Econometrica Supplementary Material

ONLINE APPENDIX FOR "FINANCIAL HETEROGENEITY AND THE INVESTMENT CHANNEL OF MONETARY POLICY"

(*Econometrica*, Vol. 88, No. 6, November 2020, 2473–2502)

PABLO OTTONELLO
Department of Economics, University of Michigan and NBER

THOMAS WINBERRY
Booth School of Business, University of Chicago and NBER

APPENDIX A: EMPIRICAL SPECIFICATION

THIS APPENDIX JUSTIFIES the choices in our baseline empirical specification (2). Section A.1 clarifies the type of permanent heterogeneity in responsiveness for which our specification controls by using only within-firm variation in financial position. Section A.2 shows that our results are qualitatively robust, but quantitatively weaker, if we do not control for differences in cyclical sensitivities across firms.

A.1. *Controlling for Permanent Heterogeneity in Responsiveness*

We discuss how our estimator controls for permanent heterogeneity in responsiveness using a simple example. Suppose the data generating process is

$$y_{jt} = \alpha_j + \lambda_t + \beta_j \varepsilon_t + \gamma x_{jt} \varepsilon_t + e_{jt}, \tag{12}$$

where y_{jt} is an outcome of interest, ε_t is an aggregate shock, x_{jt} is a firm characteristic, $\beta_j = b\mathbb{E}_j[x_{jt}]$ is a permanent characteristic that controls the responsiveness of y_{jt} to ε_t, and e_{jt} is an exogenous error term. In the main text, the outcome of interest y_{jt} is investment, the firm characteristic x_{jt} is financial position, and the aggregate shock ε_t is a monetary policy shock. The assumption $\beta_j = b\mathbb{E}_j[x_{jt}]$ implies that the average value of the firm's financial position is proportional to the permanent heterogeneity in responsiveness β_j. The coefficient of interest to be estimated is γ, which measures how changes in the characteristic x_{jt} affect the response of y_{jt} to the aggregate shock ε_t.

We assume that the aggregate shock ε_t is exogenous and homoskedastic given the entire sample of x_{jt}, which we denote $\mathbf{x}$. That is, we assume (i) $\mathbb{E}[\varepsilon_t|\mathbf{x}] = 0$ and (ii) $\mathbb{E}[\varepsilon_t^2|\mathbf{x}] = \sigma^2$, though we can relax (i) to be conditioned only on the values of $\mathbf{x}$ up to date t in the discussion below. Our interpretation of this condition is that the particular aggregate shock ε_t accounts for a vanishingly small proportion of the variation in x_{jt}. In our context, this assumption is consistent with the idea that monetary policy shocks account for a small fraction of fluctuations.

Demeaning the data generating process (12) within firm j gives $\widehat{y}_{jt} \equiv y_{jt} - \mathbb{E}_j[y_{jt}] = (\lambda_t - \mathbb{E}_j[\lambda_t]) + \beta_j \varepsilon_t + \gamma x_{jt} \varepsilon_t + e_{jt}$, which uses the facts that $\mathbb{E}_j[e_{jt}] = 0$ for all j, $\mathbb{E}_j[\varepsilon_t] = 0$ for all j, and $\mathbb{E}_j[x_{jt}\varepsilon_t] = \mathbb{E}_j[x_{jt}\mathbb{E}_j[\varepsilon_t|\mathbf{x}]] = 0$. As usual, one can estimate the time fixed effect $(\lambda_t - \mathbb{E}_j[\lambda_t])$ with time dummies, so we drop this term from the discussion going

Pablo Ottonello: pottonel@umich.edu
Thomas Winberry: Thomas.Winberry@chicagobooth.edu

 https://doi.org/10.3982/ECTA15949

forward. Using the fact that $\beta_j = b\mathbb{E}_j[x_{jt}]$, we now have

$$\widehat{y}_{jt} = b\overline{x}_j\varepsilon_t + \gamma x_{jt}\varepsilon_t + e_{jt}, \tag{13}$$

where $\overline{x}_j = \mathbb{E}_j[x_{jt}]$.

The typical within-firm fixed effects estimator will be biased due to an omitted variable problem. It estimates the misspecified model $\widehat{y}_{jt} = gx_{jt}\varepsilon_t + \nu_{jt}$. From (13), the residual ν_{jt} includes $b\overline{x}_j\varepsilon_t$, which is correlated with $x_{jt}\varepsilon_t$ in the cross-section of firms. Therefore, the estimator of g will not converge to the coefficient of interest γ. Intuitively, a high value of x_{jt} in the cross-section may influence how the firm responds to the aggregate shock through the coefficient of interest γ or through the permanent responsiveness $b\overline{x}_j$.

Our estimator solves the omitted variable problem by making the regressor orthogonal to the omitted terms. From (13), we have $\widehat{y}_{jt} = \gamma(x_{jt} - \overline{x}_j)\varepsilon_t + (\gamma + b)\overline{x}_j\varepsilon_t + e_{jt}$. Our estimator omits the second term, $(\gamma + b)\overline{x}_j\varepsilon_t$, from the regression. However, this procedure will still yield consistent estimates of γ if $\mathbb{E}[(x_{jt} - \overline{x}_j)\varepsilon_t \times \overline{x}_j\varepsilon_t] = 0$. Our assumption of a homoskedastic shock ensures that this condition holds. Intuitively, a high value of $x_{jt} - \overline{x}_j$ will only influence how the firm responds to the aggregate shock through the coefficient of interest γ because its variation is relative to the permanent differences proxied by $\overline{x}_j$.

This simple example makes clear that the standard fixed effects estimator will yield biased estimates of the coefficient of interest γ if there are permanent differences in how firms respond to the aggregate shock ε_t. Table IX shows that this is the case in our application; it estimates the standard specification $\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta x_{jt-1}\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$. These results are qualitatively consistent with our main results in the sense that firms with lower leverage or higher distance to default are more responsive to monetary policy. However, these differences are smaller and less precisely estimated, indicating that permanent heterogeneity in responsiveness is quantitatively relevant in our sample. Table IX also shows that firms with a higher credit rating are more responsive to changes in

TABLE IX

HETEROGENEOUS RESPONSES, NOT DEMEANING FINANCIAL POSITION[a]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
leverage × ffr shock	−1.00	−0.80			−0.79	−0.80	−0.71
	(0.32)	(0.29)			(0.29)	(0.41)	(0.45)
$\mathbb{1}\{\text{cr}\_jt \geq A\}\times$ ffr shock			1.64		1.36		
			(1.36)		(1.39)		
dd × ffr shock				0.91		0.53	0.71
				(0.52)		(0.52)	(0.54)
ffr shock							2.08
							(0.59)
Observations	219,402	219,402	219,402	151,027	219,402	151,027	119,750
R^2	0.113	0.124	0.120	0.141	0.124	0.142	0.151
Firm controls	no	yes	yes	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes	yes	yes	no
Time clustering	yes	yes	yes	yes	yes	yes	yes

[a]Results from estimating variants of the baseline specification $\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta x_{jt-1}\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$, where all variables are defined as in the main text or in the notes for Table 3. We have standardized leverage ℓ_{jt} and distance to default dd_{jt} over the entire sample, so their units are in standard deviations relative to the mean. Column (7) removes the sector-quarter fixed effect α_{st} and estimates $\Delta \log k_{jt+1} = \alpha_j + \alpha_{sq} + \gamma\varepsilon_t^{\mathrm{m}} + \beta x_{jt-1}\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}_1' Z_{jt-1} + \mathbf{\Gamma}_2' Y_{t-1} + e_{jt}$, where Y_t is a vector with four lags of GDP growth, the inflation rate, and the unemployment rate.

TABLE X

MAIN RESULTS, NOT CONTROLLING FOR DIFFERENCES IN CYCLICAL SENSITIVITIES[a]

	(1)	(2)	(3)	(4)
leverage × ffr shock	−0.30		−0.09	−0.07
	(0.24)		(0.32)	(0.51)
dd × ffr shock		0.96	0.91	1.11
		(0.38)	(0.35)	(0.41)
ffr shock				2.14
				(0.61)
Observations	219,402	151,027	151,027	119,750
R^2	0.124	0.141	0.142	0.151
Firm controls	yes	yes	yes	yes
Time sector FE	yes	yes	yes	no
Time clustering	yes	yes	yes	yes

[a] Results from estimating $\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$, where all variables are defined as in the main text or in the notes for Table 3 except that Z_{jt-1} does not include the interaction of lagged GDP growth with demeaned financial position.

monetary policy. We did not include that variable in the main text because the within-firm variation in credit rating is limited.

