STAFF REPORTS

NO. 904
NOVEMBER 2019

REVISED
JULY 2021

Firms' Precautionary Savings and Employment during a Credit Crisis

Davide Melcangi

FEDERAL RESERVE BANK of NEW YORK

Firms' Precautionary Savings and Employment during a Credit Crisis
Davide Melcangi
Federal Reserve Bank of New York Staff Reports, no. 904
November 2019; revised July 2021
JEL classification: E44, L25, G01, G32

Abstract

Can the macroeconomic effects of credit supply shocks be large even when a small share of firms are credit-constrained? I use U.K. firm-level accounting data to discipline a heterogeneous-firm model where the interaction between real and financial frictions induces precautionary cash holdings. In the data, firms increased their cash ratios during the last recession, and cash-intensive firms displayed higher employment growth. A tightening of firms' credit conditions generates the same dynamics in the model. Unconstrained firms pre-emptively respond to credit supply shocks; this precautionary channel, when appropriately quantified, crucially matters for the aggregate dynamics and firm-level patterns.

Key words: financial frictions, precautionary savings, employment, heterogeneous firms

---

Melcangi: Federal Reserve Bank of New York (email: davide.melcangi@ny.frb.org). An earlier version of this paper was part of the author's doctoral dissertation at University College London. The author thanks Vincent Sterk and Marco Bassetto for invaluable advice. For helpful comments, he thanks Michela Altieri, Wendy Carlin, Wei Cui, Mariacristina De Nardi, Simon Gilchrist, Gizem Kosar, Kasper Kragh-Sorensen, Morten Ravn, and many seminar and conference participants. He also thanks Meghana Gaur for superb research assistance.

1 Introduction

The Great Recession has renewed interest in financial and labour markets, and the potential interconnections that may link them. One of the proposed narratives suggests that firm credit tightening is at the root of the increase in unemployment. However, the extent to which financial frictions affect firm's decision-making, and hiring decisions in particular, is controversial. At the aggregate level, firms have large savings and generate internal funds substantially in excess of what they need to finance operations, as documented by Zetlin-Jones and Shourideh (2017) for the US and the UK. Moreover, empirical proxies suggest that only a moderate fraction of firms is credit-constrained.[1] These observations might lead one to conclude that firm-level credit constraints play a limited role for the cyclical behaviour of aggregate employment.

In this paper, I show that the macroeconomic effects of a credit tightening can be large even in economies in which the share of credit-constrained firms is small. I build a heterogeneous-firm model with shocks to firms' idiosyncratic productivity and aggregate credit uncertainty, in which precautionary savings in cash arise endogenously from the interaction between real and financial frictions, and affect the transmission mechanism of credit supply shocks onto labour demand. Real frictions, especially labour adjustment costs, amplify the extent to which financial frictions affect labour demand, while giving an enhanced role to liquidity. A persistent tightening of credit constraints not only affects the decisions of currently constrained firms, but also those of firms that are currently not credit-constrained but that face some probability of becoming constrained in the future. In the wake of a shock that restrains credit supply, these firms may cut investment in capital and hiring for *precautionary* reasons, as this allows them to build up larger cash holdings. This precautionary channel also allows the model to generate heterogeneous behaviour documented in the data.

The model's frictions, the associated channels, and their quantitative importance are motivated and disciplined by an empirical analysis of balance sheet data from UK firms. I use the FAME (Financial Analysis Made Easy) dataset, a large panel of UK firms between 2004 and 2013. This is a much broader sample than other alternatives often used in the literature, as it mainly includes private firms, whereas US Compustat, for example, is limited to publicly listed firms. This feature makes FAME particularly suitable for the study of financial frictions because private firms are often small and young. They may rely more heavily on external finance (Zetlin-Jones and Shourideh (2017)) and have a more limited access to credit (Spaliara (2009)). Finally, the data contain information on both the employment and the asset structure of the firms, used to directly discipline the

[1] Campello et al. (2010) report that 20% of US CFOs identified their firms as very affected by financial constraints. Angelini and Generale (2008) use Italian matched data and estimate a share of 5%.

model.

I document two main empirical stylised facts. First, the average cash to assets ratio increases when aggregate employment falls. With a simple back of the envelope calculation, entirely for illustrative purposes, I show that the increase in aggregate cash between 2008 and 2009 would have been more than enough to keep the net job creation at pre-crisis levels, if used to hire workers at the average wage. Even if only a share of this excess cash was allocated to the wage bill, the 2009 increase in unemployment rate would have been less than half of the one observed in reality. Moreover, the increase in cash ratios in 2009 is widespread and common to firms with different observed fundamentals. Second, I show that cash-intensive firms cut their workforces by less when aggregate employment falls. In particular, I document the time-varying patterns of the cross-sectional correlation between lagged cash ratio and employment growth, which is weakly positive until 2008, increases in 2009 and falls thereafter. Hence, I complement existing empirical evidence that focused on publicly listed firms, either for pre-post crisis comparison (e.g., Schoefer (2015), Gilchrist et al. (2017)) or documenting the average negative correlation between changes in liquidity and employment (Bacchetta et al. (2019)). By running a series of panel regressions, I confirm that not only is the relationship between cash ratios and employment growth statistically significant, but so is its variation over time.

Motivated by these facts, I build a heterogeneous-firm model with shocks to firms' idiosyncratic productivity and aggregate credit uncertainty. Precautionary savings in cash arise endogenously from the interaction between real and financial frictions, and affect the transmission mechanism of credit supply shocks to labour demand. Firms have to finance their wage bill in advance of production and can do so through accumulated cash holdings or an intraperiod loan. Such loans are collateralised with capital and subject to aggregate shocks. Cash and short-term external finance are directly tied to labour, whereas capital investment is mostly affected by costly equity issuance.[2] Theoretically, the interaction between credit constraints and other frictions can trigger precautionary behaviour. Costly adjustment of labour, for instance, can amplify financial wedges, and increase the importance of cash to mitigate the friction. In particular, labour adjustment costs induce unconstrained firms to adjust labour demand in anticipation of future financial constraints.

The quantitative importance of the precautionary channel is directly disciplined by calibrating the model to match empirical moments from UK firm-level data. The various frictions are disciplined by financial moments, the distribution of cash ratios, and the empirical properties of employment and investment. The calibrated model also performs well in approximating additional microeconomic features of the sample, not explicitly

[2]This dichotomy is reminiscent of Bacchetta et al. (2019). The timing of frictions in my model makes it less stark, giving rise to precautionary behaviour. Most importantly, other frictions such as labour adjustment costs greatly amplify a channel otherwise quantitatively limited.

targeted. For instance, it correctly predicts that more labour intensive firms will hold relatively more cash and generates a weakly positive correlation between cash ratios and employment growth.

I evaluate the model's ability to explain macroeconomic and firm-level outcomes during the aftermath of the financial crisis, simulating an exogenous tightening of the credit conditions. I show that the precautionary channel allows the model to explain the joint evolution of three key variables: (i) the decline in aggregate employment, (ii) the increase in the average cash-to-assets ratio, and (iii) the initial increase and subsequent decline in the cross-sectional correlation between the firm-level cash-to-asset ratio and employment growth rate. The predicted decline in aggregate employment is nearly as large as in the data, despite the fact that in the model the share of credit-constrained firms never exceeds 20%. I show that unconstrained firms that act for precautionary reasons account for nearly two thirds of the fall in aggregate employment upon impact and are crucial for the persistent dynamics in the following quarters.

Each of the frictions present in my model can be found in earlier literature. The collateral constraint is closely related to Jermann and Quadrini (2012). Non-smooth adjustment costs in labour and capital can be found, for example, in Bloom (2009). Costs that limit the speed at which firms can raise additional equity are often implemented in the corporate finance literature.[3] Each of these frictions is internally calibrated using firm-level empirical moments. When doing so, the precautionary channel is quantitatively salient. I show that, for the precautionary channel to arise in full, these frictions need to be included simultaneously in the model. Indeed, they all play a complementary role: they make it costly for firms to quickly circumvent the effects of a binding credit constraint by either selling capital, firing workers, or raising additional equity.

I show quantitatively that removing any one of the frictions substantially weakens the precautionary channel. In contrast with the data, these versions of the model predict smaller and more short-lived aggregate employment dynamics. Most importantly, they are not able to generate either the weakly positive steady-state correlation between cash ratios and employment growth rates, or its increase and subsequent decrease following a credit crunch. Labour adjustment costs are particularly important, as they strongly increase the ability of cash to lessen the severity of the short-term credit friction. Absent these costs, the precautionary channel is greatly limited, with unconstrained firms accounting for a negligible fraction of the fall in aggregate employment.

This paper is organized as follows. After briefly reviewing the literature, in section 2 I document empirical stylised facts on cash ratio and employment dynamics, which

[3]Falato et al. (2013) and Hennessy and Whited (2007) are some examples. Moreover, the cost is also used in the macroeconomic literature, as Jermann and Quadrini (2012).

motivate the model, described in Section 3. Section 3.5 provides intuition for the key model mechanisms. The quantitative analysis in Section 4 starts with the description of the calibration strategy and the data used. I then turn to the steady state performance of the model, before investigating the aggregate effects of a credit tightening and its microeconomic drivers. Finally, I show in Section 5 how versions of the model without some frictions fail to match key empirical predictions.

Related literature

This paper fits into the vast literature that incorporates firm-level financial frictions into macroeconomic models. Among seminal and influential contributions, Bernanke et al. (1999) propose a "financial accelerator" mechanism that amplifies and propagates shocks to the macroeconomy, while Cooley and Quadrini (2001) show that financial market imperfections, in the presence of persistent shocks, affect firm dynamics. A more recent strand of literature has focused on the direct effect of shocks to these frictions on the real economy. Examples include Khan and Thomas (2013) on capital misallocation, Bassetto et al. (2015) on the differential impact on corporate and entrepreneurial sector, and Crouzet (2017) on corporate debt choices.

The main focus of my paper, instead, is to study the effect of firm credit tightening on aggregate employment.[4] In corporate finance, most of the literature focuses on the role played by financial constraints in distorting investment decisions, as surveyed by Strebulaev and Whited (2012).[5] In particular, labour is typically hired on the spot market, and firms can always implement the static optimum; this implies that financial frictions have no direct and independent effect on employment decisions. Jermann and Quadrini (2012) develop a real business cycle model with debt and equity financing, in which a representative firm finances working capital through a collateralised intra-period loan. In their setting, financial frictions show up as a labour wedge. Representative firm models, however, are not suitable to study economies with a small share of constrained firms and a large amount of savings, as typically observed in the data. Buera et al. (2015) use a model with heterogeneous entrepreneurial productivity and search frictions to argue that a credit crunch can translate to a protracted increase in unemployment.[6] While tracing a link between credit constraints and employment, these papers do not focus on firms' precautionary savings, which is instead the central channel investigated here. I show how

[4]Examples of empirical papers of this sort are Chodorow-Reich (2013) and Duygan-Bump et al. (2015).

[5]An exception is recent work by Michaels et al. (2018), who integrate costly external finance with labour and capital adjustment costs, to study the negative correlation between wages and leverage.

[6]Petrosky-Nadeau (2014) extends the baseline search-and-matching model of equilibrium unemployment with financial constraints to vacancy posting and shows that these frictions can generate persistence in the dynamics of labour market tightness.

empirically disciplined frictions, such as labour adjustment costs, interact with firms' portfolio decisions and substantially alter the transmission of credit supply shocks.

Finally, my work contributes to the literature studying differences in liquidity across firms' assets. While firms' cash holdings, and their determinants, have been extensively studied in corporate finance,[7] they are often ignored in macroeconomic models.[8] Differently from most of the literature, I focus on employment and explicitly study its interaction with corporate precautionary savings, when aggregate financial conditions are time-varying and firms face non-smooth capital and labour adjustment costs.[9] Bacchetta et al. (2019) also combine the analysis of firms' cash holdings and employment, in order to distinguish the effects of credit and liquidity shocks. Compared to their work, I focus on the role played by firms' precautionary behaviour in amplifying the macroeconomic effects of credit tightening. This is achieved through financial constraints that bind occasionally both over time and across firms. I motivate and discipline the model with stylised facts on non-listed firms, more likely to be affected by financial frictions. In particular, I show that the relationship between liquidity and employment growth varies over time and time differences are statistically significant. Moreover, I highlight the importance of non-smooth adjustment costs, in particular labour market frictions, for firms' portfolio decisions and its interaction with changes in aggregate financial conditions.[10] The quantitative importance of such ingredients is explicitly calibrated using firm-level information. When doing so, the precautionary channel is not only quantitatively salient, but also necessary to match the empirical facts documented in this paper.

2 Stylised facts

This section documents empirical stylised facts on firms' precautionary savings and employment in the UK. I show that, during the Great Recession, the average firm started hoarding cash while simultaneously cutting employment, and that cash-intensive firms reduced their workforces by less. I will use these findings to motivate and validate a model in which firms have precautionary reasons to respond to changes in credit conditions.

[7] See for example Bates et al. (2009) for an empirical analysis of the determinants of cash holdings. Riddick and Whited (2009) study corporate accumulation of liquid assets in a dynamic partial equilibrium model. Han and Qiu (2007) stress the importance of precautionary motives for corporate cash holdings.

[8] Some recent exceptions include Cui and Radde (2016) and Kiyotaki and Moore (2012). Jeenas (2019) studies the role of firms' liquid assets for the transmission of monetary policy shocks to investment. Xiao (2019) proposes a channel by which firms borrow to save and which affects capital investment. These works, however, do not explicitly focus on employment fluctuations.

[9] Bolton et al. (2013) also study capital investment in a dynamic model with financial constraints, allowing for stochastic financing conditions.

[10] Ghaly et al. (2017) show empirically that firms' ability to adjust labour demand, due to hiring and firing costs, is a determinant of precautionary cash holdings, particularly in presence of financial constraints.

The primary data source used in this paper is the FAME (Financial Analysis Made Easy) dataset. It comprises panel data observations for a large number of UK firms for the period 2004-2013. The key advantage with respect to US Compustat is the ownership structure of the firms. Indeed, 94% of the FAME sample considered in this paper are non-publicly traded. As such, the sample is much broader and more representative than commonly used in the literature, with a size and age distribution closer to what observed in the population of UK firms. The presence of young and small firms makes FAME particularly suitable for the analysis of financial frictions, since those firms are likely to rely more heavily on external finance and face more difficulties in accessing credit. The dataset contains firm-level information on both the asset and the employment structure of the firms. It also includes data on cash holdings, recorded in firm's balance sheets as *Bank deposits*. This entry is by far the most densely populated measure among short-term financial assets in the dataset and most likely represents the lion's share of these assets for non-quoted firms.[11] Appendix A provides additional information on the data, including descriptive statistics.

I document that the average cash ratio increases when aggregate employment falls, confirming and extending earlier US findings by Bacchetta et al. (2019) to a sample not limited to publicly listed firms.[12] Figure 1 shows this by plotting first differences; in 2009, in correspondence with a sharp employment contraction, firms hoarded a large amount of cash relative to their assets. Such behaviour is widespread across firms of different size, age and industry, with the majority of firms increasing their cash ratios.

The increase in cash ratio in 2009 is quantitatively sizeable and a simple back of the envelope calculation can show this. Suppose the cash ratio remained constant after 2008, and the cash in excess of this counterfactual cash was used to hire workers at the average wage.[13] In this scenario, 329,252 additional workers would have been hired, more than offsetting the fall in aggregate employment observed in FAME.

