The State Dependent Effectiveness of Hiring Subsidies

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Abstract

The responsiveness of job creation to shocks is procyclical, while the responsiveness of job destruction is countercyclical. This new finding can be explained by a heterogeneous-firm model in which hiring costs lead to lumpy employment adjustment. The model predicts that policies that aim to stimulate employment by encouraging job creation, such as hiring subsidies, are significantly less effective in recessions: These are times when few firms are near their hiring threshold and many firms are near their firing threshold. Policies that target the job destruction margin, such as employment protection subsidies, are particularly effective at such times.

Keywords: Labor market frictions, hiring costs, hiring subsidies, employment stabilization policies, time-varying volatility

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1 Introduction

Aggregate employment growth can be decomposed into the contributions from job creation, the increase in employment coming from expanding or entering establishments, and job destruction, the decrease in employment coming from contracting or exiting establishments. In this paper I show that the relative contribution of job creation and job destruction to changes in aggregate employment is not constant over the business cycle. Job creation is significantly more responsive to aggregate shocks in expansions, while job destruction is more responsive in recessions. This time-varying responsiveness has important implications for the effectiveness of various labor market policies at different stages of the business cycle.

I begin by using panel data at the state level to show that job creation and destruction exhibit significant time-varying responsiveness. First, I show that the volatility of job creation is procyclical, while that of job destruction is countercyclical. This conditional heteroskedasticity is quantitatively significant: the volatility of the job creation rate is around 40% higher at the peak of the business cycle than at the trough. The opposite is true of the job destruction rate.

As the volatilities of job creation and job destruction move in opposite directions over the business cycle, I argue that this result is driven by time-varying responsiveness of these variables, rather than by variation in the size of underlying shocks. I then confirm this intuition by estimating the responsiveness of job creation and destruction to two different identified shocks. First, I extend the local fiscal multiplier estimates of Nakamura and Steinsson (2014) to allow for the impact of government spending to vary over the business cycle. I show that the responsiveness of job creation to fiscal stimulus is procyclical, while that of job destruction is countercyclical, consistent with the aforementioned evidence of conditional heteroskedasticity. I then show that a similar pattern emerges when considering aggregate rather than cross-sectional shocks by studying the response of job creation and destruction to shocks to credit spreads identified by Gilchrist and Zakrajšek (2012).

To understand the causes and implications of this time-varying responsiveness, I study a heterogeneous-firm business cycle model with lumpy employment adjustment. In the model, employment adjustment is lumpy because firms face per-worker hiring costs, while firing workers is costless. Such kinked adjustment costs lead to an inaction region in firms' policy functions: for a range of productivity levels, firms keep their employment unchanged.

This model is capable of generating time-varying responsiveness of job creation and destruction because of movements in the underlying distribution of firms over the business cycle. In an expansion, more firms are either hiring workers or are near their hiring threshold, and fewer firms are firing or near their firing threshold. This makes the job creation rate more responsive to either aggregate shocks or unexpected policy changes than it would be in a recession. The opposite is true for the job destruction rate.

The baseline model with lumpy employment adjustment is able to quantitatively match the time-varying volatility of job creation and destruction seen in the state-level data. I show that the presence of adjustment frictions is crucial: in a frictionless model, where there is no inaction and all firms are either hiring or firing each period, the volatility of job creation and destruction is almost acyclical.

I then investigate the aggregate implications of time-varying responsiveness by matching the model to US employment data from 1977 to the present. The model implies that the aggregate job creation rate was around 30% less responsive during the Great Recession in 2009 than it was in the pre-crisis period. Conversely, aggregate job destruction was around 30% more responsive in 2009 than in 2006. Turning to the impact of the COVID-19 pandemic, the model implies that the job creation rate was almost entirely unresponsive in the second quarter of 2020, while the job destruction rate was more than twice as responsive as usual in that quarter.

In the final section I investigate the policy implications of this time-varying responsiveness by estimating the impact on employment of unexpected hiring subsidies or employment protection subsidies at different points in time.[1] The effectiveness of these policies is highly state-dependent. The model implies that hiring subsidies, which operate at the job creation margin, are significantly less effective at stimulating employment when implemented during recessions compared to during expansions. The converse is true for employment protection subsidies (or firing taxes), which operate at the job destruction margin and are most effective when implemented during recessions.

[1] I define an employment protection subsidy as a payment made to firms whose number of employees does not decrease.

1.1 Literature Review

There is a large literature studying models of lumpy employment adjustment. The model in this paper is related to that in Hopenhayn and Rogerson (1993). However, their paper only studies the steady-state implications of adjustment frictions in the form of a firing tax, while I focus on the cyclical implications of lumpy adjustment caused by hiring costs. My model is also related to the more recent multiple-worker search and matching models of Elsby and Michaels (2013) and Fujita and Nakajima (2016). In those papers the adjustment friction takes the form of vacancy posting costs, implying that the cost of hiring a worker is time-varying, as it depends on the probability that a vacancy is filled. In contrast to these search models, in my model the cost of hiring a worker is constant over time.[2]

In this paper the focus is on the time-varying responsiveness of job creation and destruction rates over the business cycle. The mechanism in this paper is related to that in Foote (1998), which studies the implications of trend employment growth for the relative volatility of job creation and destruction rates. His paper argues that the high relative volatility of job destruction in the manufacturing sector is explained by the fact that the manufacturing sector in the US is in a secular decline, and consequently relatively more firms are close to the job destruction threshold than the job creation threshold.

There is also a link between the results in this paper and those in Davis, Faberman, and Haltiwanger (2012). One of the findings in their paper is that tracking the cross-section improves their understanding of aggregate worker flow rates. This is related to my finding that the responsiveness and volatility of aggregate job flow rates depends on the establishment-level employment growth distribution.

The model in this paper is consistent with the empirical evidence on employment adjustment put forward in Caballero, Engel, and Haltiwanger (1997). They use micro-data from the Longitudinal Research Database (LRD) to characterize the employment adjustment process of manufacturing establishments. They show that employment adjustment is characterized by both frequent inaction and an increasing adjustment hazard: firms respond more to large deviations of employment from their target level than small ones. In Section 3.6 I show that firms in my model adjust their employment in exactly this fashion.

This paper is also related to Bachmann, Caballero, and Engel (2013) and Berger and Vavra

[2]Consistent with the evidence cited in Christiano, Eichenbaum, and Trabandt (2016).

(2015). These papers show that aggregate investment and durable consumption are significantly less responsive to shocks in recessions. The key difference between the case of employment and either investment or durable consumption is that the establishment-level employment growth distribution is symmetric, implying that the job destruction and job creation margins are equally important for aggregate employment dynamics. Hence, while job creation is less responsive in recessions, job destruction is more responsive.

2 Empirical Evidence of Time-Varying Responsiveness

In this section, I provide evidence of the time-varying responsiveness of job creation and destruction using two complementary approaches. First, in Section 2.1 I investigate whether or not the volatility of job creation and destruction varies over the business cycle. Using panel data from US states I show that both variables exhibit significant conditional heteroskedasticity: the volatility of the job creation rate is around 40% higher at the peak of the business cycle than at the trough. The opposite is true of job destruction.

The fact that the volatilities of job creation and job destruction move in opposite directions over the business cycle suggests that this is likely caused by time-varying responsiveness of these variables rather than time-varying volatility of underlying shocks. In Section 2.2 I provide further evidence that this is the case, by showing that job creation and destruction exhibit time-varying responsiveness to two different sets of identified shocks. In Section 2.2.1 I use cross-sectional identification, extending the local fiscal multiplier estimates of Nakamura and Steinsson (2014) to allow for the effect of government spending on job creation and destruction to vary over the business cycle. In Section 2.2.2 I consider aggregate shocks to credit spreads, identified by Gilchrist and Zakrajšek (2012). In both cases I show that the responsiveness of job creation to these shocks is procyclical, while that of job destruction is countercyclical, consistent with the evidence of time-varying volatility in Section 2.1.

2.1 Conditional Volatility of Job Creation and Destruction

To investigate whether or not the volatility of job creation and job destruction varies over the business cycle, I consider regressions of the following form:

$$|JC_{i,t} - JC_{i,t-1}| = \alpha_i + \gamma_t + \beta g^N_{i,t-1} + \epsilon_{i,t} \tag{2.1}$$

where $JC_{i,t}$ refers to the job creation rate in state i at time t, and $g^N_{i,t-1}$ is the lagged value of employment growth (in percentage points). I include state and time fixed effects to control for state-specific differences in volatility and to control for time-varying volatility that is common to all states. The main parameter of interest is β, which measures the extent to which the volatility of the job creation rate is related to the cyclical position of the state, proxied by lagged employment growth. I also run equivalent regressions where the dependent variable is absolute change in either job destruction, $|JD_{i,t} - JD_{i,t-1}|$, or overall employment growth, $|g^N_{i,t} - g^N_{i,t-1}|$. Table 1 shows the results of estimating these regressions at the state level using quarterly data from the Business Employment Dynamics (BED) database from 1992Q4 to 2019Q4. For comparability with the model laid out in Section 3, which does not include establishment entry and exit, I use job creation and destruction rates from continuing firms.[3]

The first row of Table 1 shows that the estimated coefficient on lagged employment growth is positive for job creation, negative for job destruction, and close to zero for overall employment growth. The second and third rows quantify this time-varying volatility. The second row reports the mean value of the dependent variable. The third row calculates the log difference between the fitted values from the regression when lagged employment growth is at the 5th or 95th percentiles of its distribution, denoted $\log(\sigma_{95}) - \log(\sigma_5)$.

For example, looking at the first column, the mean value of the absolute change in the job creation rate is 0.33 percentage points, the fitted value when lagged employment growth is at the 5th percentile (-1.2%) is 0.26 percentage points and the expected value when lagged employment growth is at the 95th percentile ($+1.5\%$) is 0.40 percentage points. The log difference of these two values is $\log(0.40) - \log(0.26) = 0.42$. That is, the predicted volatility of the job creation rate is around 40 percent higher when lagged quarterly employment

[3]The BED is published by the Bureau of Labor Statistics. Appendix B gives further details on the data used in this section.

Table 1: Conditional Volatility of Job Creation and Destruction

	$\lvert\Delta$Job Creation$\rvert$	$\lvert\Delta$Job Destruction$\rvert$	$\lvert\Delta$Employment Growth$\rvert$
Lagged Employment Growth	0.050 (0.010)	-0.045 (0.013)	0.007 (0.015)
Mean of Dependent Variable	0.33	0.29	0.53
$\log(\sigma_{95}) - \log(\sigma_5)$	0.42	-0.41	0.03
Observations	5438	5438	5438
R^2	0.25	0.22	0.24

Notes: Results from estimating equation 2.1 and the analogous regressions for job destruction and overall employment growth. Robust standard errors clustered at the state level are reported in parentheses. The second row reports the average value of the absolute change in job creation/destruction or employment growth in percentage points. The third row quantifies the conditional heteroskedasticity by comparing volatility at the 5th and 95th percentiles of the lagged employment growth distribution as described in the text. I use data from the 50 US states at a quarterly frequency from the BLS Business Employment Dynamics (BED) database from 1992Q4 to 2019Q4. I winsorize the top 0.1% of the distribution of the absolute changes in job creation and job destruction, to limit the influence of outliers. The 5th and 95th percentiles of the state employment growth distribution are -1.2% and 1.5%.

growth is $+1.5\%$ than when it is -1.2%.[4]

The second column shows that while the volatility of the job creation rate is significantly procyclical, that of the job destruction rate is significantly counter-cyclical. The third column shows that the time-varying volatilities of job creation and job destruction offset each other, such that there is no evidence of time-varying volatility when looking at overall employment growth.[5]

In Appendix C I undertake a number of robustness exercises. First, I show that the results are very similar using total job creation and destruction rates, which include the contributions from entering and exiting establishments. Second, I show that very similar results are obtained using industry-level rather than state-level data. Finally, I use a panel ARCH approach to show that time-varying volatility pertains not only to *changes* in job creation and destruction rates but also to *shocks* to job creation and destruction.

In general it is difficult to determine whether time-varying volatility is caused by changes

[4] I estimate these counterfactuals at the mean value of the fixed effects.

[5] I have also estimated these regressions using the absolute value of the percentage change in job creation and destruction rates as the dependent variable (rather than percentage point change). The procyclicality of the volatility of job creation and countercyclicality of the volatility of job destruction remains in this alternative specification.

in responsiveness to shocks of a given size or by changes in the size of underlying shocks.[6] This is less of an issue here, as time-variation in the size of shocks would struggle to explain why the volatility of job creation and job destruction move in opposite directions over the business cycle. For example, if shocks are larger in recessions, we would expect the volatility of both job creation and job destruction to be larger at such times.[7]

2.2 Time-Varying Responsiveness to Identified Shocks

To provide further evidence that the conditional heteroskedasticity identified in the previous section is caused by time-varying responsiveness, I now estimate the response of job creation and destruction to particular identified shocks. I have chosen these shocks because they have previously been shown to have a significant effect on overall employment. The contribution of this section is to break that down into the effect on job creation and destruction and to investigate whether the effect on these margins varies over time.

In Section 2.2.1 I extend the local fiscal multiplier estimates of Nakamura and Steinsson (2014) to allow for the impact of government spending to vary over the business cycle. I show that an increase in government spending boosts job creation by more in expansions than in recessions, while it lowers job destruction by more in recessions than in expansions.

In Section 2.2.2 I show that this time-varying responsiveness is also evident in response to aggregate as well as cross-sectional shocks. I estimate the response of job creation and destruction to shocks to credit spreads, identified by Gilchrist and Zakrajšek (2012), and show that a similar pattern emerges: an increase in credit spreads lowers job creation by more in expansions than in recessions, and it increases job destruction by more in recessions than in expansions.

2.2.1 Regional Shocks: Fiscal Stimulus

First, I follow Nakamura and Steinsson (2014) and estimate the effect of local fiscal stimulus, using variation in military procurement spending across U.S. states to identify the effect of

[6]As emphasized by Berger and Vavra (2019).

