The State Dependent Effectiveness of Hiring Subsidies

Sebastian Graves*

October 14, 2020

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
JEL Classifications: E24, E32, E63

*Federal Reserve Board. Email: sebastian.h.graves@frb.gov. I am grateful to William Gamber, Simon Gilchrist, Virgiliu Midrigan, and seminar participants at NYU and the Federal Reserve Board for helpful comments.

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. The main contribution of this paper is to 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 and industry levels 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 50% 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 aggregate shocks. Using shocks to the excess bond premium, identified by Gilchrist and Zakrajšek (2012), I show that the responsiveness of job creation to aggregate shocks is procyclical, while that of job destruction is countercyclical, consistent with the evidence of conditional heteroskedasticity.

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 model with lumpy employment adjustment is able to quantitatively match the time-varying responsiveness 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 responsiveness of job creation and destruction to aggregate shocks is acyclical.

I then investigate the aggregate implications of time-varying responsiveness by matching the model to US employment data from 1977 to the present. Due to the sharp decline in employment associated with the COVID-19 pandemic, the model implies that the job creation rate is currently almost entirely unresponsive, while the job destruction rate is more than twice as responsive as usual. In short, job destruction is currently the only relevant margin for the vast majority of firms' employment decisions.

In the final section I investigate the policy implications of 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 during recessions. Employment protection subsidies (or firing taxes), which operate at the job destruction margin, are significantly more effective than normal at these times. This suggests that providing incentives for firms to retain their existing employees is likely the most effective way to support employment levels during the COVID-19 pandemic. Indeed, the Paycheck Protection Program in the US tries to do exactly this for small businesses. Policies that attempt to stimulate hiring would likely be entirely ineffective at this time.

[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 this paper 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.

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

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 and industries I show that both variables exhibit significant conditional heteroskedasticity: the volatility of the job creation rate is around 50% 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 must be 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 aggregate shocks. Specifically, I use shocks to the excess bond premium[3], identified as in Gilchrist and Zakrajšek (2012), as such shocks are known to have a strong effect on overall employment. I show that the responsiveness of job creation to these aggregate shocks is procyclical, while that of job destruction is countercyclical, consistent with the evidence 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:

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

where $\Delta JC_{i,t}$ refers to the change in the job creation rate, either at the state or industry level, and $g^N_{i,t-1}$ is the lagged value of employment growth. 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 or industry, proxied by lagged employment growth. I also run similar regressions where the dependent variable is either job destruction, $|\Delta JD_{i,t}|$, or overall employment growth, $|\Delta g^N_{i,t}|$. Table 1 shows the results of estimating these regressions

[3] The excess bond premium is the component of credit spreads that is not explained by firm-level default risk.

at both the state and industry levels using data from the Census Bureau's Business Dynamics Statistics (BDS) database from 1977-2014.[4]

Consider first the top panel of Table 1, which estimates these regressions using state-level data. The first row 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 row quantifies this time-varying volatility by comparing the fitted values at the 5th and 95th percentiles of the employment growth distribution.[5] The volatility of the job creation rate is around 50% higher at the 95th percentile compared to the 5th percentile of the employment growth distribution, while the opposite is true for the job destruction rate. The volatility of overall employment growth is approximately acyclical. The bottom panel of Table 1 shows a very similar pattern using industry-level data. If anything, the time-varying volatility is even more pronounced at the industry-level than at the state-level.

In general it is difficult to determine whether time-varying volatility is caused by changes in responsiveness to shocks of a given size or by changes in the size of underlying shocks.[6] For two reasons this is not an issue here. First and foremost, time-variation in the size of shocks is unable to explain why the volatility of job creation and job destruction move in opposite directions over the business cycle. Second, the inclusion of time fixed effects controls for time-variation in the size of aggregate shocks.

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 of these variables, I now estimate the response of job creation and destruction to identified aggregate shocks. I use shocks to the excess bond premium, identified by Gilchrist and Zakrajšek (2012), and estimate regressions of the following form:

$$JC_{i,t+1} - JC_{i,t-1} = \alpha_i + \beta_0 g^N_{i,t-1} + \beta_1 e^{EBP}_t + \beta_2 e^{EBP}_t \times g^N_{i,t-1} + \epsilon_{i,t} \tag{2.2}$$

where $JC_{i,t+1} - JC_{i,t-1}$ is the change in the job creation rate between the year before and the year after the shock, either at the state or industry level, e^{EBP}_t is the identified shock to the

[4] Appendix B gives further details on the data used in this section.

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

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

Table 1: Conditional Volatility of Job Creation and Destruction

(a) State Level

	$\|\Delta$Job Creation$\|$	$\|\Delta$Job Destruction$\|$	$\|\Delta$Employment Growth$\|$
Lagged Employment Growth	0.088 (0.020)	-0.079 (0.024)	0.028 (0.047)
$\log(\frac{\sigma_{95}}{\sigma_5})$	0.65	-0.45	0.11
Observations	1883	1883	1883
R^2	0.36	0.39	0.38

(b) Industry Level

	$\|\Delta$Job Creation$\|$	$\|\Delta$Job Destruction$\|$	$\|\Delta$Employment Growth$\|$
Lagged Employment Growth	0.111 (0.028)	-0.136 (0.019)	-0.009 (0.019)
$\log(\frac{\sigma_{95}}{\sigma_5})$	0.93	-0.97	-0.03
Observations	331	331	331
R^2	0.41	0.40	0.46

Notes: Results from estimating equation 2.1 and the analogous regressions for job destruction and overall employment growth. The second row of each panel quantifies the conditional heteroskedasticity by comparing volatility at the 5th and 95th percentiles of the lagged employment growth distribution (at the mean value of the fixed effects). Panel (a) uses data from the 50 US states and Washington, D.C.. Panel (b) uses data from 9 SIC sectors. In both cases the data is from the Census Bureau BDS database and from 1977-2014. 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. Robust standard errors clustered at the state or industry level are reported in parentheses. The 5th and 95th percentiles of the state (industry) employment growth distribution are -3.4% (-4.9%) and 6.5% (8.7%).

Table 2: Time-Varying Responsiveness to Aggregate Shocks

(a) State Level

	Job Creation	Job Destruction	Employment Growth
Lagged Employment Growth	-0.373	0.479	-0.852
	(0.017)	(0.022)	(0.028)
EBP Shock	-0.111	0.140	-0.250
	(0.024)	(0.021)	(0.029)
Lagged Employment Growth	-0.033	-0.056	0.022
× EBP Shock	(0.012)	(0.014)	(0.018)
Observations	1836	1836	1836
R^2	0.29	0.39	0.51

(b) Industry Level

	Job Creation	Job Destruction	Employment Growth
Lagged Employment Growth	-0.310	0.528	-0.838
	(0.053)	(0.054)	(0.029)
EBP Shock	-0.155	0.142	-0.296
	(0.034)	(0.050)	(0.064)
Lagged Employment Growth	-0.045	-0.039	-0.006
× EBP Shock	(0.016)	(0.003)	(0.018)
Observations	324	324	324
R^2	0.32	0.41	0.48

Notes: Results from estimating equation 2.2 and the analogous regressions for job destruction and overall employment growth. EBP Shock is a shock to the excess bond premium identified as in Gilchrist and Zakrajšek (2012). Panel (a) uses data from the 50 US states and Washington, D.C.. Panel (b) uses data from 9 SIC sectors. In both cases job creation, job destruction and employment data is from the Census Bureau's BDS database from 1977-2014. Robust standard errors clustered at the state or industry level are reported in parentheses.

excess bond premium, and $g^N_{i,t-1}$ is the lagged value of employment growth. As in the previous section, I also run similar regressions where the dependent variable is either the change in job destruction, $JD_{i,t+1} - JD_{i,t-1}$, or overall employment growth, $g^N_{i,t+1} - g^N_{i,t-1}$. 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. I sum these shocks to an annual frequency. Table 2 shows the results of estimating these regressions at the state and industry levels using data from the Census Bureau's Business Dynamics Statistics (BDS) database from 1977-2014.