A.2. *Role of Differences in Cyclical Sensitivities Across Firms*

Our baseline specification (2) controls for the interaction between the firm's financial position $(x_{jt-1} - \mathbb{E}_j[x_{jt}])$ and lagged GDP growth in order to control for differences in cyclical sensitivities across firms. Our motivation for this choice is that the largest shocks in our sample occur at the beginning of the two recessions, so we want to ensure that our heterogeneous responses to monetary policy are not driven by differences in cyclical sensitivities across firms. Table X shows that excluding this control does not significantly affect the differential responses by distance to default, showing that our main results are robust to this concern. However, the differential responses by leverage become significantly weaker.

Figure 9 plots the dynamics of the differential responses from specification (2) without controlling for differential responses to GDP growth. Not controlling for these differences makes the long-run differences somewhat smaller and substantially increases the standard errors, suggesting that differences in cyclical sensitivities confounds inference about the monetary shock. In any event, Figure 9 makes clear that our conclusion that long-run dynamics are imprecisely estimated is not due to controlling for differences in cyclical sensitivities.

APPENDIX B: ADDITIONAL EMPIRICAL RESULTS

B.1. *Dynamics of Average Effect of Monetary Policy*

We estimate the specification

$$\begin{aligned}\log k_{jt+h} - \log k_{jt} \\ = \alpha_{jh} + \gamma_h \varepsilon_t^{\mathrm{m}} + \beta_h \big(X_{jt-1} - \mathbb{E}_j[X_{jt}]\big)\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}'_{1h} Z_{jt-1} + \mathbf{\Gamma}'_{2h} Y_{t-1} + e_{jt},\end{aligned} \tag{14}$$

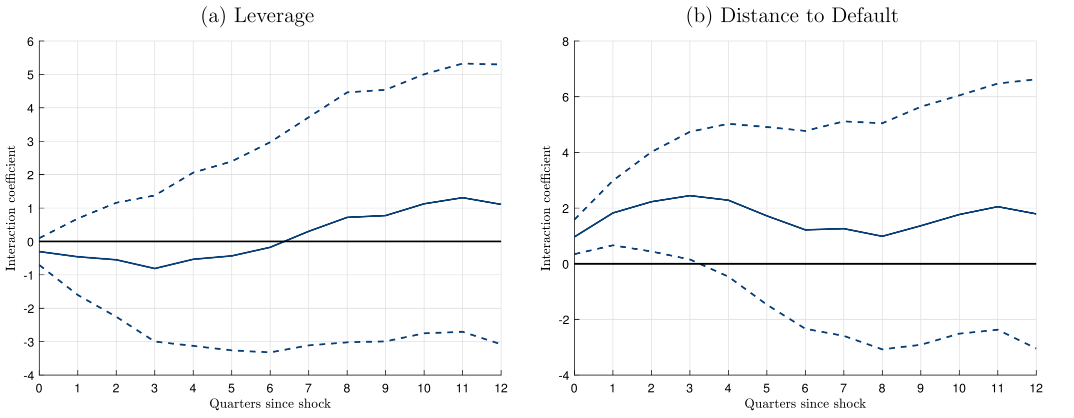

FIGURE 9.—Dynamics, not controlling for differences in cyclical sensitivities. Notes: dynamics of the interaction coefficient between financial positions and monetary shocks over time. Reports the coefficient β_h over quarters h from $\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_h(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \Gamma_h' Z_{jt-1} + e_{jt}$, where all variables are defined as in the main text or in the notes for Table 3 except that Z_{jt-1} does not include the interaction of lagged GDP growth with demeaned financial position.

where, as before, Y_t is a vector with four lags of GDP growth, the inflation rate, and the unemployment rate and X_{jt} is a vector of financial positions (leverage and distance to default). Figure 10 shows that the average response to monetary policy, γ_h, is hump-shaped and fairly persistent up to 3 years after the shock. However, these long-run effects are imprecisely estimated and not statistically significant 3 quarters after the shock and later. We have also found that these long-run effects are somewhat sensitive to the set of aggregate controls Y_{t-1}. Therefore, in the main text, we focus on the heterogeneous responses across firms, which are robustly estimated across a number of specifications.

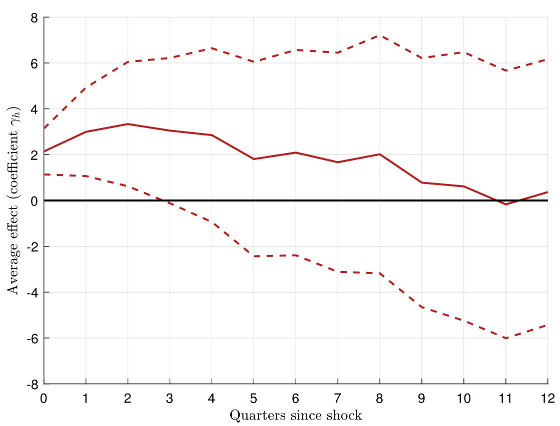

FIGURE 10.—Average investment response to monetary shock. Notes: results from estimating (14) from the text. Standard errors are two-way clustered by firms and time. Dashed lines report 90% error bands. We have normalized the sign of the monetary shocks $\varepsilon_t^{\mathrm{m}}$ so that a positive shock is expansionary corresponds to a decrease in interest rates.

TABLE XI

EXPANSIONARY VS. CONTRACTIONARY SHOCKS[a]

	(1)	(2)	(3)	(4)
leverage × ffr shock	−0.57			
	(0.27)			
leverage × pos ffr shock		−0.61		
		(0.28)		
leverage × neg ffr shock		−0.44		
		(0.93)		
dd × ffr shock			1.14	
			(0.41)	
dd × pos ffr shock				1.34
				(0.53)
dd × neg ffr shock				0.41
				(0.87)
Observations	219,402	219,402	151,027	151,027
R^2	0.124	0.124	0.141	0.141
Firm controls	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes
Time clustering	yes	yes	yes	yes

[a] Results from estimating variants of the baseline specification described in the main text and in the notes for Table 3. Columns (2) and (4) contain separate interactions for expansionary and contractionary shocks.

B.2. *Expansionary vs. Contractionary Shocks*

Table XI separately estimates heterogeneous responses for expansionary and contractionary shocks. Although the heterogeneous responses by leverage or distance to default are only significant for expansionary shocks, the differences between the two are at best marginally significant. This result is largely due to the fact that there are relatively few observations of contractionary shocks in our sample, generating large standard errors.

B.3. *Robustness Checks*

Controlling for the Information Channel of Monetary Policy. One concern about our monetary shocks $\varepsilon_t^{\mathrm{m}}$ is that the FOMC announcements on which they are based also release information about the future path of economic activity (see, e.g., Nakamura and Steinsson (2018)). Table XII show that our results are not driven by this information channel of monetary policy. Following Miranda-Agrippino and Ricco (2018), we control for information using the Greenbook forecast revisions between concurrent FOMC announcements. Our main results are robust to including this control. In addition, Table XIII shows that our results are also robust to controlling for the level of the forecasts.

Results Hold in the Post-1994 Sample. Another concern is that our monetary shocks may become less powerful after the Fed began making formal policy announcements in 1994. Columns (1)–(3) of Table XIV show that our main results concerning heterogeneous responses continue to hold in the post-1994 sample. A potential concern about this later sample is that the Fed announcements contain more information revelation than in the past. Consistent with that concern, Columns (4)–(6) of Table XIV show that the results become stronger when we control for Greenbook forecast revisions of GDP growth (similar to above).

TABLE XII

CONTROLLING FOR GREENBOOK FORECAST REVISIONS[a]

	(1)	(2)	(3)	(4)	(5)	(6)
leverage × ffr shock	−0.69		−0.88		−0.98	
	(0.27)		(0.33)		(0.32)	
dd × ffr shock		1.18		0.90		0.86
		(0.41)		(0.48)		(0.47)
Observations	219,402	151,027	219,402	151,027	219,402	151,027
R^2	0.124	0.141	0.124	0.141	0.124	0.141
Firm controls	yes	yes	yes	yes	yes	yes
Forecast rev controls	GDP	GDP	GDP Inflation	GDP Inflation	GDP Inflation Unemployment	GDP Inflation Unemployment

[a]Results from estimating the baseline specification (2), including as controls in the interaction between our variable of interest, $x_{jt-1} - \mathbb{E}_j[x_{jt}]$, and forecast revisions of output growth, inflation, and unemployment in FOMC announcements.

TABLE XIII

CONTROLLING FOR GREENBOOK FORECASTS[a]

	(1)	(2)	(3)	(4)	(5)	(6)
leverage × ffr shock	−0.91		−0.62		−0.62	
	(0.28)		(0.31)		(0.43)	
dd × ffr shock		1.22		1.12		1.04
		(0.43)		(0.39)		(0.56)
Observations	219,402	151,027	219,402	151,027	219,402	151,027
R^2	0.124	0.141	0.124	0.141	0.124	0.141
Firm controls	yes	yes	yes	yes	yes	yes
Forecast rev controls	GDP	GDP	GDP Inflation	GDP Inflation	GDP Inflation Unemployment	GDP Inflation Unemployment

[a]Results from estimating the baseline specification (2), including as controls in the interaction between our variable of interest, $x_{jt-1} - \mathbb{E}_j[x_{jt}]$, and forecasts of output growth, inflation, and unemployment in FOMC announcements.

