Default Recovery Rates and Aggregate Fluctuations*

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Abstract

Default recovery rates in the US are highly volatile and pro-cyclical. We show that state-of-the-art models with a Bernanke-Gertler-Gilchrist financial accelerator mechanism imply that recovery rates are flat over the cycle. We propose a model where financially-constrained entrepreneurs face an idiosyncratic cost of redeploying liquidated capital. The resulting endogenous liquidation costs magnify the effect of the financial accelerator. We fit the model to US data and find that it explains a substantial amount of variation in recovery rates. Our mechanism alters the transmission of structural disturbances and leads to novel policy implications about the effectiveness of subsidies for liquidated assets.

Keywords: Financial accelerator; financial frictions; recovery rates; liquidation costs.

JEL Classification Numbers: C68, E44, E61.

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1 Introduction

Default recovery rates for corporate bank loans in the United States are highly volatile and procyclical, ranging from 5 to 35 percent over the last 30 years. Models of financial frictions based on the costly enforcement approach à la Kiyotaki and Moore (1997) make no predictions on recovery rates, as they abstract from defaults in equilibrium. The literature that instead follows the costly state verification approach of Bernanke, Gertler, and Gilchrist (1999, BGG) focused mostly on the dynamics of spreads and defaults, putting little emphasis on the models' predictions for the recovery rates associated with such defaults. In this paper, we show that recovery rates in this class of models are almost flat over the cycle and rarely move by more than 2 percent from their average value. This suggests that the current framework underestimates the costs of bankruptcy for financial intermediaries in a recession and overestimates them in a boom, thereby understating the severity of financial frictions. We propose and estimate a model that helps reconcile theory and empirics on recovery rates, and explore the consequences of fluctuations in these rates for business cycles.

The volatility and cyclicality of recovery rates have an intuitive explanation, provided first by Shleifer and Vishny (1992). During a downturn it is harder for a bank to sell the assets seized from a firm in financial distress, since the most productive use of these firm-specific assets would be exercised by similar businesses, which are likely to experience comparable financial difficulties. Furthermore, in times of recession, other financial institutions are trying to sell similar assets due to widespread bankruptcies. For these reasons, foreclosed assets are sold at prices below their value in best use and default recovery rates deteriorate sharply during economic downturns. In standard models of financial frictions, however, these channels are absent, as physical capital in default is assumed to be perfectly redeployable, and is therefore traded at the same price as new capital.

In this paper, we provide a micro-foundation for countercyclical liquidation costs based on Shleifer and Vishny's (1992) idea of limited redeployability of capital and liquidity-constrained collateral values. We formalize this notion in the context of a dynamic stochastic general equilibrium (DSGE) model with agency costs à la BGG by assuming that potential buyers of assets of firms in distress are non-defaulting, financially-constrained entrepreneurs, who face an idiosyncratic cost of redeploying liquidated capital. This assumption allows us to capture the idea that the most talented entrepreneurs are better managers of liquidated assets and can therefore redeploy them more easily. At the same time, financial conditions matter, and when even the best entrepreneurs are strapped for cash, the foreclosed assets may go to less efficient managers, whose valuation of the asset is lower. In recessions, when financial constraints are tight for all entrepreneurs, marginal liquidation costs rise because assets in default find a relatively worse alternative use and are traded at lower prices relative to new capital. The rise in liquidation costs results in a fall in recovery rates and an increase in the spread on borrowing rates, as creditors try to recoup their losses.

We embed this mechanism in a medium-scale New Keynesian DSGE model that we estimate using Bayesian techniques on U.S. data to assess the quantitative relevance of our mechanism. We find that, contrary to more standard models in the literature where liquidation costs are constant, our framework can explain a considerable portion of fluctuations in recovery rates. We show that the key ingredient behind these results is the interaction of our endogenous liquidation costs mechanism and financial disturbances, which we model as shocks to the net worth of entrepreneurs. Our variance decomposition also reveals that financial shocks are almost the unique drivers of defaults, recovery rates, and spreads. In line with previous findings (e.g. Christiano, Motto, and Rostagno, 2014), we find that they are also very important drivers of the business cycle.

The presence of endogenous liquidation costs significantly amplifies the effect of financial and monetary shocks on output and other key macro variables beyond the standard financial accelerator effect. When an adverse shock hits the economy, not only do markups go up and balance sheets deteriorate, but the liquidation value of assets in default plummets, as the marginal buyer of these assets is a less efficient one than in normal times. As a result, banks become more reluctant to lend to *all* entrepreneurs even if the latter have strong balance sheets, since, for the same probability of default, the potential recovery rate for the bank is now lower. In other words, lending spreads increase for all borrowers, regardless of their balance sheets. We find these additional adverse effects to be persistent and present up to 20 quarters after the shock has hit the economy.