Table 2 shows that both job creation and job destruction exhibit significant time-varying responsiveness in response to excess bond premium shocks. In both state and industry level data, a contractionary excess bond premium shock lowers job creation, and it does so by more when lagged employment growth is high. Thus, the responsiveness of job creation to the shock is procyclical. On the other hand, a contractionary excess bond premium shock increases job destruction, but does so by less when lagged employment growth is high: The responsiveness of job destruction is countercyclical. As in Section 2.1, these two forces are offsetting, so there is no evidence that overall employment growth exhibits time-varying responsiveness to this identified aggregate shock.

Overall, the results from Section 2.1 and Section 2.2 are consistent. When employment growth is high, the job creation rate is much more responsive to shocks than the job destruction rate. The opposite is true when employment growth is low. 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. All productivity processes are AR(1) in logs. 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.[7] The firm's problem can be written recursively as:

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

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

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

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, $\underline{\mathrm{n}}(z_r, z_i; S)$ and $\bar{n}(z_r, z_i; S)$. If employment is below $\underline{\mathrm{n}}(z_r, z_i; S)$ then the firm raises employment to this threshold in the next period. If 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:[8]

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

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:

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

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

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

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:

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

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 employment adjustment in the model are the hiring cost, κ, and the dispersion of idiosyncratic and regional productivity shocks, σ_i and σ_r. 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.

Table 3: Parameter Values

Parameter		Baseline	Frictionless
Hiring cost	κ	0.47	0
Regional shock volatility	σ_r	0.003	0.0025
Idiosyncratic shock volatility	σ_i	0.105	0.079
Aggregate shock volatility	σ_A	0.0049	0.0039
Regional productivity persistence	ρ_r	0.97	0.97
Idiosyncratic productivity persistence	ρ_i	0.97	0.97
Aggregate productivity persistence	ρ_A	0.974	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	0.78	0.73

In both calibrations, I choose σ_r to match the standard deviation of annual employment growth at the state level in the US, equal to 0.012. I set σ_i to match the standard deviation of annual employment growth among continuing establishments of 0.4 reported in Davis, Haltiwanger, Jarmin, and Miranda (2007). I target continuing establishments as the model abstracts from firm entry and exit and because entry and exit do not contribute to the volatility of aggregate job creation and destruction rates.[9] I set $\rho_r = \rho_i = 0.97$ and choose ρ_A and σ_A to match the persistence and volatility of de-trended US employment.[10]

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 D.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

[9] As shown in Figure 4 in the Appendix.

[10] 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 C.

3.5 Implications of Linear Adjustment Costs

The top panel of Figure 1 shows the firm's employment policy function in the steady-state of the model. For each level of idiosyncratic productivity, the flat regions of the policy function corresponding to level of employment that firms adjust to if they either hire or fire workers. In these regions, future employment does not depend on current employment. There is also an intermediate range of employment levels where firms leave their employment unchanged. In this area of the state space, the policy function is clearly upward sloping in current employment.

The bottom panel of Figure 1 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 levels of idiosyncratic and regional productivity. Firms whose gap is small are unlikely to adjust. As the employment gap gets larger, the adjustment probabilities smoothly increase. This shows that the 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).

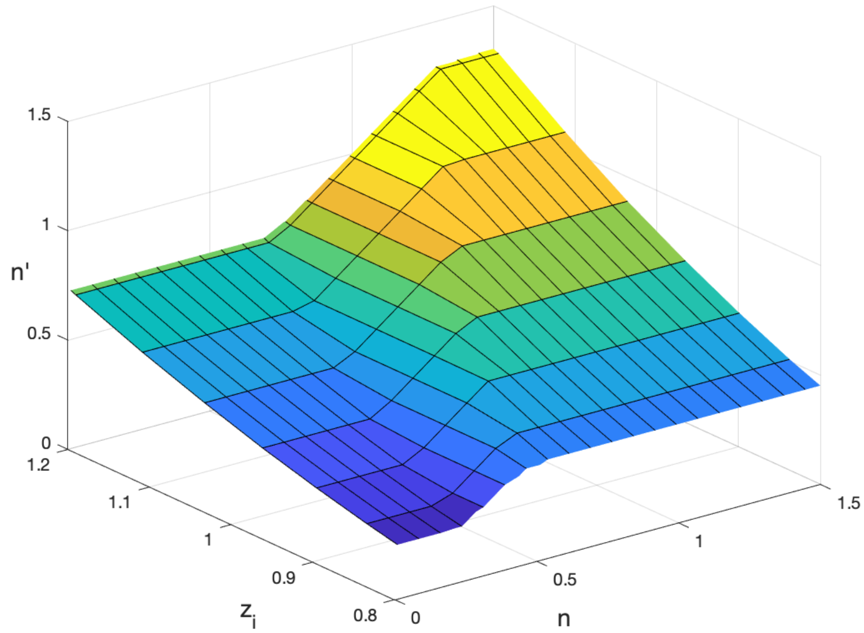
4 Model Validation: The Importance of Adjustment Costs

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

Table 4 shows the results of the volatility regressions for the baseline and frictionless models. The baseline model closely replicates the time-varying volatility seen in Table 1: the volatility of job creation is procyclical, that of job destruction is countercyclical, and the volatility of overall employment growth is acyclical. The second row of the table calculates the volatility at the 5th and 95th percentiles of the employment growth distribution and shows that the magnitude of this time-varying volatility is quantitatively close to that seen in the data.

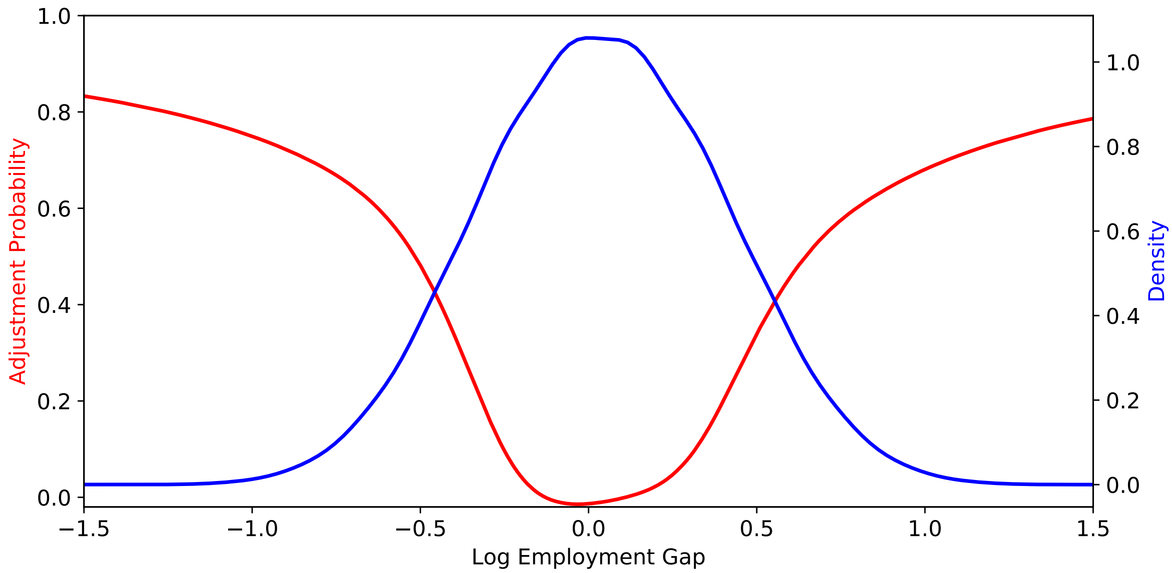
Figure 1: Lumpy Employment Adjustment in the Model

(a) Employment Policy Function



Notes: Employment policy functions shown in the steady-state of the model, holding regional productivity equal to one.

