation in the previous section. International relative prices, and terms of trade, will affect our measure of GVCs as long as the elasticity of substitution between home and foreign-produced goods is different from one. Specifically, under Cobb-Douglas aggregation, when ϕ_{Ms}, the elasticity of substitution between home and foreign-produced intermediate goods in each sector, and θ_M, the elasticity of substitution across sectoral intermediate goods, are equal to 1, our measure would boil down to

$$\frac{\sum_{s'}^{S} P_{Fs't} M_{Fss't}}{P_{st}^{M} M_{st}} = \sum_{s'}^{S} (1-\mu_{ss'})\, \omega_{ss'}.$$

Then the only channel that our GVCs measure captures is the increased openness in production. As shown, the higher the imported intermediate goods share the flatter the Phillips curve. Additionally, with a multi-sector set-up, the higher the input demand from sectors with large import share, the flatter the Phillips curve. However estimates of the elasticity of substitution between home and foreign traded goods vary significantly in the literature and they are far from 1 (e.g., see Feenstra (1994)) making CES aggregation the appropriate choice.

These relative price movements are crucial because the terms of trade directly affect our GVCs measure. The log-linearised version of our GVC measure corresponds to

$$\widehat{GVC}_{st} = \sum_{s'}^{S} \left(\hat{p}_{Fs't} - \phi_M \left(\hat{p}_{Fs't} - \hat{p}^M_{ss't} \right) - \theta_M \left(\hat{p}^M_{ss't} - \hat{p}^M_{st} \right) + \hat{m}_{st} \right) - (\hat{p}^M_{st} + \hat{m}_{st}),$$

where

$$\hat{p}_{Fs't} - \hat{p}^M_{ss't} = \mu_{ss'} \underbrace{(\hat{p}_{Fs't} - \hat{p}_{Hs't})}_{tot_{st}}.$$

Intuitively, the relative price channel operates through firms' marginal cost. In our model, the marginal cost is not only a function of wages (or cost of value added) but also domestic and imported intermediate input prices. By log-linearizing the marginal cost presented in Appendix 2.E, Equation (2.58) around the steady-state, we obtain

$$\hat{mc}_{st} = \delta_s \hat{w}_t + (1 - \delta_s) \sum_{s'=1}^{S} \omega_{ss'} [\mu_{ss'} \hat{p}_{Hs't} + (1 - \mu_{ss'}) \hat{p}_{Fs't}] - \hat{a}_t - \hat{a}_{st}. \tag{2.8}$$

The above expression shows that changes in sectoral marginal cost depend on i) the changes in wages, ii) the changes in domestic input prices, iii) the changes in imported input prices, and iv) the changes in aggregate and sector-specific productivity.[15] When domestic wages increase and home intermediate goods prices increase relative to the foreign ones, firms can switch towards cheaper imported intermediate inputs as terms of trade improve. This might shed light on why the source of GVC integration matters. It is well-known that business cycles are highly correlated across advanced economies. For instance, Kose, Otrok, and Whiteman (2003) examines the business cycle co-movements across countries and provides empirical evidence on the high degree of synchronization in business cycles among developed economies. This means that, when wages in the UK economy increase, they are likely to also increase in the EU and the US too as output is highly correlated across these countries.

To test this argument thoroughly, we now show the role of business cycle correlations of the UK with the countries that the UK economy has integrated with. We first calculate the business cycle correlation of each country c with the UK (corr(c,UK)) by using HP-filtered real GDP series between 2000Q1 and 2014Q4. Then, we separate countries into low/medium/high correlation groups depending on the correlation coefficients. Using this country classification, we calculate the imported intermediate good share from each group, e.g. the low correlation group country's share in total intermediate goods as $IIS^{Low}_{j,t} = \frac{\text{Imported Intermediate Goods}^{Low}_{j,t}}{\text{Total Intermediate Goods}_{j,t}}$. Table 2.7 in section 2.A displays the business cycle correlation category of each country with the UK.

To compare the role of integration with each group of countries, we estimate Equation (2.7) using the imported intermediate good share of low and high business cycle correlations groups and present

[15] Note that, under multi-sector, input-output linkages setting increase in the share of imported intermediates (lower $\mu_{ss'}$) not only affect the sectoral marginal cost directly but also indirectly as domestic intermediate input suppliers also use imported intermediates in their production.

Table 2.6: GVCs and the UK Phillips Curve: Business Cycle Correlations

	(1)	(2)	(3)
Dep Var: $\pi_{j,t}$	All	Low BC Corr	High BC Corr
$(y_{j,t} - y^*_{j,t})$	0.0419***	0.0349**	0.0345**
	(0.0118)	(0.0139)	(0.0133)
$IIS_{j,t}$	0.616		
	(0.533)		
$(y_{j,t} - y^*_{j,t}) \times IIS_{j,t}$	-0.0164		
	(0.0197)		
$IIS^{BClow}_{j,t}$		0.338	
		(0.215)	
$(y_{j,t} - y^*_{j,t}) \times IIS^{BClow}_{j,t}$		-0.0251**	
		(0.0121)	
$IIS^{BChigh}_{j,t}$			-0.0144
			(0.228)
$(y_{j,t} - y^*_{j,t}) \times IIS^{BChigh}_{j,t}$			-0.0014
			(0.0098)
Average of Lags	***	***	***
Industry FE	Y	Y	Y
Time FE	Y	Y	Y
No of Obs.	2158	2158	2158
R^2	0.255	0.258	0.251

Note: Driscoll-Kraay standard errors are in parenthesis with a lag of 8.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

results in Table 2.6. Column (1) shows the previous results to compare as a baseline. Columns (2) and (3) present the role of business cycle correlations on the inflation dynamics. The interaction term from column (2) suggests that rising imported intermediate goods share from countries with low business cycle correlation leads to a fall in response of inflation to real economic activity. We do not find a significant role for goods and services imported from countries with high business cycle correlations with the UK (column 3).

Comparing columns (2) and (3) from Table 2.6, we observe the new evidence that not only does the integration of a country to GVCs matter but also the correlation with the business cycle of the integrated country matters. Table 2.2 suggested a geographical interpretation of the role of GVCs on the flattening of the UK Phillips curve, emphasizing the importance of integrating toward EMEs. On the other hand, Table 2.6 provides an economic interpretation of the question of why integrating EMEs matters more significantly than AEs. Table 2.7 shows that the business cycle correlation of the UK economy is lower with EMEs than with AEs. We argue that when the UK economy is integrated into a country with low business cycle correlation, it leads to a decline in pass-through from demand-side shocks to prices. Assume a demand-side shock in the UK that generates a rise in the output gap. The increase in market demand would normally also push the input demand and their costs in the UK. However, if the UK economy is highly integrated with the GVCs, and especially to the countries that have low business cycle correlations with the UK, then firms would switch to the imported intermediate goods (from domestic goods) since these countries have not experienced a rise in their costs and prices due to lack of demand-side shock in that period. Following this shift in input demand of the UK sectors, the change in input costs would be limited. Therefore, we argue that the rise in output prices would also be limited following a demand-side shock in the UK reducing the link between inflation and the domestic demand.

2.6 Conclusion

In this paper, we studied the impact of GVC integration into EMEs on the inflation dynamics of the UK. Leveraging sectoral data we examined the impact of GVC integration on the UK inflation and the output gap relationship. We showed that a rise in imported intermediate goods dependence from EMEs implies a reduced response of inflation to the increases in domestic output gap across various reduced-form specifications. Subsequently, building a model that includes trade in intermediate inputs, we showed analytically that an increased share of imported intermediate goods in production leads to a flatter Phillips curve. We showed that international relative price movements are important in understanding why our results only hold for EMEs: sourcing inputs from countries with low business cycle correlation with the UK can mute the response of inflation to the increase in the domestic output gap.

Our findings have potential implications for understanding the implications of supply chain disruptions on inflation dynamics as well as the consequences of de-integration from GVCs and related concerns. The interaction between medium-term forces through terms of trade movements and long-term structural shifts through the slope is important for the conduct of monetary policy and is central to understanding the current debate around deglobalisation. We argue that the terms of trade movements are important to understand why we find our results only for EMEs but not for AEs.

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Appendix to Chapter 2

2.A Additional Figures and Tables

Business cycle correlations: We use OECD country-level real GDP growth statistics to calculate business correlations between countries and the UK. Table 2.7 displays the results.

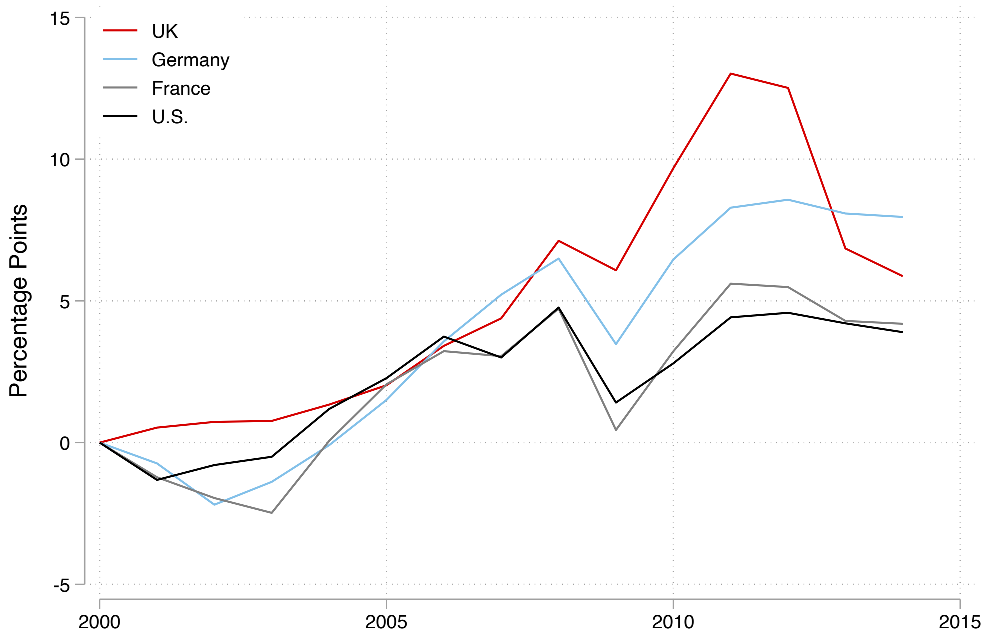


Figure 2.3: Change in Intermediate Input Share Across Other Countries

Notes: Data from WIOD. The figure shows the change in imported intermediate inputs as a share of total intermediate inputs for manufacturing sectors.

Table 2.7: Business Cycle Categories

Low Business Cycle Correlation		High Business Cycle Correlation	
Country	corr(y^{UK}, y^{C})	Country	corr(y^{UK}, y^{C})
Croatia	0.648	Estonia	0.832
Chile	0.642	United States	0.831
Slovenia	0.640	Japan	0.803
Slovakia	0.614	Latvia	0.801
Argentina	0.597	Lithuania	0.799
Korea	0.571	Hungary	0.787
Netherlands	0.565	Denmark	0.779
Norway	0.563	Mexico	0.768
Spain	0.557	Sweden	0.768
Iceland	0.547	South Africa	0.767
Israel	0.481	Belgium	0.749
New Zealand	0.456	Colombia	0.743
Bulgaria	0.441	Luxembourg	0.735
Ireland	0.429	Germany	0.730
Roumania	0.410	France	0.724
Australia	0.386	Russia	0.706
Portugal	0.289	Canada	0.699
Indonesia	0.260	Switzerland	0.686
Greece	0.251	Finland	0.685
Brazil	0.217	Turkey	0.676
Poland	0.210	Czech Republic	0.675
Saudi Arabia	-0.079	Austria	0.672
India	-0.490	Italy	0.651
Mean	0.401	Mean	0.742
Median	0.456	Median	0.743

Note: Source - OECD. The sample period is between 2000Q1 and 2014Q4 (matching the main empirical analysis period).

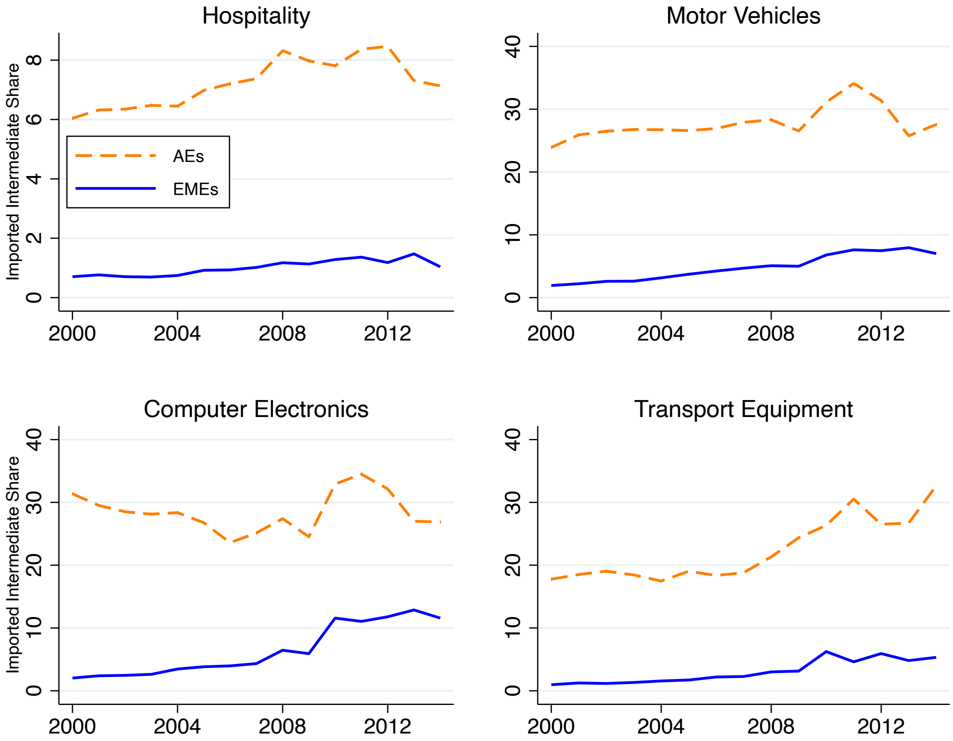


Figure 2.4: The Share of Regions in Total Inputs, by Sector

Notes: Plot of $IIS_{j,t}^{AEs}$, $IIS_{j,t}^{EMEs}$ for selected sectors. Country classifications from the IMF

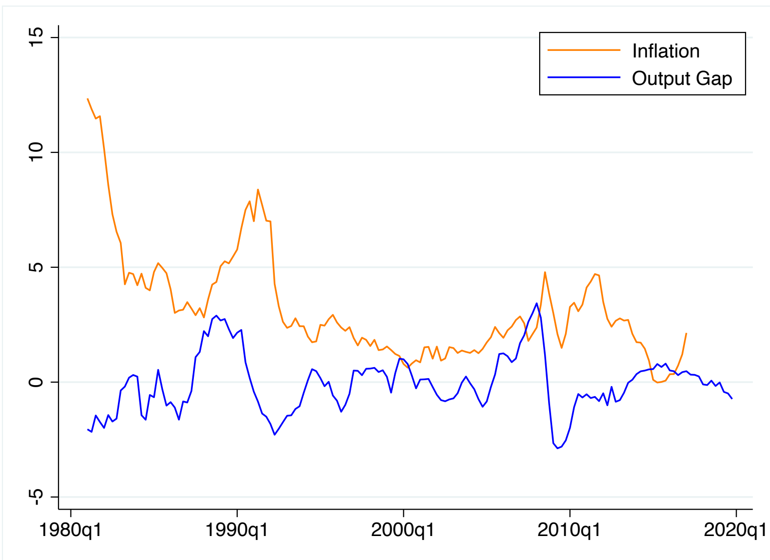


Figure 2.5: Aggregate Inflation and Output Gap

Note: Aggregate inflation is from ONS and the output gap is the deviation of real GDP from its HP-filtered trend.

2.B The Role of Trade

Here we explore the role of openness in the flattening of the UK's Phillips curve. We begin by displaying the trade openness and total import share over time (Figure 2.6) since the 1950s. Trade openness almost doubled from the mid-1980s to 2000 and then further increased by 50% from 2000 to 2020. Analogously, the share of imports doubled between the 1950s and 2010, remaining stable after that.

