Part and Full-Time Employment Over the Business Cycle*

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Abstract

We develop a model that allows us to understand the cyclicality of part and full-time employment. In the model, idiosyncratic match quality determines a jointly optimal choice of part or full-time work. This choice is based on the surplus generated by each type of employment. Because of higher fixed costs, the surplus from full-time employment is more procyclical than part-time employment. As a result, inflows from full-time employment outweigh outflows to unemployment and cause part-time employment to be countercyclical, as observed in the data. We show that this composition effect accounts for the majority of the cyclical properties of part and full-time employment. We also show that subsidizing part-time employment during a recession is far more effective at limiting a downturn in the economy than an equally expensive unemployment insurance expansion.

JEL Classification: D8, J6, D6.

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1 Introduction

The Great Recession and the recent Covid-19 experience have emphasized the importance of closely monitoring part-time employment. This is because it can provide additional information regarding the performance of an economy and has distributional implications.[1] If part-time is ignored, aggregate unemployment numbers may understate the true economic slack over the business cycle. Within the context of a labor search framework, this is the case as worker flows across different employment states are critical in shaping unemployment dynamics.[2] But, is part-time employment an important feature of the U.S. labor market? Are its associated dynamics different than those of full-time employment?

Since the mid-1990s slightly more than one in six U.S. civilian employees worked in jobs classified as part-time. Many of these part-time jobs resulted from a within-job transitions from full-time employment. This is a risk faced by a sizable share of the labor market: over this same time period, workers have transitioned from full-time to part-time employment (6.5% monthly) more frequently than from full-time work to unemployment (0.7% monthly). Not only has part-time employment been quantitatively important, it exhibits different business cycle properties than full-time employment.[3] Over the last four decades, full-time employment has been highly procylical, while part-time employment has been countercyclical and closely tracked unemployment. These differences have been driven by asymmetric response of flows between part and full-time. In an expansion workers have transitioned from part-time to full-time, while in a recession we have observed a flow from full-time to part-time employment.[4] Similar labor market regularities have been documented by Canon et al. (2014), Borowczyk-Martins and Lalé (2019) and Borowczyk-Martins and Lalé (2020), among others.

In this paper we propose a framework that can account for these empirical regularities. By considering a more granular treatment of employment, we are able to better understand the mechanisms driving employment flows and shed light some important aggregate labor market phenomena. We provide answers to the following questions: How much of the part and full-time employment rates over the business cycle is directly caused by aggregate shocks relative to the endogenous adjustments made by firms and workers? What aspects of aggregate labor outcomes do we miss when part-time employment is ignored? In particular, do we understate the

[1]Federal Reserve Chair Yellen (2014) noted that the elevated number of workers who are employed part-time but desire full-time work might imply that the degree of resource under-utilization in the labor market is greater than what is captured by the standard unemployment rate. Additional information can be found in Yellen (2014).

[2]Workers who report that they are working part-time for economic reasons rise almost in lock step with the increase in unemployment and the decline in full-time employment. This regularity is observed in virtually all developed countries.

[3]We refer the reader to Borowczyk-Martins and Lalé (2019) and the data section for more details.

[4]We refer the reader to Section 3 for more details on the empirical regularities of full and part-time employment.

size of aggregate fluctuations and their impact on welfare? Does subsidizing part-time employment during a recession help reduce the size of the recession more effectively than expanding unemployment insurance?

To answer these questions, we construct a model that builds on Mortensen and Pissarides (1994). In particular, we consider firms offering part and full-time employment. When hiring, employers face differential acyclical fixed costs that differ across employment types.[5] Given the productivity of a match, firms and workers choose the type of employment by agreeing on a match quality that constitutes a shift from full to part-time employment. Conditional on such arrangement, firms and workers contract wages through bargaining. Over time, aggregate or idiosyncratic shocks may cause the match to dissolve or transition to the other employment state. Given this structure, we estimate the model using simulated method of moments. We then perform a series of counterfactual exercises to answer the previous questions. Finally, we consider the effectiveness of different revenue neutral policies at limiting the size and duration of downturns in the labor market. In particular, we compare the labor market and output consequences of implementing an extension to unemployment insurance during a recession versus a "job-subsidy" scheme.

We find that our framework is capable of matching the degree of cyclicality in nearly all flows in the labor market, though it does not account for the entirety of the fluctuations in the data. This is possible because of two channels in our model. First, the expected surplus of a new match deteriorates during a downturn, relegating more new matches to part-time employment and leading to the dissolution of old matches. Second, many existing matches adjust from full-time to part-time.[6] This second margin of adjustment is key for understanding fluctuations in part and full-time employment.[7] As the economy enters a recession, many part-time matches dissolve as their match quality no longer justifies employment. However, the utilization adjustments within-job from full-time to part-time temper the overall effect on part-time employment. Because our calibration indicates that the surplus of full-time work is more procyclical than part-time work, the inflows from full-time to part-time dwarfs the outflows from part-time to unemployment. This leads to procyclical full-time employment, while part-time and unemployment are countercyclical. Ultimately, these composition effects account for nearly all the fluctuations in part and full-time employment.

Differences in the cyclicality of part and full-time employment have consequences for the economy. During a downturn, firms use part-time employment to prevent the loss of capital

[5] Mortensen and Nagypal (2007) showed that training costs increase the volatility of job finding.

[6] There exists ample empirical evidence that firms hire part-time workers as a form of flexible labor. Using Canadian firm-level data, Zeytinoglu (1992) finds that organizational flexibility is a major argument to hire part-time workers. On the basis of international firm-level data, Delsen (1995) finds that the introduction of part-time employment has led to positive outcomes for firms in several European countries.

[7] Using firm-level data, Friesen (1997) shows that part-time employment plays a distinct role in the adjustment strategies of UK firms.

associated with the dissolution of a match while still reducing the cost of employment, leading to a larger decline in aggregate output. Simultaneously, part-time matches that existed prior to the start of a recession are more likely to dissolve than predicted by a model that does not distinguish between full and part-time employment. These matches yield a lower surplus on average, causing a larger increase in separations. This means that a model that does not distinguish between part and full-time employment will predict a smaller decline in employment during a recession. In addition, we show that such models understate the impact on welfare and inequality caused by recessions.

Finally, taking into account the different policies implemented during Covid-19, we consider the effectiveness of extending an unemployment insurance during a recession versus a "job-subsidy" scheme.[8] In particular, we impose a 7% decline in aggregate productivity and implement different labor market policies that are revenue neutral. First, we institute a 20% increase in unemployment benefits. Then, we consider a job subsidy. Despite small changes in each acyclical costs, both job-subsidy policies recover more rapidly and suffer a smaller decline than an expansion of unemployment insurance. In particular, we find that the economy with the part-time subsidy nearly has no decline in employment despite a drop in aggregate productivity of 7%. On the other hand, the full-time job subsidy scheme results in a larger decline in employment and output than the part-time subsidy. Nevertheless, it also performs better than an expansion of unemployment insurance.

The rest of the paper is organized as follows. In section 2, we place our paper within the related literature. In section 3, we introduce empirical evidence about part and full-time employment and describe a set of facts that we use to construct our model. We follow in section 4 by introducing our model and the equilibrium and show analytically how the model is able to rationalize the empirical regularities that we observe in the data. We describe our calibration approach in section 5 and discuss our model's ability to fit non-targeted moments. In section 6, we decompose the cyclicality of part and full-time employment, and describe the predictions of counterfactual models. In section 7, we consider the effectiveness of labor market policies in mitigating an economic downturn. Section 8 concludes.

2 Literature Review

This paper contributes to the literature of part and full-time employment. Within the empirical literature, Canon et al. (2014) find that part-time workers for economic reasons are typically less educated than full-time and are typically employed in middle or low-skill occupations.[9] In the

[8]In the U.S. and Australia, among other countries, during Covid-19 policymakers have enacted increases in unemployment insurance and "job-subsidy" schemes.

[9]On average, part-time workers for economic reasons (PTER) workers earn 19 percent less than full-time workers and 9 percent less (per hour) than part-time workers for non-economic reasons (PTNER), even after

aftermath of the 2007-09 recession, Canon et al. (2014) also find that changes in the transition probabilities to and from part-time worker for economic reasons were mainly associated with changes in the composition of employment.[10] Using a Markov chain model, Borowczyk-Martins and Lalé (2019) find similar results for the U.S. and United Kingdom. In particular, the authors show that cyclical variation in hours per worker is driven to a large extent by fluctuations in the share of part-time employed workers.[11] Borowczyk-Martins and Lalé (2019) also find that the bulk of the variation in the part-time employment share is accounted for by cyclical fluctuations in transition rates between full-time and part-time employment.[12] They also show that the incidence of involuntary part-time employment among new part-time workers increases dramatically in recessions, and is mostly driven by full-time workers facing slack work conditions. Valletta et al. (2020) find that structural factors, notably shifts in the industry composition of employment, have held the incidence of involuntary part-time employment slightly more than 1 percentage point above its pre-recession level. Using these insights, Borowczyk-Martins and Lalé (2020) develop an adjustment procedure to construct U.S. monthly time series of involuntary part-time employment stocks and flows since 1976. The authors establish that involuntary part-time employment is a very transitory labor market state.[13] Its main source of variation is found to be cyclical and it is predominantly driven by within-employment reallocation.[14] Finally, Borowczyk-Martins and Lalé (2020) also find that fluctuations in involuntary part-time employment flows exhibit systematic patterns over the business cycle.

Within the context of a theoretical model, Chang et al. (2011) construct a family model of labor supply that considers full and part-time employment. Individuals are subject to idiosyncratic shocks that affect their productivity in market work. The authors assume that there is a wage penalty associated with part-time employment and can be gender specific.[15] A representative firm produces output according to a constant-returns-to-scale Cobb-Douglas technology in capital and efficiency units of labor. Using simulated data from the steady state of the calibrated model, Chang et al. (2011) find positive estimated elasticities that are larger for women and that are highly significant, but they bear virtually no relationship to the underlying preference parameters. Within a different framework, and closest to our spirit, Warren (2015)

controlling for sociodemographic and occupational characteristics. The differences persist if we compare wages of PTER to wages of other workers within broad occupational categories.

[10]The authors used counterfactual exercises similar to Shimer (2012).

[11]This holds for the major recessions of the past five decades in the U.S. and for the Great Recession in the United Kingdom.

[12]The authors also find that cyclical variation in transitions between full-time and part-time employment is predominantly accounted for by transitions at the same employer. Moreover, transitions between full-time and part-time employment at the same employer entail sizable and lumpy adjustments in individual working hours.

[13]An average spell lasts about 30% less than an average unemployment spell.

[14]Transitions to and from full-time and voluntary part-time employment account for just over three quarters of the short-run variation in involuntary part-time employment.

[15]These assumptions can help capture the fact that men and women have differential labor supply across occupations.

models part-time employment focusing on a firm's decision to hire, fire, or partially utilize its labor force. Firms are heterogeneous in size and productivity, and subject to search frictions. The model produces patterns of part-time utilization by firms over age, size, and employment growth distributions. Firm-level utilization of part-time employment is consistent with the characteristics of worker flows in the CPS. In aggregate, the model matches the relative volatility of unemployment and part-time for economic reasons over the business cycle. Part-time labor utilization by firms increases the volatility in vacancies and unemployment in the model relative to the case with only an extensive margin. Finally, Borowczyk-Martins and Lalé (2018) analyze differences in involuntary part-time employment and unemployment spells through the lens of the incomplete-market and job-search model of Acemoglu and Shimer (2000). The authors consider two sources of insurance against idiosyncratic labor market risks. There is private insurance through a risk-free asset where the worker can save but cannot borrow. In addition, there is public insurance against the risk of becoming unemployed. Since the authors are only interested in the worker's decision problem, all prices (interest rates, wages, etc.) are exogenous and fixed. A calibration of this environment, consistent with U.S. institutions and labor market dynamics, shows that involuntary part-time employment generates lower welfare losses relative to unemployment.

We complement these papers by proposing a simple framework of part and full-time employment that can capture the cyclicality of the various employment flows. We also determine importance aggregate shocks and the endogenous adjustments made by firms and workers when accounting for the business cycle. We also highlight what aspects of aggregate labor outcomes we miss when part-time employment is ignored.

3 Empirical Regularities

Before delving into the model in this section we document empirical regularities about part and full-time employment in the U.S. We focus on their dynamics over the business cycle. First, we document that full-time employment is procyclical, while part-time and unemployment are both countercyclical. Second, we show that this is primarily driven by within-job flows between part and full-time employment. In subsequent sections, we construct a model of part and full-time employment and use it to understand these empirical regularities.

We also highlight evidence about the cyclicality of flows that motivates our particular model design. First, we show that there is little appreciable difference in the cyclicality of flows to unemployment from either part or full-time employment. Then, we show that the differences in cyclicality are driven by flows between part and full-time, and in job-finding rates. We further show that there is a proportionality between these different flows. We use these empirical regularities to motivate the theoretical framework that we consider in this paper. Such environment can be used to capture salient features of the data. It can also serve as an effective tool to analyze the effectiveness of various labor market policies.

Throughout the rest of the paper the data we use is the Current Population Survey (CPS) that spans from 1996 to 2019.[16] We impose standard sample restrictions, limiting our data to white prime-age males with a Masters Degree. We limit the scope to occupations in which individuals in our sample report working part-time.[17] We follow a largely standard definition of part-time employment. In particular, we classify individuals who report working fewer than 35 hours during the previous week as part-time workers.[18]

3.1 Cyclicality of Part and Full-Time Employment

We use the CPS to document regularities about the relationship between cyclicality of part and full-time employment and aggregate employment. In the left panel of Figure 3.1 we plot aggregate employment. In the right panel, we report part-time employment (green line), full-time (red line) and the unemployment rate (blue line).

(a) Aggregate employment rate. Source: CPS.

(b) Employment rates by type. Source: CPS.

Figure 3.1: Employment rates between 1996 and 2018.

As we can see from Figure 3.1, full-time employment is procyclical, while part-time employment and unemployment are both countercyclical. Because full-time employment contributes the most, aggregate employment is then procyclical.

