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Charge-offs, Defaults and the Financial Accelerator

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Abstract

We uncover new facts: U.S. banks countercyclically vary the ratio of charge-offs to defaulted loans (COD). The variance of this ratio is roughly 15 times larger than that of GDP. Canonical financial accelerator models cannot explain this variance. We develop an expression for the wedge between charge-offs and defaults in the model and show that introducing stochastic default costs as in [Gunn and Johri \(2013a\)](#) and stochastic risk as in [Christiano et al. \(2014\)](#) into the canonical theoretical model can potentially resolve the discrepancy since both shocks have the ability to move this wedge. Estimating the augmented model using Bayesian techniques reveals that default cost shocks account for most of the variance of COD, while risk shocks account for most of the credit spread. Both shocks also matter for standard U.S. business cycle variables, with the anticipated components of each being most important.

KEYWORDS: Charge-offs and defaults, default cost shocks, news shocks, risk shocks, financial accelerator models, business cycles.

JEL CLASSIFICATION: E3, E44

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1 Introduction

Banks and regulators realize that an unpleasant but expected outcome of making loans to a large number of borrowers is that a fraction of these borrowers will default on their loans. Since banks largely make loans with borrowed funds, regulations require them to set aside funds for expected loan losses and “charge-off” the value of funds that are lost due to defaults.¹ It is well known that default rates tend to increase during recessions and fall during booms. Not surprisingly, charge-offs also appear to be positively correlated with defaults and negatively correlated with GDP. What is surprising, however, is that charge-offs do not simply follow the path of defaults. While defaults are about 15 times more volatile than output, charge-offs vary much more – about 22 times more volatile than output. Moreover, the co-movement of charge-offs and defaults is highly imperfect (correlation coefficient of 0.7). In this paper we study the cyclical behavior of aggregate defaults relative to aggregate charge-offs, show that this behavior is puzzling from the perspective of canonical financial accelerator models and propose amendments that can reconcile the discrepancy.

Figure 1 plots the behavior of U.S. output, defaults and charge-offs and clearly illustrates the features described above.² Both defaults and charge-offs are countercyclical and significantly more volatile than output. Yet charge-offs appear to rise more than defaults in recessions and fall more than defaults in booms, and there appears to be some horizontal displacement between the two series. To further investigate the joint behavior of defaults and charge-offs, we express them as a ratio and find that the ratio of charge-offs

¹Regulators expect banks to set aside resources called loan-loss provisions when making loans. As loan losses are actually realized, the bank takes charge-offs, equaling the value of loans removed from banks books. These are then deducted from the provisions that had been made for loan losses. These losses stem from at least two sources. First, the value of the repossessed collateral and any seized returns may not cover the principal and interest due to the bank. Second, there may be costs related to the default (and associated bankruptcy proceedings) which need to be accounted for.

²Using quarterly FDIC data on insured commercial banks and savings institutions covering 1984Q1 to 2016Q1, we measure charge-offs as total charge-offs while defaults are measured as loans and leases 90 days or more past due. Both series are deflated using the GDP deflator and population. All series are detrended using the HP filter with smoothing parameter $\lambda = 1600$.

to defaults (COD henceforth) is indeed highly variable, as suggested by Figure 1, and negatively correlated with GDP. In U.S. data, the standard deviation of COD relative to the standard deviation of GDP is 15.6 and the correlation between these two variables is -0.2. More empirical moments about COD are presented in section 2.

Figure 1: **U.S. GDP, Defaults and Charge-offs**

These new stylized facts raise a number of questions that we wish to explore in this paper. First, why should we expect banks to vary the ratio of charge-offs to defaults over time? Second, why is this ratio counter-cyclical? Third, is the joint behavior of charge-offs and defaults consistent with the predictions of business cycle models? Intuitively, and somewhat mechanically, the answer to the first question is obvious. If banks expect to pay higher default costs than normal or if the return on the repossessed assets is smaller than normal then banks need to charge-off more than “usual” and this results

in a rise in the ratio of charge-offs to defaults. In order to shed light on the question of why the COD ratio varies negatively with the business cycle, we turn to the canonical business cycle framework that links the banking sector with real economic activity. This framework, which encompasses the financial accelerator models of [Bernanke et al. \(1999\)](#) and [Carlstrom and Fuerst \(1997\)](#) (and models that build on it) is not only popular but particularly relevant for our question because it implies a loan contract between banks and borrowers in which the default rate is endogenously determined and responds to macroeconomic shocks. Moreover, a key aspect of the framework, consistent with reality, is a representative bank budget constraint which allows losses associated with defaults to emerge from both sources outlined above. This allows the model to make predictions about the dynamics of aggregate defaults, and also implicitly, about aggregate charge-offs. While it is well known that financial accelerator models can generate counter-cyclical defaults, little is known about their implications for charge-offs or for the COD ratio.

We take an off-the-shelf canonical financial accelerator model augmented with New-Keynesian features in order to explore the endogenous response of COD to a large number of shocks that generate business cycles. We find that none of the shocks, (together or separately) are able to capture the joint behavior of charge-offs and defaults summarized above. This canonical financial accelerator model implies a near perfect correlation between the two variables and so is unable to generate much variance in the COD ratio. We discuss the reasons behind this failure in more detail in [section 3.5](#) where we develop a model-based expression for COD.

Next, we explore the potential of two simple modifications to the canonical model to break the tight link between charge-offs and defaults. These modifications boil down to introducing two shocks that influence the loan contract. We show that COD is a function of the distribution of borrower returns and of the fraction of defaulted returns that are lost to default costs. This guides our thinking when building the augmented model. The first modification introduces exogenous variation in the default costs of the

representative bank as suggested by [Gunn and Johri \(2013a\)](#). The second modification involves introducing time variation in the distribution of borrower returns through exogenous risk shocks as suggested by [Christiano et al. \(2014\)](#). In addition, following both [Gunn and Johri \(2013a\)](#) and [Christiano et al. \(2014\)](#), we introduce anticipated elements in the exogenous processes which we will simply refer to as news shocks. We estimate this augmented version of the model using COD as one of the observables and find that while both default cost shocks and risk shocks play an important role in accounting for the credit spread, default cost shocks end up being the dominant shock in accounting for COD. Beyond the banking sector, the two introduced shocks account for considerable variation in the standard macroeconomic series studied in the business cycle literature. We think of the inclusion of COD then, as a helpful way to partition different sources of financial variation in the model to the extent that it provides additional identification of financial shocks that might otherwise have similar implications for the credit spread.

Interestingly our variance decomposition exercises suggest a strong role for news about both default cost shocks and risk shocks. The former is consistent with the episodic interpretation of the Great Recession given in [Gunn and Johri \(2011\)](#), and the latter is consistent with the estimated evidence given in [Christiano et al. \(2014\)](#). Default cost news shocks account for more than a quarter of investment variance while risk shocks explain over one-third. These shocks also account for a substantial fraction of the variance of hours and output but the variance decomposition is more evenly spread over a number of different shocks. Turning to the banking data, default cost shocks account for almost all of the variance of COD and 17% of credit spread while risk shocks account for over 70% of the variance of credit spreads but only 6% of the COD ratio. In order to understand better why default cost shocks induce the requisite variance in COD while risk shocks do not, we carry out a counter-factual exercise where we artificially set the variance of all default cost shocks to zero while maintaining the variance of all other shocks at their estimated value. The model is able to generate considerable variation in charge-offs

and in defaults but their correlation is perfect. As a result the COD ratio is unable to match the observed variance. Doubling the risk shock variance above the estimated levels barely helps increase the variance of the COD ratio. Clearly the aggregate bank data requires charge-offs to increase more than proportionately to defaults during recessions and vice versa. Risk shocks (like other shocks) are able to engender large movements in the amount of defaulted funds but cannot on their own cause chargeoffs to move more than proportionately.

To summarize, the cyclical movements of the COD ratio present a challenge to conventional financial accelerator models. The reason COD is countercyclical is because a rise in default costs causes banks to increase charge-offs more than the rise in the fraction of loans that are in default. Defaults rise because banks offer worse terms to borrowers by increasing the spread between the lending rate and the deposit rate for any given amount of leverage. These movements in credit spreads are driven mainly by the two financial shocks - risk shocks and default cost shocks. This leads to reduced borrowing in equilibrium and a recession with lower investment, output and hours. To be sure, our model assigns a prominent role to other shocks as well - both surprise and anticipated monetary policy shocks clearly influence the non-banking sector series, marginal efficiency of investment shocks play a small role in moving investment while preference shocks influence a number of series but especially consumption.

1.1 Literature review

The introduction of risk shocks into an estimated New Keynesian Financial Accelerator model was pioneered by [Christiano et al. \(2014\)](#). Our finding that risk shocks account for a large fraction of the variance of the credit spread is consistent with the results in [Christiano et al. \(2014\)](#). Unlike our paper, [Christiano et al. \(2014\)](#) do not study COD or include it as an observable when estimating the model using the value of the stock market instead as a key disciplining device. Moreover, stochastic variation in default

costs is absent. Nonetheless, like us, the authors include news shocks and find that they play an important role in the variance decomposition results.

We view our study as part of a growing literature that argues that variation in intermediation costs are a feature of U.S. data and that this variation has important implications for business cycles. [Ajello \(2016\)](#) explores stochastic variation in intermediation costs to generate movements in credit spreads and aggregate time series. Our focus on the behaviour of charge-offs relative to defaults allows us to distinguish between two distinct types of intermediation costs: those that are specifically related to defaulted funds and those that are not. While all intermediation costs create a wedge between the lending rate and the deposit rate (credit spread), only default costs create a wedge between charge-offs and defaults. We use our COD data to discipline our estimated DSGE model with stochastic default cost shocks. In their presence, the model can generate a highly volatile COD series while in their absence, the combined effect of all macroeconomic shocks is unable to generate this volatility. (Risk shocks, discussed below, could also potentially account for the volatility of COD but our estimation assigns a secondary role to them in the variance decomposition reported below.) Since [Ajello \(2016\)](#) builds on the [Kiyotaki and Moore \(2012\)](#) framework, there are no equilibrium defaults. As a result that model does not speak to our COD data. Despite these and other differences, we note some important implications that are common. Like us, [Ajello \(2016\)](#) finds that intermediation cost shocks are important drivers of aggregate output and investment. This suggests that the widely noted relationship between credit spreads and macroeconomic activity may emerge from a number of distinct sources within the financial sector.³ Our incorporation of news shocks also introduces important differences between our results and those in [Ajello \(2016\)](#).

³The negative relationship between credit spreads and aggregate economic activity has been well known for some time but has been highlighted in [Gilchrist and Zakrajšek \(2012\)](#) who construct an index of credit spreads and show that increases in this spread index are highly predictive of falls in future economic activity, even more so than the traditional spread between risky corporate bonds and government bonds.

Exogenous variation in credit spreads driven by some form of intermediation cost can be found in a number of other studies. [Curdia and Woodford \(2009\)](#) study monetary policy in a New Keynesian model where intermediaries face stochastic variation in these costs but they do not take the model to the data. Similarly, impulse responses to shocks to a more fully specified loan production technology that takes as inputs labor and collateral can be found in [Goodfriend and McCallum \(2007\)](#). News about intermediation cost shocks can be found in [Gunn and Johri \(2011\)](#). See also earlier work in [Cooper and Ejarque \(2000\)](#). Our model, building on [Gunn and Johri \(2013a\)](#), differs from all these studies in that stochastic variation in the cost of banks is embedded into a model where loan contracts with entrepreneurs are endogenously determined in equilibrium. The equilibrium combination of leverage and external finance premium (or credit spread) chosen by agents in equilibrium depend on bank costs so that neither is entirely exogenously driven but can respond to shocks within and outside the financial sector.⁴ In our model loan contracts also respond to news about future variation in default costs. Indeed the estimation assigns a significant role to news shocks. In a study of the great moderation, [Fuentes-Albero \(2019\)](#) also includes a stochastic process for default costs but does not allow for anticipated shocks or use information on defaults and charge-offs as observables when estimating the model. She also finds that shocks to default costs are large in U.S. data but while our focus is on the sources of variation in COD, her focus is on the sources of the moderation in volatility seen in aggregate series. [Fuentes-Albero \(2019\)](#) provides an extensive discussion of the institutional, legal and technological changes that may help to understand the source of variation in these costs which we will summarize here as changes to bankruptcy laws, banking sector regulation reform, financial sector technological change and innovations in financial products. We refer the reader to [Fuentes-Albero \(2019\)](#) for more details in order to not repeat this information here. In this context we note that [Gunn and Johri \(2013b\)](#) discuss how the recent development of asset backed

⁴[Aysun and Honig \(2011\)](#) study the impact of different levels of intermediation costs on an economy facing sudden stops. Unlike us, they do not model default costs as a stochastic process.

securities and credit default swaps would have created expectations that future default costs would fall thus the authors use news about these costs to generate boom-bust cycles resembling the Great Recession. Similarly, changes in laws and regulations create anticipated future changes in default costs which may help to understand why we find a large role for news shocks in our empirical work.