Both measures from Figure 2.6 point to a significantly increasing integration of the UK economy in global markets. We argue that increasing trade openness makes the prices in the UK economy less dependent on domestic factors. Therefore, the relationship between inflation and domestic economic activity weakens. To test this argument, we follow Ball (2006) and estimate the following regression where we interact aggregate output gap with trade openness

$$\pi_t = \beta_1 (y_t - y_t^*) + \beta_2 \text{Openness}_t + \beta_3 (y_t - y_t^*) \times \text{Openness}_t + \beta_4 \pi_t^M + \beta_5 \pi_t^{oil} + \beta_6 \left(\frac{1}{4} \sum_{j=1}^{4} \pi_{t-j} \right) + \varepsilon_t, \tag{2.9}$$

where $\text{Openness}_t = \frac{\text{Imports+Exports}}{\text{Real GDP}}$. This variable is standardized (around the mean) to ease the interpretation of the estimated coefficients. Previously, we have shown a positive relationship between inflation and the output gap. In this exercise, we are interested in the estimation of the interaction parameter, β_3.

Table 2.8 column (1) suggests that the coefficients attached to $(y_t - y_t^*) \times \text{Openness}_t$ is negative and statistically significant, supporting the argument that rising trade openness in the UK led to a flattening in the Phillips curve. Recall that, Openness_t is standardized, thus β_1 coefficient denotes the Phillips curve slope for the mean trade openness period (e.g., the mid-1990s) in our sample and the coefficient for the interaction term (β_3) represents the effect of a one standard deviation increase in trade openness on the slope of the Phillips curve.

As a robustness check, we control the role of the inflation targeting regime in 1992 and central bank independence in 1997. We include a dummy variable equal to 1 after 1992 ($Post_{1992}$) and another one after 1997 ($Post_{1997}$) to control separately for the possible effects of these two policies. Columns (2) and (3) show that the results remain qualitatively unchanged, implying that one standard deviation increase in the trade variable flattens the slope of the Phillips curve to roughly 0.1.

The results imply that openness may be an important driver behind the flattening of the UK Phillips curve.

2.C Indirect Effects

We examine the sensitivity of our results to the indirect effects of the rise in imported intermediate goods in production on the UK Phillips curve. The benchmark results documented the "direct" effects of the GVCs on the Phillips curve. However, a growing literature shows how a shock to one industry can propagate to other industries through sectoral linkages and generate more amplified effects on the aggregate economy. This subsection examines the role of amplified (direct+indirect) effects using input-output tables.

Let's redefine the variable $IIS_{j,t}$ from our estimations as the direct effects of the GVCs on industry j. Previous results showed that the inflation and output gap relationship is weaker in industries with higher imported intermediate goods dependence. This result also implies that the rigidity in output

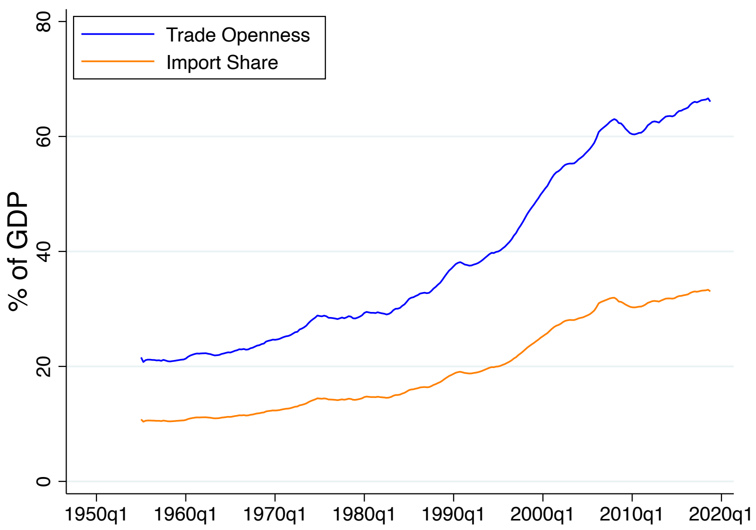


Figure 2.6: Trade Openness

Note: Trade Openness: $\frac{\text{Imports+Exports}}{\text{Real GDP}}$ and Import Share: $\frac{\text{Imports}}{\text{Real GDP}}$ using ONS data.

prices of an industry j will also be experienced by other industries that use goods/services from industry j as intermediate goods. Thus, the direct effects of $IIS_{j,t}$ to industry j propagates indirectly to its buyers. We define "Indirect effects" following Acemoglu, Autor, Dorn, Hanson, and Price (2016) as

$$IIS^{Ind}_{j,t} = \sum_{g} \omega_{gj} IIS_{gt}, \tag{2.10}$$

which is equal to the weighted average of directly imported intermediate good shares (IIS_{gt}) across all industries, indexed by g, that *supply* goods to the industry j. The weights ω_{gj} are defined as

$$\omega_{gj} = \frac{\mu_{gj}}{\sum_{g'} \mu_{g'j}}, \tag{2.11}$$

where μ_{gj} is the value of inputs used by industry j from industry g, and calculated using 2000 ONS UK input-output tables. The weight ω_{gj} in Equation (2.11) is the share of inputs from industry g in total inputs used by industry j.

We also note that the imported intermediate good dependence of industry j affects other industries (g). Then, an affected industry g would further affect industry j and so on. To take into account the full chain of effects, we use the Leontief inverse of the linkages from weights of Equation (2.11) following Acemoglu, Autor, Dorn, Hanson, and Price (2016). Thus, the total effects from GVC integration are measured using Leontief inverse matrices of weights such that

$$IIS^{Total}_{j,t} = \sum_{g} \omega^{L}_{gj} IIS_{gt}, \tag{2.12}$$

where ω^{L}_{gj} are the weights adjusted by Leontief inverses.

The intuition for the indirect effects is that when an industry j's suppliers experience a high imported intermediate good dependence from abroad, then the industry j's inputs would be further dependent on imported goods and services. Therefore, we argue that this channel would further

Table 2.8: Trade and the UK Phillips Curve
(1980Q1-2017Q1)

π_t	(1)	(2)	(3)
$(y_t - y_t^*)$	0.427***	0.426***	0.429***
	(0.0934)	(0.0936)	(0.0952)
Openness_t	0.00983	0.0804	0.238
	(0.0563)	(0.120)	(0.212)
$(y_t - y_t^*) \times \text{Openness}_t$	-0.315***	-0.316***	-0.319***
	(0.0870)	(0.0883)	(0.0892)
π_t^{oil}	0.0104*	0.0104*	0.0107*
	(0.00593)	(0.00589)	(0.00588)
π_t^M	0.0498***	0.0500***	0.0489***
	(0.0179)	(0.0173)	(0.0176)
$\frac{1}{4}\sum\limits_{j=1}^{4} \pi_{t-j}$	0.913***	0.918***	0.924***
	(0.0241)	(0.0274)	(0.0272)
Observations	149	149	149
R^2	0.9674	0.9675	0.9677
$Post_{1992}$	No	Yes	No
$Post_{1997}$	No	No	Yes

Newey-West standard errors in parentheses with a lag of 18

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

weaken the sensitivity of "output" prices against a change in economic activity as the input costs would be dependent abroad.

Note that Equation (2.12) generates a general formula to calculate the total effects of imported intermediate goods share. Thus, we focus on generating total effects for our two main results separately: Role of EMEs and low business cycle correlation countries[16].

Table (2.9) presents the results from the estimation of specification (2.7) using both direct and total effects. Comparison of the interaction terms between columns (1) and (2), and (3) and (4) cannot confirm the amplification of the GVCs' role through sectoral linkages. The interaction terms are negative and significant in each specification, but the coefficients are not different when total effects through sectoral linkages are used. Thus, the results suggest no evidence of the role of sectoral linkages amplifying the previous results.

[16] We calculate $IIS_{j,t}^{EM,Total} = \sum\limits_{g} \omega_{gj}^{L} IIS_{gt}$ and $IIS_{j,t}^{BClow,Total} = \sum\limits_{g} \omega_{gj}^{L} IIS_{gt}$ separately and use in our regressions

Table 2.9: Indirect Effects

	(EMEs)		(Low BC Corr.)	
	(1)	(2)	(3)	(4)
	Direct	Total	Direct	Total
$(y_{j,t} - y^*_{j,t})$	0.0483**	0.0490**	0.430***	0.0443***
	(0.02130)	(0.02140)	(0.01013)	(0.00994)
$IIS^{EM}_{j,t}$	0.216			
	(0.2993)			
$(y_{j,t} - y^*_{j,t}) \times IIS^{EM}_{j,t}$	-0.0429**			
	(0.0163)			
$IIS^{EM,Total}_{j,t}$		0.231		
		(0.2939)		
$(y_{j,t} - y^*_{j,t}) \times IIS^{EM,Total}_{j,t}$		-0.0410**		
		(0.0159)		
$IIS^{BClow}_{j,t}$			0.552***	
			(0.18623)	
$(y_{j,t} - y^*_{j,t}) \times IIS^{BClow}_{j,t}$			-0.0258**	
			(0.01145)	
$IIS^{BClow,Total}_{j,t}$				0.563***
				(0.18868)
$(y_{j,t} - y^*_{j,t}) \times IIS^{BClow,Total}_{j,t}$				-0.0269**
				(0.01139)
Average of Lags	0.379***	0.379***	0.364***	0.364***
	(0.1093)	(0.1092)	(0.0445)	(0.0447)
Industry FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
No of Obs.	2158	2158	2158	2158
R^2	0.537	0.537	0.561	0.561

Driscoll-Kraay standard errors are in parenthesis with a lag of 8

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.D Static Model Proofs

Proof of Lemma 1. The marginal cost can be written as

$$\log MC = \delta \log W + (1-\delta)\log P^M - \log A,$$
$$\log MC^* = \delta^* \log W^* + (1-\delta^*)\log P^{M*} - \log A^*.$$

The input price index can be written as

$$\log P^M = \mu \log P_H + (1-\mu)\log P_F,$$
$$\log P^{M*} = \mu^* \log P^*_F + (1-\mu^*)\log P^*_H,$$

Combining the last two expressions yield

$$\log MC = \delta \log W + (1-\delta)(\mu \log P_H + (1-\mu)\log P_F) - \log A,$$
$$\log MC^* = \delta^* \log W^* + (1-\delta^*)(\mu \log P^*_F + (1-\mu)\log P^*_H) - \log A^*,$$

Under producer currency pricing, we have

$$\log P_F = \log P_F^* + \log \mathcal{E},$$
$$\log P_H = \log P_H^* + \log \mathcal{E},$$

where $\mathcal{E}$ is the nominal exchange rate (units of foreign currency in home currency). Plugging in PCP yields

$$\log MC = \delta \log W + (1-\delta)(\mu \log P_H + (1-\mu)\log P_F^* + (1-\mu)\log \mathcal{E}) - \log A,$$
$$\log MC^* = \delta \log W^* + (1-\delta)(\mu^* \log P_F^* + (1-\mu^*)\log P_F - (1-\mu)\log \mathcal{E}) - \log A^*.$$

In matrix notation, we can write the previous equation as

$$\log \mathbf{MC} = \delta \cdot \log \mathbf{W} + \Omega \log \mathbf{p} + (1-\delta) \cdot \begin{pmatrix} 1-\mu \\ -(1-\mu^*) \end{pmatrix} \log \mathcal{E} - \log \mathbf{A}, \tag{2.13}$$

where $\log \boldsymbol{MC} = \begin{pmatrix} \log MC \\ \log MC^* \end{pmatrix}$. With nominal rigidities, domestic inflation is given by

$$d\log \mathbf{p} = \Theta d \log \mathbf{MC}, \tag{2.14}$$

where $\Theta = diag(1-\theta, 1-\theta^*)$. Plugging in this expression to a differenced version of (2.13), we get

$$d\log \mathbf{MC} = \delta \cdot d\log \mathbf{W} + \Omega\Theta d\log \mathbf{MC} + (1-\delta) \cdot \begin{pmatrix} 1-\mu \\ -(1-\mu^*) \end{pmatrix} d\log \mathcal{E} - d\log \mathbf{A}.$$

Rearranging for marginal cost yields

$$d\log \mathbf{MC} = (1-\Omega\Theta)^{-1} \left(\delta \cdot d\log \mathbf{W} + (1-\delta) \cdot \begin{pmatrix} 1-\mu \\ -(1-\mu^*) \end{pmatrix} d\log \mathcal{E} - d\log \mathbf{A} \right),$$

where the term $(I-\Omega\Theta)^{-1}$ captures the 'adjusted' Leontief inverse as in Rubbo (2023) - the production network structure of the economy, suitably adjusted for nominal rigidities. Plugging the previous equation into (2.14) yields

$$d\log \mathbf{p} = \Theta(1-\Omega\Theta)^{-1} \left(\delta \cdot d\log \mathbf{W} + (1-\delta) \cdot \begin{pmatrix} 1-\mu \\ -(1-\mu^*) \end{pmatrix} d\log \mathcal{E} - d\log \mathbf{A} \right). \tag{2.15}$$

CPI inflation can be written as

$$d\log \mathbf{P} = \Phi d\log \mathbf{p} + \begin{pmatrix} 1-\alpha \\ -(1-\alpha^*) \end{pmatrix} d\log \mathcal{E}, \tag{2.16}$$

where

$$\log \mathbf{P} = \begin{pmatrix} \log P \\ \log P^* \end{pmatrix}, \qquad \Phi = \begin{pmatrix} \alpha & 1-\alpha \\ 1-\alpha^* & \alpha^* \end{pmatrix}.$$

Market Clearing

Now we write the Phillips Curve in terms of output gaps between home and foreign countries. Market clearing ensures that

$$Y_H = C_H + M_H + \frac{1-n}{n}\left(C_H^* + M_H^*\right), \tag{2.17}$$

$$Y_F^* = C_F^* + M_F^* + \frac{n}{1-n}\left(C_F + M_F\right). \tag{2.18}$$

We assume that there is balanced trade in final and intermediate goods [17]

$$nP_F(C_F + M_F) = (1-n)P_H(C_H^* + M_H^*), \tag{2.19}$$

and this allows us to write the market clearing (2.17) as

$$Y_H^{VA} \equiv Y_H - M_H - \frac{P_F}{P_H}M_F = C_H + \frac{P_F}{P_H}C_F, \tag{2.20}$$

where we define the value-added output as gross output less intermediate goods, both domestic and imported. We can then rewrite the previous equation to get the real consumption in terms of real value-added

$$P_H Y_H^{VA} = P_H C_H + P_F C_F = PC \Longleftrightarrow C = \frac{P_H}{P}Y_H^{VA}, \tag{2.21}$$

Similarly, we can write foreign consumption in terms of foreign value-added

$$Y_F^{*VA} \equiv Y_F^* - M_F^* - \frac{P_H^*}{P_F^*}M_H^* = C_F^* + \frac{P_H^*}{P_F^*}C_H^*, \tag{2.22}$$

where the relative price follows from PCP. As above, we can rewrite the previous equation as

$$P_F^* Y_F^{*VA} = P_F^* C_F^* + P_H^* C_H^* = P^* C^* \Longleftrightarrow C^* = \frac{P_F^*}{P^*}Y_F^{*VA}. \tag{2.23}$$

From the intra-temporal equation, we have

$$\begin{aligned} d\log W &= d\log P + \sigma d\log C + \varphi d\log L \\ &= \sigma d\log Y_H^{VA} + \varphi d\log L + \sigma(d\log P_H - d\log P), \end{aligned}$$

where the last equality follows (2.20). Similarly for the foreign economy,

$$d\log W^* - d\log P^* = \sigma d\log Y_F^{*VA} + \varphi d\log L^* + \sigma(d\log P_F^* - d\log P^*).$$

Now we write the previous two expressions in terms of the output gap. Using the definition of the output gap, we have

$$\begin{aligned} d\log W - d\log P &= \sigma(\tilde{y}_H + y_H^{nat}) + \varphi d\log L + \sigma(d\log P_H - d\log P) \\ &= \sigma\tilde{y}_H + \sigma y_H^{nat} + \varphi d\log L + \sigma(d\log P_H - d\log P). \end{aligned} \tag{2.24}$$