It may be argued that salaries are not the only expenses that a firm faces. In the FAME data I find that the wage bill accounts, on average, for 27% of operating and capital expenditures.[14] Allocating only this share of additional cash to the wage bill, firms in FAME could have hired 89,599 additional workers in 2009, unwinding more than half of

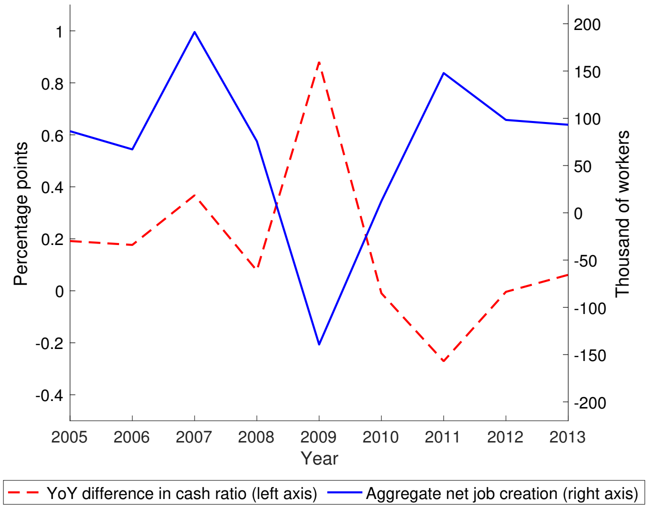
[11] Bank deposits are the British analogue of cash & equivalent in global accounting format. This limits the concern that the rise in cash is just driven by a substitution away from other cash securities. Appendix A explores this issue more in detail. Moreover, all the empirical findings shown in this section are robust to netting out cash with current liabilities.

[12] The cash ratio is defined as the share of cash holdings over total assets. The results are very similar for aggregate cash ratio and median cash ratio across firms. Moreover, these aggregate patterns are present within most sectors, such as manufacturing.

[13] The counterfactual cash is the aggregate cash required to keep the aggregate cash ratio constant, taking aggregate total assets as given. The average wage in 2008, in the FAME sample, is £31,593.

[14] Operating expenditures are all the expenses before the EBITDA.

Figure 1: Aggregate increase in cash ratio and aggregate net job creation in the UK



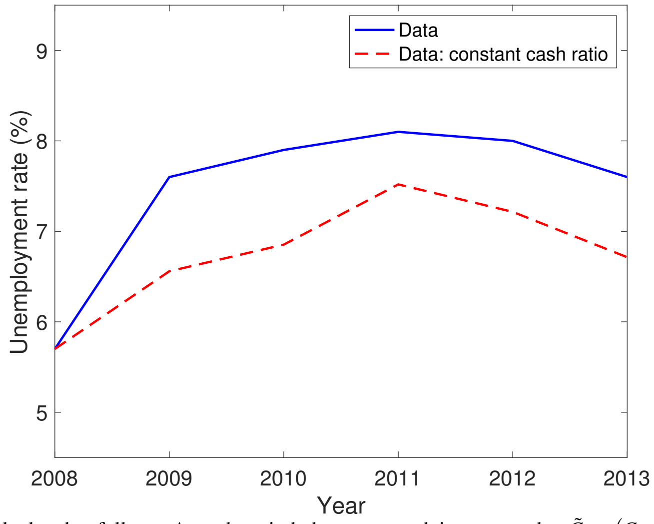
Notes: Firm-level net job creation is the difference in number of employees for a given firm from one year to the other. The cash ratio is the sum of total Bank deposits over total assets. The dashed line shows the year-on-year differences in the cross-sectional average cash ratio. Further details on the data and the sample in Appendix A.

the negative job creation. Figure 2 shows how important this is in the aggregate. I scale up FAME additional net job creation to the UK economy and compute the counterfactual unemployment rate, shown by the dashed line.[15] Under this scenario, the increase in unemployment rate in 2009 is less than half of the one observed in reality, because part of the excess cash is used to hire workers. By doing so, the firms in the counterfactual scenario have a lower stock of cash in the following years, and thus unemployment rate increases faster between 2010 and 2011 than in reality. While entirely illustrative, this exercise nevertheless shows the quantitative potential of cash for employment dynamics. The model will formally investigate this link.

Besides documenting the cyclical patterns of cash ratios, the data can shed some light on the role played by precautionary cash holdings in the transmission mechanism of credit shocks onto the labour market. Figure 3a shows, at different years, the cross-firm correlations between lagged cash ratios and employment growth rates. The relationship is weakly positive and stable in normal times, more than doubles in 2009, and then turns negative in 2011. Figure 3b shows a similar pattern. In each year, I reclassify firms according to whether their lagged cash ratio was above or below the sample average, and then compute the average employment growth rate in each group. Firms that entered the 2009 crisis with a relatively illiquid position experienced 2.6 percentage points lower employment growth than the rest of the sample, thus more than doubling the gap typically existent in normal times. Schoefer (2015) finds a similar pattern for US publicly quoted firms. Besides qual-

[15]In 2008, 29.6 million workers were employed in the UK, 3.7 times the aggregate employment in my FAME sample. This factor remains constant over time, confirming that FAME and ONS data display similar employment dynamics.

Figure 2: Cash and unemployment: a back of the envelope calculation

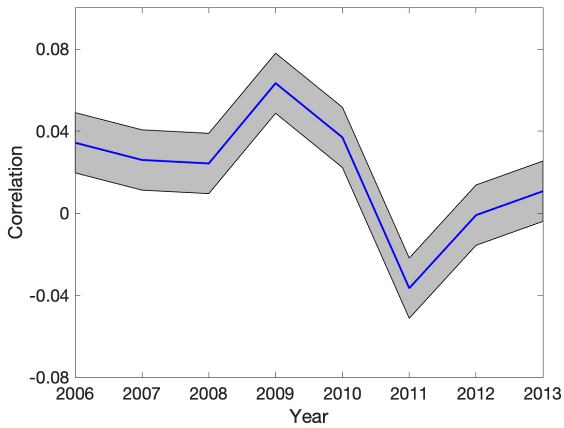


Notes: The dashed line is calculated as follows. At each period, the excess cash is computed as $\tilde{C}_t = (C_t - \hat{C}_t) - (C_{t-1} - \hat{C}_{t-1})$, where C_t is the empirically observed aggregate cash and $\hat{C}_t$ the aggregate cash required to keep the cash ratio constant at 6.44%, its value in 2008, conditional on observed aggregate total assets. Every period, 27% of $\tilde{C}_t$ is used to hire additional workers at the cross-firm average wage, and the remaining excess cash is used for other purposes and gone. The additional workers are scaled up by a factor 3.67, which is the ratio between ONS and FAME aggregate employment, and added to the time series of unemployed workers (ONS). Finally, the unemployment rate is computed by dividing the counterfactual unemployment by the ONS labour force.

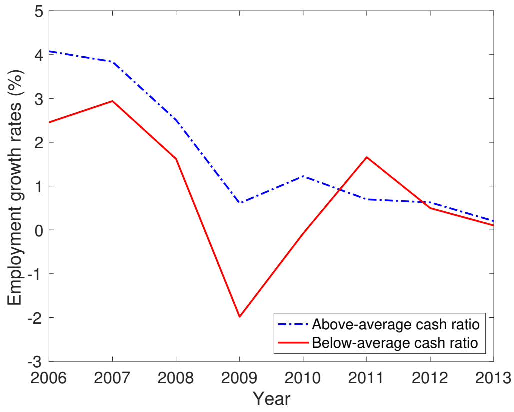
itatively confirming these patterns for a broader sample of non-listed firms, I also trace how cash ratio and employment growth interact in the following periods. In particular, in 2011, cash-rich firms experience a lower employment growth. The model presented in the remainder of the paper will be able to replicate the entire dynamics. Following a credit crunch, most firms hoard cash to partially counteract the scarce external funding, and smooth employment growth throughout the recession. A share of firms, however, is likely to be so disrupted by the credit supply shock that is not able to internally generate liquidity. This cash-scarce group of firms leads the recovery when credit conditions are restored, driving the cross-firm correlation negative. An increase in cash has a twofold effect: on one hand, it takes resources away from production, amplifying the negative effects of credit shocks. On the other hand, in the following periods, it helps the adjustment to tighter credit conditions and, coupled with labour adjustment costs, smoothens the recovery. These empirical findings also differ from Bacchetta et al. (2019) in two main ways. First, they find a negative cross-firm correlation between deviations in cash ratio and employment among US quoted firms. In contrast, I look at how levels of cash ratio are associated with differential employment growth. Second, I trace the evolution of such relationship over time.

In Table 1 I confirm the robustness of these results running a set of panel regressions. In particular, Column I – III estimate the following equation:

Figure 3: Cash ratio and employment growth



(a) Cross-firm correlations between lagged cash ratio and employment growth



(b) Average employment growth by cash ratio

Notes: Appendix A describes the data. Employment growth for a firm j at year t is calculated as $\Delta n_{j,t} = \frac{n_{j,t} - n_{j,t-1}}{\alpha n_{j,t} + (1-\alpha) n_{j,t-1}}$, with $\alpha = 0.5$; Moscarini and Postel-Vinay (2012) explain the advantages of this symmetric approach. Shaded grey bands indicate 95% confidence intervals. In figure 3b, firms are reclassified every year depending on whether their lagged cash ratio was above or below the sample average. Within group average employment growth rates are plotted.

$$\Delta n_{j,t} = \left[\beta_{pre} c_{j,t-1} + \alpha_{pre}\right] 1\left(t \leq 2008\right) + \sum_{t=2009}^{2012} \left[\beta_t c_{j,t-1} + \alpha_t\right] + \gamma' W_{j,t} + \varepsilon_{j,t} \tag{1}$$

where $\Delta n_{j,t}$ is employment growth rate as previously defined for firm j in year t, $c_{j,t-1}$ is lagged cash ratio, and W is a set of firm-specific controls. For compactness I have combined all the years before 2009 in a single dummy variable. Results are identical if estimating time dummies for those years separately. Estimates in Column I confirm that there is a weakly positive, although statistically significant, relationship between lagged cash ratio and employment growth pre-2009, as denoted by β_{pre}. In particular, 10 additional percentage points of cash ratio are associated with about 0.25 percentage-point additional employment growth. This relationship more than doubles in 2009 and then turns negative in 2011, in line with previous results. Both the increase in 2009, and the fall in 2011, are statistically different from the pre-crisis correlation, at the 1% level. In Column II and III, I show that the main findings are confirmed when controlling for sectoral dummies, as well as firm-level characteristics, respectively. The empirical patterns could be explained by the fact that firms that manage to grow even during the crisis could receive more revenues, which would translate in higher cash. As suggestive evidence against this explanation, results are confirmed when controlling for cash flow. This should also account for the possibility of an unexpected negative productivity or demand shock that induces firms to lay off workers and generates more cash flow. If that was the case, we

Table 1: Cash ratio and employment growth

	$\Delta n_{j,t}$				
	(I)	(II)	(III)	(IV)	(V)
$c_{j,t-1} \times (\text{year} \leq 2008)$	0.025***	0.018***	0.012***		0.046***
	(0.004)	(0.005)	(0.005)		(0.010)
$c_{j,t-1} \times (\text{year} = 2009)$	0.067***	0.060***	0.055***		0.072***
	(0.008)	(0.008)	(0.009)		(0.012)
$c_{j,t-1} \times (\text{year} = 2010)$	0.033***	0.026***	0.025***		0.050***
	(0.007)	(0.007)	(0.008)		(0.011)
$c_{j,t-1} \times (\text{year} = 2011)$	-0.030***	-0.037***	-0.040***		0.019*
	(0.007)	(0.007)	(0.007)		(0.011)
$c_{j,t-1}$				0.043***	
				(0.008)	
$\Delta y_{j,t}$				0.264***	0.264***
				(0.009)	(0.009)
$Pr(\beta_{2009} = \beta_{pre})$	0.000	0.000	0.000		0.021
$Pr(\beta_{2011} = \beta_{pre})$	0.000	0.000	0.000		0.007
Industry dummies		✓	✓		
Firm controls			✓		
Year dummies	✓	✓	✓	✓	✓
Firm FE				✓	✓
Observations	124,334	124,334	122,964	98,762	98,762

Notes: Panel regressions over the period 2006-2012. The dependent variable $\Delta n_{j,t}$ is employment growth rate, defined as in Figure 3a and Appendix A. $c_{j,t-1}$ is lagged cash ratio, which is interacted with year dummies. All specification include, although unreported, β_{2012}, which is typically insignificantly different from β_{pre}. Industry dummies are defined at the section level of UK SIC 2007 codes. Firm controls consist of cash flow, lagged employment in logs, lagged total assets in logs. $\Delta y_{j,t}$ is the growth rate in sales, defined in the same way as for employment. $Pr(\beta_k = \beta_h)$ reports the p-value for a Wald test of a null hypothesis that the coefficient β_k is equal to β_h. Standard errors are robust to heteroskedasticity and reported in parentheses. *,**, and *** denote significance at the 10, 5, and 1% levels respectively.

should see a drop in the correlation between cash ratio and employment growth in 2009, which does not happen instead. Moreover, year-specific coefficients remain statistically different for each other in both specifications.

Finally, I show that my results are confirmed when introducing firm fixed effects, by estimating the following equation:

$$\Delta n_{j,t} = \left[\beta_{pre} c_{j,t-1} + \alpha_{pre}\right] 1(t \leq 2008) + \sum_{t=2009}^{2012} \left[\beta_t c_{j,t-1} + \alpha_t\right] + \gamma \Delta y_{j,t} + \mu_j + \varepsilon_{j,t} \quad (2)$$

where μ_j are firm fixed effects and $\Delta y_{j,t}$ is the growth rate in firm sales, as in Gilchrist et al. (2017). Such control is aimed at absorbing firm-specific shocks that might be associated with employment fluctuations. In column IV I show that a firm with 10 percentage points additional cash ratio typically displays a 0.4 percentage-point higher employment growth. Even when controlling for permanent unobserved heterogeneity at the firm level, the relative importance of liquidity for employment growth substantially increases in 2009, and then drops in 2011, as shown in Column V. Moreover such time variation is still statistically significant at 5% level. Finally, I find that the time-varying relationships between liquidity and employment growth is still present within different industries and size or age bins. For instance, I separately estimate Equation (1) for firms whose size is above and below the median. In both groups β_{pre} is not statistically different from 0 whereas β_{2009} and β_{2011} are significantly positive and negative, respectively. Moreover, such coefficients do not statistically differ across size groups and their point estimates are close to what shown in Table 1.

3 The model

I consider a partial equilibrium model that investigates firms' behaviour. The economy is populated by heterogeneous firms that are subject to idiosyncratic productivity shocks and aggregate credit shocks. Firms can invest in physical capital, used for production together with labour, or in liquid assets. They face a liquidity need originated by the payment of the wage bill, which can be covered either by external intra-period loans or by cash holdings. This assumption generates interactions between employment and portfolio choices. Short-term borrowing is collateralised by tangible assets, in the form of capital, and subject to persistent credit shocks, which restrict the amount of loans for a given level of collateral. Firms incur non-smooth capital and labour adjustment costs and can issue equity, at an increasing and convex cost. These elements give rise to firms' precautionary behaviour, further exacerbated during tight credit periods. The presence of these frictions amplifies the quantitative importance of financial frictions, otherwise limited, and gives an enhanced role to liquidity. I will start presenting the main features of the model and the firm's value function. Section 3.5 will shed further light on the key mechanisms of the model.