Microeconomic evidence on time varying default costs can be found in the work of [Levin et al. \(2004\)](#) who construct a panel of 900 U.S. firms from 1997Q1 to 2003Q3. Using balance sheet information, expected default probabilities and credit spreads, the authors estimate the parameters that govern the financial contract implied by the [Bernanke et al. \(1999\)](#) model, including the costs associated with defaulted loans. [Levin et al. \(2004\)](#) find that these costs vary systematically over the business cycle, rising during recessions and falling below mean levels during booms. While our structural DSGE model also incorporates the same equations that characterize the loan contract between intermediaries and firms, the informational content of our estimation of default costs differs in that we do not use balance sheet data to tie down our shocks. Moreover, we use aggregate data to estimate the aggregate default costs as opposed to firm level data. In [Section 3.5](#), we show the relationship between COD, our exogenous default cost shocks and an endogenous expression that captures the general equilibrium effects of all other possible shocks. This relationship potentially defines a wedge between the implications of existing financial accelerator models and our COD data which we interpret in terms of stochastic variation in default costs and show that these shocks are empirically relevant for understanding U.S. business cycles.

We view the micro evidence in [Levin et al. \(2004\)](#) as corroborating our work based on aggregate time series. [Gunn and Johri \(2013a\)](#) incorporated surprise and anticipated shocks to default costs in a real version of a financial accelerator model in order to explain the boom-bust cycle associated with the Great Recession. While that paper was solely concerned with the financial crisis and associated recession, our work here shows that

Table 1: Dynamic Correlations of COD with select variables

Quarter	Variable		
	investment	output	credit spread
X_t	-0.29	-0.16	0.39
X_{t-1}	-0.36	-0.25	0.36
X_{t-2}	-0.41	-0.29	0.39

news shocks to the default cost process are of importance more generally in accounting for the joint dynamics of charge-offs, defaults, credit spreads, as well as other macroeconomic variables.

The rest of the paper is organized as follows. Section 2 provides evidence on the ratio of charge-offs to defaults. Section 3 presents a summary of the model with a focus on the financial intermediary while other model elements which are common to a host of New Keynesian and Financial Accelerator models are relegated to the Appendix. Section 4 describes the parametrization and the estimation of the model. We report results in Section 5 and Section 6 concludes.

2 Key moments of the charge-offs to defaults ratio

This section presents descriptive statistics on the COD ratio and documents its correlation to key macro and financial variables. We use quarterly FDIC data on insured commercial banks and savings institutions covering 1984Q1 to 2015Q4. We measure charge-offs as total charge-offs while defaults are measured as loans and leases 90 days or more past due. In terms of descriptive statistics, the COD ratio (no filtering or detrending) has a mean of 56% and a standard deviation of 22% in our sample. Clearly, the amount charged-off by banks is not a constant fraction of the amount defaulted on loans.

To document the relationship of the COD ratio with other variables over the business cycle we detrend all the time series using the HP filter with a smoothing parameter

equal to 1600.⁵ We first compare the cyclical components of COD and GDP in Figure 2. Movements in the two series appear to be negatively correlated. This pattern is especially apparent over the last two cycles. Table 1 presents the dynamic correlations of COD with hp-filtered output, investment, and credit spread. The pattern seen in Figure 2 is confirmed by the moments in the table – COD is negatively correlated with GDP (and aggregate investment) both contemporaneously and at lags of one and two quarters. Moreover, COD is positively correlated with another commonly used measure of stress in the banking sector, the credit spread at both lags as well as contemporaneously. As we will see later, this pattern of correlations of COD with aggregate activity is a feature of the augmented model as well. Table 2 shows that credit spread is more volatile than the

⁵More details on our data can be found in the Appendix.

Figure 2: **Cyclical component of COD and Y in U.S. data**

COD ratio (18 and 16.4 respectively) while investment (4.5) and GDP (1.1) are much less volatile.

Table 2: Standard deviations: 1984 Q1-2015 Q4

Y	I	credit spread	COD
1.1	4.5	18.0	16.4

We now turn to the description of our model.

3 Model

The model economy is a standard stationary New Keynesian framework with the addition of a financial accelerator mechanism from [Bernanke, Gertler and Gilchrist \(1999\)](#). The model builds on [Gunn \(2018\)](#), which is a New Keynesian interpretation of the real model of [Gunn and Johri \(2013a\)](#) that features a stochastic default cost process. In addition, the model includes risk shocks following [Christiano et al. \(2014\)](#). The economy consists of a large number of identical households, a single competitive final goods firm, a continuum of monopolistically competitive intermediate goods firms, one each of a competitive capital-producer and financial intermediary, a continuum of risk-neutral entrepreneurs indexed by $i \in [0, 1]$, a continuum of monopolistically competition labour unions, a competitive employment agency and a monetary policy authority. The nominal frictions include Calvo-style wage and price stickiness with partial indexation. We follow the decentralization of [Schmitt-Grohe et al. \(2007\)](#) and [Smets and Wouters \(2007\)](#) whereby a monopolistic union buys homogeneous labour from households, transforms it into differentiated labour inputs, and sells it to the employment agency who aggregates the differentiated labour into a composite which it then sells to intermediate goods producers. Since this particular decentralization of wage stickiness implies that consumption and hours are identical across households, for simplicity we will refer to a stand-in repre-

sentative household. The monetary policy authority sets the nominal interest rate using a rule which is a function of the inflation rate, the output growth rate and the past nominal interest rate.

Our description of the model in the main text focuses on the financial sector portion while other model elements which are common to a host of New Keynesian and Financial Accelerator models are relegated to Appendix A.

3.1 Financial Intermediary

At the end of each period t the financial intermediary makes a portfolio of loans to the measure of entrepreneurs, with B_{it+1} denoting the loan to the i^{th} entrepreneur, funding this portfolio of loans by issuing securities, A_{t+1} , to the household that promise a risk-free gross return, R_{t+1}^a . The financial intermediary has no other sources of funds, and thus it must generate a total return on its loan portfolio in each aggregate contingency to just cover its opportunity cost of funds on the household securities. As in [Bernanke et al. \(1999\)](#), each risk-neutral entrepreneur bears all the aggregate risk on its loan and thus makes state-contingent loan payments that ensure that in each aggregate state of the world the financial intermediary achieves an expected return equal to its opportunity cost of funds. This leaves the intermediary with only the idiosyncratic risk associated with individual loans, which it can diversify away by virtue of holding a large loan portfolio.

3.2 Entrepreneurs

Risk-neutral entrepreneurs accumulate physical capital and make the capacity utilization decisions for their capital. The timing of the decisions of the i^{th} entrepreneur is as follows. The entrepreneur enters into period t with predetermined capital stock K_{it} , purchased at the end of the previous period from capital producers for price q_{t-1} , as well as debt obligations B_{it} . After observing the aggregate state in period t , the entrepreneur chooses the capital utilization rate u_{it} and then rents capital services $\tilde{K}_{it} = u_{it}K_{it}$ at rental

rate r_t to intermediate goods firms. The entrepreneur then sells its entire capital stock to capital-goods producers for price $\bar{q}_t$, realizing its ex-post return to that capital, R_{it}^k , given by

$$R_{it}^k = \omega_{it} \left[\frac{u_{it}r_t - a(u_{it}) + \bar{q}_t}{q_{t-1}} \right]. \quad (1)$$

In the above expression, ω_i is a random variable providing an idiosyncratic component to entrepreneur i 's return, such that the ex-ante return to capital is subject to both idiosyncratic and aggregate risk. The random variable ω is i.i.d across firms and time, has cumulative distribution function $F_t(\omega)$, and is normalized so that $E\omega = 1$. We follow [Christiano et al. \(2014\)](#) and assume that the standard deviation of the log of ω , σ_t^e , is time-varying and follows a stationary stochastic process. This adds a stochastic element to the cross-sectional dispersion in ω , intended to reflect unpredictable swings in business risk. The risk shock σ_t^e follows a stochastic process which we discuss later. The time subscript on the distribution function $F(\cdot)$ and other distribution functions that follow reflects the time-varying effect of σ_t^e on these distribution functions.

Entrepreneurs observe their idiosyncratic component when realizing their return, but after making their capacity utilization decision. As in [Christiano et al. \(2003\)](#), entrepreneurs incur a cost $a(u_{it})$ per unit of capital in terms of goods for utilization rate u_{it} , where $a'(\cdot), a''(\cdot) > 0$, such that changing utilization influences the entrepreneur's return to capital as in (1). The parameter controlling the curvature of the cost function is denoted ϵ_u .

After realizing its return, the entrepreneur makes any necessary payments to the financial intermediary to fulfill the terms of its contract determined the previous period. Finally at the end of the period, the entrepreneur chooses its desired level of capital, K_{it+1} , to hold into the following period, buying it from the capital producer for price q_t . Entrepreneurs finance these capital purchases with their own end-of-period net-worth, X_{it+1} , and new loans from the financial intermediary B_{it+1} , such that their financing

satisfies

$$q_t K_{it+1} = X_{it+1} + B_{it+1}. \quad (2)$$

Entrepreneurs face a constant probability, γ , of surviving into the next period. When entrepreneurs die they consume their entrepreneurial equity, c_{it}^e . Finally, entrepreneurs supply a unit time endowment inelastically to the good-producers at wage-rate w_t^e .

3.3 Agency problem and debt-contract

The financial intermediary can observe the average return to capital R_t^k but not an entrepreneur's idiosyncratic component ω_{it} , unless it pays a monitoring cost. As a consequence the parties can adopt a financial contract that minimizes the expected agency costs, in the form of risky-debt where the monitoring costs are incurred only in states where an entrepreneur fails to make promised debt payments. In the model we pool this monitoring cost along with all other costs related to the default process and refer to them as "default costs." As in [Bernanke et al. \(1999\)](#) these default costs take the form of a fraction, θ_t , of the entrepreneur's gross payout, $\omega_{it} R_t^k q_{t-1} K_{it}$, however, unlike [Bernanke et al. \(1999\)](#), here θ_t is time-varying and follows an exogenous stationary stochastic process. We refer to it as a *default cost (DC) shock*, common to all entrepreneurs, and observable by all agents in the economy.

At the end of period t , the entrepreneur chooses its capital expenditures, $q_t K_{it+1}$ and associated level of borrowing, B_{it+1} , with knowledge of neither the aggregate state in period $t + 1$ nor the idiosyncratic realization of ω in period $t + 1$, ω_{it+1} . Conditional on these choices, the terms of the contract between the financial intermediary and the entrepreneur specify a contractual non-default state-contingent gross interest rate, R_{it+1}^l that ensures that in each aggregate state of the world, the financial intermediary achieves an expected return, net of costs, equal to the its opportunity cost of funds. In the event that the entrepreneur's idiosyncratic returns are insufficient to cover its contracted debt

payments, the entrepreneur defaults and goes bankrupt, handing over all remaining gross returns to the financial intermediary, leaving the gross returns less default costs to the financial intermediary. Note that given the state-contingent contract structure, the loan rate R_{it}^l will adjust in period t to reflect the ex-post realization of the aggregate state in t . We show in the appendix that such a contract results in the condition

$$[\Gamma_t(\bar{\omega}_{it+1}) - \theta_{t+1}G_t(\bar{\omega}_{it+1})] R_{t+1}^k q_t K_{it+1} = R_{t+1}^a (q_t K_{it+1} - X_{it+1}), \quad (3)$$

where $\bar{\omega}_{it+1}$ is a “cut-off” level of ω_{it} , defined by $\bar{\omega}_{it+1} R_{t+1}^k q_t K_{it+1} = R_{it+1}^l B_{it+1}$, $\Gamma_t(\bar{\omega})$ is the financial intermediary’s expected share of gross returns, given by $\Gamma_t(\bar{\omega}_{it}) = [1 - F_t(\bar{\omega}_{it})]\bar{\omega}_{it} + \int_0^{\bar{\omega}_{it}} \omega dF(\omega, \sigma_t^e)$, and where $G_t(\bar{\omega})$ is given by $G_t(\bar{\omega}_{it}) = \int_0^{\bar{\omega}_{it}} \omega dF(\omega, \sigma_t^e)$. Equation (3) defines a menu of contracts for a given level of net-worth X_{it+1} relating the entrepreneur’s choice of K_{it+1} to the cut-off level of $\bar{\omega}_{it+1}$.

