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 targeting the job creation margin, 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.

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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[1]. 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 on job creation and destruction rates at the state-level to show that job creation and destruction exhibit significant time-varying responsiveness. Using a predicted employment growth strategy, as in Bartik (1991), I show that the relative contribution of job creation and job destruction to changes in employment growth varies significantly over the business cycle. Consider a shock that raises employment. In states where annual employment growth is 3%, 50% of the increase in employment comes from higher job creation, and 50% comes from lower job destruction. However, when annual employment growth is -3%, the contribution of lower job destruction rises to 67%, and that of higher job creation falls to 33%.

An implication of this time-varying responsiveness is that the job creation rate should be more volatile when employment growth is high, and the job destruction rate should be more volatile when employment growth is low. In the state-level data I find exactly this: a one-standard deviation increase in employment growth raises the volatility of the job creation rate by just under 20%, and lowers the volatility of the job destruction rate by a similar amount.

To understand the causes and implications of this time-varying responsiveness, I build 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.

[1]These definitions were proposed by Davis, Haltiwanger, and Schuh (1998).

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 adjustment is able to quantitatively match the time-varying responsiveness of job creation and destruction seen in the data. I show that the presence of employment 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 almost three times 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 this time-varying responsiveness by estimating the impact of unexpected hiring subsidies or employment protection subsidies[2] at different points in time. 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 new hiring would likely be entirely ineffective at this time.

[2] An employment protection subsidy is a payment made to firms whose employment does not contract.

1.1 Literature Review

There is a large literature studying 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.

In this paper the focus is on the implications of lumpy employment adjustment for 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 showed 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 Appendix D 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 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, I use a local labor demand shock approach, following Bartik (1991). I construct a measure of predicted state-level employment growth, based on local industry shares, and national variation in industry employment growth rates. I then investigate the extent to which this predicted employment growth feeds through into changes in job creation or job destruction, and whether this pass-through varies over time. Second, I use a panel approach to show that the volatility of changes in job creation and destruction rates varies over the business cycle. Both approaches lead to the same conclusions: job creation is around 60% more volatile at the 95th percentile of the state-level employment growth distribution than when it is at the 5th percentile of the distribution. The opposite is true of job destruction.

2.1 Approach 1: Bartik Method

In this section, I estimate the response of state-level job creation and destruction to changes in predicted employment growth, constructed following Bartik (1991). Predicted employment growth for state i at time t is constructed using industry-level employment growth rates in the remainder of the country at time t and weights based on each industry's employment share in state i in a given base period:

$$B_{i,t} = \sum_{k=1}^{K} \varphi_{i,k,\tau} g^N_{-i,k,t} \tag{2.1}$$

where $\varphi_{i,k,\tau}$ is the employment share of industry k in state i in the base year $\tau = 1990$, and $g^N_{-i,k,t}$ is national employment growth in industry k excluding state i in year t. The Bartik method predicts high employment growth in a state if the industries that the state has specialized in are growing fast in the rest of the country[3].

Using this measure of predicted employment growth, I then use the following regression spec-

[3]This method has become popular as a method of identifying exogenous changes in labor demand at the state-level. For example, Notowidigdo (2011) or Charles, Hurst, and Notowidigdo (2012). Goldsmith-Pinkham, Sorkin, and Swift (2018) provides a thorough discussion of the Bartik approach.

ification to estimate the time-varying responsiveness of job creation and destruction:

$$\Delta Y_{i,t} = \alpha_i + \gamma_t + \beta_0 B_{i,t} + \beta_1 B_{i,t} \cdot g^N_{i,t-1} + \Gamma' Z_{i,t-1} + \epsilon_{i,t} \tag{2.2}$$

where $\Delta Y_{i,t}$ is the change in the state's job creation rate, job destruction rate, or employment growth, $g^N_{i,t-1}$ is lagged employment growth and $Z_{i,t-1}$ is a vector of control variables. The main coefficient of interest is β_1. This shows how the impact of a change in predicted employment growth on the outcome variable is affected by the current cyclical position of the state, measured by local employment growth in the previous year.

I estimate these regressions using annual data at the state-level from the Census Bureau's Business Dynamics Statistics (BDS) database. I construct the Bartik instrument using annual data on state-industry employment from the Quarterly Census of Employment and Wages (QCEW). Appendix B gives more details on the data used, the construction of the Bartik instrument, and the controls used to estimate equation 2.2. Table 1a shows the results.

The first columns shows the effect of the Bartik shock on overall employment growth. As might be expected, on average the change in employment growth predicted by the Bartik measure is correct: employment growth moves one-for-one with the Bartik shock. The second row shows that there is no evidence of time-varying responsiveness of overall employment growth. The third and fourth rows of the table use the estimated values $\hat{\beta}_0$ and $\hat{\beta}_1$ to compare estimates of the response at the mean level of lagged employment growth, and when employment growth is one standard deviation higher. The fifth row compares the responsiveness at the 5th and 95th percentiles of the state-level employment growth distribution. For total employment growth, the responsiveness is unaffected by lagged employment growth.

The next two columns show that the acyclical responsiveness of employment masks significant time-varying responsiveness in job creation and destruction. The estimate of $\hat{\beta}_1$ is positive and significantly different from zero for both job creation and job destruction. A one standard deviation increase in employment growth from its mean level increases the responsiveness of the job creation rate by just under 20%, and reduces the responsiveness of the job destruction rate by a similar amount. Looking at the tails of the distribution: job creation is around 60% more responsive at the 95th percentile compared to the 5th percentile of the employment growth distribution. The opposite is true of job destruction.