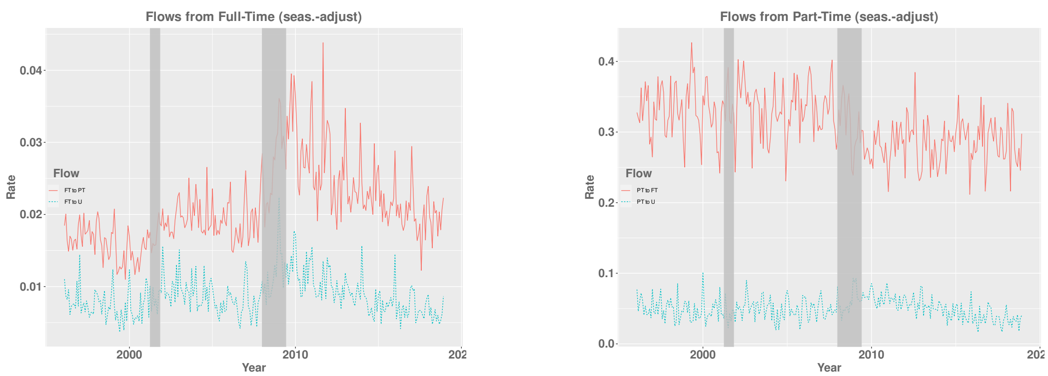
The previous employment aggregates could have been generated by a variety of different flows. To provide additional insights to these employment patterns, we also document how

[16]This is the standard data set used to explore employment dynamics in the U.S.

[17]According to Auray et al. (2018), the percentage of multiple jobholders has been declining from above 6 percent in the mid-1990s to about 5 percent in the mid-2010s. This decline is similar for both men and women. Thus, if holding multiple jobs indicates a problem, that problem seems to be less of a concern today than it was 20 years ago. Second, women are more likely than men to hold multiple jobs, although this was not the case in the early 1990s.

[18]We exclude any full to part-time transitions that occur for non-economic reasons as it is beyond the scope of this paper.

flows between part and full-time employment evolve during the business cycle. In particular, Figure 3.2 reports the gross transition rates out of part and full-time employment. In the left panel we plot flows from full-time to part-time employment and from full-time employment to unemployment. In the right panel, we report the time series corresponding to the flows from part-time to full-time employment and part-time employment to unemployment.



(a) Flows from full-time employment. Source: CPS.

(b) Flows from part-time employment. Source: CPS.

Figure 3.2: Employment flows.

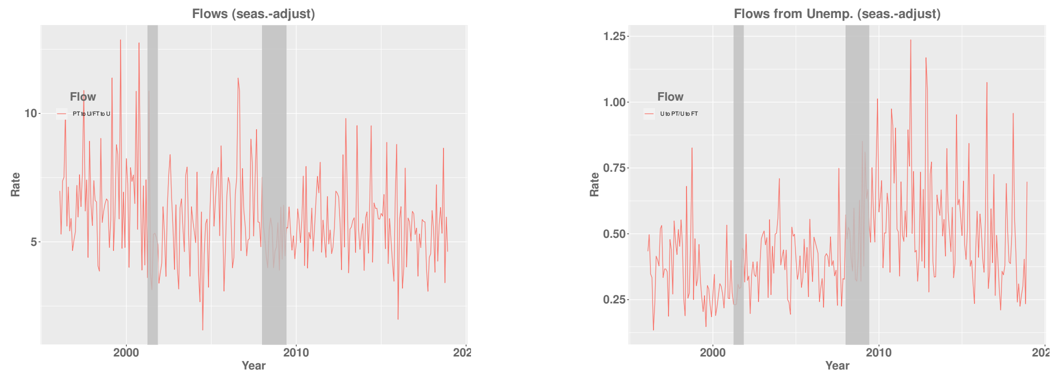
Figure 3.2 clearly shows that flows out of full-time employment are countercyclical, while flows from part-time to full-time employment are procyclical. In contrast, flows from part-time employment to unemployment are acyclical.

3.2 Further Motivating Evidence

To better inform the design of our theoretical framework, we now explore the relative cyclicality of each flow. In particular, we first compare the cyclicality of flows from part and full-time employment into unemployment. We also consider flows between part and full-time employment and flows out of unemployment. Finally, we discuss the implications of our empirical findings when developing our theoretical framework.

We start by comparing the cyclicality of flows to and from unemployment. To do this, we plot the ratio of flows into unemployment from part and full-time employment and the ratio of flows out of unemployment to part and full-time employment. These ratios are depicted in Figure 3.3. In the left panel, we plot the ratio of flows from full-time to unemployment over the flows from part-time to unemployment. In the right panel, we plot the ratio of flows from unemployment to full-time over the flows from unemployment to part-time.

These two ratios show a striking difference. While the flows into unemployment exhibit similar degrees of cyclicality, flows from unemployment to full-time employment are far more cyclical than flows from unemployment to part-time work. This suggests that the underlying process leading to separations is similar for part and full-time employment. However, the



(a) Ratio of flows to unemployment. Source: CPS.

(b) Ratio of flows from unemployment. Source: CPS.

Figure 3.3: Ratio of employment flows.

process leading to finding a job over the business cycle is quite different.

Now, we consider flows between part and full-time employment. In Figure 3.4, we plot the ratio of full-time to part-time flows over part-time to full-time flows.

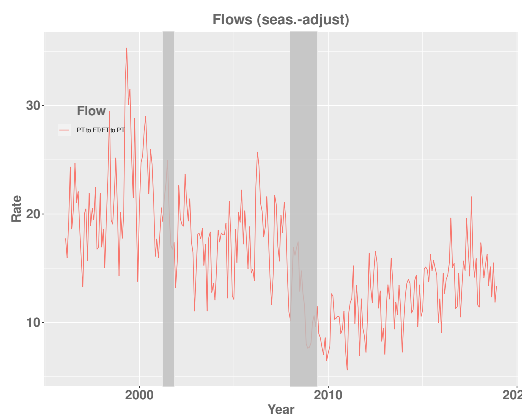


Figure 3.4: Ratio of PT→FT to FT→PT. Source: CPS.

As Figure 3.4 shows, flows from full to part-time employment are far more countercyclical than the reverse flows. This should not be surprising given that the flows from part-time to full-time are procyclical and that flows from full to part-time are countercyclical.[19]

More striking, however, is that this plot mirrors the cyclicality of the flows out of unemployment. In fact, when we divide these ratios, the resulting series closely reflects the cyclicality of flows into unemployment. This ratio is depicted in Figure 3.5.

We interpret this to mean that the underlying process causing the cyclicality of flows between part and full-time employment is also causing the cyclicality in flows out of unemployment.

There is ample evidence that although most transitions to part-time employment are within a job. Part and full-time employment entail different costs and production efficiencies. Jepsen

[19] We refer to we found in Figure 3.2b.

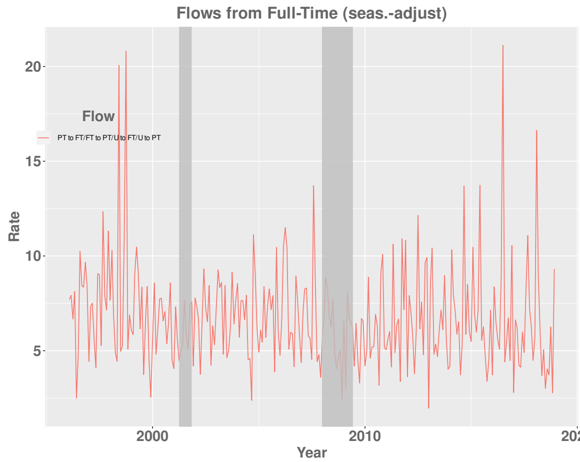


Figure 3.5: $PT \to FT/FT \to PT/U \to FT/U \to PT$ Source: CPS.

(2001) finds that part-time employment require fewer skills, and thus less training than full-time jobs. This training is often firm-specific, and entails a cost, in the event of separation, that is shared by both parties. Research also suggests that training costs are acyclical or mildly procyclical (Mendez and Sepulveda, 2012). Furthermore, Bonamy and May (1997) find that part-time employment is often inefficient because it can create communication gaps. As a result, it may produce a lower surplus when firms and workers choose part-time employment in lieu of full-time. Fixed costs (such as administrative costs, provision of fringe benefits, etc.) are also likely to be independent of hours. Thus, these are likely to increase non-linearly with the amount of hours worked (Montgomery, 1988).

Consistent with previous work, we also document similar results as shown by Figure 3.6 . In particular, using data on hourly benefits from the BLS, we find that the cost of providing benefits to part-time workers is both acyclical. Moreover, these are consistently lower than the cost of providing benefits to full-time workers. This is the case even on an hourly basis.

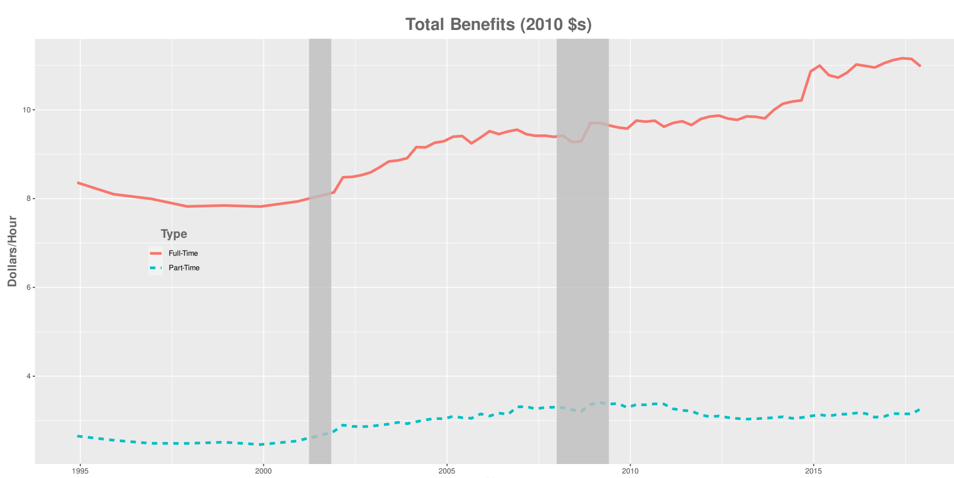


Figure 3.6: Cost of total benefits (hourly). Source: CPS.

It is importanty to highlight that the BLS calculates these benefits both as the total cost of benefits and the cost of providing those benefits. These benefits may be available to the unemployed, provided inefficiently, or never used by workers. This would lead to a deadweight loss, thus lowering the total surplus of a match. Taken together, previous work suggests that part and full-time employment yield different levels of output and our findings here indicate that they entail different costs. Moreover, these costs may be sunk in the event of unemployment, and that they are largely acyclical.

Our theoretical framework that we introduce in the next section takes these regularities into account. We allow part and full-time work to yield different levels of output, and incur different acyclical costs. Our insights about the cyclicality of flows (Figure 3.5 and Figure 3.4) lead us to consider an environment where separations from part or full-time are equally procyclical. We further allow flows between part and full-time employment and flows out of unemployment to vary with the business cycle, which is based by the same underlying stochastic process.

4 Framework

We extend Mortensen and Pissarides (1994) to incorporate part and full-time employment. Upon meeting, firms and workers choose optimally whether their match is best served with full-time employment, part-time employment, or by both parties pursuing other matches. They contract on both a wage and employment schedule by bargaining, given the productivity of a match. There is a unit mass of atomistic workers, and an infinite mass of atomistic firms. Time is continuous, and the payoff flow for both firms and workers is discounted at rate r. Workers may be either unemployed and receive flow utility b, or employed and receive a flow payout w, which depends on match characteristics. Firms may be unmatched, and waiting to match with a worker, or matched. When they are paired with a worker, firms receive flow profits given by

$$z\epsilon Y_T - w - \tau_T;$$

where ϵ is a match-specific component, z represents common aggregate shocks, Y_T denotes the type-specific productivity and τ_T is an acyclical cost. This is different depending on employment type, but not aggregate productivity.

Firms can open a vacancy to attract a worker at cost κ, but ex-ante do not know whether the match will result in full or part-time employment. Workers match randomly with posting firms. We assume that there exists a constant returns to scale matching technology, $M(u, v)$, that is common to all labor market participants. Following the common convention, we define u as the stock of unemployed workers and v as the stock of vacancies. The matching function determines the number of matches as well as the worker-finding rate for firms, $\frac{M(u,v)}{v} = M(\frac{u}{v}, 1) \equiv q(\theta)$, and the job-finding rate of workers, $\frac{M(u,v)}{v} \equiv p(\theta) = \theta q(\theta)$, where θ denotes labor market tightness, $\theta = \frac{v}{u}$.

Workers and firms are ex-ante identical, but experience shocks while in a match. Upon meeting, workers realize an iid match-specific productivity draw from a common distribution $\epsilon \sim F(\epsilon)$. This evolves over the duration of the match at a rate λ_T. After observing the match-specific productivity realization, firms and workers jointly decide whether the match should result in part-time employment, full-time employment, or it is better to continue to search for a different match. Below the productivity threshold ϵ_P, a worker prefers to continue searching for employers, while the firm would similarly prefer to open a new vacancy and search for a better suited worker. A draw above this threshold ensures that the match will continue (the first margin), but the type of match remains to be determined. Above a second productivity threshold, which we denote by ϵ_F, workers and firms agree to make the employment full-time. Thus, productivity draws between ϵ_P and ϵ_F result in part-time employment. After determining the type of employment, firms and workers agree on a schedule of wages according to a surplus splitting rule (Nash Bargaining). Both the wage and the employment type (part or full-time) may change in response to future productivity shocks.

At any point, an idiosyncratic productivity shock may realize and alter the employment relationship. Workers and firms continue to follow the wage schedule, but the job may transition from full-time to part-time employment, should a realization $\epsilon' \in [\epsilon_P, \epsilon_F)$, $\epsilon \geq \epsilon_F$ occur, or part-time to full-time if $\epsilon' \geq \epsilon_F$, $\epsilon \in [\epsilon_P, \epsilon_F)$. Similarly, the match may realize a productivity shock $\epsilon' < \epsilon_P$, in which case the match dissolves.

We assume that workers with part and full-time employment operate different production technologies. In particular, we have that technologies used in part-time employment yields lower output so that $Y_P < Y_F$. In addition to different production technologies, part and full-time employment incur different flow costs. We denote these as τ_P, and τ_F, for part and full-time employment, respectively. We further assume that $\tau_P \leq \tau_F$.[20] For analytical simplicity, we assume that these costs differ only by employment type, and that they are acyclical. Initially, we assume that the aggregate state is stationary, $z = \bar{z}$, but we relax this assumption when we simulate the model.

In what follows, we consider the steady-state equilibrium and perform comparative statics on aggregate observables. After characterizing the existence of part and full-time employment, we generalize the model to include out of steady-state dynamics.

[20]We do not take an explicit stand on the interpretation of these costs, and interpret them as a composite of costs associated with maintaining fixed capital, training workers to use production technologies, taxes that would not be incurred in the absence of a match, and required benefits that are either provided in unemployment or involve dead-weight loss in their acquisition.

