The State Dependent Effectiveness of Hiring Subsidies: Online Appendix

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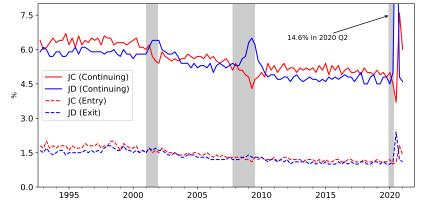
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7 Supplementary Figures

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

Notes: Quarterly job creation and destruction rates broken down into the contribution from continuing establishments and from those establishments that are entering or exiting. Data from the BLS Business Employment Dynamics database.
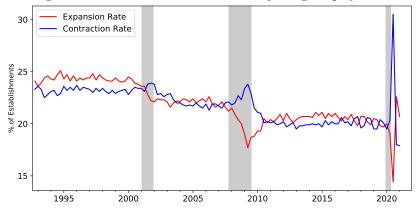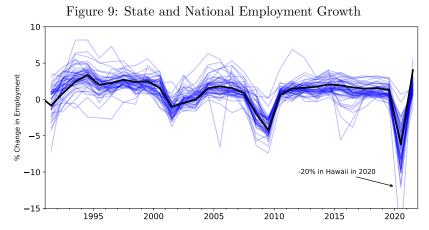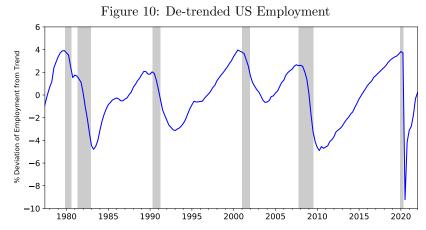
Figure 8: Fraction of Establishments Adjusting Employment
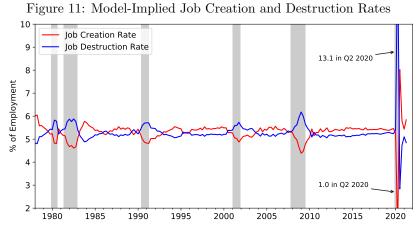

Notes: Fraction of establishments whose employment is either expanding or contracting each quarter. Data from the BLS Business Employment Dynamics database.

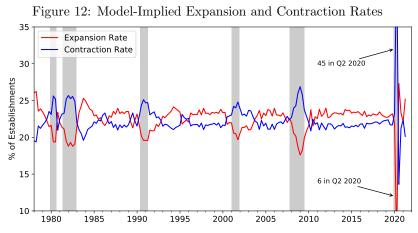Figure 9: State and National Employment Growth

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Figure 10: De-trended US Employment

Notes: Cyclical component of quarterly US employment de-trended using the Hodrick-Prescott filter with $\lambda = 1e5$.
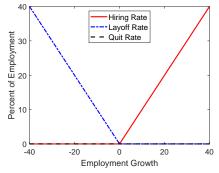
Figure 11: Model-Implied Job Creation and Destruction Rates

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

Figure 12: Model-Implied Expansion and Contraction Rates

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

Figure 13: Model-Implied Worker Flow Rates:Baseline Model

Notes: Worker flow rates as a function of establishment-level employment growth. The base-line model abstracts from quits.

Figure 14: Model-Implied Worker Flow Rates: Model with Quits

Notes: Worker flow rates as a function of establishment-level employment growth. The extended model considered in Appendix 11 has a quarterly quit rate of 6.5%.

8 Data Sources

For Sections II.A, II.B and Appendix 3 I use state and industry-level data on job creation and destruction rates derived from establishment-level data from the US Bureau of Labor Statistics' Business Employment Dynamics database. At the state level I use data from the 50 US states as the data from Washington D.C. only begins in 2000. At the industry level I use data from 84 3-digit NAICS sectors. This is all the 3-digit industries for which the BLS database has job creation and destruction rates apart from two industries: Scenic and Sightseeing Transport, and Support Activities for Mining. I remove these industries as their employment growth is significantly more volatile than that of the other industries in the sample. In the state-level data for Section II.A 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 II.B I use annual data on job creation and destruction rates at the state level from the Census Bureau Business Dynamics Statistics database. I merge this with the data on military spending provided by (Nakamura & Steinsson 2014).

For Section II.B I also use shocks to the excess bond premium, identified by (Gilchrist & 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 & Zakrajšek 2012).