[7]In principle it is possible that different shocks could be driving job creation and job destruction, and that these different shocks display time-varying volatility of the kind seen in the data. However, it is hard to reconcile this explanation with the relatively strong negative correlation of -0.43 between quarterly changes in job creation and job destruction rates at the state level.

government spending on employment. Expanding equation (1) from Nakamura and Steinsson (2014) to allow for the effect of fiscal stimulus to vary with lagged employment growth, my empirical specification is:

$$\frac{JC_{i,t} + JC_{i,t-1}}{E_{i,t-2}} = \alpha_i + \gamma_t + \beta_0 \frac{G_{i,t} - G_{i,t-2}}{Y_{i,t-2}} + \beta_1 \frac{G_{i,t} - G_{i,t-2}}{Y_{i,t-2}} \times g^N_{i,t-2} + \boldsymbol{\delta}'\mathbf{X}_{i,t-2} + \epsilon_{i,t} \quad (2.2)$$

The dependent variable is the two-year state-level job creation rate, i.e. job creation in state i in years t and $t-1$ divided by the level of employment in year $t-2$, $G_{i,t}$ is per capita military procurement spending, $Y_{i,t}$ is per capita output, $g^N_{i,t-2}$ is the lagged value of annual employment growth, and $\mathbf{X}_{i,t-2}$ is a vector of control variables.[8] I follow Nakamura and Steinsson (2014) in using two-year changes as a simple way to capture dynamic effects, as well as in using state and time fixed effects to control for state-specific trends as well as aggregate shocks and aggregate policy.[9] The coefficients of interest are β_0, which estimates the effect of military spending on the job-creation rate, and β_1 which captures how this "multiplier" varies with lagged employment growth. As local military spending is potentially endogenous, I use the "Bartik" approach employed by Nakamura and Steinsson (2014) to instrument for local military spending, scaling the national change in military spending by the fraction of military spending in output in each state at the beginning of their sample.[10]

Panel 2a in Table 2 shows the results of estimating equation 2.2 as well as equivalent regressions for job destruction and overall employment growth. I estimate these regressions using annual data on job creation and destruction rates from the Census Bureau Business Dynamic Statistics database from 1977 to 2006.[11]

Panel 2a shows that the responsiveness of job creation to local fiscal stimulus is procyclical, while that of job destruction is countercyclical. The estimates in the first column show that an increase in local military spending of one percent of output leads to the job creation rate rising by 1.3 percentage points if lagged annual employment growth is zero, but by around 2 percentage points if lagged employment growth is +2%. The second column shows that the opposite is true of job destruction: in response to the same stimulus it falls by 2.5 percentage

[8] I include two lags of state-level annual employment growth as controls: $g^N_{i,t-2}$ and $g^N_{i,t-3}$.

[9] The estimated time-varying responsiveness is quantitatively similar using one-year changes.

[10] Further details on this approach are provided in Section 2 and Table 3 of Nakamura and Steinsson (2014). I use their "Bartik" approach rather than their alternative instrumental variable approach due to the issues that can occur in small samples with many instruments, as mentioned in their footnote 30 (my sample is shorter, beginning in 1977, whereas theirs begins in 1966).

[11] For overall employment growth, the dependent variable is $\frac{E_{i,t}-E_{i,t-2}}{E_{i,t-2}}$

points if lagged annual employment growth is zero, but by only around 1.8 percentage points if lagged employment growth is +2%. The third column shows that these forces are offsetting, such that there is no evidence of time-varying responsiveness of aggregate employment growth.[12]

2.2.2 Aggregate Shocks: Credit Spreads

Alternatively, I can estimate the time-varying responsiveness of job creation and destruction to aggregate rather than cross-sectional shocks. In this section, I use shocks to credit spreads, identified by Gilchrist and Zakrajšek (2012), and estimate regressions of the following form:

$$JC_{i,t} - JC_{i,t-1} = \alpha_i + \beta_0 e_t^{EBP} + \beta_1 e_t^{EBP} \times g_{i,t-1}^N + \boldsymbol{\delta}'\mathbf{X}_{i,t-1} + \epsilon_{i,t} \tag{2.3}$$

where $JC_{i,t} - JC_{i,t-1}$ is the change in the job creation rate in state i, e_t^{EBP} is the identified shock to the "excess bond premium"[13], $g_{i,t-1}^N$ is the lagged value of employment growth and $\mathbf{X}_{i,t-1}$ is a vector of control variables.[14] Given that the identification in this section relies on aggregate shocks, I only use state fixed effects. While the shock is common to all states, their cyclical position when the shock occurs is not. Thus, in this Section I estimate how the effect of a common aggregate shock on local job creation and destruction rates varies with the local cyclical position, proxied by lagged employment growth.

I also run equivalent regressions where the dependent variable is either the change in job destruction or overall employment growth. Gilchrist and Zakrajšek (2012) identify shocks to the excess bond premium using a VAR framework with a Cholesky decomposition. Appendix B gives further details on the identification of shocks to the excess bond premium. As these shocks are identified at a quarterly frequency, I estimate these regressions at the state level using quarterly data from 1992Q4 to 2010Q3. Given the quarterly frequency, the data on job creation, job destruction and employment growth is from the BED database, as in Section 2.1. Panel 2b of Table 2 shows the results.

[12]The estimated effect of fiscal stimulus on employment is larger here than estimated in Nakamura and Steinsson (2014) (for comparison, see specification 2 in Table 3 in their paper). However, these regressions are not directly comparable, as they differ in the sample period and the source of employment data used. Also, Nakamura and Steinsson (2014) use the change in the employment-to-population ratio as their dependent variable, whereas I use overall employment growth.

[13]The "excess bond premium" is the component of credit spreads that is not explained by systematic movements in firm-level default risk.

[14]As in the previous section, I include two lags of state employment growth as controls: $g_{i,t-1}^N$ and $g_{i,t-2}^N$.

Table 2: Time-Varying Responsiveness to Identified Shocks

(a) Local Shock: Fiscal Stimulus

	Job Creation	Job Destruction	Employment Growth
Prime Military Contracts	1.3	-2.5	4.5
	(1.3)	(0.6)	(1.6)
Prime Military Contracts	0.33	0.34	-0.06
× Lagged Employment Growth	(0.22)	(0.20)	(0.23)
Observations	1275	1275	1275
R^2	0.73	0.68	0.24

Notes: Results from estimating equation 2.2 and the equivalent regressions for job destruction and overall employment growth. Robust standard errors clustered at the state level are reported in parentheses. The instrument for state spending is national military spending scaled by the fraction of military spending in the state in 1966-1971 relative to the average. Job creation, job destruction and employment data is from the Census Bureau Business Dynamic Statistics database for the 50 U.S. states and the District of Columbia from 1977-2006. I include two lags of state employment growth as control variables.

(b) Aggregate Shock: Credit Spreads

	Job Creation	Job Destruction	Employment Growth
Excess Bond Premium Shock	-0.073	0.035	-0.108
	(0.006)	(0.005)	(0.008)
Excess Bond Premium Shock	-0.033	-0.023	-0.010
× Lagged Employment Growth	(0.009)	(0.012)	(0.019)
Observations	3539	3539	3539
R^2	0.20	0.18	0.29

Notes: Results from estimating equation 2.3 and the equivalent regressions for job destruction and overall employment growth. Robust standard errors clustered at the state level are reported in parentheses. Excess Bond Premium Shock is a shock to credit spreads identified in Gilchrist and Zakrajšek (2012). Job creation, job destruction and employment data is from the BLS Business Employment Dynamics (BED) database for the 50 U.S. states from 1992Q4 to 2010Q3. I include two lags of state employment growth as control variables.

As with the results in Section 2.2.1, Panel 2b shows that the responsiveness of job creation to shocks to credit spreads is procyclical, while the responsiveness of job destruction is countercyclical, and these forces are offsetting such that there is no significant evidence of time-varying responsiveness of overall employment growth to shocks to aggregate credit spreads. Again, this time-varying responsiveness is economically significant. For example, the first column of Panel 2b implies that a 1 percentage point increase in the excess bond premium lowers the job creation rate by 0.07 percentage points within the same quarter when lagged employment growth is zero, but by around 0.15 percentage points if lagged employment growth is +2%.

Overall, the results from Section 2.1 and Section 2.2 are consistent. The job creation rate is much more responsive to shocks when employment growth is high than when it is low. The opposite is true of the job destruction rate. This provides an explanation for why the job creation rate is more volatile in expansions than in recessions, while the job destruction rate is more volatile in recessions than in expansions. In the remainder of the paper I explain this finding using a model in which expansions are times when many firms are near a hiring threshold, where they decide to hire extra workers, while in recessions more firms are close to a firing threshold, where they decide to lay off employees. Movements in the distribution of firms over the business cycle can explain the time-varying responsiveness of job creation and destruction rates.

3 A Model of Lumpy Employment Adjustment

In this section, I study a heterogeneous-firm business cycle model, in order to understand the causes and implications of the time-varying responsiveness of job creation and job destruction rates. In the baseline model, firms are subject to linear hiring costs, which leads to infrequent employment adjustment. By comparing this model to one in which employment adjustment is frictionless, I will show that infrequent adjustment is crucial for matching the empirical evidence presented in Section 2. Below I describe the firm problem, then that of the representative household, before defining an equilibrium and discussing computational issues.

3.1 The Firm's Problem

The economy consists of a continuum of regions, each containing a continuum of firms. The mass of firms and regions is normalized to one. Each firm operates a decreasing returns to scale production function using only labor, n, as an input. Firms are subject to aggregate, regional, and idiosyncratic productivity shocks. The production function is:

$$y = Az_r z_i n^{\alpha} \tag{3.1}$$

where A, z_r, and z_i denote aggregate, regional, and idiosyncratic productivity, respectively, which follow AR(1) processes. The firm's idiosyncratic state variables are their employment level, n, and their idiosyncratic and regional productivity, z_i and z_r. The aggregate state variables are the distribution of firms over their idiosyncratic states, μ, and aggregate productivity, A. I denote the aggregate state by $S = (A, \mu)$.

Firm employment is predetermined. After productivity shocks are realized, firms make their employment decision for the next period. Firing workers is costless, but firms are subject to a per-worker hiring cost, κ, paid in units of output.[15] The firm's problem can be written recursively as:

$$V(z_r, z_i, n; S) = \max_{n'} Az_r z_i n^{\alpha} - w(S)n - g(n, n') + \mathbb{E}_{z_r', z_i', A'}[\Lambda(S, S')V(z_r', z_i', n'; S')] \tag{3.2}$$

$$\begin{aligned} &\text{subject to} \\ g(n, n') &= \kappa(n' - n)\mathbb{1}(n' > n) \\ \mu' &= \Gamma(A, \mu) \\ A' &= (1 - \rho_A) + \rho_A A + \sigma_A \epsilon_A' \\ z_r' &= (1 - \rho_r) + \rho_r z_r + \sigma_r \epsilon_r' \\ \log z_i' &= \rho_i \log z_i + \sigma_i \epsilon_i' \end{aligned}$$

where ϵ_A', ϵ_r', and ϵ_i' are iid $N(0, 1)$ random variables, $w(S)$ is the wage, and $\Lambda(S, S')$ is the stochastic discount factor of the representative household, whose problem is outlined in the next section. The presence of the linear hiring cost means that the firm's optimal employment decision is characterized by two thresholds, $\underline{n}(z_r, z_i; S)$ and $\bar{n}(z_r, z_i; S)$. If employment is below $\underline{n}(z_r, z_i; S)$ then the firm raises employment to this threshold in the next period. If

[15] As in Bentolila and Bertola (1990).

employment is above $\bar{n}(z_r, z_i; S)$ then the firm reduces its employment to this threshold. If employment is between these thresholds then the firm leaves employment unchanged. The thresholds are defined by following first-order conditions:

$$\mathbb{E}_{z_r',z_i',A'}[\Lambda(S,S')V_n(z_r', z_i', \underline{\mathrm{n}}(z_r, z_i; S); S')] = \kappa \tag{3.3}$$

$$\mathbb{E}_{z_r',z_i',A'}[\Lambda(S,S')V_n(z_r', z_i', \bar{n}(z_r, z_i; S); S')] = 0 \tag{3.4}$$

where $E_{z_r',z_i',A'}[\Lambda(S,S')V_n(z_r', z_i', n; S')]$ is the expected marginal benefit of a worker to the firm.

3.2 The Household's Problem

Firms are owned by a continuum of identical households. As in Khan and Thomas (2008), it is sufficient to focus on the first-order conditions of the household's problem that determines the equilibrium wage and stochastic discount factor. Households have the following preferences:[16]

$$U(C, N) = \frac{1}{1-\gamma}\left(C - \psi\frac{N^{1+\phi}}{1+\phi}\right)^{1-\gamma} \tag{3.5}$$

Consequently, the stochastic discount factor can be written as:

$$\Lambda(S, S') = \beta\left(\frac{C(S') - \psi\frac{N(S')^{1+\phi}}{1+\phi}}{C(S) - \psi\frac{N(S)^{1+\phi}}{1+\phi}}\right)^{-\gamma} \tag{3.6}$$

The first-order conditions of the household's intra-temporal problem define the equilibrium wage:

$$w(S) = -\frac{U_N(C, N)}{U_C(C, N)} = \psi N(S)^{\phi} \tag{3.7}$$

The choice of preferences, combined with the fact that labor is predetermined in the model, implies that the wage is also predetermined. In Appendix E.1 I show that the results are robust to using separable preferences.

[16] As in Greenwood, Hercowitz, and Huffman (1988).

3.3 Equilibrium Definition

A recursive competitive equilibrium of the model is a set of functions $\{V, n', w, \Lambda, C, N, \Gamma\}$ such that:

1. Taking w, Λ, Γ as given, $n'(z_r, z_i, n; S)$ solves the firm's problem (3.2) and $V(z_r, z_i, n, S)$ is the associated value function.

2. Taking w as given, household's labor supply satisfies (3.7). Λ is implied by household consumption and labor supply as in (3.6).

3. The goods market clears:

$$C(S) = \int [Az_r z_i n^\alpha - \kappa(n'(z_r, z_i, n; S) - n)\mathbb{1}(n'(z_r, z_i, n; S) > n)]\, d\mu$$

4. The labor market clears:

$$N(S) = \int n d\mu$$

5. The evolution of the distribution, $\mu' = \Gamma(A, \mu)$ is induced by the policy function $n'(z_r, z_i, n; S)$ and the exogenous processes for z_r, z_i and A.