3.1 Technology

The economy is populated by a very large number of infinitely-lived heterogeneous firms that use capital k and labour n to produce a final good. I assume that each firm operates a diminishing returns to scale production function with capital and labour as the variable inputs. A firm produces output y according to:

$$y_t = z_{j,t} k_t^{\nu} n_t^{\omega} \ , \nu + \omega < 1 \tag{3}$$

where $z_{j,t}$ is a stochastic and persistent idiosyncratic productivity[16] that follows a Markov chain: $z \in Z \equiv z_1, .., z_{N_z}$, with $Pr(z_{t+1} = z_i | z_t = z_j) = \pi^z_{ji} \geq 0$ and $\sum_{i=1}^{N_z} \pi^z_{ji} = 1$.

3.2 Working capital constraint

Firms need to pay their wage bill in advance of production. As in Jermann and Quadrini (2012), this stems from the cash-flow mismatch between the payments made at the beginning of the period and the realization of revenues.[17] Corugedo et al. (2011) analyse UK firms working capital positions over the business cycle and find that firms have typically a funding gap between the payments of the costs of the inputs to production and the sales revenues, which typically come much later. Short-term loans are particularly important for small and medium enterprises, as shown by Caglio et al. (2021). Such firms comprise the very large majority of the entire distribution and this is reflected in the dataset used in this paper. Nicolas (2021) empirically shows the importance of short-term financial constraints for French firms' investment decisions.

The timing goes as follows. At the beginning of the period, after the realization of the idiosyncratic and aggregate shocks, firms choose the stock of workers that will be productive in the same period. They have to pay the associated wage bill $\overline{w}n_t$ out of accumulated cash m_t, before the realization of revenues, which come at the end of the period. If the wage bill exceeds the accumulated cash, firms can obtain external funds at the beginning of the period and repay at the end of it. This form of intra-period loan entails no interest, as in Jermann and Quadrini (2012), and cannot be larger than a stochastic fraction ϕ of collateral, that is, the liquidation value of capital. The following equation describes how, according to the collateral constraint, the financing funds need to be greater or equal than the financing needs:

$$\underbrace{\phi_{s,t}(1-\vartheta)(1-\delta_k)k_t + m_t}_{\text{financing funds}} \geq \underbrace{\overline{w}n_t}_{\text{financing needs}} \tag{4}$$

The ability to borrow intra-temporally is bounded by the limited enforceability of debt contracts. Since liquidity can be easily diverted, the only asset available for the liquidation is physical capital k_t, as in Kiyotaki and Moore (1997). In particular, this will

[16]Since the model is in partial equilibrium, the production function can be seen as a revenue function where z combines productivity and demand terms into one index, as in Bloom (2009).

[17]Christiano et al. (2010) and Mendoza (2010) are other examples of models with similar constraints.

be the non-depreciated fraction of capital; moreover, lenders incorporate the fact that, in case of default, they will sell the seized capital at a lower, resale price $(1-\vartheta)$. This form of partial irreversibility will be described in the following subsection.

The collateral fraction $\phi \in \phi_1, .., \phi_{N_\phi}$ is assumed to be common to all firms and will be referred to as *credit tightness*. It is assumed to follow a Markov chain, with $Pr(\phi_{t+1} = \phi_m | \phi_t = \phi_s) = \pi^{\phi}_{sm} \geq 0$ and $\sum_{m=1}^{N_\phi} \pi^{\phi}_{sm} = 1$. This variable can be interpreted in many ways. It could reflect the efficiency of the economy's financial sector, as in Khan and Thomas (2013), or capture the variations over time in the degree of credit market tightness (Finocchiaro and Mendicino (2016)). Eisfeldt and Rampini (2006) provide some evidence about the cyclicality of ϕ. The quantitative analysis in Section 4 will consider a drop in ϕ, resembling an exogenous reduction in the amount of available external funds.

Similarly to Svensson (1985), cash holdings decisions are made before the realization of the shocks, which gives rise to precautionary incentives to accumulate cash. The latter will be softened by the possibility to top up the wage bill payment through external financing. As will be explained later, the presence of real frictions act in the opposite direction, amplifying the incentives to behave pre-emptively. Finally, the wage is assumed to be fully rigid and common across firms.[18]

3.3 Other frictions

Besides the working capital constraint, firms face three additional frictions. As will be made clearer later on, the interaction between these frictions and the collateral constraint implies that precautionary cash holdings arise endogenously in the model.

Firms face linear and symmetric hiring and firing costs, as in Bloom et al. (2018). The firm begins the period t with a pre-determined employment stock n_{t-1}, a fraction δ_n of whom immediately separates. Firms choose the new stock of workers, pay the wage bill and use pre-determined capital and the newly available labour to produce. The labour adjustment costs can be summarized as follows:

$$AL(n_{t-1}, n_t) = \chi \, | \, (n_t - (1-\delta_n) \, n_{t-1}) \, | \tag{5}$$

Consistent with the typical timing convention, capital k_t is chosen at time $t-1$ and predetermined at time t. It evolves according to $k_{t+1} = (1-\delta_k)k_t + i_t$ where i_t is investment and δ_k is the depreciation rate. As in Bloom (2009), capital is partially irreversible and its installation is subject to fixed costs. Firms buy capital at a unitary price, as in a neoclassical growth model, but, for each unit of used assets, only $(1-\vartheta)$ fraction is use-

[18] Wage rigidity is often assumed in quantitative macroeconomic models, as in Christiano et al. (2005), and, for a study of the Great Recession, in Ravn and Sterk (2017).

ful for other buyers. ϑ represents the reallocation costs, the partial irreversibility of the capital stock due to capital specificity or adverse selection problems. Capital investment, net of partial irreversibility cost, is then given by:

$$AC^P(k_t, k_{t+1}) = \begin{cases} k_{t+1} - (1-\delta_k)k_t & \text{if } k_{t+1} \geq (1-\delta_k)k_t \\ -(1-\vartheta)[(1-\delta_k)k_t - k_{t+1}] & \text{if } k_{t+1} < (1-\delta_k)k_t \end{cases} \tag{6}$$

Moreover, when new capital is installed or gross investment is negative, a fixed fraction Θ of output is lost. Therefore I define fixed adjustment costs of capital as:

$$AC^F(k_t, k_{t+1}, y_t) = \begin{cases} \Theta y_t & \text{if } k_{t+1} \neq (1-\delta_k)k_t \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Finally, I assume that firms incur in a quadratic cost[19] when they deviate from a target level of dividends, given by: $\xi(d_t) = \kappa(d_t - \overline{d})^2$, as in Jermann and Quadrini (2012). This cost is in line with empirical evidence that underwriting fees display increasing marginal cost in the size of the offering (Altinkilic and Hansen (2000)). It is also a reduced form to capture the fact that managers are concerned with smoothing dividends over time. The seminal work by Lintner (1956), repeatedly confirmed by more recent studies, found that approximately 90% of firms smooth their dividend payments with respect to their earnings. For simplicity, the dividend target $\overline{d}$ is set to 0. This choice also helps the interpretation of the cost in terms of equity issuance.

3.4 The Firm's value function

I denote $V(m_t, k_t, n_{t-1}, z_{j,t}; \phi_{s,t})$ the value function of a firm. The 5 state variables are given by (1) the firm's cash stock m_t, (2) the firm's capital stock k_t, (3) the firm's stock of workers n_{t-1}, (4) the firm's idiosyncratic productivity $z_{j,t}$ and (5) the aggregate credit tightness $\phi_{s,t}$. The dynamic programming problem of the firm consists of choosing dividends, labour, capital next period and cash next period to maximise the present discounted value of future dividends:

[19]The majority of macroeconomic models with heterogeneous firms restrictively assumes no equity issuance. Given the absence of inter-temporal debt, I allow all firms to issue equity, but at a cost. As such, negative d could be broadly interpreted as long-term external finance. I return on this point in Section 4.2.

$$V(m_t,k_t,n_{t-1},z_{j,t};\phi_{s,t}) = \max_{d_t,m_{t+1},k_{t+1},l_t,n_t,y_t} \Bigg\{ d_t - \xi(d_t) + \beta \sum_{m=1}^{N_\phi} \pi^{\phi}_{sm} \sum_{i=1}^{N_z} \pi^{z}_{ji} V(m_{t+1},k_{t+1},n_t,z_{i,t+1};\phi_{m,t+1}) \Bigg\}$$

subject to:

$$\begin{aligned}
y_t - l_t &= AC^P(k_t,k_{t+1}) + AC^F(k_t,k_{t+1},y_t) + AL(n_{t-1},n_t) + m_{t+1} + d_t && (8)\\
l_t &= \overline{w}n_t - m_t && (9)\\
l_t &\leq \phi_{s,t}(1-\vartheta)(1-\delta_k)k_t && (10)\\
m_{t+1} &\geq 0 && (11)\\
\xi(d_t) &= \kappa d_t^2 && (12)
\end{aligned}$$

and Equations (3), (5), (6) and (7), where l_t is the intra-period loan that the firm receives at the beginning of the period and repays at the end of it. Firms borrow exactly the amount of wage bill that exceeds the accumulated cash. In contrast, (10) binds occasionally over time and across firms. All firms face the same aggregate credit tightness $\phi_{s,t}$. Let $k^*(m_t,k_t,n_{t-1},z_{j,t};\phi_{s,t})$, $m^*(m_t,k_t,n_{t-1},z_{j,t};\phi_{s,t})$, $n^*(m_t,k_t,n_{t-1},z_{j,t};\phi_{s,t})$ and $d^*(m_t,k_t,n_{t-1},z_{j,t};\phi_{s,t})$ represent the optimal choices of next-period capital and cash, labour and dividends respectively, made by the firm with current idiosyncratic productivity $z_{j,t}$ and under aggregate credit tightness $\phi_{s,t}$. I characterize these decision rules in Section 3.5.

3.5 Firm's behaviour

Before turning to the quantitative part of the paper, it is useful to shed some light on the main mechanisms generated by the model. I will start by showing the trade-off between capital and cash, and how this is affected by the frictions firms face. I will then turn to the hiring decision and finally show how the precautionary mechanism falls apart when each of the real frictions is removed.

Firms face a trade-off between very liquid but unproductive assets, denoted as cash, and productive but partly liquid and partly collateralizable assets, capital. This is shown in Equations (13) and (14), which show the first order conditions of a firm with idiosyncratic productivity $z_{j,t}$ for capital and cash respectively:

$$\beta \mathbb{E}_t \left[\lambda_{t+1} \left(\underbrace{v \frac{y_{t+1}}{k_{t+1}}}_{\mathrm{I}} - \underbrace{AC^P_{k_{t+1}}(k_{t+1}, k_{t+2})}_{\mathrm{II}} - \underbrace{AC^F_{k_{t+1}}(k_{t+1}, k_{t+2}, y_{t+1})}_{\mathrm{III}} \right) + \underbrace{\phi_{t+1}(1-\vartheta)(1-\delta_k)\mu_{t+1}}_{\mathrm{IV}} \right] =$$
$$\lambda_t AC^P_{k_{t+1}}(k_t, k_{t+1}) + \lambda_t AC^F_{k_{t+1}}(k_t, k_{t+1}, y_t) \quad (13)$$

$$\beta \mathbb{E}_t [\lambda_{t+1} + \mu_{t+1}] = \lambda_t - \psi_t \quad (14)$$

where λ_t, μ_t and ψ_t are the Lagrange multipliers associated to (8), (10) and (11), respectively. For illustrative purposes, I leave the derivatives of labour and capital adjustment costs unspecified.[20] The left hand side of equations (13) and (14) shows the marginal benefit of holding an additional unit of capital and cash, respectively. For (13), this can be decomposed in three parts: (I) the expected marginal product of capital, [(II) + (III)] the expected marginal net benefit of an additional unit of capital brings tomorrow in terms of adjustment costs and, finally, (IV) the expected marginal benefit of holding capital as collateral. Capital is only partly collateralizable and hence its *financing return* $\beta \mathbb{E}_t \phi_{t+1} \mu_{t+1}$ is scaled down by a factor $(1-\vartheta)(1-\delta_k) < 1$. The portfolio allocation between capital and cash is forward-looking, since decisions taken this period affect the financing conditions in the following. In other words, employment growth can be sustained by different allocations of internal and external financing.

Adjustment costs play a crucial role for the endogenous accumulation of cash. Capital adjustment costs make this factor less liquid and, in turn, shift the portfolio allocation towards cash. Partial irreversibility scales down the *financing return* by a factor $(1-\vartheta)$, as shown in III. Moreover, both costs affect the marginal benefit and cost of holding capital. Intuitively, firms incorporate the fact that a negative shock may require them to sell off capital at a lower resale price. Moreover, this will trigger the fixed adjustment cost. Hence, they act pre-emptively and hoard more cash instead.

The dividend cost also adds to firms' precautionary incentives. It implies that the

[20]The non-smoothness in labour and capital adjustment costs introduces kinks in the value function. Cui (2017) proves the differentiability of the value function. Appendix C deals with this issue and shows how the FOCs can be rewritten in terms of marginal values of capital and labour that satisfy the envelope condition, without loss of generality. In any case, the numerical solution presented in Appendix B does not use the optimality of the first order conditions. With a slight abuse of notation, $AC^F_{k_{t+1}}(k_{t+1}, k_{t+2}, y_{t+1})$ refers to the total derivative of fixed adjustment costs with respect to k_{t+1}, including its effect through y_{t+1}. For all the equations of this section, the expectation operator $\mathbb{E}_t$ is used as a reduced form for $\sum_{m=1}^{N_\phi} \pi^\phi_{sm} \sum_{i=1}^{N_z} \pi^z_{ji}$.

shadow value of wealth can be different than 1, as shown in the FOC for dividends:

$$1 - 2\kappa d_t = \lambda_t \tag{15}$$

On one hand, it limits the room for issuing equity in face of negative shocks, therefore inducing firms to accumulate cash instead. On the other hand, it also induces firms to retain cash instead of distributing it as dividends after a positive productivity shock. Both effects go in the same direction, implying that cash is used as a tool to move resources from one period to the other. This feature has been documented empirically by Dittmar and Duchin (2011). In the quantitative part of the paper I will show that, in the absence of inter-temporal substitution in the savings decision, relevant empirical moments of UK firm-level data would be missed by the model. Capital and labour optimal decisions are also affected by the dividend cost. Indeed, the Tobin's Q for capital fluctuates around 1 even without capital adjustment costs. Moreover, firms cannot freely finance additional capital through equity issuance, and thus easily circumvent the financial constraint. This possibility could generate a counter-factual increase in investment during credit crunches, as discussed in Section 5.

Finally, labour adjustment costs have two opposite effects, which show up in the optimal decision for labour:

$$\lambda_t \omega \frac{y_t}{n_t} - \beta \mathbb{E}_t \lambda_{t+1} AL_{n_t}(n_t, n_{t+1}) - \overline{w}\mu_t = \\ \lambda_t \left[\overline{w} + AL_{n_t}(n_{t-1}, n_t) + AC^F_{y_t}(k_t, k_{t+1}, y_t)\, \omega \frac{y_t}{n_t} \right] \tag{16}$$

On one hand, hiring costs induce labour hoarding and make it less likely for booming firms to face a binding collateral constraint, because they increase the marginal cost of labour. On the other hand, firing costs imply that firms "on the way down", those that face negative shocks, may fear to be at the binding collateral constraint. Intuitively, the firing cost reduces the possibility of cutting labour. This affects the expected marginal benefit of having an additional worker next period, $\mathbb{E}_t \lambda_{t+1} AL_{n_t}(n_t, n_{t+1})$. The dividend cost affects labour optimal choices through the budget constraint; in turn, currently unconstrained firms may have incentives to adjust labour to changes to credit conditions.