3.4 Entrepreneur’s problem

The i^{th} entrepreneur’s gross return in period t , after realization of the aggregate state but before the resolution of idiosyncratic risk, is given by

$$V_{it}^k = \int_{\bar{\omega}_{it}}^{\infty} \omega R_t^k q_{t-1} K_{it} dF(\omega, \sigma_t^e) - R_{it}^l B_{it}. \quad (4)$$

Given the definition of R_{it}^k in (1), all entrepreneurial-indexed variables are predetermined at the timing of the utilization decision, and thus we can simply represent the entrepreneur as choosing capacity utilization u_{it} to maximize $u_{it}r_t - a(u_{it})$, yielding the first-order condition

$$r_t = a'(u_{it}). \quad (5)$$

For a given level of net-worth X_{it+1} , the entrepreneur then chooses K_{it+1} capital and the loan cut-off ω_{it+1} to maximize $E_t\{V_{it+1}^k\}$ subject to the condition that the financial

intermediary's expected return on the contract equal its opportunity cost of its borrowing, equation (3). Letting λ_{it+1} be the ex-post value of the Lagrange multiplier conditional on realization of the aggregate state, and writing the period $t + 1$ ex-post gross returns as $V_{it+1}^k = [1 - \Gamma(\bar{\omega}_{it+1})] R_{t+1}^k q_t K_{it+1}$, where $1 - \Gamma(\bar{\omega}_{it+1})$ is the entrepreneur's expected share of gross returns, the first-order conditions are then

$$\Gamma'_t(\bar{\omega}_{it+1}) - \lambda_{t+1} [\Gamma'_t(\bar{\omega}_{it+1}) - \theta_{t+1} G'_t(\bar{\omega}_{it+1})] = 0 \quad (6)$$

$$E_t \left\{ [1 - \Gamma_t(\bar{\omega}_{it+1})] \frac{R_{t+1}^k}{R_{t+1}^a} + \lambda_{t+1} \left([\Gamma_t(\bar{\omega}_{it+1}) - \theta_{t+1} G_t(\bar{\omega}_{it+1})] \frac{R_{t+1}^k}{R_{t+1}^a} - 1 \right) \right\} = 0 \quad (7)$$

$$[\Gamma_t(\bar{\omega}_{it+1}) - \theta_{t+1} G_t(\bar{\omega}_{it+1})] R_{it+1}^k q_t K_{it+1} - R_{t+1}^a (q_t K_{it+1} - X_{it+1}) = 0, \quad (8)$$

where (6) and (8) hold in each contingency, but (7) holds only in expectation.

3.5 Charge-offs and defaults

In Sections 1 and 2 we reported that defaults and charge-offs are not perfectly correlated in U.S. banking data and that their ratio, COD, is highly volatile. Here we show why the canonical model has a hard time replicating these facts and how the introduction of default cost and risk shocks can, in theory, help the model match those facts.

We calculate the value of defaults in the model as

$$Def_t = F_t(\bar{\omega}_t) R_t^\ell B_t = F_t(\bar{\omega}_t) \bar{\omega}_t R_t^k q_t K_t. \quad (9)$$

Charge-offs are the difference between the value of defaulted loans and the resources obtained by financial intermediaries as part of the default process after incurring all associated expenses. These include monitoring entrepreneurs who defaulted and the resources needed to appropriate the returns of these projects. They are calculated as

follows

$$Chof_t = F_t(\bar{\omega}_t)R_t^\ell B_t - (1 - \theta_t)G_t(\bar{\omega}_t)R_t^k q_t K_t = [F_t(\bar{\omega}_t)\bar{\omega}_t - (1 - \theta_t)G_t(\bar{\omega}_t)]R_t^k q_t K_t. \quad (10)$$

We can combine the two equations above to write

$$COD_t = \frac{Chof_t}{Def_t} = \left[1 - \frac{(1 - \theta_t)G_t(\bar{\omega}_t)}{F_t(\bar{\omega}_t)\bar{\omega}_t} \right] \quad (11)$$

which makes it clear that the wedge between charge-offs and defaults depends on the ratio appearing in square brackets. This ratio can change via three channels: (i) variation in θ_t , (ii) variation σ_t through its impact on changing the distributions $G_t(\cdot)$ and $F_t(\cdot)$, and, (iii) variation in $\bar{\omega}_t$. If θ and σ^e were fixed as in a standard financial accelerator model, then $COD_t = \left[1 - \frac{(1-\theta)G(\bar{\omega}_t)}{F(\bar{\omega}_t)\bar{\omega}_t} \right]$ and only general equilibrium changes in $\bar{\omega}_t$ would produce variation in this wedge. As explained in section 3.3, $\bar{\omega}_t$ is the cutoff value of ω_t such that the entrepreneur's gross payout exactly equals the contracted amount. In other words, $\bar{\omega}_t$ is defined by $\bar{\omega}_t R_t^k q_{t-1} K_t = R_t^\ell B_t$ and it adjusts in response to period t shocks. For example, in response to a positive productivity shock, the average return to capital R_t^k increases while the loan rate R_t^ℓ decreases forcing $\bar{\omega}_t$ down. This implies that fewer entrepreneurs (with worse shocks) default on their loans. At the same time, the average return on the defaulted projects is also lower. Recall that $G_t(\bar{\omega}_t)$ calculates the average productivity of entrepreneurs who default while $F_t(\bar{\omega})$ is a CDF which implies that both of these quantities are increasing in $\bar{\omega}$. The simultaneous impact of a change in $\bar{\omega}_t$ on both the numerator and denominator of COD should imply relatively small changes in COD compared to the data. If our conjecture is correct, then a model with no variation in θ and σ^e would display: (i) a high correlation between charge-offs and defaults, and (ii) a low variance in the COD ratio. Of course, very large shocks of just the right magnitude could in principle generate the required volatility but they would run afoul of other macroeconomic data such as real GDP, aggregate investment etc. In any

case, we begin the next section by exploring the ability of shocks working only through $\bar{\omega}$ to influence COD.

Now suppose that θ_t and σ_t^e are exogenous random variables. As can be seen from (11), shocks to θ_t have a direct positive effect on COD over and above the general equilibrium effect coming through the response of $\bar{\omega}$ discussed above. Similarly, shocks to σ_t^e have a direct impact on $G_t(\cdot)$ and $F_t(\cdot)$ and thus COD over and above the general equilibrium effects. As a result, both these shocks break the tight link that exists between charge-offs and defaults in a standard financial accelerator model and potentially provide a source for increasing the variance of COD relative to the standard model. If, however, changes in $\bar{\omega}_t$ undo the impact of changes in θ_t or σ_t^e , then we may not get the desired results. Additionally, since $G_t(\cdot)$ and $F_t(\cdot)$ show up in the numerator and denominator respectively, the impact of σ_t^e will depend on their relative change, similar to our discussion above about the impact of a change in $\bar{\omega}$. The overall impact of both endogenous and exogenous sources of movement in COD can only be ascertained by estimating and simulating the model which we do in the next section.

3.6 Stochastic Processes

There are nine stochastic processes in the model: z_t (neutral technology), m_t (marginal efficiency of investment), g_t (government spending), η_t (monetary policy), ν_{p_t} (price markup), ν_{w_t} (wage markup), J_t (preference), θ_t (default cost) and σ_t^e (risk). Since θ_t is a fractional term and like a “rate” (ie we will see later that our prior for steady state θ is 0.12), we define $\Theta_t = 1 + \theta_t$ and then specify the stochastic process for Θ_t . All the stochastic processes Ξ_t , where $\Xi = z_t, m_t, g_t, \eta_t, \nu_{p_t}, \nu_{w_t}, J_t, \Theta_t, \sigma_t^e$, evolve according to the stationary process

$$\ln(\Xi_t/\Xi) = \rho_\Xi \ln(\Xi_{t-1}/\Xi) + u_{\Xi t}, \quad (12)$$

where $\rho_{\Xi} < 1$, Ξ denotes the mean of the process and $u_{\Xi t}$ is the shock innovation. Note that Θ_t following the AR(1) process given in (12) is approximately equivalent to θ_t following an AR(1) in absolute deviations, $d_t^{\theta} = \rho_{\theta} d_{t-1}^{\theta} + u_{\theta,t}$, given $d_t^{\theta} = \theta_t - \theta_{ss}$.

We potentially allow for news shocks such that the innovation $u_{\Xi t}$ contains both unanticipated and anticipated components, whereas for the remaining stochastic processes, the innovation $u_{\Xi t}$ contains only an unanticipated component, such that

$$u_{\Xi t} = \epsilon_{\Xi t-p}^p + \epsilon_{\Xi t-p-1}^{p-1} + \dots \epsilon_{\Xi t}^0 \quad (13)$$

where $p > 0$, $\epsilon_{\Xi t-p}^p$ is a news shock that agents receive in period $t-p$ about the innovation in t , and $\epsilon_{\Xi t}^0$ is a surprise shock. All shocks are mean zero and uncorrelated over time and with each other. The news and surprise shocks have standard deviation σ_{Ξ}^p and σ_{Ξ}^0 respectively.

4 Parameterization and Bayesian Inference

In this section we describe our parameterization and estimation of the model. We refer to the model with all nine stochastic processes detailed in the previous section as the *Full Model*. We estimate a linearized approximation of this model around its steady state using Bayesian methods as in [An and Schorfheide \(2007\)](#) using nine US aggregate quarterly time-series between the period of 1984Q1 to 2015Q4 as observables. Our observables are the log-difference of real GDP, the log-difference of real consumption, the log-difference of real investment, the log-difference of the real wage, the log of hours-worked, inflation, the federal funds rate, the credit spread and the charge-offs-to-defaults ratio (COD). Inflation is calculated as the log-difference of the GDP deflator. The credit spread is calculated using Moody's Seasoned Baa Corporate Bond Yield Relative to the Yield on 10-Year Treasury Constant Maturity bonds. COD is the ratio of Total Charge-offs divided by Total Loans and Leases over Loans 90 days or more past due for all FDIC-Insured

Institutions. All series are de-measured and scaled by 100 to express them in percentage units. The first seven of these observables are general business cycle variables commonly used in the literature. The last two are financial variables, with the credit spread being common to nearly all studies that estimate DSGE models with a financial component. The addition of COD as an observable is novel to our study. Appendix B gives further details on data construction and sources.

To aid our analysis, we also consider a specialized version of the model where we shut-down the default cost and risk shock stochastic processes so that the default cost θ and the standard deviation of the idiosyncratic return σ^e are both constant, leaving an essentially canonical financial accelerator model with only the seven stochastic processes commonly found in the literature. We refer to this specialized version of the model as the *Benchmark* model. We solve and estimate the *Benchmark Model* using the same methods and same nine data observables as in the *Full Model* estimation, as well as the same calibrated parameters and priors (less the parameters of the excluded θ and σ^e stochastic process). Since the *Benchmark Model* is not central to our analysis, we only estimate it at its mode. We also add a single measurement error to this second version of the model to avoid stochastic singularity during estimation (there is no measurement error in the *Full Model*). We only report estimation results for the *Benchmark Model* in the main body of the paper pertinent to the discussion, leaving remainder of the details to the Appendix.

4.1 Parameterization

In this section we explain how we attribute values to parameters. We group model parameters in two sets. The first one contains parameters that are not estimated while the second one contains those estimated using Bayesian methods.

For parameters in the non-estimated set, we use typical values established in the literature or we choose the parameters to match relevant steady state quantities in the model

economy with analogous quantities in the data. The values of parameters not estimated are shown in Table 3. Beginning with the preference side, we set the household’s subjective discount factor β to 0.99, implying a net annualized risk-free interest rate of 4.1%, and implying a quarterly gross return on household financial assets $R^d = (1+r^f)^{0.25} = 1.0101$. We follow Christiano et al (2014a) and set the curvature parameter on the disutility of labour $\sigma_L = 1$, and we set the weight on the disutility of labour in the utility function Ψ_L so that the household time allocated to market work hours is normalized to 0.3. On the production side, we set the share of labor in production, α to 0.67, and the depreciation of physical capital, δ to 0.025. We set the steady-state government spending-GDP ratio G/Y to 0.18 as in Smets and Wouters (2007). On the New Keynesian side of the model, we set both the steady-state wage and price markups, λ_p and λ_w to 1.10. For the parameters associated with the financial contract and the entrepreneur, we fix the external finance spread, $R^k - R^d$, to 0.005 quarterly to yield a leverage, K/X of approximately 2, and the quarterly survival rate of entrepreneurs to 0.9799, based on Bernanke et al. (1999). We estimate and calculate the remainder of the parameters of the financial contract which we describe below.

The processes for all shocks except preference and markup shocks include an eight-period ahead and twelve-period ahead anticipated component. During the mode-finding exercise we compared several different possible alternative surprise and news shocks specifications, including a “no-news” specification with no anticipated components on any stochastic process (ie surprise shocks only). Table A.1 in the Appendix shows the result of these mode determinations for the following specifications: no news, four-period & eight-period, eight-period & twelve-period, four-period, eight-period & twelve-period.⁶ As the table shows, the log data density favoured the eight-period & twelve-period specification.

We estimate the remainder of the economic and shock parameters using the prior

⁶For each shock specification tested we ran a succession of at least four different mode-finding methods, each using the results of the preceding determination as a starting point.

Table 3: *Full Model* and *Benchmark Model*: Parameters not estimated

Description	Parameter	Value
Household subjective discount factor	β	0.99
Curvature on disutility of labour	σ_L	1
Steady state hours-worked	N_{ss}	0.3
Labour share in production	α	0.67
Household share of total labour in production	τ	0.99
Steady state government spending-GDP ratio	$\frac{G}{Y}$	0.18
Steady state price markup	$\lambda_p \equiv 1/\nu_p$	1.1
Steady state wage markup	$\lambda_w \equiv 1/\nu_w$	1.1
Steady state external finance premium	EFP	0.005
Quarterly survival rate of entrepreneurs	γ	0.9799

distributions reported in Tables 4 and 5 respectively, drawing primarily from Justiniano et al. (2011) as well as Smets and Wouters (2007) and Christiano et al. (2014).