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

9 Additional Empirical Results

9.1 Conditional Volatility of Total Job Creation and Destruction

In Section II.A I use the job creation and destruction rates for continuing establishments, which excludes the contribution to total job creation and destruction of entering and exiting establishments. The results of estimating equation 1 using total job creation and destruction rates are shown in Table 8. The estimates of conditional volatility using total job creation and destruction are very similar to those in Table 1.

9.2 Conditional Volatility without Fixed Effects

Table 9 shows the results of estimating equation 1 without state or time fixed effects. The procyclicality of the volatility of job creation and the countercyclicality of the volatility of job destruction remains.

9.3 Conditional Volatility at the Industry Level

In Section II.A I show that job creation and destruction exhibit time-varying volatility using state-level data. In this section I show that the same pattern emerges using industry-level data. I re-estimate equation 1 using data from 84 3-digit NAICS industries. As with the state-level data, this is from the BLS Business Employment Dynamics database at a quarterly frequency from 1992Q4 to 2019Q4. The estimates are shown in Table 10. The time-varying volatility of job creation and destruction rates in industry-level data is very similar to that seen in state-level data.

9.4 Conditional Volatility Using a Panel ARCH Approach

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

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

$$\Delta JC_{i,t} = \alpha + \sum_{j=1}^{J} \beta_j \Delta JC_{i,t-j} + \epsilon_{i,t} \tag{16}$$

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

$$|\hat{\epsilon}_{i,t}| = \alpha_i + \gamma_t + \beta \Delta g_{i,t-1}^N + \eta_{i,t} \tag{17}$$

In the second stage I include state and time fixed effects, as in Section II.A. I follow the same process for the job destruction rate and overall employment growth. Table 11 shows the estimates of β in equation 17 from estimating the above regressions with $J = 2$ in the first stage. As in Table 1, the second and third rows quantify this time-varying volatility. The second row reports the mean value of the dependent variable. The third row calculates the log difference between the fitted values from the regression when lagged employment growth is at the 5th or 95th percentiles of its distribution, denoted $\log(\sigma_{95}) - \log(\sigma_5)$. The results are similar to those in Table 1: the size of shocks to the job creation rate is significantly procyclical, the size of shocks to the job destruction rate is significantly countercyclical, and the size of shocks to overall employment

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Table 8: Conditional Volatility of Total Job Creation and Destruction

	|ΔJob Creation|	|ΔJob Destruction|	|ΔEmp. Growth|
Lagged Employment Growth	0.058 (0.012)	-0.065 (0.014)	-0.000 (0.020)
Mean of Dependent Variable	0.41	0.37	0.63
$\log(\sigma_{95}) - \log(\sigma_5)$	0.39	-0.47	-0.00
Observations	5439	5439	5439
R^2	0.21	0.21	0.22

Notes: Results from estimating equation 1 and the analogous regressions for job destruction and overall employment growth. Robust standard errors clustered at the state level are reported in parentheses. The second row reports the average value of the absolute change in job creation/destruction or employment growth in percentage points. The third row quantifies the conditional heteroskedasticity by comparing volatility at the 5th and 95th percentiles of the lagged employment growth distribution as described in the text. I use data from the 50 US states at a quarterly frequency from the BLS Business Employment Dynamics (BED) database from 1992Q4 to 2019Q4. I winsorize the top 0.1% of the distribution of the absolute changes in job creation and job destruction, to limit the influence of outliers. The 5th and 95th percentiles of the state (industry) employment growth distribution are -1.2% and 1.5%.

Table 9: Conditional Volatility without Fixed Effects

	|ΔJob Creation|	|ΔJob Destruction|	|ΔEmp. Growth|
Intercept	0.326 (0.016)	0.304 (0.013)	0.538 (0.024)
Lagged Employment Growth	0.029 (0.008)	-0.050 (0.007)	-0.026 (0.012)
Mean of Dependent Variable	0.33	0.29	0.53
$\log(\sigma_{95}) - \log(\sigma_5)$	0.24	-0.46	-0.13
Observations	5438	5438	5438
R^2	0.004	0.016	0.001

Notes: Results from estimating equation 1 and the analogous regressions for job destruction and overall employment growth without fixed effects. Robust standard errors clustered at the state level are reported in parentheses. The second row reports the average value of the absolute change in job creation/destruction or employment growth in percentage points. The third row quantifies the conditional heteroskedasticity by comparing volatility at the 5th and 95th percentiles of the lagged employment growth distribution as described in the text. I use data from the 50 US states at a quarterly frequency from the BLS Business Employment Dynamics (BED) database from 1992Q4 to 2019Q4. I winsorize the top 0.1% of the distribution of the absolute changes in job creation and job destruction, to limit the influence of outliers. The 5th and 95th percentiles of the state employment growth distribution are -1.2% and 1.5%.