The precautionary mechanism shows up in full if all frictions are included simultaneously. In Section 5 I show that even small departures from the baseline model – e.g., $\kappa = 0$ or $\chi = 0$ – lead to markedly different model implications and inability to match empirical patterns. To fix ideas, I show below a version of the model with no frictions other than the collateral constraint. Equations (17)–(19) show the optimal decisions for capital, cash and labour in this case:

$$\beta \mathbb{E}_t \left[\nu \frac{y_{t+1}}{k_{t+1}} + 1 - \delta_k \right] + \beta \mathbb{E}_t \phi_{t+1} (1 - \delta_k) \mu_{t+1} = 1 \tag{17}$$

$$\beta \mathbb{E}_t \left[1 + \mu_{t+1} \right] = 1 - \psi_t \tag{18}$$

$$\omega \frac{y_t}{n_t} = \overline{w} \left[1 + \mu_t \right] \tag{19}$$

The timing assumption of the working capital constraint potentially gives rise to precautionary cash holdings by itself and therefore, even in this version of the model, optimal capital and cash decisions still depend on the expectation of a binding financial constraint next period. Nevertheless, these expectations do not feed into the hiring decision through the budget constraint because the absence of dividend costs implies that $\lambda_t = 1$. In other words, labour decisions of credit-unconstrained firms - for which $\mu_t = 0$ - are not affected by aggregate credit conditions when there are no real frictions. The dividend cost by itself is not enough to induce forward-looking hiring decisions: the combination of labour adjustment costs and dividend rigidity is required. However, it affects the accumulation of cash, as shown quantitatively in the following sections. Similarly, capital adjustment costs also induce firms to tilt their portfolio allocation towards cash.

In the next sections I show quantitatively the role of each of these frictions. Only when all of them are present, as estimated by the internal calibration, the precautionary mechanism is quantitatively salient and the model can replicate a number of empirical patterns.

4 Quantitative exploration

This section considers a quantitative version of the theoretical framework, in order to investigate the effect of an exogenous tightening of the collateral constraint. The model is calibrated to the UK economy, using aggregate and microeconomic moments. In the steady state, the model is able to match a set of additional moments not explicitly targeted. I then show the effects of a credit supply shock, in the form of a drop in ϕ, both in terms of aggregate dynamics and microeconomic forces driving them.

4.1 Calibration

I set the time period to a quarter. Idiosyncratic productivity is assumed to follow a AR(1) in logs, discretized following Tauchen and Hussey (1991) to obtain $\left(\pi^z_{ij}\right)_{i,j=1}^{N_z}$. The model entails aggregate uncertainty with respect to the credit tightness ϕ, whose stochastic process is discretized using a 2-states Markov chain over possible values $\{\phi_L, \phi_H\}$.

Table 2: Parameter values

Internally calibrated								
ω	ν	κ	ρ_z	σ_{ε_z}	ϕ_H	ϑ	Θ	χ
0.7682	0.1287	1.1428	0.9167	0.1164	0.5177	0.3312	0.0514	0.0875

Pre-defined values		
β	0.98	Firm discount factor
$\overline{w}$	1	Wage (normalisation)
δ_k	0.0375	15% annual depreciation of capital stock (Riddick and Whited, 2009)
δ_n	0.025	UK (ONS) average quarterly voluntary job separation rate 1996-2007
Aggregate credit shock		
π^{ϕ}_{HH}	0.978	Quarterly transition probability of remaining in high ϕ
π^{ϕ}_{LH}	0.212	Quarterly transition probability from low to high ϕ
ϕ_L	$\frac{9}{10}\phi_H$	Tight credit conditions

Table 2 summarizes the parameter values used in the quantitative analysis. Nine parameters are jointly calibrated using the simulated method of moments, allowing for aggregate uncertainty but keeping ϕ at its high value. Table 3 compares empirical and model-generated moments. Nearly all the empirical moments are obtained using UK firm-level balance sheets from the FAME dataset and are averages of the pre-crisis period 2004-2006. Appendix B describes the model matching exercise in detail.

All moments are affected by all parameters, but some have more direct relationships. For instance, the exponent on capital in the production function, ν, is directly tied to the fixed assets to sales ratio. The labour exponent of the production function is calibrated to match the aggregate labour share. Ceteris paribus, a higher ϕ_H monotonically decreases the average cash ratio, operating through a relaxation of the financial constraint. Since precautionary cash holdings are a key feature of the model, I do not only target first moments, but also the cross-sectional standard deviation of firm-level cash ratios. The standard deviation of idiosyncratic productivity shocks is important in determining the dispersion of cash ratios. Indeed, higher dispersion of shocks magnifies the precautionary savings motive. The persistence of the productivity process, ρ_z, affects most of the targeted moments but it is mainly identified by the autocorrelation of investment ratios, as in Khan and Thomas (2013). Moreover, this moment is affected by capital adjustment costs. The dividend cost is disciplined by matching the cross-firm correlation between

Table 3: Model fit

Targeted Moments	Model	Data
Aggregate labour share	0.720	0.720
Aggregate fixed assets to sales ratio	0.572	0.548
Average cash-to-assets ratio	0.183	0.183
Cross-firm standard deviation of cash ratios	0.217	0.223
Cross-firm correlation between dividends and sales	0.655	0.685
Autocorrelation of investment rates	0.046	0.069
Autocorrelation of employment growth	0.089	0.094
Cross-firm standard deviation of investment rates	0.474	0.418
Frequency of investment spikes	0.230	0.201

Notes: Labour share is from the Bank of England and it is defined as share of GDP, whole economy, excluding rents, averaged between 1950 and 2006. All the other moments are constructed using FAME data and are averages for the period 2004-2006. Investment rate for a firm j at time t is defined as $\frac{k_{j,t}-k_{j,t-1}}{\alpha k_{j,t}+(1-\alpha)k_{j,t-1}}$, with $\alpha = 0.5$, where k is the book value of fixed assets as recorded at balance sheet. Autocorrelation is one year. Investment spike defined as an investment rate above 0.2. Cash-to-assets ratio in the model is $\frac{m}{m+k}$.

dividends and sales. A higher (lower) κ monotonically decreases (increases) the correlation, all other parameters equal. Finally, labour and capital adjustment costs are estimated to match relevant cross-sectional features of employment growth and investment ratios. Following Khan and Thomas (2013), I target the frequency of positive investment spikes, defined as the fraction of observations with an investment rate above 20%, as well as the dispersion of investment rates. A higher fixed cost of capital adjustment, Θ, for example, increases the frequency of investment spikes. The calibrated value for χ, governing the labour adjustment costs, is slightly higher than what estimated by Bloom (2009) for the US, as a per-worker share of annual wage bill. The investment resale loss is nearly the same, as denoted by ϑ.

A credit shock consists of a fall in ϕ. Hence, I consider a credit crunch that entirely operates through short-term borrowing, and as such could also be defined as a liquidity shock, as in Bacchetta et al. (2019). While the Great Financial Crisis could have also been characterized by other types of financial shocks, liquidity shocks and reductions in short-term debt have been shown in the literature to be salient.[21] Moreover, they operate through a type of financial constraint that has been shown to be very important for the large

[21] See Adrian et al. (2013) for a detailed discussion of the financial channels operating during the 2007-09 financial crisis. While beyond the scope of the paper, I have confirmed that combining a reduction in ϕ with an increase in κ for equity issuers does not alter the main conclusions of the paper. The latter shock could be broadly interpreted as an increase in the cost of longer term external finance.

majority of firms. Agents form their expectations over future credit conditions according to the transition probability matrix. I define a credit shock as a 10% drop in ϕ. This implies that a credit tightening in the model generates a reduction in short-term loans in line with what experienced by UK firms between 2008 and 2009, about 9%. The issues related with the estimation of the credit shock process are particularly relevant for the UK, where data on aggregate financial conditions (i.e.: Bank of England Credit Conditions Survey) start in Q1 2007. In terms of timing, both survey and lending measures suggest that firms' credit conditions started to deteriorate only at the beginning of 2009.[22] I set the transition probabilities such that the credit tightening lasts on average 13 months and occurs every 10 years. The length of the credit tightening is in line with a various range of financial indicators in the UK. The frequency may seem high, especially if we interpret it as a financial crisis. Nevertheless, liquidity shocks of the type studied in this paper are likely to happen more frequently, as also shown in Bacchetta et al. (2019). Moreover, relatively frequent credit tightening episodes should dampen the disruptive effects of a credit supply shock, since firms have an additional incentive to save ahead of the crisis and therefore are better equipped to face episodes of credit crunch.

The remaining parameters are externally set. Firms' discount factor needs to be sufficiently low to ensure that at least some firms do not accumulate enough assets to completely save themselves out of the constraint. The calibrated value is consistent with an annual steady state return from holding shares of 8.4%, slightly higher than in Jermann and Quadrini (2012). The discount factor is, however, larger than in Bacchetta et al. (2019), where all firms are constrained. The exogenous job separation rate δ_n is directly taken from ONS data on UK average quarterly voluntary job separation rate between 1996 and 2007.

4.2 Steady state

The stationary distribution of firms in the stochastic steady state, with $\phi = \phi_H$, is in line with a number of UK empirical moments that are not explicitly targeted in the calibration. Table 4 shows some of them. First, the model generates the weakly positive relationship between lagged cash ratio and employment growth that we observe in the data and that was discussed in Section 2. This relationship and its evolution over time will be extensively discussed in the next sections. The negative cross-firm correlation between cash ratio and capital to labour ratio also informs us about important model dynamics. Consider a firm with a low capital to labour ratio: this implies that it needs to finance a large wage

[22] Among others, Ivashina and Scharfstein (2010) document that US firms drew down on their lines of credit during 2008. Bacchetta et al. (2019) build a liquidity measure consistent with a fall in firm's access to liquidity starting at the beginning of 2009.

Table 4: Additional fit of the model

Non-targeted Moments	Model	Data
Cross-firm correlation between cash ratio and employment growth	0.062	0.040
Cross-firm correlation between cash ratio and capital-labour ratio	-0.242	-0.128
Scaled average volatility of dividends	0.741	0.382
Cross-firm standard deviation of dividend ratios	0.229	0.149
Average external finance-to-capital ratio	0.361	0.531
Cross-firm standard deviation of external finance-to-capital ratios	0.750	0.740
25th percentile of cash ratio	0	0.020
75th percentile of cash ratio	0.263	0.263
Frequency of investment inaction	0.082	0.079
P90-P10 of investment rate	0.905	0.740

Notes: All the data moments are constructed using FAME and are averages over the period 2004-06. Empirical capital to labour is the ratio of fixed assets over number of employees. Capital to labour ratios are winsorized at the upper 99th percentile both in the model and in the data. In both cross-firm correlations, cash ratio is lagged as in Figure 3a. Scaled average volatility of dividends: for each firm in a simulated panel with $\phi = \phi_h$, I calculate the standard deviation of annualized dividends over time. Then I take the cross-sectional average of these standard deviations, and scale it by the cross-sectional average level of dividends. In the data, I follow the same approach, before 2006. Extending the sample to 2013 increases the moment to 0.54. Similarly, including the credit crunch period in the model simulation increases the volatility to 0.82. Dividend ratios are firm-level ratios of dividends to sales, winsorized at 1 both in the model and in the data. Winsorization affects about 1% of the pre-2006 sample. External finance is defined as long-term debt in the data and negative d in the model, as discussed in the text. Average and standard deviation are computed for the subset of firms with positive ratios, both in the model and in the data. External finance ratios are winsorized at 3 both in the model and in the data. Winsorization affects about 5% of the pre-2006 sample. Investment inaction is defined as the share of firm-year observations with investment rate less than 0.01 in absolute value. P10 stands for the 10-th percentile whereas P90 for the 90th.

bill, especially relative to the available collateral. Hence, the firm has incentives to shift towards a more cash-intensive portfolio.

With regard to the financial features of the distribution of firms, the model also does a very good job at matching the distribution of cash ratios, beyond the first two moments. In addition to the targeted moment, the dividend cost also reduces the volatility of dividends over time. Following a positive productivity shock, for instance, a firm would like to distribute more dividends to the shareholders. The dividend cost limits the amount of additional dividends the firm will pay out. As shown in Table 4, the model overshoots the volatility of dividends over time compared to the data. First, I compute the standard deviation of dividends over time for each firm, and then take the average of these volatilities across firms and scale it by the cross-sectional average of dividends, to allow for comparability between the model and the data. Similarly, the model's implied cross-sectional dispersion of dividend to sales ratios is only slightly higher than in the data. The parameter

κ, as well as the other parameters, also affect the extent of external finance. On average, 13% of firms issue equity every quarter, a proportion in line with other studies as Gilchrist et al. (2014) and that is difficult to confidently estimate with the FAME data. Moreover, the interpretation of negative d could be broadened to include long-term debt. Using this definition, the model falls slightly short of the average external finance to capital ratio, and does a very good job when it comes to its dispersion.

Finally, the model does fairly well when we look at other moments that are likely related to labour and capital adjustment costs. The average employment growth rate, as well as the average investment rate, are just a couple of percentage points lower than in the data. In the model, as well as in the data, about 8% of firms have an investment rate below 1% in absolute magnitude. The ability to hit this moment on investment inaction is crucially related to fixed capital adjustment costs. The model also does a good job in matching measures of dispersion beyond the standard deviation of investment rates. For instance, the gap between the 10th and the 90th percentile of investment rates is only slightly larger than in the data.

4.3 The aggregate response to a credit shock

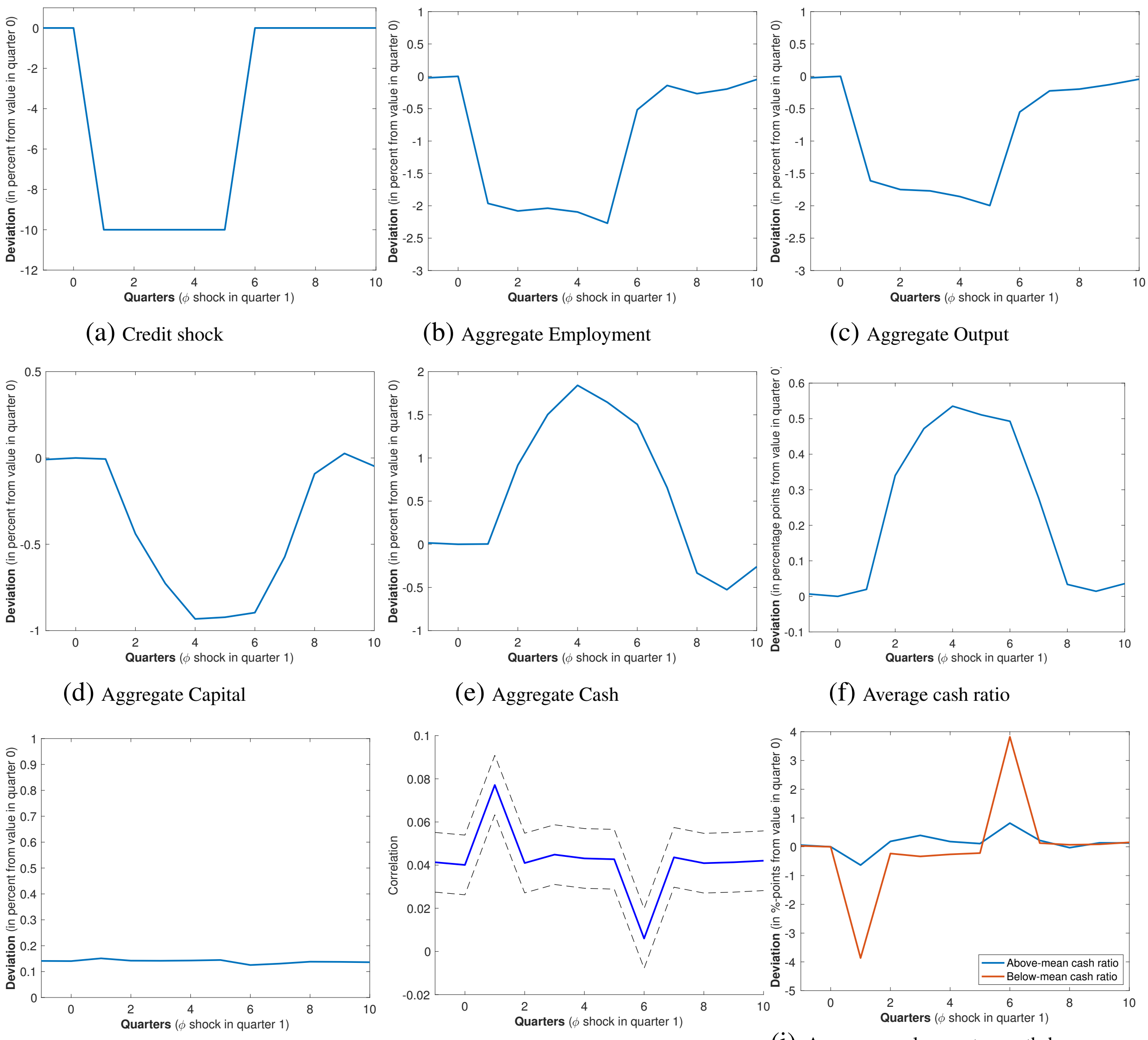
I simulate the aggregate dynamics of the model following a tightening of the collateral constraint. This consists in a 10% drop in ϕ, as discussed in section 4.1, and can be interpreted as an increase in the haircut applied on collateral.