The priors for the non-financial parameters in Table 4 are common to standard DSGE models. To determine the financial contract, we calculate the value of the standard deviation of $\log(\bar{\omega})$, σ^e , that is consistent with the model equilibrium given the other parameters, including the steady state default cost θ and default rate $F(\omega)$ which we estimate. We set the prior means for θ and $F(\omega)$ to 0.12 and 0.0076 respectively based on the calibration detailed in Bernanke et al. (1999), as well as the microeconomic estimates of θ in Levin et al. (2004). The combination of calibrated and prior values for the financial contract then imply a value of 0.30 for the steady state value of the standard deviation of $\log \omega$, σ^e , which is consistent with the microeconomic estimates of 0.40 by Levin et al. (2004) for this parameter over the 1997 to 2003 period.

The prior means for the autocorrelation coefficients and surprise shock standard deviations in Table 5 for the seven stochastic processes that exclude the θ and σ^e processes are taken from Justiniano et al. (2011). The priors related to the θ and σ^e processes are not well established in the literature, and so we provide some additional discussion. First, we set the prior means of the autocorrelation coefficients for both of these processes to 0.5 to be consistent with the other seven stochastic process. Beginning with the standard

deviation for θ , since θ itself is a fractional variable, with a rather small steady-state prior mean (0.12), any reasonable change in this variable would require a larger shock in percentage terms. For example, a 50% shock would be required to take θ from 0.12 to 0.18. Since we defined the stochastic process for θ_t in terms of absolute deviations from the steady state, this same example change from 0.12 to 0.18 would correspond to a 0.06 shock in absolute deviations, or 600 basis points⁷. Indeed, microeconomic estimates of [Levin et al. \(2004\)](#) suggests that this parameter moved in a range between 0.08 and 0.16 in the late 1990's, and up to 0.5 in the early 2000's, suggesting a considerable amount of variability and thus large shock magnitudes for this parameter. Relative to these large episodic spikes evidenced in [Levin et al. \(2004\)](#), we assume a more conservative prior of 200 basis points or 0.02 in absolute deviations over our sample period, which would constitute just over a 16% movement of θ from its prior mean of 0.12 (ie to 0.14). Turning next to the standard deviation of σ^e , the process for σ^e is defined in units of %-deviations from steady state. Microeconomic estimates by [Levin et al. \(2004\)](#) of this idiosyncratic volatility parameter indicate relatively little time variation across the distribution of firms in the their panel, remaining in a fairly narrow range of about 0.38 to 0.45 (with mean of 0.40) over the period 1997 to 2003. Additionally, in their structural estimation, [Christiano et al. \(2014\)](#) report 0.2 and 7 respectively for the prior and posterior mode for this parameter (converted into our %-units). We assume a prior mean of 2 within this range, slightly higher than for the other shock processes excluding θ , but reflective of this information from these other studies. To account for our higher level of uncertainty about the prior means for the shocks of these two processes however, and to allow for a reasonable possibility for these shocks to be much smaller or larger, we include very wide priors of 10 for both shocks (relative to 1 for all the other stochastic processes).

Additionally, for those processes that contain anticipated shocks, we set prior means

⁷In our model and estimation, where all data has been scaled by a factor of 100 to work in units of %, this change would then show up as 6, in units of hundreds of basis points.

and standard deviations for the anticipated components equal to those of the surprise component of the corresponding process. Finally, the standard deviations of all anticipated and unanticipated innovations share an inverse gamma distribution.

Table 4: *Full Model*: priors and posteriors - Economic parameters

Description	Parameter	Prior mean	Posterior mean	90% HPD interval		Prior distrib.	Prior std dev.
Habit in consumption	b	0.5	0.6411	0.5462	0.7353	beta	0.1
Curvature, investment adjust cost	s''	4	8.0813	5.2235	11.1445	norm	2
Curvature, utilization cost	ϵ_u	0.5	0.6053	0.4298	0.7797	beta	0.1
Monetary policy smoothing parameter	ρ_R	0.75	0.8706	0.8426	0.899	beta	0.1
Monetary policy weight on inflation	ϕ_π	1.5	1.6769	1.1891	2.2418	gamm	0.25
Monetary policy weight on output	ϕ_y	0.25	0.3659	0.2441	0.4807	gamm	0.05
Calvo price stickiness	ζ_p	0.66	0.9589	0.9359	0.979	beta	0.15
Calvo wage stickiness	ζ_w	0.66	0.8763	0.7893	0.9423	beta	0.15
Price indexing weight on inflation	ι_p	0.5	0.2966	0.1232	0.459	beta	0.15
Price indexing weight on wage inflation	ι_w	0.5	0.3908	0.1637	0.6068	beta	0.15
Steady state default cost	θ	0.12	0.166	0.1265	0.2029	beta	0.1
Steady state default rate	$F(\bar{\omega})$	0.0076	0.0059	0.0047	0.0071	gamm	0.001

Table 5: *Full Model*: priors and posteriors - Shock parameters

Description	Parameter	Prior mean	Posterior mean	90% HPD interval		Prior distrib.	Prior std dev.
autocorrelation of shocks							
Technology process	ρ_z	0.5	0.9402	0.9001	0.9806	beta	0.2
MEI process	ρ_{mei}	0.5	0.4511	0.0763	0.9901	beta	0.2
Government spending process	ρ_g	0.5	0.9464	0.9106	0.9843	beta	0.2
Price markup process	ρ_{ν_p}	0.5	0.2158	0.038	0.3842	beta	0.2
Wage markup process	ρ_{ν_w}	0.5	0.0686	0.0096	0.1247	beta	0.2
Preference process	ρ_J	0.5	0.9418	0.9074	0.9784	beta	0.2
Default cost process	ρ_θ	0.5	0.8264	0.7775	0.8759	beta	0.2
Risk process	ρ_{σ^e}	0.5	0.9687	0.935	0.9959	beta	0.2
standard deviation of shocks							
Technology, unanticipated	ϵ_z	0.5	0.3024	0.1596	0.4457	invg	1
Technology, anticipated 8pd	ϵ_z^8	0.5	0.2917	0.1592	0.4281	invg	1
Technology, anticipated 12pd	ϵ_z^{12}	0.5	0.31	0.1691	0.4447	invg	1
MEI, unanticipated	ϵ_m	0.5	0.5478	0.1397	0.9527	invg	1
MEI, anticipated 8pd	ϵ_m^8	0.5	0.4252	0.1426	0.7672	invg	1
MEI, anticipated 12pd	ϵ_m^{12}	0.5	0.8243	0.1773	1.5872	invg	1
Gov't spending, unanticipated	ϵ_g	0.5	1.3796	0.1752	2.2898	invg	1
Gov't spending, anticipated 8pd	ϵ_g^8	0.5	0.9189	0.1486	2.193	invg	1
Gov't spending, anticipated 12pd	ϵ_g^{12}	0.5	0.7274	0.1317	2.0501	invg	1
Monetary policy, unanticipated	ϵ_η	0.1	0.101	0.0746	0.1281	invg	1
Monetary policy, anticipated 8pd	ϵ_η^8	0.1	0.0529	0.0299	0.0751	invg	1
Monetary policy, anticipated 12pd	ϵ_η^{12}	0.1	0.0593	0.034	0.083	invg	1
Price markup	ϵ_{ν_p}	0.1	0.1123	0.0921	0.1325	invg	1
Wage markup	ϵ_{ν_w}	0.1	0.4137	0.3646	0.4624	invg	1
Preferences	ϵ_J	0.1	1.9834	1.2906	2.6625	invg	1
Default cost, unanticipated	ϵ_θ	2	1.4078	0.4831	2.4205	invg	10
Default cost, anticipated 8pd	ϵ_θ^8	2	2.439	0.4659	6.0543	invg	10
Default cost, anticipated 12pd	ϵ_θ^{12}	2	5.3253	1.8125	8.092	invg	10
Risk, unanticipated	ϵ_{σ^e}	2	1.18	0.6736	1.6584	invg	10
Risk, anticipated 8pd	$\epsilon_{\sigma^e}^8$	2	1.359	0.5862	2.2417	invg	10
Risk, anticipated 12pd	$\epsilon_{\sigma^e}^{12}$	2	1.8793	0.8506	2.6447	invg	10

5 Results

We begin our analysis by asking the following question: can a canonical financial accelerator DSGE model account for the properties of COD in the data highlighted earlier? To answer this, we present some key estimation results of our *Benchmark Model* which is essentially a standard financial accelerator DSGE model (yet without stochastic default costs or risk). Following this, we then turn to presenting and discussing our estimation results for the *Full Model* that includes stochastic default costs and risk.

5.1 Benchmark Model: No Default Cost or Risk Shocks

Our derivation of the COD ratio implied by the Benchmark Model (see section 3.5) led to the conjecture that the model with constant θ and σ^e would generate a very low variance in that ratio and nearly perfectly correlated charge-offs and defaults. We test this conjecture by studying the implications of the Benchmark Model after estimating the model parameters. As mentioned previously, measurement error is introduced on COD so that stochastic singularity is avoided. The estimated economic and shock parameters are available in the Appendix in Table A.2 and Table A.3 respectively. Since these results are not remarkably different from earlier studies we do not focus on them and instead concentrate our discussion on the implications of the Benchmark Model.

5.1.1 Implications of estimated Benchmark Model

We now compare the Benchmark Model's predictions to the statistics reported in the first panel of Table 6 based on U.S. data. The key moment of interest here is that COD is 15.6 times more volatile than output. The second panel of that table reports two sets of statistics from the estimated Benchmark Model. The first row reports the theoretical moments of HP filtered variables implied by the estimated shock parameters. The second set uses the smoothed time series implied by both the parameter estimates

Table 6: Data and Model Moments

	$\frac{SD(COD)}{SD(y)}$	$cor(chof, def)$
<i>Panel 1: U.S. data 1984Q1-2015Q4 (HP 1600)</i>		
	15.6	0.70
<i>Panel 2: Estimated Benchmark Model (no Default Cost or Risk shocks)</i>		
Theoretical (HP 1600)	6.8	1
Smoothed (HP 1600)	0.7	1
<i>Panel 3: Estimated Full Model (with Default Cost and Risk shocks)</i>		
Theoretical (HP 1600)	14.1	0.80
Smoothed (HP 1600)	15.6	0.63
<i>Panel 4: Counterfactual (Theoretical (HP 1600))</i>		
A: $\sigma_{\theta}^0, \sigma_{\theta}^8, \sigma_{\theta}^{12} = 0$	1.3	1
B: A + double $\sigma_{risk}^0, \sigma_{risk}^8, \sigma_{risk}^{12}$	1.7	1

and the estimated shocks (we HP filter the smoothed series just like we HP filter U.S. time series). As conjectured, the relative standard deviation of COD is much lower than its counterpart in U.S. data. Here, the theoretical moments perform better than when the smoothed shocks are taken into account (6.8 times compared to less than 1). As seen in the last column of the table, the problem is that the correlation of defaults and charge-offs is nearly perfect in the Benchmark Model so that COD does not move as much as in the data, whereas the correlation in the data is 0.7.

In order to understand if conventional shocks can be a source of movement in COD in the Benchmark Model, we report the unconditional variance decomposition of all observables in Table 7. As the table shows, structural shocks account for 100 percent of the variance of all other conventional observables, but just 7.4 percent of the variance of COD, with measurement error accounting for over 92 percent. This point is reiterated in Figure 3 which plots the smoothed COD series induced by structural shocks against the US data counterpart. Recalling equation (11) and our associated discussion, it is apparent that the endogenous variation in $\bar{\omega}$ in response to all the structural shocks is insufficient to induce the necessary variation in COD.

Table 7: Benchmark Model (no Default Cost or Risk Shocks): COD Unconditional Variance Decomposition

Observable	Shock	
	<i>meas. error</i>	<i>all structural</i>
COD	92.6	7.4
Output growth	0	100
Investment growth	0	100
Consumption Growth	0	100
Hours	0	100
Wage Growth	0	100
Nom Int Rate	0	100
Inflation	0	100

5.2 Full Model: Default Costs and Risk Shocks

The results in Table 6 reveal that the endogenous movements in $\bar{\omega}$ in response to various non-financial shocks do not result in sufficient variation in COD. We will now discuss the same moments as generated by the estimated Full Model with default cost and risk shocks in order to see if it is able to deliver moments that are closer to the data. Before discussing these moments, we first turn to the estimated parameters of the Full model.