We show that policymakers might reduce the effect of fire sales of assets in default by subsidizing liquidated capital. In our model, the subsidy can be directed to the supply side of liquidated assets represented by financial intermediaries, or to non-defaulting entrepreneurs on the demand side. If the market for liquidated capital were frictionless, the two subsidies should lead to the same allocation. This is not the case in our model because entrepreneurs are financially constrained. Paying the subsidy to entrepreneurs ex-post allows less efficient ones to buy assets in default. The resulting upward pressure on the price of liquidated capital ex-ante also reduces the purchasing power of the most efficient entrepreneurs. As a result, total liquidation costs increase. Conversely, when the subsidy is directed to financial intermediaries, it directly increases their recovery value from defaults, thereby allowing them to charge lower interest rates on existing debt obligations. Lower debt repayments increase the wealth of non-defaulting entrepreneurs, allowing the most efficient ones to redeploy a larger share of foreclosed assets. The resulting lower liquidation costs generate a smaller deadweight loss and a stronger stabilizing effect on the economy.

We make several contributions to the literature. First, we show that standard nominal rigidities and balance sheet channels in agency costs models are not sufficient to generate the pattern of recovery rates observed in the data. Second, we provide a micro-foundation for counter-cyclical liquidation costs in agency costs models based on Shleifer and Vishny (1992), which allows us to reconcile the theory and the data. Third, we show that these counter-cyclical liquidation costs propagate to the broader economy through the spread on loans charged by the banking sector, strengthening the effect of financial shocks on key macroeconomic variables. Finally, our structural estimation provides new evidence that financial shocks are the unique drivers of recovery rates, spreads, and defaults. In line with previous findings, we find that they are also very important drivers of the business cycle.

Related literature. Our paper is at the intersection of macroeconomics and finance, and bridges two literatures that have so far been relatively disconnected. There is a small empirical literature that has documented the relationship between the recovery rates at the aggregate (Mora, 2012) and industry level (Acharya, Bharath, and Srinivasan, 2007).The finance literature has analyzed jointly the behavior of defaults and recovery rates with credit risk or value-at-risk models (see Altman, Brady, Resti, and Sironi, 2005) or with more agnostic econometric models (Bruche and González-Aguado, 2010). We contribute to this literature by linking defaults and recoveries to macroeconomic fundamentals with a general equilibrium model.

There is a vast literature that uses estimated DSGE models to study business cycle fluctuations (Justiniano, Primiceri, and Tambalotti, 2010; Del Negro, Giannoni, and Schorfheide, 2015). One of our contributions is to bring recovery rates to the attention of macroeconomists. Among the literature that incorporates financial frictions, Fuentes-Albero (2019) explores the role of changes in financial factors, such as bankruptcy costs, as a source of business cycle fluctuations. Microeconomic evidence on time-varying bankruptcy costs can be found in Levin, Natalucci, and Zakrajsek (2004) who estimate the parameters of the financial contract of the BGG model, including the costs associated with defaults, on a panel of 900 U.S. firms from 1997Q1 to 2003Q3. While Fuentes-Albero (2019) models variations in the costs associated with bankruptcy as an exogenous process, we treat these costs as an endogenous object that depends on the developments of the market for the liquidated assets underlying bankruptcy. In this sense, we provide a micro-foundation for variation in bankruptcy costs that can be used for policy analysis. We provide an example of such a policy analysis that sheds light on the differential effectiveness of subsidies to the demand and supply side of assets in default.