3.4 Equilibrium Calibration and Computation

The model period is one quarter. Table 3 summarizes the parameter values for the baseline and frictionless versions of the model. The key parameters governing the shape of the establishment-level employment growth distribution in the model are the hiring cost, κ, and the dispersion of idiosyncratic productivity shocks, σ_i. In the baseline model, I set κ equal to 60% of the quarterly wage in steady-state, in line with the evidence provided by Silva and Toledo (2009). This value corresponds broadly to the lower end of estimates of hiring costs in the literature.

In both calibrations, I choose σ_r, the dispersion of regional productivity shocks, to match the average value of the absolute quarterly change in state job creation and destruction rates reported in Table 1 of approximately 0.3. I set the dispersion of idiosyncratic productivity shocks, σ_i, such that the average level of quarterly job creation and destruction rates in the

Table 3: Parameter Values

Parameter		Baseline	Frictionless
Hiring cost	κ	0.55	0
Regional shock volatility	σ_r	0.005	0.0013
Idiosyncratic shock volatility	σ_i	0.135	0.053
Aggregate shock volatility	σ_A	0.0047	0.0038
Regional productivity persistence	ρ_r	0.976	0.984
Idiosyncratic productivity persistence	ρ_i	0.97	0.97
Aggregate productivity persistence	ρ_A	0.976	0.984
Decreasing returns to scale	α	0.65	0.65
Discount factor	β	0.99	0.99
Risk aversion	γ	1	1
Elasticity of labor supply	$\frac{1}{\phi}$	2	2
Disutility of labor supply	ψ	0.91	0.69

model is 5.5%, the average among continuing firms in the BLS data (see Figure 7 in Appendix A). I target the average job creation and destruction rates of continuing establishments as the model abstracts from firm entry and exit and also because entry and exit do not contribute to the volatility of aggregate job creation and destruction rates.[17] I set $\rho_i = 0.97$ and choose the persistence and volatility of aggregate productivity, ρ_A and σ_A, to match the persistence and volatility of de-trended US employment. I set the persistence of regional productivity, ρ_r, to that of aggregate productivity.[18]

I follow Cooper, Haltiwanger, and Willis (2007) in setting the curvature of the production function, α, to 0.65. I set the remaining parameters to conventional values. The discount factor β is 0.99 and I assume that the household has log preferences. I set $\phi = 0.5$, implying a Frisch elasticity of labor supply of 2. In Appendix E.3 I show that the main results are robust to lower values of the labor supply elasticity. I select ψ, the parameter governing the disutility of labor supply, to normalize aggregate employment to 1 in the steady-state of the model.

It is not computationally feasible to solve the firm's problem (3.2), as μ is an infinite dimensional object. I use the method proposed in Krusell and Smith (1998) and approximate μ by the first moment of the employment distribution. Further details of my computational

[17] This is also clear in Figure 7 in Appendix A.

[18] I de-trend quarterly US employment using the HP filter with $\lambda = 10^5$, the parameter used in Shimer (2005) and subsequent papers.

strategy and proof of its accuracy are given in Appendix D.

3.5 The Model's Employment Growth Distribution

Both the baseline and frictionless models are calibrated such that the average quarterly job creation and destruction rates are 5.5%. In Table 4 I show that the baseline model provides a significantly better fit to three other untargeted moments of the establishment-level employment growth distribution.

First, I consider a measure of dispersion. In the data, the standard deviation of annual employment growth at the establishment level is approximately 0.60.[19] The first row of Table 4 shows that the baseline model generates almost exactly this amount of dispersion, while the value in the frictionless model is less than half that in the data.

Second, I consider how often establishments have large changes in their employment. Davis et al. (2012) use BED microdata to show that the fraction of employees working at establishments with quarterly employment changes of less than 10% is around 70%.[20] Again this is almost exactly the figure in the baseline model, while in the frictionless model only 55% of employees work at such establishments. Thus, the frictionless model generates too many large employment changes, despite the fact that the overall dispersion of employment growth is significantly less than seen in the data.

Finally, I consider evidence on how often establishments adjust their employment. The BED data reports the fraction of establishments expanding or contracting each quarter (plotted in Figure 8 in Appendix A). This data implies that on average 56% of establishments have unchanged employment from one quarter to the next. This is exactly the figure in the baseline model, whereas in the frictionless model almost no firms keep their employment unchanged from quarter to quarter.

[19] Fujita and Nakajima (2016) use this moment from Davis, Haltiwanger, Jarmin, and Miranda (2007) to calibrate the dispersion of idiosyncratic shocks in their related model.

[20] In Figure 13 in the Appendix I show that the model naturally generates "hockey-sticks" for the hiring and separation rates as documented by Davis et al. (2012) in JOLTS microdata. The main difference between the "hockey-sticks" in the baseline model and those in the data is the lack of quits in the model. In Appendix E.4 I extend the baseline model to allow for quits, generating "hockey-sticks" that are more similar to those in Davis et al. (2012), and show that the time-varying responsiveness implied by the model is unchanged.

Table 4: Untargeted Moments of the Employment Growth Distribution

Moment	Data	Baseline	Frictionless	Source
S.D. of annual emp. growth	0.6	0.56	0.27	Davis et al. (2007)
Fraction with absolute emp. growth $\leqslant 10\%$	0.72	0.71	0.55	Davis et al. (2012)
Fraction with no emp. change	0.56	0.56	0.00	BED Data

Notes: Data is calculated using establishment level data. The second and third rows refer to quarterly changes. The fraction in the second row is weighted by employment.

3.6 Further Implications of Linear Adjustment Costs

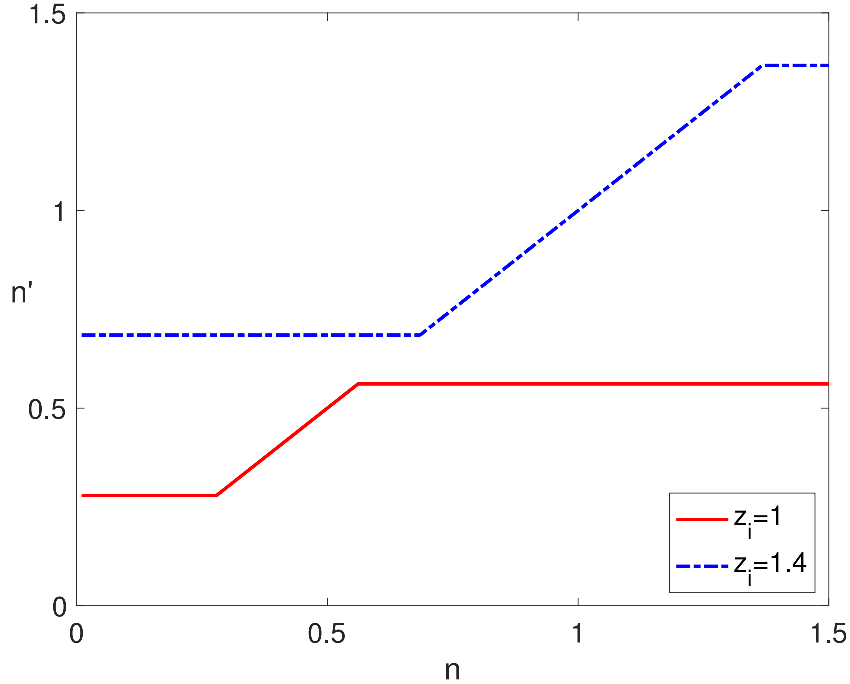
Figure 1 shows the firm's employment policy function in the steady-state of the model for two different levels of idiosyncratic productivity. For each level of idiosyncratic productivity, the flat regions of the policy function correspond to level of employment that firms adjust to if they either hire or fire workers. Within these regions, future employment does not depend on current employment. There is also an intermediate range of employment levels where future employment is equal to current employment, as firms leave their employment unchanged between the thresholds defined in Section 3.1.

Figure 2 shows the distribution of employment gaps and adjustment probabilities implied by the model, where I define a firm's target employment level as the mid-point between the hiring and firing thresholds for their current level of productivity. Firms whose employment gap is small are unlikely to adjust. As the employment gap gets larger, the adjustment probabilities smoothly increase. This shows that the baseline model is capable of generating employment gaps and adjustment probabilities that are qualitatively similar to those estimated using Longitudinal Research Database (LRD) micro-data by Caballero et al. (1997). There is no such analog in the frictionless model, where all firms adjust their employment each period.

4 Model Validation: The Importance of Adjustment Costs

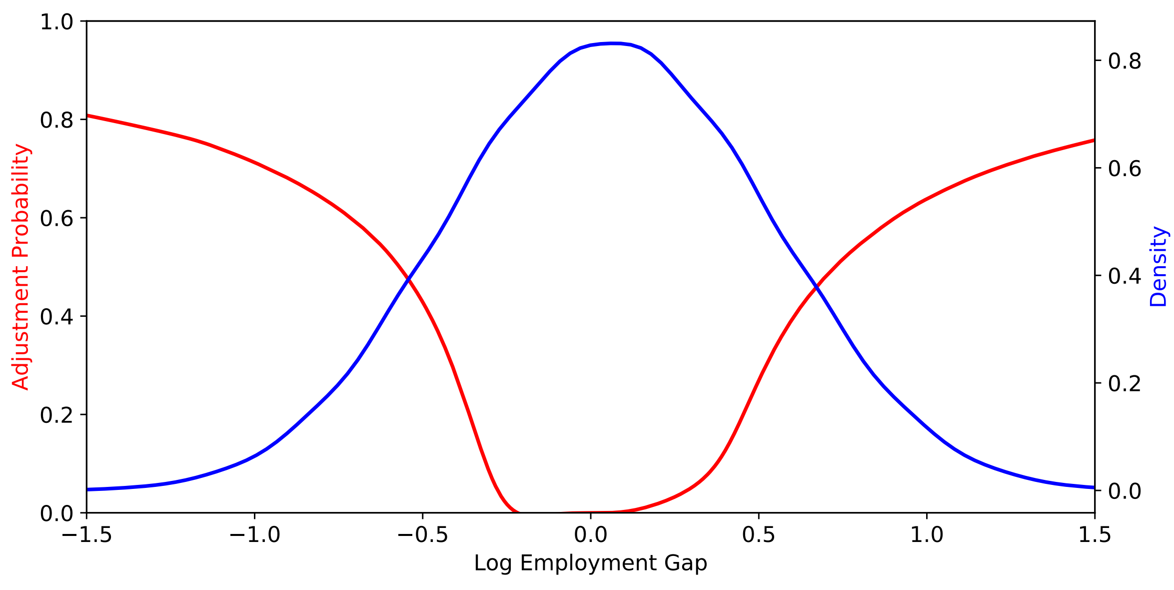
To show the importance of adjustment frictions in generating time-varying responsiveness, I now replicate the regressions from Section 2.1 in both versions of the model.

Figure 1: Lumpy Employment Adjustment in the Baseline Model



Notes: Employment policy functions shown in the steady-state of the model, holding regional productivity equal to one. n denotes current employment, n' denotes employment in the next period, and z_i is idiosyncratic firm productivity.

Figure 2: Employment Gaps and Adjustment Probabilities



Notes: Employment gap is defined as the deviation between current employment and the mid-point of the hiring and firing thresholds for the current level of productivity.

To do this, I simulate data from the baseline and frictionless models for 50 regions and 109 periods, the same number of states and quarters used in the Section 2.1, and estimate equation 2.1 and the equivalent regressions for job destruction and employment growth using the data generated from the model. I repeat this process a large number of times to construct confidence intervals for these model-implied estimates of β. The results are shown in Table 5, which also replicates the other statistics calculated in Table 1.

Both the baseline and frictionless models are calibrated such that the average absolute value of the quarterly change in state-level job creation and destruction rates is the same in the model and in the data (compare the second rows of Tables 1 and 5). Consequently, the estimates of β from the model and the data are directly comparable.

The results for the baseline model, shown in Panel 5a, show that it generates time-varying volatility in job creation and destruction rates that is close to that seen in the data. The coefficient on lagged employment growth in the estimates of equation 2.1 from model-generated data is significantly positive when the dependent variable is the job creation rate and is significantly negative when it is the job destruction rate. The third row of Panel 5a shows that this time-varying volatility is quantitatively close to that seen in the data: in the model the job creation rate is around 50 percent more volatile at the 95th percentile of lagged employment growth distribution than the 5th percentile, while the job destruction rate is around 40 percent less volatile when comparing the same points in the distribution.

The results for the frictionless model, shown in Panel 5b, show that this alternative model generates very little time-varying volatility in job creation and destruction rates. The coefficient on lagged employment growth in the estimates of equation 2.1 is close to and not significantly different from zero in each of the three specifications. In conclusion, the baseline model is able to closely replicate the time-varying volatility seen in the data while the frictionless model is not. The next section explains why this occurs.

4.1 What Causes Time-Varying Responsiveness?

Why is the baseline model is able to generate a significant degree of time-varying responsiveness of both job creation and destruction rates, whereas the frictionless model fails to do so?