Table 10: Conditional Volatility of Industry-Level Job Creation and Destruction

	$\|\Delta$Job Creation$\|$	$\|\Delta$Job Destruction$\|$	$\|\Delta$Emp. Growth$\|$
Lagged Employment	0.071	-0.084	-0.001
Growth	(0.014)	(0.012)	(0.022)
Mean of Dependent Variable	0.54	0.53	0.93
$\log(\sigma_{95}) - \log(\sigma_5)$	0.67	-0.74	-0.00
Observations	9138	9138	9138
R^2	0.41	0.37	0.40

Notes: Results from estimating equation 1 and the analogous regressions for job destruction and overall employment growth. Robust standard errors clustered at the industry level are reported in parentheses. The second row of each panel reports the average value of the absolute change in job creation/destruction or employment growth. The third row quantifies the conditional heteroskedasticity by comparing volatility at the 5th and 95th percentiles of the lagged employment growth distribution as described in the text. I use data from 84 NAICS 3-digit sectors at a quarterly frequency from the BLS Business Employment Dynamics (BED) database from 1992Q4 to 2019Q4. I winsorize the top 0.1% of the distribution of the absolute changes in job creation and job destruction, to limit the influence of outliers. The 5th and 95th percentiles of the industry employment growth distribution are -2.5% and 2.2%.

Table 11: Conditional Volatility Using Panel ARCH Approach

	$\|\Delta$Job Creation$\|$	$\|\Delta$Job Destruction$\|$	$\|\Delta$Emp. Growth$\|$
Lagged Employment	0.019	-0.030	-0.013
Growth	(0.008)	(0.014)	(0.014)
Mean of Dependent Variable	0.27	0.27	0.46
$\log(\sigma_{95}) - \log(\sigma_5)$	0.19	-0.30	-0.08
Observations	5339	5339	5339
R^2	0.23	0.26	0.28

Notes: Results from estimating equation 17 and the analogous regressions for job destruction and overall employment growth. Robust standard errors clustered at the state level are reported in parentheses. The second row reports the average value of the size of the shock to job creation/destruction or employment growth. The third row quantifies the conditional heteroskedasticity by comparing the estimated size of shocks at the 5th and 95th percentiles of the lagged employment growth distribution. I use data from the 50 US states at a quarterly frequency from the BLS Business Employment Dynamics (BED) database from 1992Q4 to 2019Q4. The 5th and 95th percentiles of the state employment growth distribution are -1.2% and 1.5%.

growth is acyclical. These results are robust to different lag orders in the first stage.

10   Computational Method

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

10.1   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 & Nakajima 2016). I follow (Khan & Thomas 2008) and re-write the firm's recursive problem in terms of utils of the representative household. Consequently, the problem can be written:

$$V(z_r, z_i, n; S) = \max_{n'} p(S)[A z_r z_i n^\alpha - w(S)n - \kappa(n' - n)\mathbb{1}(n' > n)] \tag{18}$$

$$+ \beta\mathbb{E}_{z_r', z_i', A'}[V(z_r', z_i', n'; S')] \tag{19}$$

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

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

where

$$p(S) \equiv U_C(C, N) = \left(C - \psi\frac{N^{1+\psi}}{1+\psi}\right)^{-\gamma} \tag{20}$$

The above problem is not computable due to the infinite dimensionality of μ. I use the technique of (Krusell & 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:

$$V(z_r, z_i, n; A, N) = \max_{n'} p(A, N)[A z_r z_i n^\alpha - w(N)n - \kappa(n' - n)\mathbb{1}(n' > n)]$$

$$\tag{21}$$

$$+ \beta\mathbb{E}_{z_r', z_i', A'}[V(z_r', z_i', n'; A', N')]$$

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

$$\log N' = a_N + b_N \log N + c_N \log A$$

$$\log p = a_p + b_p \log N + c_p \log A$$

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

$$\mathbb{E}_{z_r', z_i', A'}V_n(z_r, z_i, \underline{n}(z_r, z_i; A, N, p); A, N) = p\kappa \tag{22}$$

$$\mathbb{E}_{z_r', z_i', A'}V_n(z_r, z_i, \bar{n}(z_r, z_i; A, N, p); A, N) = 0 \tag{23}$$