(b) 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.

Table 4: 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	0.059	-0.039	0.020
$\log(\frac{\sigma_{95}}{\sigma_5})$	0.68	-0.56	0.12

(b) Frictionless Model

	$\lvert\Delta$Job Creation$\rvert$	$\lvert\Delta$Job Destruction$\rvert$	$\lvert\Delta$Employment Growth$\rvert$
Lagged Employment Growth	0.016	-0.006	0.010
$\log(\frac{\sigma_{95}}{\sigma_5})$	0.08	-0.04	0.03

Notes: Results from estimating equation 2.1 and the analogous regressions for job destruction and overall employment growth. The second row of each panel quantifies the conditional heteroskedasticity by comparing volatility at the 5th and 95th percentiles of the lagged employment growth distribution (at the mean value of the fixed effects). Regressions use data simulated from 51 regions for a large number of periods. As the model does not include trend growth, for the 5th and 95th percentiles of the state-level employment growth distribution I use -5% and 5%, centering the values from the data.

In contrast, the frictionless model generates almost no time-varying volatility. The estimated coefficients on lagged employment growth are all close to zero and the second row of the table show that in a model without employment adjustment frictions there is no time-varying volatility in job creation and destruction over the business cycle.

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 decomposed 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 5 and 9 in the Appendix show the fraction of establishments creating or destroying jobs in each quarter in the data and the baseline model. 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.

Figure 2a shows the importance of adjustment frictions in a stylized way, by sketching the distribution of firms over the marginal benefit of an extra worker, $\mathbb{E}[\Lambda(S, S')V_n(z_i', z_s', n; S')]$. 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 the effectiveness of different types of employment stabilization policy at different points in time. 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 2a 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 much more potent in a recession than in an expansion.

4.2 Alternative Forms of Adjustment Costs

The results in Table 4 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 D 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 hiring is frictionless) generates the same time-varying responsiveness seen in the baseline model.

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 E 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

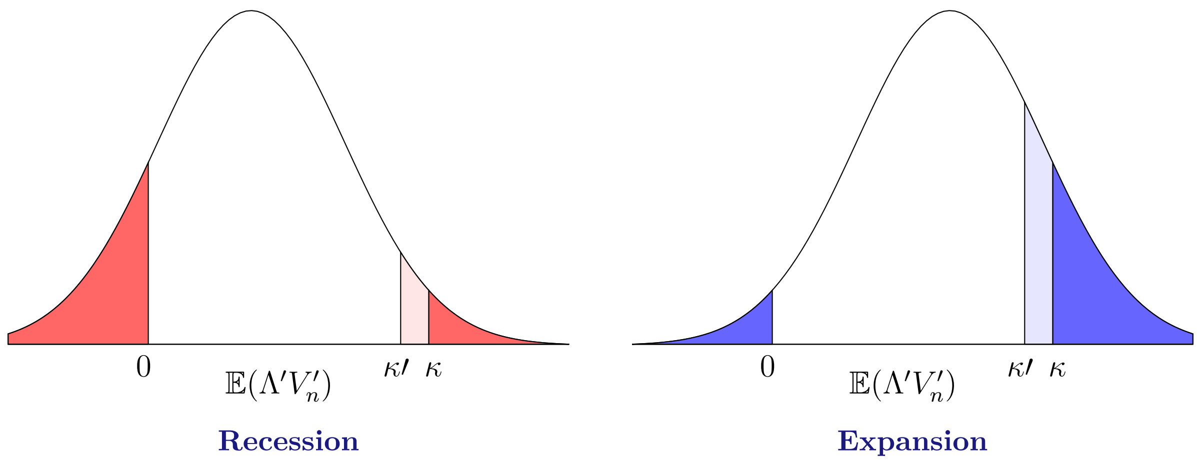
The previous section showed that the baseline model is consistent with the cross-sectional evidence from Section 2. In this section, I consider the aggregate implications of time-varying responsiveness. First, I match the model to the US data, and show that the time-varying responsiveness of aggregate 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 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.[11] 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 measure the impact of a one standard deviation aggregate productivity shock on job creation, job destruction, and

[11] 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. In the Appendix, Figures 8 and 9 show that the model exhibits realistic movements in quarterly job creation and destruction rates, as well as the proportion of firms expanding or contracting.

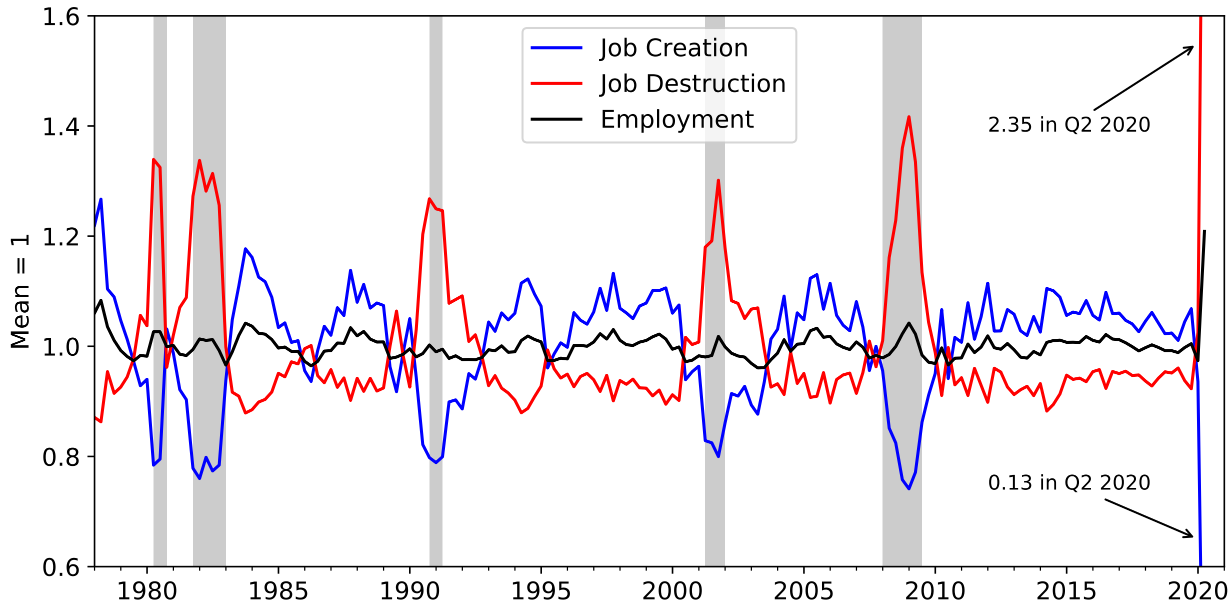
Figure 2: Time-Varying Responsiveness of Job Creation and Destruction

(a) Sketch of Model Distribution



Notes: The distribution sketched is over the expected marginal benefit of an extra worker. When this is above κ the firm increase its employment. When it is below 0 the firm will fire workers.

(b) 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.

employment growth at each point in time:

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

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

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

Figure 2b 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 almost 40% less responsive during the Great Recession in 2009 than it was in the pre-crisis period. Conversely, job destruction was almost 50% more responsive in 2009 than in 2006. Turning to the most recent data, the model implies that the job creation rate is currently almost entirely unresponsive, while the job destruction rate is more than twice as responsive as usual. In short, job destruction is the only relevant margin for the vast majority of firms' employment decisions in response to the COVID-19 pandemic.