As emphasized by Caballero and Engel (2007), time-varying responsiveness can be decom-

Table 5: Time-Varying Volatility in the Model

(a) Baseline Model

	$\lvert\Delta$Job Creation$\rvert$	$\lvert\Delta$Job Destruction$\rvert$	$\lvert\Delta$Employment Growth$\rvert$
Lagged Employment Growth	0.064	-0.039	0.025
	(0.052,0.076)	(-0.047,-0.029)	(0.005,0.045)
Mean of Dependent Variable	0.35	0.28	0.63
$\log(\sigma_{95}) - \log(\sigma_5)$	0.49	-0.37	0.10

(b) Frictionless Model

	$\lvert\Delta$Job Creation$\rvert$	$\lvert\Delta$Job Destruction$\rvert$	$\lvert\Delta$Employment Growth$\rvert$
Lagged Employment Growth	0.013	-0.005	0.008
	(-0.007,0.036)	(-0.023,0.013)	(-0.031,0.048)
Mean of Dependent Variable	0.37	0.33	0.69
$\log(\sigma_{95}) - \log(\sigma_5)$	0.10	-0.05	0.03

Notes: Results from estimating equation 2.1 and the analogous regressions for job destruction and overall employment growth using simulated data from the model for 50 regions and 109 periods. Point estimates are the mean values of the regression coefficients from 100 simulations of the model. Parenthesis contain 95 percent confidence intervals from these simulations. The second row of each panel reports the average value of the absolute change in job creation/destruction or employment growth in percentage points. The third row quantifies the conditional heteroskedasticity by comparing volatility at the 5th and 95th percentiles of the lagged employment growth distribution as described in the text in Section 2.1. As the model does not include trend employment growth, for the 5th and 95th percentiles of the state-level employment growth distribution I use -1.35% and +1.35%, centering the values from the data.

posed into extensive and intensive margin effects. For example, a positive aggregate productivity shock will increase job creation by increasing the number of firms that increase their employment (the extensive margin) as well as by increasing the job creation of firms who would already have been hiring (the intensive margin). Consequently, the responsiveness of the job creation rate depends on the number of firms already adjusting, as well as the number of firms that are near their hiring threshold.

In the baseline model both of these forces contribute to procyclical time-varying responsiveness of the job creation rate and countercyclical time-varying responsiveness of the job destruction rate: in an expansion more firms are either creating jobs or are close to their job creation threshold, while the opposite is true in recessions. Figures 8 and 12 in the Appendix show the fraction of establishments creating or destroying jobs each quarter in the data and the baseline model.[21] The model is able to generate similar cyclicality of these variables to that which is seen in the data. In contrast, in a frictionless model there is little variation in the fraction of firms creating or destroying jobs over time as there is no inaction region in the frictionless model: it is always the case that close to half of firms are creating jobs and close to half of firms are destroying jobs each period.

Figure 3 shows the importance of adjustment frictions in a stylized way, by sketching the distribution of firms over the marginal benefit of an extra worker, $\mathbb{E}[\Lambda(S,S')V_n(z_i', z_s', n; S')]$, in the baseline model. The shaded area in the left tail denotes firms that are firing, while the shaded area on the right denotes firms that are hiring. The unshaded section of the distribution shows firms that keep their employment unchanged. The left panel sketches the distribution in a recession, while the right panel plots the distribution in an expansion. As the distribution shifts over time, it clearly affects both the number of firms creating or destroying jobs, as well as the number that are close to the thresholds.

As I will show in Section 5.1, time-varying responsiveness has significant implications for how the effectiveness of policies that aim to boost employment varies over the business cycle. Consider the effect of a one-period unexpected hiring subsidy equal to τ per new worker. The effect of this policy in the model is to temporarily lower the hiring cost from κ to $\kappa' = \kappa - \tau$ for one period. This policy will increase job creation through the intensive and extensive margins described above. Figure 3 predicts that both of these mechanisms will be weaker in a recession than in an expansion. In contrast, policies which aim to stimulate aggregate employment by discouraging job destruction, such as an employment protection subsidy (or firing tax) are likely to be more potent in a recession than in an expansion.

4.2 Alternative Forms of Adjustment Costs

The results in Table 5 show that a model with linear hiring costs is able to generate the time-varying responsiveness seen in the data, whereas a model with frictionless labor adjustment is not. A natural question is whether or not linear hiring costs are the only way of generating the time-varying responsiveness seen in the data.

In Appendix E I show that it is not important that the adjustment costs in the baseline model are specified on hiring. A model in which instead firing is subject to linear costs (and

[21] Construction of model-implied times series is explained in Section 5.

hiring is frictionless) generates the same time-varying responsiveness seen in the baseline model.[22]

However, not all forms of adjustment cost are able to generate the time-varying responsiveness seen in the data. This implies that the empirical evidence in Section 2 is useful for discriminating between different models of frictional labor adjustment. In Appendix F I consider a model in which firms face fixed costs of adjusting labor. I show that this model generates a small amount of time-varying responsiveness, but not nearly as much as seen in the data. I also show that fixed adjustment cost models perform less well than linear adjustment cost models when it comes to explaining the prevalence of small employment adjustments seen in the data.

5 Aggregate Implications

The previous section showed that the baseline model is consistent with the cross-sectional evidence from Section 2. In this section, I consider the aggregate implications of time-varying responsiveness. First, I match the model to the US data, and show that the time-varying responsiveness of aggregate job creation and destruction is quantitatively significant. I then investigate the implications of this for various policies that are used to support employment during recessions.

To match the baseline model to the US data, I find the particular sequence of aggregate productivity shocks such that aggregate employment in the model exactly replicates the path of the cyclical component of US employment from 1977 to the present.[23] Comparing Figures 7 and 11 in the Appendix shows that the model exhibits realistic movements in quarterly job creation and destruction rates. Comparing Figures 8 and 12 shows that the same is true of the proportion of firms expanding or contracting each quarter.[24]

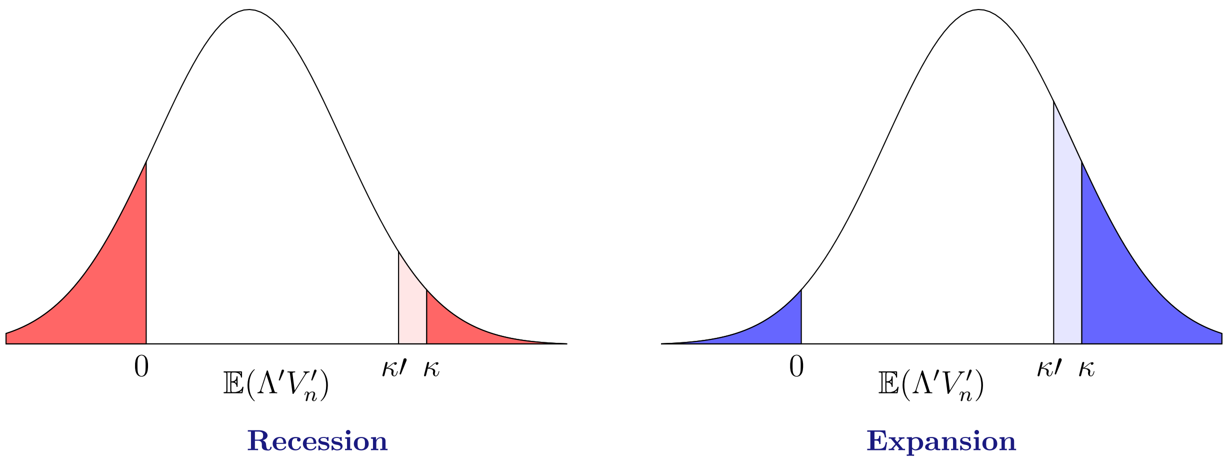
To estimate the degree of time-varying responsiveness of job creation and destruction in the model, I follow Bachmann et al. (2013) in constructing "responsiveness indices", which

[22]This is to be expected given the symmetry of linear hiring and firing costs and is consistent with Cooper et al. (2007).

[23]Bachmann et al. (2013) and Berger and Vavra (2015) use a similar procedure to show time-varying responsiveness of investment and durable consumption. I assume that the model is in steady-state in June 1977.

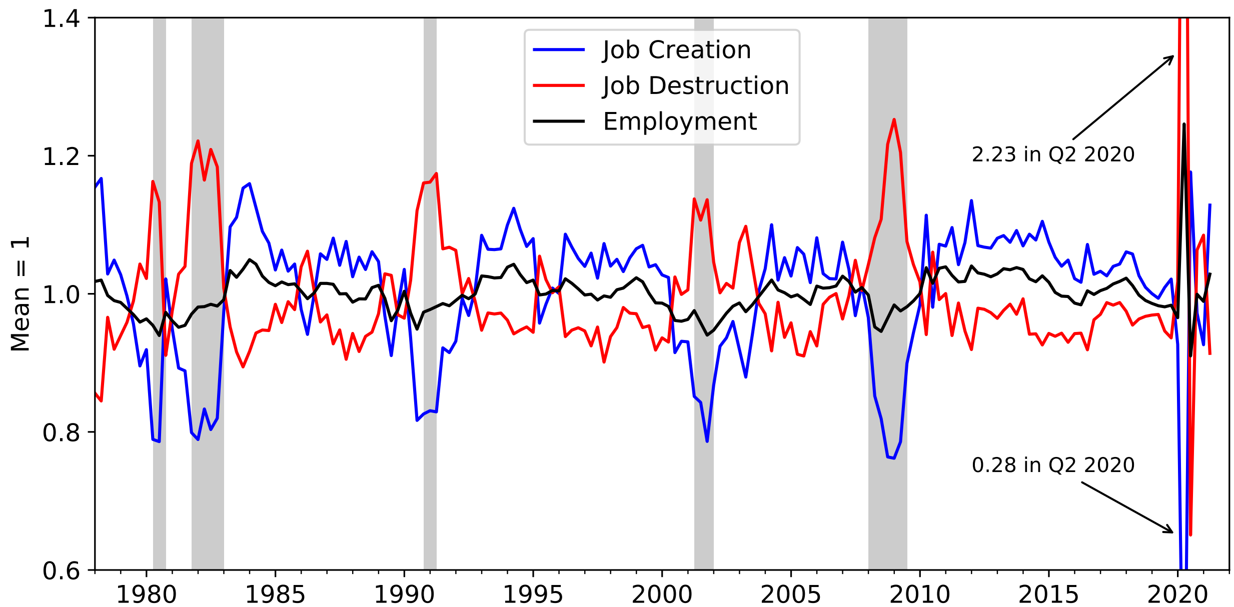
[24]These time-series are only available in the data from 1992 onwards.

Figure 3: Model Distribution in Recessions and Expansions



Notes: The distribution sketched is over the expected marginal benefit of an extra worker. In the model firms increase their employment while this is above κ and decrease their employment while it is below 0. A temporary hiring subsidy lowers the hiring threshold from κ to κ'.

Figure 4: Model-Implied Responsiveness Indices



Notes: Responsiveness indices show the impact on job creation, job destruction and employment of a one SD aggregate productivity shock. The mean response is normalized to one.

measure the impact of a one standard deviation aggregate productivity shock on job creation, job destruction, and overall employment at each point in time:

$$R_t^{JC} \equiv JC(A_t + \sigma_A, \mu_t) - JC(A_t, \mu_t) \tag{5.1}$$

$$R_t^{JD} \equiv JD(A_t + \sigma_A, \mu_t) - JD(A_t, \mu_t) \tag{5.2}$$

$$R_t^{N} \equiv N(A_t + \sigma_A, \mu_t) - N(A_t, \mu_t) \tag{5.3}$$

Figure 4 plots the responsiveness indices for the baseline model, normalized such that the mean value is equal to one. The baseline model implies a significant degree of time-varying responsiveness in aggregate job creation and destruction. The model implies that the job creation rate was around 30% less responsive during the Great Recession in 2009 than it was in the pre-crisis period. Conversely, job destruction was around 30% more responsive in 2009 than in 2006. Turning to the impact of the COVID-19 pandemic, the model implies that the job creation rate was almost entirely unresponsive in the second quarter of 2020, while the job destruction rate was more than twice as responsive at that time.[25]

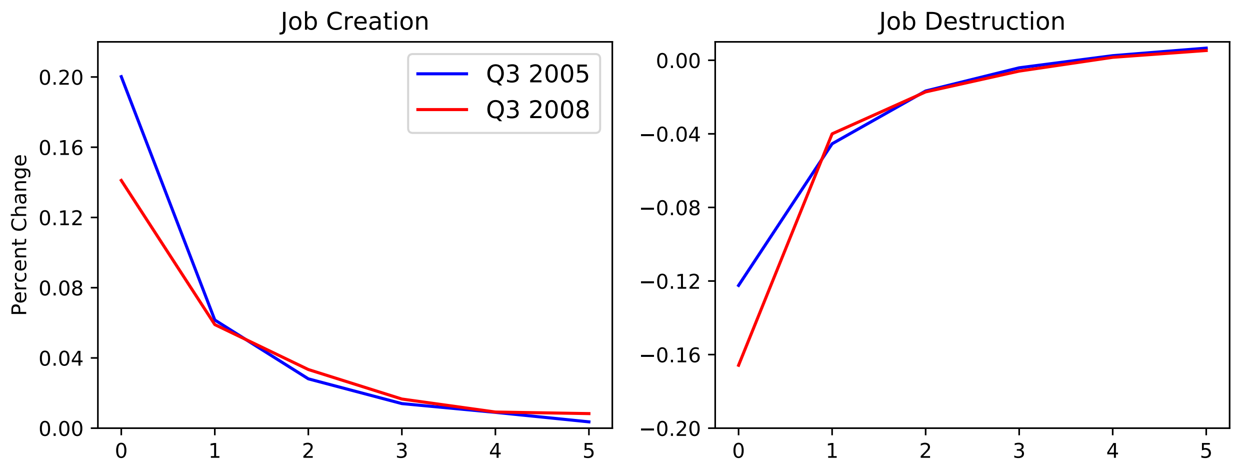
Another way of seeing the time-varying responsiveness generated by the baseline model is to plot the response of job creation and destruction to an aggregate shock at different points in time. Figure 5 plots the impulse response function to a positive aggregate productivity shock in the baseline model in the third quarter of 2005 and compares this to the response if the same shock had occurred in the third quarter of 2008. As implied by Figure 4, during a recession the impact of the shock on job destruction is larger and on job creation is smaller.