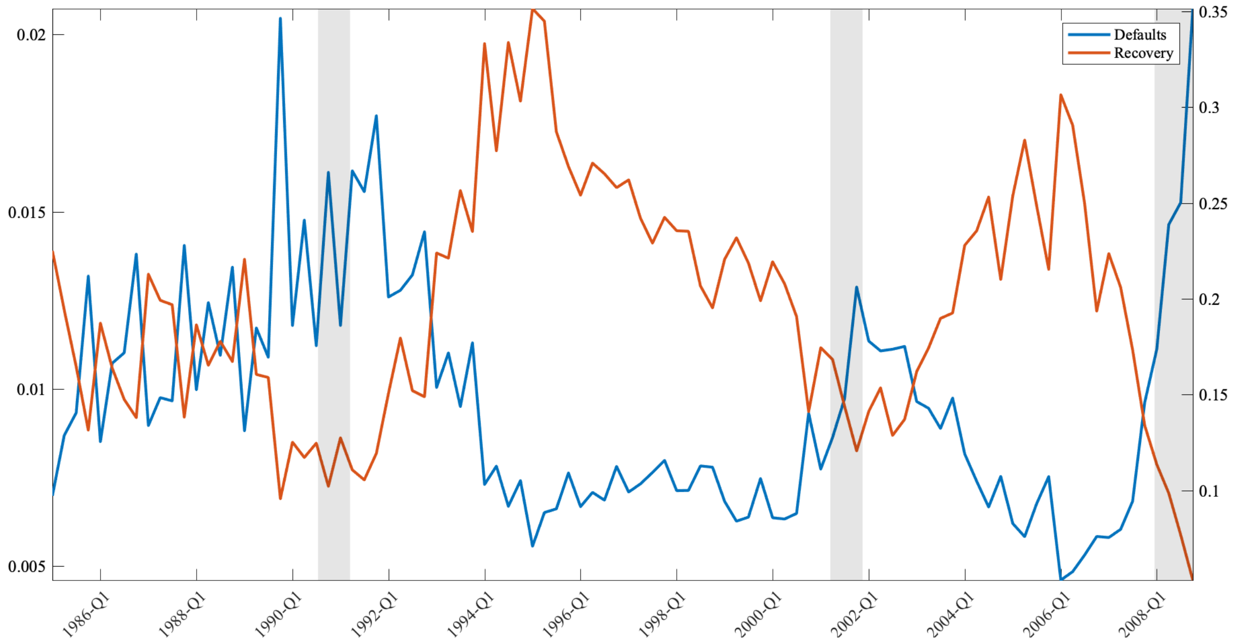
In a related paper, Choi and Cook (2012) study the effect of a concave production function for liquidation services in a small-scale financial accelerator model and show that this concavity can generate higher volatility of recovery rates. We differ from their work in two respects. First, we provide a micro-foundation for the liquidation process of foreclosed assets, which introduces an explicit role for the balance sheet of potential buyers of these assets. This leads to important differences concerning policy implications. While in their frictionless environment subsidizing the supply or demand side of the market is equivalent, in our model it is not, because the demand side of foreclosed asset is financially constrained. Second, while their findings are based on a small-scale model calibrated to match a specific set of moments, we build a medium-scale DSGE model that we estimate on macroeconomic and financial variables using full-information Bayesian methods. Our likelihood-based approach has at least two advantages. First, our approach allows us to conduct variance decompositions, model comparisons, and simulations based on estimated shocks that can improve our understanding of historical macroeconomic developments. Second, using a medium-scale model we can appraise the effect of variation in recovery rates across a number of structural shocks that have been deemed to be important for business cycles. One of our new findings is that marginal efficiency to investment shocks seem to be less important than previously thought because they imply counter-cyclical movements in asset prices and, hence, in recovery rates.

The rest of the paper proceeds as follows. Section 2 presents empirical evidence on the behavior of recovery rates over the business cycle. Section 3 develops our model with endogenous liquidation costs. Section 4 discusses our empirical approach. Section 5 presents our main results and Section 6 concludes.

2 Recovery Rates and the Business Cycle

In this section, we document the cyclical properties of defaults and recovery rates and investigate whether current macroeconomic models with financial frictions are able to explain them. Recovery rates measure the extent to which the creditor recovers the principal and accrued interest due on a defaulted debt. Our quarterly aggregate data come from Federal Deposit Insurance Corporation's (FDIC) Historical Statistics on Banking. Default rates are defined as the ratio of Gross Charge-offs to Total Loans and Leases, and recovery rates as the ratio of Recoveries to Gross Charge-offs, both for commercial banks.

Figure 1: FDIC Defaults and Recovery Rates



Notes: The figure depicts quarterly recovery and default rates using the data from FDIC's Historical Statistics on Banking for the period 1985-2008 at annual frequency. Recovery rates (right scale) are the ratio of recoveries to gross charge-offs; and default rates (left scale) are the ratio of gross charge-offs to gross loans.