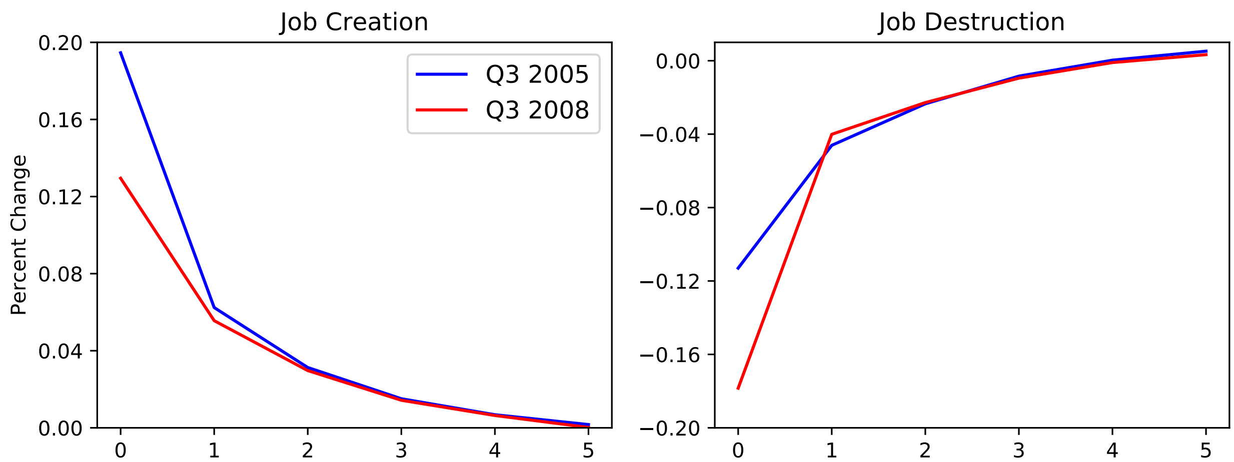
Another way of seeing the time-varying responsiveness generated by the baseline model is to plot the response of job creation and destruction to an aggregate shock at different points in time. Figure 3a plots the impulse response function to a positive aggregate productivity shock in the baseline model 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 2b, 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? The answer is yes, as the time-varying responsiveness of job creation and destruction has significant policy implications.

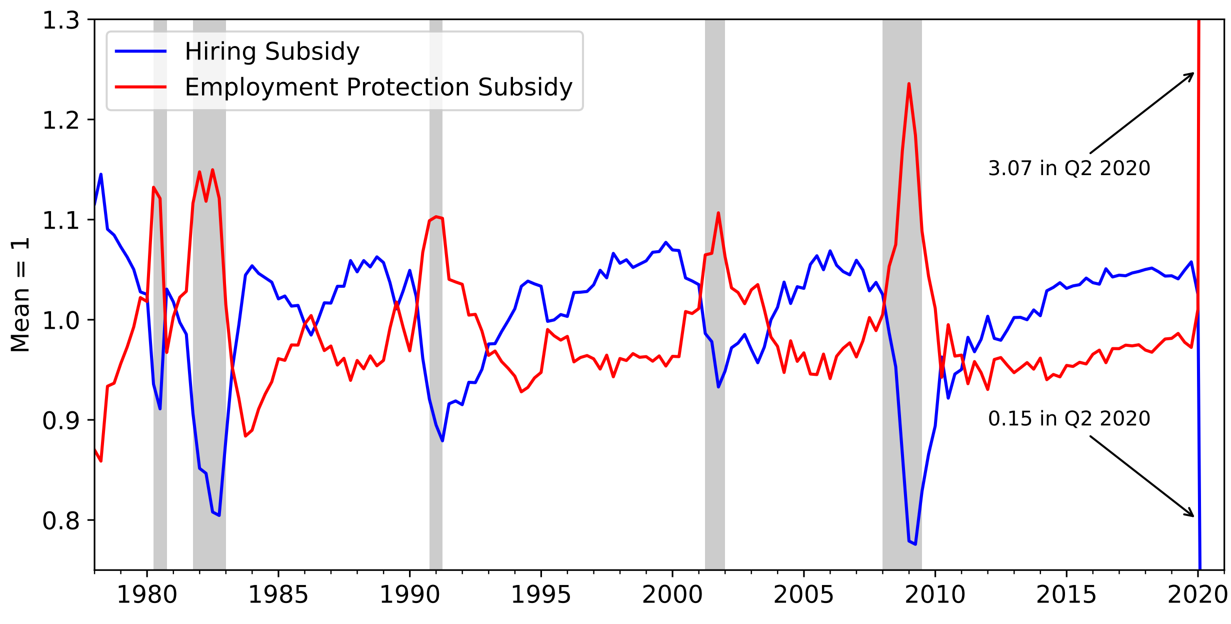
Figure 3: State Dependence of IRFs and Policy Effectiveness

(a) 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.

(b) 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.

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. The Paycheck Protection Program that the US Small Business Administration (SBA) has implemented in response to the COVID-19 pandemic is an example of a policy that aims to discourage job destruction. The program provides loans to small businesses that will be forgiven "if all employees are kept on the payroll for eight weeks and the money is used for payroll, rent, mortgage interest, or utilities".[12] 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.[13]

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.[14] The New Jobs Tax Credit (NJTC) of 1977-1978 provided a significant wage subsidy for firms who increased their employment by more than 2%.

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.[15] 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 3b shows the impact of these policies on aggregate employment at each point in time

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

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

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

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

in the baseline model, with the mean impact normalized to one. The impacts of the policies broadly mirror the responsiveness indices shown in Figure 2b. The effect of a hiring subsidy on aggregate employment is significantly procyclical, while that of an employment protection subsidy is significantly 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 particularly effective in recessions, given that they operate on the job destruction margin.

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 50% 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 suggests that the sharp decline in employment induced by the COVID-19 pandemic means that the aggregate job creation rate is currently almost entirely unresponsive, while the job destruction rate is significantly more responsive than usual. This implies that providing incentives for firms to retain their existing employees is likely the most effective way to support employment levels during the COVID-19 pandemic.

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 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.

References

Bachmann, R., R. J. Caballero, and E. M. Engel (2013). Aggregate implications of lumpy investment: new evidence and a dsge model. *American Economic Journal: Macroeconomics 5*(4), 29–67.

Bentolila, S. and G. Bertola (1990). Firing costs and labour demand: how bad is eurosclerosis? *The Review of Economic Studies 57*(3), 381–402.

Berger, D. and J. Vavra (2015). Consumption dynamics during recessions. *Econometrica 83*(1), 101–154.

Berger, D. and J. Vavra (2019). Shocks versus responsiveness: What drives time-varying dispersion? *Journal of Political Economy 127*(5), 2104–2142.

Blatter, M., S. Muehlemann, and S. Schenker (2012). The costs of hiring skilled workers. *European Economic Review 56*(1), 20–35.

Caballero, R. J. and E. M. Engel (2007). Price stickiness in ss models: New interpretations of old results. *Journal of monetary economics 54*, 100–121.

Caballero, R. J., E. M. Engel, and J. Haltiwanger (1997, March). Aggregate Employment Dynamics: Building from Microeconomic Evidence. *American Economic Review 87*(1), 115–137.

Cahuc, P., S. Carcillo, and T. Le Barbanchon (2019). The effectiveness of hiring credits. *The Review of Economic Studies 86*(2), 593–626.

Christiano, L. J., M. S. Eichenbaum, and M. Trabandt (2016). Unemployment and business cycles. *Econometrica 84*(4), 1523–1569.

Cooper, R., J. Haltiwanger, and J. L. Willis (2007). Search frictions: Matching aggregate and establishment observations. *Journal of Monetary Economics 54*, 56–78.

Cooper, R., J. Haltiwanger, and J. L. Willis (2015). Dynamics of labor demand: Evidence from plant-level observations and aggregate implications. *Research in Economics 69*(1), 37–50.