Table 1: Empirical Evidence of Time-Varying Responsiveness

(a) Bartik Method

	$\Delta g^N_{i,t}$	$\Delta JC_{i,t}$	$\Delta JD_{i,t}$
$B_{i,t}$	0.99	0.40	-0.59
	(0.20)	(0.13)	(0.14)
$B_{i,t} \cdot g^N_{i,t-1}$	-0.003	0.025	0.027
	(0.017)	(0.010)	(0.010)
$\hat{\beta}_0 + \hat{\beta}_1 \bar{g}^N$	0.99	0.45	-0.53
$\hat{\beta}_0 + \hat{\beta}_1(\bar{g}^N + 1\text{SD})$	0.98	0.54	-0.44
$\log(\frac{\sigma_{95}}{\sigma_5})$	-0.03	0.60	-0.55
Observations	1173	1173	1173
R^2	0.415	0.305	0.369

Notes: Data from 1990-2014. Standard errors clustered by state. The mean and standard deviation of state-level employment growth are 2.1% and 3.3%. The 5th and 95th percentiles of the state-level employment growth distribution are -3.4% and 7.1%.

(b) Conditional Heteroskedasticity

	$\lvert\Delta g^N_{i,t}\rvert$	$\lvert\Delta JC_{i,t}\rvert$	$\lvert\Delta JD_{i,t}\rvert$
$g^N_{i,t-1}$	0.015	0.080	-0.101
	(0.028)	(0.013)	(0.024)
$\lvert\widehat{\Delta Y_{i,t}}(\bar{g}^N)\rvert$	2.46	1.41	1.70
$\lvert\widehat{\Delta Y_{i,t}}(\bar{g}^N + 1\text{SD})\rvert$	2.50	1.68	1.37
$\log(\frac{\sigma_{95}}{\sigma_5})$	0.06	0.63	-0.64
Observations	1836	1836	1836
R^2	0.17	0.06	0.16

Notes: Data from 1977-2014. Standard errors clustered by state. The mean and standard deviation of state-level employment growth are 2.1% and 3.3%. The 5th and 95th percentiles of the state-level employment growth distribution are -3.4% and 7.1%.

2.2 Approach 2: Conditional Heteroskedasticity

An alternative approach to measuring time-varying responsiveness is simply to investigate whether or not the volatility of job creation and destruction is state dependent. If the job creation rate is particularly responsive during expansions, then the volatility of the job creation rate should be higher at such times. The opposite should be true of the job destruction rate.

To test this prediction, I use the same state-level panel of job creation and destruction rates from the BDS database. I then regress the absolute value of changes in a variable on its lagged value and the lagged value of employment growth in that state.

$$|\Delta Y_{i,t}| = \alpha_i + \gamma_t + \beta_0 |\Delta Y_{i,t-1}| + \beta_1 g^N_{i,t-1} + \epsilon_{i,t} \tag{2.3}$$

Again, the main parameter of interest is β_1. In this case, β_1 measures the extent to which the absolute size of changes in a variable are related to lagged employment growth. Table 1b shows the results of estimating this regression for employment growth, job creation, and job destruction.

The results mirror those using the Bartik approach: There is no evidence of time-varying volatility of total employment growth, the job creation rate is more volatile when lagged employment growth is high, and the job destruction rate is more volatile when lagged employment growth is low. The magnitude of these effects is also similar to those from the Bartik approach. A one-standard deviation increase in employment growth raises the volatility of the job creation rate by just under 20% and lowers the volatility of the job destruction rate by the same amount[4].

Overall, the results from Section 2.1 and Section 2.2 are consistent and quantitatively significant. 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. This suggests that in expansions, 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. In the next section, I study a model which formalizes this argument.

[4] I estimate these counterfactuals at the mean value of the fixed effects estimated across states, holding the lagged value of volatility at its average level.

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, region, 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. The firm's problem can be written recursively as:

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

$$\text{subject to}$$

$$g(n, n') = \kappa(n' - n)\mathbb{1}(n' > n)$$

$$\mu' = \Gamma(A, \mu)$$
$$\log A' = \rho_A \log A + \sigma_A \epsilon'_A$$
$$\log z'_r = \rho_r \log z_r + \sigma_r \epsilon'_r$$
$$\log z'_i = \rho_i \log z_i + \sigma_i \epsilon'_i$$

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[5]:

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

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

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. This simplifies computation of the model substantially, as discussed in Appendix C.

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.

Table 2: Parameter Values

Parameter		Baseline	Frictionless
Hiring cost	κ	0.47	0
Regional shock volatility	σ_r	0.0045	0.0025
Idiosyncratic shock volatility	σ_i	0.10	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

3.4 Equilibrium Calibration and Computation

The model period is one quarter. Table 2 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)[6]. This value corresponds broadly to the lower end of estimates of hiring costs in the literature.

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 choose 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 choose to target only continuing establishments as the model abstracts from firm entry and exit, and because Figure 3 in the Appendix shows that entry and exit do not contribute to the volatility of aggregate job creation and destruction rates. 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[7].

I follow Cooper, Haltiwanger, and Willis (2007) in setting the curvature of the production

[6]This corresponds to 5% for the cost of recruiting and 55% for the cost of training a worker.

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

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 the Appendix I show that the main results are robust to lower values of the labor supply elasticity or a risk-neutral representative household. 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 strategy and proof of its accuracy are given in Appendix C.

4 Model Validation: The Importance of Hiring Costs

To show the importance of hiring costs in generating time-varying responsiveness, I now replicate the experiments from Section 2 in each version of the model.

As the model does not include industries, it is not possible to exactly replicate the Bartik experiment in the model. However, it is possible to use aggregate employment growth as a measure of predicted regional employment growth, in order to run the same regressions as in Section 2.1. In the model, aggregate employment growth is equal to mean regional employment growth by construction. For the volatility regressions in Section 2.2, it is possible to run the regressions exactly as in the data.

Table 3a shows the results of the Bartik regressions for the baseline and frictionless models. In both cases, I simulate the aggregate economy and one region for 1200 periods (approximately the same number of observations as used in Section 2.1) and then run the regressions on the data generated from the model. The coefficients and confidence intervals are then constructed by repeating this process a large number of times.

The baseline model replicates closely the time-varying responsiveness seen in Table 1a: employment growth does not exhibit time-varying responsiveness, while the responsiveness of job creation is procyclical, and that of job destruction is countercyclical. The final three rows of the table show that the magnitudes of the time-varying responsiveness are quantitatively very close to those seen in Table 1a.