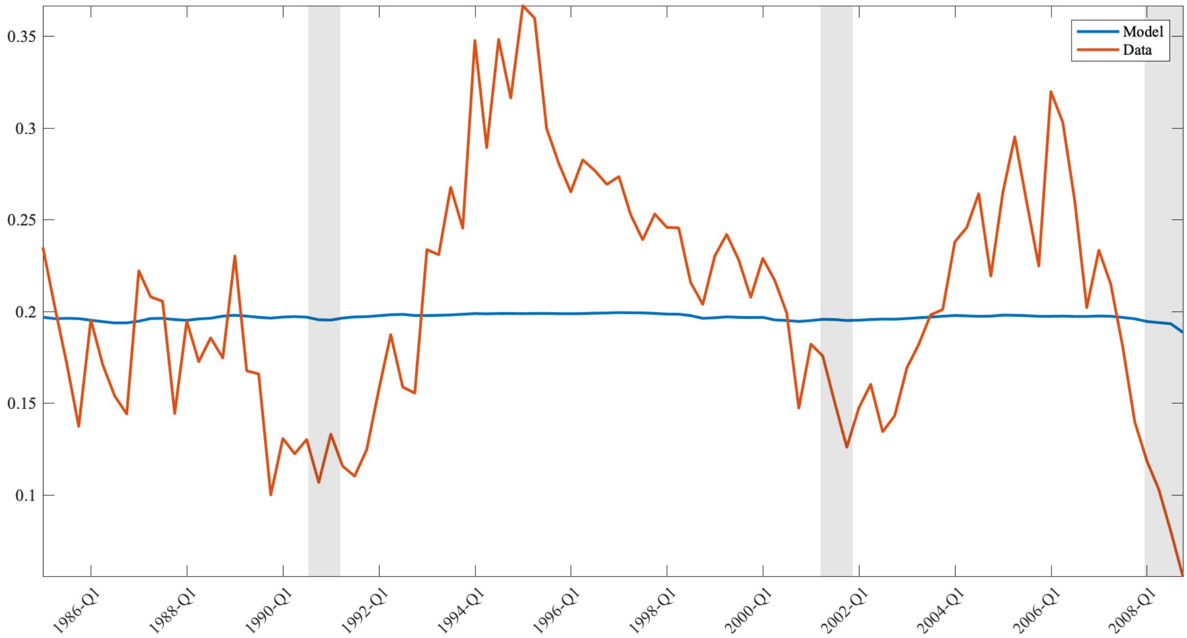
Figure 1 depicts these measures of defaults and recovery rates for the period 1985:Q1-2008:Q4. Default rates, on average less than 1% per year, are highly volatile (std. 19.91%) with notable peaks during the recessions of the early 1990s and 2000s following credit booms. Recovery rates, on average about 20%, are somewhat more volatile than defaults, with a standard deviation of 14.98%. Default rates soared, and recovery rates declined upon the crisis starting from 2007. These findings are consistent with previous evidence by Frye (2000a,b) and Schuermann (2004), who show that in a recession, recovery is about a third lower than in an expansion. The correlation between defaults and recovery rates with GDP growth is -0.23 and 0.21, respectively. Mora (2012) also documents a similar macroeconomic dependence of recovery rates.

We now examine the behavior of aggregate recovery rates through the lens of a general equilibrium model with financial frictions. A strand of the macroeconomic literature has focused on the ability of this class of models to explain the behavior of spreads and defaults over the business cycle but so far their implications for recoveries remains unexplored. For our analysis we use a medium-scale New Keynesian DSGE model with financial frictions à la Bernanke, Gertler, and Gilchrist (1999) estimated on U.S. data. Our model choice is guided by two facts. First, this class of models features equilibrium defaults and associated bankruptcy costs. Hence, it is straightforward to construct a measure of the aggregate recovery rate in the model that can be compared with the data. Second, this class of models has proven to be relatively successful at explaining the time-variation in defaults observed in the data. Indeed, in a posterior predictive check, Christiano, Motto, and Rostagno (2014, CMR) show that this model successfully accounts for the dynamics of delinquency rates for the U. S. over the last two decades. It is then natural to ask whether this class of models is able to also explain the dynamics of recovery rates.

To answer this question, we conduct a Bayesian estimation of the model described in section 3 under the common assumption in the literature of fixed liquidation costs. The model is estimated using the standard set of macroeconomic variables of Smets and Wouters (2007) and two financial variables: recovery rates and the spread between BAA-rated corporate bonds and the ten-year US government bond rate. We introduce a shock to the observation equation of recovery rates that is meant to capture both intrinsic measurement error and model misspecification. In this way, we let the data tell us how much of the variation in this variable is captured by the model and how much is left unexplained. We then compute the smoothed path of recovery rates implied by the model when we feed in the estimated structural shocks and compare it with the actual data. As can be seen from the results presented in Figure 2, the implied recovery rate from the model are essentially flat, displaying only a small blip at the beginning of the Great Recession. On the other hand, the recovery rate from the FDIC data features a much higher volatility.