TABLE XIV

POST-1994 ESTIMATES[a]

	(1)	(2)	(3)	(4)	(5)	(6)
leverage × ffr shock	−0.71		−0.28	−0.84		−0.22
	(0.35)		(0.50)	(0.34)		(0.50)
dd × ffr shock		1.13	1.01		1.35	1.24
		(0.44)	(0.44)		(0.45)	(0.46)
Observations	174,274	118,496	118,496	174,274	118,496	118,496
R^2	0.138	0.154	0.155	0.138	0.154	0.155
Firm controls	yes	yes	yes	yes	yes	yes
Time sector FE	yes	yes	yes	yes	yes	yes
Time clustering	yes	yes	yes	yes	yes	yes
Controls Greenbook Forecast Revisions	no	no	no	yes	yes	yes

[a]results from estimating variants of $\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \beta(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}' Z_{jt-1} + e_{jt}$, where all variables have been defined in the main text and the notes to Table 3. Columns (1)–(3) show the results of estimating our baseline model using with only data after 1994. Columns (4)–(6) include in the vector of firm-level controls Z_{jt-1} the interaction between our variable of interest, $x_{jt-1} - \mathbb{E}_j[x_{jt}]$, and forecast revisions of output growth in FOMC announcements.

TABLE XV

LAGGED INVESTMENT[a]

	(1)	(2)	(3)	(4)
leverage × ffr shock	−0.39		−0.17	−0.07
	(0.27)		(0.36)	(0.59)
$\Delta \log k_{jt}$	0.20	0.15	0.14	0.15
	(0.01)	(0.01)	(0.01)	(0.01)
dd × ffr shock		0.88	0.80	0.66
		(0.38)	(0.37)	(0.37)
Observations	219,402	151,027	151,027	119,750
R^2	0.159	0.159	0.160	0.169
Firm controls	yes	yes	yes	yes
Time sector FE	yes	yes	yes	no
Time clustering	yes	yes	yes	yes

[a]Results from estimating variants of the baseline specification $\Delta \log k_{jt+1} = \alpha_j + \alpha_{st} + \rho \Delta \log k_{jt} + \beta(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \Gamma' Z_{jt-1} + e_{jt}$, where all variables are defined as in the main text or in the notes for Table 3. Standard errors are two-way clustered by firms and quarters. We have normalized the sign of the monetary shock $\varepsilon_t^{\mathrm{m}}$ so that a positive shock is expansionary (corresponding to a decrease in interest rates). We have standardized within-firm leverage ($\ell_{jt} - \mathbb{E}[\ell_{jt}]$) and within-firm distance to default ($\mathrm{dd}_{jt} - \mathbb{E}[\mathrm{dd}_{jt}]$) over the entire sample, so their units are in standard deviations relative to the mean.

Results Robust to Controlling for Lagged Investment. Eberly, Rebelo, and Vincent (2012) showed that lagged investment is a powerful predictor of current investment in a balanced panel of large firms in Compustat. Motivated by this finding, Table XV shows that our main results continue to hold when we control for lagged investment. In addition, the top panel of Figure 11 shows that the dynamics of these differential responses are also persistent to controlling for lagged investment.

Unlike Eberly, Rebelo, and Vincent (2012), the R^2 of our regressions does not significantly increase when we control for lagged investment. The bottom panel of Figure 11 suggests that the main reason for this difference is that we use quarterly data while Eberly, Rebelo, and Vincent (2012) use annual data. It shows that the R^2 of the regression increases as we take longer-run changes in capital on the left-hand side. In addition, Eberly, Rebelo, and Vincent (2012) used a balanced panel of only large firms, while we use an unbalanced panel of all firms.

APPENDIX C: COMPARISON TO EXISTING EMPIRICAL LITERATURE

In this subsection, we relate our findings to empirical studies documenting heterogeneous responses across firms with different size, age, and liquidity. Section C.1 replicates the results of Gertler and Gilchrist (1994) regarding firm size in our sample and shows that including their measure of size does not affect our results. Section C.2 replicates the results of Cloyne et al. (2018) regarding firm age and shows that including their measure of age also does not affect our results. Section C.3 reconciles our results with recent work by Jeenas (2019).

C.1. *Relation to Gertler and Gilchrist (1994) and Firm Size*

Gertler and Gilchrist (1994) showed that small firms' sales and inventory holdings were more sensitive to monetary contractions. In this subsection, we replicate their results in our sample and show that firm size does not affect our main findings. Following Gertler

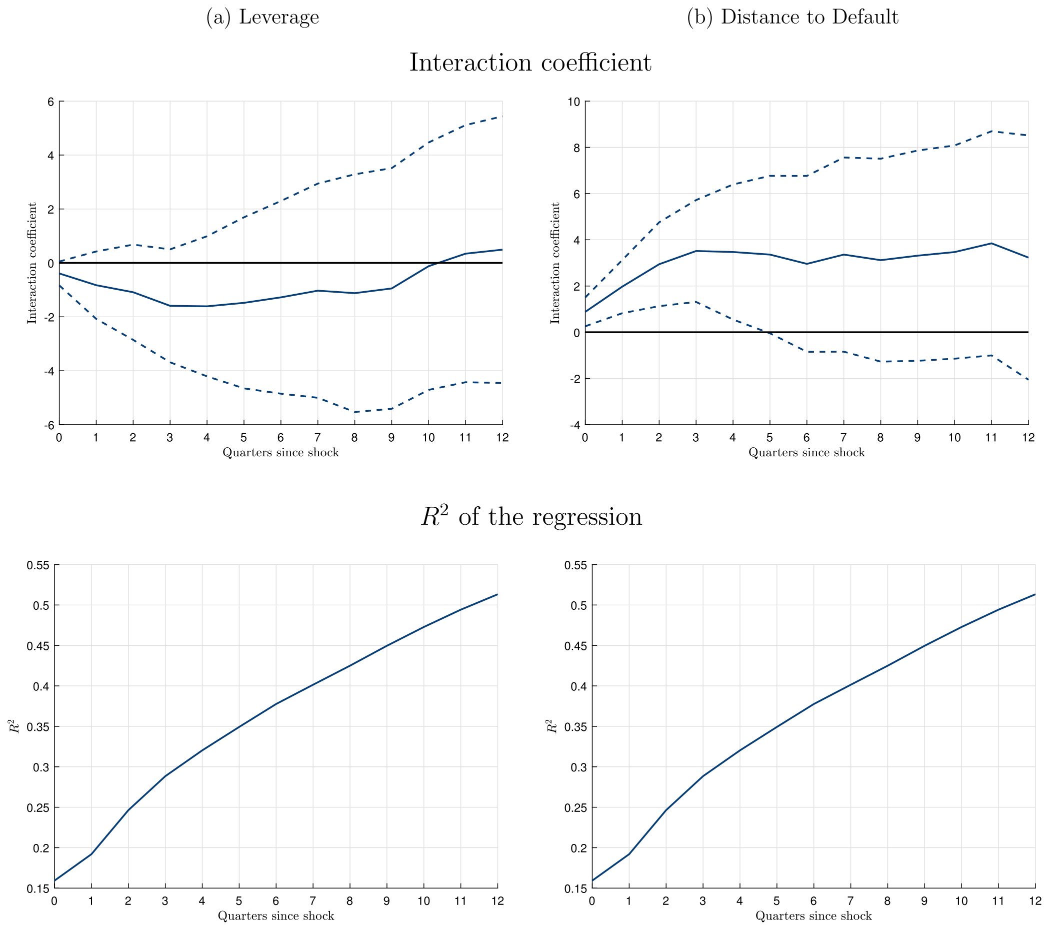

FIGURE 11.—Dynamics controlling by lagged investment. Notes: dynamics of the interaction coefficient between financial positions and monetary shocks over time. Reports the coefficient β_h over quarters h from $\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \rho \Delta \log k_{jt} + \beta_h (x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}'_h Z_{jt-1} + e_{jt}$, where all variables are defined in the main text and notes to Table 3.

and Gilchrist (1994), we identify a small firm if their average sales over the past 10 years is below the 30th percentile of the distribution.[1] We then estimate our baseline dynamic model (4) using this measure of size as the financial position x_{jt}.

Figure 12 replicates the spirit of Gertler and Gilchrist (1994)'s results for investment in our sample. Panel (a) measures monetary contractions as the Romer and Romer (1990) dates in our version of Gertler and Gilchrist (1994)'s time period 1972–1989. It shows that small firms cut investment by more than large firms following a monetary contraction. Panel (b) shows that these results also hold using our measure of monetary shocks $\varepsilon_t^{\mathrm{m}}$ in our time period 1990–2007, although the estimates are only marginally statistically significant.[2]

[1]These results are similar if we use five or twenty year averages.