4.1 Benchmark Model

We first describe an environment where workers may be unemployed, or employed either in full or part-time employment. Within this environment, unemployed workers receive flow utility that is given by:

$$r\ U = b + p(\theta) \int (\max\{W^F(x), W^P(x), 0\} - U)\ dF(x); \tag{4.1}$$

where $T \in \{P, F\}$ indexes part and full-time employment, respectively. Unemployed workers match with firms at a rate $p(\theta)$, and transition to employment if the realized productivity $\epsilon \geq \epsilon_P$. When matched they receive the following flow value:

$$r\ W^T(\epsilon) = w + \lambda_T \alpha \int (\max\{S^F(x), S^P(x), 0\} - S^T(\epsilon))\ dF(x); \tag{4.2}$$

where w is the wage and λ_T is the rate at which the match experiences idiosyncratic productivity shocks. It is worth emphasizing that a full-time worker may transition to part-time, and vice-versa, depending on the idiosyncratic productivity level of the match. Within a match, workers transition from full to part-time employment when $\epsilon' < \epsilon_F$ and from employment to unemployment when $\epsilon' < \epsilon_P$.

Unfilled vacancies receive the following flow value:

$$r\ V = -\kappa + q(\theta) \int (\max\{J^F(x), J^P(x), 0\} - V)\ dF(x)); \tag{4.3}$$

where $q(\theta)$ is the contact rate of workers. Firms pay a flow cost of κ until they meet a worker, and they continue to enter until it is no longer profitable. These features yield the free entry condition:

$$q(\theta) = \frac{\kappa}{\int \max\{J^F(x), J^P(x), 0\}\ dF(x)}. \tag{4.4}$$

Once matched, firms receive the following flow value:

$$r\ J^T(\epsilon) = z\epsilon Y_T - \tau_T - w + \lambda_T(1-\alpha) \int (\max\{S^F(x), S^P(x), 0\} - S^T(\epsilon))\ dF(x); \tag{4.5}$$

where $z\epsilon Y_T$ is the output associated with a type $T = \{P, F\}$ employed worker, and τ_T is the corresponding firm's flow cost, $\tau_T = \{\tau_P, \tau_F\}$, depending on whether the match results in full or part-time employment, respectively. Without loss of generality, we focus on environments where $\epsilon_F \geq \epsilon_P$.

In any match, the surplus that takes into account worker's productivity ϵ, employment type

T, wages and profits, net of outside options and costs, is given by:

$$S^T(\epsilon) = W^T(\epsilon) - U + J^T(\epsilon) - V. \tag{4.6}$$

After imposing the free entry condition ($V = 0$), we then have that:

$$S^T(\epsilon) = W^T(\epsilon) - U + J^T(\epsilon). \tag{4.7}$$

Substituting Equation 4.2, Equation 4.1, and Equation 4.5 into this expression, and using the free entry conditions and surplus sharing rules yield the following expression for the surplus:

$$\begin{aligned}(r + \lambda_T)\, S^T(\epsilon) &= z\epsilon Y_T - \tau_T \\ &\quad + \lambda_T[\int_{\epsilon_F}^{\bar{\epsilon}} S^F(x)dF(x) + \int_{\epsilon_P}^{\epsilon_F} S^P(x)dF(x)] - b - \frac{\alpha}{1-\alpha}\theta\kappa.\end{aligned} \tag{4.8}$$

Given ϵ_P and ϵ_F, net worker flows into part-time employment, $\dot{e}^P$, full-time employment, $\dot{e}^F$, and unemployment, $\dot{u}$, are given by:

$$\dot{e}^P = (P(\theta)u + \lambda_F e^F)[F(\epsilon_F) - F(\epsilon_P)] - (\lambda_P[1 - F(\epsilon_F) + F(\epsilon_P)])e^P; \tag{4.9}$$

$$\dot{e}^F = (P(\theta)u + \lambda_P e^P)[1 - F(\epsilon_F)] - (\lambda_F F(\epsilon_F))e^F; \tag{4.10}$$

$$\dot{u} = \lambda_P F(\epsilon_P)e^P + \lambda_F F(\epsilon_P)e^F - p(\theta)[1 - F(\epsilon_P)]u. \tag{4.11}$$

For simplicity, from now on we assume that exogenous separations are zero. We can also define the evolution of distribution of match quality according to the following:

$$\begin{aligned}\dot{G}(x) &= (P(\theta)u + \lambda_P e^P + \lambda_F e^F)[F(x) - F(\epsilon_P)] \\ &\quad - \lambda_P G(x)(1-u) - (\lambda_F - \lambda_P)\mathbb{1}_{x \geq \epsilon_F}[G(x) - G(\epsilon_F)](1-u);\end{aligned} \tag{4.12}$$

where $\mathbb{1}_{x \geq \epsilon_F}$ is an indicator function that takes on the value 1 if x lies in the range of matches that constitute full-time employment. This is because the outflows from full-time and part-time employment differ due to different arrival rates. These are denoted by λ_P and λ_F, respectively.

4.2 Characterization of Equilibrium

Any equilibrium in this model is characterized by a wage function, w, a market tightness θ, and thresholds ϵ_P and ϵ_F. There are additional transition rates $\dot{e}^F$, $\dot{e}^P$, and $\dot{u}$, and associated stocks e^F, e^P, and u for full-time and part-time employment, and unemployment, respectively. These functions satisfy:

1. θ is determined by vacancy posting and is consistent with the free entry condition.

2. ϵ_P is the threshold productivity at which firms and workers are indifferent between remaining matched.

3. ϵ_F is the threshold productivity at which firms and workers are indifferent between part and full-time work.

4. Wages w are determined by Nash bargaining over the surplus of a match with worker bargaining power equal to α.

5. The employment rates are consistent with employment flows and both are consistent with worker and firm decisions.

4.2.1 Stationary Equilibrium

The steady-state for this economy is defined by a policy tuple $(\epsilon_P, \epsilon_F, \theta, w^*, h^*)$, and steady-state employment rates e^{P*}, e^{F*}, u^*. The policy functions are defined as above, and the employment rates are given by:

$$e^P = \frac{\left(P(\theta)u + \lambda_F e^F\right)\left[F(\epsilon_F) - F(\epsilon_P)\right]}{\left(\lambda_P[1 - F(\epsilon_F) + F(\epsilon_P)]\right)}; \tag{4.13}$$

$$e^F = \frac{\left(P(\theta)u + \lambda_P e^P\right)\left[1 - F(\epsilon_F)\right]}{\left(\lambda_F F(\epsilon_F)\right)}; \tag{4.14}$$

$$u = \frac{\lambda_P F(\epsilon_P) e^P + \lambda_F F(\epsilon_P) e^F}{p(\theta)[1 - F(\epsilon_P)]}. \tag{4.15}$$

In addition, we can define the steady state match quality distribution for part-time matches, $x \leq \epsilon_F$, as followis:

$$G(x) = \frac{(P(\theta)u + \lambda_P e^P + \lambda_F e^F)[F(x) - F(\epsilon_P)]}{\lambda_P(1-u)}; \tag{4.16}$$

while for full-time matches,$x \geq \epsilon_F$ is given by:

$$G(x) = \frac{(P(\theta)u + \lambda_P e^P + \lambda_F e^F)[F(x) - F(\epsilon_P)] - \lambda_P e^P}{\lambda_F(1-u)}. \tag{4.17}$$

4.2.2 Productivity Thresholds and Flows

There are two unique productivity shocks that define separation thresholds, ϵ_F, and ϵ_P. In particular, ϵ_F represents the productivity threshold above which matches are full-time. This threshold is determined by this indefference condition

$$S^F(\epsilon_F) = S^P(\epsilon_F).$$

At this point, a match of productivity ϵ_F is equally-profitable when constituted as either part or full-time employment. Productivity below this threshold implies part-time employment. The second margin of adjustment is captured by threshold ϵ_P. This is characterized by the indifference condition between part-time employment and unemployment, $S^P(\epsilon_P) = 0$.

Proposition 1. *The full-time threshold is given by*

$$\begin{aligned}\epsilon_F = &\frac{(r+\lambda_P)\tau_F - (r+\lambda_F)\tau_P}{z((r+\lambda_P)Y_F - (r+\lambda_F)Y_P)} + \frac{(\lambda_P - \lambda_F)(b + \frac{\alpha}{1-\alpha}\theta\kappa)}{z((r+\lambda_P)Y_F - (r+\lambda_F)Y_P)} \\ &+ \frac{\lambda_P(r+\lambda_F)^2 - \lambda_F(r+\lambda_P)^2}{((r+\lambda_P)Y_F - (r+\lambda_F)Y_P)(r+\lambda_P)(r+\lambda_F)}[Y_F \int_{\epsilon_F}^{\bar{\epsilon}} [1-F(x)]dx + Y_P \int_{\epsilon_P}^{\epsilon_F} [1-F(x)]dx];\end{aligned} \tag{4.18}$$

when $\lambda_P = \lambda_F$,

$$\epsilon_F = \frac{\tau_F - \tau_P}{z(Y_F - Y_P)}. \tag{4.19}$$

Figure 4.1 depicts the relationship between these thresholds and the stock of employment across states.

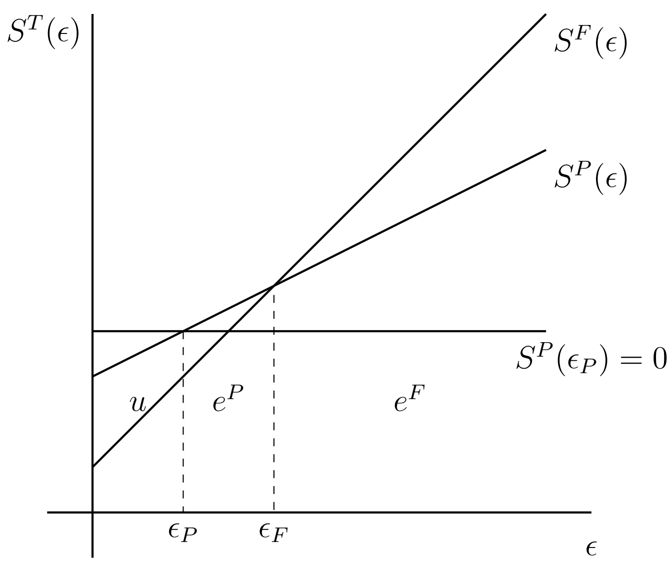


Figure 4.1: Surplus functions and employment thresholds.

Proposition 2. *The part-time threshold is given by:*

$$\begin{aligned}\epsilon_P = &\frac{\tau_P + b + \frac{\alpha}{1-\alpha}\theta\kappa}{zY_P} \\ &- \frac{\lambda_P}{r+\lambda_P}[(\frac{Y_F}{Y_P}) \int_{\epsilon_F}^{\bar{\epsilon}} [1-F(x)]dx + \int_{\epsilon_P}^{\epsilon_F} [1-F(x)]dx].\end{aligned} \tag{4.20}$$

Each threshold provides information on what drives part and full-time employment. For full-time employment, the measure of workers is determined by the difference in cost and productivity with part-time workers. As productivity of full-time workers increase, ϵ_F falls and more workers move from part to full-time work. When we assume that $\lambda_P = \lambda_F$, it is also easy to see how aggregate shocks will shift this threshold. The part-time threshold responds both to the cost-benefit ratio for part-time employment (the first line in Equation 4.20), and the continuation value accrued from increases in idiosyncratic productivity and transitions to full-time employment.

4.3 Equilibrium Properties

In this section we explore the model properties. We start by showing that steady-state flows in our model are consistent with our empirical findings in Section 3. Next, we perform a series of comparative statics and show that they are qualitatively consistent with our previous findings. In particular, we focus on transitions between part and full-time employed and show that they can deliver the patterns observed in Figure 3.1b.

4.4 Steady-State Flows

Having defined the productivity thresholds, we can characterize the flows between employment types in the steady state. We are primarily interested in model predictions about the ratio of transitions between employment states that we described in Section 3. We start by characterizing the ratio of flows from part and full-time jobs to unemployment in the steady state.

Proposition 3. *The ratio of the PT→U rate to the FT→U rate is constant and given by:*

$$\frac{\frac{e^{P}\to u}{e^{P}}}{\frac{e^{F}\to u}{e^{F}}} = \frac{\lambda_P}{\lambda_F}. \tag{4.21}$$

Consistent with the findings in Section 3, the model predicts a constant ratio of these flows, which is equal to the ratio of the arrival rates of the two shocks. Next, we show the ratio of flows between part and full-time employment.

Proposition 4. *The ratio of the PT→FT rate to the FT→PT rate in the steady-state is given by:*

$$\frac{\frac{e^{P}\to e^{F}}{e^{P}}}{\frac{e^{F}\to e^{P}}{e^{F}}} = \frac{\lambda_P[1-F(\epsilon_F)]}{\lambda_F[F(\epsilon_F)-F(\epsilon_P)]}. \tag{4.22}$$

Further, it is sufficient for flows from part to full-time employment exceed full to part-time employment in steady-state if $\lambda_P > \lambda_F$ and $[1 - F(\epsilon_F)] > [F(\epsilon_F) - F(\epsilon_P)]$.

This proposition shows that if we restrict the parameter space, the model is able to replicate the findings in Section 3 that flows from part to full-time employment exceed full to part-time employment. In particular, when $\lambda_P > \lambda_F$ and $[1 - F(\epsilon_F)] > [F(\epsilon_F) - F(\epsilon_P)]$ flows from part-time to full-time exceed full-time to part-time in steady-state.

Last, we show that the model predicts that the ratio of flows out of unemployment to full and part-time employment is proportional to flows between part and full-time employment, consistent with our previous empirical findings.

Proposition 5. *The ratio of the U→PT rate to the U→FT rate in the steady-state is given by:*

$$\frac{\frac{u \to e^F}{u}}{\frac{u \to e^P}{u}} = \frac{[1 - F(\epsilon_F)]}{[F(\epsilon_F) - F(\epsilon_P)]}; \tag{4.23}$$

which is proportional to flows between full and part-time employment (Equation 4.22) without the proportionality factor $\frac{\lambda_P}{\lambda_F}$.

It is worth highlighting that Figure 3.3b shows that this ratio is roughly equal to the ratio of flows from part and full-time employment to unemployment times flows between part and full-time employment. Such pattern is also predicted by our model.

In the next section we explore how these flows vary over the business cycle and under what conditions our model will yield results consistent with our findings in Section 3.

4.5 Adjustments over the Business Cycle

Next, we assess how employment in our model responds to changes in aggregate productivity by conducting a series of comparative statics. Our model contains two key margins of adjustment that determine employment. One is the utilization threshold, ϵ_F, the other one is the separation threshold, ϵ_P. The magnitude of the response of both thresholds to aggregate shocks dictates how employment adjusts in our economy.