Part of the right-hand side is equal to

$$\begin{aligned} \sigma y_H^{nat} + \varphi d\log L &= \sigma y_H^{nat} + \varphi(d\log L - d\log L^{nat}) + \varphi d\log L^{nat} \\ &= \sigma y_H^{nat} + \varphi\tilde{y}_H + \varphi d\log L^{nat}, \end{aligned}$$

[17] Imposing this condition implies that the country size parameter no longer appears in the derivation below. However, the share parameters α and μ capture an equivalent notion.

where the last equation follows from the equation $Y = AL$ since labor is the only factor of production. Continuing, we have

$$\begin{aligned}\sigma y_H^{nat} + \varphi d\log L &= \sigma(d\log L^{nat} + d\log A) + \varphi\tilde{y}_H + \varphi d\log L^{nat} \\ &= \varphi\tilde{y}_H + \sigma d\log A + (\sigma+\varphi)d\log L^{nat}.\end{aligned}$$

By Lemma 6 of Rubbo (2020)

$$d\log L^{nat} = \frac{1-\sigma}{\sigma+\varphi} d\log A, \tag{2.25}$$

hence

$$\begin{aligned}\sigma y_H^{nat} + \varphi d\log L &= \varphi\tilde{y}_H + \sigma d\log A + (\sigma+\varphi)\frac{1-\sigma}{\sigma+\varphi} d\log A \\ &= \varphi\tilde{y}_H + d\log A.\end{aligned} \tag{2.26}$$

Plugging the last equation into (2.24), we get

$$d\log W - d\log P + (\sigma+\varphi)\tilde{y}_H + d\log A + \sigma(d\log P_H - d\log P). \tag{2.27}$$

A similar expression can be derived for the foreign economy. Hence, in matrix form, we have

$$d\log \mathbf{W} - d\log \mathbf{P} = (\sigma+\varphi)\tilde{y} + d\log A + \sigma(d\log \mathbf{P} - d\log \mathbf{p}), \tag{2.28}$$

where $\tilde{y} = \begin{pmatrix}\tilde{y}_H \\ \tilde{y}_F^*\end{pmatrix}$. The last term of the previous equation is

$$\sigma(d\log \mathbf{P} - d\log \mathbf{p}) = \left(\sigma(I-\Phi)d\log \mathbf{p} - \begin{pmatrix}1-\alpha \\ -(1-\alpha^*)\end{pmatrix} d\log \mathcal{E}\right). \tag{2.29}$$

Hence we can rewrite (2.28) as

$$d\log \mathbf{W} - d\log \mathbf{P} = (\sigma+\varphi)\tilde{y} + d\log \mathbf{A} + \sigma(I-\Phi)d\log \mathbf{p} - \sigma\begin{pmatrix}1-\alpha \\ -(1-\alpha^*)\end{pmatrix} d\log \mathcal{E}. \tag{2.30}$$

Using (2.16), we can also write

$$d\log \mathbf{W} - d\log \mathbf{P} = d\log \mathbf{W} - \Phi d\log \mathbf{p} - \begin{pmatrix}1-\alpha \\ -(1-\alpha^*)\end{pmatrix} d\log \mathcal{E}. \tag{2.31}$$

Plug in for $d\log \mathbf{p}$ using (2.15), we get

$$\begin{aligned}d\log \mathbf{W} - d\log \mathbf{P} = d\log \mathbf{W} &- \Phi\Theta(I-\Omega\Theta)^{-1} \\ &\left[\delta\cdot d\log \mathbf{W} + (1-\delta)\cdot\begin{pmatrix}1-\mu \\ -(1-\mu^*)\end{pmatrix} d\log \mathcal{E} - d\log \mathbf{A}\right] \\ &- \begin{pmatrix}1-\alpha \\ -(1-\alpha^*)\end{pmatrix} d\log \mathcal{E}.\end{aligned} \tag{2.32}$$

Expand and collect

$$\begin{aligned}d\log \mathbf{W} - d\log \mathbf{P} = &\left[I - \Phi\Theta(I-\Omega\Theta)^{-1}\delta\right] d\log \mathbf{W} + \Phi\Theta(I-\Omega\Theta)^{-1} d\log \mathbf{A} \\ &- \left[\Phi\Omega(I-\Omega\Theta)^{-1}(1-\delta)\cdot\begin{pmatrix}1-\mu \\ -(1-\mu^*)\end{pmatrix} + \begin{pmatrix}1-\alpha \\ -(1-\alpha^*)\end{pmatrix}\right] d\log \mathcal{E}.\end{aligned} \tag{2.33}$$

Combine (2.30) and (2.33)

$$(\sigma+\varphi)\widetilde{y}+\sigma(I-\Phi)d\log\mathbf{p}-\sigma\begin{pmatrix}1-\alpha\\-(1-\alpha^*)\end{pmatrix}d\log\mathcal{E}=\left[I-\Phi\Theta(I-\Omega\Theta)^{-1}\delta\right]d\log\mathbf{W}$$
$$+\Phi\Theta(I-\Omega\Theta)^{-1}d\log\mathbf{A}$$
$$-\left[\Phi\Theta(I-\Omega\Theta)^{-1}(1-\delta)\cdot\begin{pmatrix}1-\mu\\-(1-\mu^*)\end{pmatrix}+\begin{pmatrix}1-\alpha\\-(1-\alpha^*)\end{pmatrix}\right]d\log\mathcal{E}. \tag{2.34}$$

Collect terms

$$\begin{aligned}&(\sigma+\varphi)\widetilde{y}+\left[I-\Phi\Theta(I-\Omega\Theta)^{-1}\right]d\log\mathbf{A}\\&+\left[\Phi\Theta(I-\Omega\Theta)^{-1}(1-\delta)\cdot\begin{pmatrix}1-\mu\\-(1-\mu^*)\end{pmatrix}+(1-\sigma)\begin{pmatrix}1-\alpha\\-(1-\alpha^*)\end{pmatrix}\right]d\log\mathcal{E}\\&+\sigma(I-\Phi)d\log\mathbf{p}=[I-\Phi\Theta(I-\Omega\Theta)^{-1}\delta]d\log\mathbf{W}.\end{aligned} \tag{2.35}$$

Plug in for $d\log\mathbf{p}$ using (2.15)

$$\begin{aligned}&(\sigma+\varphi)\widetilde{y}+[I-\Phi\Theta(I-\Omega\Theta)^{-1}]d\log\mathbf{A}\\&+\left[\Phi\Theta(I-\Omega\Theta)^{-1}(1-\delta)\cdot\begin{pmatrix}1-\mu\\-(1-\mu^*)\end{pmatrix}+(1-\sigma)\begin{pmatrix}1-\alpha\\-(1-\alpha^*)\end{pmatrix}\right.\\&\left.+\sigma(I-\Phi)\Theta(I-\Omega\Theta)^{-1}(1-\delta)\cdot\begin{pmatrix}1-\mu\\-(1-\mu^*)\end{pmatrix}\right]d\log\mathcal{E}\\&=\left[I-\Phi\Theta(I-\Omega\Theta)^{-1}\delta-\sigma(I-\Phi)\Theta(I-\Omega\Theta)^{-1}\delta\right]d\log\mathbf{W}.\end{aligned} \tag{2.36}$$

Collect terms

$$\begin{aligned}&(\sigma+\varphi)\widetilde{y}+\left[I-\Phi\Theta(I-\Omega\Theta)^{-1}-\sigma(I-\Phi)\Theta(I-\Omega\Theta)\right]d\log\mathbf{A}\\&+\left[\Phi\Theta(I-\Omega\Theta)^{-1}(1-\delta)\cdot\begin{pmatrix}1-\mu\\-(1-\mu^*)\end{pmatrix}+(1-\sigma)\begin{pmatrix}1-\alpha\\-(1-\alpha^*)\end{pmatrix}\right.\\&\left.+\sigma(I-\Phi)\Theta(I-\Omega\Theta)^{-1}(1-\delta)\cdot\begin{pmatrix}1-\mu\\-(1-\mu^*)\end{pmatrix}\right]d\log\mathcal{E}\\&=\left[I-\Phi\Theta(I-\Omega\Theta)^{-1}\delta-\sigma(I-\Phi)\Theta(I-\Omega\Theta)^{-1}\delta\right]d\log\mathbf{W}.\end{aligned} \tag{2.37}$$

Simplify

$$\begin{aligned}&(\sigma+\varphi)\widetilde{y}+\left[I-((1-\sigma)I+\sigma\Phi)\Theta(I-\Omega\Theta)^{-1}\right]d\log\mathbf{A}\\&+\left[((1-\sigma)I-\sigma\Phi)\Theta(I-\Omega\Theta)^{-1}(1-\delta)\cdot\begin{pmatrix}1-\mu\\-(1-\mu^*)\end{pmatrix}+(1-\sigma)\begin{pmatrix}1-\alpha\\-(1-\alpha^*)\end{pmatrix}\right]d\log\mathcal{E}\\&=[I-((1+\sigma)\Phi-\sigma I)\Theta(I-\Omega\Theta)^{-1}\delta]d\log\mathbf{W}.\end{aligned} \tag{2.38}$$

Rearrange for $d\log\mathbf{W}$

$$\begin{aligned}&d\log\mathbf{W}=[I-((1+\sigma)I+\sigma\Phi)\Theta(I-\Omega\Theta)^{-1}\delta]^{-1}\\&[(\sigma+\varphi)\widetilde{y}+[I-[(1-\sigma)I+\sigma\Phi]\Theta(I-\Omega\Theta)^{-1}]d\log\bar{A}\\&+\left[((1-\sigma)I-\sigma\Phi)\Theta(I-\Omega\Theta)^{-1}(1-\delta)\cdot\begin{pmatrix}1-\mu\\-(1-\mu^*)\end{pmatrix}+(1-\sigma)\begin{pmatrix}1-\alpha\\-(1-\alpha^*)\end{pmatrix}\right]d\log\mathcal{E}.\end{aligned} \tag{2.39}$$

Plug back into (2.15)

$$
\begin{aligned}
d\log \mathbf{p} = \Theta(I-\Omega\Theta)^{-1}\delta\Bigg(& [I-((1+\sigma)\Phi-\sigma I)\Theta(I-\Omega\Theta)^{-1}\delta]^{-1} \\
& \Big\{(\sigma+\varphi)\widetilde{y} + \left[I-((1-\sigma)I+\sigma\Phi)\Theta(I-\Omega\Theta)^{-1}\right] d\log \mathbf{A} \\
+\left[((1-\sigma)I-\sigma\Phi)\Theta(I-\Omega\Theta)^{-1}(1-\delta)\begin{pmatrix}1-\mu\\-(1-\mu^*)\end{pmatrix} + (1-\sigma)\begin{pmatrix}1-\alpha\\-(1-\alpha^*)\end{pmatrix}\right] & d\log\mathcal{E}\Big\}\Bigg) \\
+\Theta(I-\Omega\Theta)^{-1}\left[(1-\delta)\cdot\begin{pmatrix}1-\mu\\-(1-\mu^*)\end{pmatrix} d\log\mathcal{E} - d\log\mathbf{A}\right]. &
\end{aligned}
\tag{2.40}
$$

Collect terms

$$
\begin{aligned}
& d\log \mathbf{p} = \Theta(I-\Omega\Theta)^{-1}\delta \\
& \left[I-((1+\sigma)\Phi-\sigma I)\Theta(I-\Omega\Theta)^{-1}\delta\right]^{-1}(\sigma+\varphi)\widetilde{y} \\
& + \Bigg[\Theta(I-\Omega\Theta)^{-1}\delta[I-((1+\sigma)\Phi-\sigma I)\Omega(I-\Omega\Theta)^{-1}\delta]^{-1}[I-((1-\sigma)I\sigma\Phi)\Theta(I-\Omega\Theta)^{-1}] \\
& - \Theta(I-\Omega\Theta)^{-1}\Bigg] d\log\mathbf{A} \\
& + \Bigg[\Theta(I-\Omega\Theta)^{-1}\delta[I-((1+\sigma)\Phi-\sigma I)\Theta(I-\Omega\Theta)^{-1}\delta]^{-1} \\
& \left\{((1+\sigma)I-\sigma\Phi)\Theta(I-\Omega\Theta)^{-1}(1-\delta)\begin{pmatrix}1-\mu\\-(1-\mu^*)\end{pmatrix} + (1-\sigma)\begin{pmatrix}1-\alpha\\-(1-\alpha^*)\end{pmatrix}\right\} \\
& + \Theta(I-\Omega\Theta)^{-1}(1-\delta)\cdot\begin{pmatrix}1-\mu\\-(1-\mu^*)\end{pmatrix}\Bigg] d\log\mathcal{E}.
\end{aligned}
\tag{2.41}
$$

Use (2.16) to get CPI Phillips Curves

$$
\begin{aligned}
& d\log \mathbf{P} = \Phi\Theta(I-\Omega\Theta)^{-1}\delta\left[I-((1+\sigma)\Phi-\sigma I)\Theta(I-\Omega\Theta)^{-1}\delta\right]^{-1}(\sigma+\varphi)\widetilde{y} \\
& + \Phi\Bigg[\Theta(I-\Omega\Theta)^{-1}\delta[I-((1+\sigma)\Phi-\sigma I)\Omega(I-\Omega\Theta)^{-1}\delta]^{-1}[I-((1-\sigma)I+\sigma\Phi)\Theta(I-\Omega\Theta)^{-1}] \\
& - \Theta(I-\Omega\Theta)^{-1}\Bigg] d\log\mathbf{A} \\
& + \Phi\Bigg[\Theta(I-\Omega\Theta)^{-1}\delta[I-((1+\sigma)\Phi-\sigma I)\Theta(I-\Omega\Theta)^{-1}\delta]^{-1} \\
& \left\{((1+\sigma)I-\sigma\Phi)\Theta(I-\Omega\Theta)^{-1}(1-\delta)\cdot\begin{pmatrix}1-\mu\\-(1-\mu^*)\end{pmatrix} + (1-\sigma)\begin{pmatrix}1-\alpha\\-(1-\alpha^*)\end{pmatrix}\right\} \\
& + \Theta(I-\Omega\Theta)^{-1}(1-\delta)\cdot\begin{pmatrix}1-\mu\\-(1-\mu^*)\end{pmatrix}\begin{pmatrix}1-\alpha\\-(1-\alpha^*)\end{pmatrix}\Bigg] d\log\mathcal{E},
\end{aligned}
\tag{2.42}
$$

where

$$\mathcal{K} = \Phi\Theta(I-\Omega\Theta)^{-1}\delta\left[I-((1+\sigma)\Phi-\sigma I)\Theta(I-\Omega\Theta)^{-1}\delta\right]^{-1}(\sigma+\varphi),$$

$$\mathcal{G} = \Phi\Bigg[\Theta(I-\Omega\Theta)^{-1}\delta[I-((1+\sigma)\Phi-\sigma I)\Omega(I-\Omega\Theta)^{-1}\delta]^{-1}$$
$$[I-((1-\sigma)I+\sigma\Phi)\Theta(I-\Omega\Theta)^{-1}]-\Theta(I-\Omega\Theta)^{-1}\Bigg],$$

and

$$\mathcal{H} = \Phi\Bigg[\Theta(I-\Omega\Theta)^{-1}\delta[I-((1+\sigma)\Phi-\sigma I)\Theta(I-\Omega\Theta)^{-1}\delta]^{-1}$$
$$\left\{((1+\sigma)I-\sigma\Phi)\Theta(I-\Omega\Theta)^{-1}(1-\delta)\begin{pmatrix}1-\mu\\-(1-\mu^*)\end{pmatrix}+(1-\sigma)\begin{pmatrix}1-\alpha\\-(1-\alpha^*)\end{pmatrix}\right\}$$
$$+\Theta(I-\Omega\Theta)^{-1}(1-\delta)\cdot\begin{pmatrix}1-\mu\\-(1-\mu^*)\end{pmatrix}+\begin{pmatrix}1-\alpha\\-(1-\alpha^*)\end{pmatrix}\Bigg].$$

2.E A Dynamic Model of GVCs

Building on the static model we presented, here we introduce a two-country, multi-sector New Keynesian model with production networks.[18] The two countries, home (H) and foreign (F), are populated by a continuum of infinitely lived households with a fraction of (n) and (1-n) of the total world population, respectively. Foreign country variables will be denoted by an asterisk ($*$).