5.2.1 Estimation of the Full Model

Table 4 and Table 5 display the economic and shock parameter estimation results respectively for the Full Model.⁸ There is some variation across shocks in their degree of persistence and volatility. Risk shocks are most persistent while wage and price markup shocks exhibit very little serial correlation (coefficient=0.07 and 0.2 respectively). Marginal efficiency of investment shocks also stand out with a serial correlation coefficient of 0.45. The persistence of other shocks hover around 0.94. As expected from the high variance of

⁸We also explore an alternate version of the Full Model where we add net-worth shocks (surprise and anticipated) in place of marginal efficiency of investment shocks, such that on the financial side the model includes stochastic processes for net-worth, default cost and risk. In the estimated version of this model, net-worth shocks play a minimal role in accounting for COD as well as the other observables, while default cost and risk shocks play an even more significant role than in the Full Model. The log data density strongly favours the Full Model to this alternate one, however, so we do not present the results of this alternative model.

Figure 3: **Benchmark Model (no Default Cost or Risk Shocks): Historical COD and Smoothed COD.** Historical COD is actual observed data. Smoothed COD is estimate of COD derived from the Kalman smoother at the posterior mode, given all observations. The difference between the two lines indicates the role of measurement error in accounting for the variation of Historical COD.

COD, anticipated and unanticipated default cost shocks have amongst the highest standard deviations (1.4 for the unanticipated component and 2.4 and 5.3 for the anticipated ones). The posterior mean of the standard deviations of risk shocks, preference shocks, and government spending shocks are not far behind. Monetary policy and price markup shocks display standard deviation that are the smallest. Turning to the posterior mean of the economic parameters in Table 4, we see estimates that are in line with the literature for the most part. We note that the estimate of the steady state default cost is somewhat lower (0.17) than in [Christiano et al. \(2010\)](#) (0.21) but higher than the calibrated value

used in [Bernanke et al. \(1999\)](#).

Panel 3 of Table 6 displays the relative standard deviation of the COD ratio for the smoothed COD series based on the actual estimated shocks in the Full Model as well as the implied theoretical moments which are only based on the estimated parameters of the shock processes. It is not at all surprising that the model can fully replicate the COD series and therefore exactly match the observed relative variance of COD equal to 15.6 when using the smoothed shocks. More interestingly, the theoretical relative standard deviation of COD also comes very close (14.1 vs. 15.6 in the data). Recall that the equivalent theoretical moment without risk and default costs was 6.8 in comparison. The Full Model is also successful at lowering the correlation of charge-offs and defaults (0.8 *versus* 1 in the Benchmark Model).

The success of the Full Model raises the question of which of the two new shocks contributes more to delivering a high variance in COD. In order to disentangle the relative contribution of risk versus default cost shocks we calculate the same theoretical moments using the estimated posterior means as before except we set the variance of all default costs to zero. This causes a dramatic fall in the relative standard deviation of COD to a value of 1.3 while the correlation of charge-offs and defaults is 1. Doubling the variance of both anticipated and unanticipated risk shocks barely helps change the moments suggesting that the primary driver of COD variation are default cost shocks.

5.2.2 Variance decompositions

The top panel of Table 9 reports the unconditional variance decomposition results for all observables followed by one, eight and 12 period ahead results. When reporting the contribution of news shocks we have pooled news shocks at 8 and 12 periods ahead together for readability. Beginning with COD, we see that news about default costs explain 91 percent of the unconditional variance while unanticipated shocks explain another 6 percent. The impact of news versus surprise shocks reverses in panel 2 where 97 percent of

the variance in one period ahead COD comes from unanticipated shocks to default costs. As the horizon increases, the role of surprise shocks to θ fall while that of news shocks increases. Together, risk shocks account for the remainder of the variance of COD at any horizon suggesting that the general equilibrium impact of non-financial macroeconomic shocks on COD is quite small. Given the results in Table 6 discussed above, this concentration of the variance decomposition of COD is to be expected, however, the Full Model estimation allows us to investigate the ability of the added shocks (θ, σ) to move other variables of interest. Unlike measurement error in the Benchmark Model which can only account for variation in COD by construction, in the Full Model, default cost and risk shocks can (and do) play an important role in U.S. business cycles. Anticipated default cost shocks explain 17 percent of the variation in the credit spread in panel 1 while news about risk shocks account for 61 percent of the variation which is in keeping with the empirical findings of [Christiano et al. \(2010\)](#) and consistent with the theoretical results in [Gunn and Johri \(2013a\)](#). Unanticipated risk shocks account for another 11 percent. The remaining ten percent or so is spread over the other shocks. At shorter horizons (see panel 2 for example) unanticipated default cost shocks account for 15 percent of the one period ahead variation in the credit spread while unanticipated shocks to risk account for 73 percent and monetary policy shocks account for 6 percent. Turning to non-financial variables, news about default costs account for 27 percent of investment growth while unanticipated and anticipated risk shocks account for 6 and 31 percent. Shocks to monetary policy and marginal efficiency of investment are the other sources of variation. Our two financial shocks play a reduced but still important role in output growth (and hours variation), as do shocks to monetary policy and preferences. Wage and price markup shocks appear to drive the bulk of movements in wage growth and inflation while nominal interest rate movements come from monetary policy, preference as well as default cost and risk shocks mainly. Like [Christiano et al. \(2010\)](#), our study

finds only a marginal role for technology shocks (whether anticipated or not).⁹

5.2.3 Dynamic correlations and impulse responses

In order to get further insight into the ability of the Full Model to capture the dynamic correlation patterns uncovered in U.S. data in Section 2, we calculate theoretical moments implied by the Full Model using the estimated parameters. These are displayed in Table 8. Like the data, the Full Model displays negative correlations between COD and investment (as well as output, but at a lower degree) both contemporaneously, and when lagged by one or two quarters. Moreover, the model displays a positive correlation between COD and the credit spread series which is also a feature of the data. Given our choice of observables in the estimation, the dynamic correlations calculated with smoothed series match those reported in Table 1.

Table 8: Dynamic theoretical correlations of COD: Full Model

Quarter	Variable		
	output	investment	credit spread
X_t	-0.06	-0.16	0.59
X_{t-1}	-0.04	-0.11	0.33
X_{t-2}	-0.02	-0.06	0.13

We now present impulse responses to the two key shocks that influence COD in order to understand the co-movement patterns discussed thus far. Figures 4, 5, 6 and 7 show the impulse responses to a surprise θ shock, an anticipated 12 period-out θ shock, a surprise σ^e shock and an anticipated 12 period-out σ^e shock respectively. Each figure shows

⁹In order to understand if the presence of COD as an observable is crucial to our finding that default cost and risk shocks play an important role in both financial and non financial variables over the business cycle, we also estimated the Full Model without including COD as an observable. The results of this estimation are available from the authors. The unconditional variance decomposition results for the importance of default cost news shocks are similar to those shown in the paper, however surprise shocks play more of a role in explaining non-financial variables. Risk shocks play less of a role overall at all horizons, especially for the credit spread and investment with default cost shocks gaining at the expense of risk shocks. The weakening of the importance of risk shocks in the absence of another financial variable beyond the credit spread is similar to the findings in [Christiano et al. \(2010\)](#).

the Bayesian impulse response in percent deviations from steady state to an estimated standard deviation of the respective shock, shown in the last panel.¹⁰

Firstly, we note in all four figures, a positive shock triggers a co-moving fall in the median response of consumption, investment, output and hours. Additionally, inflation and the nominal interest rate move only slightly. The underlying intuition of how a financial accelerator model economy such as this responds to these various shocks was discussed in considerable detail in [Gunn and Johri \(2013a\)](#), [Christiano et al. \(2014\)](#) and [Gunn \(2018\)](#), so we summarize these effects only briefly here and refer to those works for details. For both the θ and σ^e processes, a surprise shock has the net effect of shifting the menu of contracts available under the debt contract, altering the leverage available, and resulting in a change in demand by entrepreneurs for new physical capital. With adjustment costs to investment, the propagation mechanisms implicit in the financial accelerator then take effect as the change in investment in equilibrium leads to a change in asset prices, immediately impacting entrepreneurial net-worth and furthering the impact on terms of credit and investment. In the cases of anticipated shocks for both these processes, agents look forward to the effects described above in the future when the shock is expected to hit. The asset pricing-balance sheet feedback of the financial accelerator then plays a critical role in transferring this news to the real economy in the present: asset prices react immediately to the expected future events, leading to a change in credit conditions and thus investment in the present.¹¹ As should be clear, in all cases, investment in physical capital is a key conduit for these shocks, and the significant role of investment in the variance decomposition discussed earlier is testament to this.

¹⁰Recall that the shock process for θ was specified as percent deviations of the “gross rate” $1 + \Theta_t$ from steady state, which is approximately equivalent to absolute deviations of θ_t from steady state. For comparability, we show the θ shocks in the impulse responses in units of percent deviations from steady state of θ_t implied by the estimated posterior mean of the standard deviation.

¹¹The particular “flow-form” of investment adjustment costs used here - and ubiquitous in the DSGE literature - also play a role in transferring the expected future events to the present through the investment channel, but they are not necessary. See [Gunn and Johri \(2013a\)](#) and [Gunn \(2018\)](#) for versions of the model that use the “level-form” of adjustment costs used by [Bernanke et al. \(1999\)](#) in the original financial accelerator model.

Overall, the four figures suggest that the qualitative response of these six main business cycle variables is very similar for all four shocks. Where the four cases differ, however, is in the responses of the credit spread and COD. A surprise shock to either θ or σ^e leads to an immediate rise in the credit spread and COD followed by a gradual fall back towards steady state. In contrast, the associated news shocks for θ and σ^e result in a muted initial response of both the credit spread and COD as the other real variables fall, followed by an eventual rise in the credit spread and COD as the real variables trough.

While it is clear the two news shock cases for θ and σ^e are qualitatively similar, Figures 5 and 7 show that there is an important relative quantitative difference between the two cases. While each respective shock eventually causes output to trough in the order of 1% below steady state, the accompanying rise in COD is significantly larger for the θ shock than for the σ^e shock. Given the high volatility of COD in the data, this relative magnitude feature is likely a factor leading to the anticipated component of θ shocks accounting for a much larger proportion of COD in the variance decomposition shown earlier than that of the anticipated component of σ^e shocks. It is also worth noting that this relative magnitude difference between the two shocks would not likely be rectified by assigning a "larger" shock size to σ^e : such a shock would only move output (and COD) more, but do nothing to change the relative magnitude of the response of COD and output. Recall that the variation in COD in the data is much larger than the variation in output.

The dynamic co-movement patterns found in the data and displayed by the model reflect these impulse responses as well. Note the hump-shaped pattern in the response of output and investment which trough about eight quarters after the surprise default cost shock and more than ten quarters after the surprise risk shock. In contrast, COD peaks immediately on impact of both shocks. This dynamic negative relationship between COD and economic activity is considerably weakened in the case of anticipated risk shocks because COD shows a tendency to fall in the quarters immediately prior to the actual

realization of the anticipated shock. This reflects the impact of the fall in investment on the price of capital and thereby on net worth and leverage (not shown) which, in turn, causes movement in $\bar{\omega}$. Recall that prior to period 12, the distribution of idiosyncratic shocks to entrepreneurs has not yet changed, so COD can only respond to $\bar{\omega}$. The positive co-movement between COD and credit spread can also be clearly seen in these impulse responses, which, as we discussed earlier is a feature of the unconditional data.

We conclude that a business cycle model augmented with default cost shocks can not only help rationalize the behavior of COD and credit spread but also play an important role in the observed variation of hours worked, investment growth, and output growth over the business cycle.