The degree of cyclicality that each threshold exhibits depends upon the cyclicality of rents as well as gains or losses from changes in employment utilization. The following proposition shows the response for the full-time threshold.

Proposition 6. *Holding all else equal, the response of the utilization threshold to a change in* *aggregate productivity is given by:*

$$\frac{\partial \epsilon_F}{\partial z} = \frac{-(r+\lambda_P)(\tau_F + b + \frac{\alpha}{1-\alpha}\kappa(\theta - z\frac{\partial \theta}{\partial z}))}{z^2((r+\lambda_P)Y_F - (r+\lambda_F)Y_P - \lambda_F(Y_F - Y_P)(1-F(\epsilon_F)))} - \frac{Y_P(r+\lambda_F F(\epsilon_P))}{(r+\lambda_P)Y_F - (r+\lambda_F)Y_P - \lambda_F(Y_F - Y_P)(1-F(\epsilon_F))}\frac{\partial \epsilon_P}{\partial z}; \tag{4.24}$$

when $\lambda_P = \lambda_F$,

$$\frac{\partial \epsilon_F}{\partial z} = -\frac{\tau_F - \tau_P}{z^2(Y_F - Y_P)}. \tag{4.25}$$

It is worth noting that the first expression in this proposition can not always be unambiguously signed. The first term shows that as the cost of full-time employment increases, this threshold becomes more countercyclical (equivalently, the measure of shocks that result in full-time employment becomes more procyclical). The second term highlights the interaction between the responses of part and full-time employment. If an aggregate shock makes part-time employment more lucrative (ϵ_P decreases by more), the impact on full-time employment is muted. Workers and firms would prefer more matches to end in part-time employment, limiting the scope of the effect on full-time employment.

When we impose that $\lambda_P = \lambda_F$ this threshold is clearly countercyclical. It is also clear that costs drive this cyclicality. On the other hand, if $\tau_F - \tau_P < Y_F - Y_P$ an increase in τ_F and Y_F, that leaves net output unchanged. This will increase the countercyclicality of this threshold.

Like the utilization threshold, the separation threshold depends on costs and the response of full-time employment. We show the corresponding response in the following proposition.

Proposition 7. *Holding all else equal, the response of the separation threshold to a change in aggregate productivity is given by:*

$$\frac{\partial \epsilon_P}{\partial z} = \frac{-\tau_P - b - \frac{\alpha}{1-\alpha}\kappa(\theta - z\frac{\partial \theta}{\partial z})}{Y_P(r+\lambda_P F(\epsilon_P))} + \frac{\lambda_P(Y_F - Y_P)(1-F(\epsilon_F))}{Y_P(r+\lambda_P F(\epsilon_P))}\frac{\partial \epsilon_F}{\partial z} \tag{4.26}$$

when $Y_F = Y_P$,

$$\frac{\partial \epsilon_P}{\partial z} = \frac{-\tau_P - b - \frac{\alpha}{1-\alpha}\kappa(\theta - z\frac{\partial \theta}{\partial z})}{Y_P(r+\lambda_P F(\epsilon_P))}. \tag{4.27}$$

This comparative static yields similar insights as the previous one. To have a better understanding, we focus on the second equation of Proposition 7. When part and full-time employment yield the same output (i.e., there is only one type of employment), changes in costs amplify the countercyclicality of this threshold, a point noted by Pissarides (2009).

Now we explore what conditions on these thresholds are required for our model to be consistent with our findings in Section 3. We start with the ratio of flows into unemployment.

Proposition 8. *The ratio of flows to unemployment is acyclical. This results in the following:*

$$\frac{\partial \frac{PT \to U}{FT \to U}}{\partial z} = 0. \tag{4.28}$$

Because the separation thresholds are identical for part and full-time employment, this ratio is acyclical. It is worth noting that when we depart from a steady-state analysis, the previous result will no longer hold. However, the separation thresholds will remain close to acyclical out of steady state. Next, we turn to flows out of unemployment and flows between part and full-time employment.

Proposition 9. *The cyclicality of the ratio of flows from unemployment to full-time relative to flows from unemployment to part-time is given by:*

$$\frac{\partial \frac{U \to FT}{U \to PT}}{\partial z} = -\frac{[(1-F(\epsilon_P))f(\epsilon_F)\frac{\partial \epsilon_F}{\partial z} - (1-F(\epsilon_F))f(\epsilon_P)\frac{\partial \epsilon_P}{\partial z}]}{[F(\epsilon_F) - F(\epsilon_P)]^2}; \tag{4.29}$$

and this ratio is procyclical if the following condition is satisfied:

$$(1-F(\epsilon_P))f(\epsilon_F)\frac{\partial \epsilon_F}{\partial z} \leq (1-F(\epsilon_F))f(\epsilon_P)\frac{\partial \epsilon_P}{\partial z}. \tag{4.30}$$

If flows from full to part-time employment are countercyclical $\left(f(\epsilon_F)\frac{\partial \epsilon_F}{\partial z} \leq f(\epsilon_P)\frac{\partial \epsilon_P}{\partial z}\right)$, this requires that the measure of shocks that yield employment $(1 - F(\epsilon_P))$ to be large enough relative to shocks that yield full-time employment $(1 - F(\epsilon_F))$.

Finally, we explore the properties of flows between part and full-time employment over the business cycle, which is given by Equation 4.22. This is identical to the ratio of flows out of unemployment, scaled by the frequency of shocks.

Proposition 10. *The cyclicality of the ratio of flows between part and full-time employment is given by:*

$$\frac{\partial \frac{PT \to FT}{FT \to PT}}{\partial z} = -\frac{\lambda_P[(1-F(\epsilon_P))f(\epsilon_F)\frac{\partial \epsilon_F}{\partial z} - (1-F(\epsilon_F))f(\epsilon_P)\frac{\partial \epsilon_P}{\partial z}]}{\lambda_F[F(\epsilon_F) - F(\epsilon_P)]^2}; \tag{4.31}$$

and this flow ratio is procyclical if the following condition is satisfied:

$$(1-F(\epsilon_P))f(\epsilon_F)\frac{\partial \epsilon_F}{\partial z} \leq (1-F(\epsilon_F))f(\epsilon_P)\frac{\partial \epsilon_P}{\partial z}. \tag{4.32}$$

This finding is simply scaling the flows out of unemployment by $\frac{\lambda_P}{\lambda_F}$. This reflects the fairly stable relationship between these ratios that we reported in Figure 3.5.

To be able to determine the procyclicality of the ratio of flows from unemployment to full-time employment relative to flows from unemployment to part-time employment, we need to determine how the different endogenous employment thresholds respond. Figure 4.2 depicts the impact of an aggregate shock to the steady-state employment thresholds.

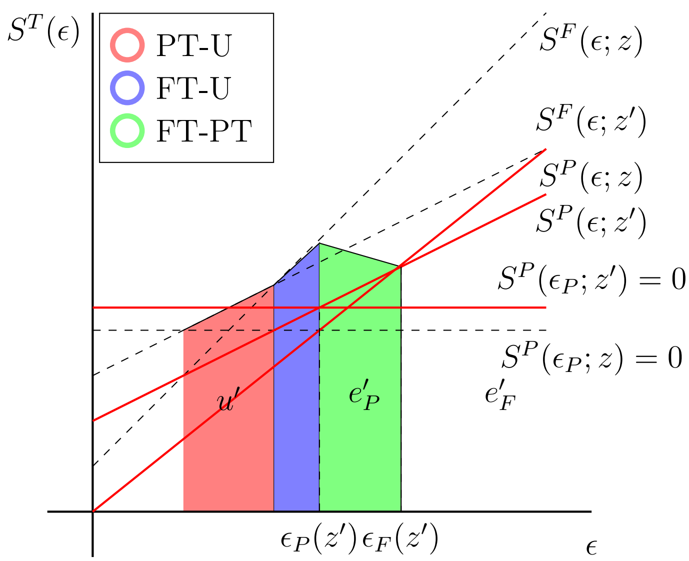


Figure 4.2: Graphical response of surplus and thresholds to aggregate shocks.

As we can see, the model's prediction can be consistent with Proposition 9. Findings in Section 3 suggest that flow from full-time employment to part-time employment is pro-cyclical. This type of flow is mainly observed among workers staying within the same firm. Similarly, flows from part-time employment to full-time employment is counter-cyclical, and is also found primarily with workers staying within the same firm.

4.6 Acyclical Costs and Employment

An important aspect of our economic environment is that employers face differential acyclical fixed costs that differ by worker utilization. This model feature reflects the fact that part and full-time employment are critically shaped by legislation, resulting in different costs and legal requirements.[21] Next we analyze how changes in these costs affect the endogenous employment thresholds. We first start with the full-time threshold.

Proposition 11. *The effect of a change in full-time costs on the part/full separation threshold*

[21]For instance, in the U.S., full-time jobs often offer paid time-off and employer-sponsored retirement programs. Moreover, employing firms are required to provide health insurance to workers. These features are not present in part-time employment arrangements.

is given by:

$$\frac{\partial \epsilon_F}{\partial \tau_F} = \frac{(r+\lambda_P)(r+\lambda_F)[(r+\lambda_P)+(\lambda_P-\lambda_F)\kappa\frac{\alpha}{1-\alpha}\frac{\partial\theta}{\partial\tau_F}] - (r^2-\lambda_P\lambda_F)(\lambda_P-\lambda_F)[1-F(\epsilon_P)]\frac{\partial\epsilon_P}{\partial\tau_F}}{((r+\lambda_P)Y_F-(r+\lambda_F)Y_P)(r+\lambda_P)(r+\lambda_F)-(r^2-\lambda_P\lambda_F)(\lambda_P-\lambda_F)[1-F(\epsilon_F)](Y_P-Y_F)}; \tag{4.33}$$

and when $\lambda_F = \lambda_P$,

$$\frac{\partial \epsilon_F}{\partial \tau_F} = \frac{1}{z(Y_F - Y_P)}. \tag{4.34}$$

Like our findings for aggregate productivity in Section 4.5, the utilization threshold responds in two distinct ways to changes in costs. First, the threshold increases because full-time matches produce less surplus. Note, however, that the second term is ambiguous. The threshold may decrease because the value of part-time employment is partially dependent on the possibility that a worker may eventually transition to full-time employment. However, it may also amplify the impact if part-time employment is profitable on its own. The key takeaway is that as the value of full-time work declines, it has a long lasting effect on part-time employment. Next, we consider how the part-time threshold responds to changes as costs vary.

Proposition 12. *The effect of a change in part-time costs on the employment/unemployment separation threshold is given by:*

$$\frac{\partial \epsilon_P}{\partial \tau_P} = \frac{r+\lambda_P}{(r+F(\epsilon_P))zY_P} + \frac{\lambda_P}{r+F(\epsilon_P)}[1-F(\epsilon_F)](\frac{Y_F}{Y_P}-1)\frac{\partial \epsilon_F}{\partial \tau_P}. \tag{4.35}$$

As before, this expression varies with the response of the full-time threshold to part-time costs. If the expected surplus of full-time employment declines, the utilization threshold may increase as well, exacerbating the effects. If the surplus is largely unaffected, firms may shift workers to full-time employment.

5 Model Parametrization and Quantitative Results

In this section we describe how we take our model to the data. To do so, first we use functional forms and a subset of parameters values commonly accepted in the search literature. After external calibration of some parameter values, we use simulated method of moments by matching implied steady-state flows generated by the model.

From now on, we approximate our model in discrete time at a weekly frequency, with discount factor $\beta = \frac{1}{1+r}$, and allow for aggregate productivity, z, to evolve in response to shocks.

5.1 External Calibration

In terms of functional forms, we make the common assumption that the matching function is Cobb-Douglas, $M(u,v) = Au^{\eta}v^{1-\eta}$, where η is the elasticity parameter, and A the efficiency parameter. We further assume that idiosyncratic productivity is described by $\epsilon \sim LN(\mu_{\epsilon}, \sigma_{\epsilon})$, and the evolution of aggregate productivity is given by $ln(z_{t+1}) = \rho_Z ln(z_t) + \nu$, where $\nu \sim N(0, \sigma_z)$. Throughout the rest of our quantitative analysis, we approximate the dynamics of the aggregate shock using the method described in Tauchen (1986).

Given our functional forms, we follow the literature and externally calibrate a subset of our parameters. We set the matching function elasticity to $\eta = 0.72$, following Shimer (2005), who estimates this parameter directly from the data. We also make the common assumption that the Hosios Condition holds. As a result, the bargaining power of a worker equals the elasticity of the matching function with respect to unemployment; i.e, $\alpha = \eta = 0.72$. We normalize output of a part-time employment to be $Y_P = 1$, so that all parameters are relative to part-time output. We follow Fujita and Ramey (2012) and set vacancy creation cost, κ, the productivity cost of 6.7 hours of work. We assume the work is part-time and which yields $\kappa = 0.2939$ by taking 6.7 hours divided by an average of 22.8 hours per week for part-time work in our sample. The appropriate value for unemployment utility is contentious, ranging from 0.4 estimated by Shimer (2005) to 0.955, estimated by Hagedorn and Manovskii (2008), and has important implications for labor market fluctuations in search models (Hagedorn and Manovskii, 2008). We follow Mortensen and Nagypal (2007) and set unemployment utility to $b = 0.7$. This is conservative in our model because b is typically targeted as a fraction of average productivity, which in our model exceeds 1. However, a high b results in little or no part-time employment. As a result, we target 70% of part-time output. We consider an annual interest rate of 4%, which yields a weekly interest rate of $r = 0.0012$. This results in a discrete discount factor, $\beta = \frac{1}{1+r}$, of 0.9992. For parameters describing the aggregate productivity process, we follow Hagedorn and Manovskii (2008), who estimate an AR(1) productivity process in a search model yielding $\rho_Z = 0.9895$ and $\sigma_Z = 0.0034$.

After implementing this parametrization, we are left with 8 parameters to estimate: Y_F, τ_F, τ_P, λ_F, λ_P, σ_{ϵ}, and A. We choose to calibrate these parameters internally rather than externally because they are either novel $(Y_F, Y_P, \tau_F, \tau_P, \lambda_F, \lambda_P)$, affect the endogenous productivity process (σ_{ϵ}), or are a normalization (A). We first impose the restriction on the arrival rate of idiosyncratic shocks implied by Equation 4.21, $\frac{PT-U}{FT-U} = \frac{\lambda_P}{\lambda_F}$. In our data, the average arrival rates for $PT - U$ and $FT - U$ are 0.546 and 0.0087, respectively. Such values imply $\lambda_P = 6.23\lambda_F$.

5.2 Simulated Methods of Moments

To determine the 6 remaining parameters we use the simulated method of moments procedure. In particular, we target steady state flows between full-time, part-time, and unemployment as well as steady-state rates of part and full-time employment to discipline the value of the remaining parameters. To do so, we estimate these series at a monthly frequency in the CPS between 1996 and 2019, using the same sample restrictions that we described in Section 3.