Table 3: Time-Varying Responsiveness in the Model

(a) Bartik Method

	Baseline Model			Frictionless Model		
	$\Delta g_{i,t}^N$	$\Delta JC_{i,t}$	$\Delta JD_{i,t}$	$\Delta g_{i,t}^N$	$\Delta JC_{i,t}$	$\Delta JD_{i,t}$
$B_{i,t}$	1.05	0.59	-0.46	1.00	0.54	-0.45
	(0.97,1.14)	(0.54,0.63)	(-0.50,-0.43)	(0.93,1.07)	(0.50,0.58)	(-0.49,-0.42)
$B_{i,t} \cdot g_{i,t-1}^N$	0.006	0.028	0.022	0.000	0.002	0.001
	(-0.02,0.03)	(0.01,0.04)	(0.01,0.04)	(-0.02,0.02)	(-0.01,0.01)	(-0.01,0.01)
$\hat{\beta}_0 + \hat{\beta}_1 \bar{g}^N$	1.05	0.59	-0.46	1.00	0.54	-0.45
$\hat{\beta}_0 + \hat{\beta}_1(\bar{g}^N + 1\text{SD})$	1.07	0.68	-0.39	1.00	0.54	-0.45
$\log(\frac{\sigma_{95}}{\sigma_5})$	0.06	0.50	-0.50	0.01	0.03	-0.03

Notes: 90% confidence intervals in parenthesis, calculated using 500 simulations of the model for 1200 periods. I use the same set of control variables as described in Appendix B.1. In the model mean employment growth is zero. I use the standard deviation of state employment growth of 3.3% estimated in the data. For the 95th and 5th percentiles of the employment growth distribution I use -5.2% and 5.2% (de-meaning the values of -3.4% and 7.1% from the data).

(b) Conditional Heteroskedasticity

	Baseline Model			Frictionless Model		
	$\lvert\Delta g_{i,t}^N\rvert$	$\lvert\Delta JC_{i,t}\rvert$	$\lvert\Delta JD_{i,t}\rvert$	$\lvert\Delta g_{i,t}^N\rvert$	$\lvert\Delta JC_{i,t}\rvert$	$\lvert\Delta JD_{i,t}\rvert$
$g_{i,t-1}^N$	0.02	0.069	-0.049	0.006	0.012	-0.005
	(-0.01,0.05)	(0.05,0.09)	(-0.06,-0.03)	(-0.04,0.05)	(-0.01,0.04)	(-0.02,0.01)
$\lvert\widehat{\Delta Y_{i,t}}\rvert(\bar{g}^N)$	1.99	1.11	0.88	3.78	2.05	1.72
$\lvert\widehat{\Delta Y_{i,t}}\rvert(\bar{g}^N + 1\text{SD})$	2.06	1.35	0.72	3.80	2.10	1.71
$\log(\frac{\sigma_{95}}{\sigma_5})$	0.10	0.67	-0.59	0.02	0.06	-0.03

Notes: 90% confidence intervals in parenthesis, calculated using 500 simulations of the model for 1200 periods. In the model mean employment growth is zero. I use the standard deviation of state employment growth of 3.3% estimated in the data. For the 95th and 5th percentiles of the employment growth distribution I use -5.2% and 5.2% (de-meaning the values of -3.4% and 7.1% from the data).

The frictionless model generates almost no time-varying responsiveness. The coefficient on the interaction term is not significantly different from zero for any of the variables, and the final three rows of the table show that there is no quantitatively significant time-varying responsiveness. Without employment adjustment frictions, the relative contribution of job creation and destruction to changes in employment growth does not vary over the business cycle.

Table 3b shows the results of the volatility regressions for both versions of the model. Once again, the baseline model with lumpy employment adjustment generates time-varying volatility that is almost exactly the same magnitude as seen in the data. In contrast, in the frictionless version of the model the volatility of employment growth, job creation, and job destruction is acyclical.

4.1 What Causes Time-Varying Responsiveness?

The previous section showed that 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. Why is this the case?

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.

Figure 3 shows this in a stylized way in the model by plotting the distribution over the marginal benefit of an extra worker, $\mathbb{E}[\Lambda(S,S')V(z_i',z_s',n;S')]$. 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 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 much more potent in a recession than in an expansion.

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[8] such that aggregate employment in the model exactly replicates the path of the cyclical component of US employment from 1977 to the present[9]. 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

[8] Bachmann et al. (2013) and Berger and Vavra (2015) use a similar procedure to show time-varying responsiveness of investment and durable consumption.

[9] I assume that the model is in steady-state in June 1977. In the Appendix, Figure 7 shows the implied path of aggregate productivity in the model and 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.

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 1b 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 around 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 almost three times 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 2a plots the impulse response 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 1b, during a recession the impact of the shock on job destruction is larger and on job creation is smaller.

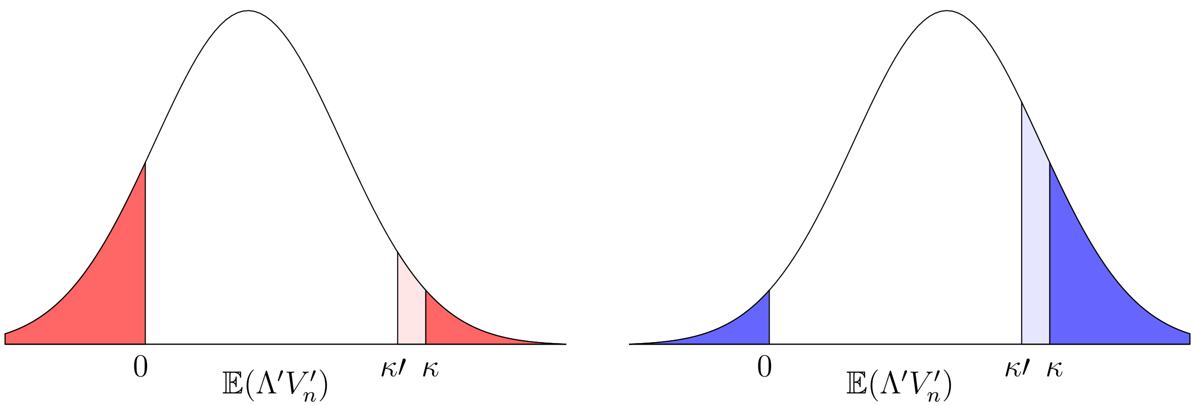
5.1 Time-Varying Policy Effectiveness

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.