5.1 Time-Varying Policy Effectiveness

The previous sections have shown that the responsiveness of job creation is procyclical, the responsiveness of job destruction is countercyclical, that this time-varying responsiveness is quantitatively significant, and that it is offsetting such that aggregate employment shows little time-varying responsiveness. But if aggregate employment does not exhibit time-varying responsiveness, should macroeconomists care about the implications of lumpy employment adjustment at the microeconomic level? I believe that the answer is yes, as the time-varying

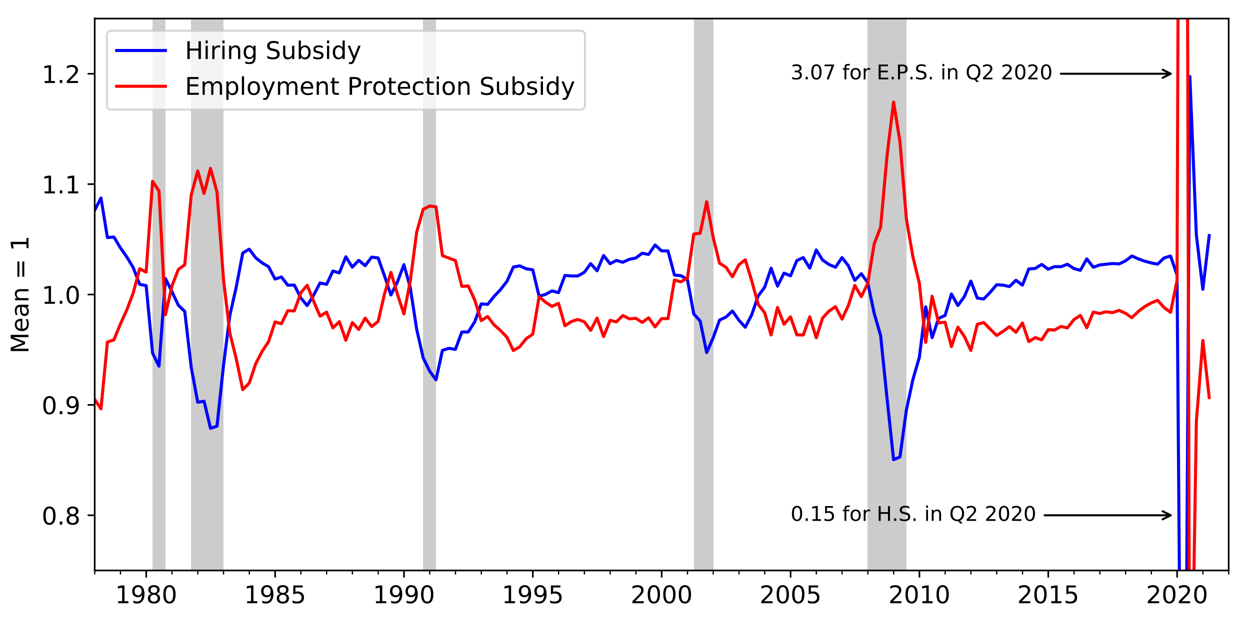
[25] As the model does not include the ability for firms to temporarily layoff their employees it is more difficult to use it to study the implications of the COVID-19 pandemic than a more standard recession.

Figure 5: State Dependence of Impulse Response Functions



Notes: Impact on job creation and job destruction of a one SD aggregate productivity shock in an expansion and in a recession.

Figure 6: Time-Varying Policy Effectiveness



Notes: Impact on employment of an unanticipated hiring subsidy or employment protection subsidy equal to 25% of the average quarterly wage. The mean response is normalized to one.

responsiveness of job creation and destruction has implications for how the effectiveness of different labor market policies varies over time.

Employment stabilization policies can be categorized into those that aim to encourage job creation, those that aim to discourage job destruction, and those that aim to operate on both margins. For example, the Paycheck Protection Program that the US Small Business Administration (SBA) implemented in response to the COVID-19 pandemic is an example of a policy that aims to discourage job destruction. The program provided loans to small businesses that are forgiven "if all employees are kept on the payroll for eight weeks and the money is used for payroll, rent, mortgage interest, or utilities".[26] This policy has similarities with the short-time work schemes that are common in European countries. In such schemes, firms are able to temporarily reduce employee's working hours, with the government providing income support to these workers.[27]

On the other hand, in previous recessions many employment policies in the US have focused on the job creation margin. For example, the original version of the 2010 Hiring Incentives to Restore Employment (HIRE) Act proposed a \$5,000 tax credit for every net new employee hired by small businesses.[28] The New Jobs Tax Credit (NJTC) of 1977-1978 provided a significant wage subsidy for firms who increased their employment by more than 2%.

Given the relatively simple real business cycle structure of the model in this paper, a social planner would never choose to implement such policies. However, the model can still be used to provide a positive analysis of how effective such policies would be at different points in the business cycle.

To investigate the quantitative impact of time-varying responsiveness for different labor market policies in the model, I consider the impact on aggregate employment of one-period unanticipated policy shocks at each point in time. In particular, I consider the effect on employment of an unexpected hiring subsidy or an unexpected employment protection subsidy equal to 25% of the average quarterly wage.[29] My aim in this section is not to compare hiring subsidies against employment protection subsidies, but to compare each of these policies with the same policy at a different point in the business cycle.

[26] https://www.sba.gov/funding-programs/loans/coronavirus-relief-options/paycheck-protection-program

[27] For more detail on such schemes, see Hijzen and Venn (2011).

[28] Cahuc, Carcillo, and Le Barbanchon (2019) analyze the effectiveness of a similar policy implemented by France during the Great Recession.

[29] The impact of an employment protection subsidy on the firing threshold is exactly equivalent to a firing tax of the same magnitude.

A hiring subsidy of τ reduces the cost of increasing employment from κ to $\kappa - \tau$. The hiring threshold now satisfies:

$$\mathbb{E}_{z_r',z_i',A'}[\Lambda(S,S')V_n(z_r',z_i',\underline{\mathrm{n}}(z_r,z_i;S);S')] = \kappa - \tau \tag{5.4}$$

I model an employment protection subsidy as a payment of τ per worker to any firm that does not decrease their employment level. This changes the firing threshold to :

$$\mathbb{E}_{z_r',z_i',A'}[\Lambda(S,S')V_n(z_r',z_i',\bar{n}(z_r,z_i;S);S')] = -\tau \tag{5.5}$$

Figure 6 shows the impact of these policies on aggregate employment at each point in time in the baseline model, with the mean impact normalized to one.[30]

The variation in the effectiveness of these policies over the business cycle broadly mirrors the responsiveness indices shown in Figure 4 for the margin on which the policy operates. The effect of a hiring subsidy on aggregate employment is procyclical, while that of an employment protection subsidy is countercyclical. While it is beyond the scope of the model in this paper to study the impact of short-time work schemes, it is likely that they are also most effective in recessions, given that they operate on the job destruction margin.

Figure 6 shows that the timing of the implementation of such policies is key in determining their effectiveness. Considering the Great Recession period, the model predicts that hiring subsidies would have been least effective if implemented to try and prevent the decline in employment that occured in 2009. Their effectiveness would have been significantly higher if implemented during the recovery in 2011 or 2012. Similarly, the model suggests that policies aiming to encourage hiring would have been very ineffective in the early stages of the COVID-19 recession. However, it is important to recognize the limitations of the model for studying policy during the COVID-19 period given that the model abstracts from temporary layoffs, which played a large role in the sharp decline and then rebound in employment during 2020.

The above analysis shows that the effectiveness of labor market policies varies over the

[30] While my focus is on variation in the effectiveness of these policies over time, it is also important to question whether the impact of a hiring subsidy in the model is consistent with empirical evidence. Cahuc et al. (2019) find that the "cost-per-job" of a hiring credit implemented in France from December 2008 to 2009 is equal to around one quarter of wages. While it is not possible to replicate that experiment exactly, it is broadly consistent with the "cost-per-job" implied by the unexpected one period hiring subsidy in the model.

business cycle depending on whether these policies target the hiring margin or the firing margin. That said, it is beyond the scope of this paper to undertake a normative analysis of optimal labor market policy. A key consideration of such an analysis would be the very different fiscal implications of the different policy options.[31] It would also be important to take into account the timing and duration of such policies and how firms in the model take such policy measures into account.[32]

6 Conclusion

In this paper I have used state-level data to show that job creation and destruction rates exhibit significant time-varying responsiveness. The job creation rate is most responsive in expansions, while the job destruction rate is most responsive in recessions. This time-varying responsiveness is quantitatively significant: the responsiveness of the job creation rate is around 40% higher at the peak of the business cycle than at the trough. I have shown that a heterogeneous-firm business cycle model with lumpy employment adjustment is capable of explaining this new fact. The job creation rate is more responsive in expansions as these are times when more firms are either already hiring or are near their hiring threshold. The opposite is true for the job destruction rate.

The model also has important policy implications. Policies which target the job creation margin, such as hiring subsidies, are likely to be less effective at stimulating employment when implemented in recessions compared to expansions, as recessions are times when fewer firms can be encouraged to increase their employment. Policies that target the job destruction margin, on the other hand, tend to be more effective in recessions than in expansions, as recessions are times when many firms are considering laying off workers.

In future work, I plan to use a similar model to study the impact of undertaking labor market reforms at different times in the business cycle. The direct effect of removing firing costs is that it is cheaper for firms in the left-tail of the distribution to fire workers. The indirect effect is that firms in the right-tail have a larger incentive to hire workers, as they no longer expect to have to pay firing costs if they need to fire those workers in the future. My model

[31] Employment protection subsidies are more expensive than hiring subsidies as they require payments not only to firms that increase their employment but also to firms that leave their employment unchanged. Firing taxes on the other hand raise revenue for the government.

[32] This issue is avoided in the current analysis by only studying one-period unexpected policy shocks.

would suggest that the direct effect is likely to be larger in recessions, and consequently that the short-run impact on employment of removing firing costs may be most negative at these times.

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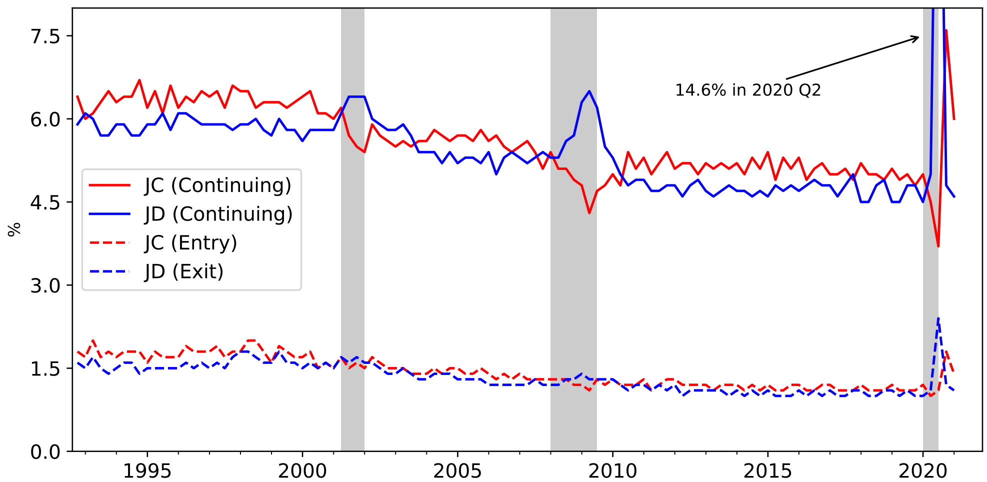
Appendix For Online Publication

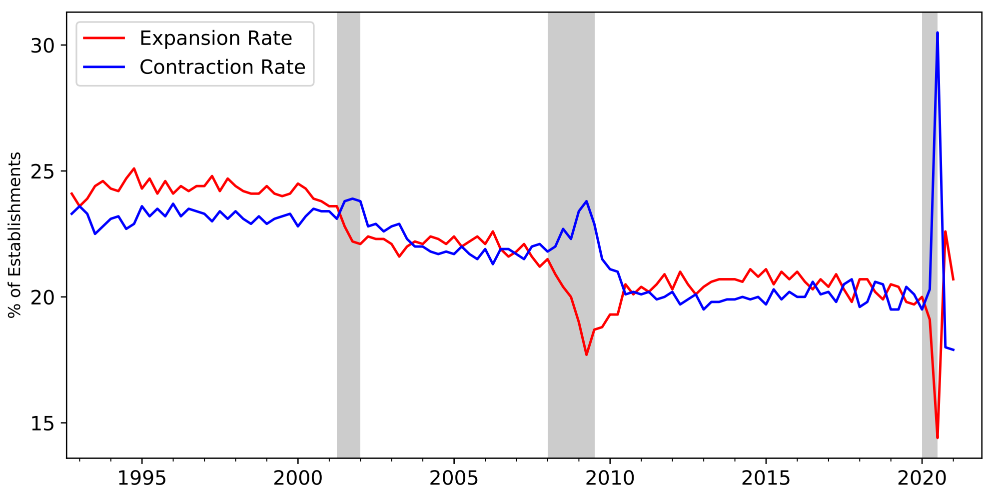
A Supplementary Figures

Figure 7: Job Creation and Destruction Rates: Continuing vs. Entry/Exit



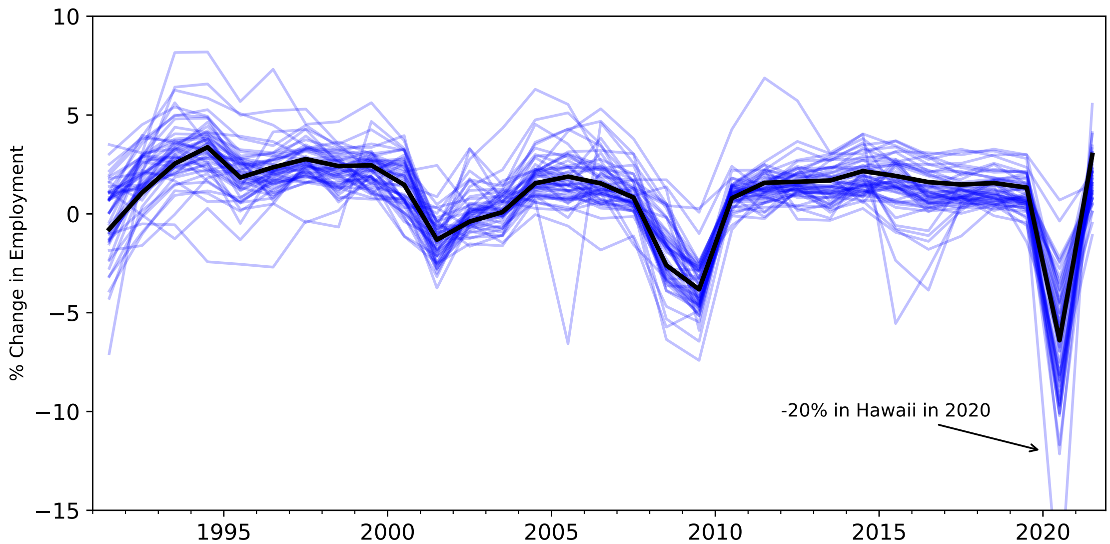
Notes: Quarterly job creation and destruction rates broken down into the contribution from continuing establishments and from those establishments that are entering or exiting. Data from the BLS Business Employment Dynamics database.