Although our parameters are jointly estimated and therefore their sources of identification are difficult to pin down explicitly, we can outline the moments most closely associated with each parameter. The cost and productivity parameters Y_F, τ_F, τ_P determine the relative net output of part and full-time work, and therefore primarily adjust employment levels. The arrival rate of match-specific shocks for full-time work, λ_F, determines the frequency with which a full-time worker may transition to part-time or unemployment, and σ_ϵ determines the probability of such a transition, and therefore are primarily identified by flows out of full and part-time employment. The final parameter, A, proportionally changes the job-finding rate, and as a result can be primarily associated with flows out of unemployment. The underlying parameter values are reported in Table 1.

Parameter	Value	Comment
Y_F	5.51	Full-time prod.
Y_P	1.00	Part-time prod. (normalized)
τ_P	0.1602	Part-time cost
τ_F	4.24	Full-time cost
λ_F	0.0218	Rate of full-time ϵ shocks
λ_P	0.1363	Rate of part-time ϵ shocks (fixed to 6.23 times λ_F)
σ_ϵ	0.1717	SD of ϵ shocks
A	0.1557	Matching efficiency
b	0.7	Unemp. utility (Mortensen and Nagypal, 2007)
η	0.7	Matching elasticity (Shimer, 2005)
α	0.7	Hosios condition
β	0.9992	Annual discount rate of
κ	0.2939	Vacancy creation cost (Fujita and Ramey, 2012)
ρ_Z	0.9895	Agg. shock persistence (Hagedorn and Manovskii, 2008)
σ_Z	0.0034	SD of agg. shocks (Hagedorn and Manovskii, 2008)

Table 1: Parameter values.

5.3 Targeted Moments

After we assign parameter values according to the previous procedure, we find that the benchmark model is able to closely match all of the estimated targets. These are reported in Table 2.

As we can see, our model narrowly undershoots the job-finding rate of part-time work (0.0856 in the data versus 0.0807 in the model). As a result, the model overshoots the job-finding rate

Moment	Data	Model
Full-Time Emp.	0.9059	0.9031
Part-Time Emp.	0.0567	0.0592
$U \to FT$	0.2086	0.2134
$U \to PT$	0.0856	0.0807
$FT \to PT$	0.0211	0.0224
$PT \to FT$	0.3399	0.3389
$FT \to U$	0.0087	0.0088
$PT \to U$	0.0546	0.0537

Table 2: Estimation results.

of full-time work (0.2086 in the data versus 0.2134 in the model). Nevertheless, both of these equilibrium outcomes are still close to their data counterparts. The remaining moments are within fractions of a percent. We achieve this fit with parameter values that closely align with the results from previous papers.[22]

5.4 Non-Targeted Moments

In order to assess the performance of our benchmark parametrization, we now compare our model predictions of non-targeted moments generated by the model with the corresponding data counterparts. In particular, we first compare whether our model can produce similar levels of cyclicality among employment stocks and flows as in the data. Then, we compare our model's predictions about employment stocks and flows between 1996 and 2020 to the data using an estimated productivity series.

To do this comparison, we consider two simulations. First, we simulate the model with 1000 random series of productivity draws. Then, we use our estimated productivity series for the period between 1996 and 2020. For each of the simulations, we calculate the covariance between labor productivity and a set of detrended series, including part and full-time employment as well as each flow between labor market states, part-time, full-time, and unemployed.[23] We present our findings in Table 3.

Shocks	FT Emp.	PT Emp	FT→PT	PT→FT	FT→U	PT→U	U→FT	U→PT
Data	0.84	-0.80	-0.52	0.19	-0.55	-0.18	0.58	0.43
Simulated	0.94	-0.91	-0.42	0.23	-0.96	-0.70	0.96	-0.12
Great Rec.	0.93	-0.88	-0.16	0.14	-0.96	-0.74	0.97	0.06

Table 3: Non-targeted cyclicality moments.

[22]Our best fit yields a standard deviation of idiosyncratic shocks (σ_ϵ) of 0.172 and a matching scale parameter (A) of 0.156, both slightly higher than their estimates in Fujita and Ramey (2012), 0.16 and 0.094. We find that shocks arrive for full-time workers with probability $\lambda_F = 0.0218$ each week, which corresponds to $\lambda_P = 0.1363$ (6.23 times λ_F). We estimate that acyclical costs constitute about 13.5% of part-time output ($\tau_P = 0.1602$ with Y_P normalized to 1) and 77.0% of full-time output ($\tau_F = 4.24$ and $Y_F = 5.51$).

[23]We measure this as output/hours. In our model simulations, we set full and part-time hours to their averages between 1996 and 2020, 46 and 22.8 hours respectively.

Table 3 shows that the benchmark model is able to replicate the cyclicality of the majority of series. The anomaly is that it predicts a weakly negative correlation between labor productivity and the job-finding rate rate of part-time employment. The data predicts a positive correlation. However, this is weakly negative and as our Great Recession shocks indicate, the model is capable of producing a positive correlation as well. Under either set of shocks, the model matches the cyclicality of part and full-time employment, and nearly replicates the flows between part and full-time employment and flows to unemployment. It also does a reasonable job matching the cyclicality with a one quarter lead or lag as we show in Section A.2.

To further determine the performance of our framework, we simulate the model to the data between 1996 and 2020. To do this, we first estimate a sequence of aggregate shocks $Z_1, ..., Z_T$ by targeting quarterly labor productivity in the data. We do this because productivity in our model is endogenous. This is the case as both part and full-time work have different base levels of productivity and because separation thresholds vary over time. We then feed this series into the model and compare our results with the corresponding data counterparts. These different series are depicted in Figure 5.1. The top two figures plot full and part-time employment in the left and right panels, respectively. The bottom two figures display the aggregate employment and unemployment rates. In each figure, the dashed blue line with triangle markers denotes the simulated data, while the red line with circle markers corresponds to the observed data.

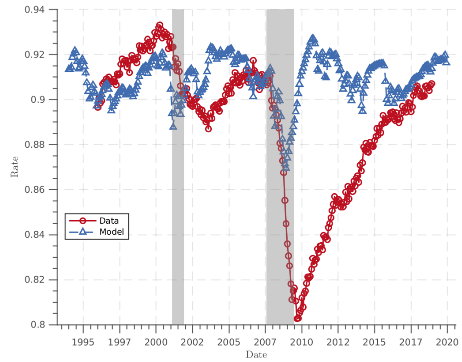
Again, these figures show that our model does a good job replicating the cyclicality of each series. In particular, we find that both full-time employment and aggregate employment are procyclical, while it predicts that both part-time employment and unemployment are countercyclical. This is precisely what is observed in Section 3. While the model does a reasonable job matching the data for most years, the model does not generate fluctuations of the same magnitude during the Great Recession. This suggests that in addition to the mechanisms in the presented in the model, there are other forces at play, such as demand-side fluctuations.[24]

The model is able to replicate the flows observed in the data. In the top two panels of Figure 5.2, we plot the flows from full-time to part-time (left) and part-time to full-time (right). In the bottom two panels, we plot the flows from full-time to unemployment and part-time to unemployment.

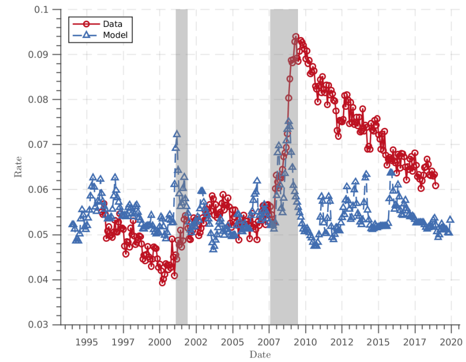
Although the model accounts for a large share of the volatility of each series, it does not quite capture the persistent increase in either the rate of workers flowing from full-time to part-time or the rate of workers flowing from full-time to unemployment.

The reason for the apparent inconsistency between the ability of our model to match flows out of part and full-time employment and its inability to replicate the stock of employed workers in Figure 5.1 is due to a well-known puzzle in the search and matching literature emphasized by (Shimer, 2005). The model does not replicate the degree of volatility in the job-finding rate

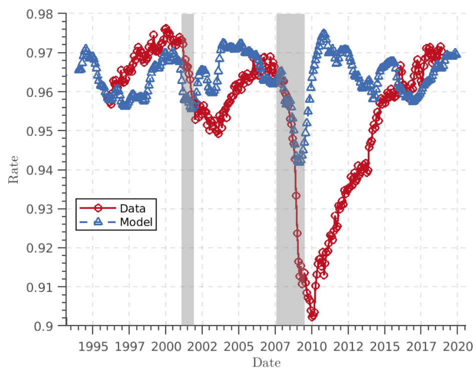
[24] We refer to (Warren, 2015) for more on this.



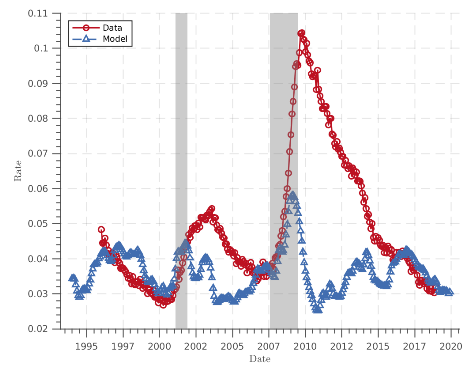
(a) Full-Time Employment



(b) Part-Time Employment



(c) Employment Rate

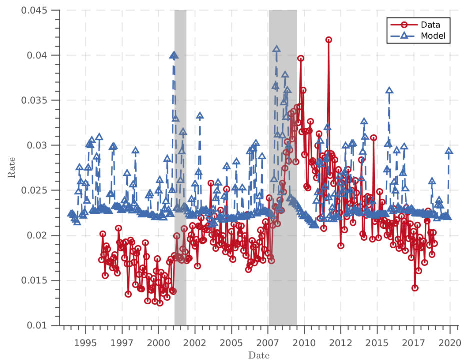


(d) Unemployment Rate

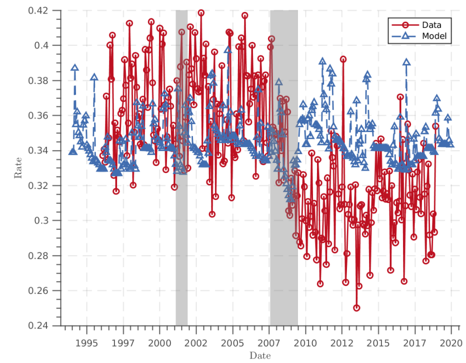
Figure 5.1: Comparison between observed and model generated employment rates.

that we observe in the data. We plot the job-finding rate of unemployed workers for full-time jobs (left panel) and part-time employment (right panel) in Figure 5.3.

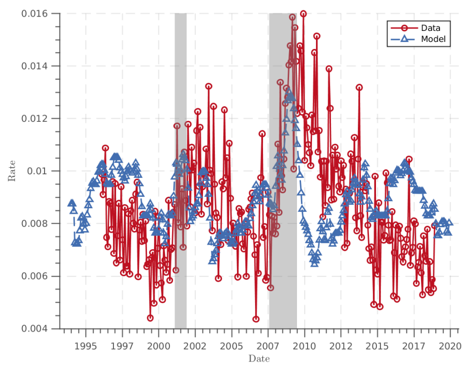
While the model does better at capturing fluctuations in the full-time job-finding rate, it predicts negligible fluctuations in the part-time job-finding rate. As pointed out by Shimer (2005), Hagedorn and Manovskii (2008), and Hall and Milgrom (2008), among many others, this occurs because the bulk of the fluctuations in productivity are reflected by changes in wages.



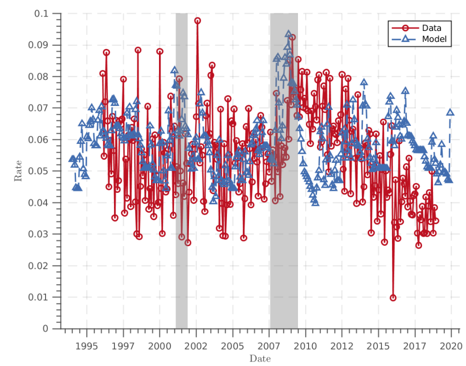
(a) Full-time to part-time



(b) Part-time to full-time

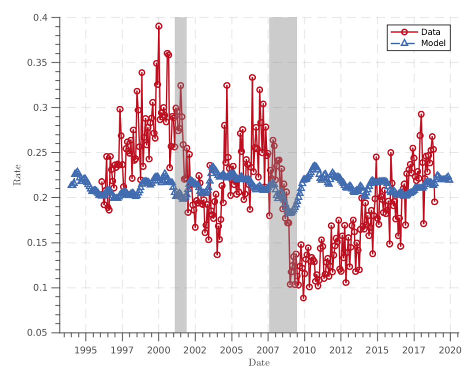


(c) Full-time to unemployment.

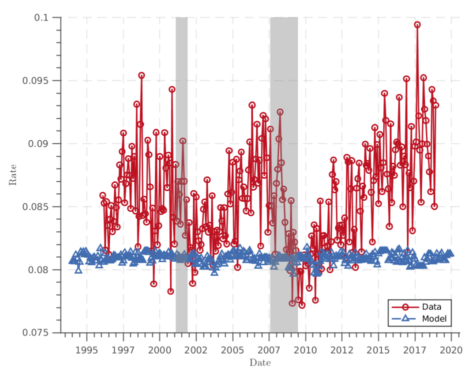


(d) Part-time to unemployment

Figure 5.2: Observed and model generated employment flows.



(a) Unemployment to full-time.



(b) Unemployment to part-time.

Figure 5.3: Observed and model generated employment flows from unemployment.

6 Exploring the Mechanisms

6.1 The Cyclicality of Part and Full-Time Employment

Before delving into the sources of cyclicality in the model, we explore the mechanisms that result in the dynamics of the model. First, we explore how the utilization and separation thresholds, ϵ_F and ϵ_P, respectively, fluctuate in response to aggregate shocks. Second, we describe how the endogenous distribution of match quality evolves over the business cycle. Finally, we show how aggregate shocks affect vacancy creation, which in turn impacts market tightness and the job-finding rate. Each of these mechanisms are determined in equilibrium and contribute to the variability and cyclicality of our model implied labor market series.