Employment stabilization policies can be categorized into those that aim to encourage job

Figure 1: Time-Varying Responsiveness of Job Creation and Destruction

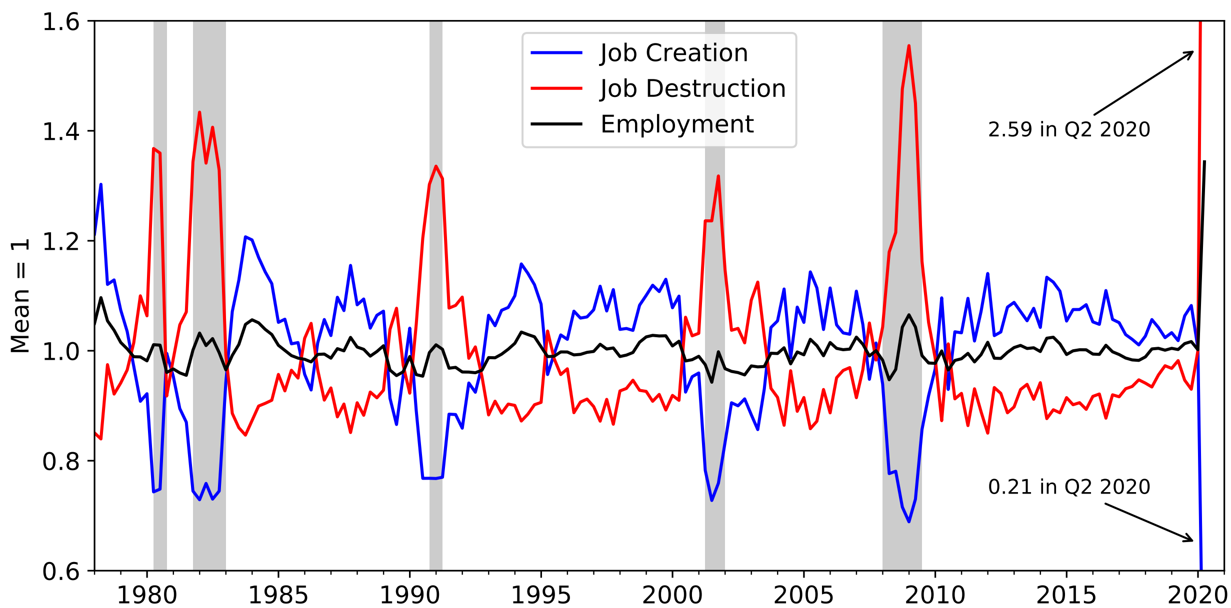
(a) Sketch of Model Distribution



Recession **Expansion**

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.

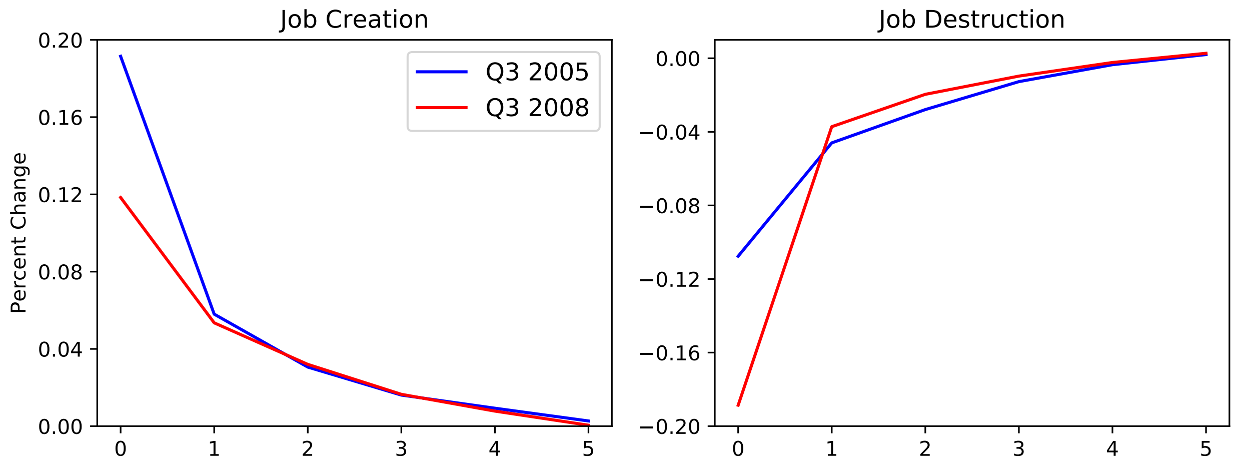
(b) Model-Implied Responsiveness Indices



Notes: Impact on job creation, job destruction and employment of a one SD aggregate productivity shock. The mean response is normalized to one.