[2]Our findings here are consistent with the analysis in Crouzet and Mehrotra (2020).

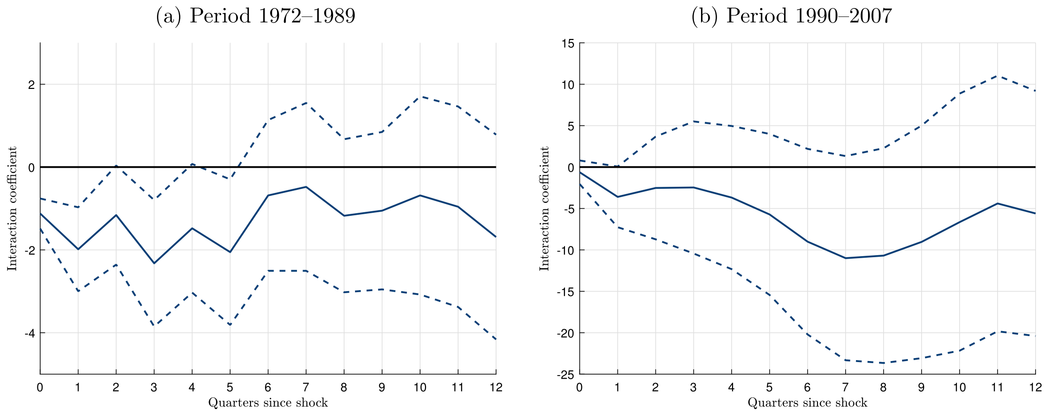

FIGURE 12.—Dynamics of differential responses to monetary shocks by size. Notes: dynamics of the interaction coefficient between size and monetary shocks. Reports the coefficient β_h over quarters h from $\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_h size^s_{jt-1}\varepsilon^{\mathrm{m}}_t + \boldsymbol{\Gamma}'_h Z_{jt-1} + e_{jth}$, where $size^s_{jt}$ is a measure of firm size taking the value of one if firm j is "large" in period t and zero otherwise (see main text for definition) and all other variables defined in the main text or notes to Table 3, except that Z_{jt-1} additionally includes the variable $size^s_{jt-1}$. Monetary shocks in panel (a) correspond to the Romer and Romer (1990) dates.

Figure 13 shows that our main results are unaffected by controlling for Gertler and Gilchrist (1994)'s measure of size using the local projection:

$$\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_{1h}\big(x_{jt-1} - \mathbb{E}_j[x_{jt}]\big)\varepsilon^{\mathrm{m}}_t + \beta_{2h} size^s_{jt-1}\varepsilon^{\mathrm{m}}_t + \boldsymbol{\Gamma}'_h Z_{jt-1} + e_{jth}. \quad (15)$$

Panel (a) reports results for $x_{jt} = \ell_{jt}$ and panel (b) reports results for $x_{jt} = \mathrm{dd}_{jt}$. In both cases, the dynamics of the differential response β_{1h} are virtually identical to the main text.[3] This occurs because size and our measures of financial position are largely uncorrelated in our sample. Hence, we view our work as simply focusing on a different feature of the data than Gertler and Gilchrist (1994).

C.2. *Relation to Cloyne et al. (2018) and Firm Age*

Recent work Cloyne et al. (2018) argues that younger firms are more responsive to monetary policy in both the U.S. and the U.K. In this subsection, we replicate the spirit of their results in our sample and show that they do not affect our main results. Following Cloyne et al. (2018), we measure age as time since incorporating, which is available from Datastream.

Figure 14 replicates the spirit of Cloyne et al. (2018)'s results and show that our main findings are robust to controlling for age. Following Cloyne et al. (2018), we classify firms as "young" (whose age since incorporation is less than 15 years), "middle aged" (between 15 and 50 years), and "older" (more than 50 years). Panel (a) shows that, conditional on the interaction between leverage and the monetary shock, middle-aged and old firms are less responsive to monetary shocks as in Cloyne et al. (2018).[4] However, panel (b) shows

[3]This result is robust to measuring size with capital or total assets instead of sales.

[4]These differences are not statistically significant for most horizons in our specification and sample. A potentially important difference between our specifications is that Cloyne et al. (2018) measure monetary policy shocks with a VAR approach and use the high-frequency shocks as an instrumental variable.

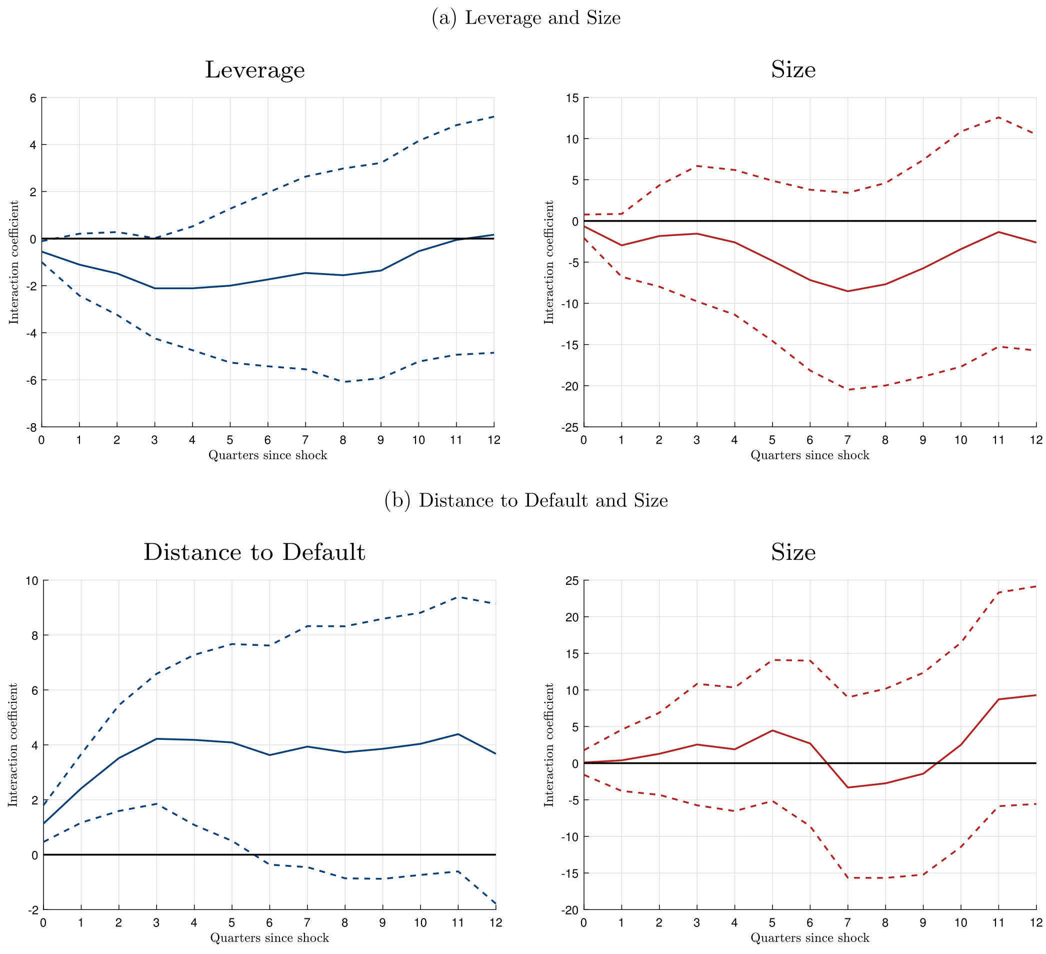

FIGURE 13.—Joint dynamics of financial position and size. Notes: dynamics of the interaction coefficient between financial position monetary shocks and between size and monetary shocks. Reports the coefficients β_{1h} and β_{2h} over quarters h from $\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_{1h}(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \beta_{2h} size_{jt-1}^{s} \varepsilon_t^{\mathrm{m}} + \Gamma_h' Z_{jt-1} + e_{jt}$, where here $size_{jt}^{s}$ is a measure of firm size taking the value of one if firm j is "large" in period t and zero otherwise (see main text for definition) and all other variables defined in the main text or notes to Table 3, except that Z_{jt-1} additionally includes the variable $size_{jt-1}^{s}$. Panel (a) runs our baseline specification with leverage $x_{jt} = \ell_{jt}$. Panel (b) runs our preferred specification with distance to default $x_{jt} = \mathrm{dd}_{jt}$.

that the differences by age largely disappear once we control for the interaction between distance to default and the monetary shock. In both cases, the interaction with financial position is similar to our results in the main text. We view these findings as reflecting the fact that we analyze a different dimension of the data than Cloyne et al. (2018).

C.3. *Relation to Jeenas (2019) and Firm Liquidity*

In this subsection, we relate our findings to recent work by Jeenas (2019) along two dimensions. First, we show that the differences between our estimated dynamics are accounted for by permanent heterogeneity in responsiveness across firms. Second, we show that our results are not driven by differences in liquidity across firms.