It is important to highlight that in our framework there are six flows and an equilibrium match quality distribution that fluctuate in response to exogenous disturbances. To better identify and understand these responses, we first consider how the evolution of match quality changes when workers and firms face exogenous aggregate shocks. Such marginal effect is given by:

$$\begin{aligned}\dot{G}(x) = (P(\theta)u + \lambda_P e^P + \lambda_F e^F)[F(x) - F(\epsilon_P)] - \lambda_P G(x)(1-u) - \\ - (\lambda_F - \lambda_P)\mathbb{1}_{x \geq \epsilon_F}[G(x) - G(\epsilon_F)](1-u) + \gamma[G(\epsilon_P) - G(\tilde{\epsilon}_P)];\end{aligned} \tag{6.1}$$

where γ denotes the arrival rate of aggregate shocks, and $\tilde{\epsilon}_P$ represents the separation threshold for part-time employment after the arrival of an aggregate shock. The arrival of an aggregate shock yields asymmetric changes in this distribution. In particular, if $\tilde{\epsilon}_P > \epsilon_P$, matches with productivity $\epsilon \in [\epsilon_P, \tilde{\epsilon}_P]$ dissolve. In contrast, when $\tilde{\epsilon}_P < \epsilon_P$, there is no instantaneous effect on the match quality distribution because employment is not a jump variable. Aggregate shocks also affect the match quality distribution by changing the arrival rate of offers, $p(\theta)$, and the frequency with which they result in a match, $[1 - F(\epsilon_P)]$.

The flows in the stochastic version of the model are very similar to the steady-state version, which are described in Section 4. The main difference is that in the stochastic version there is an endogenous response of the distribution of match quality to aggregate shocks. Flows between part and full-time employment respond to idiosyncratic shocks. In addition, the evolution of the distribution of match quality as well as flows into unemployment also change. More precisely, we have the following:

$$\frac{e^F \to e^P}{e^F} = \lambda_F[F(\epsilon_F) - F(\epsilon_P)] + \gamma[G(\epsilon_F) - G(\tilde{\epsilon}_F)]; \tag{6.2}$$

$$\frac{e^P \to e^F}{e^P} = \lambda_P[1 - F(\epsilon_F)] + \gamma[G(\tilde{\epsilon}_F) - G(\epsilon_F)] + \gamma[G(\epsilon_P) - G(\tilde{\epsilon}_P)]; \tag{6.3}$$

$$\frac{e^F \to u}{e^F} = \lambda_F F(\epsilon_P) + \gamma G(\epsilon_P); \tag{6.4}$$

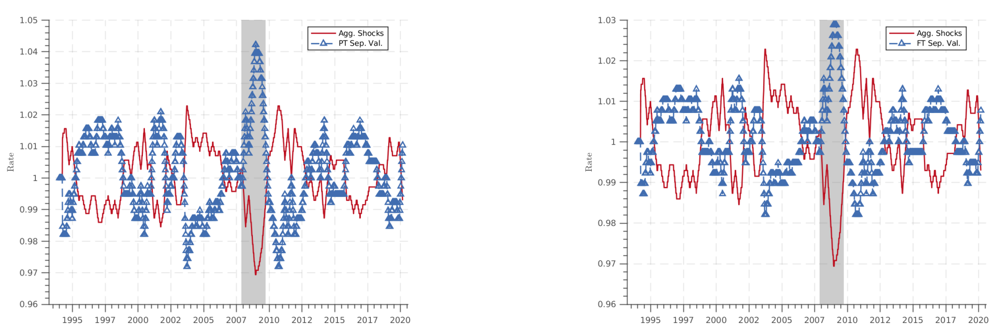
$$\frac{e^P \to u}{e^P} = \lambda_P F(\epsilon_P) + \gamma G(\epsilon_P); \tag{6.5}$$

where $\tilde{\epsilon}_F$ represents the separation thresholds for full-time employment after the arrival of an aggregate shock. The final two flows, those out of unemployment, are determined by both changes in the utilization, separation thresholds and the response of vacancy creation to aggregate shocks. In particular, we have that

$$\frac{u \to e^F}{u} = p(\theta)[1 - F(\epsilon_F)]; \tag{6.6}$$

$$\frac{u \to e^P}{u} = p(\theta)[F(\epsilon_F) - F(\epsilon_P)]. \tag{6.7}$$

Utilization and separation decisions are clearly important for understanding the variability and cyclicality of labor market flows. They lead to adjustments within already-existing matches. Moreover, they affect the creation of new matches in the economy. To understand the role of adjustment along these margins, we plot the utilization and separation thresholds along with the aggregate shock, normalized to their values prior to the Great Recession (Figure 6.1). The left panel plots the separation threshold, ϵ_P, as a dashed blue line with triangle markers, while aggregate productivity is depicted by a solid red line. The right panel of Figure 6.1 plots the utilization threshold, ϵ_F, as a dashed blue line with triangle markers. In both of the panels we normalize the initial period of each series to 1.



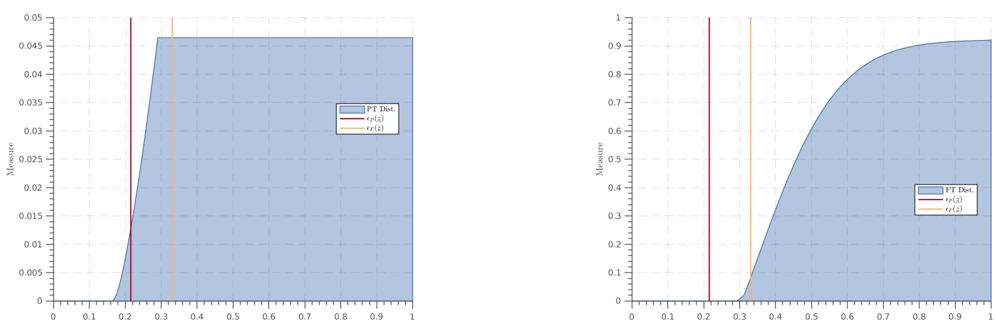
(a) Separation threshold.

(b) Utilization threshold.

Figure 6.1: Thresholds over time, plotted with aggregate productivity. Normalized to 1.

Both thresholds exhibit the same sort of countercyclical pattern, although the part-time threshold varies more. These fluctuations are at the core of the model's ability to explain the data. Workers continue to separate from part-time employment, leading to the countercyclical flow from part-time to unemployment. This occurs while simultaneously full-time matches reduce their utilization to part-time employment. Because full-time employment constitutes the bulk of aggregate employment, these inflows outweigh outflows to unemployment and cause part-time employment to be countercyclical.

Given this mechanism, we now study how the endogenous distribution of match quality evolves over the business cycle for part and full-time employment. Both flows between part and full-time employment and into unemployment respond to changes in the evolution of the distribution of match quality. In turn, this distribution changes when aggregate shocks affect the utilization and separation thresholds that workers and firms face. To illustrate these different source of fluctuations, we consider the distribution of match quality at two points in time. First, we plot the (un-normalized) CDF of part-time employment across the domain of idiosyncratic productivity, which we normalize so that it is between 0 and 1. We also include two lines that denote the separation threshold (red line) and utilization threshold (yellow line) at the bottom of the trough of the Great Recession. We repeat the procedure for full-time employment. The corresponding CDFs for part-time employment and full-time employment are reported in the on the left and right panel of Figure 6.2.



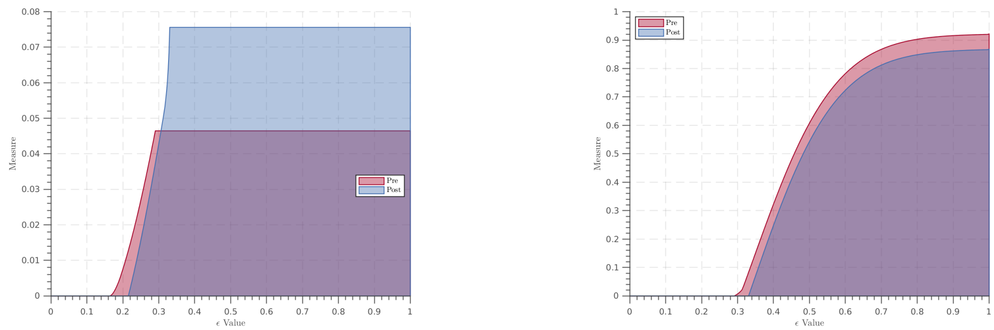
(a) Part-time match quality distribution.

(b) Full-time match quality distribution.

Figure 6.2: Match quality cumulative distributions at the peak prior to the Great Recession.

Next, we compare the match quality distributions at the peak and trough of the Great Recession. In what follows, we represent the peak distribution in blue, while the trough distribution is in red. We then overlay the match quality distribution of the trough on the match quality distribution of the peak prior to the Great Recession for part and full-time employment. These results are depicted in Figure 6.3. The left panel plots the part-time distribution, while the right one plots the full-time distribution.

As we have shown in Section 6.1.1, while the difference between the distributions is small,



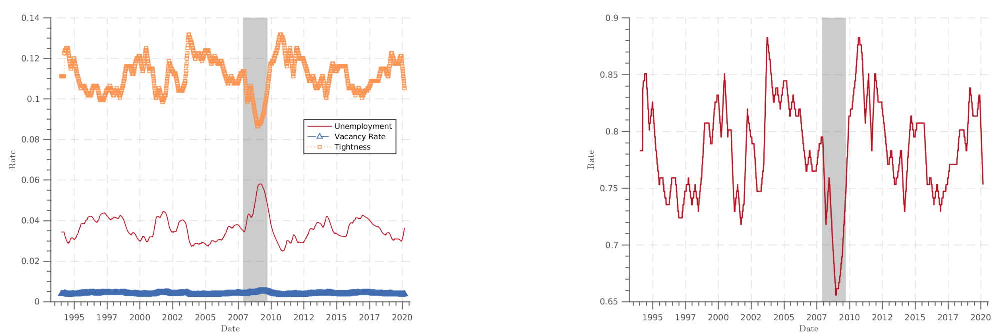
(a) Part-time match quality distribution.

(b) Full-time match quality distribution.

Figure 6.3: Match quality cumulative distributions at the peak prior to the Great Recession.

it has a sizable effect on employment.

Finally, we explore the evolution of vacancy creation over the Great Recession generated by our model. From Equation 6.6 and Equation 6.7, we can see that vacancy creation is key for job-finding rates. To see how this changes over the business cycle, we plot the vacancy rate and the unemployment rate as well as the expected surplus of a match during the Great Recession. This can be found in Figure 6.4 where the left panel shows the vacancy rate (blue dashed line) and the unemployment rate (red solid line). We also plot the resulting labor market tightness as a dotted orange line. In the right panel, we plot the expected surplus of a match.[25]



(a) Vacancy and unemployment rates.

(b) Expected surplus of a match.

Figure 6.4: Determinants of vacancy creation and the job-finding rate.

This shows that labor market tightness is strongly countercyclical, driven primarily by the increase in unemployment with no corresponding increase in vacancies. The expected surplus of a match declines, and although the contact rate increases for firms due to the increase in unemployed, the overall decline in the economic environment limits their response.

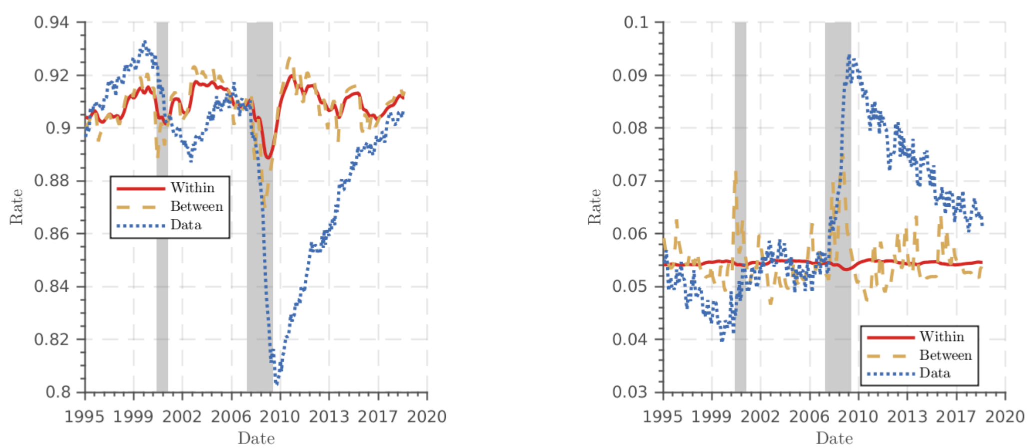
[25]A constant fraction $1-\alpha$ of which is the value of opening a vacancy to an unmatched firm.

6.1.1 Worker Composition and Labor Market Volatility

In this section, we formally consider the role that the composition of match quality plays in labor market fluctuations. To do so, we impose restrictions on our baseline model. These restrictions allow us to separately attribute variability to between-individual variation in match quality and within-individual variation in the aggregate state. Finally, we decompose the within-individual variation into the contribution of fluctuations in the job-finding rate and the separation rate.

In what follows, we first impose that the distribution of match quality is always proportional to the steady-state distribution. We also impose that separations do not depend on match quality. In particular, we assume that the separation and job-finding probabilities are set to their cross-sectional averages at each time, t, $\delta_t = \frac{e_t \to u_{t+1}}{e_t}$, and $p(\theta_t) = \frac{u_t \to e_{t+1}}{u_t}$. Separations occur with equal probability for all matches at time t. We assign new matches to be part or full-time based on the steady-state measures of employment in each state. That is, new matches result in full-time employment with probability e^{F*} and part-time employment with probability e^{P*}, where e^{F*} and e^{P*} are the steady-state measures of full and part-time employment, respectively. These restrictions allow us to isolate the effect of match quality because there is no variation in match quality between workers. In this context, all fluctuations are caused by aggregate shocks that affect the trajectory of the average worker.

The effect of match composition on employment in part and full-time employment is shown in Figure 6.5. The left panel reports part-time employment, while the right panel shows full-time employment. In both panels, the baseline model is represented by a solid red line, while our restricted model is denoted by a dashed yellow line, and the data is represented by a dotted blue line.



(a) Full-time employment. (b) Part-time employment.

Figure 6.5: Comparison between baseline and fixed composition models and the data.

Comparing our models with the data, it is clear that composition plays an important role in part and full-time fluctuations. While the fixed composition model predicts a decline in full-time employment, the decline is smaller than the model that includes composition effects. This difference is more clear for part-time employment: while the baseline model largely tracks the data, the fixed composition model counterfactually predicts procyclical part-time employment. This demonstrates the importance of the composition effects in explaining part-time employment.