Figures 4a-4f show the aggregate dynamics of a credit tightening that lasts 5 quarters. A credit crunch has two main effects. First, it causes a substitution from capital to cash. During credit tightening periods, capital is worth less in terms of collateral. For this reason, firms switch from external financing to internally generated liquidity. Credit shocks have the potential to interact with capital inaction regions typical of non-smooth adjustment costs. This translates into a relatively sluggish recovery in capital. Aggregate cash levels adjust faster, fuelling employment growth in the recovery.

The second effect is a sizeable fall in aggregate employment, which remains persistently subdued. Less available credit implies that some firms are not able to finance the same wage bill as before, and thus they have to reduce their workforces. The credit crunch therefore affects the allocation of factors, with a persistent increase in the dispersion of marginal products of labour. Aggregate employment rebounds as ordinary credit conditions are restored, prompted by a cash burn, although it takes many quarters to completely come back to pre-crisis levels.

These large aggregate effects materialize even though the share of constrained firms is small. As shown in Figure 4g, the share of firms facing a currently binding credit constraint slightly increases during credit tightening periods, but never exceeds 20%. As

Figure 4: The effects of a credit supply shock



(a) Credit shock

(b) Aggregate Employment

(c) Aggregate Output

(d) Aggregate Capital

(e) Aggregate Cash

(f) Average cash ratio

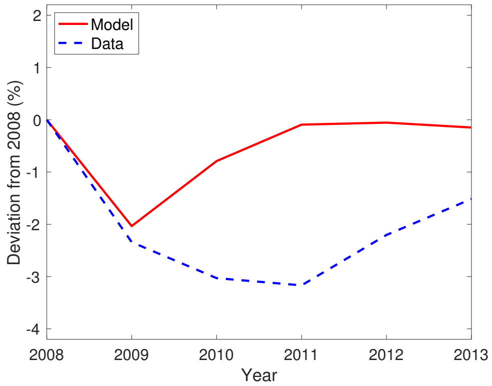
(g) Share of constrained firms

(h) $\text{Corr}_t\left(\frac{m_{i,t-1}}{m_{i,t-1}+k_{i,t-1}}, \%\Delta n_{i,t}\right)$

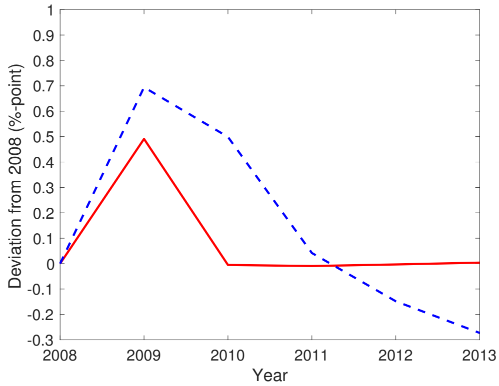
(i) Average employment growth by cash ratios

Notes: 20,000 firms are simulated for 400 periods allowing for aggregate uncertainty but forcing $\phi = \phi_H$. ϕ falls to its low value thereafter, stays there for 5 quarters and reverts back. Simulations have been repeated 100 times. The IRFs show the mean response (across simulations). Shaded grey bands indicate 95% confidence intervals. Constrained firms are those for which Equation (10) binds. Capital and cash are beginning of period.

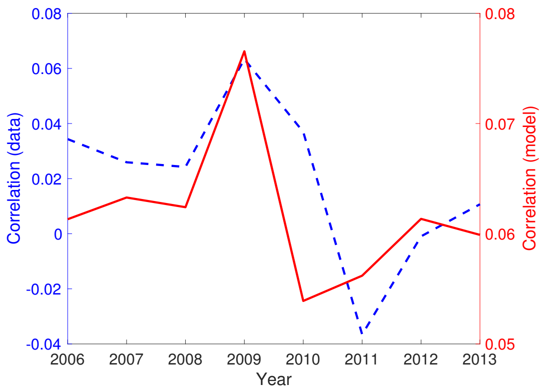
Figure 5: Model performance to the UK economy



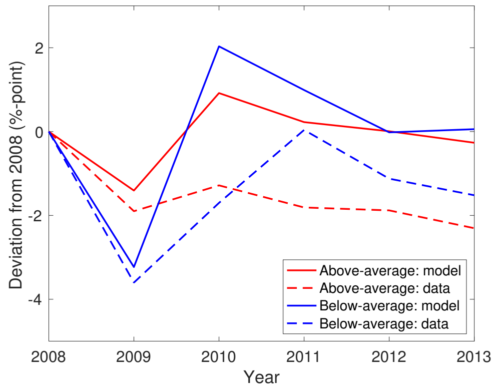
(a) Aggregate employment



(b) Average cash to assets ratio



(c) Cross-firm correlations between lagged cash ratio and employment growth



(d) Average employment growth by cash ratio

Notes: Model-generated data refer to the same simulation outlined in Figure 4. Quarterly simulated data have been annualised using standard accounting techniques, as explained in Appendix B. The credit shock hits the economy in the first quarter of 2009. UK data for aggregate employment refer to employment rate (aged 16-64) from the Office for National Statistics (ONS). Data for panel b are from the FAME dataset, where previous notes apply. To account for an upward trend in average cash ratios over the time period, the series is linearly de-trended. The figure shows the difference, in percentage points, from 2008.

a direct consequence of this, in the aggregate, the available financing funds are largely in excess of firms' financing needs, as documented in the data by Zetlin-Jones and Shourideh (2017).

Figures 5a and 5b compare the effects of a credit shock in the model to the UK experience after 2008. Aggregate employment falls, upon impact, nearly as much in the model as in the data. The credit tightening in the model also explains about 70% of the empirical increase in the average cash ratio in 2009. The recovery of aggregate employment is faster in the model than in the data, and so are the aggregate dynamics of cash. This is likely due to the absence of demand effects that may propagate the effects of a credit shock.

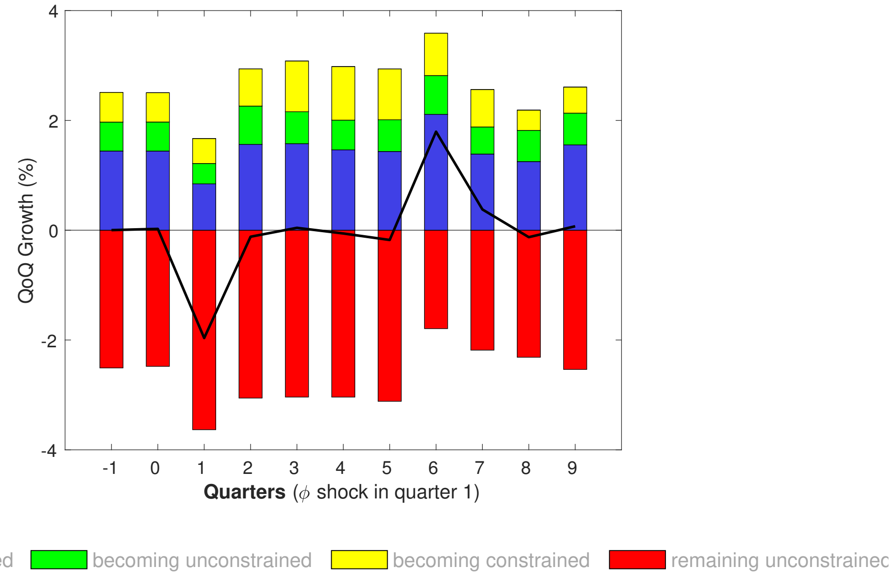
4.4 Micro-level effects of a credit shock

In addition to correctly predicting the evolution of key aggregate variables, the model is able to replicate the dynamic evolution of the cross-firm correlation between lagged cash ratio and employment growth, as shown in Figure 4h. An alternative way to visualize this pattern is by looking at the differential behaviour of employment growth rates for firms above and below the average cash ratio, see Figure 4i. The model mechanisms help rationalise this result. Firms face a tradeoff when choosing their cash ratio. On the one hand, firms may reduce all factors of production while increasing their cash intensity. In particular, they may need to reduce their hiring because cutting on dividends or capital investment is limited by the associated frictions. Moreover, reducing the capital stock exerts further negative pressure on labour through the production function. On the other hand, more cash alleviates the extent to which the credit constraint binds and helps sustain employment growth. In normal times, these two effects generally offset each other, as shown in Figure 4h. As in the data, the steady state correlation is mildly positive because firms with a lagged cash ratio above average exhibit higher employment growth. After a credit supply shock that dries up liquidity, cash becomes an even more valuable source of financing. Cash-intensive firms are associated with higher employment growth throughout the crisis.

To better visualize the model performance to the data, Figures 5c and 5d show the yearly dynamics. In 2009, firms whose cash ratio was above average cut employment growth by about 1.4 additional percentage points in the model, while this drop is twice as large for cash-rich firms. In the data we observe a quantitatively similar pattern. Similarly, the correlation between lagged cash ratio and employment growth increases in 2009 both in the model and in the data, but this spike is quantitatively smaller in the model simulations. In the following years, employment growth at cash-scarce firms rebounds more than for the rest of the population. This rebound is faster in the model, in line with less sluggish employment – and cash – dynamics discussed previously. Moreover, the employment growth gap in the model is slightly smaller than in the data. As a result, the correlation between cash ratio and employment growth falls below pre-crisis levels after 2009 both in the model and in the data, although this swing is more pronounced in the data. As will be shown in the next section, these patterns crucially depend on the extent to which the precautionary behaviour unfolds entirely. Weakening this mechanism limits the model's ability to replicate the empirically observed dynamics.

The key mechanism that characterizes this paper is a precautionary behaviour in anticipation of future financial constraints. In order to evaluate its quantitative importance, for each period in the credit tightening simulation I classify firms in four groups, depending on whether they faced a currently binding credit constraint in the current and/or previous

Figure 6: The importance of unconstrained firms



Notes: Each period t, firms are classified in 4 groups: "remaining constrained" if they faced a binding financial constraint in t and $t-1$, "becoming unconstrained" if they moved from constrained to unconstrained, "becoming constrained" from unconstrained to constrained, "remaining unconstrained" if they remained unconstrained. Each bar denotes the contribution of the group to growth. The black solid line shows the aggregate employment growth, quarter on quarter, which equates the sum of the four bars. The economy starts with normal credit conditions and experiences a credit tightening in quarter 1, lasting 5 quarters. Previous notes on the simulation apply. I repeat the same decomposition for 100 economies, and then take the average across.

period. Firms that do not face a binding constraint are loosely labelled as unconstrained, although they will be clearly affected by financial frictions and more so the closer they are to the binding constraint. Figure 6 shows, for each period, the contribution of each group to the growth of aggregate employment. In normal times constrained firms are booming and hoard cash to sustain their employment growth. When a credit shock hits the economy, all the four groups are affected. Unconstrained firms react to changes in credit conditions by cutting employment more than in normal times. Upon impact, they account for nearly two thirds of the total fall in aggregate employment.[23] In the second quarter, constrained firms are already growing more than in normal times. In other words, these firms drive the recovery even before ordinary credit conditions are restored. In contrast, unconstrained firms have a persistently lower employment growth, as shown by the red bars being persistently below their pre-shock levels. It is because of the precautionary behaviour of these firms that aggregate employment takes several quarters to come back to pre-crisis levels.

[23] For each group, I compute the difference in employment growth between a certain quarter and the steady state (i.e.: quarter 0). Then I divide this object by aggregate employment growth. This allows me to compute contributions to growth that clean out for the fact that certain groups are associated with negative or positive employment growth rates in normal times.

5 The importance of the precautionary mechanism

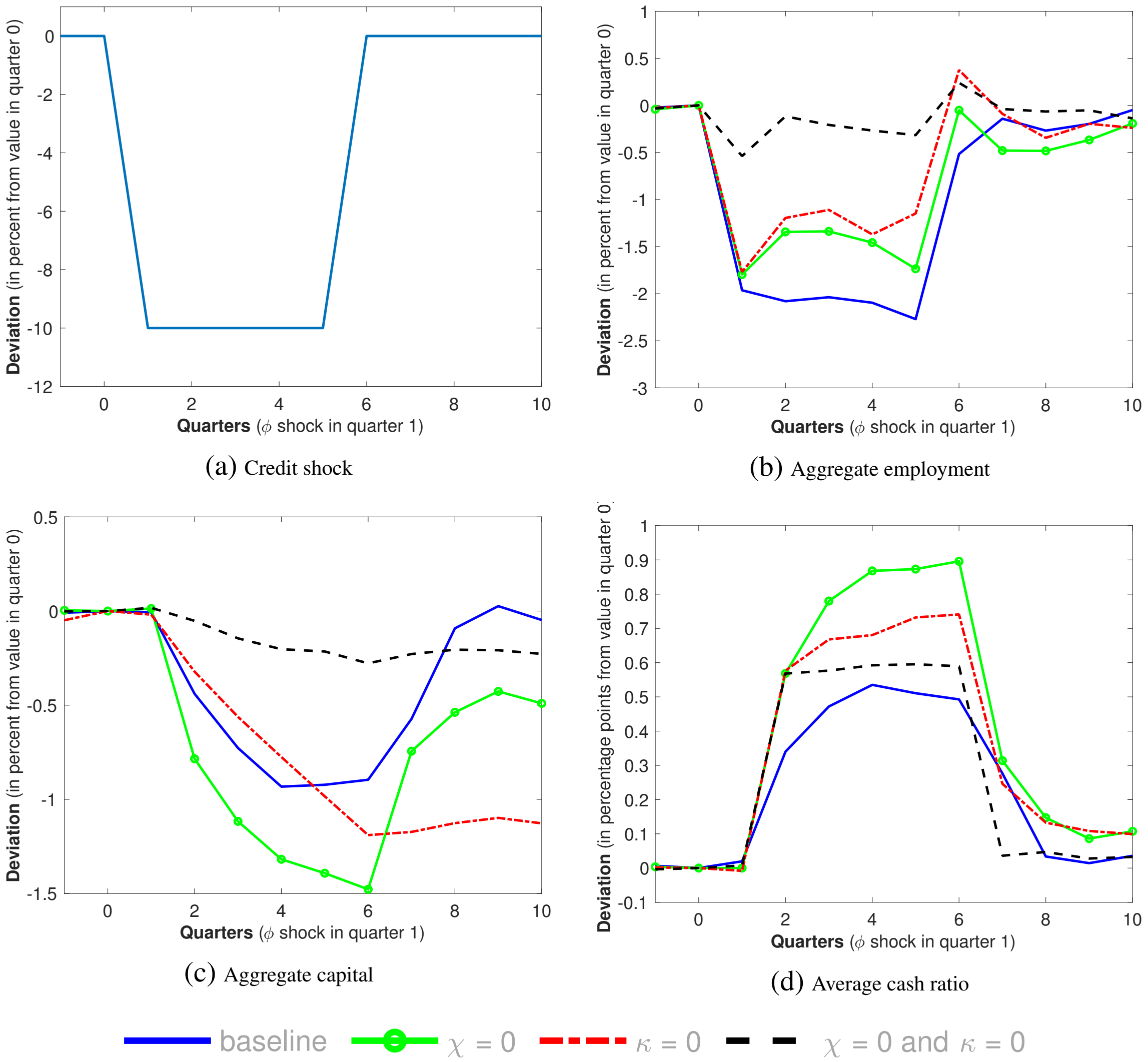
Previous sections have already shown how the precautionary channel allows the baseline model to generate predictions in line with the data. In this final section, I expand on this by considering three variations of the baseline model shown in section 3. First, I consider a model in which there are no labour adjustment costs, such that $\chi = 0$. Second, I shut down the rigidity on dividends, by setting $\kappa = 0$. Finally, I consider a third model alternative in which both labour and dividend adjustment costs are absent. In order to have a fairer comparison, I recalibrate each alternative model such that the average cash ratio, in steady state, matches the data. This is particularly important for the two counterfactuals with $\kappa = 0$, which require ϕ_H to be recalibrated to meaningfully lower values.[24] Results for these alternative models without recalibration are shown in Appendix D.1.