In each country, there is a continuum of firms indexed by $i \in [0,1]$ and each firm belongs to a sector, $s \in 1, ..., S$. Firms produce differentiated products which can be sold domestically or exported for consumption and production. Our model thus incorporates GVCs through trade in intermediate inputs. In each sector, monopolistically competitive firms produce their output using labor and intermediate goods as inputs. In each period, producers choose how much intermediate input they want to buy from each sector and then they decide whether to buy home or foreign-produced intermediates. Similarly, we assume that aggregate consumption is a composite of sectoral consumption goods and each of these goods is a CES aggregate of home and foreign-produced goods. Thus, there is trade in final goods as well. We assume that international asset markets are complete in the sense that consumers have access to state-contingent bonds that can be traded internationally.

2.E.1 Households

Household preferences are identical across countries. Therefore we only explain the intertemporal decision of a representative household in the home country. Households receive utility from consumption, C, and disutility from supplying labor, L. The lifetime utility function of the representative household is given by

$$U = \mathbb{E}_t \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\sigma}}{1-\sigma} - \Xi \frac{L_t^{1+\varphi}}{1+\varphi}\right], \tag{2.43}$$

[18] The modelling is quite standard. For instance Comin and Johnson (2020) presents a similar small open economy model with Rotemberg price adjustments instead of Calvo.

where $\mathbb{E}_t$ is the expectations operator conditional on time t information, $\beta \in (0,1)$ is the discount factor, σ and φ denote the inverse of intertemporal elasticity of substitution and Frisch elasticity of labor supply, respectively. Finally, Ξ is a preference parameter that allows us to fix the hours worked in the steady state.

Households finance expenditure on consumption goods through labor income and profits from the ownership of firms. We assume that the international asset markets are complete in the sense that households can trade state-contingent securities that are denominated in the home currency to buy consumption goods. We assume that only bonds that are issued by home can be traded internationally. The period budget constraint of the home household is

$$P_t C_t + \mathbb{E}_t Q_{t,t+1} B_{Ht+1} \leq B_{Ht} + W_t L_t + \Pi_t,$$

where P_t is the CPI, W_t is the nominal wage and Π_t is the nominal profits. B_{Ht+1} denotes the home households holding of nominal state-contingent internationally traded bonds which deliver one unit of home currency in period *t+1* if a particular state occurs. $Q_{t,t+1}$ is the price of such bond at time t.

First-order conditions to the home household's utility maximization problem yields

$$\Xi\, C_t^{\sigma}\, L_t^{\varphi} \;=\; \frac{W_t}{P_t}, \tag{2.44}$$

and

$$Q_{t,t+1} = \beta \mathbb{E}_t \left[\left(\frac{C_{t+1}}{C_t} \right)^{-\sigma} \left(\frac{P_t}{P_{t+1}} \right) \right]. \tag{2.45}$$

Let the return on the nominal state contingent bond is equal to $(1 + i_t) = 1/Q_{t,t+1}$. We then have the usual Euler equation

$$\frac{1}{1+i_t} = \beta \mathbb{E}_t \left[\left(\frac{C_{t+1}}{C_t} \right)^{-\sigma} \left(\frac{P_t}{P_{t+1}} \right) \right]. \tag{2.46}$$

The foreign household's intertemporal decision yields similar expressions

$$\Xi\; (C_t^*)^{\sigma}\; (L_t^*)^{\varphi} \;=\; \frac{W_t^*}{P_t^*}, \tag{2.47}$$

$$\frac{1}{1+i_t^*} = \beta \mathbb{E}_t \left[\left(\frac{C_{t+1}^*}{C_t^*} \right)^{-\sigma} \left(\frac{P_t^*}{P_{t+1}^*} \right) \right], \tag{2.48}$$

and

$$Q_{t,t+1} = \beta \mathbb{E}_t \left[\left(\frac{C_{t+1}^*}{C_t^*} \right)^{-\sigma} \left(\frac{S_t\, P_t^*}{S_{t+1}\, P_{t+1}^*} \right) \right], \tag{2.49}$$

where S_t is the nominal exchange rate defined as the home currency price of foreign currency.

Households' choice on internationally traded bonds, Equations (2.45) and (2.49), yield the international risk-sharing condition

$$q_t = \Psi \left(\frac{C_t}{C_t^*} \right)^{\sigma}, \tag{2.50}$$

where $q_t = S_t P_t^* / P_t$ is the real exchange rate and $\Psi = Q_0 \left(\frac{C_0}{C_0^*}\right)^{\sigma}$ is a constant.

Each period households optimally allocate their total expenditure across sectoral goods. The final consumption basket, C_t, is a CES aggregate of finitely many sectoral goods ($s \in \{1, 2, \ldots, S\}$) in each country

$$C_t = \left[\sum_{s=1}^{S} \eta_s^{\frac{1}{\theta_C}} (C_{st})^{\frac{\theta_C - 1}{\theta_C}} \right]^{\frac{\theta_C}{\theta_C - 1}}, \tag{2.51}$$

where θ_C is elasticity of substitution between sectoral consumption goods and η_s is the share of sector s in total consumption with $\Sigma_s \eta_s = 1$.

Sectoral goods themselves are also CES aggregates of home, C_{Hst}, and foreign, C_{Fst}, consumption goods such as

$$C_{st} = \left[\alpha_s^{\frac{1}{\phi_{Cs}}} (C_{Hst})^{\frac{\phi_{Cs} - 1}{\phi_{Cs}}} + (1 - \alpha_s)^{\frac{1}{\phi_{Cs}}} (C_{Fst})^{\frac{\phi_{Cs} - 1}{\phi_{Cs}}} \right]^{\frac{\phi_{Cs}}{\phi_{Cs} - 1}}, \tag{2.52}$$

where α_s represents the share of home-produced goods in sectoral consumption and ϕ_{Cs} is the elasticity of substitution between home and foreign-produced consumption goods which is allowed to be different across sectors. As in the static set-up, the share of imported goods in each sector is a function of relative country size, $1 - n$, and the degree of openness in final demand, v_{Cs}: $1 - \alpha_s = (1 - n)\, v_{Cs}$. When $\alpha_s > 0.5$, there is home bias in preferences in a given sector. Household expenditure minimization yields the following optimal demand for sectoral goods

$$C_{st} = \eta_s \left(\frac{P_{st}}{P_t} \right)^{-\theta_C} C_t,$$

where the aggregate price index is $P_t = [\sum_{s=1}^{S} \eta_s P_{st}^{1-\theta_C}]^{\frac{1}{1-\theta_C}}$. Then, sectoral consumption is further allocated between home and foreign goods

$$C_{Hst} = \alpha_s \left(\frac{P_{Hst}}{P_{st}} \right)^{-\phi_{Cs}} C_{st}, \quad C_{Fst} = (1 - \alpha_s) \left(\frac{P_{Fst}}{P_{st}} \right)^{-\phi_{Cs}} C_{st},$$

where the sectoral price index is $P_{st} = [\alpha_s P_{Hst}^{1-\phi_{Cs}} + (1 - \alpha_s) P_{Fst}^{1-\phi_{Cs}}]^{\frac{1}{1-\phi_{Cs}}}$. We assume that the law-of-one-price holds such that the price of foreign goods in the units of home currency is $P_{Fst} = S_t P_{Fst}^*$ and the price of home goods in the units of foreign currency is $P_{Hst}^* = P_{Hst} / S_t$. The situation of foreign households is analogous.

2.E.2 Firms

The supply side of the economy consists of perfectly competitive sectoral producers at the retail level and monopolistically competitive firms at the wholesale level.

Retail Producers

Infinitely many competitive firms aggregate firm level domestic varieties $Y_{Hst}(i)$ into sectoral goods Y_{Hst} using the following production function

$$Y_{Hst} = \left[\int_0^1 Y_{Hst}^{\frac{\epsilon_s}{\epsilon_s - 1}}(i) di \right]^{\frac{\epsilon_s - 1}{\epsilon_s}},$$

where ϵ_s is the elasticity of substitution between varieties within a sector. The solution to this aggregation problem implies the following demand for varieties

$$Y_{Hst}(i) = \left(\frac{P_{Hst}(i)}{P_{Hst}}\right)^{-\epsilon_s} Y_{Hst}.$$

Wholesale Producers

Now, we introduce the production process of individual varieties. Firms use labor and intermediate inputs to produce a unit of output. The production function is given by

$$Y_{Hst}(i) = A_t A_{st} L_{st}(i)^{\delta_s} M_{st}(i)^{1-\delta_s}, \tag{2.53}$$

where L_{st} denotes firm i's labor demand and δ_s denotes the share of labor in production. Aggregate and sectoral productivity assumed to follow an AR(1) process and are represented by A_t and A_{st}, respectively

$$\log A_t = (1-\rho_A)\log \overline{A} + \rho_A \log A_{t-1} + \varepsilon_{At}, \tag{2.54}$$

$$\log A_{st} = (1-\rho_{As})\log \overline{A_s} + \rho_{As} \log A_{st-1} + \varepsilon_{Ast}, \tag{2.55}$$

where $\overline{A}$ and $\overline{A_s}$ represent the steady state values, $\rho_A \in (0,1)$ and $\rho_{A_s} \in (0,1)$ denote the persistence, and $\varepsilon_{A,t} \sim N(0, \sigma_A^2)$ and $\varepsilon_{A_s t} \sim N(0, \sigma_{A_s}^2)$ are iid innovations.

Each firm, i, uses intermediate good, $M_{st}(i)$, which is a CES aggregate of sectoral goods

$$M_{st}(i) = \left[\sum_{s'=1}^{S} \omega_{ss'}^{\frac{1}{\theta_M}} \left(M_{ss't}(i)\right)^{\frac{\theta_M - 1}{\theta_M}}\right]^{\frac{\theta_M}{\theta_M - 1}}, \tag{2.56}$$

where $M_{ss't}$ is the intermediate good demand of sector s from sector s' at time t, and $\omega_{ss'}$ is the share of sector s' in total intermediate good expenditure of sector s with $\sum_{s'=1}^{S} \omega_{ss'} = 1$. The elasticity of substitution across sectoral intermediate goods is denoted by θ_M.

Firms' sectoral input demand is a CES aggregate of domestic and foreign intermediate goods as in the consumption case

$$M_{ss't}(i) = \left[\mu_{ss'}^{\frac{1}{\phi_{Ms}}} \left(M_{Hss't}(i)\right)^{\frac{\phi_{Ms}-1}{\phi_{Ms}}} + (1-\mu_{ss'})^{\frac{1}{\phi_{Ms}}} \left(M_{Fss't}(i)\right)^{\frac{\phi_{Ms}-1}{\phi_{Ms}}}\right]^{\frac{\phi_{Ms}}{\phi_{Ms}-1}}, \tag{2.57}$$

where $M_{Hss't}(i)$ and $M_{Fss't}(i)$ denote domestic and foreign intermediate good demand of sector s from sector s' at time t, respectively. There exists sectoral home bias at the intermediate level denoted by $\mu_{ss'}$, and ϕ_{Ms} denotes the elasticity of substitution between home and foreign-produced intermediate goods which is allowed to be different across sectors. Similar to consumption preference structure, we assume that the share of imported intermediate goods is a function of relative country size, $(1-n)$, and the degree of openness in intermediate goods in a sector, $v_{Mss'}$: $1-\mu_{ss'} = (1-n)\, v_{Mss'}$.

Every period, firms choose the labor and intermediate inputs to minimize their costs. Optimal input demands then can be shown as

$$L_{st} = \delta_s \left(\frac{MC_{st}}{W_t}\right) Y_{Hst}, \quad M_{st} = (1-\delta_s)\left(\frac{MC_{st}}{P_{st}^M}\right) Y_{Hst},$$

where MC_{st} is sectoral marginal cost (will be defined below) and P^M_{st} is the intermediate input price index for sector s. Firms also optimally choose sectoral intermediate goods as

$$M_{ss't} = \omega_{ss'} \left(\frac{P^M_{ss't}}{P^M_{st}} \right)^{-\theta_M} M_{st},$$

where intermediate input price index is $P^M_{st} = \left[\sum_{s'=1}^{S} \omega_{ss'} \left(P^M_{ss't}\right)^{1-\theta_M} \right]^{\frac{1}{1-\theta_M}}$, and the demand for home and foreign sectoral inputs is given by

$$M_{Hss't} = \mu_{ss'} \left(\frac{P_{Hs't}}{P^M_{ss't}} \right)^{-\phi_{Ms}} M_{ss't}\ , \quad M_{Fss't} = (1-\mu_{ss'}) \left(\frac{P_{Fs't}}{P^M_{ss't}} \right)^{-\phi_{Ms}} M_{ss't},$$

where sectoral intermediates price index is a weighted average of home and foreign sectoral output prices $P^M_{ss't} = \left[\mu_{ss'} P^{1-\phi_{Ms}}_{Hs't} + (1-\mu_{ss'}) P^{1-\phi_{Ms}}_{Fs't} \right]^{\frac{1}{1-\phi_{Ms}}}$.

By using firms' demand for factors of production, we can derive the sectoral nominal marginal cost

$$MC_{st} = \frac{1}{A_t A_{st}} \left(\frac{W_t}{\delta_s} \right)^{\delta_s} \left(\frac{P^M_{st}}{1-\delta_s} \right)^{1-\delta_s}. \tag{2.58}$$

Note that sectoral linkages through input-output relationships at the intermediate goods level imply a sectoral marginal cost that depends on other sectors' output prices.

Firm's Pricing Decision

We assume that firms are subject to Calvo-type price rigidities such that a firm can update its price with a probability of 1-θ_s, where θ_s denotes the sector-specific price stickiness. Wholesale producer, i, that can re-set its price, maximizes the present discounted future value of profits

$$\mathbb{E}_t \sum_{k=0}^{\infty} \beta^k \frac{C^{-\sigma}_{t+k}}{C^{-\sigma}_t} \theta^k_s \left[P_{Hst}(i) Y_{Hst}(i) - MC_{st}(i) Y_{Hst}(i) \right],$$

subject to demand function

$$Y_{Hst}(i) \leq \left(\frac{P_{Hst}(i)}{P_{Hst}} \right)^{-\epsilon_s} Y_{Hst}.$$

The FOC to this problem implies the following nonlinear relationship between firms' reset prices and marginal cost

$$\overline{P}_{Hst} = \frac{\epsilon_s}{\epsilon_s - 1} \frac{\mathbb{E}_t \sum_{k=0}^{\infty} \beta^k C^{-\sigma}_{t+k} \theta^k_s MC_{st+k} P^{\epsilon_s}_{Hst+k} Y_{Hst+k}}{E_t \sum_{k=0}^{\infty} \beta^k C^{-\sigma}_{t+k} \theta^k_s P^{\epsilon_s}_{Hst+k} Y_{Hst+k}},$$

where $\overline{P}_{Hst}$ is the reset price.

2.E.3 Market Clearing

Sectoral output can be used domestically for consumption and for further production as intermediate inputs or it can be exported, X_{st}. Exports can be consumed by foreign consumers or used by foreign firms as inputs. Thus, we can write the goods market clearing condition such that

$$Y_{Hst} = C_{Hst} + \sum_{s'=1}^{S} M_{Hs'st} + \underbrace{\frac{1-n}{n}\left(C^{*}_{Hst} + \sum_{s'=1}^{S} M^{*}_{Hs'st}\right)}_{X_{st}}.$$

We assume that labor is perfectly mobile across sectors but not across countries. Labor market clearing conditions can then be expressed as

$$L_t = \sum_{s=1}^{S} L_{st}.$$

2.E.4 Monetary Policy

Monetary policy authority sets the nominal interest rate following a Taylor-type rule that targets the CPI inflation

$$\frac{i_t}{i} = \left(\frac{i_{t-1}}{i}\right)^{\Gamma_i} \left(\frac{\pi_t}{\pi}\right)^{\Gamma_\pi(1-\Gamma_i)} \exp(\epsilon_{mt}),$$

where $\epsilon_{mt} \sim N(0, \sigma_m^2)$ is the shock to the monetary policy.