Next, following the literature we perform a decomposition exercise that considers worker composition and wage growth.[26] We quantify the effect of worker composition by taking the difference between variables of interest from our baseline and that of our restricted model. In our baseline model, the observable x_t can be written as follows:

$$x_t = \gamma_t^B + \gamma_t^W; \tag{6.8}$$

where γ_t^B denotes the share explained by between-individual match quality variation and γ_t^W represents the share explained by within-individual variation. In our restricted specification, the same observable becomes

$$\hat{x}_t = \gamma_t^W. \tag{6.9}$$

Note that since the between individual variation is restricted to be zero, then the difference between the baseline and restricted model yields the following:

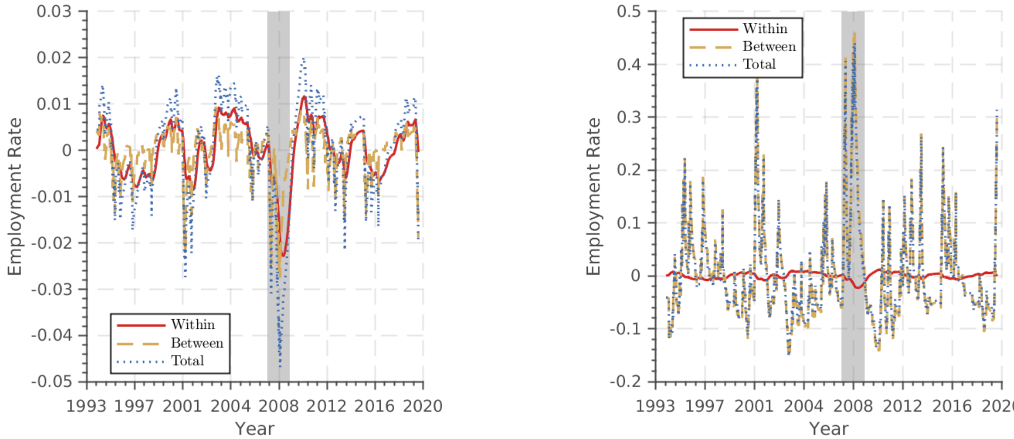
$$x_t - \hat{x}_t = \gamma_t^B. \tag{6.10}$$

Thus, we can easily determine the worker composition contribution. Thus, this decomposition allows us to assess the relative importance of fluctuations stemming from aggregate productivity and from the composition of workers.

This decomposition is illustrated in Figure 6.6. The right panel reports part-time employment, while full-time employment is in the left panel. In both figures, the solid red line denotes the total effect on employment, the dashed yellow line represents the "between" worker composition effect, and the dotted blue line shows the "within" aggregate productivity effect. In each case, the difference is calculated relative to the average level of employment over this time series. We present this decomposition alongside the data in Figure A.1.

As these figures show, the determinants of part and full-time employment fluctuations are markedly different. Changes in full-time employment are largely driven by aggregate shocks, with worker composition largely mirroring the within effects. These are only exceeding aggregate shocks during the very trough of the Great Recession. In contrast, part-time employment fluctuates almost entirely due to worker composition. This is especially the case during the

[26]We refer to Solon et al. (1994) and Daly and Hobijn (2017) for more on this type of exercise.



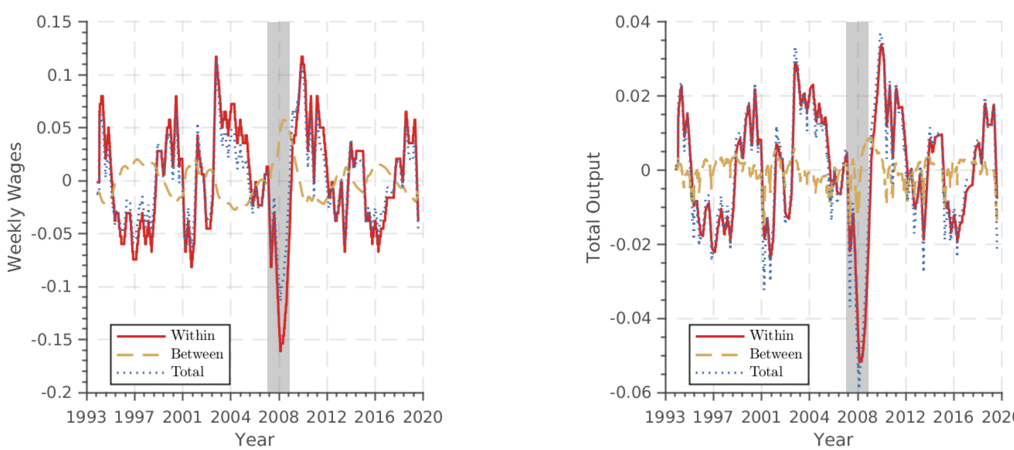
(a) Full-time employment.

(b) Part-time employment.

Figure 6.6: Employment decomposition.

Great Recession. If the average quality of part-time matches had not improved during the Great Recession (due to firms changing their utilization), part-time employment would have fallen even more. Instead, composition effects caused a 2.5 percentage point increase in part-time employment.

Next, we consider the impact of the composition effect on wages and output, which are illustrated by Figure 6.7.



(a) Wages.

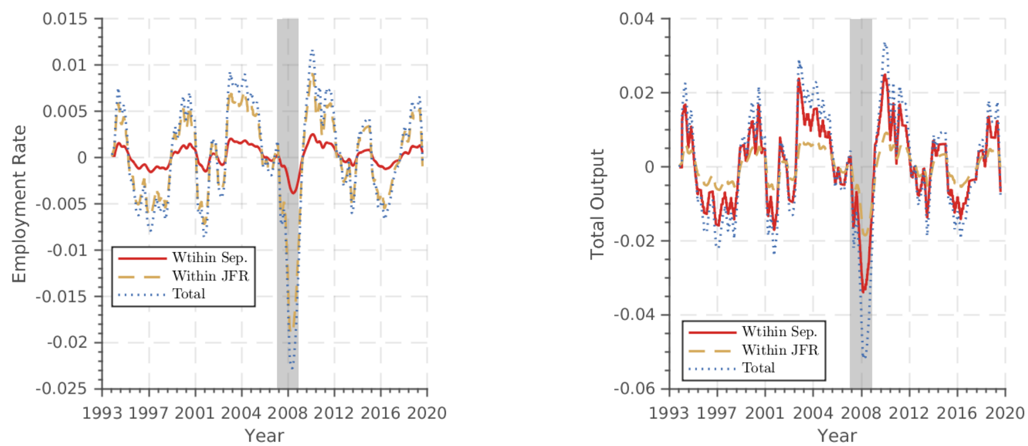
(b) Aggregate output.

Figure 6.7: Wage and output decomposition.

In both cases, the composition and aggregate effects partially offset each other. Similar to Daly and Hobijn (2017), we find that improvements in worker composition during the Great Recession muted the overall decline in wages. However, the total effect more closely mirrors the aggregate shock. The overall pattern indicates a procyclical real wage, which is contentious within the literature, but our finding of a procyclical composition effect mirrors the findings of

Daly and Hobijn (2017). Output exhibit similar patterns. The total effect largely mirrors the aggregate shock, but is muted somewhat by changes in worker composition.

Finally, we explore what drives the within variation. To do so, we further restrict our baseline model so that separation rates do not fluctuate with aggregate shocks. Thus, we set the probability of separation such that $\delta_t = \delta = E[\frac{e_t \to u_{t+1}}{e_t}]$, which is applied exogenously to all matches, effectively making the model identical to Shimer (2005). This allows us to assess how much of the within individual variation results from fluctuations in the job-finding rate and the separation rate. This is case as the only remaining source of fluctuations within the restricted model is the job-finding rate. We repeat our previous analysis on employment and output, but we just focus on the within decomposition. We present our findings in Figure 6.8, with aggregate employment on the left and total output on the right panels, respectively. The within effect of separations is denoted by a solid red line, the within effect of the job-finding rate is represented by the dashed yellow line, and the total effect is given by the dotted blue line.



(a) Aggregate employment.

(b) Aggregate output.

Figure 6.8: Within decomposition of employment and output.

Surprisingly, we find that the most important component is different depending which series we consider. For employment, the effect of the aggregate shock on the job-finding rate plays a larger role, explaining nearly all of the effect. In contrast, the separation rate plays a larger role in determining the aggregate effect on output.

6.2 The Importance of Part-Time Employment

In this section, we show that ignoring employment utilization has important implications for predictions about labor market fluctuations and the cost of downturns for workers.[27] We first

[27] This is important because only a handful of search models incorporate this dichotomy. Among them are Warren (2015), Borowczyk-Martins and Lalé (2020).

demonstrate that a model that pools part and full-time employment together will both i) under-predict the size of the decline in employment during a recession and ii) understate the impact of a downturn on workers. Next, we simulate a counterfactual model without a utilization distinction that matches the same steady-state as our baseline model and show the differences in predictions during the Great Recession.

Frameworks based on Mortensen and Pissarides (1994) are such that steady-state employment is determined by the expected surplus and the separation threshold. These same quantities determine steady-state employment in our model. The differences in that part and full-time employment introduce a non-convexity in the surplus in our model. This means that given a match quality $\epsilon \in [\epsilon_P, \epsilon_F)$, workers in our model are more likely to separate than workers in equally productive matches in a model without part-time employment when both models are subject to a negative aggregate shock. We plot the intuition for this result in Figure 6.9, by comparing a hypothesized surplus function for our model with a model that lacks a utilization dichotomy. The dashed red line shows the surplus in our baseline model, while the dashed blue line shows the surplus in the hypothesized model without part-time employment. The solid red and blue lines show the response of the surplus to aggregate shocks for our model and the counterfactual model, respectively.

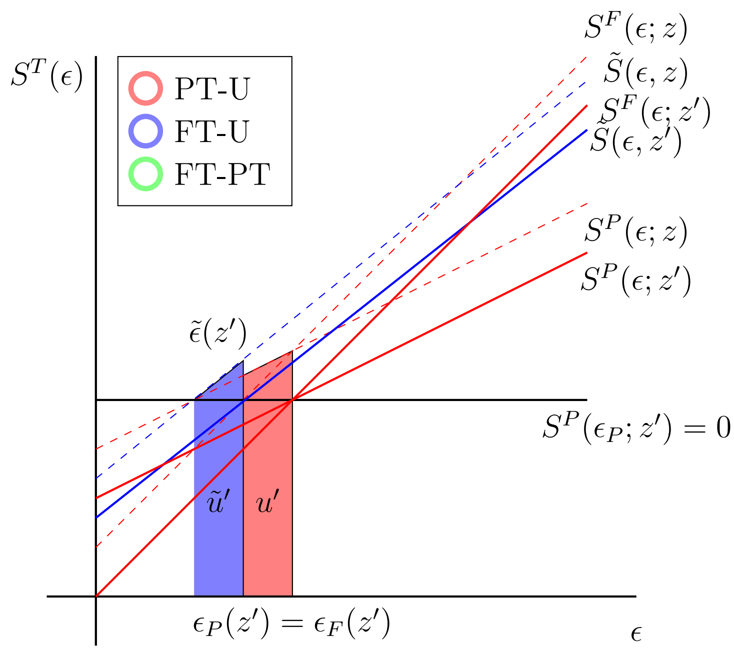
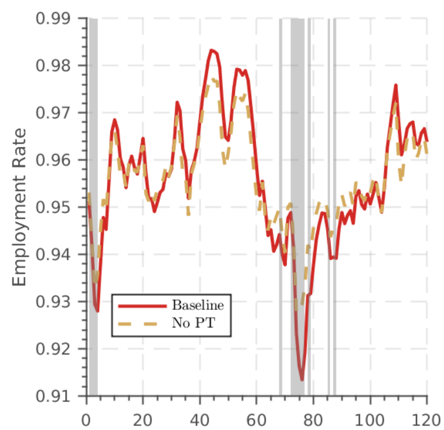


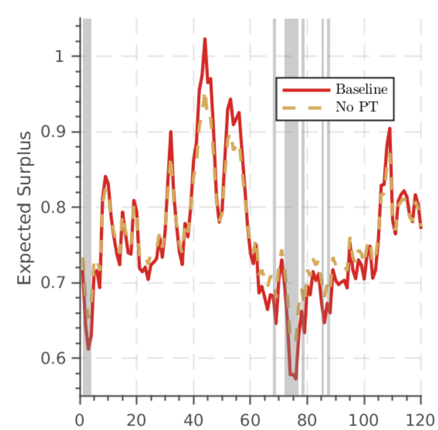
Figure 6.9: Graphical response to aggregate shocks for the baseline and no part-time economies.

Intuitively, while both economies suffer a decline in aggregate productivity, the lower surplus among the part-time employment causes a larger decline in employment. In the economy without a utilization dichotomy, unemployment increases by $\tilde{u}'$. In our economy, unemployment would increase by $\tilde{u}' + u'$. To further highlight this mechanism, we now calibrate a canonical search model and compare it to our benchmark model.

To determine the effects of removing the intensive margin, we estimate a counterfactual model in which there is no distinction between part and full-time employment. The model retains the same estimate of A as in the baseline model and we set the arrival rate of shocks λ to the population average in the baseline model, $\lambda = \lambda_P e^P + \lambda_F e^F$. The only distinction between our counterfactual and the Mortensen and Pissarides (1994) model is that we include an acyclical cost, τ, to keep rents procyclical so that our findings are comparable to our baseline model. We subject the two models to the same series of aggregate shocks and compare them. In the left panel, we compare the impact of aggregate shocks on employment in both economies. In the right panel, we depict the average surplus in both economies over this period. In both panels, the baseline economy is the solid red line and the economy without part-time employment is represented by the dashed line.



(a) Average employment.



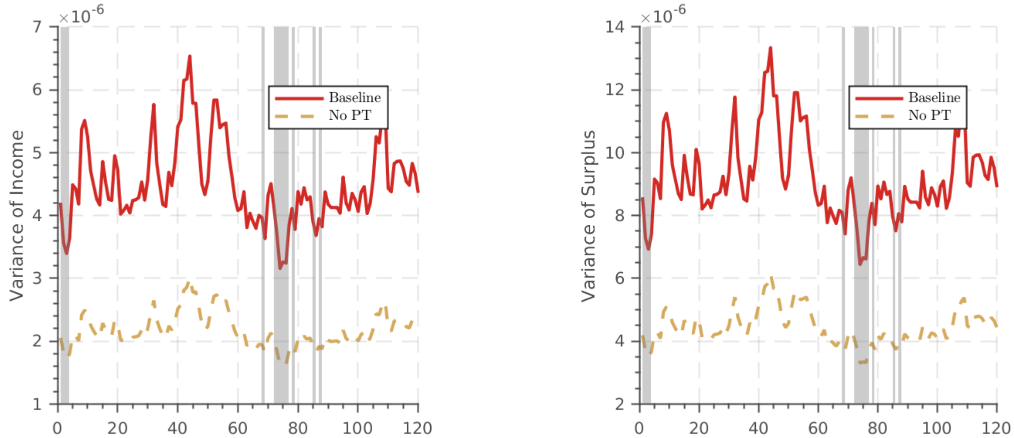
(b) Expected surplus of a match.