Figure 8: Fraction of Establishments Adjusting Employment



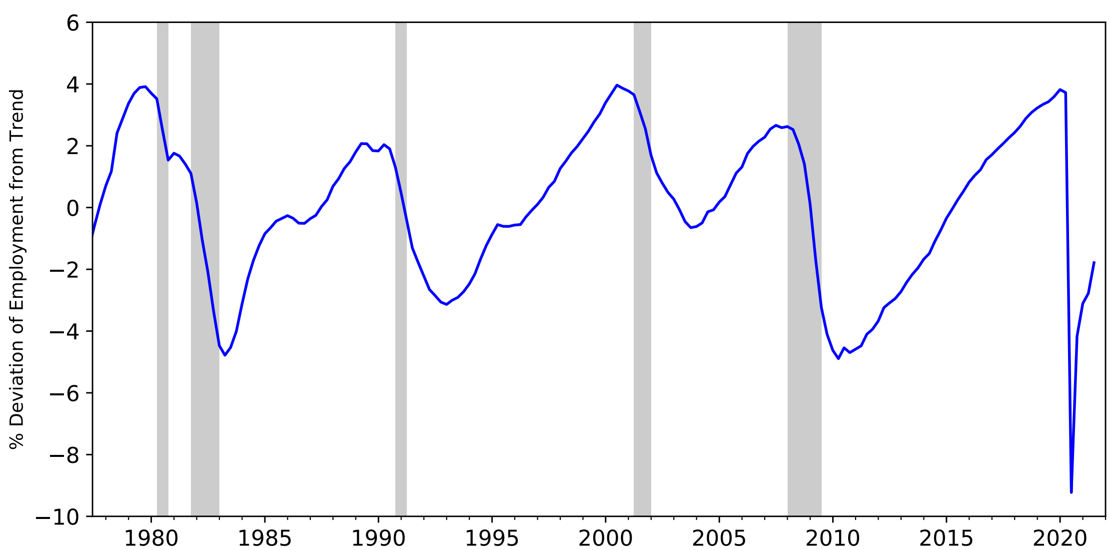
Notes: Fraction of establishments whose employment is either expanding or contracting each quarter. Data from the BLS Business Employment Dynamics database.

Figure 9: State and National Employment Growth



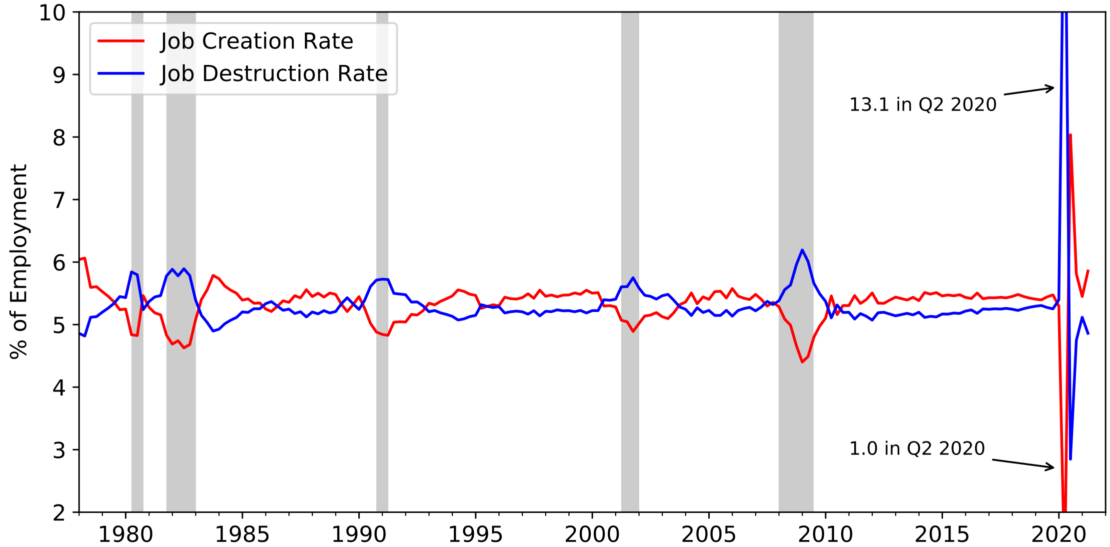
Notes: Blue lines depict state-level annual employment growth. Black line depicts national annual employment growth. Data is total nonfarm employment from the BLS Current Employment Statistics Database.

Figure 10: De-trended US Employment



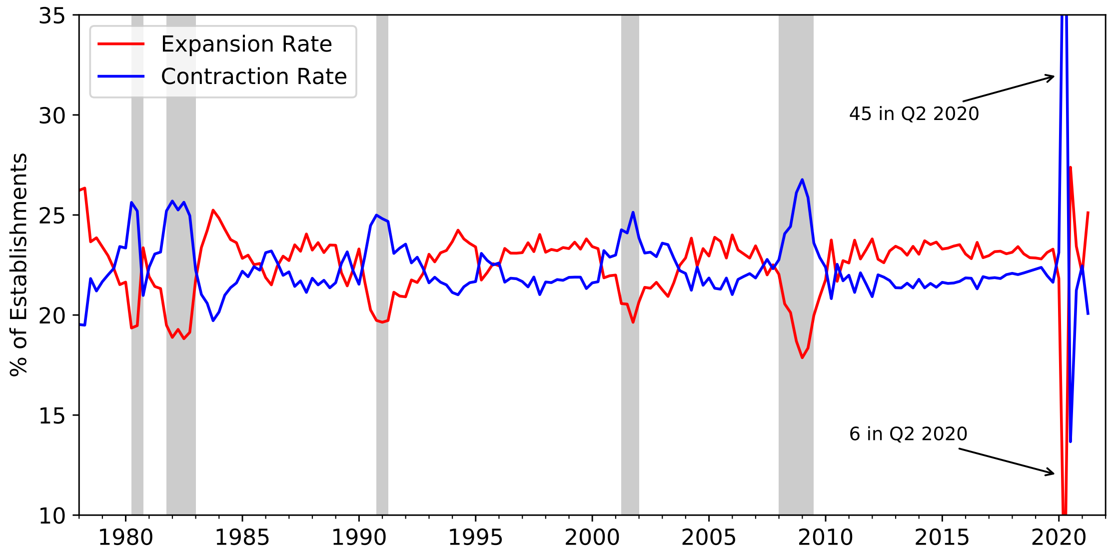
Notes: Cyclical component of quarterly US employment de-trended using the Hodrick-Prescott filter with $\lambda = 1e5$.

Figure 11: Model-Implied Job Creation and Destruction Rates



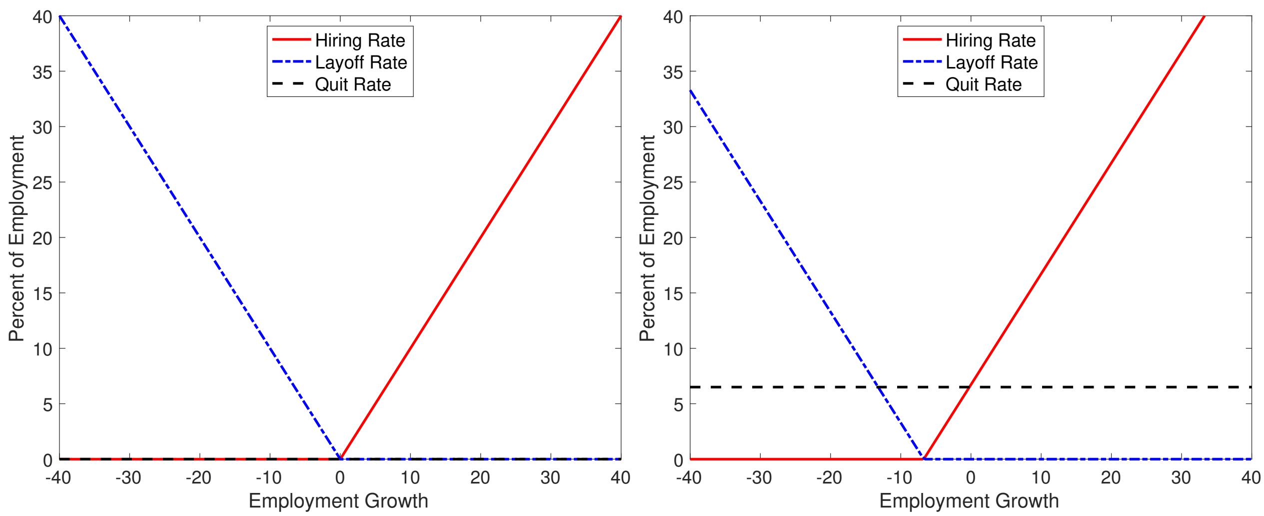
Notes: Quarterly job creation and destruction rates implied by the baseline model when it is matched to detrended US employment.

Figure 12: Model-Implied Expansion and Contraction Rates



Notes: Quarterly establishment expansion and contraction rates implied by the baseline model when it is matched to detrended US employment.

Figure 13: Model-Implied Worker Flow Rates



(a) Baseline Model **(b) Model with Quits**

Notes: Worker flow rates as a function of establishment-level employment growth. The baseline model abstracts from quits. The extended model considered in Appendix E has a quarterly quit rate of 6.5%.

B Data Sources

For Sections 2.1, 2.2.2 and C.3 I use state and industry-level data on job creation and destruction rates derived from establishment-level data from the US Bureau of Labor Statistics' Business Employment Dynamics database. At the state level I use data from the 50 US states as the data from Washington D.C. only begins in 2000. At the industry level I use data from 84 3-digit NAICS sectors. This is all the 3-digit industries for which the BLS database has job creation and destruction rates apart from two industries: Scenic and Sightseeing Transport, and Support Activities for Mining. I remove these industries as their employment growth is significantly more volatile than that of the other industries in the sample. In both the state-level and industry-level data for Section 2.1 I winsorize the top 0.1% of the distribution of the absolute changes in job creation and job destruction, to limit the influence of outliers.

For Section 2.2.1 I use annual data on job creation and destruction rates at the state level from the Census Bureau Business Dynamics Statistics database. I merge this with the data on military spending provided by Nakamura and Steinsson (2014).

For Section 2.2.2 I also use shocks to the excess bond premium, identified by Gilchrist and Zakrajšek (2012). These shocks are identified from a VAR with the following variables: the log-difference of personal consumption expenditures, the log-difference of real private domestic investment, the log-difference of real GDP, the log-difference of the GDP price deflator, the quarterly average of the excess bond premium, the quarterly value-weighted excess stock market return, the ten-year treasury yield, and the federal funds rate. Shocks to the excess bond premium are identified by a Cholesky decomposition. The identifying assumption is that shocks to the excess bond premium affect economic activity and inflation with a one quarter lag. Interest rates and the stock market are able to react in the same quarter. Further details are provided in Gilchrist and Zakrajšek (2012).

In Section 5 I use total non-farm payrolls from the BLS (FRED code: PAYEMS) as my measure of US employment.

C Additional Empirical Results

C.1 Conditional Volatility of Total Job Creation and Destruction

In Section 2.1 I use the job creation and destruction rates for continuing establishments, which excludes the contribution to total job creation and destruction of entering and exiting establishments. The results of estimating equation 2.1 using total job creation and destruction rates are shown in Table 6. The estimates of conditional volatility using total job creation and destruction are very similar to those in Table 1.

C.2 Conditional Volatility without Fixed Effects

Table 7 shows the results of estimating equation 2.1 without state or time fixed effects. The procyclicality of the volatility of job creation and the countercyclicality of the volatility of job destruction remains.

C.3 Conditional Volatility at the Industry Level

In Section 2.1 I show that job creation and destruction exhibit time-varying volatility using state-level data. In this section I show that the same pattern emerges using industry-level data. I re-estimate equation 2.1 using data from 84 3-digit NAICS industries. As with the state-level data, this is from the BLS Business Employment Dynamics database at a quarterly frequency from 1992Q4 to 2019Q4. The estimates are shown in Table 8. The time-varying volatility of job creation and destruction rates in industry-level data is very similar to that seen in state-level data.

C.4 Conditional Volatility Using a Panel ARCH Approach

In Section 2.1 I show that *changes* in job creation and destruction rates exhibit conditional heteroskedasticity. In this section I use a panel ARCH approach to show that this is also true of *shocks* to job creation and destruction rates.

I employ a two-step process, similar to that used in Bachmann et al. (2013). First, I estimate an auto-regressive process for the job creation rate:

Table 6: Conditional Volatility of Total Job Creation and Destruction

	$\lvert\Delta$Job Creation$\rvert$	$\lvert\Delta$Job Destruction$\rvert$	$\lvert\Delta$Employment Growth$\rvert$
Lagged Employment Growth	0.057	-0.065	0.000
	(0.012)	(0.014)	(0.020)
Mean of Dependent Variable	0.41	0.37	0.62
$\log(\sigma_{95}) - \log(\sigma_5)$	0.39	-0.47	0.00
Observations	5439	5439	5439
R^2	0.21	0.21	0.22

Notes: Results from estimating equation 2.1 and the analogous regressions for job destruction and overall employment growth. Robust standard errors clustered at the state level are reported in parentheses. The second row reports the average value of the absolute change in job creation/destruction or employment growth in percentage points. The third row quantifies the conditional heteroskedasticity by comparing volatility at the 5th and 95th percentiles of the lagged employment growth distribution as described in the text. I use data from the 50 US states at a quarterly frequency from the BLS Business Employment Dynamics (BED) database from 1992Q4 to 2019Q4. I winsorize the top 0.1% of the distribution of the absolute changes in job creation and job destruction, to limit the influence of outliers. The 5th and 95th percentiles of the state (industry) employment growth distribution are -1.2% and 1.5%.