Chapter 3

The Micro Anatomy of International Remittance Flows

This chapter is co-authored with Maria Ludovica Ambrosino.

3.1 Introduction

Remittances - flows between individuals in different countries - have increased ten-fold in real terms in the last 30 years. Since the onset of the pandemic, there has been a renewed interest in understanding its role. Figure 3.1 shows that remittance flows to low-and middle-income countries (LMICs) are both large and stable in comparison to other external flows. Recently, they have represented one of the largest sources of external finance to LMICs, overtaking FDI. Figure 3.2 shows a map of the main economies involved. In 2021, the main net senders as a share of total World remittances, were the United States (24.8%), Saudi Arabia (6.0%), and the United Arab Emirates (5.8%). The main net receivers were India (10.4%), Mexico (6.5%), and China (6.4%).

Given their global significance, there is surprisingly little work on understanding remittance flows at the individual level. This paper asks, 'What are the patterns of remittance flows at the micro-level?' Whilst aggregate remittance data are readily available through the balance of payments accounts, they suffer from coverage issues and low frequency. To answer this question, we leverage administrative data from a large global money transfer operator (MTO) operating in over 170 different countries spanning the period from 2014 to 2023. The data captures over 150 million transactions and in the latter periods, covers around 1% of all worldwide remittance flows. Crucially, we observe all transactions between individual senders and recipients that are sent through the platform. This paper is the first to document the micro-level behaviour of remittance senders across multiple remittance corridors spanning a long period and has five main findings.

First, we find that remittance senders use their local currency as the reference currency as opposed to the recipient's local currency. In particular, remittance flows tend to be sent in round numbers only in the sender's currency. For example, the U.S.-Mexico remittance corridor features mass points for the transaction amounts at multiples of $100. However, we find no mass points at round numbers in the recipient's local currency. This suggests that remittance senders do not use the receiver's local currency as a target amount. Senders are more likely to send $100 per month as opposed to the dollar

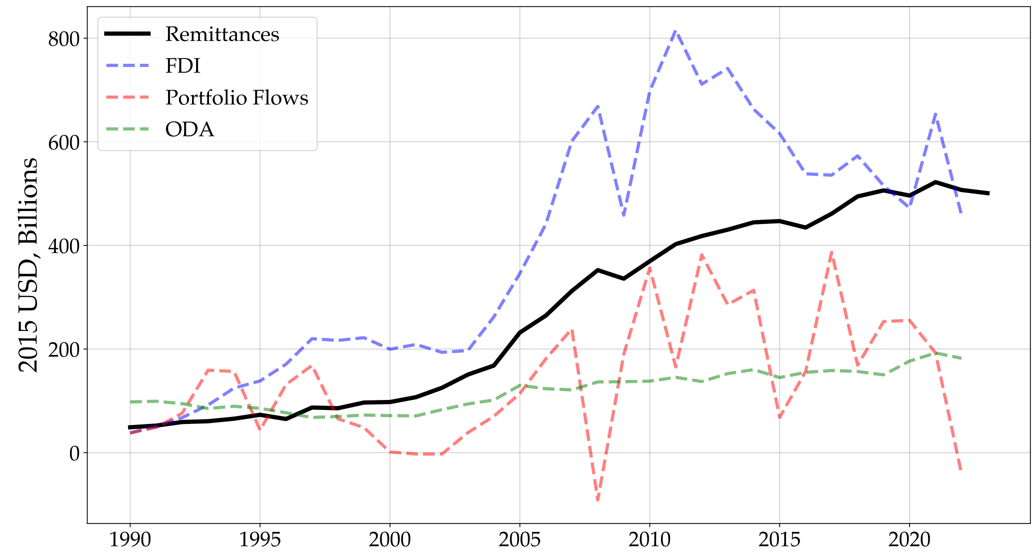


Figure 3.1: Capital Flows to Low-and-Middle-Income Countries

Notes: Data - World Bank–KNOMAD staff; World Development Indicators; IMF Balance of Payments Statistics. FDI = foreign direct investment; ODA = official development assistance.

equivalent of 2,000 Mexican pesos per month.

Second, we find that an individual sender's remittance amount doesn't change frequently. That is, remittance amounts are sticky. To arrive at this conclusion, we apply methods used to document price stickiness. Concentrating on the six biggest remittance corridors, we find that on average, 50-60% of sender-recipient pairs change the amount of remittance sent per transaction in a given year. The mean duration of the remittance amount is between 1.09 to 1.47 years.

The first two findings imply that remittances are sticky in the sender's local currency. This implies that the dynamics of aggregate remittance flows behave closer to 'producer currency pricing' as opposed to 'local currency pricing' features in Open Economy New-Keynesian models and implies a higher pass-through of exchange rate fluctuations to the amount of remittances received by recipients.

Third, we find that on average, a given sender has multiple recipients which tend to be located in one country. The median sender in the U.S. and Canada has sent remittances to 7 recipient accounts while this number is slightly higher in the UK at 9. Conversely, on average, a given recipient account receives remittance flows from one sender account.

Fourth, we find that the recipient's local currency is the most common receiving currency, but the U.S. dollar is a prominent receiving currency in some Emerging Markets. In the data, 86% of all remittance flows are received in the recipient's local currency. Therefore the bilateral exchange rate is the most important for the real value of remittances. However, there exist many remittance corridors, in which the U.S. is not involved directly, but the U.S. dollar is prominent. Examples include Nigeria, Turkey, Russia and Uruguay. 81% of incoming transactions to Turkey are received in U.S. dollars, of which only 44% are sent from the U.S.

Fifth, we find that during the pandemic, there was an increase in the number of transfers and volume of remittance flows through the MTO and this was driven in equal parts by existing and

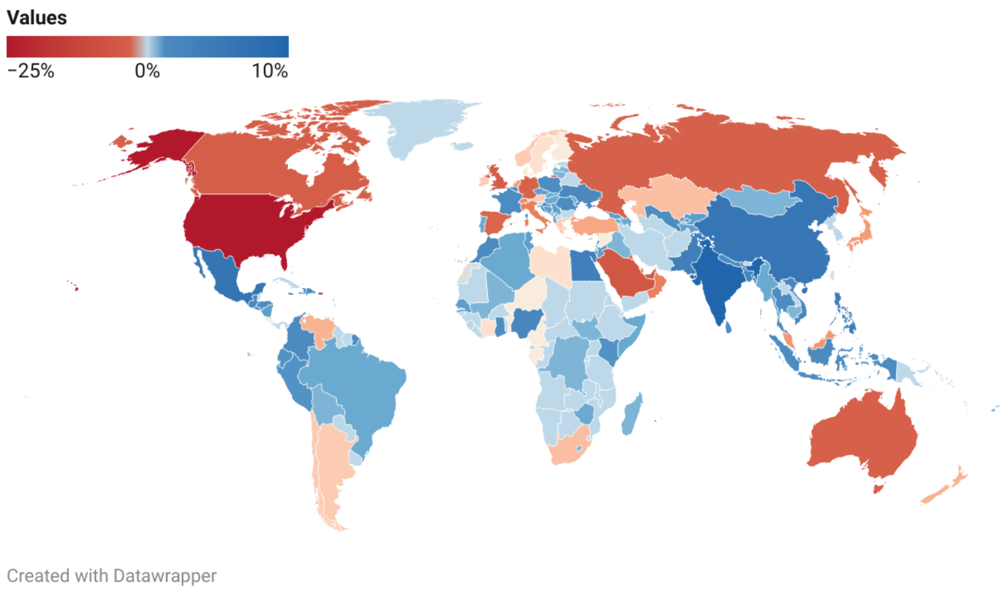


Figure 3.2: Net Senders and Receivers of Remittances, as Share of Total Remittances in 2021

Notes: Data source - World Bank and KNOMAD, authors' calculations. Red colours signify economies that are net senders of remittances. Blue colours signify economies that are net recipients of remittances.

new senders to the platform. To arrive at this conclusion, we classify senders and recipients in the platform by whether they have used the platform prior to March 2020. The three types are existing senders to existing recipients, existing senders to new recipients and new senders to new recipients.[1]

During the period between 2020 and 2021, we find that the growth in remittances was driven by all three types of senders and recipients, with the relative contribution of each type varying by corridors. Notably, the aggregate effect was not driven solely by new senders joining the platform due to the inability to send remittances through informal methods.

Literature. This paper is related to two strands of literature. First, there is a literature in development economics that study the drivers of remittances and is summarised by Yang (2011).[2]The closest papers to this paper are Joseph, Nyarko, and Wang (2018) and De Arcangelis, Fertig, Liang, Srouji, and Yang (2023). Joseph, Nyarko, and Wang (2018) use data from a money transfer operator in the UAE and find that migrants' earnings affect their remittances through the observability of migrants' incomes. When income shocks are easier to observe, the elasticity of remittance flows to income shocks is higher. De Arcangelis, Fertig, Liang, Srouji, and Yang (2023) combine data from the same money transfer operator and a survey for Filippino migrants in the UAE to measure errors in remittance flows. They find that survey measures of remittance flows tend to be similar to the administrative data for senders of remittances, but are under-reported by recipients. Relative to this literature, this paper is the first to document the behaviour of remittance senders from a global money transfer operator that operates over multiple remittance corridors and over a long time horizon.

[1]We did not find many transactions between new senders to existing recipients across all corridors.

[2]These include Rapoport and Docquier (2006), Yang and Martinez (2005), Yang and Choi (2007), Yang (2008b), Clemens and McKenzie (2018) Bettin, Jallow, and Zazzaro (2023).

Second, there is a more limited literature that studies remittance flows at the macroeconomic level. These include Mandelman and Zlate (2012), Mandelman (2013), Acosta, Lartey, and Mandelman (2013), Finkelstein Shapiro and Mandelman (2016) and Bahadir, Chatterjee, and Lebesmuehlbacher (2018). Relative to this literature, we document a series of facts about the behaviour of remittance flows at the micro and macro level which could be used to micro-found and calibrate the macroeconomic models in this literature.

Roadmap. The paper is organized as follows. Section 3.2 provides an overview of the money transfer operator, the data and its strengths and limitations. In section 3.3, we document facts in the time series at the individual and aggregate levels. Section 3.4 documents cross-sectional facts across remittance corridors while section 3.5 documents how remittance flows were affected by the pandemic. Section 3.6 concludes.

3.2 Overview of the Data

In this section, we explore the main features of the transaction data and compare them to aggregate data.

3.2.1 Background

The data is obtained from a Financial Technology company founded in the 2010s. We have access to an anonymised version of the database of all transactions that were sent through the MTO. The data spans from 2014 to 2023 and covers more than 150 million transactions covering around £30 billion in remittances. Senders in our sample come from 65 countries and transfer remittances to 157 countries around the world.[3]

Customers sign up for an account with the MTO either on the website or the mobile app. There is no possibility of depositing cash in person. Payments are funded through debit cards or by bank transfer. The sender is then shown a screen where they choose the amount they would like to send, and if available, the currency to be used to fund the transaction. Simultaneously, the sender is also shown the amount the recipient would receive and if available, the set of currencies that can be received.[4] Moreover, the platform also shows the exchange rate that the sender would effectively pay net of any margin taken by the MTO. The transfer fees are also shown along with any opportunities to enter promotion codes.[5]

Finally, the sender chooses the method in which the recipient receives the funds. Examples include bank transfers and cash pickups. The transfer fee and exchange rate may depend on the receiving method and are clearly displayed before finalising the transaction. In contrast to many other MTOs, our partner firm operates using both a transaction fee and a foreign exchange margin. This implies that the customer base of our firm skews towards those who send a higher volume of remittances.

Importantly, the sender can choose to fill out either the 'You Send' box or the 'They Receive' box. Figure 3.3a shows an example of sending 100 Pounds to Indonesia.[6]Alternatively, the sender can choose the amount the recipient receives in Indonesian Rupiah and the app will calculate the amount to be paid in Pounds. Figure 3.3b shows the possibility of sending the equivalent of 2,000,000 Indonesian Rupiah.

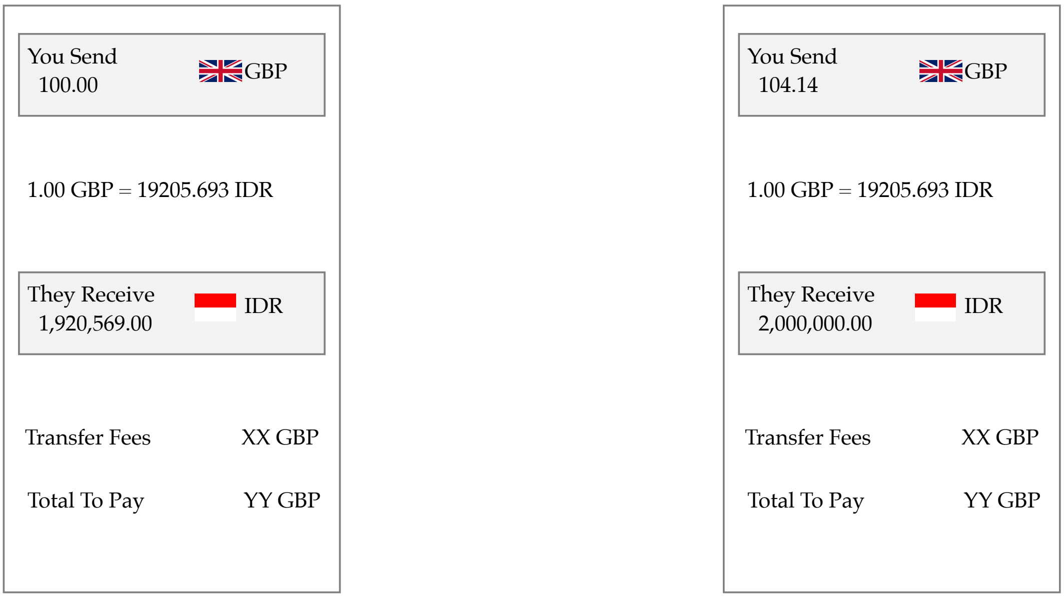
Our unit of analysis is a transaction between a sender account and a recipient account. Throughout the paper, we refer to a 'sender' as the outflow account of a remittance transaction and a 'recipient' as the inflow account of a remittance transaction. In particular, we observe the exact time of the transaction, the transaction amount, the currency sent by the sender, the currency received by

[3]The largest sending countries in the data are the U.S., UK, Australia and Canada. The largest recipient countries in the data are the Philippines (18%), Kenya (10%), Ghana (10%), Nigeria (8.5%), Zimbabwe (6.5%), Uganda (5.5%) and India (4.5%).

[4]For most remittance corridors, there is only one sending currency and one receiving currency available. However, as we document in section 3.4.2, some corridors feature multiple receiving currencies.

[5]While fee-free transfer promotions were used to encourage customers to join the platform, exploiting multiple accounts to take advantage of the promotion was generally difficult as the customer was asked for both an email address and a mobile phone number. Such exploitation is easily detected and prohibited by the MTO.

[6]Note that 100.00 is the default amount shown on the screen.



(a) Sending 100 GBP to Indonesia from the UK

(b) Sending the equivalent of 2,000,000 IDR to Indonesia from the UK

Figure 3.3: Example of Screen from the MTO's Mobile App

Notes: Figures accurate on 22 April 2024, 14:30 BST using the mobile app. Panel (a) shows the screen when the customer fills in '100.00' to the 'You Send' box. Panel (b) shows the screen when the customer fills in '2,000,000.00' to the 'They Receive' box.

the receiver, the transaction fee paid, the exchange rate at the time of the transaction, and any discounts offered at the time by the platform. We link transactions across senders over time through their unique identification numbers to create a panel at the daily and monthly frequency. In terms of demographics, we observe the sex of the sender.

Strengths. The data features three key strengths. The first key strength of the data is that it is administrative. Previous work in the international remittances literature typically relies on surveys.[7]Therefore, measurement error is of concern. In particular, surveys may suffer from recall bias that favours answering the same number for all previous transactions. Moreover, surveys typically have a short, infrequent panel dimension which makes it difficult to study questions about the Macroeconomy.