Even small deviations from the baseline model, as shown in this section, imply a substantial weakening of the precautionary channel and the model's reduced ability to replicate empirical patterns. Labour adjustment costs play an especially important role: in their absence, labour demand is not forward looking, thus greatly limiting the precautionary channel operating through hiring. When only the collateral constraint is present, the precautionary channel is basically absent, and the model has counterfactual predictions vis-a-vis the data. I show this extreme case in Appendix D.2.

Figure 7 shows the aggregate dynamics following a credit tightening in these model counterfactuals. In all model alternatives, aggregate employment recovers much more quickly than in the baseline, rebounding back to pre-crisis levels as soon as credit conditions go back to normal. Therefore, labour adjustment costs generate an extra degree of propagation when operating in conjunction with the dividend rigidity. Absent both these costs, the fall in aggregate employment is much more limited and short-lived, as shown by the dashed black line. In this model counterfactual, aggregate capital is also barely affected. Finally, all models generate an increase in the average cash ratio. In the counterfactuals with either $\chi = 0$, or $\kappa = 0$, the increase in cash ratio is larger and more persistent, driven by a very persistent fall in aggregate capital. In contrast, capital is barely affected when both labour and dividend adjustment costs are absent. A credit tightening has two counteracting effects. On the one hand, firms need to pledge more capital to finance the same wage bill, for a given amount of internal liquidity. On the other hand, a reduction in ϕ makes capital marginally less valuable as an indirect source of financing. Absent the equity friction, firms can raise capital more easily, helping the first channel. Nevertheless,

[24] The model with only $\chi = 0$, instead, predicts an average cash ratio slightly higher than in the data. I recalibrate κ downwards, rather than ϕ_H, given a stronger sensitivity of the average cash ratio to κ in a region of high values of ϕ. The results shown in this section, however, are broadly unchanged with an alternative recalibration.

Figure 7: Impulse response functions to a credit supply shock - alternative versions of the model



Notes: The economy starts with normal credit conditions and experiences a credit tightening in quarter 1, lasting 5 quarters. Previous notes on the simulation apply. χ has been set to 0 in the model shown by the green dotted lines and the black dashed impulse response, while κ is 0 in the red dash-dotted and black dashed impulse responses. Except for the baseline model, shown in solid blue, all the other variants have been recalibrated such that the economy matches the empirical average cash ratio in steady state. When $\chi = 0$, κ has been recalibrated to 0.74. When $\kappa = 0$, ϕ_H is 0.145, while it is 0.195 in the economy with both κ and χ set to 0.

Table 5: Fit of alternative versions of the model

Moments	Data	Baseline model	$\chi = 0$	$\kappa = 0$	$\chi = 0,\, \kappa = 0$
$\mathbb{E}\frac{m}{m+k}$	0.18	0.18	0.18	0.18	0.18
$\sigma\left(\frac{m}{m+k}\right)$	0.22	0.22	0.15	0.12	0.13
$P_{25}\left(\frac{m}{m+k}\right)$	0.02	0	0.06	0.05	0.06
$P_{75}\left(\frac{m}{m+k}\right)$	0.26	0.26	0.28	0.27	0.28
$corr(d,y)$	0.69	0.65	0.60	0.92	0.86
$corr(\frac{m}{m+k},\frac{k}{n})$	-0.13	-0.24	-0.27	$-$ 0.54	-0.68

Notes: Stochastic steady state of the model, with credit tightness ϕ_H. Notes on Figure 7 and Table 3 and Table 4 apply.

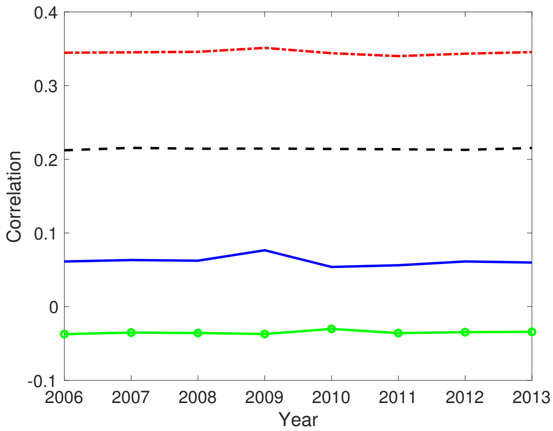
other frictions interact with firms' optimal decisions, in particular labour and capital adjustment costs.[25] These results highlight how capital adjustment costs interact differently with the other frictions present in the model.

Next, I show how these model counterfactuals are unable to generate most of the heterogeneous empirical patterns previously discussed. As a useful starting point, Table 5 shows how model alternatives are unable to hit empirically observed cross-sectional moments. For instance, even when recalibrating ϕ_H to match the average cash ratio in the data, they fall short of the dispersion in cash ratios, mainly because they are not able to generate the correct degree of right skewness. Absent the dividend cost, dividends are not sticky and thus counterfactually very correlated with sales, as discussed in Section 4.1. Finally, the collateral constraint implies that labour intensive firms have a strong incentive to raise cash because they have to finance a relatively large wage bill. Both the dividend cost and labour adjustment frictions dampen this negative relationship. When both are absent, the correlation between liquidity and capital intensity is very negative, at -0.68, much more than in the data and the baseline model.

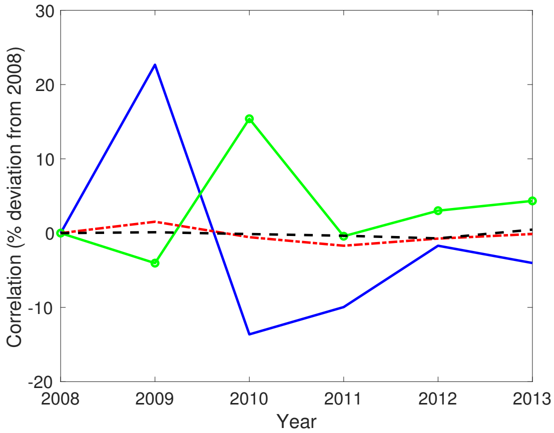
Most importantly, alternative models are not able to generate the dynamic patterns of the correlation between cash ratios and employment growth rates. Figure 8a shows that a model without labour adjustment costs counterfactually implies that cash-rich firms grow slightly less – i.e., negative correlation – even pre 2008. In contrast, other alternative models predict an excessively strong positive relationship. When credit conditions tighten, the correlation increases in the baseline model, as shown by the blue solid line in Figure 8b.

[25]The level of ϕ_H also turns out to be important, per se and via its effect on the stationary distribution of firms. As shown in Appendix D.1, when ϕ_H is not recalibrated, the models with $\kappa = 0$ predict an increase in aggregate capital.

Figure 8: Cash and employment growth



(a) Raw correlation



(b) Rescaled correlation

Notes: Notes on Figure 7 and 5 apply.

The 2009 jump is about 25% in the baseline model, smaller than what observed in the data, but definitely closer to the empirical behaviour than the small jump in the alternative models.[26] In fact, the correlation actually drops in 2009 when there are no labour adjustment costs. In line with the data, the baseline model predicts a drop in the correlation when credit conditions are restored. This pattern, in contrast, is absent from any of the alternative models.

The ability of the baseline model to match this heterogeneous behaviour crucially hinges on the precautionary channel described in this paper and, in particular, its effect on labour demand. Indeed, relaxing only one friction is enough to weaken substantially this mechanism, and implies the model inability to match the empirical relationship between cash and employment growth over time. To quantify the weakening of the precautionary channel, I repeat the analysis presented in Figure 6, for the alternative models presented in this section. In Table 6 I report the contribution to aggregate employment growth for each group, in the first quarter of credit tightening. As previously discussed, unconstrained firms in the baseline model contribute to two thirds of the initial drop in aggregate employment, mainly driven by firms remaining unconstrained. These firms, although they do not face a currently binding collateral constraint, respond in anticipation of future constraints.

This precautionary behaviour is substantially weaker in the alternative models, as un-

[26]The model is solved quarterly and aggregated to annual frequency to align with the data. This step reduces the volatility of the correlation for all models by a similar extent. As shown in Figure 4h, the quarterly correlation nearly doubles in the baseline model, whereas the quarterly increase is just 14% when $\kappa = 0$.

Table 6: The precautionary channel

	Contribution to aggregate employment growth (%)			
	Baseline model	$\chi = 0$	$\kappa = 0$	$\chi = 0,\ \kappa = 0$
Remaining constrained	30	43	58	21
Becoming unconstrained	8	4	0	−6
Becoming constrained	4	51	25	90
Remaining unconstrained	58	2	17	−5

Notes: Same decomposition as in Figure 6. For each group, I compute the difference in employment growth between the first quarter of credit tightening and the previous quarter (i.e.: quarter 0), and then divide this object by aggregate employment growth. The table shows the average across simulations.

constrained firms account for a much smaller portion of aggregate employment growth. This is especially true when there are no labour adjustment costs. As previously shown in Section 3.5, when $\chi = 0$ labour demand of unconstrained firms is basically unaffected by a credit crunch, even when $\kappa > 0$. In fact, this group of firms can contribute negatively to aggregate employment growth since their population share falls during a credit tightening, as is the case in the model with $\chi = 0$ and $\kappa = 0$, as well as in alternative models shown in the Appendix D.2.

As shown in Figure 6, unconstrained firms are also crucially important for the persistent dynamics of aggregate employment. I repeat the same decomposition for the entire credit tightening period and sum the group-specific contributions.[27] In the baseline model, unconstrained firms account for the large majority of cumulative employment growth.[28] Such contribution is much smaller for the alternative models, a third of the baseline at most. Differently from what shown in Table 6, cumulative effects also take into account the precautionary channel that operates through capital and cash, rather than directly through labour demand. This channel is present even when $\chi = 0$, as discussed in Section 3.5, but is weaker as frictions are gradually removed.

[27]For each period and each group, I compute the difference in employment growth rate between the first quarter of credit tightening and quarter 0, sum them over time and divide by the cumulative growth in aggregate employment.

[28]In the baseline model, constrained firms start growing more than normal already in the second quarter of credit tightening, as shown in Figure 6. Hence, firms remaining unconstrained (for two consecutive periods) account for 145% of cumulative employment growth over the credit crunch, whereas firms that remain constrained have a contribution of 14%. The other two groups contribute negatively to aggregate employment cumulative growth.

6 Conclusions

The quantitative role of firm-level financial frictions and credit supply shocks in affecting the real economy is still the object of debate in the literature. In this paper I argue that a precautionary mechanism, which induces firms to respond to changes in credit conditions in anticipation of future idiosyncratic shocks, plays a quantitatively important role. This paper entails two main contributions. Using UK firm-level data on a broad and diverse section of firms, I document that firms accumulated cash during the great recession and cash-intensive firms decreased their workforces by less. I trace the relationship between cash ratios and employment growth over time and show that this cyclicality is robust and statistically significant. Motivated by these facts, I build a heterogeneous-firm model where precautionary cash holdings arise endogenously from the interaction between real and financial frictions. The frictions featured in the model, and therefore the quantitative importance of the precautionary channel, are internally calibrated using firm-level empirical information. Credit tightening implies a sizeable fall in aggregate employment and a substitution from capital to cash. As a key result, these aggregate dynamics are driven by firms not facing a currently binding constraint, who behave pre-emptively in anticipation of future shocks. The quantitative bite of the financial constraint, and the role played by liquid assets, crucially depends on the interaction between frictions, especially labour adjustment costs, which amplify the precautionary channel and propagate the responses to a credit tightening. Only when the precautionary mechanism is quantitatively estimated, the model generates the empirically documented weakly positive correlation between liquidity and employment growth, as well as its evolution over time.

References

Adrian, Tobias, Paolo Colla, and Hyun Song Shin, "Which financial frictions? Parsing the evidence from the financial crisis of 2007 to 2009," *NBER Macroeconomics Annual*, 2013, *27* (1), 159–214.

Altinkilic, Oya and Robert S. Hansen, "Are there economies of scale in underwriting fees? Evidence of rising external financing costs," *The Review of Financial Studies*, 2000, *13* (1), 191–218.

Angelini, Paolo and Andrea Generale, "On the evolution of firm size distributions," *American Economic Review*, 2008, *98* (1), 426–38.

Bacchetta, Philippe, Kenza Benhima, and Céline Poilly, "Corporate Cash and Employment," *American Economic Journal: Macroeconomics*, 2019, *11* (3), 30–66.

Bassetto, Marco, Marco Cagetti, and Mariacristina De Nardi, "Credit crunches and credit allocation in a model of entrepreneurship," *Review of Economic Dynamics*, 2015, *18* (1), 53–76.

Bates, Thomas W, Kathleen M Kahle, and René M Stulz, "Why do US firms hold so much more cash than they used to?," *The journal of finance*, 2009, *64* (5), 1985–2021.

Bernanke, Ben S, Mark Gertler, and Simon Gilchrist, "The financial accelerator in a quantitative business cycle framework," *Handbook of macroeconomics*, 1999, *1*, 1341–1393.

Bloom, Nicholas, "The impact of uncertainty shocks," *econometrica*, 2009, *77* (3), 623–685.

_ , Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J Terry, "Really uncertain business cycles," *Econometrica*, 2018, *86* (3), 1031–1065.

Bolton, Patrick, Hui Chen, and Neng Wang, "Market timing, investment, and risk management," *Journal of Financial Economics*, 2013, *109* (1), 40–62.

Brav, Omer, "Access to capital, capital structure, and the funding of the firm," *Journal of Finance*, 2009, *64* (1), 263–308.