The firm's envelope condition for this problem is:

$$V_n(z_r, z_i, n; A, N) = p(A, N)[Az_r z_i \alpha n^{\alpha-1} - w(N)]$$

$$+ \begin{cases} 0 & \text{if } \beta\mathbb{E}[V_n(z_r', z_i', n; A', N')] < 0 \\ \beta\mathbb{E}[V_n(z_r', z_i', n; A', N')] & \text{if } 0 \leq \beta\mathbb{E}[V_n(z_r', z_i', n; A', N')] \leq p(A, N)\kappa \\ p(A, N)\kappa & \text{if } \beta\mathbb{E}[V_n(z_r', z_i', n; A', N')] > p(A, N)\kappa \end{cases} \tag{24}$$

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

$$W(z_r, z_i, n; A, N) \equiv \mathbb{E}_{z_r', z_i', A'} V_n(z_r, z_i, n; A, N) \tag{25}$$
$$= \mathbb{E}_{z_r', z_i', A'}[A' z_r' z_i' \alpha n^{\alpha-1} - w + \min(\max[\beta W(z_r', z_i', n; A', N), 0], p(A', N)\kappa)]$$

10.1.1 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 (25) until convergence.

3. Use the expected marginal value function along with the FOCs (22 and 23) 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.

10.2 Frictionless Model

In the frictionless model the firm's problem is:

$$V(z_r, z_i, n; S) = \max_{n'} p(S)[Az_r z_i n^{\alpha} - w(S)n] + \beta\mathbb{E}_{z_r', z_i', A'}[V(z_r', z_i', n'; S')] \tag{26}$$

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

where

$$p(S) \equiv U_C(C, N) = \left(C - \psi \frac{N^{1+\psi}}{1+\psi}\right)^{-\gamma} \tag{27}$$

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

$$\mathbb{E}_{z_r', z_i', A'} V_n(z_r, z_i, n; A, N) = 0 \tag{28}$$

The firm's envelope condition is:

$$V_n(z_r, z_i, n; S) = p(S)[A z_r z_i \alpha n^{\alpha-1} - w(S)] \tag{29}$$

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

$$n'(z_r, z_i; S) = \left[\alpha \mathbb{E}_{z_r', z_i', A'} \left[\frac{A' z_r' z_i'}{w(S')}\right]\right]^{\frac{1}{1-\alpha}} \tag{30}$$

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.

10.2.1 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 30.

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.

10.3 Computational Accuracy

Table 12 shows the coefficients of the estimated log-linear forecast rules in the (Krusell & 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

Table 12: Accuracy of Equilibrium Forecasting Rules

	Baseline	Frictionless
a_N	0.000	-0.009
b_N	0.427	0.000
c_N	0.670	1.170
a_p	0.207	N/A
b_p	-0.218	N/A
c_p	-1.531	N/A
R_N^2	0.999933	1.000000
R_p^2	0.999990	N/A
Max Error N (%)	0.14	0.10
Mean Error N (%)	0.03	0.09
Max Error p (%)	0.09	N/A
Mean Error p (%)	0.03	N/A

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

of periods $(T = 5000)$[1]. 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 12 show that both mean and maximum percentage errors from the forecast rule system are small. This confirms that the (Krusell & Smith 1998) approach provides a very accurate approximation.

11   Robustness

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

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

11.1 Separable Preferences

First I consider alternative preferences for the representative household. As in (Hopenhayn & 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):

$$U(C, N) = \frac{C^{1-\gamma} - 1}{1 - \gamma} - \psi N \tag{31}$$

I assume that $\gamma = 0.5$ and recalibrate ψ to keep mean employment equal to 1. Figures 15 and 16 shows that the responsivness indices from this model are very similar to those from the baseline model (Figure **??**).