A second key strength of our data is the frequency. As we observe transactions, we do not suffer from any aggregation bias. This allows us to observe the exact amount per transaction as opposed to an aggregated statistic. This is important to shed light on the true remittance-sending behaviour of individuals.

A third key strength of our data is the scope across remittance corridors. Whereas other papers in the literature have used administrative data from one source country, we observe remittance flows from many sender countries and many recipient countries. This allows us to study the behaviour of remittance flows across many different types of remittance corridors and across many different types of exchange rate regimes.

[7]The exception to this is Joseph, Nyarko, and Wang (2018) who have access to data from UAE Exchange.

Table 3.1: Summary Statistics - Largest Corridors

Corridor	Transactions	Total	Mean Trans. Amount	Median Trans. Amount
Australia-India	3.0m	1.5bn	458	202
Australia-Philippines	5.5m	750m	148	70
United Kingdom-Zimbabwe	6.5m	1.0bn	146	64
U.S.-Ghana	6.0m	750m	124	172
U.S.-Nigeria	6.0m	1.75bn	293	92
U.S.-Philippines	9.0m	1.75bn	208	82

Notes: Total, mean and median are reported in GBP.

Limitations. One limitation of the data is that we only observe transactions that are executed through our firm. A particular concern is if a sender uses multiple platforms. We would not be able to observe any other transactions the sender makes. Therefore, the sample selection skews towards less price and exchange-rate-sensitive individuals.

A second limitation of the data is that we have limited information on recipients. We only observe the account and the method of reception on the transfer. Therefore, should a recipient change the account they wish to receive remittance flows into, we would not be able to distinguish this with a new recipient. Furthermore, we do not observe other variables of interest such as income and wealth.

3.2.2 Comparison with Aggregate Data

Our data covers 0.09% of worldwide remittance flows in 2014 to more than 1% in 2022.[8] In our analysis, we focus on the six largest corridors in terms of the total amount over the sample. Table 3.1 shows summary statistics for the six largest corridors. For confidentiality purposes, we report the number of transactions to the closest 500k and the total remittance flows to the closest 250m.

Comparison within Corridors. High-frequency time series on bilateral remittance corridors are largely unavailable. Therefore, to gauge the relevance of our data, we take as the frame of reference the Bilateral Remittance Matrix, published by KNOMAD/World Bank periodically.[9]Table 3.2 presents an overview of our coverage progression.

Over time, we see a rising trend in total share we observe through the MTO. This is especially evident for the UK-Zimbabwe corridor, for which the Bilateral Remittance Matrix does not report data for 2016 and 2017. This highlights the advantages that this dataset offers for analysing remittances in the global system. The high-frequency data encompasses a significant portion of total global

[8]The total value of World remittances are taken from the World Bank.

[9]These estimates are based on the methodology described in Ratha and Shaw (2007). Inward remittances are allocated to various source countries in proportion to their stock of migrants and per capita PPP income in the destination and origin countries. The Bilateral Migration Matrix is published by the United Nations (UN DESA), Eurostat, national statistical offices, the UNHCR and the OECD.

Table 3.2: Largest Corridors - Transactions through MTO as Share of Total Remittances

	2016	2017	2018	2021
Australia-India	5.5	7.8	7.6	9.5
Australia-Philippines	5.7	6.9	5.9	9.6
UK-Zimbabwe	NA	NA	11.4	62.4
U.S.-Ghana	1.8	5.2	7.2	28.3
U.S.-Nigeria	0.1	0.6	2.1	9.1
U.S.-Philippines	0.1	0.3	0.6	3.5

Notes: MTO data. Author's calculations.

transactions and provides insights into corridors that were previously challenging to access through aggregate data sources.

Comparison with Specific Countries. To further establish the relevance of our data, we compare it with publicly available data with higher-than-annual frequency. The scope of our comparison is limited by the few publicly available sources of remittance flows with this criteria.

We begin by examining two major recipients of remittances - Mexico and Bangladesh.[10] Figures 3.4a and 3.4b show a comparison of aggregate remittance inflows compared to an aggregated version of transactions from the MTO data. Our data closely follows the trends and movements observed in the aggregate data. Although the coverage is limited to an average of approximately 0.1% and 0.3% of the total flows to Mexico and Bangladesh respectively, the correlation with the official data series is notably strong at 0.94 and 0.7.

We also compare our data to aggregate remittance outflows. In particular, quarterly remittance outflows are publicly available for Italy, which is a relatively large sender within the European Union. Figure 3.4c shows the comparison. Similarly to Bangladesh and Mexico, there is a high correlation between the aggregate data and MTO data of 0.72. However, we only cover 0.5% of total transactions on average. Overall, the MTO transaction-level data offers good coverage and relevance for the aggregate remittances outflows and inflows around the world.

[10] Data from the World Bank show that in 2022, remittance flows were around 4.2% of GDP for Mexico and 4.7% of GDP for Bangladesh.

(a) Inflows - Mexico (b) Inflows - Bangladesh (c) Outflows - Italy

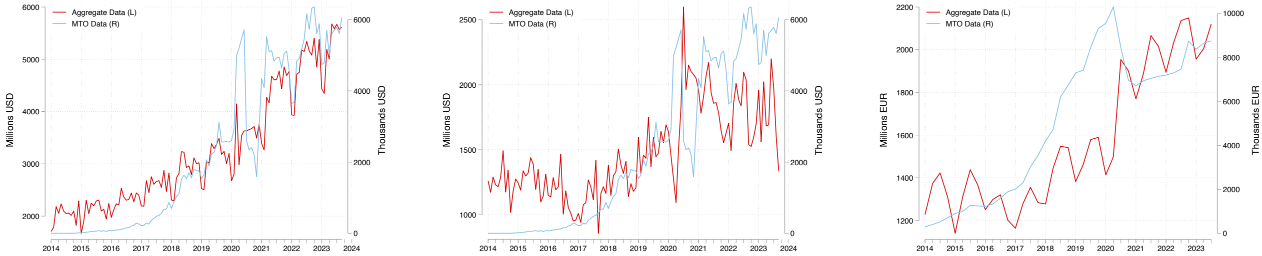


Figure 3.4: Comparison of Aggregate and MTO Data

Notes: Data - MTO, Banco de Mexico, Central Bank of Bangladesh and Banca d'Italia.

3.3 Remittance Flows Over Time

In this section, we document three facts regarding the behaviour of remittance flows over time. First, we find that remittance flows tend to be sent in round numbers in the sender's currency as opposed to the receiver's currency. Second, we document stickiness in the transaction amounts. Third, we document strong seasonal patterns in remittance flows across many corridors.

3.3.1 The Reference Currency of Remittance Senders

In which currency do remittance senders use as a frame of reference? We explore this question by documenting the distribution of transaction amounts in a given corridor. A strength of our data is that we observe both the sender's amount and currency and the receiver's amount and currency (net of exchange rate margins).

Figure 3.5 shows the main results. The grey bars show the distribution of transaction amounts sent in the sender's currency. We find that individuals appear to favour sending round numbers to their receivers. For example, in U.S. outflow corridors, we observe spikes in the distribution of transaction amounts at numbers such as 50, 100 and 200 U.S. dollars. We also observe this pattern across multiple outflow corridors such as Australia and the UK with spikes in the distribution at 100 Australian Dollars or British Pounds.[11]

Next, we plot the distribution amount received in the receiver currency. We do not observe spikes around the round numbers in the receiver currency. Instead, the spikes we observe line up with the spikes of the round numbers in the sender currency once we adjust by the exchange rate. The blue bars of Figure 3.5 show this distribution.[12]Therefore, individuals aim at transferring a given amount set in the currency of the country where they are located rather than in the receiving currency. This can be linked to the fact that individuals aim at sending a given amount of their income which is set in the sender's currency.

[11]'Round-number heuristics' have also been documented in other household decisions such as retirement savings. See for example Benartzi and Thaler (2007).

[12]We use the daily spot exchange rate from Bloomberg.

Table 3.3: Average Number of Transactions within a Sender-Recipient Pair

	Month	Quarter	Year	Entire Sample
Australia-India	1.5	2.4	3.7	6.1
Australia-Philippines	2.3	3.7	6.1	9.1
United Kindom-Zimbabwe	1.5	2.2	3.3	5.0
U.S.-Ghana	2.1	2.9	4.3	5.9
U.S.-Nigeria	1.8	2.6	3.9	5.3
U.S.-Philippines	2.0	3.2	5.1	7.1

Notes: MTO data. Author's calculations.

The main result is more than 'round-number heuristics' per sé. It's that the 'round-number heuristics' only appear in the sender's currency, which suggests that remittance senders use the sender's currency as the reference currency. In reference to the earlier Figure 3.3, we see more individuals behaving as in panel (a) as opposed to panel (b).

3.3.2 Stickiness in Transaction Amounts

The previous section documented how remittance flows tend to be sent in the sender's currency. However, the overall effect on the recipient also depends on the transaction amounts. Do senders change the amount sent? If so, how often? We approach this question by studying both the amount sent and the frequency of transactions within a given sender-recipient pair. Note that senders have access to the history of their past transactions sent through the MTO.

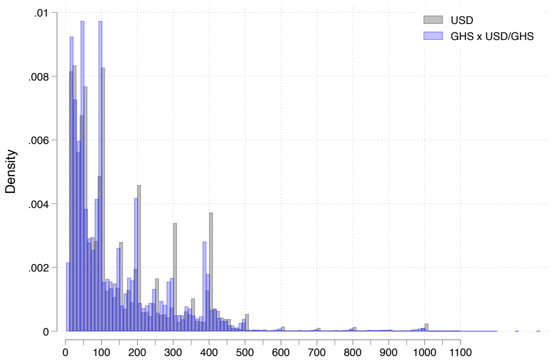
We focus on how often senders in a given sender-remittance pair change the amount sent. We do so by exploiting the methodology used in price-stickiness literature such as Bils and Klenow (2004) and Nakamura and Steinsson (2008). The frequency of price changes is typically calculated by dividing the number of price changes in the month considered by the number of observations for which a price change was possible during that particular month, i.e. the number of products for which there are two consecutive price observations in the database.

To determine the appropriate period over which we can define our frequency of amount change, we look at how many times in a month, quarter, year and entire sample a given sender-receiver pair make a transaction. Table 3.3 shows that the average number of transactions per month is small, ranging from 1.5 to 2.3. Therefore, we choose to calculate the frequency at the annual level.

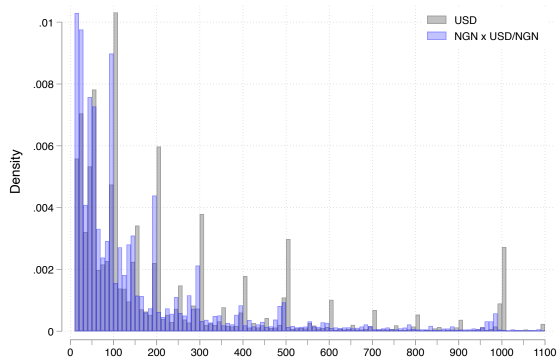
We start by looking at the size of the change in the amount sent in the sender's currency. Figure 3.6 shows that around 20% of the transactions in each year stay unchanged across the corridors. We then calculate the frequency of the change in the amount sent. Let j denote a given sender-recipient pair (dyad) within a remittance corridor. For a given year t and dyad j, we calculate,

$$F_{j,t} = \frac{\sum_i^{N_{j,t}} \mathbb{1}(\Delta \text{ amount sent}_{jt} \neq 0)}{N_{j,t} - 1} \quad , \tag{3.1}$$

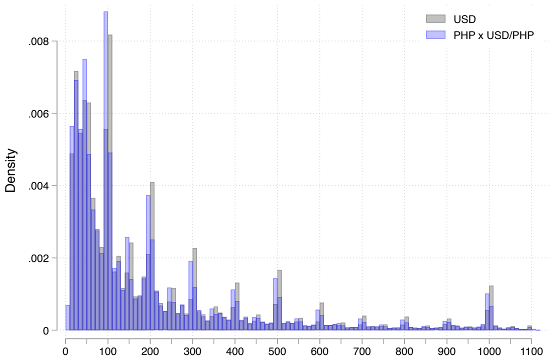
where $\mathbb{1}(\Delta \text{ amount sent}_{jt} \neq 0)$ equals 1 if the difference in the amount in two consecutive sender-currency transactions within dyad j, in year t, is different from 0. $N_{j,t}$ is the total number of transac-



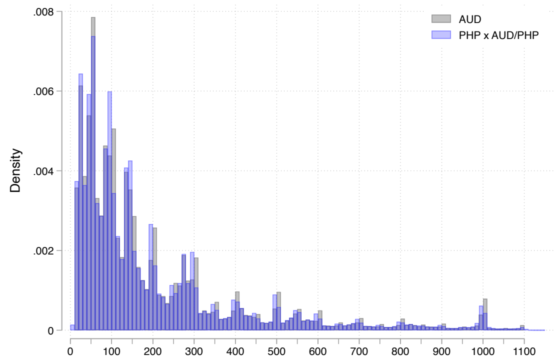
(a) U.S.-Ghana



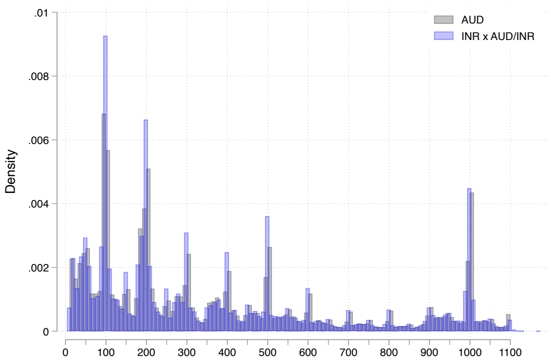
(b) U.S.-Nigeria



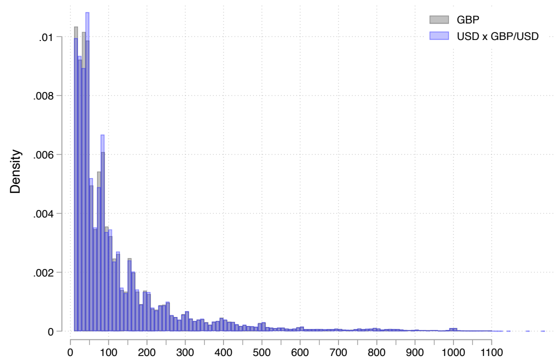
(c) U.S.-Philippines



(d) Australia-Philippines



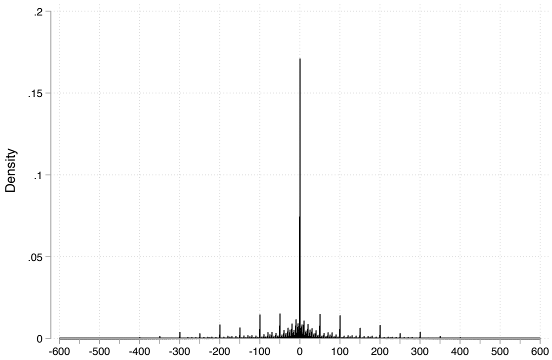
(e) Australia-India



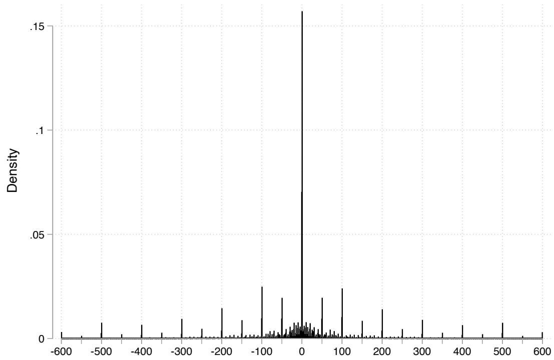
(f) UK-Zimbabwe

Figure 3.5: Amount Sent in Sender Currency vs Amount Sent in Receiver Currency Adjusted by the Exchange Rate

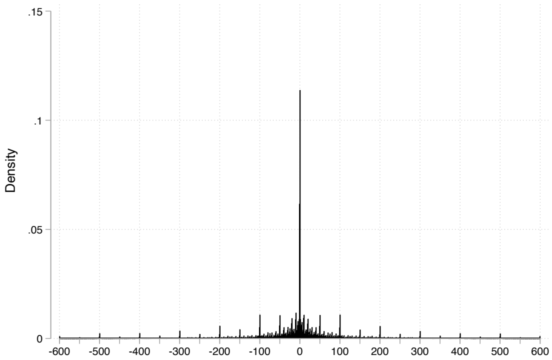
Notes: MTO data. Author's calculations. In the UK-Zimbabwe corridor, the only receiving currency available is the U.S. dollar.