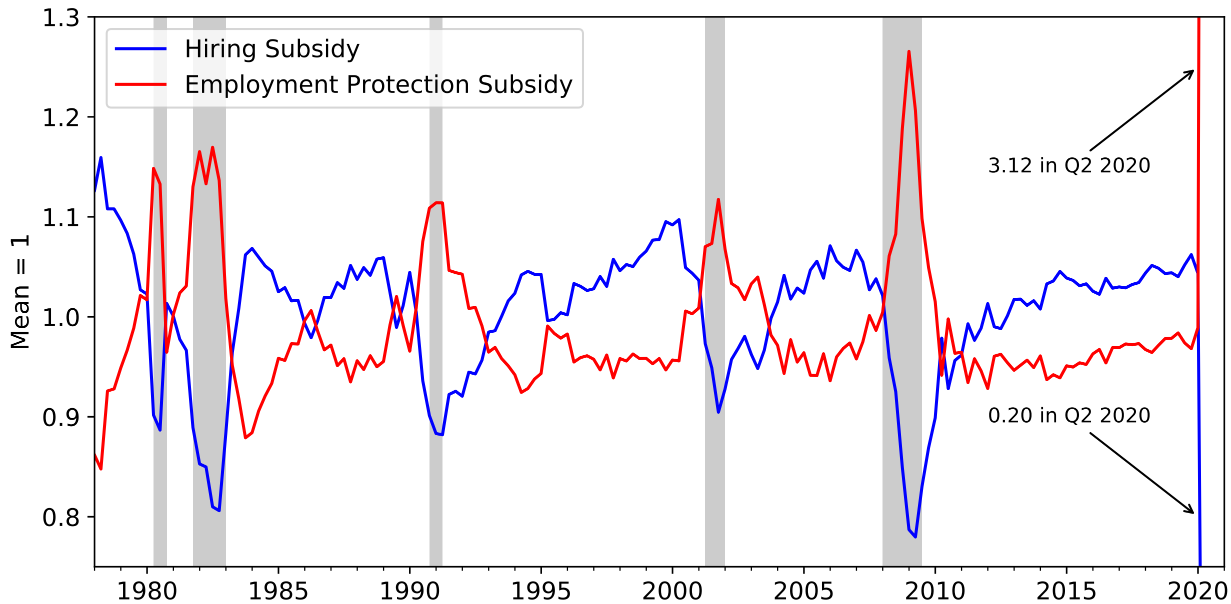
Figure 2: State Dependence of IRFs and Policy Effectiveness

(a) Impulse Response Functions



Notes: Impact on job creation and job destruction of a one SD aggregate productivity shock at two points in the business cycle.

(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.

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 initiated 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"[10]. 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[11].

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. 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 of employment of an unexpected hiring subsidy or an unexpected employment protection subsidy equal to 25% of the average quarterly wage[12]. 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 2b 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. As might be expected, the impacts of the policies broadly mirror the responsiveness indices shown in Figure 1b. The

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

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

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

effectiveness 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: a one standard deviation in state-level employment growth leads to an almost 20% increase in the responsiveness of job creation and a 20% decline in the responsiveness of job destruction.

I have shown that a heterogeneous-firm business cycle model with lumpy employment adjustment is capable of explaining this 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.

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Appendix For Online Publication

A Supplementary Figures

Figure 3: Job Creation and Destruction Rates: Continuing vs. Entry/Exit

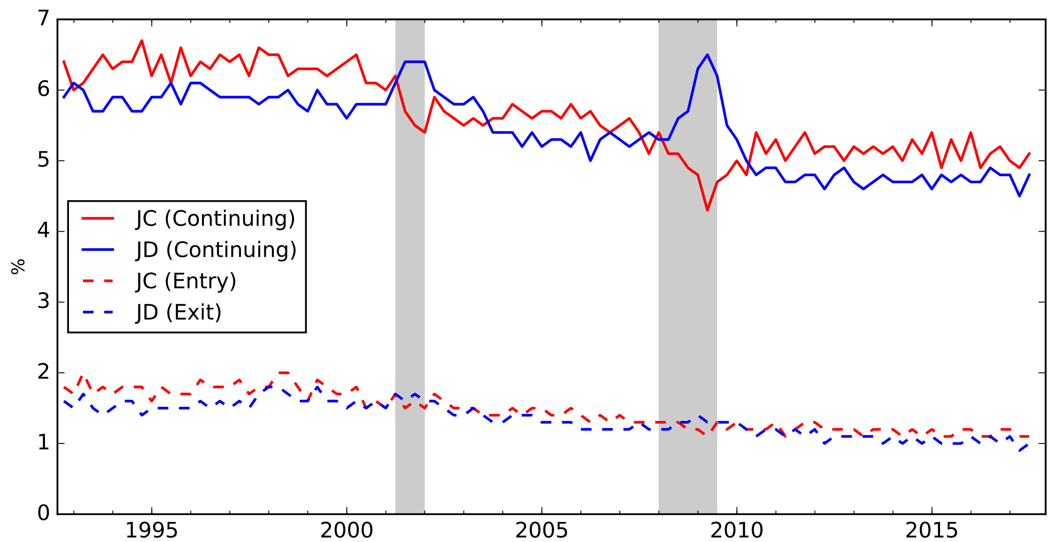
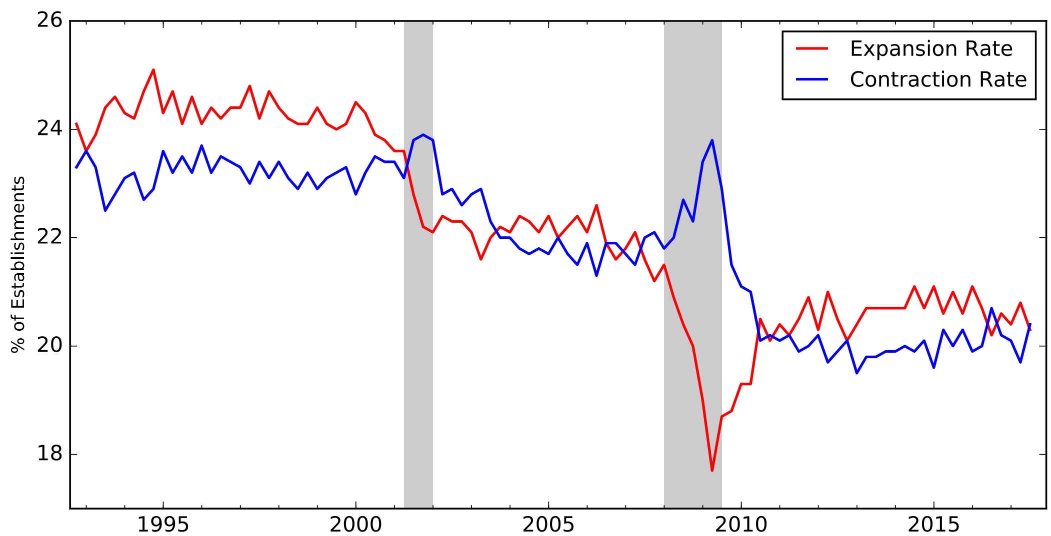
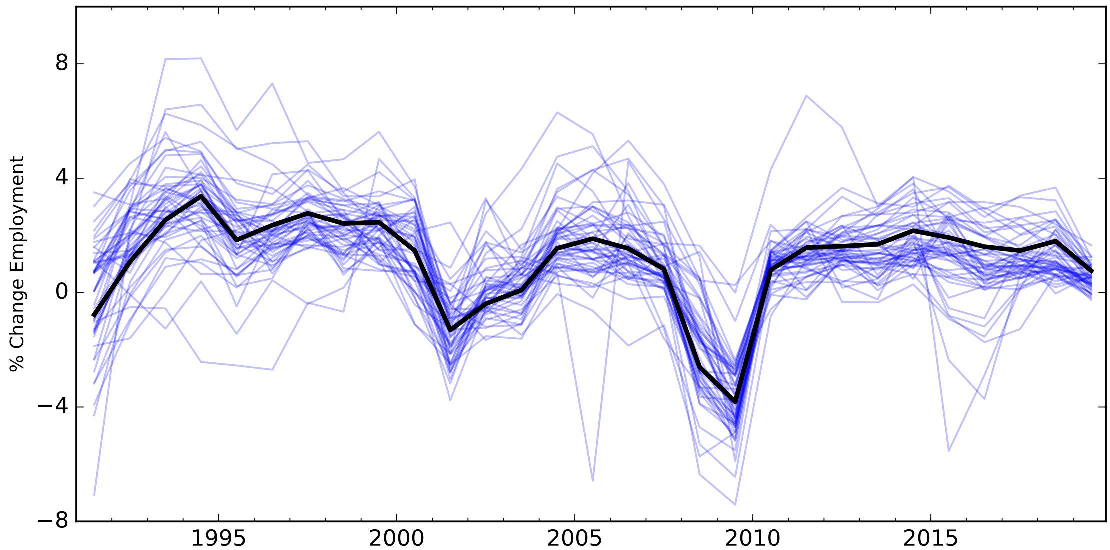