11.2 Risk-Neutral Representative Household

(Khan & 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, Figures 15 and 16 shows that the responsiveness indices from this model are very similar to those in the baseline model.
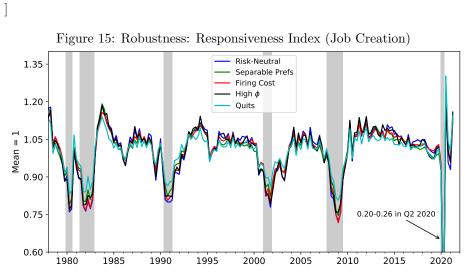
Why do real interest rate movements have such a limited effect in the case of lumpy labor adjustment? The key reason is that the timing of employment adjustment has little impact on consumption of the representative household. In the model of (Khan & Thomas 2008), general equilibrium effects are important 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.

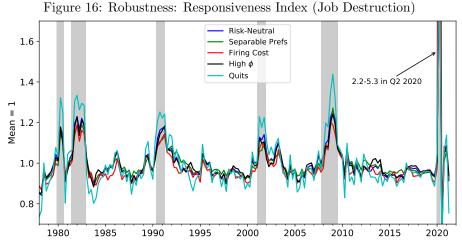## 11.3 Lower Labor Supply Elasticity

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 Figures 15 and 16 are almost identical to those in Figure 1. 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.

11.4 Quits

The baseline model does not include quits as doing so means that the model would be inconsistent with the large fraction of establishments that keep their

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Figure 15: Robustness: Responsiveness Index (Job Creation)

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

Figure 16: Robustness: Responsiveness Index (Job Destruction)

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

number of employees unchanged from quarter to quarter. However, a large number of employees do quit their jobs each quarter, as shown in Figure 1 in (Davis, Faberman & Haltiwanger 2012).

In this section I assume that a fraction q of employees quit their jobs each quarter. The firm's problem is the same as in equation 5, but now the cost of adjusting employment is:

$$g(n, n') = \kappa(n' - n(1-q))\mathbb{1}(n' > n(1-q)) \tag{32}$$

I assume that 6.5% of employees quit their job each quarter. The responsiveness indices shown in Figures 15 and 16 are very similar to those in the baseline model.

11.5 Firing Costs Rather Than Hiring Costs

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

$$V(z_r, z_i, n; S) = \max_{n'} Az_r z_i n^\alpha - w(S)n - g(n, n') + \mathbb{E}_{z_r', z_i', A'}[\Lambda(S, S')V(z_r', z_i', n'; S')] \tag{33}$$

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

I set the value of the firing tax equal to the value of the hiring cost in the baseline calibration of the model. Again, Figures 15 and 16 shows that the responsiveness indices implied by the model are almost unchanged.

12 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 III.A and shown in Figure 1.

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

to adjust their employment. Their problem is as follows:

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

(34)

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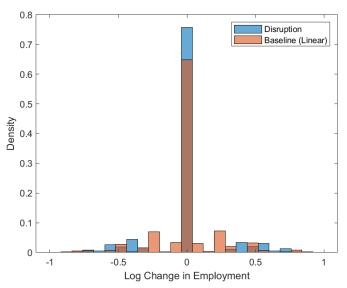$$z'_r = (1 - \rho_r) + \rho_r z_r + \sigma_r \epsilon'_r$$
$$\log z'_i = \rho_i \log z_i + \sigma_i \epsilon'_i$$

I set the value of λ equal to 2%, similar to that estimated by (Cooper & 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 17 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, Haltiwanger & Willis 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 13 I replicate the estimates of equation 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 17: 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 13: Time-Varying Volatility in Disruption Cost Model

	$|\Delta\text{Job Creation}|$	$|\Delta\text{Job Destruction}|$	$|\Delta\text{Emp. Growth}|$
Lagged Employment Growth	0.027	-0.016	0.011
	(0.010 , 0.046)	(-0.030 , 0.000)	(-0.021 , 0.046)
Mean of Dependent Variable	0.36	0.30	0.65
$\log(\sigma_{95}) - \log(\sigma_5)$	0.22	-0.16	0.05

Notes: Results from estimating equation 1 and the analogous regressions for job destruction and overall employment growth using simulated data from the disruption cost model for 50 regions and 109 periods. Point estimates are the mean values of the regression coefficients from 100 simulations of the model. Parenthesis contain 95 percent confidence intervals from these simulations. The second row of each panel reports the average value of the absolute change in job creation/destruction or employment growth. The third row quantifies the conditional heteroskedasticity by comparing volatility at the 5th and 95th percentiles of the lagged employment growth distribution as described in the text in Section II.A. As the model does not include trend growth, for the 5th and 95th percentiles of the state-level employment growth distribution I use -1.35% and +1.35%, centering the values from the data.

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