Cooper, R., M. Meyer, and I. Schott (2017, August). The employment and output effects of short-time work in germany. Working Paper 23688, National Bureau of Economic

Research.

Cooper, R. and J. L. Willis (2009). The cost of labor adjustment: Inferences from the gap. *Review of Economic dynamics 12*(4), 632–647.

Davis, S. J., J. Haltiwanger, R. Jarmin, and J. Miranda (2007, March). Volatility and Dispersion in Business Growth Rates: Publicly Traded versus Privately Held Firms. In *NBER Macroeconomics Annual 2006, Volume 21*, NBER Chapters, pp. 107–180. National Bureau of Economic Research, Inc.

Davis, S. J., J. C. Haltiwanger, and S. Schuh (1998, March). *Job Creation and Destruction*, Volume 1 of *MIT Press Books*. The MIT Press.

Den Haan, W. J. (2010). Assessing the accuracy of the aggregate law of motion in models with heterogeneous agents. *Journal of Economic Dynamics and Control 34*(1), 79–99.

Elsby, M. W. and R. Michaels (2013). Marginal jobs, heterogeneous firms, and unemployment flows. *American Economic Journal: Macroeconomics 5*(1), 1–48.

Foote, C. L. (1998). Trend Employment Growth and the Bunching of Job Creation and Destruction. *The Quarterly Journal of Economics 113*(3), 809–834.

Fujita, S. and M. Nakajima (2016). Worker flows and job flows: A quantitative investigation. *Review of Economic Dynamics 22*, 1–20.

Gilchrist, S. and E. Zakrajšek (2012). Credit spreads and business cycle fluctuations. *American Economic Review 102*(4), 1692–1720.

Greenwood, J., Z. Hercowitz, and G. W. Huffman (1988). Investment, capacity utilization, and the real business cycle. *The American Economic Review*, 402–417.

Hansen, G. D. (1985). Indivisible labor and the business cycle. *Journal of monetary Economics 16*(3), 309–327.

Hijzen, A. and D. Venn (2011). The role of short-time work schemes during the 2008-09 recession.

Hopenhayn, H. and R. Rogerson (1993). Job turnover and policy evaluation: A general equilibrium analysis. *Journal of political Economy 101*(5), 915–938.

Ilut, C., M. Kehrig, and M. Schneider (2018). Slow to hire, quick to fire: Employment dynamics with asymmetric responses to news. *Journal of Political Economy 126*(5), 2011–2071.

Khan, A. and J. K. Thomas (2008). Idiosyncratic shocks and the role of nonconvexities in plant and aggregate investment dynamics. *Econometrica 76*(2), 395–436.

Krusell, P. and A. A. Smith, Jr (1998). Income and wealth heterogeneity in the macroeconomy. *Journal of political Economy 106*(5), 867–896.

OECD (2010). *OECD Employment Outlook 2010*.

Rogerson, R. (1988). Indivisible labor, lotteries and equilibrium. *Journal of monetary Economics 21*(1), 3–16.

Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies. *American economic review 95*(1), 25–49.

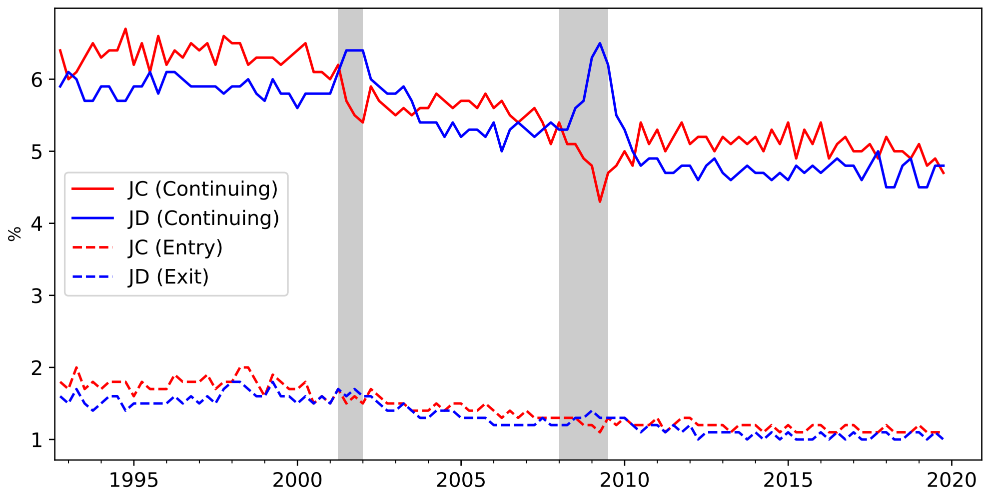
Silva, J. I. and M. Toledo (2009). Labor turnover costs and the cyclical behavior of vacancies and unemployment. *Macroeconomic Dynamics 13*(S1), 76–96.

Young, E. R. (2010). Solving the incomplete markets model with aggregate uncertainty using the krusell–smith algorithm and non-stochastic simulations. *Journal of Economic Dynamics and Control 34*(1), 36–41.

Appendix For Online Publication

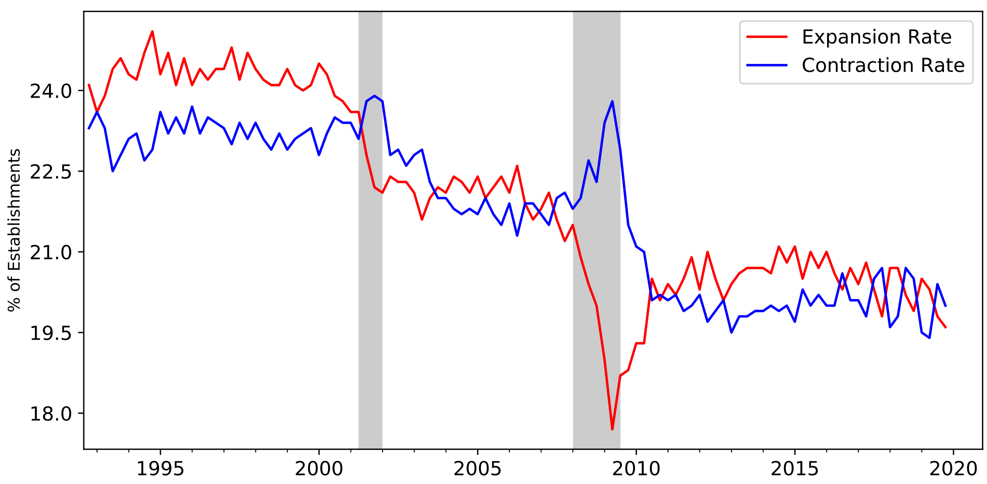
A Supplementary Figures

Figure 4: Job Creation and Destruction Rates: Continuing vs. Entry/Exit



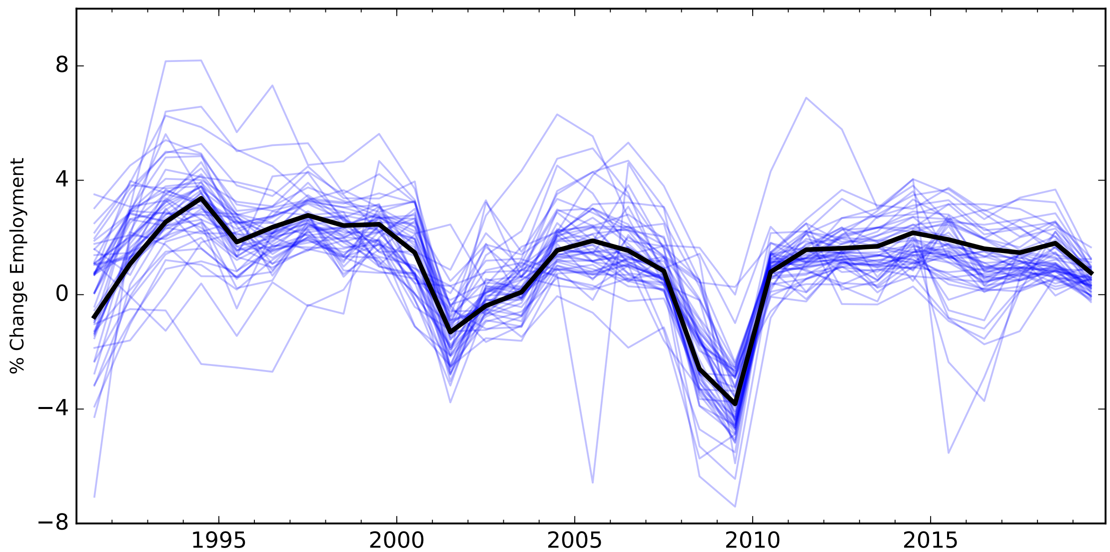
Notes: Quarterly job creation and destruction rates broken down into the contribution from continuing establishments and from those establishments that are entering or exiting. Data from the BLS Business Employment Dynamics database.