Table 7: Conditional Volatility without Fixed Effects

	$\lvert\Delta$Job Creation$\rvert$	$\lvert\Delta$Job Destruction$\rvert$	$\lvert\Delta$Employment Growth$\rvert$
Intercept	0.326	0.304	0.538
	(0.016)	(0.013)	(0.024)
Lagged Employment Growth	0.029	-0.050	-0.026
	(0.008)	(0.007)	(0.012)
Mean of Dependent Variable	0.33	0.29	0.53
$\log(\sigma_{95}) - \log(\sigma_5)$	0.24	-0.46	0.13
Observations	5438	5438	5438
R^2	0.005	0.016	0.001

Notes: Results from estimating equation 2.1 and the analogous regressions for job destruction and overall employment growth without fixed effects. Robust standard errors clustered at the state level are reported in parentheses. The second row reports the average value of the absolute change in job creation/destruction or employment growth in percentage points. The third row quantifies the conditional heteroskedasticity by comparing volatility at the 5th and 95th percentiles of the lagged employment growth distribution as described in the text. I use data from the 50 US states at a quarterly frequency from the BLS Business Employment Dynamics (BED) database from 1992Q4 to 2019Q4. I winsorize the top 0.1% of the distribution of the absolute changes in job creation and job destruction, to limit the influence of outliers. The 5th and 95th percentiles of the state employment growth distribution are -1.2% and 1.5%.

Table 8: Conditional Volatility of Industry-Level Job Creation and Destruction

	$\lvert\Delta$Job Creation$\rvert$	$\lvert\Delta$Job Destruction$\rvert$	$\lvert\Delta$Employment Growth$\rvert$
Lagged Employment Growth	0.071 (0.014)	-0.084 (0.011)	-0.001 (0.022)
Mean of Dependent Variable	0.54	0.53	0.93
$\log(\frac{\sigma_{95}}{\sigma_5})$	0.67	-0.74	0.00
Observations	9138	9138	9138
R^2	0.41	0.37	0.40

Notes: Results from estimating equation 2.1 and the analogous regressions for job destruction and overall employment growth. Robust standard errors clustered at the industry level are reported in parentheses. The second row of each panel reports the average value of the absolute change in job creation/destruction or employment growth. The third row quantifies the conditional heteroskedasticity by comparing volatility at the 5th and 95th percentiles of the lagged employment growth distribution as described in the text. I use data from 84 NAICS 3-digit sectors at a quarterly frequency from the BLS Business Employment Dynamics (BED) database from 1992Q4 to 2019Q4. I winsorize the top 0.1% of the distribution of the absolute changes in job creation and job destruction, to limit the influence of outliers. The 5th and 95th percentiles of the industry employment growth distribution are -2.5% and 2.2%.

Table 9: Conditional Volatility Using Panel ARCH Approach

	$\lvert\Delta$Job Creation$\rvert$	$\lvert\Delta$Job Destruction$\rvert$	$\lvert\Delta$Employment Growth$\rvert$
Lagged Employment Growth	0.019 (0.008)	-0.030 (0.014)	-0.014 (0.014)
Mean of Dependent Variable	0.27	0.27	0.46
$\log(\sigma_{95}) - \log(\sigma_5)$	0.20	-0.31	-0.08
Observations	5339	5339	5339
R^2	0.23	0.26	0.28

Notes: Results from estimating equation C.2 and the analogous regressions for job destruction and overall employment growth. Robust standard errors clustered at the state level are reported in parentheses. The second row reports the average value of the size of the shock to job creation/destruction or employment growth. The third row quantifies the conditional heteroskedasticity by comparing the estimated size of shocks at the 5th and 95th percentiles of the lagged employment growth distribution. I use data from the 50 US states at a quarterly frequency from the BLS Business Employment Dynamics (BED) database from 1992Q4 to 2019Q4. The 5th and 95th percentiles of the state employment growth distribution are -1.2% and 1.5%.

$$\Delta JC_{i,t} = \alpha + \sum_{j=1}^{J} \beta_j \Delta JC_{i,t-j} + \epsilon_{i,t} \tag{C.1}$$

I then use the residuals from the above regression in order to investigate whether or not the size of shocks to the job creation rate is related to the state of the business cycle:

$$|\hat{\epsilon}_{i,t}| = \alpha_i + \gamma_t + \beta \Delta g_{i,t-1}^{N} + \eta_{i,t} \tag{C.2}$$

In the second stage I include state and time fixed effects, as in Section 2.1. I follow the same process for the job destruction rate and overall employment growth. Table 9 shows the estimates of β in equation C.2 from estimating the above regressions with $J = 2$ in the first stage. As in Table 1, the second and third rows quantify this time-varying volatility. The second row reports the mean value of the dependent variable. The third row calculates the log difference between the fitted values from the regression when lagged employment growth is at the 5th or 95th percentiles of its distribution, denoted $\log(\sigma_{95}) - \log(\sigma_5)$. The results are similar to those in Table 1: the size of shocks to the job creation rate is significantly procyclical, the size of shocks to the job destruction rate is significantly countercyclical, and the size of shocks to overall employment growth is acyclical. These results are robust to different lag orders in the first stage.

D Computational Method

Below I outline the computational algorithms used to solve the baseline and frictionless model.

D.1 Baseline Model

To solve the firm's problem, I approximate the expected marginal value function using linear splines. A similar computational procedure is used in Fujita and Nakajima (2016). I follow Khan and Thomas (2008) and re-write the firm's recursive problem in terms of utils of the representative household. Consequently, the problem can be written:

$$V(z_r, z_i, n; S) = \max_{n'} p(S)[Az_r z_i n^\alpha - w(S)n - \kappa(n' - n)\mathbb{1}(n' > n)] + \beta\mathbb{E}_{z_r', z_i', A'}[V(z_r', z_i', n'; S')] \tag{D.1}$$

$$\text{s.t.}$$
$$\mu' = \Gamma(A, \mu)$$

where

$$p(S) \equiv U_C(C, N) = \left(C - \psi\frac{N^{1+\psi}}{1+\psi}\right)^{-\gamma} \tag{D.2}$$

The above problem is not computable due to the infinite dimensionality of μ. I use the technique of Krusell and Smith (1998) and approximate μ by the first moment of its distribution over employment (equivalent to aggregate employment). I approximate Γ using log-linear forecast equations. The problem which I compute is:

$$\begin{aligned} V(z_r, z_i, n; A, N) = \max_{n'} & \, p(A, N)[Az_r z_i n^\alpha - w(N)n - \kappa(n' - n)\mathbf{1}(n' > n)] \qquad \text{(D.3)} \\ & + \beta\mathbb{E}_{z_r', z_i', A'}[V(z_r', z_i', n'; A', N')] \\ & \text{s.t.} \\ \log N' &= a_N + b_N \log N + c_N \log A \\ \log p &= a_p + b_p \log N + c_p \log A \end{aligned}$$

The firm's hiring and firing thresholds are described by the following FOCs:

$$\mathbb{E}_{z_r', z_i', A'} V_n(z_r, z_i, \underline{n}(z_r, z_i; A, N, p); A, N) = p\kappa \tag{D.4}$$

$$\mathbb{E}_{z_r', z_i', A'} V_n(z_r, z_i, \bar{n}(z_r, z_i; A, N, p); A, N) = 0 \tag{D.5}$$

The firm's envelope condition for this problem is:

$$\begin{aligned} V_n(z_r, z_i, n; A, N) &= p(A, N)[Az_r z_i \alpha n^{\alpha-1} - w(N)] \\ &+ \begin{cases} 0 & \text{if } \beta\mathbb{E}[V_n(z_r', z_i', n; A', N')] < 0 \\ \beta\mathbb{E}[V_n(z_r', z_i', n; A', N')] & \text{if } 0 \leqslant \beta\mathbb{E}[V_n(z_r', z_i', n; A', N')] \leqslant p(A, N)\kappa \\ p(A, N)\kappa & \text{if } \beta\mathbb{E}[V_n(z_r', z_i', n; A', N')] > p(A, N)\kappa \end{cases} \end{aligned} \tag{D.6}$$

The expected marginal value function, before the realization of z_i,z_r and A, is then:

$$\begin{aligned} W(z_r, z_i, n; A, N) &\equiv \mathbb{E}_{z_r', z_i', A'} V_n(z_r, z_i, n; A, N) \\ &= \mathbb{E}_{z_r', z_i', A'}[A' z_r' z_i' \alpha n^{\alpha-1} - w + \min(\max[\beta W(z_r', z_i', n; A', N), 0], p(A', N)\kappa)] \end{aligned} \tag{D.7}$$

D.1.1 Equilibrium Algorithm (Baseline Model)

1. Guess an initial forecast rule system: $\hat{\Gamma} = \{a_i, b_i, c_i\}_{i=N,p}$
2. Given the forecast rule system, solve for the expected marginal value function by iterating equation (D.7) until convergence.
3. Use the expected marginal value function along with the FOCs (D.4 and D.5) to approximate the thresholds that describe the firm's policy function: $\underline{\mathrm{n}}(z_r, z_i; A, N, p)$ and $\bar{n}(z_r, z_i; A, N, p)$. Note that the firm's policy can depend on the market-clearing price p.
4. Simulate the model for T periods using the non-stochastic approach of Young (2010), i.e. on a discrete (but dense) grid of points for z_r, z_i and n. Each period in the simulation, the market-clearing price p_t must be determined.
5. When the simulation for T periods is complete, discard an initial $\bar{T}$ periods, and then use the remaining periods to update the forecast rules using OLS regression. If these coefficients $\tilde{\Gamma}$ have converged with $\hat{\Gamma}$, the algorithm is complete. Otherwise, update $\hat{\Gamma}$ and return to step 2.

D.2 Frictionless Model

In the frictionless model the firm's problem is:

$$\begin{aligned} V(z_r, z_i, n; S) &= \max_{n'} p(S)[A z_r z_i n^\alpha - w(S)n] + \beta \mathbb{E}_{z_r', z_i', A'}[V(z_r', z_i', n'; S')] \\ &\text{s.t.} \\ &\mu' = \Gamma(A, \mu) \end{aligned} \tag{D.8}$$

where

$$p(S) \equiv U_C(C, N) = \left(C - \psi \frac{N^{1+\psi}}{1+\psi}\right)^{-\gamma} \tag{D.9}$$

The firms employment decision for the following period is implied by the following first-order condition:

$$\mathbb{E}_{z'_r,z'_i,A'}V_n(z_r,z_i,n;A,N)=0 \tag{D.10}$$

The firm's envelope condition is:

$$V_n(z_r,z_i,n;S)=p(S)[Az_rz_i\alpha n^{\alpha-1}-w(S)] \tag{D.11}$$

Using the previous two equations, the employment policy function is given by:

$$n'(z_r,z_i;S)=\left[\alpha\mathbb{E}_{z'_r,z'_i,A'}\left[\frac{A'z'_rz'_i}{w(S')}\right]\right]^{\frac{1}{1-\alpha}} \tag{D.12}$$

Consequently, in the frictionless version of the model there is no need to forecast p in order to find the firm's policy functions. This simplifies the algorithm.

D.2.1 Equilibrium Algorithm (Frictionless Model)

1. Guess an initial forecast rule system: $\hat{\Gamma}=\{a_N,b_N,c_N\}$
2. Given the forecast rule system, solve for the firm's policy functions using equation D.12.
3. Simulate the model for T periods using the non-stochastic approach of Young (2010), i.e. on a discrete (but dense) grid of points for z_r, z_i and n.
4. When the simulation for T periods is complete, discard an initial $\bar{T}$ periods, and then use the remaining periods to update the forecast rules using OLS regression. If these coefficients $\tilde{\Gamma}$ have converged with $\hat{\Gamma}$, the algorithm is complete. Otherwise, update $\hat{\Gamma}$ and return to step 2.

D.3 Computational Accuracy

Table 10 shows the coefficients of the estimated log-linear forecast rules in the Krusell and Smith (1998) approach in both the baseline and frictionless models. It is clear from these coefficients that the baseline model induces persistence in aggregate employment. The most basic test of accuracy of these forecast equations is their R^2. While these are extremely high, they are also a poor measure of accuracy, as pointed out by Den Haan (2010). The basic issue is that one-period ahead forecast errors are a poor way of ensuring that the approximated law of motion for the model is close to the true one. Consequently, I follow Den Haan's recommendation and simulate the model for

Table 10: Accuracy of Equilibrium Forecasting Rules

	Baseline	Frictionless
a_N	0.001	-0.009
b_N	0.426	0.000
c_N	0.670	1.170
a_p	0.210	N/A
b_p	-0.216	N/A
c_p	-1.533	N/A
R^2_N	0.999934	0.999999
R^2_p	0.999990	N/A
Max Error N(%)	0.14	0.10
Mean Error N (%)	0.03	0.09
Max Error p (%)	0.09	N/A
Mean Error p (%)	0.03	N/A

Notes: Mean/maximum errors constructed by simulating the model for 5000 periods and comparing p and N series from the model with those from the forecasting rules.

a large number of periods (T = 5000)[33]. I then compare the average and maximum percentage deviation between levels of p and N implied by the model and those that occur from iterating on the estimated forecast rule system. The last four rows of Table 10 show that both mean and maximum percentage errors from the forecast rule system are small. This confirms that the Krusell and Smith (1998) approach provides a very accurate approximation.

E Robustness

In this section I show that the time-varying responsiveness of job creation and job destruction is robust to a number of alternative calibrations of the model. In the first, I consider household preferences that are separable between labor and consumption. In the second, I consider the implications of a risk-neutral representative household. Third, I consider a lower aggregate labor supply elasticity. Fourth, I extend the model to allow for quits. Finally, I consider a model in which labor adjustment is infrequent due to costs of firing rather than hiring workers. In all cases, I recalculate the responsiveness indices from Section 5 and show that the time-varying responsiveness of aggregate job creation and destruction rates predicted by the model is very similar.

[33]Note, this is not the same sample for which the equilibrium coefficients of the forecast rules were found.