Figure 4: Fraction of Establishments Adjusting Employment



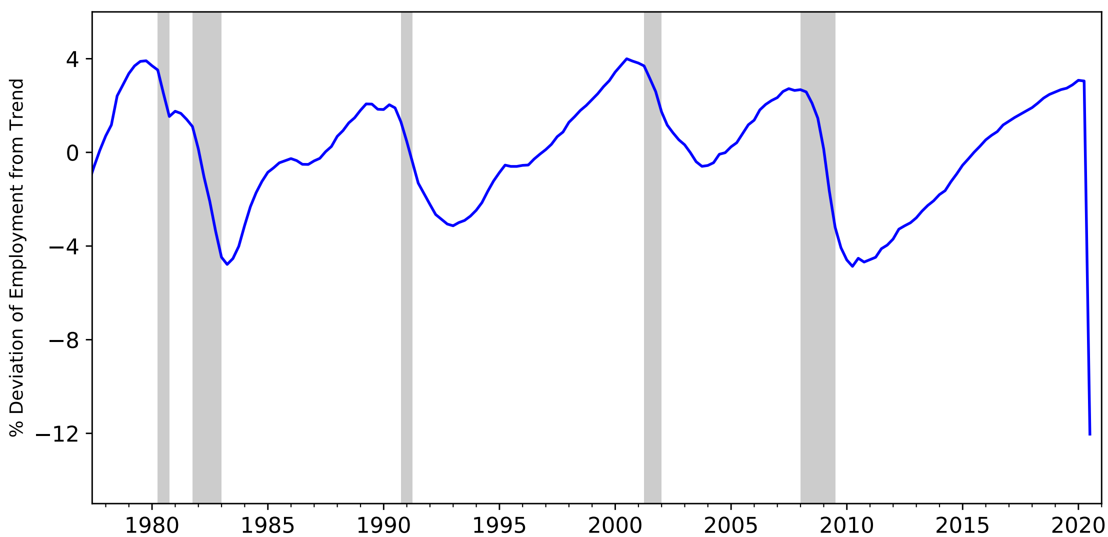
Notes: Data from the BLS Business Employment Dynamics database.

Figure 5: State and National Employment Growth



Notes: Light-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 6: Cyclical Component of US Employment