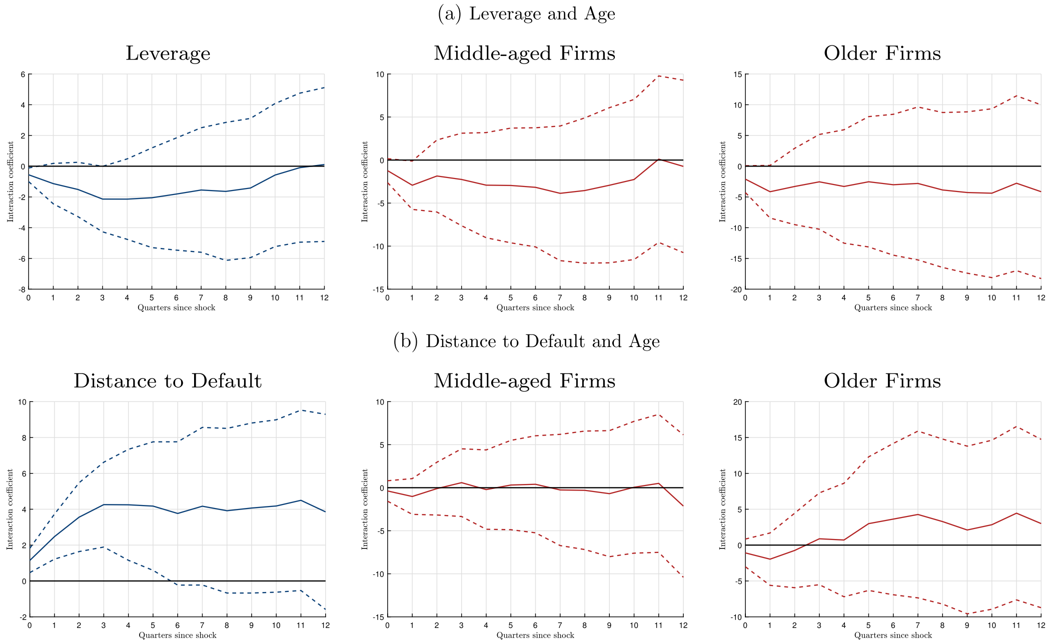

FIGURE 14.—Joint dynamics of financial position and age. Notes: dynamics of the interaction coefficient between financial positions and monetary shocks and between age and monetary shocks. Reports the coefficients β_{1h} and $\boldsymbol{\beta}_{2h}$ over quarters h from $\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_{1h}(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \boldsymbol{\beta}_{2h}' age_{jt}\varepsilon_t^{\mathrm{m}} + \boldsymbol{\Gamma}_h' Z_{jt-1} + e_{jt}$, where $age_{jt} \equiv [middleage_{jt} oldage_{jt}]'$ is a vector with two dummy variables measuring firm age (see main text for definition), and all other variables defined in the main text or notes to Table 3, except that Z_{jt-1} additionally includes the vector age_{jt}. Dashed lines report 90% error bands. Panel (a) runs our baseline specification with leverage $x_{jt} = \ell_{jt}$. Panel (b) runs our preferred specification with distance to default $x_{jt} = \mathrm{dd}_{jt}$.

Dynamics. We begin by replicating Jeenas (2019)'s results in our sample. For reference, Panel (a) of Figure 15 plots the dynamics of the interaction of within-firm leverage and the monetary shock $(\ell_{jt-1} - \mathbb{E}_j[\ell_{jt}])\varepsilon_t^{\mathrm{m}}$ from the local projection

$$\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_h\big(\ell_{jt-1} - \mathbb{E}_j[\ell_{jt}]\big)\varepsilon_t^{\mathrm{m}} + \boldsymbol{\Gamma}_h' Z_{jt-1} + e_{jth}, \quad (16)$$

which simply extends Figure 1 from the main text out to 20 quarters. Jeenas (2019)'s specification differs from ours in two key ways. First, Jeenas (2019) drops observations in the top 1% of the leverage distribution while we winsorize the top 0.5%.[5] Second, Jeenas (2019) computes the interaction between the monetary shock and the firm's average leverage over the past 4 quarters, $\widehat{\ell_{jt-1}}$, rather than the within-firm variation in the stock of leverage in the past quarter, $\ell_{jt} - \mathbb{E}_j[\ell_{jt}]$. Panel (d) applies these two operations and recovers the spirit of Jeenas (2019)'s result: high-leverage firms become substantially more responsive to the shock after approximately 4 quarters. Quantitatively, this point estimate implies that 4 years after a 1-percentage point expansionary shock, a firm with one standard deviation more leverage than the average firm increases its capital stock by over 10-percentage points more than the average firm.

[5]We winsorize the top 0.5% rather than drop the top 1% because the most highly indebted firms are the most likely to have substantial default risk, which is our object of interest.

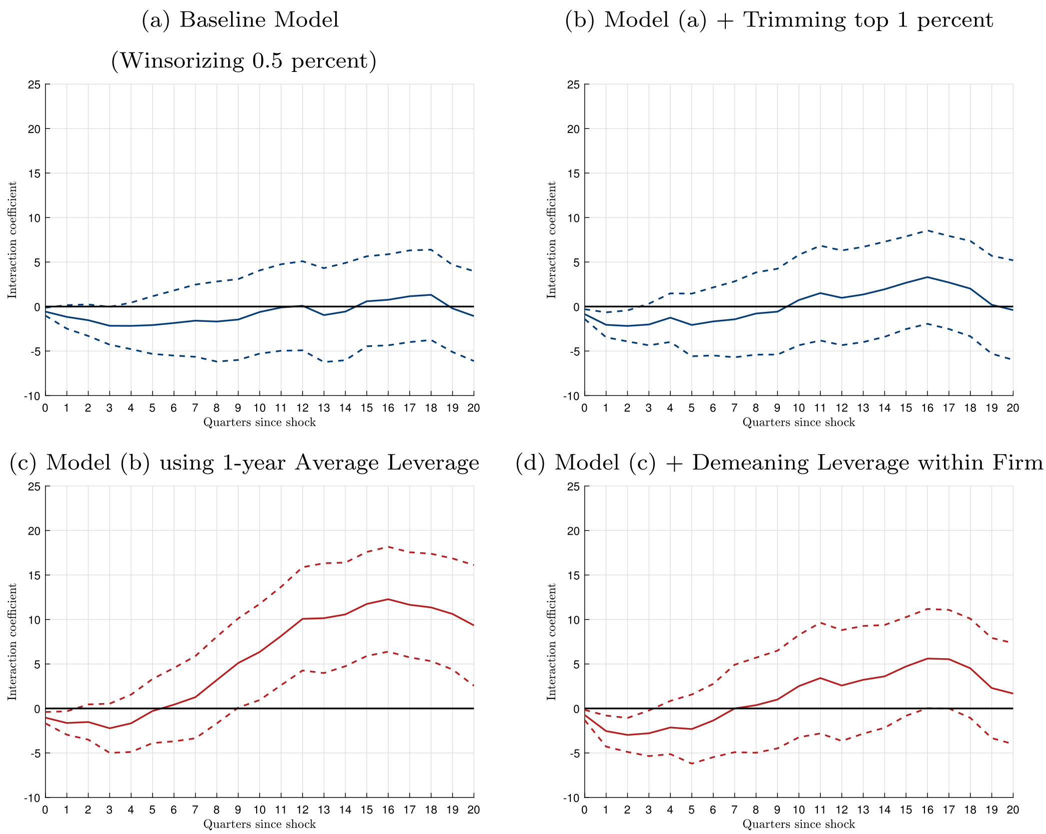

FIGURE 15.—Comparison of our dynamic results to Jeenas (2019). Notes: dynamics of the interaction coefficient between leverage and monetary shocks over time. Reports the coefficient β_h over quarters h from $\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_h(\ell_{jt-1} - \mathbb{E}_j[\ell_{jt}])\varepsilon_t^{\mathrm{m}} + \boldsymbol{\Gamma}_h' Z_{jt-1} + e_{jt}$, where all variables are defined in the main text or the notes to Table 3. Panel (b) drops the top 1% of the observations in the leverage variable used in the particular forecasting horizons. Panel (c) applies this operation and replaces demeaned leverage $\ell_{jt-1} - \mathbb{E}_j[\ell_{jt}]$ with the firm's average leverage over the last 4 quarters, $\widehat{\ell}_{jt-1}$. Panel (d) estimates this specification using only within-firm variation in averaged leverage $\widehat{\ell}_{jt-1} - \mathbb{E}[\widehat{\ell}_{jt}]$.

The remaining panels of Figure 15 decompose the effect of these two differences between our specifications on the estimated dynamics. Panel (b) shows that Jeenas (2019)'s more aggressive trimming of high-leverage observations has an insignificant effect on the estimated dynamics. In this panel, we estimate our baseline specification (16) after dropping observations in the top 1% of the leverage distribution and find that high-leverage firms are not statistically significantly more responsive to monetary policy.