Figure 5: Fraction of Establishments Adjusting Employment



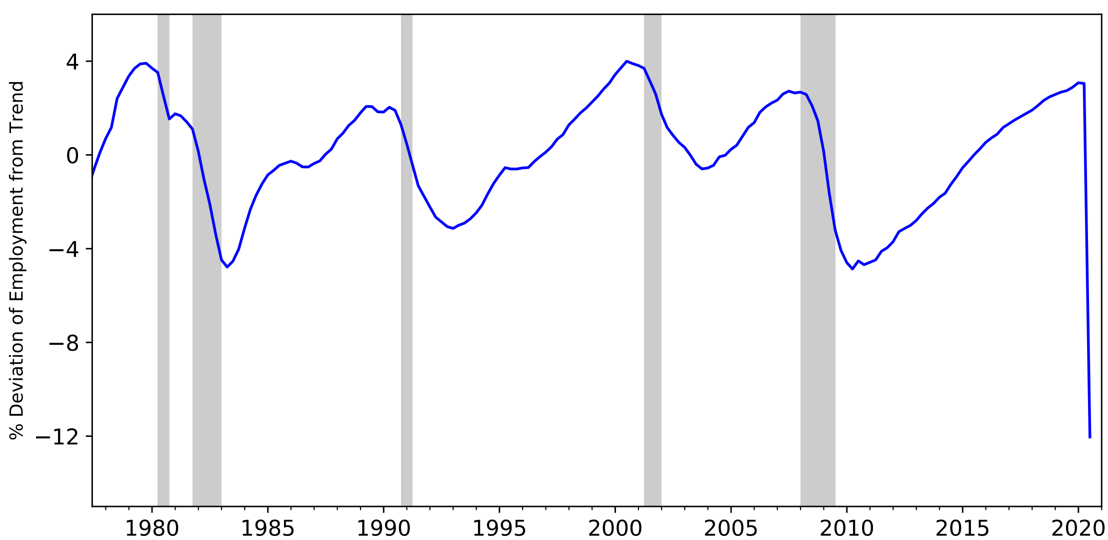
Notes: Fraction of establishments whose employment is either expanding or contracting each quarter. Data from the BLS Business Employment Dynamics database.

Figure 6: State and National Employment Growth



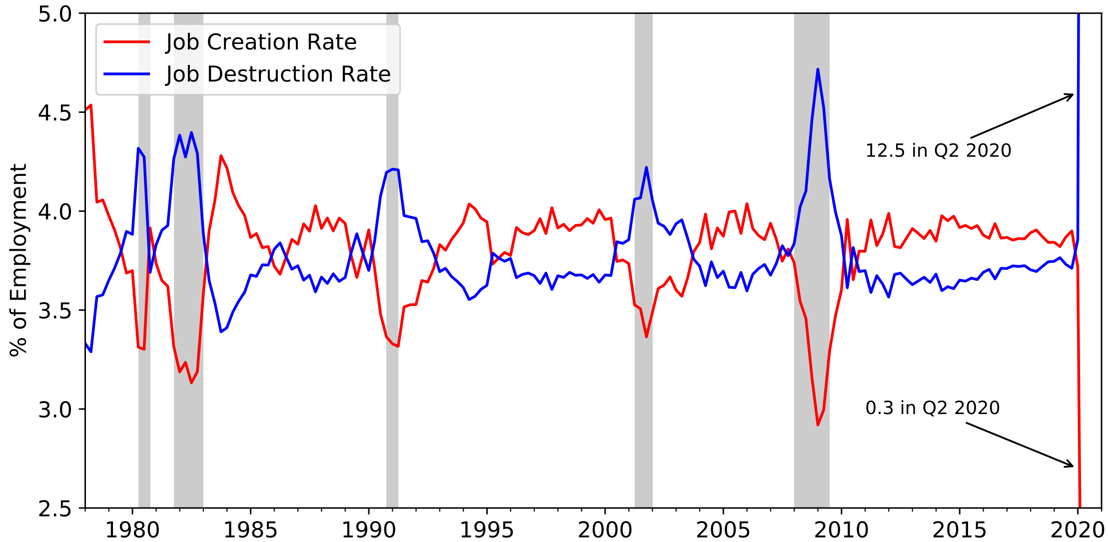
Notes: Blue lines depict state-level annual employment growth. Black line depicts national annual employment growth. Data is total nonfarm employment from the BLS Current Employment Statistics Database.

Figure 7: De-trended US Employment



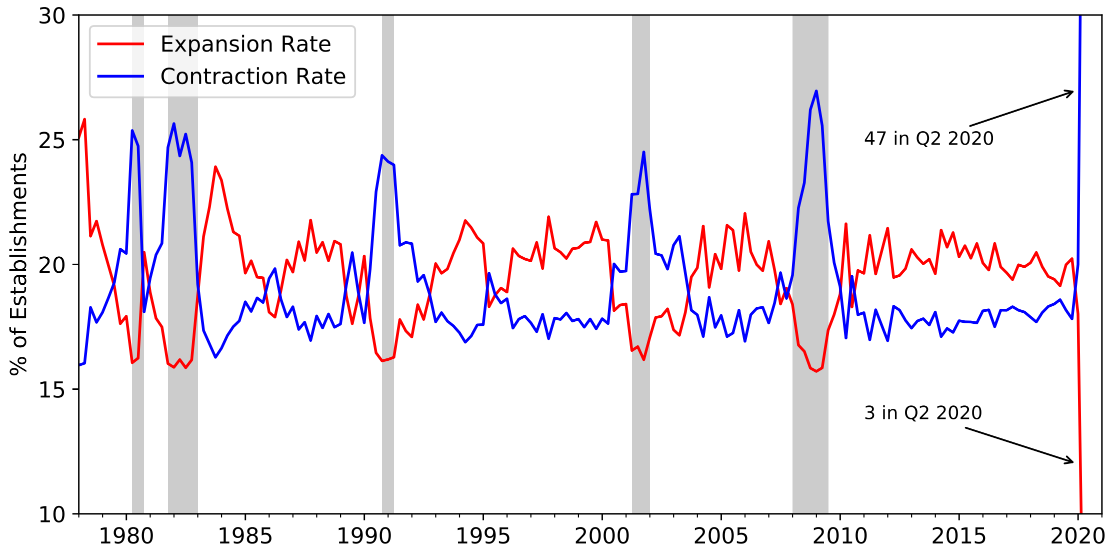
Notes: Cyclical component of quarterly US employment de-trended using the Hodrick-Prescott filter with $\lambda = 1e5$.

Figure 8: 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 9: 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.