Table 9: Full Model (with Default Cost and Risk shocks): Variance Decomposition

<i>Unconditional</i> Observable	Shock														
	<i>tech</i>	<i>tech_{news}</i>	<i>mei</i>	<i>mei_{news}</i>	<i>gov</i>	<i>gov_{news}</i>	<i>mp</i>	<i>mp_{news}</i>	<i>mkp_p</i>	<i>mkp_w</i>	<i>pref</i>	<i>dc</i>	<i>dc_{news}</i>	<i>risk</i>	<i>risk_{news}</i>
Hours	0.7	1.1	0.4	0.5	1.3	0.7	5.5	15.4	1.6	6.6	9.9	0.1	16.7	5.4	34.4
Consumption growth	0.5	1.8	0.0	0.0	0.1	0.2	9.4	10.9	3.3	3.1	66.9	0.0	1.6	0.3	1.8
Output growth	0.3	1.2	1.3	4.3	7.4	5.8	10.5	13.0	3.9	1.7	18.8	0.1	14.6	2.7	14.4
Investment growth	0.2	0.7	3.8	13.0	0.0	0.0	4.9	10.4	2.2	0.9	0.0	0.2	26.7	6.0	31.2
Nom Int Rate	0.8	3.0	0.2	0.4	0.6	0.7	19.0	16.6	6.8	4.5	13.9	0.0	9.4	3.0	21.0
Inflation	1.2	3.5	0.0	0.0	0.3	0.3	0.4	2.1	67.3	6.3	11.2	0.0	1.2	0.7	5.5
Wage growth	0.0	0.2	0.0	0.0	0.0	0.0	0.2	0.6	4.5	92.2	0.5	0.0	0.5	0.2	1.2
Credit spread	0.4	1.2	0.2	0.1	0.0	0.0	0.6	4.2	0.3	2.3	1.5	0.2	17.0	11.0	61.0
COD	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.1	0.1	5.7	91.3	0.6	2.0
<i>Period 1</i>															
Hours	18.3	0.4	1.8	0.1	13.3	0.1	13.6	7.3	2.1	11.5	21.2	0.1	5.2	1.4	3.7
Consumption growth	0.4	1.4	0.0	0.0	0.1	0.2	11.0	8.7	3.2	2.5	71.9	0.0	0.5	0.0	0.1
Output growth	0.2	0.7	2.4	0.1	17.7	0.1	18.6	10.2	5.4	0.9	29.2	0.1	7.3	2.0	5.2
Investment growth	0.0	0.1	21.0	0.5	0.0	0.0	10.3	8.5	4.2	0.2	0.0	0.5	23.5	8.3	22.9
Nom Int Rate	0.0	0.0	0.2	0.0	1.5	0.0	81.5	1.1	10.9	0.0	3.2	0.0	0.7	0.2	0.7
Inflation	0.2	0.1	0.0	0.0	0.0	0.0	0.1	0.2	97.7	0.8	0.6	0.0	0.0	0.0	0.3
Wage growth	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	4.7	95.0	0.1	0.0	0.0	0.0	0.1
Credit spread	0.0	0.0	0.0	0.0	0.0	0.0	6.5	0.6	1.3	0.2	0.0	15.0	2.1	73.1	1.2
COD	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	97.3	0.0	2.6	0.0
<i>Period 8</i>															
Hours	2.5	1.3	1.0	0.4	2.8	0.1	11.2	16.4	3.5	7.3	21.3	0.1	15.5	3.2	13.5
Consumption growth	0.6	1.8	0.0	0.0	0.1	0.2	9.9	10.4	3.4	3.2	69.1	0.0	0.9	0.1	0.3
Output growth	0.3	1.1	1.7	0.3	10.4	0.1	13.7	13.6	4.9	1.8	24.6	0.1	12.8	2.8	11.9
Investment growth	0.1	0.4	6.5	1.0	0.0	0.0	6.9	11.2	3.1	0.6	0.0	0.2	28.8	7.8	33.2
Nom Int Rate	0.2	0.2	0.3	0.1	1.1	0.0	41.7	8.7	15.1	1.0	14.5	0.0	5.5	1.9	10
Inflation	1.1	1.6	0.0	0.0	0.2	0.1	0.4	1.5	81.9	5.0	5.2	0.0	0.2	0.3	2.7
Wage growth	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.4	4.6	93.7	0.4	0.0	0.2	0.1	0.4
Credit spread	0.2	0.0	0.7	0.1	0.0	0.0	5.3	0.6	0.9	0.9	0.3	8.6	2.2	78.0	2.1
COD	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	95.1	0.0	4.7	0.0
<i>Period 12</i>															
Hours	1.4	1.5	0.7	0.6	2.0	0.4	9.0	18.1	2.7	6.7	16.6	0.1	18.4	3.7	18.3
Consumption growth	0.5	1.8	0.0	0.0	0.1	0.2	9.9	10.3	3.5	3.1	68.8	0.0	1.1	0.1	0.6
Output growth	0.3	1.1	1.5	1.4	9.4	4.5	12.4	12.8	4.5	1.7	22.6	0.1	12.5	2.6	12.7
Investment growth	0.1	0.5	6.0	5.2	0.0	0.0	6.2	10.7	2.8	0.7	0.0	0.2	26.7	7.2	33.7
Nom Int Rate	0.4	0.5	0.2	0.2	0.9	0.4	32.2	13.7	11.8	1.6	14.9	0.0	6.4	2.4	14.5
Inflation	1.2	2.4	0.0	0.0	0.2	0.1	0.4	1.9	76.9	5.7	7.0	0.0	0.2	0.4	3.5
Wage growth	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.4	4.5	93.3	0.5	0.0	0.3	0.1	0.6
Credit spread	0.4	0.1	1.1	0.3	0.0	0.0	3.3	2.5	0.7	1.6	0.7	5.3	12.0	52.2	20
COD	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	29.6	67.9	1.7	0.7

Figure 4: **Bayesian IRF to Surprise Default Cost shock.** Plots represent the posterior distribution of impulse responses. The solid line is the mean and the shaded gray areas indicate the 90 percent highest posterior data interval.. The units of the vertical axes are percentage deviations.

6 Conclusions

U.S. banks are required to charge-off the value of losses incurred on delinquent loans after taking into account the funds that can be recovered net of all costs incurred as part of the default process. We show that the total amount charged-off does not mechanically follow the total value of defaulted funds as both vary over the business cycle. Moreover, the ratio of charge-offs to defaults is highly volatile and negatively correlated with investment and positively correlated with the credit spread.

In this paper we show that the canonical business cycle model with bank lending and endogenous defaults associated with [Bernanke et al. \(1999\)](#) cannot explain the patterns discussed above. This occurs because the funds that are charged off rise and fall in proportion to the value of defaulted loans. We obtain an expression for the ratio of

Figure 5: **Bayesian IRF to Anticipated 12-period out Default Cost shock.** Plots represent the posterior distribution of impulse responses. The solid line is the mean and the shaded gray areas indicate the 90 percent highest posterior data interval. The units of the vertical axes are percentage deviations.

charge-offs to defaults from the model and discuss the elements needed to create large fluctuations in it. We show that the usual estimated shock processes associated with typical New Keynesian models are unable to deliver the necessary volatility. This leads us to focus on two aggregate shocks that have the potential to move the ratio since they directly influence the loan contract between borrowers and lenders, namely risk shocks and default cost shocks. We augment the New Keynesian Financial Accelerator model with these two shocks and show that the estimated risk and default cost shock series not only account for most of the variance in the banking sector variables such as the ratio of charge-offs to defaults and the credit spread but also play a significant role in accounting for U.S. macroeconomic data such as investment, hours and output. Our model specification allows for both anticipated and unanticipated stochastic elements and we find that the former are very important in accounting for the variance of these variables at medium frequencies. Beyond variance decomposition, the estimated model

Figure 6: **Bayesian IRF to Surprise Risk shock.** Plots represent the posterior distribution of impulse responses. The solid line is the mean and the shaded gray areas indicate the 90 percent highest posterior data interval. The units of the vertical axes are percentage deviations.

delivers theoretical moments that display the same dynamic correlation patterns as seen in U.S. data while also generating the requisite volatility in COD.

Figure 7: **Bayesian IRF to Anticipated 12-period out Risk shock.** Plots represent the posterior distribution of impulse responses. The solid line is the mean and the shaded gray areas indicate the 90 percent highest posterior data interval.. The units of the vertical axes are percentage deviations.

References

- Ajello, A., 2016. Financial intermediation, investment dynamics, and business cycle fluctuations. *American Economic Review* 106, 2256–2303.
- An, S., Schorfheide, F., 2007. Bayesian Analysis of DSGE Models. *American Economic Review* 26, 113–172.
- Aysun, U., Honig, A., 2011. Bankruptcy costs, liability dollarization, and vulnerability to sudden stops. *Journal of Development Economics* 95, 201–211.
- Bernanke, B.S., Gertler, M., Gilchrist, S., 1999. The financial accelerator in a quantitative business cycle framework, in: Taylor, J.B., Woodford, M. (Eds.), *Handbook of Macroeconomics*. volume 1 of *Handbook of Macroeconomics*. chapter 21, pp. 1341–1393.
- Carlstrom, C.T., Fuerst, T.S., 1997. Agency costs, net worth, and business fluctuations: A computable general equilibrium analysis. *American Economic Review* 87, 893–910.
- Christiano, L., Motto, R., Rostagno, M., 2010. Financial factors in economic fluctuations. Working Paper Series. European Central Bank.
- Christiano, L.J., Eichenbaum, M., Evans, C.L., 2005. Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy. *Journal of Political Economy* 113, 1–45. URL: <http://ideas.repec.org/a/ucp/jpolec/v113y2005i1p1-45.html>.
- Christiano, L.J., Motto, R., Rostagno, M., 2003. The Great Depression and the Friedman-Schwartz hypothesis. *Proceedings* , 1119–1215 URL: <http://ideas.repec.org/a/fip/fedcpr/y2003p1119-1215.html>.
- Christiano, L.J., Motto, R., Rostagno, M., 2014. Risk shocks. *American Economic Review* 104, 27–65.
- Cooper, R., Ejarque, J., 2000. Financial intermediation and aggregate fluctuations: A quantitative analysis. *Macroeconomic Dynamics* 4, 423–447.
- Curdia, V., Woodford, M., 2009. Conventional and unconventional monetary policy .
- Fuentes-Albero, C., 2019. Financial Frictions, Financial Shocks, and Aggregate Volatility. *Journal of Money, Credit and Banking* 51, 1581–1621. URL: <https://ideas.repec.org/a/wly/jmoncb/v51y2019i6p1581-1621.html>, doi:10.1111/jmcb.12554.
- Gilchrist, S., Zakrajšek, E., 2012. Credit spreads and business cycle fluctuations. *American Economic Review* 102, 1692–1720.
- Goodfriend, M., McCallum, B.T., 2007. Banking and interest rates in monetary policy analysis: A quantitative exploration. *Journal of Monetary Economics* 54, 1480–1507. URL: <https://ideas.repec.org/a/eee/moneco/v54y2007i5p1480-1507.html>.

- Gunn, C.M., 2018. Overaccumulation, Interest, and Prices. *Journal of Money, Credit and Banking* 50, 479–511. URL: <https://ideas.repec.org/a/wly/jmoncb/v50y2018i2-3p479-511.html>.
- Gunn, C.M., Johri, A., 2011. News, Intermediation Efficiency and Expectations-driven Boom-bust Cycles. Department of Economics Working Papers. McMaster University.
- Gunn, C.M., Johri, A., 2013a. An expectations-driven interpretation of the “great recession”. *Journal of Monetary Economics* 60, 391–407.
- Gunn, C.M., Johri, A., 2013b. News, Credit Spreads and Default Costs: An expectations-driven interpretation of the recent boom-bust cycle in the U.S. Technical Report.
- Justiniano, A., Primiceri, G.E., Tambalotti, A., 2010. Investment shocks and business cycles. *Journal of Monetary Economics* 57, 132–145. URL: <https://ideas.repec.org/a/eee/moneco/v57y2010i2p132-145.html>.
- Justiniano, A., Primiceri, G.E., Tambalotti, A., 2011. Investment shocks and the relative price of investment. *Review of Economic Dynamics* 14, 102–121.
- Kiyotaki, N., Moore, J., 2012. Liquidity, Business Cycles, and Monetary Policy. Working Paper 17934. National Bureau of Economic Research.
- Levin, A.T., Natalucci, F.M., Zakrajsek, E., 2004. The magnitude and cyclical behavior of financial market frictions. Technical Report.
- Schmitt-Grohe, S., Uribe, M., et al., 2007. Optimal inflation stabilization in a medium-scale macroeconomic model. *Monetary policy under inflation targeting*, 125–186.
- Smets, F., Wouters, R., 2007. Shocks and frictions in us business cycles: A bayesian dsge approach. *The American Economic Review* 97, 586–606.

7 Appendix

A Additional Model Detail

A.1 Agency problem and debt-contract

The discussion in the main text regarding the financial intermediary implies that in each aggregate state in period t , the financial intermediary's budget constraint is

$$\xi_t = R_t^a A_t, \quad (\text{A.1})$$

where ξ_t is the intermediary's return on its entire loan portfolio after idiosyncratic uncertainty has been realized, and where R_t^a and A_t are predetermined.

In the financial contract, the cut-off value $\bar{\omega}_{it}$ is defined as

$$\bar{\omega}_{it+1} R_{t+1}^k q_t K_{it+1} = R_{t+1}^l B_{it+1}. \quad (\text{A.2})$$

If the entrepreneur's realization exceeds the threshold such that $\omega_{t+1}(i) \geq \bar{\omega}_{t+1}(i)$, the entrepreneur pays the financial intermediary the contracted amount $R_{it+1}^l B_{it+1}$, keeping the amount $\omega_{it+1} R_{t+1}^k q_t K_{it+1} - R_{it+1}^l B_{it+1}$. If $\omega_{it+1} < \bar{\omega}_{it+1}$, the entrepreneur defaults, receives nothing, and the financial intermediary receives $(1 - \theta_t) \omega_{it+1} R_{t+1}^k q_t K_{it+1}$. As with R_{it}^l , $\bar{\omega}_{it}$ adjusts to reflect the aggregate ex-post realizations of the aggregate state in period t .