Panel (c) shows that sorting firms by the average of their past 4 quarters of leverage $\widehat{\ell}_{jt-1}$ accounts for the difference between our results. In this panel, we reestimate our dynamic specification (16) after dropping the top 1% of leverage observations and replacing the within-firm variation in last quarter's stock of leverage $\ell_{jt} - \mathbb{E}_j[\ell_{jt}]$ with Jeenas (2019)'s moving average $\widehat{\ell}_{jt-1}$. The moving average eliminates high-frequency variation in leverage within a firm, implying that the estimated dynamics are more strongly driven by permanent heterogeneity across firms. Consistent with this idea, Panel (d) shows that using only within-firm variation in averaged leverage $\widehat{\ell}_{jt-1} - \mathbb{E}_j[\widehat{\ell}_{jt}]$ renders the long-horizon dynamics smaller and insignificant, largely consistent with our baseline specification. We prefer our specification because it maps more directly into our economic model in which heterogeneity in leverage is driven by ex post realizations of idiosyncratic shocks and lifecycle dynamics across firms. We focus our analysis of the model on the heterogeneous responses upon impact, which are robustly estimated in both our specification and Jeenas (2019) and survive the litany of robustness checks in this Online Appendix and the Supplemental Material.[6]

Heterogeneous Responses not Driven by Liquidity. Jeenas (2019) argued that the dynamics of heterogeneous responses by leverage documented above are driven by differences in liquidity across firms. Figure 16 shows that our results are not driven by liquidity once we use within-firm variation as in our main specification (2). We estimate the local projection

$$\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_{1h}\big(x_{jt-1} - \mathbb{E}_j[x_{jt}]\big)\varepsilon_t^{\mathrm{m}} + \beta_{2h}\big(y_{jt-1} - \mathbb{E}_j[y_{jt}]\big)\varepsilon_t^{\mathrm{m}} + \boldsymbol{\Gamma}_h' Z_{jt-1} + e_{jth}, \tag{17}$$

where $y_{jt} - \mathbb{E}_j[y_{jt}]$ is the within-firm variation in liquidity. Panel (a) shows that the point estimate of the leverage dynamics are similar to those presented in the main text, although the standard errors are wider given the correlation between leverage and liquidity. Panel (b) shows that the dynamics of distance to default are strongly and significantly positive, as in the main text. In that case, the dynamics of liquidity are always statistically insignificant, suggesting that default risk is the primary source of heterogeneous responses across firms when using within-firm variation.

APPENDIX D: ANALYSIS OF CALIBRATED MODEL

In this appendix, we analyze firms' decision rules in our calibrated steady state and show that the financial heterogeneity in our model is broadly comparable to that in the data.

D.1. *Identification of Fitted Parameters*

Figure 17 reports information to help assess the sources of identification in our calibration exercise. The top panel reports the local elasticities of targeted moments with respect to the parameters chosen in our calibration, computed at the estimated parameters. The patterns that emerge are intuitive. For example, increasing the volatility of productivity shocks σ increases the dispersion of investment rates across firms but decreases default rates and leverage ratios (because it makes right-tail positive outcomes more likely). In contrast, increasing the volatility of capital quality shocks makes left-tail negative outcomes more likely and, therefore, increases default rates (consistent with our discussion in footnote 6). Increasing the operating cost ξ or decreasing lenders' recovery rates α

[6] An additional difference between our specification and Jeenas (2019)'s is that we control for differences in cyclical sensitivities while Jeenas (2019) does not. We include these controls because we have found that there are significant differences in long-run cyclical sensitivities and that GDP growth is correlated with monetary shocks over these horizons in our sample. Online Appendix A.2 shows that excluding these controls does not affect the point estimates in our specification but does increase the standard errors. We have also found that excluding these controls does not strongly affect the point estimates or standard errors in Jeenas (2019)'s baseline specification with averaged leverage $\widehat{\ell}_{jt}$. Excluding these controls slightly increases the responsiveness of firms with high demeaned average leverage $\widehat{\ell}_{jt} - \mathbb{E}_j[\widehat{\ell}_{jt}]$, but the difference from Panel (d) in Figure 15 is small and not statistically significant.

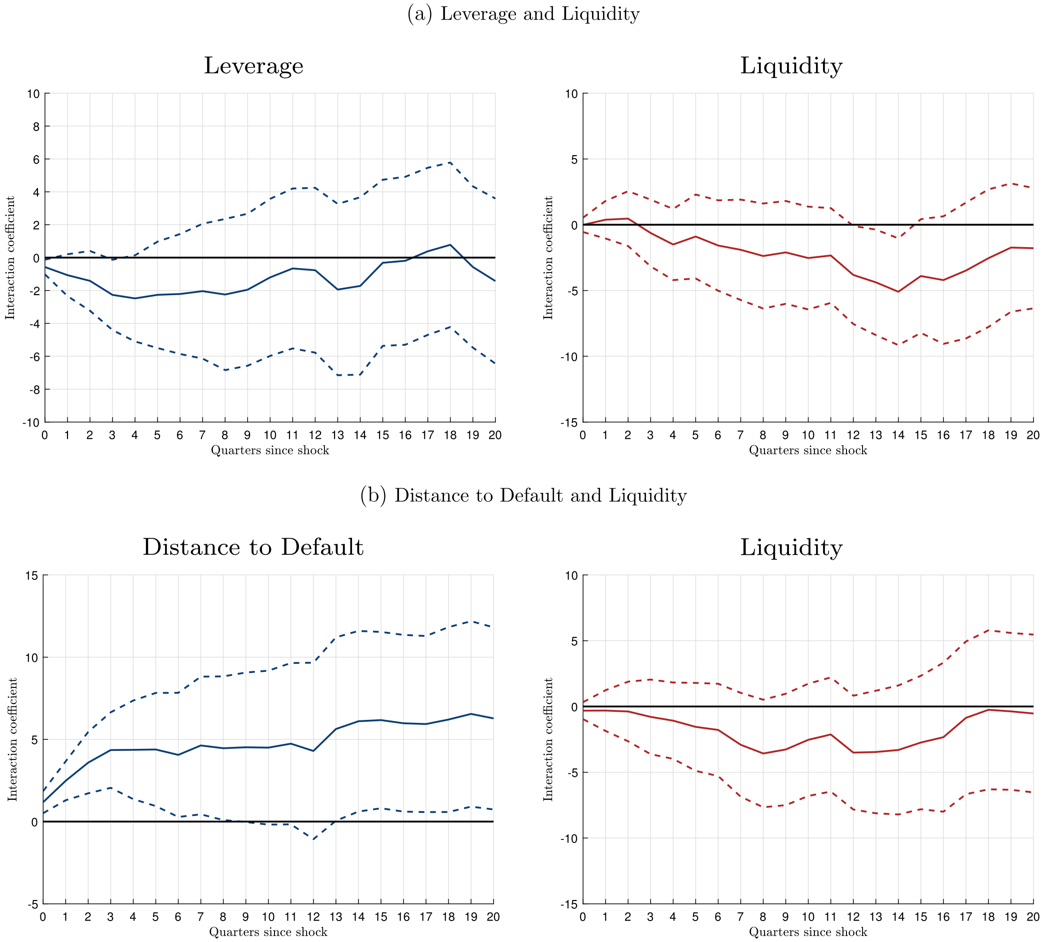

FIGURE 16.—Joint dynamics of financial position and liquidity. Notes: the coefficients β_{1h} and β_{2h} over quarters h from $\log k_{jt+h} - \log k_{jt} = \alpha_{jh} + \alpha_{sth} + \beta_{1h}(x_{jt-1} - \mathbb{E}_j[x_{jt}])\varepsilon_t^{\mathrm{m}} + \beta_{2h}(y_{jt-1} - \mathbb{E}_j[y_{jt}])\varepsilon_t^{\mathrm{m}} + \mathbf{\Gamma}_h' Z_{jt-1} + e_{jt}$, where $y_{jt} - \mathbb{E}_j[y_{jt}]$ is the within-firm variation in liquidity and all other variables are defined in the main text or the notes to Table 3, except that Z_{jt-1} additionally includes the variable $y_{jt} - \mathbb{E}_j[y_{jt}]$. We have also standardized demeaned liquidity $y_{jt} - \mathbb{E}_j[y_{jt}]$ over the entire sample.

tightens the financial constraints and leads to higher default rates among firms. Finally, increasing the initial size of new firms k_0 makes default less likely.