B Data

For Section 2.1 and 2.2 I use state and industry-level data on job creation and destruction rates derived from establishment-level data from the US Census Bureau's Business Dynamics Statistics (BDS) database from 1977 to 2014. At the state level, I use data from all 50 states as well as Washington, D.C.. At the industry level, I use data from 9 top-level industries: agriculture, mining, construction, manufacturing, transport & utilities, wholesale trade, retail trade, finance, and services. 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 I also use shocks to the excess bond premium, identified as in 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). I run the VAR using quarterly data and then sum the shocks to the excess bond premium to an annual frequency.

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

B.1 Additional Empirical Specifications

In this Section I show that the results in Section 2 are robust to the removal of state and year fixed effects. Table 5 shows the results of estimating equation 2.1 at the state and industry level without any fixed effects. Table 6 does the same for equation 2.2. At both the state and industry levels the time-varying volatility (or responsiveness) of job creation remains significantly procyclical and that of job destruction remains significantly countercyclical.

Table 5: Conditional Volatility Estimates without Fixed Effects

(a) State Level

	$\lvert\Delta$Job Creation$\rvert$	$\lvert\Delta$Job Destruction$\rvert$	$\lvert\Delta$Employment Growth$\rvert$
Intercept	1.252	1.871	2.445
	(0.051)	(0.059)	(0.092)
Lagged Employment Growth	0.085	-0.075	0.016
	(0.016)	(0.018)	(0.036)
$\log(\frac{\sigma_{95}}{\sigma_5})$	0.63	-0.43	-0.06
Observations	1883	1883	1883
R^2	0.04	0.02	0.00

(b) Industry Level

	$\lvert\Delta$Job Creation$\rvert$	$\lvert\Delta$Job Destruction$\rvert$	$\lvert\Delta$Employment Growth$\rvert$
Intercept	1.606	2.208	3.040
	(0.209)	(0.250)	(0.496)
Lagged Employment Growth	0.087	-0.120	-0.045
	(0.034)	(0.026)	(0.048)
$\log(\frac{\sigma_{95}}{\sigma_5})$	0.69	-0.87	-0.20
Observations	331	331	331
R^2	0.04	0.06	0.00

Notes: Results from estimating equation 2.1 and the analogous regressions for job destruction and overall employment growth without fixed effects. The second row of each panel quantifies the conditional volatility by comparing volatility at the 5th and 95th percentiles of the lagged employment growth distribution. Panel (a) uses data from the 50 US states and Washington, D.C.. Panel (b) uses data from 9 SIC sectors. In both cases the data is from the Census Bureau BDS database and from 1977-2014. Robust standard errors clustered at the state or industry level are reported in parentheses. The 5th and 95th percentiles of the state (industry) employment growth distribution are -3.4% (-4.9%) and 6.5% (8.7%).

Table 6: Time-Varying Responsiveness Estimates without Fixed Effects

(a) State Level

	Job Creation	Job Destruction	Employment Growth
Intercept	0.210	-1.255	1.465
	(0.036)	(0.062)	(0.088)
Lagged Employment Growth	-0.359	0.452	-0.811
	(0.017)	(0.021)	(0.025)
EBP Shock	-0.115	0.148	-0.263
	(0.024)	(0.021)	(0.029)
Lagged Employment Growth	-0.030	-0.061	0.031
× EBP Shock	(0.012)	(0.014)	(0.017)
Observations	1836	1836	1836
R^2	0.28	0.36	0.49

(b) Industry Level

	Job Creation	Job Destruction	Employment Growth
Intercept	-0.032	-1.080	1.048
	(0.101)	(0.267)	(0.348)
Lagged Employment Growth	-0.290	0.450	-0.740
	(0.042)	(0.062)	(0.060)
EBP Shock	-0.157	0.137	-0.293
	(0.034)	(0.051)	(0.068)
Lagged Employment Growth	-0.045	-0.032	-0.013
× EBP Shock	(0.016)	(0.005)	(0.020)
Observations	324	324	324
R^2	0.31	0.34	0.43

Notes: Results from estimating equation 2.2 and the analogous regressions for job destruction and overall employment growth without fixed effects. EBP Shock is a shock to the excess bond premium identified as in Gilchrist and Zakrajšek (2012). Panel (a) uses data from the 50 US states and Washington, D.C.. Panel (b) uses data from 9 SIC sectors. In both cases job creation, job destruction and employment data is from the Census Bureau's BDS database from 1977-2014. Robust standard errors clustered at the state or industry level are reported in parentheses.

C Computational Method

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

C.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:

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

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

where

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

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:

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

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

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

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

The firm's envelope condition for this problem is:

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

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

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

C.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 (C.7) until convergence.

3. Use the expected marginal value function along with the FOCs (C.4 and C.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.

C.2 Frictionless Model

In the frictionless model the firm's problem is:

$$V(z_r, z_i, n; S) = \max_{n'} p(S)[Az_r z_i n^{\alpha} - w(S)n] + \beta \mathbb{E}_{z'_r, z'_i, A'}[V(z'_r, z'_i, n'; S')] \tag{C.8}$$

$$\text{s.t.}$$

$$\mu' = \Gamma(A, \mu)$$

where

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

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

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

The firm's envelope condition is:

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

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

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

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.

C.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 C.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.

C.3 Computational Accuracy

Table 7 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 a large number of periods (T = 5000)[16]. 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 7 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.

D 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. 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 unaffected by any of these calibration changes.

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

Table 7: Accuracy of Equilibrium Forecasting Rules

	Baseline	Frictionless
a_N	0.001	-0.004
b_N	0.515	0.000
c_N	0.555	1.170
a_p	0.365	N/A
b_p	-0.184	N/A
c_p	-1.569	N/A
R^2_N	0.99982	0.99999
R^2_p	0.99997	N/A
Max Error N(%)	0.17	0.11
Mean Error N (%)	0.04	0.10
Max Error p (%)	0.11	N/A
Mean Error p (%)	0.04	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.

D.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):

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

I assume that $\gamma = 0.5$ and recalibrate ψ to keep mean employment equal to 1. Figure 10 shows that the responsivness indices from this model are very similar to those from the baseline model (Figure 2b).

D.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 10 shows that the responsiveness indices from this model, which 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.

D.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 in Figure 10 are almost identical to those in Figure 2b. 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.

D.4 Firing Costs Rather Than Hiring Costs

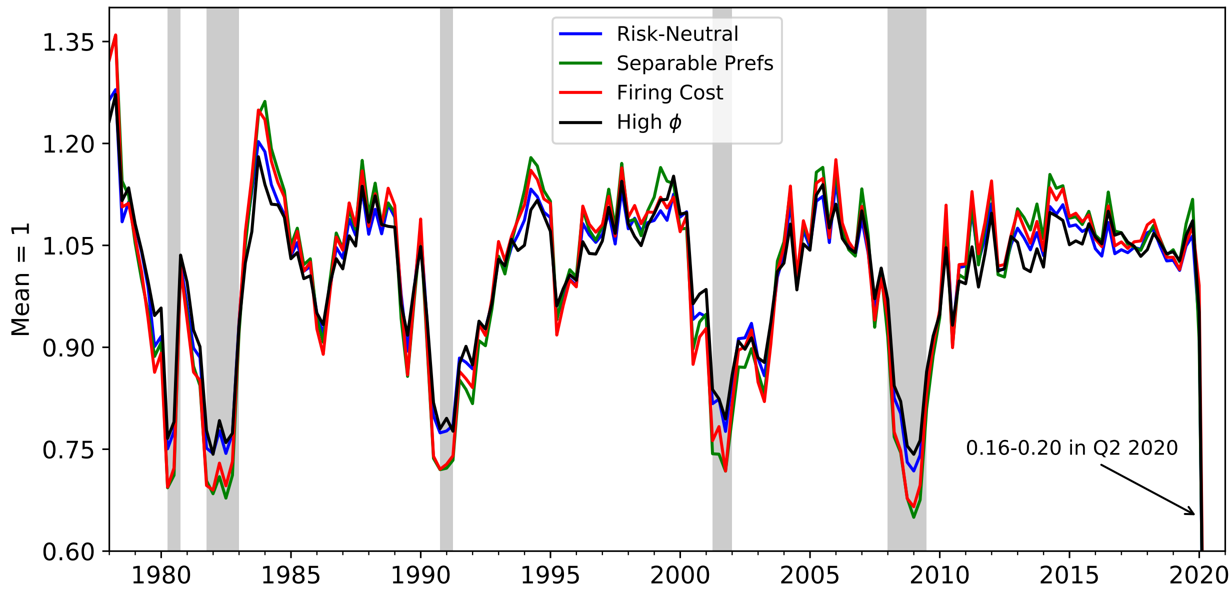
In this section I show that the results are not sensitive to the linear adjustment costs being on the hiring margin rather than the firing margin. I remove the hiring costs from the model, and instead assume that firms face a linear firing tax, F. The firm problem is then:

$$V(z_r, z_i, n; S) = \max_{n'} Az_r z_i n^\alpha - w(S)n - g(n, n') + \mathbb{E}_{z'_r, z'_i, A'}[\Lambda(S, S')V(z'_r, z'_i, n'; S')] \tag{D.2}$$

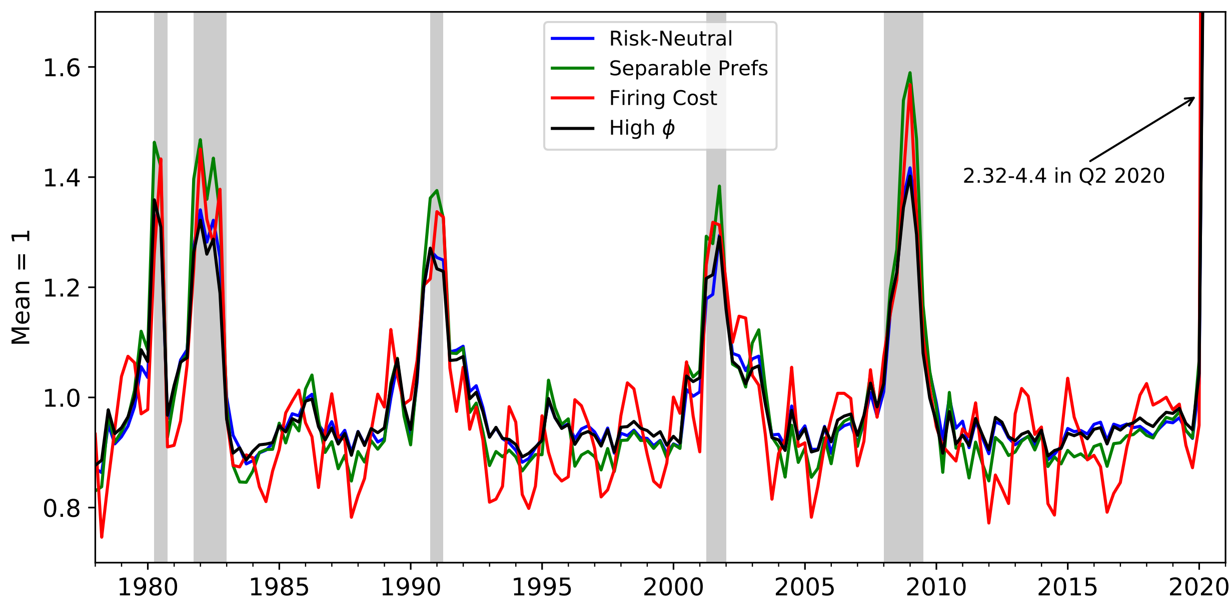
$$\begin{aligned} &\text{subject to} \\ g(n, n') &= F(n - n')\mathbb{1}(n' < n) \\ \mu' &= \Gamma(A, \mu) \\ \log A' &= \rho_A \log A + \sigma_A \epsilon'_A \\ \log z'_r &= \rho_r \log z_r + \sigma_r \epsilon'_r \\ \log z'_i &= \rho_i \log z_i + \sigma_i \epsilon'_i \end{aligned}$$

Figure 10: 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.

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 10 shows that the responsiveness indices implied by the model are almost unchanged.

E 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:

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

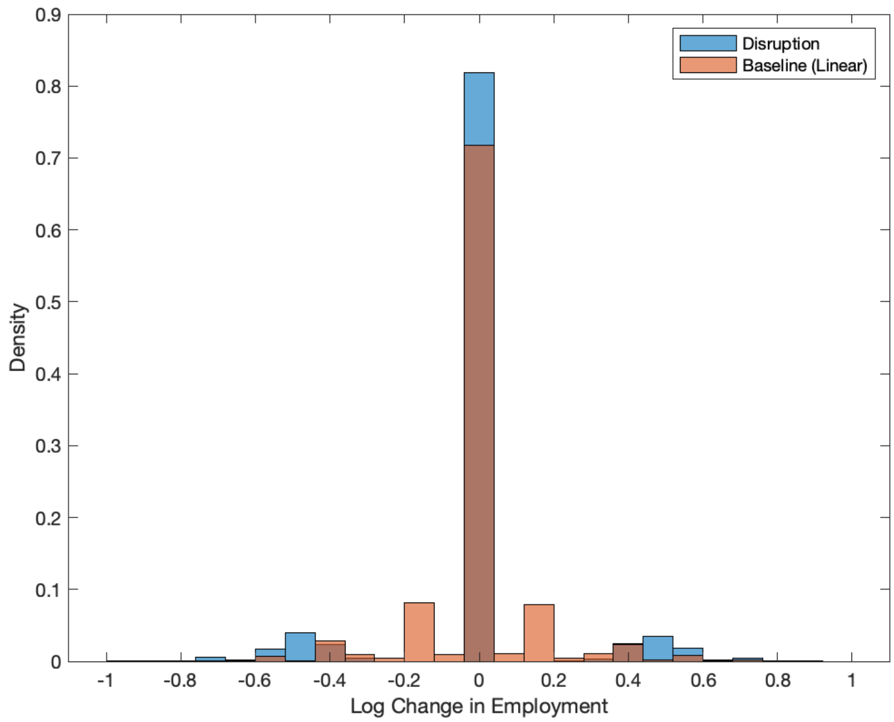
$$\begin{aligned} &\text{subject to} \\ g(n, n') &= \lambda A z_r z_i n^{\alpha} \mathbb{1}(n' \neq n) \\ \mu' &= \Gamma(A, \mu) \\ \log A' &= \rho_A \log A + \sigma_A \epsilon'_A \\ \log z'_r &= \rho_r \log z_r + \sigma_r \epsilon'_r \\ \log z'_i &= \rho_i \log z_i + \sigma_i \epsilon'_i \end{aligned}$$

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 11 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 8 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 11: 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 8: Conditional Volatility in Disruption Cost Model

	$\vert\Delta$Job Creation$\vert$	$\vert\Delta$Job Destruction$\vert$	$\vert\Delta$Employment Growth$\vert$
Lagged Employment Growth	0.034	-0.017	0.017
$\log(\frac{\sigma_{95}}{\sigma_5})$	0.25	-0.14	0.07

Notes: Results from estimating equation 2.1 and the analogous regressions for job destruction and overall employment growth. The second row of each panel quantifies the conditional heteroskedasticity by comparing volatility at the 5th and 95th percentiles of the lagged employment growth distribution (at the mean value of the fixed effects). Regressions use data simulated from 51 regions for a large number of periods. As the model does not include trend growth, for the 5th and 95th percentiles of the state-level employment growth distribution I use -5% and 5%, centering the values from the data.