E.1 Separable Preferences

First I consider alternative preferences for the representative household. As in Hopenhayn and Rogerson (1993), I endow the household with separable preferences between consumption and leisure, assuming that households participate in employment lotteries as in Hansen (1985) and Rogerson (1988):

$$U(C,N) = \frac{C^{1-\gamma}-1}{1-\gamma} - \psi N \tag{E.1}$$

I assume that $\gamma = 0.5$ and recalibrate ψ to keep mean employment equal to 1. Figure 14 shows that the responsivness indices from this model are very similar to those from the baseline model (Figure 4).

E.2 Risk-Neutral Representative Household

Khan and Thomas (2008) showed that procyclical real interest rates in general equilibrium have the ability to neutralize the time-varying responsiveness of aggregate investment in models of lumpy capital adjustment. To understand the impact of general equilibrium effects on the time-varying responsiveness in the case of labor adjustment, I consider a model where the representative household is risk-neutral, i.e. $\gamma = 0$, and consequently where real interest rates are constant. Again, Figure 14 shows that the responsiveness indices from this model are very similar to those in the baseline model.

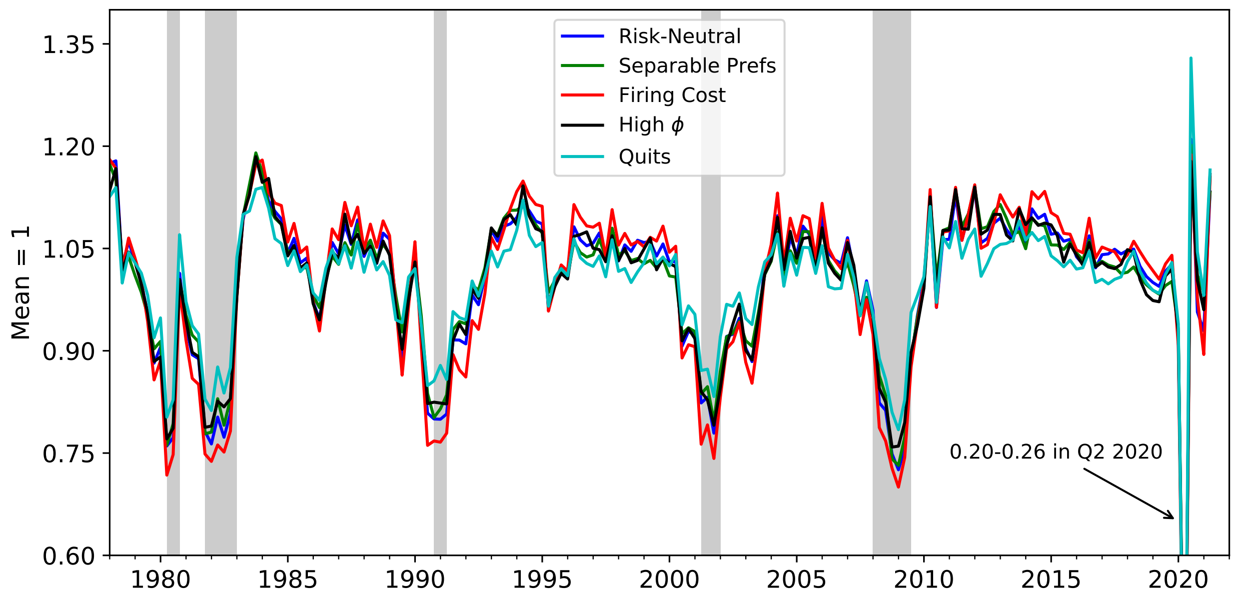
Why do real interest rate movements have such a limited effect in the case of lumpy labor adjustment? The key reason is that the timing of employment adjustment has little impact on consumption of the representative household. In the model of Khan and Thomas (2008), general equilibrium effects are important because of the consumption smoothing motive of the representative household, which causes large real interest rate movements in the face of consumption volatility. In this model the only impact that employment adjustment has on consumption is through the hiring cost, which is small.

E.3 Lower Labor Supply Elasticity

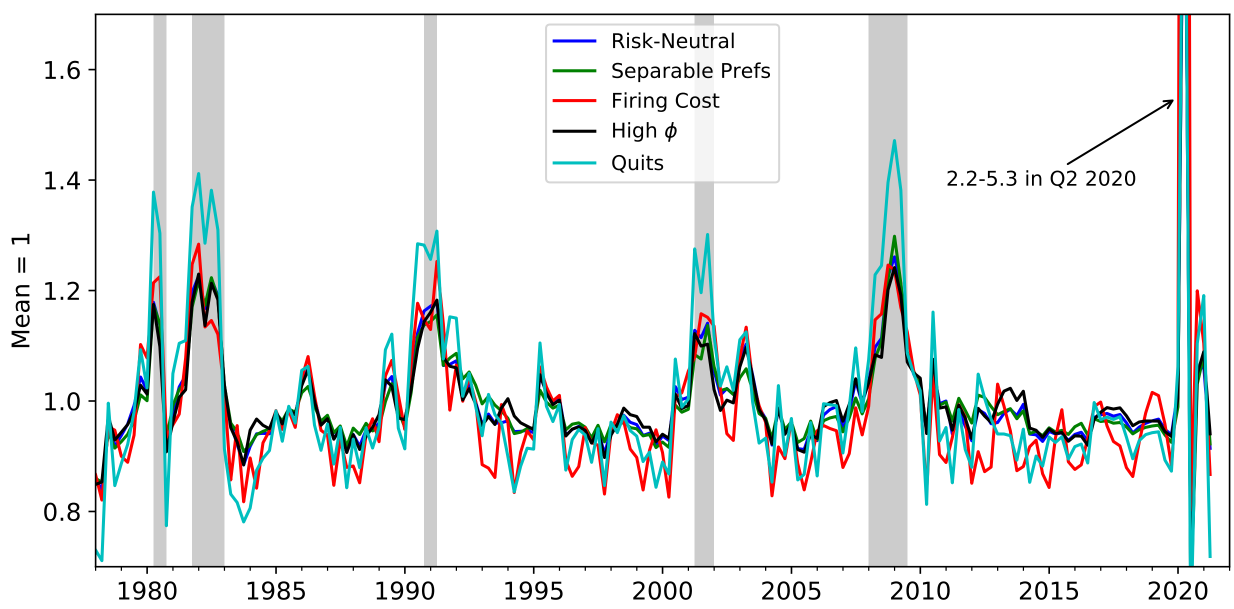
In the baseline calibration I use a Frisch labor supply elasticity of 2, a value that is common in the macro literature but higher than micro estimates. In this section I repeat the experiment of Section 5 assuming that the Frisch labor supply elasticity is lowered to 1. The responsiveness indices shown

Figure 14: Robustness: Model-Implied Responsiveness Indices

(a) Job Creation



(b) Job Destruction



Notes: Responsiveness indices show the impact on job creation, job destruction and employment of a one SD aggregate productivity shock. The mean response is normalized to one.

in Figure 14 are almost identical to those in Figure 4. The only difference between this calibration of the model and the baseline calibration is that aggregate productivity now needs to be more volatile to induce the changes aggregate employment seen in the data.

E.4 Quits

The baseline model does not include quits as doing so means that the model would be inconsistent with the large fraction of establishments that keep their number of employees unchanged from quarter to quarter. However, a large number of employees do quit their jobs each quarter, as shown in Figure 1 in Davis et al. (2012).

In this section I assume that a fraction q of employees quit their jobs each quarter. The firm's problem is the same as in equation 3.2, but now the cost of adjusting employment is:

$$g(n, n') = \kappa(n' - n(1-q))\mathbb{1}(n' > n(1-q)) \tag{E.2}$$

I assume that 6.5% of employees quit their job each quarter. The responsiveness indices shown in Figure 14 are very similar to those in the baseline model.

E.5 Firing Costs Rather Than Hiring Costs

In this section I show that the results are not sensitive to the linear adjustment costs being on the hiring margin rather than the firing margin. I remove the hiring costs from the model, and instead assume that firms face a linear firing tax, F. The firm problem is then:

$$V(z_r, z_i, n; S) = \max_{n'} Az_r z_i n^{\alpha} - w(S)n - g(n, n') + \mathbb{E}_{z'_r, z'_i, A'}[\Lambda(S, S')V(z'_r, z'_i, n'; S')] \tag{E.3}$$

$$\begin{aligned}
&\text{subject to}\\
g(n, n') &= F(n - n')\mathbb{1}(n' < n)\\
\mu' &= \Gamma(A, \mu)\\
A' &= (1-\rho_A) + \rho_A A + \sigma_A \epsilon'_A\\
z'_r &= (1-\rho_r) + \rho_r z_r + \sigma_r \epsilon'_r\\
\log z'_i &= \rho_i \log z_i + \sigma_i \epsilon'_i
\end{aligned}$$

I set the value of the firing tax equal to the value of the hiring cost in the baseline calibration of the model. Again, Figure 14 shows that the responsiveness indices implied by the model are almost unchanged.

F Fixed Costs of Labor Adjustment

The baseline model includes linear hiring costs. This leads to employment policies that follow two adjustment thresholds, as described in Section 3.1 and shown in Figure 1.

Alternatively, firms may face fixed adjustment costs that do not vary with the number of employees that they hire or fire. I now consider a model where firms face a disruption cost equal to a fraction λ of their output if they choose to adjust their employment. Their problem is as follows:

$$V(z_r, z_i, n; S) = \max_{n'} Az_r z_i n^\alpha - w(S)n - g(n, n') + \mathbb{E}_{z'_r, z'_i, A'}[\Lambda(S, S')V(z'_r, z'_i, n'; S')] \tag{F.1}$$

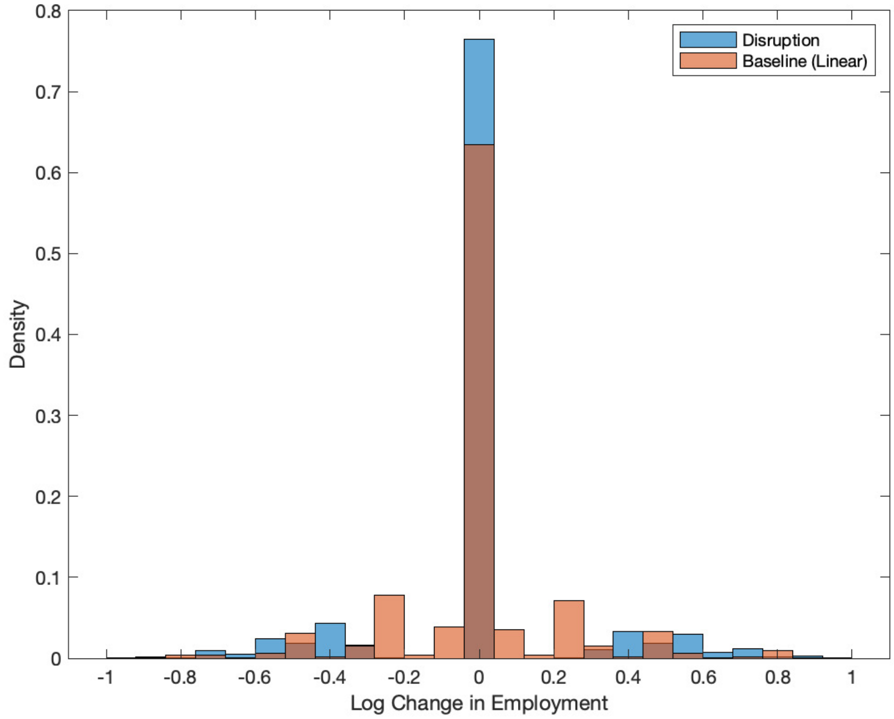
$$\begin{aligned} &\text{subject to} \\ g(n, n') &= \lambda A z_r z_i n^\alpha \mathbb{1}(n' \neq n) \\ \mu' &= \Gamma(A, \mu) \\ A' &= (1 - \rho_A) + \rho_A A + \sigma_A \epsilon'_A \\ z'_r &= (1 - \rho_r) + \rho_r z_r + \sigma_r \epsilon'_r \\ \log z'_i &= \rho_i \log z_i + \sigma_i \epsilon'_i \end{aligned}$$

I set the value of λ equal to 2%, similar to that estimated by Cooper and Willis (2009) and recalibrate the other parameters to maintain their existing targets.

Fixed adjustment costs have a number of different implications to the linear adjustment costs considered in the baseline model. One implication is that such models struggle to generate small changes in employment. Figure 15 shows the distribution of quarterly log employment changes in the baseline model and the disruption cost model. The disruption cost model generates no small changes in employment, whereas in the baseline model a large fraction of adjustments involve employment changing by 20% or less, as shown in the data by Cooper et al. (2007).

Another implication of the disruption cost model is that the employment choice conditional on adjustment is independent of a firm's current employment. This significantly reduces the persistence of the distribution of employment gaps in the model. In Table 11 I replicate the estimates of equation 2.1 in the fixed cost model. While the model does generate some time-varying volatility, it is much less than in the data or in the baseline model, as documented in Sections 2 and 4.

Figure 15: Histograms of Quarterly Employment Adjustment



Notes: Histograms of quarterly log employment change in the baseline model and a model where firms face a fixed (disruption) cost of employment adjustment.

Table 11: Conditional Volatility in Disruption Cost Model

	$\lvert\Delta$Job Creation$\rvert$	$\lvert\Delta$Job Destruction$\rvert$	$\lvert\Delta$Employment Growth$\rvert$
Lagged Employment Growth	0.027	-0.015	0.011
	(0.012,0.048)	(-0.028,0.000)	(-0.014,0.048)
Mean of Dependent Variable	0.35	0.30	0.65
$\log(\sigma_{95}) - \log(\sigma_5)$	0.22	-0.14	0.06

Notes: Results from estimating equation 2.1 and the analogous regressions for job destruction and overall employment growth using simulated data from the disruption cost model for 50 regions and 109 periods. Point estimates are the mean values of the regression coefficients from 100 simulations of the model. Parenthesis contain 95 percent confidence intervals from these simulations. The second row of each panel reports the average value of the absolute change in job creation/destruction or employment growth. The third row quantifies the conditional heteroskedasticity by comparing volatility at the 5th and 95th percentiles of the lagged employment growth distribution as described in the text in Section 2.1. As the model does not include trend growth, for the 5th and 95th percentiles of the state-level employment growth distribution I use -1.35% and +1.35%, centering the values from the data.