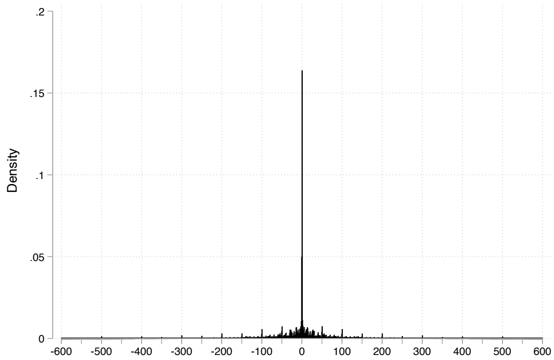
(a) U.S.-Ghana



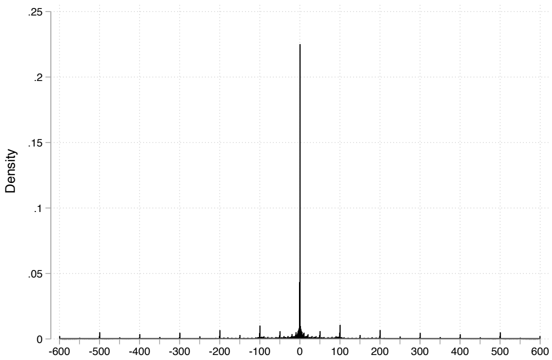
(b) U.S.-Nigeria



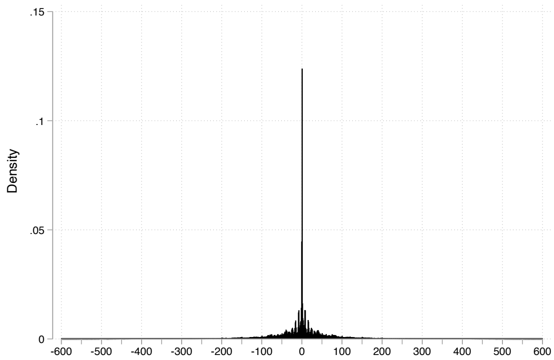
(c) U.S.-Philippines



(d) Australia-Philippines



(e) Australia-India



(f) UK-Zimbabwe

Figure 3.6: Change in Value of Amount Sent in Sender Currency

Notes: MTO data.

Table 3.4: Remittance Changes over the Whole Sample

	Yearly Mean Frequency (%)	Mean Duration (Years)
Australia-India	58.9	1.12
Australia-Philippines	60.0	1.09
United Kingdom-Zimbabwe	50.9	1.41
U.S.-Ghana	49.4	1.47
U.S.-Nigeria	49.9	1.45
U.S.-Philippines	57.5	1.17

Notes: MTO data. Author's calculations.

tions in year t for dyad j.[13] Finally, to obtain the yearly mean frequency (F) and mean duration (D), we take the average over dyads over time,

$$F = \frac{1}{T}\frac{1}{J}\sum_{t=1}^{T}\sum_{j=1}^{N_{j,t}} F_{j,t} \quad , \tag{3.2}$$

$$D = -\frac{1}{\ln(1-F)} \quad , \tag{3.3}$$

where T is the total number of years and J is the total number of dyads within a corridor. D is calculated according to the assumption that individuals can change the amount sent at any moment, not just at yearly intervals, then the instantaneous probability of a price change is $-\ln(1-F)$. Therefore, amounts remain unchanged for $-1/\ln(1-F)$ years.

Table 3.4 shows the mean frequency and duration across the six corridors. Overall, we find some heterogeneity in the frequency and duration across corridors. The U.S.-Ghana corridor features the lowest adjustment frequency with a mean duration of remittance amount of around 1.47 years. On the other end of the spectrum, the Australia-Philippines corridor features the highest adjustment frequency with the mean duration of remittance amount lasting 1.09 years.

Stickiness in Sender's Currency. The results regarding the reference currency and the stickiness in transaction amounts imply that remittances are sticky in the *sender's currency*. This matters for the effect of exchange rate fluctuations on remittance inflows to the recipient economy. The overall effect is closer to 'producer currency pricing' as opposed to 'local currency pricing' featured in Open Economy New-Keynesian models. This implies that exchange rate fluctuations have a full pass-through into remittance flows in the recipient's local currency compared to the zero pass-through under the sticky local currency case.

3.3.3 Regular Senders

How does the remittance-sending behaviour differ for those who use the platform regularly? To shed light on this question, we define a criteria for which a sender is classified as 'regular'. Specifically,

[13] We restrict the sample to those with $N_{j,t} \geq 2$, as we require at least two transactions within a year to experience a change in the amount sent.

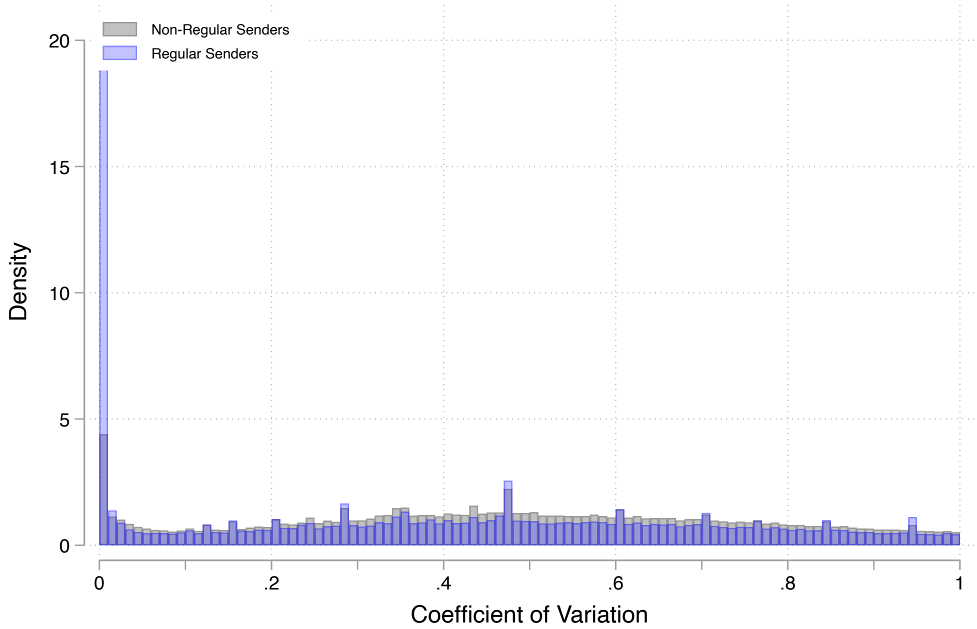


Figure 3.7: Coefficient of Variation of Transaction Amounts

Notes: MTO data. Author's calculations. Pooled across the six largest corridors.

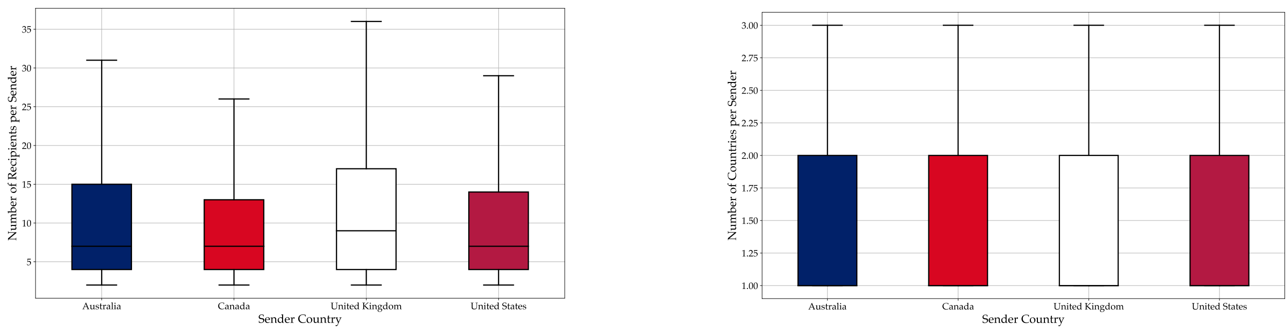
we calculate the number of transactions sent between a given sender-recipient pair in a quarter. We then compute the two-quarter moving average and define a 'regular' sender-recipient pair as those whose moving average number of transactions is always above two.

Given the transactions carried out by the sender-recipient pair, we then compute the mean and standard deviation of the transaction amounts to obtain the coefficient of variation. This represents a weighted spread of the transaction amounts.[14] Relative to the exercise in section 3.3.2, this measure gives us a sense of the overall spread in transaction amounts instead of changes between subsequent transactions.

Figure 3.7 shows the results. The grey bars show the distribution of the coefficient of variation for non-regular senders and the blue bars show the distribution for regular senders.[15] Notice that there is a prominent mass at 0 for both regular and non-regular senders, but the mass is larger for the regular senders. A coefficient of variation of zero results from a case where the standard deviation transaction amounts are zero. That is, within a sender-recipient pair, the sender has sent the same transaction amount each time in the sender's currency. This behaviour is more common for individuals whom we classify as regular senders.

[14]Specifically, we choose the coefficient of variation as the same dispersion matters less when the average amount is higher. For example, the coefficient of variation is lower when the standard deviation is $50 and the average transaction amount is $500 as opposed to $100.

[15]Note that the coefficient of variation is unbounded. We chose to truncate the figure at 1.



(a) Recipient Accounts per Sender

(b) Countries per Sender

Figure 3.8: Recipients and Countries Sent per Sender

Notes: MTO data. Author's calculations.

3.4 Remittance Flows Across Countries

In this section, we document facts in the cross-section of remittance flows. First, we document the 'network' of senders and recipients. Second, we find that the U.S. dollar is commonly used as a receiving currency even in remittance corridors not involving the U.S.

3.4.1 The Network of Senders and Recipients

To how many recipients depend on each sender? How many remittance corridors does each sender participate in? To answer these questions, we focus on individuals based in the four largest sending countries, which are Australia, Canada, the United Kingdom and the U.S. Figure 3.8a shows the distribution of the number of accounts that each sender sends to. We've restricted the sample of recipients to include only those who have received at least three transactions from a given sender.[16] On average, senders in the UK send to more accounts than those in Australia, which in turn has sent to more accounts than those in the U.S. and Canada. The median number of recipients ranges from 7 in the U.S. and Canada, to 9 in the UK.

Conversely, we find that on average each recipient account only receives remittance inflows from one sender account. Note that as mentioned in section 3.2.1, we have much more limited information regarding recipients. However, even if recipients have multiple accounts, they do not appear to receive remittance inflows from the same sender account. This suggests that the network of recipients is concentrated on a given sender as the given sender sends remittance flows to multiple recipient accounts.

What do we know about how many remittance corridors each sender participates in? Figure 3.8b shows the distribution of the number of countries each sender sends remittances. We find that each sender sends to between 1 and 3 countries, with the majority sending to just one country. Overall, this suggests that the network of senders and recipients is sparse across remittance corridors but is more concentrated within a corridor.

[16] We do this to exclude one-off transactions sent through the MTO.

3.4.2 The prominence of the U.S. Dollar

In the majority of remittance corridors, the received currency is the local currency of the receiving country. The main reason for this is that it's usually the only currency offered by the MTO.[17] This accounts for around 86% of all transactions. Of the remaining transactions, almost all are received in U.S. dollars.[18] Figure 3.9 shows the most prominent instances of the U.S. dollar being used as the received currency despite neither the sender's nor recipient's countries being the U.S. These include Nigeria, Turkey, Russia and Uruguay. These represent corridors in which more than one currency is available in the sender's choice set of receiving currencies.

The figure shows the sender countries on the left and the recipient countries on the right. The links represent the remittance flows and the colour of the links represent the received currency. Red flows represent the flows received in U.S. dollars. Notice that there are prominent red flows from non-U.S. senders towards recipient countries. The blue links represent flows where the receiving currency is Euros and all other colours represent flows where the receiving currency is the recipient country's local currency. The main takeaway is that the U.S. dollar is used as a receiving currency for remittance flows even in transactions not involving the U.S.

In Turkey, 81% of transactions are received in U.S. dollars and the remainder in Euros (18%) and Turkish Lira (1%). Of the transactions received in U.S. dollars, only 44% are sent from the U.S. with the remainder from outside the U.S. The Euro transactions are mostly sent by Germany, Netherlands, Ireland, Finland, France and Belgium. A similar pattern features in Russia as only 1% of the transactions are received in Rubles. Notably, 62% of the transactions are received in U.S. dollars and around 50% of these transactions come from non-US countries. In particular Romania, Poland, Czechia and Hungary. The remaining 37% is performed in Euros and mostly sent from Germany, France, the Netherlands and Norway.

In Nigeria around 27% of the transactions are received in U.S. dollars. Of these, 67.5% come from the U.S., 10% from the UK, and 4.5% from Canada. Note that for Nigeria, the share of transactions received in U.S. dollars has fluctuated over time. This is partly due to the policy of the Central Bank of Nigeria on allowing foreign currency transactions within Nigeria. In Uruguay, 52% of transactions are received in U.S. dollars and 40% of those come from New Zealand. Only 7.5% are from the U.S.[19]

In summary, though the receiver's local currency is usually the most common receiving currency, there exist corridors for which the U.S. dollar is a receiving currency. This reflects a combination of demand for U.S. dollars in recipient countries, the ease with which the MTO has partners that can facilitate transactions in U.S. dollars and monetary policy.

[17] For example, in Zimbabwe 100% of the transactions are received in the U.S. dollar. This is due to the fact that the MTO only offers the possibility to send U.S. dollars. For Argentina, 100% of the transactions are received in Argentine Pesos. Similarly, this is due to the fact that MTO only allows transactions in Argentine Pesos to Argentina.

[18] The U.S. Dollar accounts for 99.3% of these transactions. The remaining transactions are received in Euros and were sent from countries in the European Economic Area.

[19] Other countries where the U.S. dollar is a prominent receiving currency include Cambodia, where 77% of transactions are received in U.S. dollars. Of these, 25% are from the U.S. with 11% from the UK and 24% from Australia. Ethiopia, where 64% of transactions are received in U.S. dollars, but only 25% come from the U.S., 11% from the UK and 21% from Australia. Peru, where 73% of transactions are received in U.S. dollars. Of these U.S. dollar transactions, 37% are from the U.S., 11% from the UK and 29% from Australia.

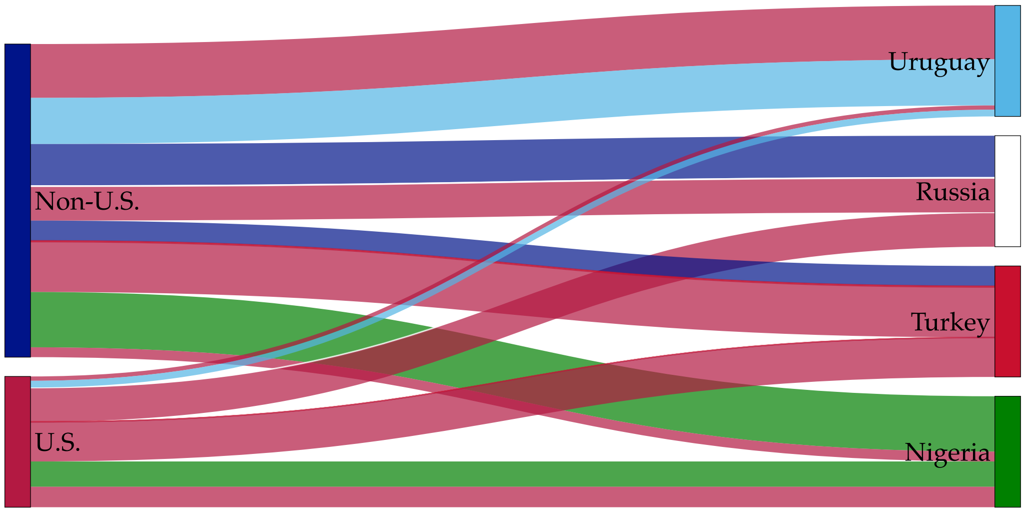


Figure 3.9: Selected Remittance Flows by Currency

Notes: MTO data. Author's calculations.