Given these contract details, we can write the financial intermediary's expected return on a given loan contract in a given aggregate contingency in period $t + 1$ as

$$\xi_{it+1} = [1 - F_t(\bar{\omega}_{it+1})] R_{it+1}^l B_{it+1} + (1 - \theta_{t+1}) \int_0^{\bar{\omega}_{it+1}} \omega R_{t+1}^k q_t K_{it+1} dF(\omega, \sigma_t^e) \quad (\text{A.3})$$

Substituting in (A.2), we can write (A.3) in terms of the cut-off $\bar{\omega}$ as

$$\xi(\bar{\omega}_{it+1}, \theta_{t+1}) = \left[[1 - F_t(\bar{\omega}_{it+1})] \bar{\omega}_{it+1} + (1 - \theta_{t+1}) \int_0^{\bar{\omega}_{it+1}} \omega dF(\omega, \sigma_t^e) \right] R_{t+1}^k q_t K_{it+1}. \quad (\text{A.4})$$

Defining the financial intermediary's expected share of gross returns $\Gamma(\bar{\omega})$ as

$$\Gamma_t(\bar{\omega}_{it}) = [1 - F_t(\bar{\omega}_{it})] \bar{\omega}_{it} + \int_0^{\bar{\omega}_{it}} \omega dF(\omega, \sigma_t^e), \quad (\text{A.5})$$

and defining $G_t(\bar{\omega})$ as

$$G_t(\bar{\omega}_{it}) = \int_0^{\bar{\omega}_{it}} \omega dF(\omega, \sigma_t^e), \quad (\text{A.6})$$

we can re-write the financial intermediary's expected return on a given loan contract in

a given aggregate contingency as

$$\xi_{t+1}(\bar{\omega}_{it+1}, \theta_{t+1}) = [\Gamma_t(\bar{\omega}_{it+1}) - \theta_{t+1}G_t(\bar{\omega}_{it+1})] R_{t+1}^k q_t K_{it+1}, \quad (\text{A.7})$$

where the terms in square brackets represent the financial intermediary's share of profits net of default costs. The requirement that the financial intermediary earn an expected return in every aggregate contingency equal to its opportunity cost of funds,

$$\xi_{t+1}(\bar{\omega}_{it+1}, \theta_{t+1}) = R_{t+1} B_{it+1} \quad (\text{A.8})$$

then serves as a restriction to define a menu of contracts over loan quantity and cut-off value for the entrepreneur. Substituting in $q_t K_{it+1} = X_{it+1} + B_{it+1}$ and (A.7) we can then write this as

$$[\Gamma_t(\bar{\omega}_{it+1}) - \theta_{t+1}G_t(\bar{\omega}_{it+1})] R_{t+1}^k q_t K_{it+1}(i) = R_{t+1}^a (q_t^n K_{it+1} - X_{it+1}) \quad (\text{A.9})$$

which for a given level of net-worth X_{it+1} defines a menu of contracts relating the entrepreneur's choice of K_{it+1} to the cut-off $\bar{\omega}_{it+1}$.

A.2 Entrepreneur's contract problem

The entrepreneur's expected gross return, conditional on the ex-post realization of the aggregate state but before the resolution of idiosyncratic risk, is given by

$$V_{it+1}^k = \int_{\bar{\omega}_{it+1}}^{\infty} \omega R_{t+1}^k q_t K_{it+1} dF(\omega) - R_{it+1}^l B_{it+1}. \quad (\text{A.10})$$

Substituting in the definitions above yields

$$V_{it+1}^k = [1 - \Gamma_t(\bar{\omega}_{it+1})] R_{t+1}^k q_t K_{it+1}, \quad (\text{A.11})$$

where $1 - \Gamma(\bar{\omega}_{it+1})$ is the entrepreneur's expected share of gross returns.

For a given level of net-worth X_{it+1} , the entrepreneur's optimal contacting problem is then

$$\max_{K_{it+1}, \bar{\omega}_{it+1}} E_t \{V_{it+1}^k\} \quad (\text{A.12})$$

subject to the condition that the financial intermediary's expected return on the contract equal its opportunity cost of its borrowing, equation (3). Letting λ_{it+1} be the ex-post value of the Lagrange multiplier conditional on realization of the aggregate state, the first-order conditions are then

$$\Gamma'_t(\bar{\omega}_{it+1}) - \lambda_{t+1} [\Gamma'_t(\bar{\omega}_{it+1}) - \theta_{t+1}G'_t(\bar{\omega}_{it+1})] = 0 \quad (\text{A.13})$$

$$E_t \left\{ [1 - \Gamma_t(\bar{\omega}_{it+1})] \frac{R_{t+1}^k}{R_{t+1}^a} + \lambda_{t+1} \left([\Gamma_t(\bar{\omega}_{it+1}) - \theta_{t+1}G_t(\bar{\omega}_{it+1})] \frac{R_{t+1}^k}{R_{t+1}^a} - 1 \right) \right\} = 0 \quad (\text{A.14})$$

$$[\Gamma_t(\bar{\omega}_{it+1}) - \theta_{t+1}G_t(\bar{\omega}_{it+1})] R_{it+1}^k q_t K_{it+1} - R_{t+1}^a (q_t^n K_{it+1} - X_{it+1}) = 0 \quad (\text{A.15})$$

where (A.13) and (A.15) hold in each contingency, but (A.14) holds only in expectation.

A.3 Household

The stand-in household's lifetime utility is given by

$$E_0 \sum_{t=0}^{\infty} \beta^t J_t \left[\log(C_t - bC_{t-1}) - \Psi_L \frac{N_t^{h^{1+\sigma_L}}}{1 + \sigma_L} \right] \quad (\text{A.16})$$

where C_t is consumption, N_t is hours-worked, β is the subjective discount factor and J_t follows an exogenous stochastic preference process which we refer to as a *preference shock*.

The household enters into each period with real financial securities A_t which serve as deposits with the financial intermediary, and nominal bonds B_t^n , earning risk-free gross real rate of return R_t^a and risk-free gross nominal rate of return R_t^n respectively, receiving nominal wage W_t^h for supplying hours N_t^h to the labour union, and receiving a share of real profits from the capital-producers, goods-producers, financial intermediary, labour union and employment agency, denoted collectively as F_t . At the end of the period, the household chooses its consumption C_t , its holdings of financial securities A_{t+1} and nominal bonds B_{t+1}^n . The household's period t budget constraint is given by

$$C_t + A_{t+1} + \frac{B_{t+1}^n}{P_t} = R_t^a A_t + R_t^n \frac{B_t^n}{P_t} + \frac{W_t^h}{P_t} N_t^h + F_t, \quad (\text{A.17})$$

where P_t is the price of the final good in terms of the nominal unit under the control of the central bank. The household's problem is to choose sequences of C_t , N_t^h , A_{t+1} and B_{t+1}^n to maximize (A.16) subject to (A.17).

Letting λ_t be the Lagrange multiplier associated with the household's budget constraint, the first-order conditions with respect to C_t , N_t^h , A_{t+1} and B_{t+1}^n are respectively

$$\lambda_t = \frac{J_t}{C_t - bC_{t-1}} - \beta b E_t \frac{J_{t+1}}{C_{t+1} - bC_t} \quad (\text{A.18})$$

$$\lambda_t \frac{W_t^h}{P_t} = \Psi_L J_t N_t^{h\sigma_L} \quad (\text{A.19})$$

$$\lambda_t = \beta E_t R_{t+1}^a \quad (\text{A.20})$$

$$\lambda_t = \beta E_t R_{t+1}^n \frac{P_t}{P_{t+1}}. \quad (\text{A.21})$$

A.4 Final goods firm and intermediate goods firms

The final goods firm produces the final good Y_t by combining differentiated intermediate goods $y_{jt}, j \in [0, 1]$, according to the technology

$$Y_t = \left[\int_0^1 y_{jt}^{\nu_{pt}} dj \right]^{\frac{1}{\nu_{pt}}}, \quad 0 < \nu_p \leq 1. \quad (\text{A.22})$$

where ν_{pt} follows an exogenous stochastic process which we refer to as a *price markup shock*. The producer acquires each j^{th} intermediate good at price P_{jt} , and sells the final good at price P_t where it may be used as a consumption or as an input into the production of investment goods. Each period the producer chooses intermediate goods $y_{jt} \forall j$ to maximize profits $P_t Y_t - \int_0^1 P_{jt} y_{jt} dj$, yielding a standard demand curve

$$y_{jt} = \left[\frac{P_{jt}}{P_t} \right]^{\frac{1}{\nu_p - 1}} Y_t, \quad (\text{A.23})$$

for the j^{th} intermediate good, and nominal price index

$$P_t = \left[\int_0^1 P_{jt}^{\nu_p / (\nu_p - 1)} dj \right]^{\frac{(\nu_p - 1)}{\nu_p}}. \quad (\text{A.24})$$

The j^{th} intermediate goods firms produces the differentiated good y_{jt} according to the technology

$$y_{jt} = z_t \tilde{n}_{jt}^\alpha \tilde{k}_{jt}^{1-\alpha}, \quad (\text{A.25})$$

where z_t is total factor productivity that follows an exogenous stochastic process which we refer to as a *technology shock*, $\tilde{n}_{jt}$ is total hours-worked, and $\tilde{k}_{jt}$ is physical capital services. Hours-worked is a composite of both household and entrepreneurial labour, such that $\tilde{n}_{jt} = n_{jt}^\Omega (n_{jt}^e)^{1-\Omega}$, where n_{jt} is worker labour, n_{jt}^e is entrepreneurial labour, and where Ω parameterizes the elasticity of the hours composite to household labour. Capital services is defined by $\tilde{k}_{jt} = u_{jt} k_{jt}$, where k_{jt} is the stock of physical capital and u_{jt} is the utilization rate of that stock, chosen by the entrepreneurs.

The j^{th} firm hires n_{jt} and n_{jt}^e at wage rates W_t and w_t^e respectively, rents capital services $\tilde{k}_{jt}$ at rate r_t , and sells its output at price P_{jt} . Intermediate goods firms have market power, and can thus set prices subject to the demand curve (A.23). The firms face Calvo frictions in setting their prices such that each period they can re-optimize prices with probability $1 - \zeta_p$. A firm that is unable to re-optimize its price in a given period re-sets it according to the indexation rule $P_{jt} = P_{jt-1} \pi_{t-1}^{\iota_p} \pi^{1-\iota_p}$, $0 \leq \iota_p \leq 1$, where $\pi_t = P_t/P_{t-1}$ and π is its steady state, and where $0 \leq \iota_p \leq 1$. A firm that can re-optimize its price in period t chooses its price P_{jt}^* to maximize

$$E_t \sum_{s=0}^{\infty} \zeta_p^s \beta^s \frac{\lambda_{t+s} P_t}{\lambda_t P_{t+1}} [P_{jt}^* (\Pi_{k=1}^s \pi_{t+k-1}^{\iota_w} \pi^{1-\iota_w}) y_{jt+s} - P_{t+s} S(y_{jt+s})], \quad (\text{A.26})$$

where $\beta^s \frac{\lambda_{t+s} P_t}{\lambda_t P_{t+1}}$ is the household owner's nominal discount factor, given the production technology (A.25) and the demand curve for y_{jt} , and where $S(y_{jt})$ is the firm's real cost function as a solution to its cost-minimization problem for a given level of output y_{jt} .

A.5 Employment agency and employment unions

The employment agency combines differentiated labour $n_{qt}, q \in [0, 1]$, into a composite N_t according to

$$N_t = \left[\int_0^1 n_{qt}^{\nu_{wt}} dq \right]^{\frac{1}{\nu_{wt}}}, \quad 0 < \nu_w \leq 1. \quad (\text{A.27})$$

where ν_{wt} follows an exogenous stochastic process which we refer to as a *wage markup shock*. Each period the agency acquires each q^{th} differentiated labour service at wage W_{qt} from the labour union, and sells the composite labour to the intermediate goods producers for wage W_t . The agency chooses $n_{qt} \forall q$ to maximize profits $W_t N_t - \int_0^1 W_{qt} n_{qt} dq$, yielding a demand function

$$n_{qt} = \left[\frac{W_{qt}}{W_t} \right]^{\frac{1}{\nu_w - 1}} N_t, \quad (\text{A.28})$$

for the q^{th} labour type, and wage index

$$W_t = \left[\int_0^1 W_{qt}^{\nu_w / (\nu_w - 1)} dq \right]^{\frac{(\nu_w - 1)}{\nu_w}}. \quad (\text{A.29})$$

The q^{th} labour union acquires labour N_t^h from the household at wage W_t^h , differentiates it into labour type $n_{qt}, q \in [0, 1]$, and then sells it to the employment agency for wage W_{qt} . The unions have market power, and can thus choose the wage for each labour type subject to the labour demand curve (A.28). The unions face Calvo frictions in setting their wages, such that each period they can re-optimize wages with probability $1 - \zeta_w$. A union that is unable to re-optimize wages re-sets it according to the indexation rule $W_{qt} = W_{qt-1} \pi_{t-1}^{\iota_w} \pi^{1-\iota_w}$, $0 \leq \iota_w \leq 1$, where $\pi_t = P_t/P_{t-1}$ and π is its steady state, and where $0 \leq \iota_w \leq 1$. A union that can re-optimize its wage in period t chooses its wage W_{qt}^* to maximize

$$E_t \sum_{s=0}^{\infty} \zeta_w^s \beta^s \frac{\lambda_{t+s} P_t}{\lambda_t P_{t+1}} \left[W_{qt}^* (\Pi_{k=0}^s \pi_{t+k-1}^{\iota_w} \pi^{1-\iota_w}) - W_{t+s}^h \right] n_{qt+s}, \quad (\text{A.30})$$

subject to the demand curve for n_{qt} .