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

Figure 7: Model-Implied Aggregate Productivity Series

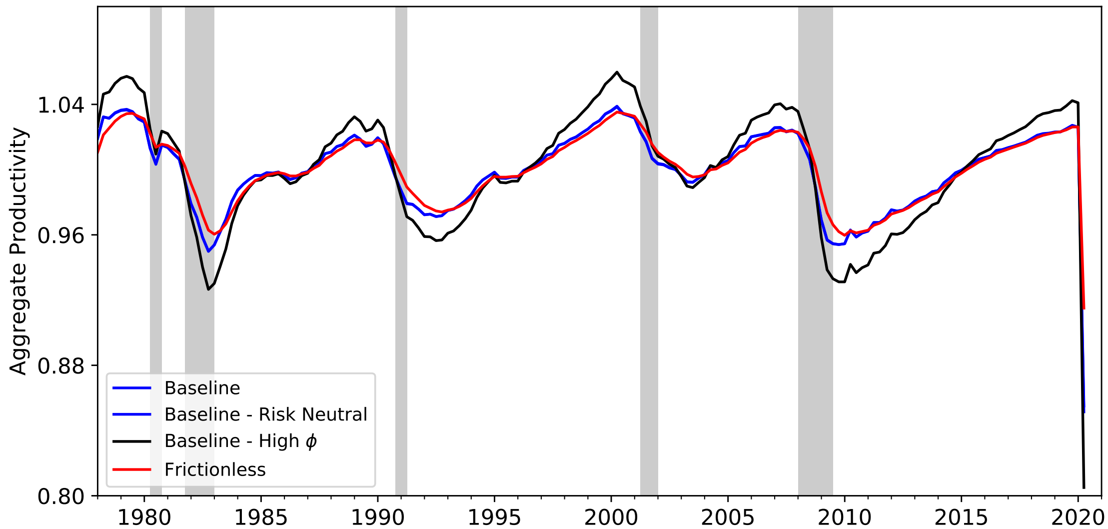
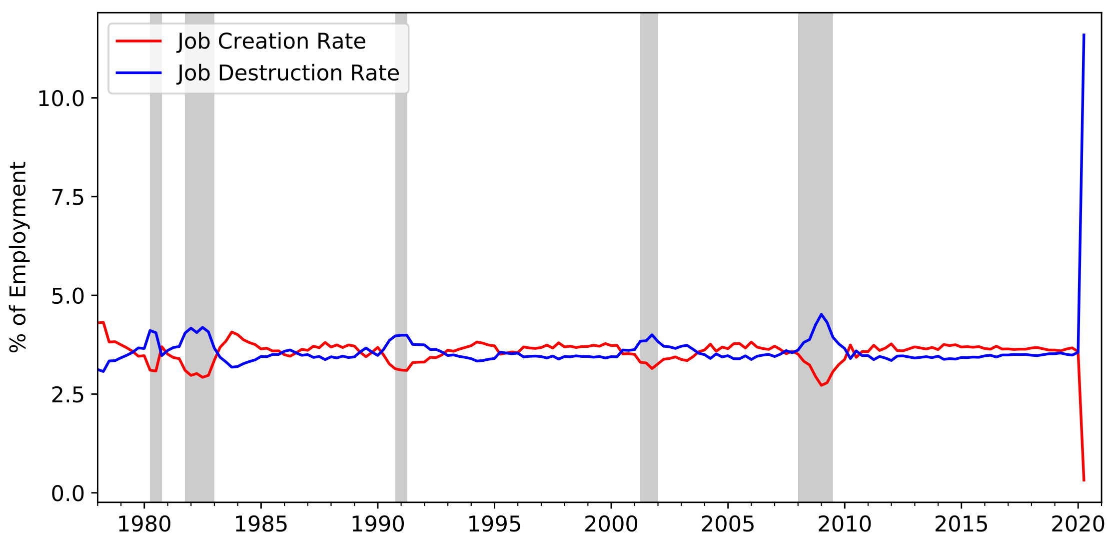


Figure 8: Model-Implied Job Creation and Destruction Rates

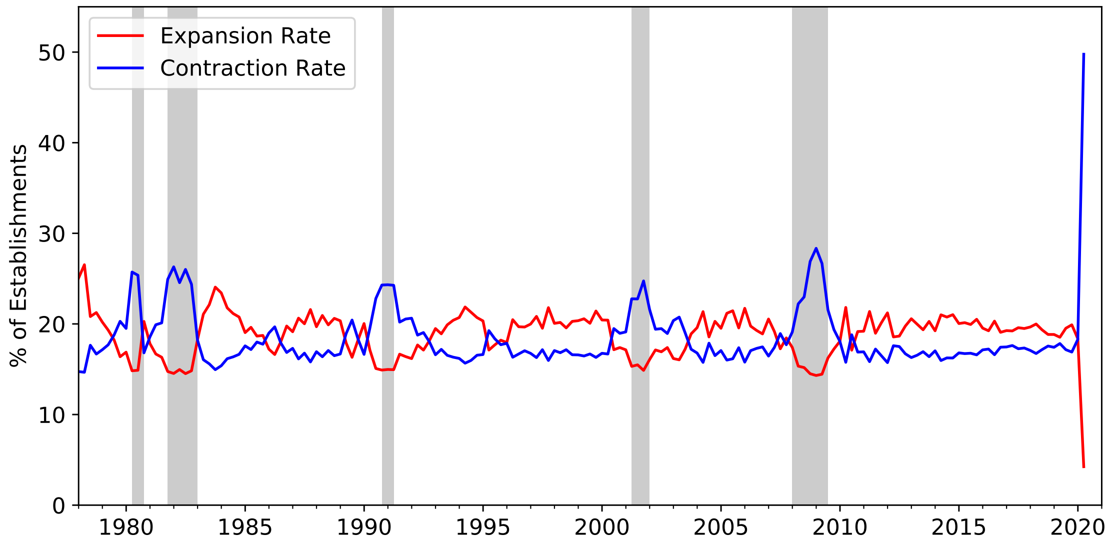


B Data

For Section 2.1 and Section 2.2 I use state-level data on job creation and destruction rates derived from establishment-level data from the US Census Bureau's Business Dynamics Statistics (BDS) database. This provides annual data from 1977 to 2014.

For Section 2.1, I also require state-industry employment data. This is available on an annual

Figure 9: Model-Implied Expansion and Contraction Rates



basis from the BLS Quarterly Census of Employment and Wages (QCEW) database from 1990 to 2016. In both cases I use data on the 50 states of the US as well as the District of Columbia.

In Section 5 I use total non-farm payrolls from the BLS[13] as my measure of US employment.

B.1 Details on Bartik Approach

To construct a Bartik measure of predicted employment growth, I use state-industry employment data at the 3-digit NAICS level. I use all 3-digit industries apart from those with the following NAICS codes: 482, 491, 516, 521. This leaves $K = 88$ industries. Bartik predicted employment growth is defined as:

$$B_{i,t} = \sum_{k=1}^{K} \varphi_{i,k,\tau} g_{-i,k,t} \tag{B.1}$$

$\varphi_{i,k,\tau}$ is the employment share of industry k in state i in the base year $\tau = 1990$. If any state-industry employment observations are missing for 1990 then I set $\varphi_{i,k,\tau} = 0$ for those

[13]FRED code: PAYEMS

observations. $g_{-i,k,t}$ is national employment growth in industry k excluding state i in year t. Goldsmith-Pinkham et al. (2018) point out that it is important to drop state i when calculating national employment growth rates in this stage.

In equation 2.2 the vector of control variables $Z_{i,t-1}$ contains two lags of the change in the job creation and destruction rates, the lagged level of employment growth, and the lagged value of Bartik predicted employment growth.