The bottom panel of Figure 17 plots the inverse of the mapping in the top panel, that is, it plots the local elasticities of estimated parameters with respect to moments as in Andrews, Gentzkow, and Shapiro (2017). This inverse mapping clarifies how variation in targeted moments would influence estimated parameter values, taking into account the joint dependencies across moments in the data. An important limitation of this exercise is that the relevant size of the variation in the moments is not clear; nevertheless, we believe it contains additional useful information. For example, it shows that the dispersion of investment rates across firms is a particularly informative moment for all parameters, especially those governing the lifecycle of young firms. This result may be surprising in light of the top panel, which shows that the dispersion of productivity shocks is the only parameter that strongly influences the dispersion of investment rates; it is nonetheless

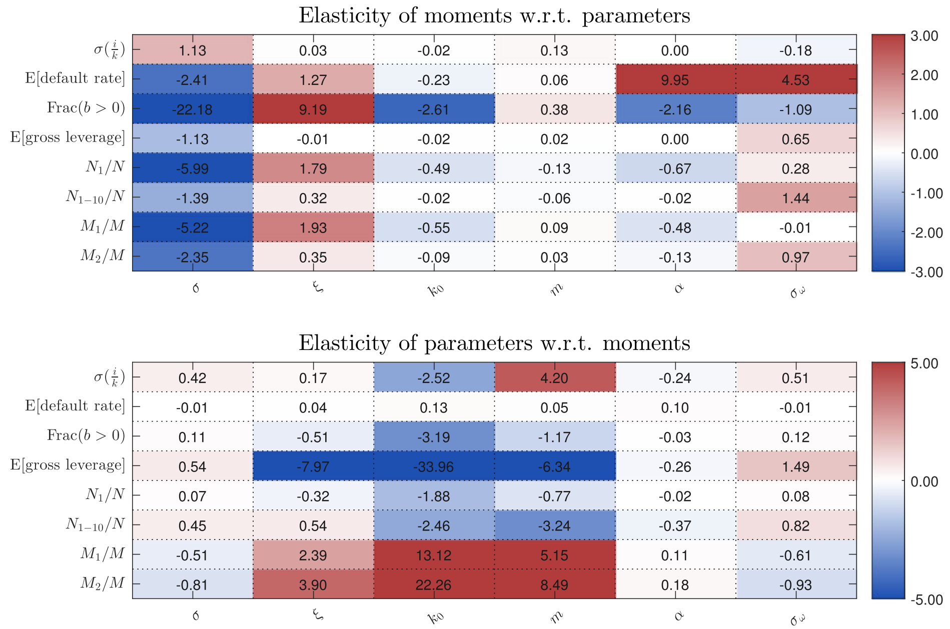

FIGURE 17.—Sources of identification. Notes: top panel computes the local elasticities of moments (rows) with respect to parameters (columns) at the estimated parameter values. Bottom panel computes the local elasticities of estimated parameters (columns) to moments (rows) computed as in Andrews, Gentzkow, and Shapiro (2017).

an influential moment because changing the productivity process changes other moments and, therefore, other parameter estimates, as well.

D.2. *Firm Dynamics*

Firms' Decision Rules. Figure 18 plots the investment, borrowing, and dividend payment decisions of firms. Firms with net worth n below the default threshold $\underline{n}_t(z)$ do not operate. Once firms clear this default threshold, they lever up to increase their capital to its optimal scale $k_t^*(z)$. Once capital is at its optimal level $k_t^*(z)$, firms use additional net worth to pay down their debt until they reach the unconstrained threshold $\overline{n}_t(z)$. Only unconstrained firms pay positive dividends.

The curvature in the policy functions over the region with low net worth n reflects the role of financial frictions in firms' decisions. Without frictions, all nondefaulting firms would borrow the amount necessary to reach the optimal scale of capital $k_t^*(z)$. However, firms with low net worth n would need to borrow a substantial amount in order to do so, increasing their risk of default and, therefore, borrowing costs. Anticipating these higher borrowing costs, firms with low net worth n accumulate capital below its optimal scale.

The right axis of Figure 18 plots the stationary distribution of firms. 51.8% of firms pay a risk premium, that is, are "risky constrained." These firms are in the region with curved policy functions described above. 47.5% of firms are constrained but do not currently pay a risk premium, that is, are "risk-free constrained." These firms have achieved their optimal scale of capital $k_t^*(z)$ and have linear borrowing policies. The remaining 0.6% of firms are unconstrained.

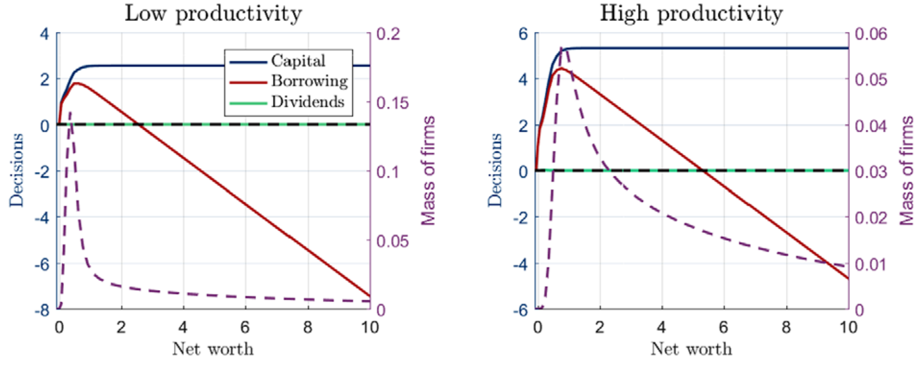

FIGURE 18.—Steady state decision rules. Notes: Left panel plots decision rules and stationary distribution of firms conditional on idiosyncratic productivity one standard deviation below the mean. Right panel plots the same objects conditional on productivity one standard deviation above the mean. The left y-axis measures the decision rules (capital accumulation, borrowing, and dividend payments) as a function of net worth n. The right y-axis measures the stationary distribution of firms (dashed purple line).

Figure 18 makes clear that there are two key sources of financial heterogeneity in the model. First, reading the graphs from left to right captures heterogeneity due to lifecycle dynamics; young firms accumulate debt in order to reach their optimal level of capital $k_t^*(z)$ and then pay down that debt over time. Second, moving from the left to the right panel captures heterogeneity due to idiosyncratic productivity shocks; a positive shock increases the optimal scale of capital $k_t^*(z)$, again leading firms to first accumulate and then decumulate debt.[7,8]

Lifecycle Dynamics. Figure 19 plots the dynamics of key variables over the firm lifecycle. New entrants begin with a low initial capital stock k_0 and, on average, a low draw of idiosyncratic productivity z. As described above, young firms take on new debt in order to finance investment, which increases their default risk and credit spreads. Over time, as firms accumulate capital and productivity reverts to its mean, they reach their optimal capital stock $k_t^*(z)$ and begin paying down their debt.

D.3. *Cross-Sectional Distribution of Investment and Leverage*

Table XVI shows that our model is broadly consistent with key features of the distributions of investment and leverage not targeted in the calibration. The top panel analyzes the distribution of investment rates in the annual Census data reported by Cooper and Haltiwanger (2006). We present the corresponding statistics in our model for a selected sample—conditioning on firms that survive at least 20 years to mirror the selection into the LRD— and in the full sample. Although we have calibrated the selected sample to match the dispersion of investment rates, the mean and autocorrelation of investment rates in the selected sample are also reasonable. The mean investment rate in the full sample is higher than the selected sample because the full sample includes young, growing firms.

[7]A third source of financial heterogeneity is the capital quality shocks, which simply generate variation in firms' net worth n.

[8]Buera and Karmakar (2018) studied how the aggregate effect of an interest rate shock depends on these two sources of heterogeneity in a simple two-period model.

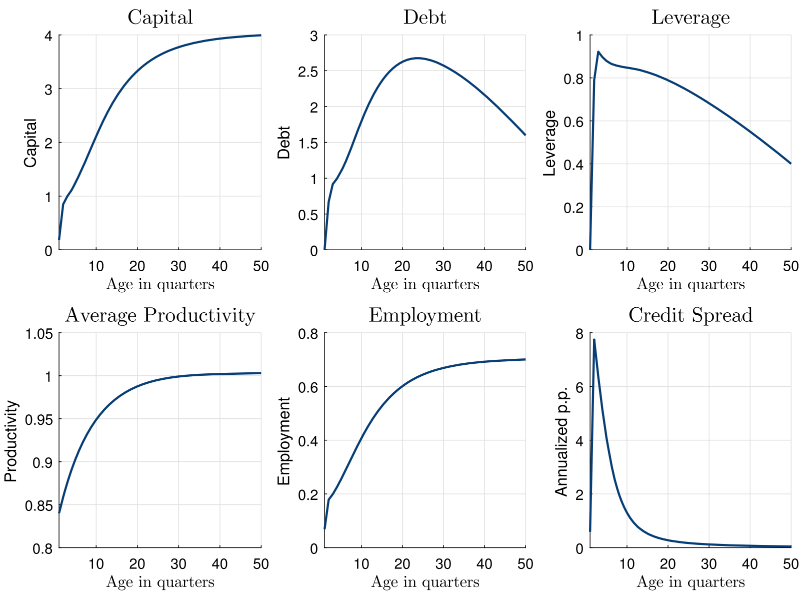

FIGURE 19.—Lifecycle dynamics in model. Notes: Average capital, debt, leverage, productivity, employment, and credit spread conditional on age in steady state.