A.6 Capital-producer

The competitive capital-goods producer operates a technology that combines existing capital with new investment goods to create new installed capital. At the end of each period it purchases existing capital K_t^k from entrepreneurs at price $\bar{q}_t$, combining it with investment I_t to yield new capital stock K_t^{nk} , which it sells back to entrepreneurs in the

same period at price q_t . The capital-producer faces investment adjustment costs in the creation of new capital, and incurs depreciation in the process, so that

$$K_t^{nk} = (1 - \delta)K_t^k + I_t \left[1 - S \left(\frac{m_t I_t}{I_{t-1}} \right) \right], \quad (\text{A.31})$$

where m_t follows an exogenous stochastic process that we refer to as a *marginal efficiency of investment (MEI) shock* (see Justiniano et al. (2010)), and $S(x)$ is an investment adjustment cost function based on Christiano et al. (2005) with the properties $S(x) = 0$, $S'(x) = 0$, and $S''(x) = s''$, where s'' is a parameter. The capital producer's period t profits are given by $\Pi_t^k = q_t^n K_t^{nk} - q_t K_t^k - I_t$. Since the capital producer faces intertemporal investment adjustment costs, it faces a dynamic problem, choosing K_t^{nk} , K_t^k and I_t to maximize

$$E_0 \sum_{t=0}^{\infty} \frac{\beta^t \lambda_t}{\lambda_0} \Pi_t^k \quad (\text{A.32})$$

subject to (A.31).

The capital producer's first-order conditions are given by

$$\bar{q}_t = q_t(1 - \delta) \quad (\text{A.33})$$

$$q_t^n - \frac{1}{\Upsilon_t} - q_t^n S \left(\frac{m_t I_t}{I_{t-1}} \right) - q_t^n S' \left(\frac{m_t I_t}{I_{t-1}} \right) \frac{m_t I_t}{I_{t-1}} + E_t \left\{ \frac{\beta \lambda_{t+1}}{\lambda_t} q_{t+1}^n m_{t+1} \frac{I_{t+1}^2}{I_t^2} S' \left(\frac{m_{t+1} I_{t+1}}{I_t} \right) \right\}. \quad (\text{A.34})$$

A.7 Monetary policy

Monetary policy takes the form of a monetary authority that sets the gross nominal interest rate R_{t+1}^n according to a rule in the form

$$\frac{R_{t+1}^n}{R^n} = \left(\frac{R_t^n}{R^n} \right)^{\rho_R} \left[\left(\frac{\Pi_t}{\Pi} \right)^{\phi_\pi} \left(\frac{Y_t}{Y_{t-1}} \right)^{\phi_y} \right]^{1-\rho_R} \eta_t, \quad (\text{A.35})$$

where variables without subscripts are steady-state values, Π_t is the gross inflation rate, and η_t follows an exogenous stochastic process that we refer to as a *monetary policy shock*.

A.8 Equilibrium

Equilibrium in this economy is defined by contingent sequences of C_t , $c_t^e(i) \forall i$, N_t , N_{th} , $n_{jt} \forall j$, $u_{jt} \forall j$, $n_{jt}^e \forall j$, $P_{jt} \forall j$, $y_{jt} \forall j$, I_t , A_{t+1} , $K_{it+1} \forall i$, $u_{it} \forall i$, $B_{it+1} \forall i$, $\bar{\omega}_{it+1} \forall i$, K_t^{nk} , K_t^k , B_{t+1}^n , W_t , W_t^h , W_t^e , W_{qt} , r_t , R_{t+1}^a , $R_{it+1}^l \forall i$, R_t^k , $\bar{q}_t$, q_t , R_t^n , P_t , that satisfy the following conditions: (i) the allocations solve the household's, final goods-producer's, intermediate goods producers', financial intermediary's, entrepreneurs', capital producer's, employment agency's and employment union's problems, taking prices as given, (ii) all markets clear, (iii) the resource constraint $C_t + C_t^e + q_t^n \Phi \left(\frac{I_t}{K_t} K_t \right) + \theta_t G(\bar{\omega}_t) q_{t-1}^n R_t^k K_t = Y_t$ holds, where

$\int_0^1 K_{it+1} = K_{t+1}$, $\int_0^1 B_{it+1} = B_{t+1}$, $\int_0^1 X_{it+1} = X_{t+1}$, $\int_0^1 c_{it+1}^e = C_{t+1}^e$, $\int_0^1 N_i^e = N^e = 1$ and where all entrepreneurs choose the same cut-off such that $\bar{\omega}_{it+1} = \bar{\omega}_{t+1} \quad \forall i$, and therefore $R_{it+1}^l = R_{t+1}^l \quad \forall i$.

Equilibrium in the capital goods market implies that $K_t^{nk} = K_{t+1}$ and $K_t^k = K_t$, and equilibrium in the securities market implies that $A_t = B_t$. Nominal bonds are in zero net-supply such that $B_t^n = 0$.

In equilibrium the financial intermediary's return on its entire loan portfolio just covers its opportunity cost of funds, implying that its budget constraint holds in every aggregate contingency and after idiosyncratic uncertainty is resolved as

$$[\Gamma_t(\bar{\omega}_{t+1}) - \theta_{t+1}G_t(\bar{\omega}_{t+1})] R_{t+1}^k q_t K_{t+1} = R_{t+1}^a A_{t+1}. \quad (\text{A.36})$$

Aggregate net-worth evolves as the accumulated gross returns of surviving entrepreneurs plus their labour income. Letting V_t be aggregate gross entrepreneurial returns, we can compute it as the average gross idiosyncratic returns,

$$V_t = [1 - \Gamma_t(\bar{\omega}_t)] R_t^k q_{t-1}^n K_t, \quad (\text{A.37})$$

which after making substitutions yields

$$V_t = R_t^k q_{t-1}^n K_t - [R_t^a B_t + \theta_t G_t(\bar{\omega}_t) R_t^k q_{t-1}^n K_t], \quad (\text{A.38})$$

so that aggregate net-worth evolves as

$$X_{t+1} = \gamma V_t + w_t^e. \quad (\text{A.39})$$

Finally, entrepreneurial consumption C_t^e is equal to the aggregated gross return of dying entrepreneurs,

$$C_t^e = (1 - \gamma)V_t. \quad (\text{A.40})$$

For reference later in the discussion of our results, we also define the equilibrium real risk-free net interest rate as $r_t^f = \frac{1}{E_t \beta \frac{\lambda_{1t} + 1}{\lambda_{1t}}} - 1$, the credit spread as $R_t^l - R_t^a$, and leverage as $L_t = \frac{q_t^n K_{t+1}}{X_{t+1}}$.

B Data

- Real Gross Domestic Product, 3 Decimal, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate.
Source: search on series code GDPC96 at <https://fred.stlouisfed.org/>
- Gross Domestic Product - Implicit Price Deflator - 1996=100, Seasonally Adjusted
Source: search on series code GDPDEF at <https://fred.stlouisfed.org/>
- Personal Consumption Expenditures, Billions of Dollars, Seasonally Adjusted Annual Rate
Source: search on series code PCEC at <https://fred.stlouisfed.org/>
- Fixed Private Investment, Billions of Dollars, Seasonally Adjusted Annual Rate
Source: search on series code FPI at <https://fred.stlouisfed.org/>
- Civilian Employment: Sixteen Years and Over, Thousands, Seasonally Adjusted
Source: search on series code CE16OV at <https://fred.stlouisfed.org/>
- Effective Federal Funds Rate
Source: search on FEDFUNDS at <https://fred.stlouisfed.org/>
- Average Weekly Hours Duration, Nonfarm Business, All Persons, : index, 1992 = 100, Seasonally Adjusted
Source: search on series code PRS85006023 at <https://fred.stlouisfed.org/>
- Hourly Compensation Duration, Nonfarm Business, All Persons, : index, 1992 = 100, Seasonally Adjusted.
Source: Search series id PRS85006103 at U.S. Bureau of Labour Statistics, <http://data.bls.gov/cgi-bin/srgate>
- Labor Force Status : Civilian noninstitutional population - Age : 16 years and over - Seasonally Adjusted - Number in thousands.
Source: Search series id LNS10000000 at U.S. Bureau of Labour Statistics, <http://data.bls.gov/cgi-bin/srgate>
- Credit Spread: Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity, Percent, Quarterly, Not Seasonally Adjusted.
Source: search on series code BAA10YM at <https://fred.stlouisfed.org/>
- Charge-offs: Total charge-offs on Total Loans and Leases, All FDIC-Insured Institutions, Millions of Dollars,
Source: Quarterly Loan Portfolio Performance Indicators
<https://www.fdic.gov/bank/analytical/qbp/timeseries/loan-performance.xls>
- Defaults: Loans 90 days or more past due, All FDIC-Insured Institutions, Millions of Dollars,
Source: Quarterly Loan Portfolio Performance Indicators
<https://www.fdic.gov/bank/analytical/qbp/timeseries/loan-performance.xls>

- QUSPAMUSDA: Total Credit to Private Non-Financial Sector, Adjusted for Breaks, for United States. Source: search on series code QUSPAMUSDA at <https://fred.stlouisfed.org/>

Table A.1: Comparison of alternative news specifications evaluated at the mode.

Specification	Log Data Density
No News	-1836.25
News 4pd and 8pd	-1830.36
News 8pd and 12 pd	-1826.86
News 4pd, 8pd and 12pd	-1829.33

Table A.2: *Benchmark Model*: priors and posteriors - Economic parameters

Description	Parameter	Prior mean	Posterior mode	90% HPD interval	Prior distrib.	Prior std dev.
Habit in consumption	b'	0.5	0.40	0.0067	beta	0.1
Curvature, investment adjust cost	s''	4	2.07	0.1101	norm	2
Curvature, utilization cost	ϵ	0.5	0.42	0.0101	beta	0.1
Monetary policy smoothing parameter	ρ_{rn}	0.75	0.94	0.0087	beta	0.1
Monetary policy weight on inflation	ϕ_{pi}	1.5	2.50	0.0245	gamm	0.25
Monetary policy weight on output	ϕ_y	0.25	0.42	0.0089	gamm	0.05
Calvo price stickiness	ζ_p	0.66	0.86	0.0077	beta	0.15
Calvo wage stickiness	ζ_w	0.66	0.83	0.0078	beta	0.15
Price indexing weight on inflation	ι_p	0.5	0.20	0.021	beta	0.15
Price indexing weight on wage inflation	ι_w	0.5	0.78	0.0102	beta	0.15
Steady state default cost	θ	0.12	0.05	0.0013	beta	0.1
Steady state default rate	$F(\bar{\omega})$	0.008	0.02	0.0002	gamm	0.001

Table A.3: *Benchmark Model*: priors and posteriors - Shock parameters

Description	Parameter	Prior mean	Posterior mode	90% HPD interval		Prior distrib.	Prior std dev.
autocorrelation of shocks							
Technology process	ρ_z	0.5	0.61	0.0123	beta	0.2	
MEI process	ρ_{mei}	0.5	0.72	0.0069	beta	0.2	
Preference process	ρ_J	0.5	0.98	0.0154	beta	0.2	
Government Spending process	ρ_g	0.5	1.00	0.0332	beta	0.2	
Price markup process	ρ_{ν_p}	0.5	0.14	0.0192	beta	0.2	
Wage markup process	ρ_{ν_w}	0.5	0.19	0.0222	beta	0.2	
standard deviation of shocks							
Technology, unanticipated	ϵ_z	0.5	0.15	0.0703	invg	1	
Technology, anticipated 8pd	ϵ_z^8	0.5	0.14	0.0193	invg	1	
Technology, anticipated 12pd	ϵ_z^{12}	0.5	0.60	0.0927	invg	1	
MEI, unanticipated	ϵ_m	0.5	4.98	0.416	invg	1	
MEI, anticipated 8pd	ϵ_m^8	0.5	0.14	0.0043	invg	1	
MEI, anticipated 12pd	ϵ_m^{12}	0.5	0.44	0.0278	invg	1	
Preferences	ϵ_J	0.1	2.32	0.0577	invg	1	
Monetary policy, unanticipated	ϵ_η	0.1	0.08	0.0073	invg	1	
Monetary policy, anticipated 8pd	ϵ_η^8	0.1	0.08	0.0079	invg	1	
Monetary policy, anticipated 12pd	ϵ_η^{12}	0.1	0.09	0.0161	invg	1	
Gov't spending, unanticipated	ϵ_g	0.5	2.61	0.0186	invg	1	
Gov't spending, anticipated 8pd	ϵ_g^8	0.5	1.43	0.1963	invg	1	
Gov't spending, anticipated 12pd	ϵ_g^{12}	0.5	1.41	0.0838	invg	1	
Price markup	ϵ_{ν_p}	0.1	0.33	0.0165	invg	1	
Wage markup	ϵ_{ν_w}	0.1	0.37	0.0352	invg	1	
Measurement error	ϵ_{meas}	0.5	20.31	0.5077	invg	1	