Buera, Francisco J, Roberto N Fattal Jaef, and Yongseok Shin, "Anatomy of a credit crunch: from capital to labor markets," *Review of Economic Dynamics*, 2015, *18* (1), 101–117.

Caglio, Cecilia R, R Matthew Darst, and ?ebnem Kalemli-Özcan, "Risk-Taking and Monetary Policy Transmission: Evidence from Loans to SMEs and Large Firms," Technical Report, National Bureau of Economic Research 2021.

Campello, Murillo, John R Graham, and Campbell R Harvey, "The real effects of financial constraints: Evidence from a financial crisis," *Journal of financial Economics*, 2010, *97* (3), 470–487.

Chodorow-Reich, Gabriel, "The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis," *The Quarterly Journal of Economics*, 2013, *129* (1), 1–59.

Christiano, Lawrence J, Martin Eichenbaum, and Charles L Evans, "Nominal rigidities and the dynamic effects of a shock to monetary policy," *Journal of political Economy*, 2005, *113* (1), 1–45.

_ , Roberto Motto, and Massimo Rostagno, "Financial factors in economic fluctuations," 2010.

Cooley, Thomas F and Vincenzo Quadrini, "Financial markets and firm dynamics," *American economic review*, 2001, *91* (5), 1286–1310.

Corugedo, Emilio Fernández, Michael F McMahon, Stephen Millard, and Lukasz Rachel, "Understanding the macroeconomic effects of working capital in the United Kingdom," 2011.

Crouzet, Nicolas, "Aggregate implications of corporate debt choices," *The Review of Economic Studies*, 2017, *85* (3), 1635–1682.

Cui, Wei, "Macroeconomic Effects of Delayed Capital Liquidation," 2017.

_ and Sören Radde, "Money and asset liquidity in frictional capital markets," *American Economic Review*, 2016, *106* (5), 496–502.

Dittmar, Amy and Ran Duchin, "The Dynamics of Cash," 2011.

Duygan-Bump, Burcu, Alexey Levkov, and Judit Montoriol-Garriga, "Financing constraints and unemployment: Evidence from the Great Recession," *Journal of Monetary Economics*, 2015, *75*, 89–105.

Eisfeldt, Andrea L and Adriano A Rampini, "Capital reallocation and liquidity," *Journal of monetary Economics*, 2006, *53* (3), 369–399.

Falato, Antonio, Dalida Kadyrzhanova, and Jae Sim, "Rising intangible capital, shrinking debt capacity, and the US corporate savings glut," 2013.

Finocchiaro, Daria and Caterina Mendicino, "Financial shocks, comovement and credit frictions," *Economics Letters*, 2016, *143*, 20–23.

Ghaly, Mohamed, Viet Anh Dang, and Konstantinos Stathopoulos, "Cash holdings and labor heterogeneity: the role of skilled labor," *The Review of Financial Studies*, 2017, *30* (10), 3636–3668.

Gilchrist, Simon, Jae W. Sim, and Egon Zakrajsek, "Uncertainty, financial frictions, and investment dynamics," *National Bureau of Economic Research*, 2014, (20038).

_ , Raphael Schoenle, Jae Sim, and Egon Zakrajšek, "Inflation dynamics during the financial crisis," *American Economic Review*, 2017, *107* (3), 785–823.

Han, Seungjin and Jiaping Qiu, "Corporate precautionary cash holdings," *Journal of Corporate Finance*, 2007, *13* (1), 43–57.

Hennessy, Christopher A and Toni M Whited, "How costly is external financing? Evidence from a structural estimation," *The Journal of Finance*, 2007, *62* (4), 1705–1745.

Ivashina, Victoria and David Scharfstein, "Bank lending during the financial crisis of 2008," *Journal of Financial economics*, 2010, *97* (3), 319–338.

Jeenas, Priit, "Firm balance sheet liquidity, monetary policy shocks, and investment dynamics," Technical Report, Working paper 2019.

Jermann, Urban and Vincenzo Quadrini, "Macroeconomic effects of financial shocks," *American Economic Review*, 2012, *102* (1), 238–71.

Khan, Aubhik and Julia K Thomas, "Credit shocks and aggregate fluctuations in an economy with production heterogeneity," *Journal of Political Economy*, 2013, *121* (6), 1055–1107.

Kiyotaki, Nobuhiro and John Moore, "Credit cycles," *Journal of political economy*, 1997, *105* (2), 211–248.

_ and _ , "Liquidity, business cycles, and monetary policy," 2012.

Lintner, John, "Distribution of incomes of corporations among dividends, retained earnings, and taxes," *American economic review*, 1956, *46* (2), 97–113.

Mendoza, Enrique G, "Sudden stops, financial crises, and leverage," *American Economic Review*, 2010, *100* (5), 1941–66.

Michaels, Ryan, T Beau Page, and Toni M Whited, "Labor and capital dynamics under financing frictions," *Review of Finance*, 2018, *23* (2), 279–323.

Michaely, Roni and Michael R. Roberts, "Corporate Dividend Policies: Lessons from Private Firms," *The Review of Financial Studies*, 2011, *25* (3), 711–746.

Moscarini, Giuseppe and Fabien Postel-Vinay, "The contribution of large and small employers to job creation in times of high and low unemployment," *American Economic Review*, 2012, *102* (6), 2509–39.

Nicolas, Théo, "Short-term financial constraints and SMEs? investment decision: evidence from the working capital channel," *Small Business Economics*, 2021, pp. 1–30.

Petrosky-Nadeau, Nicolas, "Credit, vacancies and unemployment fluctuations," *Review of Economic Dynamics*, 2014, *17* (2), 191–205.

Ravn, Morten O and Vincent Sterk, "Job uncertainty and deep recessions," *Journal of Monetary Economics*, 2017, *90*, 125–141.

Riddick, Leigh A and Toni M Whited, "The corporate propensity to save," *The Journal of Finance*, 2009, *64* (4), 1729–1766.

Schoefer, Benjamin, "The Financial Channel of Wage Rigidity," 2015.

Spaliara, Marina-Eliza, "Do financial factors affect the capital–labour ratio? Evidence from UK firm-level data," *Journal of banking & finance*, 2009, *33* (10), 1932–1947.

Strebulaev, Ilya A and Toni M Whited, "Dynamic models and structural estimation in corporate finance," *Foundations and Trends® in Finance*, 2012, *6* (1–2), 1–163.

Svensson, Lars EO, "Money and asset prices in a cash-in-advance economy," *Journal of political Economy*, 1985, *93* (5), 919–944.

Tauchen, George and Robert Hussey, "Quadrature-based methods for obtaining approximate solutions to nonlinear asset pricing models," *Econometrica: Journal of the Econometric Society*, 1991, pp. 371–396.

Xiao, Jasmine, "Borrowing to save and investment dynamics," 2019.

Zetlin-Jones, Ariel and Ali Shourideh, "External financing and the role of financial frictions over the business cycle: Measurement and theory," *Journal of Monetary Economics*, 2017, *92*, 1–15.

Appendix

A Data

The primary data source used in this paper is FAME dataset, gathered by Bureau van Dijk. It contains information on over 9 million companies in UK and Ireland, 2 million of which are in detailed format, over the period 2004-2013.[29] I restrict the dataset to UK only. A standard company report includes a balance sheet, profit and loss account, turnover, employees and industry codes.[30] In contrast to other datasets such as US Compustat, 93.7% of the firms contained in the FAME sample are non-publicly traded.[31] This implies that there is a large number of small and medium-sized companies.[32] Since the model does not feature life cycle dynamics, I restrict the sample to a balanced panel; firms that have weakly positive observations for employment, cash and total assets are kept in the sample. Following the standard procedure employed in similar studies, I exclude from the sample firms with UK SIC code referring to "Financial and insurance activities". The final sample consists of 17,762 firms each year. Cash is recorded in firm's balance sheets as *Bank Deposits*, which is the British format for cash & equivalent. Hence, this definition should already account for a potential substitution among cash securities. Moreover, the average share of short-term investments to total assets stays constant between 2009 and 2010 and even rises in the following year. This further excludes that the increase in cash is driven by a reduction in other liquid assets. Net job creation is defined as the difference in number of employees for a given firm from one year to the other. I define employment growth for a firm j at year t as $\Delta n_{j,t} = \frac{n_{j,t}-n_{j,t-1}}{\alpha n_{j,t}+(1-\alpha)n_{j,t-1}}$, with $\alpha = 0.5$. Moscarini and Postel-Vinay (2012) explain the advantages of this symmetric approach, which bounds employment growth between -2 and 2. Finally, I define investment ratio using the same strategy as for employment growth. Investment ratio for a firm j at time t is defined as $\frac{k_{j,t}-k_{j,t-1}}{\alpha k_{j,t}+(1-\alpha)k_{j,t-1}}$, with $\alpha = 0.5$, where k is the book value of fixed assets as recorded at balance sheet. All base variables are winsorized at the 99.75 percentile. Table 7 reports descriptive statistics for the sample. Although the reporting requirements slightly bias the sample towards large firms, the size distribution is much closer to the UK universe than

[29] A maximum of 10 years data history can be downloaded at once. Companies are registered at Companies House in the UK.

[30] Some firms report also the Cash Flow statement. Moreover, the data includes detailed ownership and subsidiary information.

[31] This share is comparable to recent studies that use the FAME database, as Brav (2009) and Michaely and Roberts (2011).

[32] Unlike in the US, UK firms have to disclose their accounts even when not traded on the stock market. Following the UK Companies Act 1985, large firms have to report detailed accounts, whereas medium-size companies do not have to disclose turnover details and small firms are required to submit only an abridged balance sheet.

Table 7: Descriptive Statistics

	Employment	Total Assets	Cash ratio	Employment growth rate	Investment rate
Mean	448	95,511	0.19	0.01	0.02
Std. Dev.	2,340	635,232	0.23	0.21	0.41
25th	29	3.009	0.02	-0.04	-0.11
Median	78	7,664	0.10	0	-0.01
75th	191	22,590	0.28	0.08	0.10
N Obs	177,620	177,620	177,620	159,858	134,123

Notes: Moments computed over the entire sample period 2004-2013. Total assets in Thousands GBP.

a dataset with only publicly quoted firms. For instance, the median firm in the sample has 78 employees. The sample is representative also in terms of aggregate dynamics. The evolution of aggregate employment, for instance, closely resembles the one for Non-financial corporations published by the UK Office for National Statistics.

B Numerical Method

The firm's problem is solved with value function iteration. The AR(1) process for the the log of idiosyncratic productivity is discretized using Tauchen and Hussey (1991) method over 7 grid points. The aggregate credit shock ϕ can take on two values, as described in Section 4.1. In the spirit of Khan and Thomas (2013), I specify the value function over $\left(n_{t-1}, \frac{m_t}{k_t}, k_t, z_t, \phi_t\right)$. Using $\frac{m}{k}$ allows me to restrict the knot points to the feasible set. I set 20 grid points for the grid on $\frac{m}{k}$ and 27 points for the state grid for capital. The choice grid for capital contains twice as many points as it always comprises the inaction decision $k_{t+1} = (1-\delta_k)k_t$; this is quantitatively important given the capital adjustment costs. The choice grid for labour exploits the features of the financial constraint and thus has 22 points for each $\left(k, \frac{m}{k}, \phi\right)$ triplet, therefore effectively consisting of 23,760 points. As such, the binding financial constraint can be identified precisely. Alternative models with $\chi = 0$ have a reduced state space, since labour is not a state variable. In those models, the solution can computationally accommodate 80 grid points for the state grid for capital and 55 for $\frac{m}{k}$. Having defined the value function, I iterate on the Bellman equation until convergence. At each round of iteration, the value function is interpolated using linear interpolation, to accommodate the discrepancy in the number of grid points between states and choices. Linear interpolation has the advantage of preserving the shape of the policy functions and the kinks arising from the constraints that characterize the model.

The internal calibration is implemented as follows. For each set of parameters, I solve the dynamic program allowing for aggregate uncertainty. I then fix the policy functions to the steady state aggregate credit tightness ϕ_H, and simulate 20,000 firms – which is roughly the same number of firms in the FAME dataset – for 400 quarters. I repeat this simulation for 25 economies with a different draw of the simulated panel of idiosyncratic productivity. In each economy, I compute the moments discarding the first 300 quarters, and then average out the moments across the economies. In the simulations, the transition back from fine choices to coarser states is implemented using a nearest neighbour approach; the simulation keeps track of sequential inaction choices and adjusts the policy functions accordingly. As a first approach to the joint calibration, I compute several moments across a large multi-dimensional grid of parameters. This allows me to identify the strongest relationships between parameters and moments and get closer to the global minimum. I then minimize the sum of squared differences between model and data moments, using a Nelder-Mead minimization routine.

The quantitative exploration and the impulse responses shown in Section 4.3, 4.4 and 5 are obtained with a similar approach, but implement 5 quarters of ϕ_L after 400 quarters of ϕ_H and then ϕ_H thereafter. I repeat the simulation for 100 economies, which does not affect the moments but improves the precision of the aggregate impulse responses.

The time period in the model is a quarter, and the results shown in the paper follow this frequency. Little information on the frequency of the decision making at firm level is known (Bloom (2009)). Thus, I decide to strike a balance between monthly frequency of board meetings in public firms and the annual balance sheet data. When required, model-generated quarterly data is converted into annual figures using standard accounting techniques. Flow figures from the Income Statement are added across the quarters of the year, stock figures from the Balance sheet are taken from the year end values. As reported in FAME company reports, the number of employees is the average over the accounting year.

C The firm's problem

As mentioned in Section 3.5, non-smooth labour and capital adjustment costs raise potential concerns with respect to the differentiability of the value function. As shown by Cui (2017), the value function $V(m_t, k_t, n_{t-1}, z_t; \phi_t)$ is differentiable at $k_t > 0$ and satisfies the envelope condition.[33]

The first order conditions that pin down the optimal decisions for dividends, labour, capital and cash respectively, of a firm with idiosyncratic productivity $z_{j,t}$, are shown below. Equation (9) is always binding, which allows to combine it with (10) in (4). With a slight abuse of notation, V' is a compact form for $V\left(m_{t+1}, k_{t+1}, n_t, z_{t+1}; \phi_{t+1}\right)$. Then:

$$\begin{aligned} 1 - 2\kappa d_t &= \lambda_t & (20)\\ \lambda_t \omega \frac{y_t}{n_t} + \beta \frac{\partial \mathbb{E} V'}{\partial n_t} &= \overline{w}\mu_t + \lambda_t \left[\overline{w} + AL_{n_t}\left(n_{t-1}, n_t\right) + AC_y^F\left(k_t, k_{t+1}, y_t\right)\omega \frac{y_t}{n_t}\right] & (21)\\ \beta \frac{\partial \mathbb{E} V'}{\partial k_{t+1}} &= \lambda_t \left[AC_{k_{t+1}}^P\left(k_t, k_{t+1}\right) + AC_{k_{t+1}}^F\left(k_t, k_{t+1}, y_t\right)\right] & (22)\\ \beta \frac{\partial \mathbb{E} V'}{\partial m_{t+1}} &= \lambda_t - \psi_t & (23) \end{aligned}$$

And the envelope conditions for labour, capital and cash are:

$$V_{n_{t-1}}\left(m_t, k_t, n_{t-1}, z_{j,t}; \phi_t\right) = -\lambda_t AL_{n_{t-1}}\left(n_{t-1}, n_t\right) \quad (24)$$

$$V_{k_t}\left(m_t, k_t, n_{t-1}, z_{j,t}; \phi_t\right) = \lambda_t \left[\nu \frac{y_t}{k_t} - AC_{k_t}^P\left(k_t, k_{t+1}\right) - AC_{k_t}^F\left(k_t, k_{t+1}, y_t\right)\right] + \phi_t(1-\vartheta)(1-\delta_k)\mu_t \quad (25)$$

$$V_{m_t}\left(m_t, k_t, n_{t-1}, z_{j,t}; \phi_t\right) = \lambda_t + \mu_t \quad (26)$$

Combining equations (20-26) gives the first order conditions (13)-(15) shown in Section 3.5. Following Cui (2014), it is possible to further decompose the derivatives with respect to labour and capital adjustment costs. For instance, let $q\left(m_t, k_t, n_{t-1}, z_{j,t}; \phi_t\right)$ be the marginal value of capital that satisfies the envelope condition, which we shall refer to as q_t thereafter. Then, Equation (25) can be rewritten as:

$$V_{k_t}\left(m_t, k_t, n_{t-1}, z_{j,t}; \phi_t\right) = \lambda_t \left[\nu \frac{y_t}{k_t}\left(AC_y^F\left(k_t, k_{t+1}, y_t\right) + 1\right) + q_t(1-\delta_k)\right] + \phi_t(1-\vartheta)(1-\delta_k)\mu_t \quad (27)$$

Intuitively, q_t is the marginal reward of adjusting capital. When it reaches 1, a firm buys capital. The lower bound of q_t is instead $1-\vartheta$; selling capital is associated to this marginal reward to decrease capital. When the firm is inactive in its capital investment decision, q_t is less than 1 and greater than $1-\vartheta$. Inside the inaction region, q_t is the

[33] The differentiability of $V(m_t, k_t, n_{t-1}, z_t; \phi_t)$ when $k_{t+1} \neq (1-\delta_k)k_t$ and $n_t \neq (1-\delta_n)n_{t-1}$ is standard, as proved by Benveniste and Scheinkman (1979). The differentiability at $k_{t+1} = (1-\delta_k)k_t$ and $n_t = (1-\delta_n)n_{t-1}$ can be proved using methods from Clausen and Strub (2012), as shown by Cui (2014). The intuition is that the value function is super-differentiable, but also sub-differentiable, given the potential downward kink stemming from the adjustment costs. Being both super-differentiable and sub-differentiable implies the differentiability of the value function.