3.5 Remittance Flows and the Pandemic

In this section, we study the behaviour of remittance volumes and transactions during the pandemic.

Early in the pandemic, the World Bank predicted that annual remittance flows to low- and middle-income countries would drop by 20%. However, actual remittance flows fell by much less, closer to 7%. One of the arguments proposed to explain the discrepancy was the rise of the formalisation of remittance flows.[20] As borders were shut, families turned to money transfer operators as the method of sending remittances as opposed to other informal methods such as taking cash across the border or *hawala*.[21]

We document the behaviour of senders who joined the platform prior to 1^{st} March 2020 ('existing senders') and those who joined it after ('new senders'). We use a similar definition for recipients. Figure 3.10 plots the volume of remittance flows in the six largest corridors from 2018 to 2023. The black line shows the total remittance flows in a given month. We decompose the total number of transactions into three categories. The green bars show remittance flows made by existing senders to existing recipients whilst the blue bars show the remittance flows made by existing senders to new recipients. The grey bars show the remittance flows made by new senders to new recipients.[22]

Panels (a), (b) and (c) show cases where the U.S. is the sender country. Notice the number of remittance transactions falls during the latter half of 2020. In our conversations with the MTO, we established that this effect was due to an issue with the product in the U.S. Note that the beginning of 2021 saw a large rise in the number of transactions - larger than those in the first half of 2020.

Excluding the U.S., all other corridors featured a qualitative pattern similar to that of panels (d), (e) and (f). The key takeaway from these figures is that the volume of remittance flows increased temporarily during the latter half of 2020 before stabilising at a level that is higher than before the

[20] Dinarte-Diaz, Jaume, Medina-Cortina, and Winkler (2022) find that the rise of formal remittance flows is significant for the case of the U.S-Mexico remittance corridor.

[21] Hawala refers to an informal network of wire transfers without using the banking system.

[22] There were little to no remittance flows made by new senders to existing recipients across all corridors.

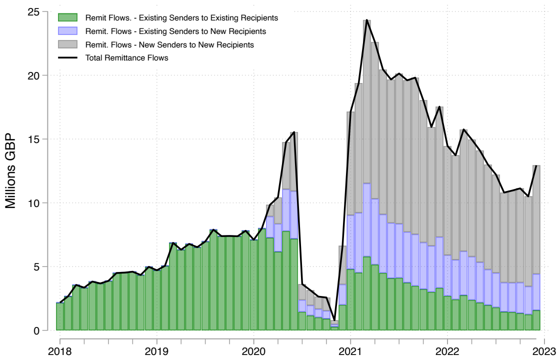
pandemic. Delving into the composition of transactions, we find that at the onset of the pandemic, the majority of the level of remittance flows is attributed to transactions between existing senders and existing recipients, but the majority of the growth in the remittance flows is attributed to transactions to new recipients. These originate from both new and existing senders.

One should be careful in interpreting transactions between new senders to new recipients as evidence of the 'formalisation' of remittance flows as we do not have any prior information on the method of sending remittance flows between these individuals prior to the pandemic. Therefore it is difficult to disentangle a story of formalisation as opposed to an increase in the market share of a given MTO. Figure 3.12 in Appendix 3.B shows a similar pattern for the number of transactions instead of the volume of remittance flows.

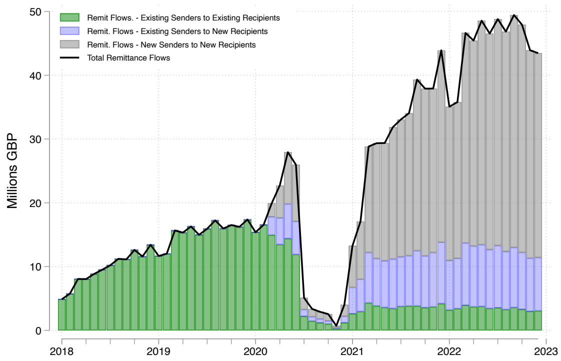
3.6 Conclusion

This paper documents five facts regarding the micro-level patterns of international remittance flows using administrative data from a money transfer operator. We find that remittance flows are sent in the sender's local currency and are sticky. Moreover, a given remittance sender has multiple recipients, all usually residing in the same country. The U.S. dollar is used as a receiving currency even in corridors not directly involving the U.S. The burst of MTO remittance flows during the pandemic is driven by both existing and new senders to the platform.

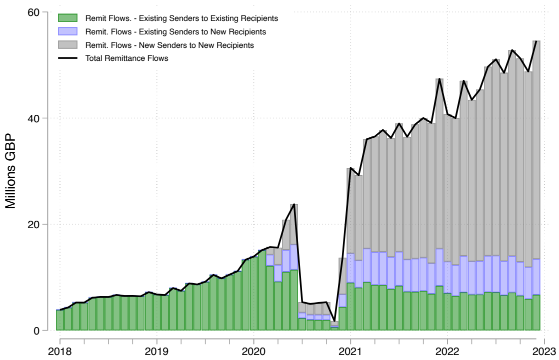
One interesting avenue is to formally test which theories of remittance flows put forward by Rapoport and Docquier (2006) fit with the microdata. Another interesting avenue could be to study how remittance flows react to macroeconomic shocks such as monetary policy shocks and exchange rate fluctuations. It would be interesting to quantify the role of remittance flows in providing risk-sharing across individuals based in different countries.



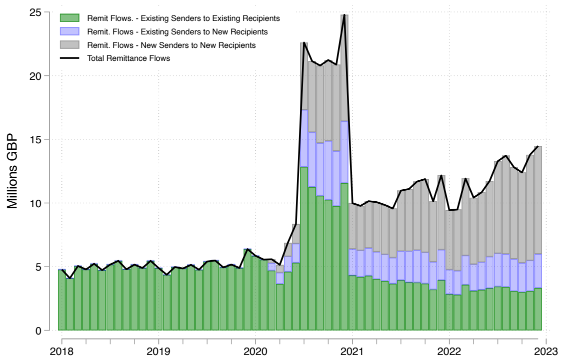
(a) U.S.-Ghana



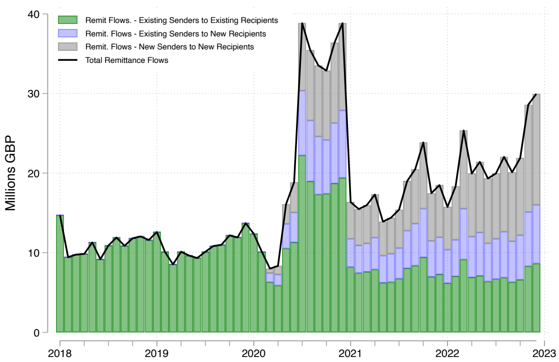
(b) U.S.-Nigeria



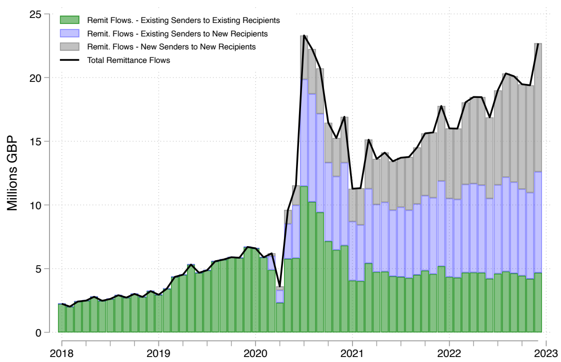
(c) U.S.-Philippines



(d) Australia-Philippines



(e) Australia-India



(f) UK-Zimbabwe

Figure 3.10: Volume of Remittance Flows during the Pandemic

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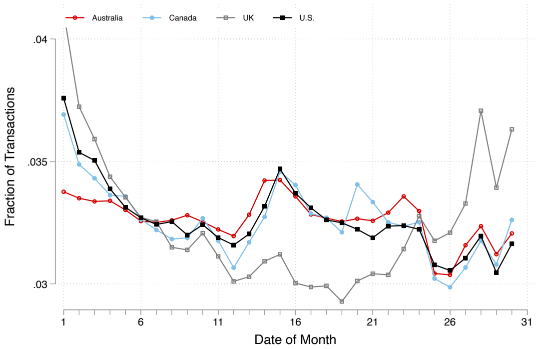
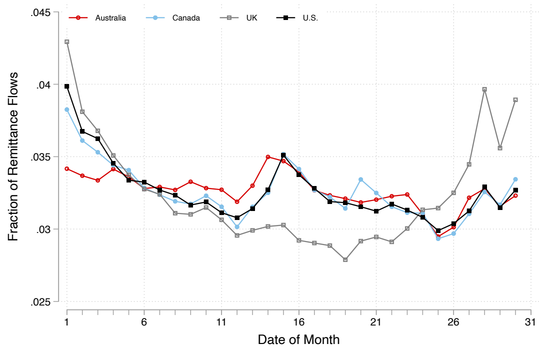
Appendix to Chapter 3

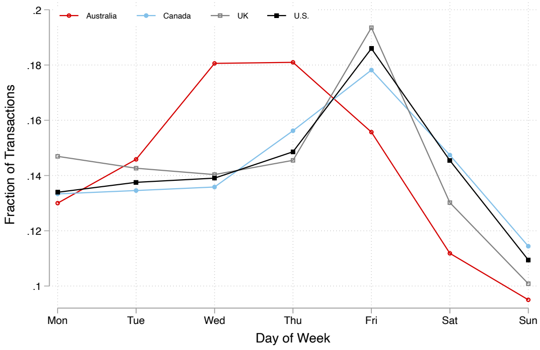
3.A Seasonality in Remittance Flows



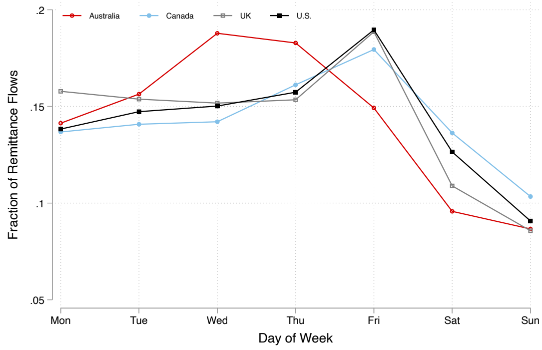
(a) Transactions by Date of Month



(b) Volume by Date of Month



(c) Transactions by Day of Week



(d) Volume by Daw of Week

Figure 3.11: Seasonality in Remittance Flows

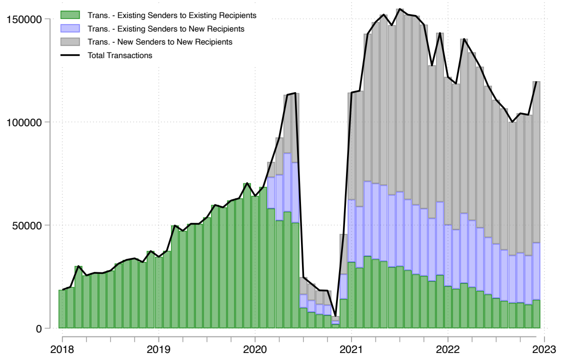
Notes: MTO data. Author's calculations.

In this section, we document that remittance transactions and volumes exhibit a strong seasonality pattern. As we observe the exact time of transactions, we are able to show the proportion of all remittance flows by the date of the month and the day of the week. Figures 3.11a and 3.11b show the results for remittance outflows from Australia, Canada, the United Kingdom and the United States.

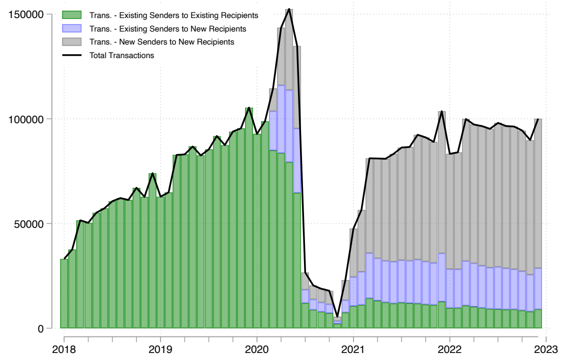
We find that remittance transactions and volumes are higher at the beginning of a calendar month. This is the case for all four of the countries that we show. For the UK, we find a second prominent spike around the 28th-30th of the calendar month. This could be driven by paydays in the UK, which occur around the same period. For the other three countries, we do not find a similar pattern at the end of the calendar month. Rather, we find a second spike around the 15th of the month, albeit this spike is smaller.

In Figures 3.11c and 3.11d, we repeat the same exercise and show the proportions by the day of the week. With the exception of Australia, we find that Fridays are the most common day for remittance transactions. For Australia, Wednesday and Thursday are the most popular days. In all four countries, we find evidence that remittance outflows are lower during weekends. Note that the MTO does not have any physical branches and therefore the effect is not driven by branch opening hours.

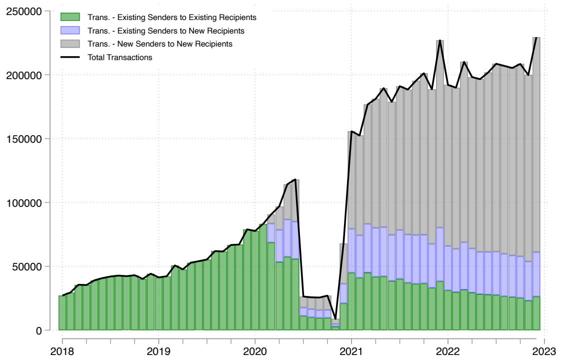
3.B Additional Figures



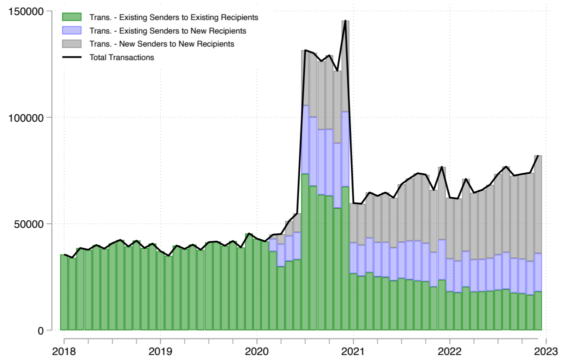
(a) U.S.-Ghana



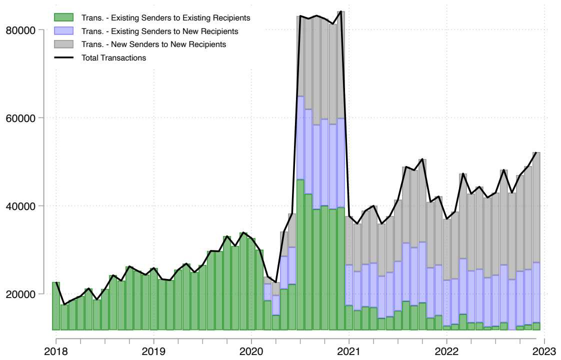
(b) U.S.-Nigeria



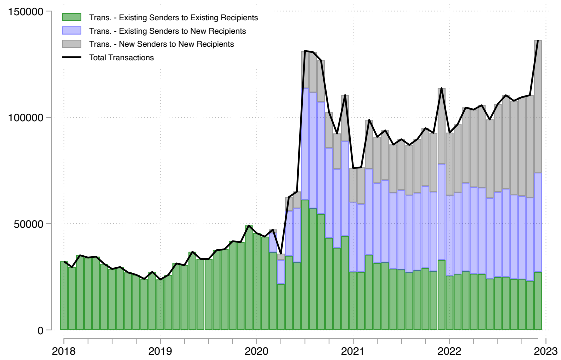
(c) U.S.-Philippines



(d) Australia-Philippines



(e) Australia-India



(f) UK-Zimbabwe

Figure 3.12: Fraction of Transactions and Volume by Day of Month