Compustat Firms in the Model and the Data. We account for the sample selection into Compustat by conditioning on firms that have survived for at least 7 years. According to Wilmer Cutler Pickering Hale and Dorr LLP (2017), the median time to IPO has ranged

TABLE XVI

INVESTMENT AND LEVERAGE HETEROGENEITY[a]

Moment	Description	Data	Model (selected)	Model (full)
Investment heterogeneity (annual LRD)				
$\mathbb{E}[\frac{i}{k}]$	Mean investment rate	12.2%	13.9%	28.4%
$\sigma(\frac{i}{k})$	SD investment rate (calibrated)	33.7%	36.7%	48.3%
$\rho(\frac{i}{k}, \frac{i}{k}_{-1})$	Autocorr investment rate	0.06	−0.14	−0.14
Joint investment and leverage heterogeneity (quarterly Compustat)				
$\rho(\frac{b}{k}, \frac{b}{k}_{-1})$	Autocorr leverage ratio	0.94	0.96	0.96
$\rho(\frac{i}{k}, \frac{b}{k})$	Corr. of leverage and investment	−0.08	−0.08	−0.01
Average indebtedness of firms (quarterly Compustat)				
$\mathbb{E}[\frac{\max\{b,0\}}{k+\max\{-b,0\}}]$	Mean gross leverage	0.27	0.34	0.49
$\mathbb{E}[\frac{b}{k+\max\{-b,0\}}]$	Mean net leverage	−0.04	0.13	0.32
$\mathrm{Frac}(b > 0)$	Fraction with positive debt	0.85	0.59	0.70

[a]Statistics about the cross-sectional distribution of investment rates and leverage ratios in steady state. Data for investment heterogeneity are drawn from Cooper and Haltiwanger (2006). Model (selected) for investment heterogeneity corresponds to firms alive for longer than 20 years in a panel simulation, time aggregated to the annual frequency. Model (full) corresponds to the full sample of firms in a panel simulation, time aggregated to the annual frequency. Data for joint investment and leverage heterogeneity and the average indebtedness of firms drawn from quarterly Compustat data. Model (selected) for these panels corresponds to firms alive for longer than 7 years in a panel simulation. Model (full) corresponds to the full sample of firms in a panel simulation.

TABLE XVII

PUBLIC VS. PRIVATE FIRMS IN THE MODEL AND DATA[a]

	Data	Model
$\frac{\mathbb{E}[n\|\text{public}]}{\mathbb{E}[n\|\text{private}]}$	62	1.68
$\frac{\mathbb{E}[age\|\text{public}]}{\mathbb{E}[age\|\text{private}]}$	2.18	6.60
$\frac{\sigma(\frac{1}{2}\frac{n_{jt}-n_{jt-1}}{n_{jt}+n_{jt-1}}\|\text{public})}{\sigma(\frac{1}{2}\frac{n_{jt}-n_{jt-1}}{n_{jt}+n_{jt-1}}\|\text{private})}$	0.65	0.62

[a]Comparison of public and private firms. "Public" firms in the model are those who reach 7 years old (the median time to IPO in Wilmer Cutler Pickering Hale and Dorr LLP (2017)). $\frac{\mathbb{E}[n|\text{public}]}{\mathbb{E}[n|\text{private}]}$ computes the average size of firms measured by employment; data comes from Dinlersoz et al. (2018) Table 3. $\frac{\mathbb{E}[age|\text{public}]}{\mathbb{E}[age|\text{private}]}$ computes the average age; data comes from Dinlersoz et al. (2018) Table 3. $\frac{\sigma(\frac{1}{2}\frac{l_{jt}-l_{jt-1}}{l_{jt}+l_{jt-1}}|\text{public})}{\sigma(\frac{1}{2}\frac{l_{jt}-l_{jt-1}}{l_{jt}+l_{jt-1}}|\text{private})}$ computes the dispersion of growth rates; data comes from Davis et al. (2006) Figure 2.5.

from roughly 6 to 8 years over the last decade.[9] The bottom panels of Table XVI shows that the model-implied distribution of investment rates and leverage ratios in Compustat is aligned with the data. Leverage is highly autocorrelated and weakly correlated with investment in both the model and the data. The model roughly captures both the mean gross and net leverage in Compustat, as well as the fraction of firms with positive debt.

Table XVII compares public and private firms in our model to the data along three key dimensions. First, public firms are substantially larger than private firms in our model; however, our model comes nowhere close to the size gap observed in the data. An important reason for this discrepancy is that, in the data, many firms are born small and never grow; therefore, there is a large mass of permanently small firms which is outside of our model.[10] Second, public firms are older than private firms in both our model and the data; the gap is larger in our model since we select firms based solely on age. Finally, the dispersion of growth rates is smaller among public firms in both the model and data. In our model, private firms' growth rates are more disperse since they are more strongly affected by financial frictions.

REFERENCES

ANDREWS, I., M. GENTZKOW, AND J. SHAPIRO (2017): "Measuring the Sensitivity of Parameter Estimates to Estimation Moments," *The Quarterly Journal of Economics*, 132 (4), 1553–1592. [14,15]

BUERA, F., AND S. KARMAKAR (2018): "Real Effects of Financial Distress: The Role of Heterogeneity," Banco de portugal working paper no. 6, available at SSRN, https://ssrn.com/abstract=2997983. [16]

CLOYNE, J., C. FERREIRA, M. FROEMEL, AND P. SURICO (2018): "Monetary Policy, Corporate Finance and Investment," National Bureau of Economic Research w25366. [7,9,10]

COOPER, R. W., AND J. C. HALTIWANGER (2006): "On the Nature of Capital Adjustment Costs," *The Review of Economic Studies*, 73, 611–633. [16,17]

[9]Our results are robust to sensitivity analysis around this cutoff.

[10]Gavazza, Mongey, and Violante (2018) used permanent heterogeneity in returns to scale to match this group of permanently small firms. We have solved a related version of our model in which there are two types of firms: one with low returns to scale, which reach their optimal size relatively quickly, and another with the returns to scale of our baseline model. This model generates a skewed size distribution, as in the data, but by construction does not directly affect the behavior of the large "Compustat" firms in our model. In addition, these small firms make up a small share of aggregate investment and are therefore unlikely to have a substantial influence on aggregate dynamics.

CROUZET, N., AND N. MEHROTRA (2020): "Small and Large Firms Over the Business Cycle," Working paper, persistent link, https://EconPapers.repec.org/RePEc:cen:wpaper:18-09. [8]

DAVIS, S. J., J. HALTIWANGER, R. JARMIN, AND J. MIRANDA (2006): "Volatility and Dispersion in Business Growth Rates: Publicly Traded versus Privately Held Firms," *NBER Macroeconomics Annual*, 21, 107–179. [18]

DINLERSOZ, E., S. KALEMLI-OZCAN, H. HYATT, AND V. PENCIAKOVA (2018): "Leverage Over the Life Cycle and Implications for Firm Growth and Shock Responsiveness," National Bureau of Economic Research w25226. [18]

EBERLY, J., S. REBELO, AND N. VINCENT (2012): "What Explains the Lagged-Investment Dynamics?" *Journal of Monetary Economics*, 59, 370–380. [7]

GAVAZZA, A., S. MONGEY, AND G. L. VIOLANTE (2018): "Aggregate Recruiting Intensity," *American Economic Review*, 108 (8), 2088–2127. [18]

GERTLER, M., AND S. GILCHRIST (1994): "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms," *The Quarterly Journal of Economics*, 109 (2), 309–340. [7-9]

JEENAS, P. (2019): "Firm Balance Sheet Liquidity, Monetary Policy Shocks, and Investment Dynamics," Working paper. [7,10-13]

MIRANDA-AGRIPPINO, S., AND G. RICCO (2018): "The Transmission of Monetary Policy Shocks," CEPR discussion paper no. DP13396, available at SSRN, https://ssrn.com/abstract=3302647. [5]

NAKAMURA, E., AND J. STEINSSON (2018): "High-Frequency Identification of Monetary Non-Neutrality: The Information Effect," *The Quarterly Journal of Economics*, 133 (3), 1283–1330. [5]

ROMER, C., AND D. ROMER (1990): "New Evidence on the Monetary Transmission Mechanism," *Brookings Papers on Economic Activity*, 21, 149–214. [8,9]

WILMER CUTLER PICKERING HALE AND DORR LLP (2017): "2017 IPO Report," Technical report. Available at https://www.wilmerhale.com/en/insights/publications/2017-ipo-report. [17,18]

Co-editor Giovanni L. Violante handled this manuscript.

Manuscript received 17 December, 2017; final version accepted 19 June, 2020; available online 14 July, 2020.