Figure 6.10: Measures of labor market performance.

What these figures make clear is that for the same set of aggregate shocks, the impact is muted in the counterfactual economy. While the downturn is still sizable in the counterfactual economy, at the trough it remains 1.5 percentage points higher. The right panel shows that the counterfactual economy continues to understate the effect on the average surplus from a match.

This last finding provides suggestive evidence that the counterfactual economy may understate the impact on welfare and inequality. To see this, we place the variance in income in both economies (left panel) as well as the variance in the surplus (right panel) in Figure 6.11. Both calculations include unemployed workers, who receive identical incomes b and surplus $S(\epsilon_{P(z)}, z)$. As before, in both panels the baseline economy is plotted as a solid red line and the counterfactual economy is plotted as a dashed blue line.

While these values appear small, it's worth noting that these are both weekly values averaged



(a) Variance of income.

(b) Variance of the surplus.

Figure 6.11: Measures of inequality in our baseline and no part-time economies.

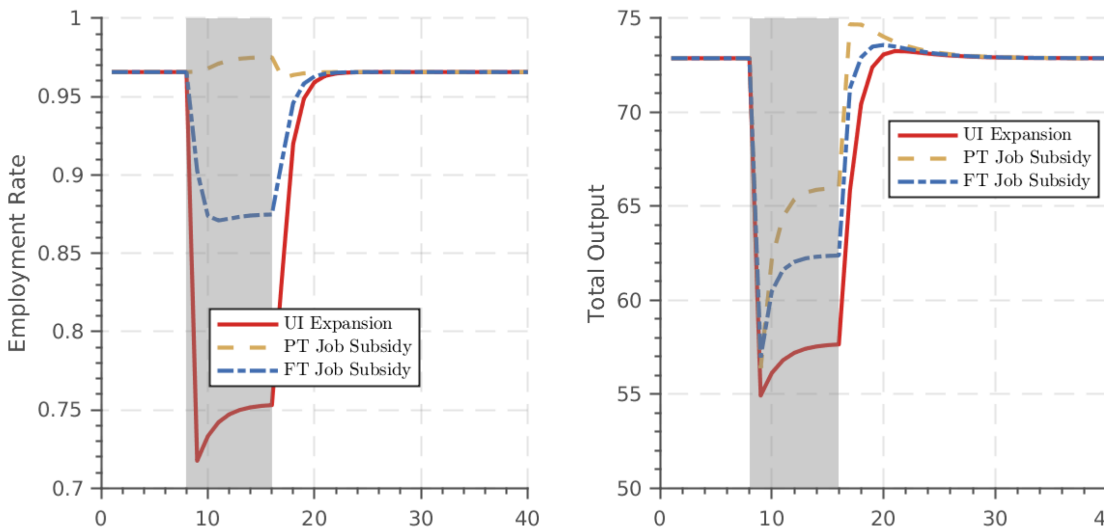
over a quarter. Given that our weekly wages are around 1 and average annual income in the United States is around \$35,000, these predicted differences become sizable at an annual frequency. Our baseline economy consistently predicts a variance of income more than double that of the economy without part-time utilization. In addition, because agents in our model are risk neutral, the effect on welfare is muted; in a model with risk averse agents, it is not difficult to conjecture that the variance in welfare could be much larger because of the higher degree of unemployment and the lower wages among part-time workers.

7 Policy Experiments

Our model presents a natural setting in which to consider the effectiveness of labor market policies at limiting the size and duration of downturns in the labor market. Because unemployment insurance (UI) is often extended during recessions (both the Great Recession and the Covid-19 Recession), we consider this to be our baseline policy. As an alternative, we consider an equally costly "job-subsidy," in which the government instead finances transfers to firms to retain employees. We compare the effect of these two policies on the labor market recovery as well as output.

To compare these revenue neutral policies during a downturn, we impose a 7% decline in aggregate productivity (the lower limit of our productivity grid) and then implement policies as follows. First, we implement a 20% increase in unemployment utility, b. We further assume that is completely financed by the government through non-distortionary taxes. Then, we consider a job subsidy τ_T' (either part or full-time), where $\tau_T - \tau_T'$ is also financed by the government. We impose that the cost of the job subsidy be equal to the cost of the UI program. In each experiment, we assume that the economy is in the steady-state prior to the recession. Moreover, these labor market policies are unanticipated. Once these policies are implemented, workers and firms expect them to last for the duration of the recession. More precisely, in our experiment, after 8 quarters, we assume that aggregate productivity returns to the steady-state and policies return to their baseline levels. Thus, agents no longer anticipate the previous policies. To achieve the same costs, τ_P fell from 0.1602 to -0.011 in the part-time employment subsidy, while τ_F fell from 4.24 to 4.19.

Despite small changes in each acyclical cost, both job-subsidy economies recover more rapidly and suffer a smaller decline than the economy with a UI expansion. We first explore differences in aggregate outcomes. These are reported in Figure 7.1. We first start by comparing aggregate employment (left panel) and aggregate output (right panel) for the three policies. We do so at a quarterly frequency. In each plot, the UI expansion is denoted by the solid red line, the part-time subsidy is represented by the dashed yellow line, and the full-time subsidy is given by the dashed blue line.



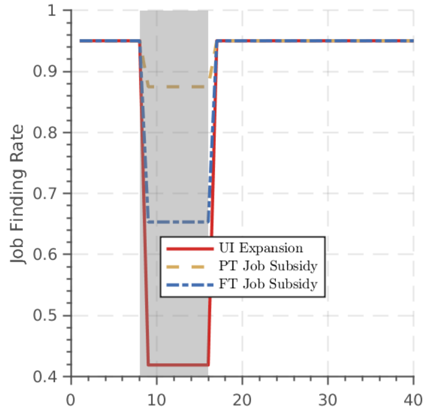
(a) Employment

(b) Output

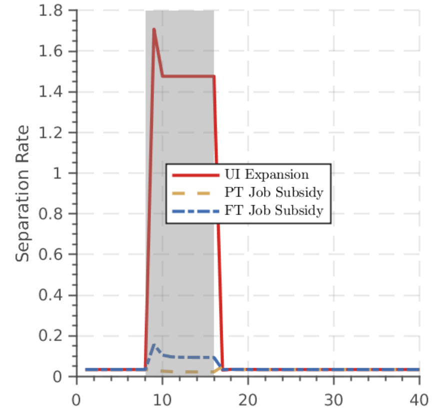
Figure 7.1: Comparison between employment and output in each policy experiment economy.

The economy with the part-time subsidy endures both a smaller decline in employment and a smaller decline in output. In fact, there is nearly no decline in employment despite a drop in aggregate productivity of 7%. The full-time job subsidy also performs better than the UI expansion. Nevertheless, it results in a larger decline in employment and output than the part-time subsidy.

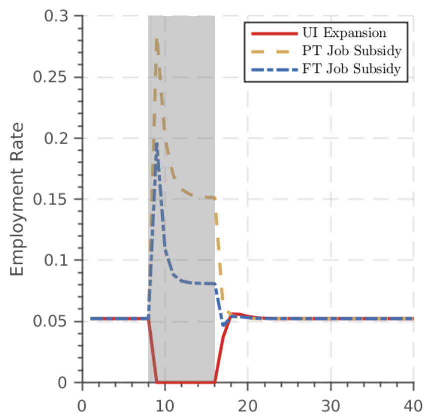
Next, we explore the reasons for the smaller decline in employment and output for the two job subsidy policies. In Figure 7.2, we show the job-finding rate (top left panel), the separation rate (top right panel), part-time employment (bottom left panel) and full-time employment (bottom right panel).



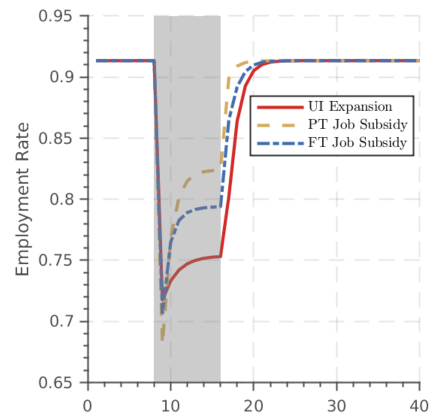
(a) Job-finding rate.



(b) Job separation rate.



(c) Part-time employment rate.



(d) Full-time employment rate.

Figure 7.2: Comparison between employment flows and by type in each policy experiment economy.

Our findings provide some insight into the reasons why part-time subsidies outperform the two alternative policies. In the economy with part-time subsidies, there is still a decline in job-finding. This indicates that the expected surplus of a match falls. However, there is only a marginal increase in the separation rate. Why is that the case? This is so as vacancy creation is costly and retaining a match provides more surplus than searching for a new one. In both the part and full-time subsidy economies, firms hoard workers at part-time utilization, while part-time falls to zero in the UI expansion economy.

8 Conclusion

In this paper we propose a framework that can account for the cyclicality of part and full-time employment. We accomplish this by extending a canonical search model to include acyclical costs that, along with output, vary by part or full-time utilization. This allows firms and workers another margin of adjustment in response to shocks that alter aggregate productivity or match quality.

We show that adjustments in utilization in response to aggregate shocks play a key role in the cyclicality of part and full-time employment. Adjustment in separation and utilization both increase the procyclicality of part-time employment. However, the movement from full-time to part-time employment causes part-time employment to become countercyclical. This composition effect is key for understanding the cyclicality of part-time employment and contributes to the cyclicality of full-time employment. We also show that models with a single extensive margin understate both the degree of employment fluctuations and the impact of those fluctuations on inequality.

We additionally show that part-time employment can be exploited by policy-makers to limit the size and duration of downturns in the labor market. We compare an expansion in unemployment insurance scheme, a policy undertaken in each of the last three recessions, against a subsidy offered to firms that retain workers part-time. We find that the "job subsidy" strongly outperforms the expansion in unemployment insurance, despite holding costs fixed under both policies. Although this policy prevents low quality matches from separating, it also prevents a sizable loss of intangible capital caused by matching frictions. We view this as a strong endorsement of a job-subsidy scheme in response to future downturns.

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A Appendix

A.1 Proofs

Proof of Equation 4.18 and Equation 4.20

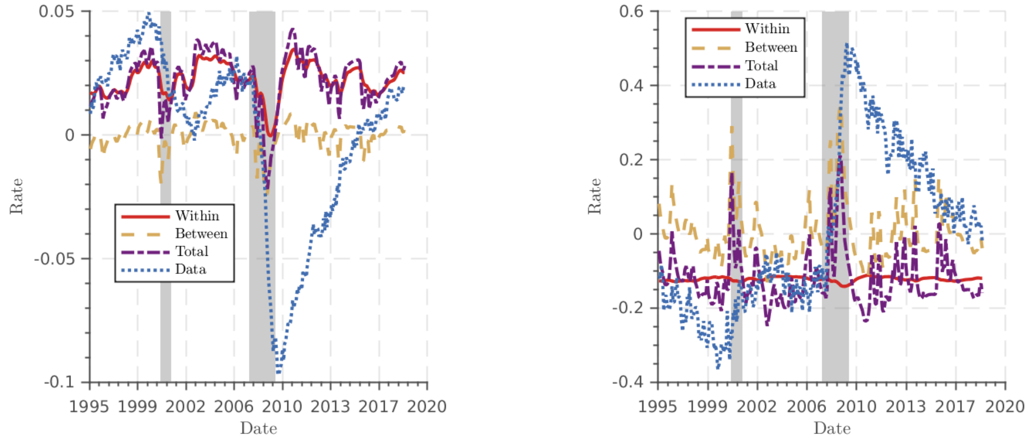
Proof. Both thresholds can be solved explicitly by operating on the surplus equation. Without loss of generality, we assume that $\epsilon_F \geq \epsilon_P$. Integrating by parts, the surplus in Equation 4.8 is generically expressed as follows:

$$\begin{aligned}(r+\lambda_T)\, S^T(\epsilon) &= z\epsilon Y_T - \tau_T - b - \frac{\alpha}{1-\alpha}\theta\kappa \\ &\quad + \frac{z\lambda_T}{r+\lambda_T}\left[Y_F\int_{\epsilon_F}^{\bar{\epsilon}}[1-F(x)]\,dx + Y_P\int_{\epsilon_P}^{\epsilon_F}[1-F(x)]\,dx\right]. \qquad \text{(A.1)}\end{aligned}$$

□

A.2 Tables and Figures

We present our within and between decomposition that we describe in Section 6.1.1 of employment in Figure A.1. The full-time decomposition is on the left and the part-time decomposition is on the right. In each figure, the solid red line is the share explained by the within variation, the dashed yellow line is the share explained by the between variation, and the dash-dot purple line is the total explained by the model. The data is presented as a dotted blue line.



(a) Full-time employment decomposition.

(b) Part-time employment decomposition.

Figure A.1: Comparison of baseline and fixed composition models with the data.

In the following tables, we consider the ability of our model to match the cross-correlation of various labor market flows with labor productivity. Table 4 shows these results for the baseline model and Table 5 shows the results for our series of aggregate shocks during the Great Recession.

	FT Emp.		PT Emp		FT→PT		PT→FT		FT→U		PT→U		U→FT		U→PT	
Lag	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data
-1	0.45	0.72	-0.47	-0.70	-0.22	-0.51	0.10	0.19	-0.47	-0.55	-0.35	-0.23	0.46	0.49	-0.08	0.30
0	0.94	0.84	-0.91	-0.80	-0.42	-0.52	0.23	0.19	-0.96	-0.55	-0.70	-0.18	0.96	0.58	-0.12	0.43
+1	0.61	0.89	-0.26	-0.81	-0.00	-0.50	0.06	0.23	-0.65	-0.48	-0.27	-0.10	0.65	0.68	-0.08	0.46

Table 4: Non-targeted cyclicality moments with simulated shocks.

	FT Emp.		PT Emp		FT→PT		PT→FT		FT→U		PT→U		U→FT		U→PT	
Lag	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data
-1	0.47	0.72	-0.47	-0.70	-0.38	-0.51	0.32	0.19	-0.51	-0.55	-0.60	-0.23	0.52	0.49	0.06	0.30
0	0.93	0.84	-0.88	-0.80	-0.16	-0.52	0.14	0.19	-0.96	-0.55	-0.74	-0.18	0.97	0.58	0.06	0.43
+1	0.64	0.89	-0.30	-0.81	-0.18	-0.50	0.20	0.23	-0.70	-0.48	-0.53	-0.10	0.70	0.68	0.20	0.46

Table 5: Non-targeted cyclicality moments with shocks estimated from the Great Recession.