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:

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

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

where

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

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:

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

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: $\underline{n}(z_r, z_i; A, N, p)$ 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:

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

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

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

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:

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

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 4 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 basis 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)[14]. 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 4 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 Implications of Hiring Costs

The top panel of Figure 10 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

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

Table 4: 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.

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.

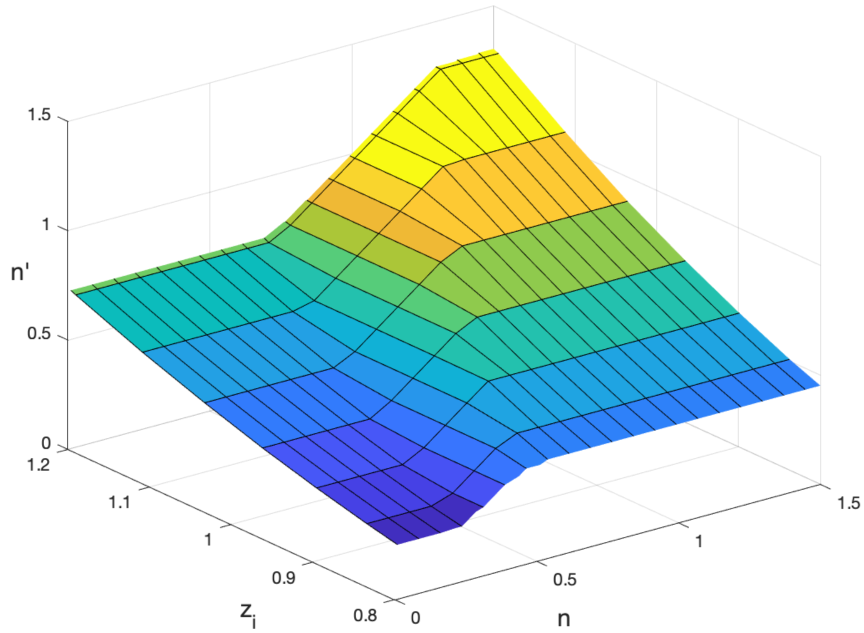
The bottom panel of Figure 10 shows the distribution of employment gaps and adjustment probabilities implied by the model, where I define a firm's target employment level as the mid-point between the hiring and firing thresholds for their current levels of idiosyncratic and regional productivity. Firms 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).

E Robustness

In this section I show that the time-varying responsiveness of job creation and job destruction is robust to two alternative calibrations of the model: one with a risk-neutral representative household, and one with a lower aggregate labor supply elasticity. I show that the time-varying responsiveness of aggregate job creation and destruction rates predicted by the model is unaffected by either of

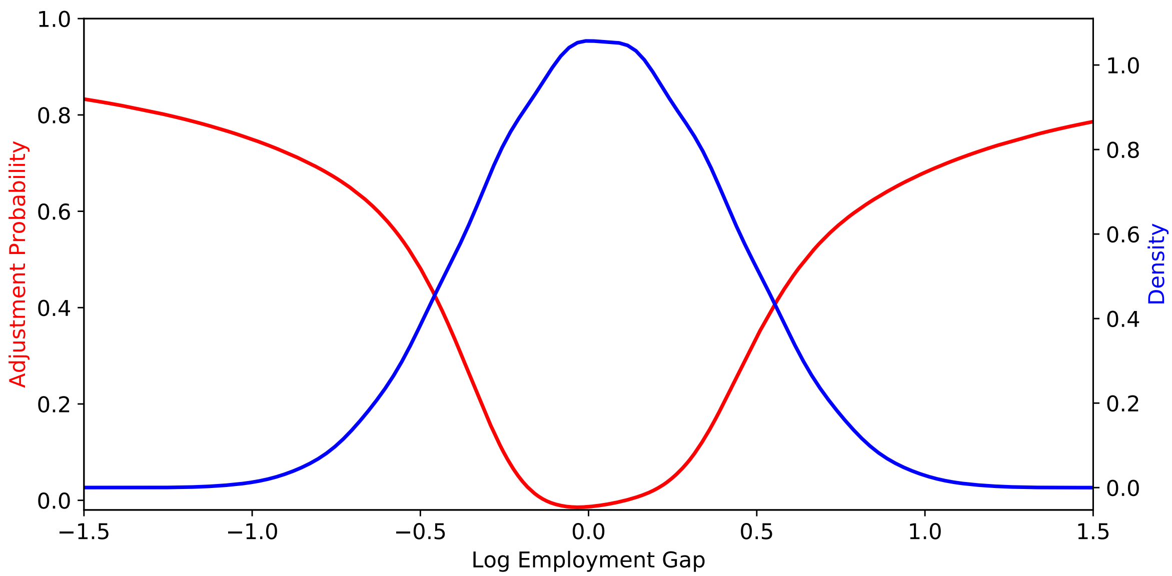
Figure 10: Lumpy Employment Adjustment in the Model

(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.

these calibration changes.

E.1 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. The baseline model in this paper uses a standard specification of the representative household's stochastic discount factor, which implies similar movements in real interest rate movements, yet this model generates significant time-varying responsiveness of job creation and destruction rates. To understand the impact of general equilibrium effects on the time-varying responsiveness in the model, I redo the exercise of Section 5 in a model where the representative household is risk-neutral, i.e. $\gamma = 0$, and consequently where real interest rates are constant. Figure 11 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.

E.2 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 by generating "responsiveness indices" for the model assuming that the Frisch labor supply elasticity is lowered to 1. The responsiveness indices shown in Figure 11 are almost identical to those in Figure 1b. 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: the standard deviation of aggregate productivity shocks is raised from 0.0049 in the baseline model to 0.0073 with the lower labor supply elasticity. This can be seen in Figure 7: the baseline model requires a productivity decline of around 6% to generate the decline in employment seen in the Great Recession. For the model with a low labor supply elasticity (high ϕ), the required decline in productivity is closer to 10%.

Figure 11: Robustness: Model-Implied Responsiveness Indicies