Table 8: Fit of alternative versions of the model (without recalibration)

Moments	Data	Baseline model	$\chi = 0$	$\kappa = 0$	$\chi = 0$, $\kappa = 0$
$\mathbb{E}\frac{m}{m+k}$	0.18	0.18	0.22	0.07	0.07
$\sigma\left(\frac{m}{m+k}\right)$	0.22	0.22	0.16	0.10	0.09
$P_{25}\left(\frac{m}{m+k}\right)$	0.02	0	0.07	0	0
$P_{75}\left(\frac{m}{m+k}\right)$	0.26	0.26	0.32	0.11	0.15
$corr(d,y)$	0.69	0.65	0.51	0.94	0.89
$corr(\frac{m}{m+k}, \frac{k}{n})$	−0.13	−0.24	−0.07	− 0.36	−0.52

Notes: Stochastic steady state of the model, with credit tightness ϕ_H. Notes on Figure 7 and Table 3 and 4 apply.

option value of remaining inactive.[34]

D Supplemental results on alternative models

D.1 Alternative models without recalibration

In this appendix I repeat the analysis of Section 5, without recalibrating the model counterfactuals. Figure 9 shows the aggregate dynamics in response to a credit tightening.

Without recalibration, the model counterfactuals do not match the empirical average cash ratio, as shown in Table 8. This is particularly apparent when $\kappa = 0$, which delivers much smaller cash ratios.

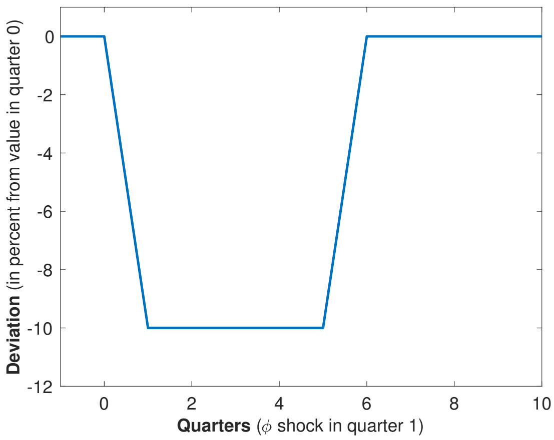
The time-varying correlation between cash ratio and employment growth is roughly similar with and without recalibration, as shown by Figure 10. No alternative model is able to replicate the empirically observed patterns. This is because the precautionary channel is very limited, as confirmed in Table 9.

D.2 Alternative models without frictions

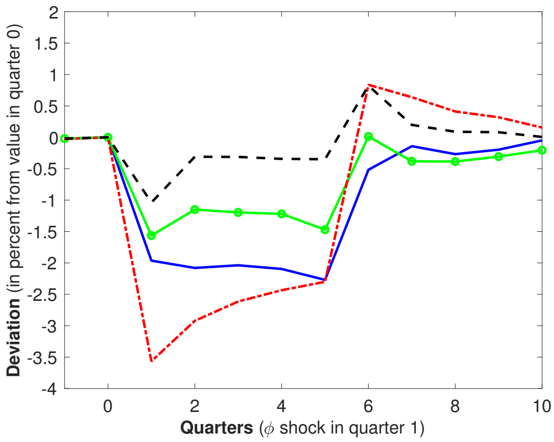
In this appendix I repeat the analysis of Section 5 for a model in which the only friction is the working capital collateral constraint. Hence, in this model I also shut down the capital adjustment costs, such as $\vartheta = 0$ and $\Theta = 0$, besides $\kappa = 0$ and $\chi = 0$. Figure 11 shows the responses of aggregate employment and the average cash ratio to a credit tightening

[34] As in the main text, AC_k^F is the total derivative of the fixed adjustment cost with respect to capital, incorporating the indirect effect via the production function. Similarly, the intuition about q disregards this channel.

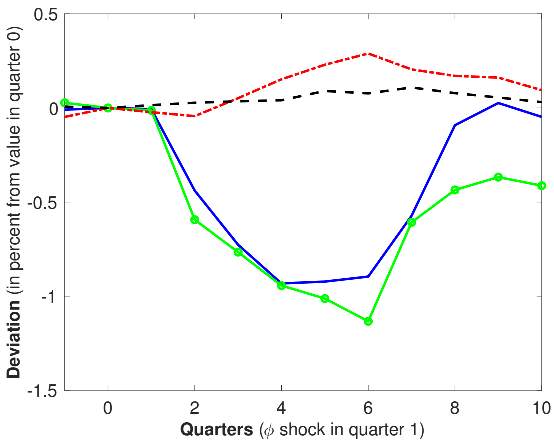
Figure 9: Impulse response functions to a credit supply shock - alternative versions of the model (without recalibration)



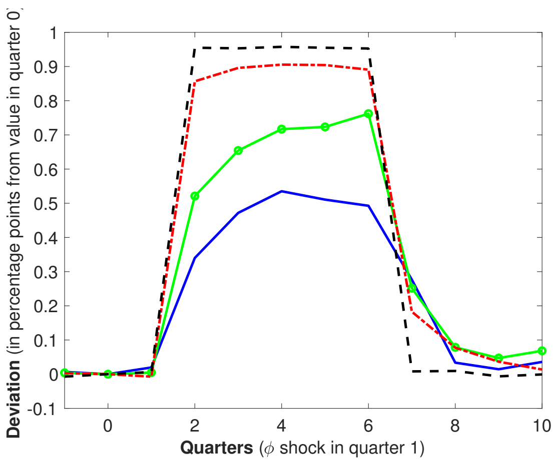
(a) Credit shock



(b) Aggregate employment



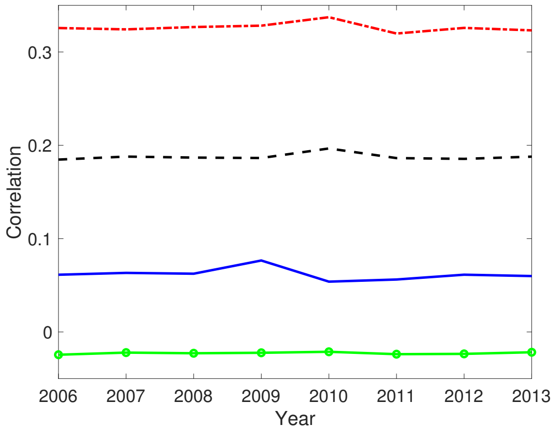
(c) Aggregate capital



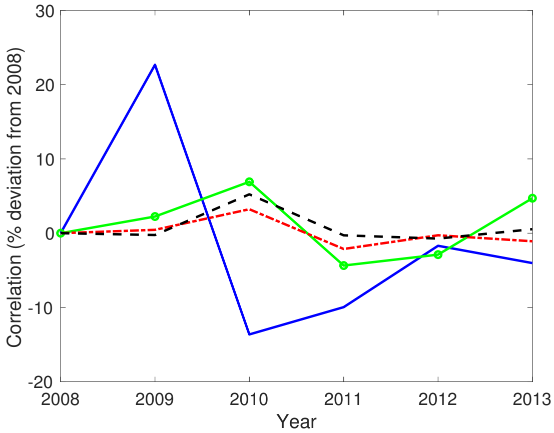
(d) Average cash ratio

Notes: The economy starts with normal credit conditions and experiences a credit tightening in quarter 1, lasting 5 quarters. Previous notes on the simulation apply. χ has been set to 0 in the model shown by the green dotted lines and the black dashed impulse response, while κ is 0 in the red dash-dotted and black dashed impulse responses. The other parameters are maintained fixed at their baseline values.

Figure 10: Cash and employment growth (without recalibration)



(a) Raw correlation



(b) Rescaled correlation

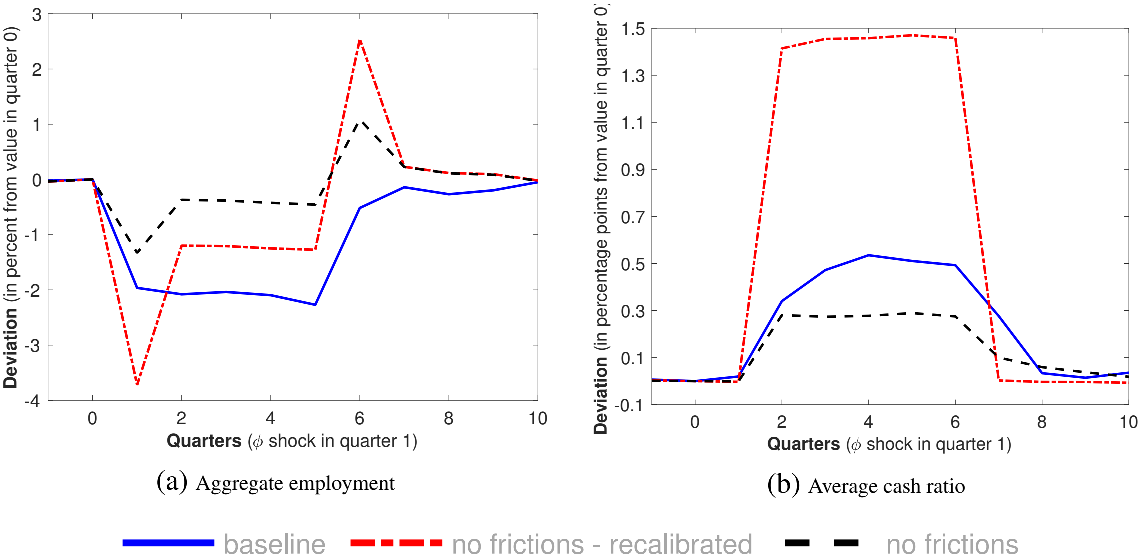
Notes: Notes on Figure 5 and 7 apply.

Table 9: The precautionary channel in alternative models (without recalibration)

	Contribution to aggregate employment growth (%)			
	Baseline model	$\chi = 0$	$\kappa = 0$	$\chi = 0,\ \kappa = 0$
Remaining constrained	30	57	-83	17
Becoming unconstrained	8	0	129	-5
Becoming constrained	4	46	42	94
Remaining unconstrained	58	-3	12	-5

Notes: Same notes as Table 9.

Figure 11: Impulse response functions to a credit supply shock - model with collateral constraint only

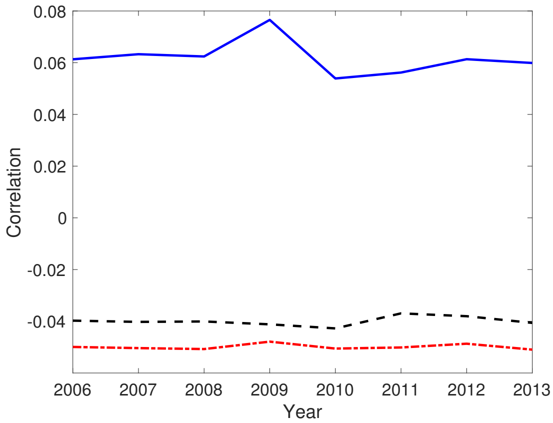


Notes: The economy starts with normal credit conditions and experiences a credit tightening in quarter 1, lasting 5 quarters. Previous notes on the simulation apply. The solid blue lines depicts the baseline model whereas $\vartheta = 0$, $\Theta = 0$, $\kappa = 0$ and $\chi = 0$ in the other two models. In the dash-dotted red model, ϕ_H has been recalibrated to 0.285, in order to match the empirical average cash ratio.

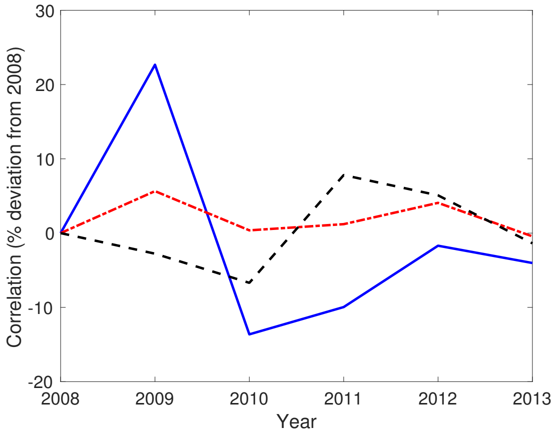
as the one shown in Figure 4a. The black dashed line shows the alternative model without recalibration. In this setting, a credit crunch reduces aggregate employment by much less than the baseline upon impact. Moreover, the response is very short-lived and quickly overshoots above pre-crisis levels when credit conditions are restored. This absence of persistent effects is confirmed when recalibrating ϕ_H to match the empirical average cash ratio, as shown by the red dash-dotted impulse responses. Moreover, in this case the response of average cash ratio is excessively large, twice as much as in the data.

When only the collateral constraint is present, the correlation between cash ratio and employment growth is weakly negative, as shown in Figure 12a. Recalibrating ϕ_H allows the model to generate an increase in the correlation following a credit crunch, albeit much smaller than in the baseline. However, in the following periods, the correlation does not fall below 2008 levels. Finally, Table 10 shows how, absent all real frictions, the precautionary channel is basically not existent.

Figure 12: Cash and employment growth (no frictions)



(a) Raw correlation



(b) Rescaled correlation

Notes: Notes on Figure 5 and 11 apply.

Table 10: The precautionary channel in alternative models (no frictions)

	Contribution to aggregate employment growth (%)		
	Baseline model	No frictions	No frictions recalibrated
Remaining constrained	30	37	86
Becoming unconstrained	8	−9	−2
Becoming constrained	4	110	16
Remaining unconstrained	58	−38	0

Notes: Same notes as Table 9.