These stark findings indicate that current models of financial frictions tend to underestimate the cost of bankruptcy in a recession and overestimate them in a boom. So long as bankruptcy costs impede the flow of funds from lenders to borrowers, these results imply that current frameworks might be understating the severity of financial frictions and their effects on macroeconomic aggregates. In the next section, we introduce a new channel in the financial accelerator model that is able to explain the behavior of recoveries and we study its effect on aggregate fluctuations.

Figure 2: Recovery rates - Model and Data



Notes: The figure depicts the FDCI recovery rate data (orange) and the smoothed recovery rates (blue) implied by the estimated model of Section 3 under the assumption of fixed liquidation costs.

3 The Model

Our framework is a New Keynesian model based on Christiano, Eichenbaum, and Evans (2005), augmented with technology shocks in the production of installed capital, following the contribution of Justiniano, Primiceri, and Tambalotti (2010). The model consists of several agents: households, labor packers, capital producers, intermediate good producers, retailers, financial intermediaries, entrepreneurs, and a policymaker. We introduce financial frictions in the form of an agency problem between financial intermediaries and entrepreneurs à la Bernanke, Gertler, and Gilchrist (1999). We begin by describing entrepreneurs, financial intermediaries, and the market for liquidated capital. Our main theoretical contribution lies in the modeling of the liquidation process. We then proceed to describe the more standard parts of the model. The typical model of the financial accelerator that is commonly estimated in the literature (e.g. Christiano, Motto, and Rostagno, 2014; Del Negro, Giannoni, and Schorfheide, 2015) can be obtained as a special case of our framework by assuming that marginal liquidation costs are fixed.

3.1 Entrepreneurs and Financial Intermediaries

There is a continuum of entrepreneurs indexed by j. At time t, entrepreneur j purchases raw capital from capital builders, $\bar{K}_{t+1}(j)$, at a unit price of Q_t. The entrepreneur uses his net worth, $N_t(j)$, and a one-period loan, $B_{t+1}(j)$, from a financial intermediary (or bank) to purchase his desired level of capital:

$$Q_t \bar{K}_{t+1}(j) = N_t(j) + B_{t+1}(j). \tag{1}$$

At the beginning of period $t+1$, the entrepreneur is hit with an idiosyncratic shock, $\omega_{t+1}(j)$, that follows a log-normal distribution, $\mathcal{LN}(-\frac{1}{2}\sigma_\omega^2, \sigma_\omega)$, so that the mean of ω is equal to 1. We denote by $f = f(\omega)$ and $F = F(\omega)$ the probability density function and cumulative distribution function of ω_t, respectively.

After observing the period $t+1$ aggregate returns and prices, the entrepreneur determines the optimal utilization rate, u_{t+1}, of its effective capital units and supplies capital services, $u_{t+1}\omega_{t+1}(j)\bar{K}_{t+1}$ to a competitive market at rental rate r^k_{t+1}. At the end of period $t+1$ the entrepreneur is left with $(1-\delta)\omega_{t+1}(j)\bar{K}_{t+1}$ units of undepreciated capital. A solvent entrepreneur earns a return by supplying capital services and reselling the undepreciated capital to capital builders at price Q_{t+1}. His return is thus given by:

$$R^k_{t+1} \equiv \frac{(1-\tau^k)[u_{t+1}r^k_{t+1} - a(u_{t+1})]P_{t+1} + (1-\delta)Q_{t+1} + \tau^k\delta Q_t}{Q_t}, \tag{2}$$

where a is an increasing and convex function capturing the cost of capital utilization and τ^k indicates the tax rate on capital income. The utilization rate is set to its optimal level, which satisfies

$$a'(u_{t+1}) = r^k_{t+1}. \tag{3}$$

In steady state, $u = 1$, $a(1) = 0$ and $\sigma_a \equiv a''(1)/a'(1)$. The utilization rate transforms raw capital into effective capital services according to $K_t = u_t \bar{K}_{t-1}$.

The financial contract requires the entrepreneur to pay off their debt at a nominal interest rate, Z_{t+1}. The minimum level of idiosyncratic technology, $\bar{\omega}_{t+1}$, that will allow the entrepreneur to pay off their debt is

$$B_{t+1}(j)Z_{t+1} = Q_t \bar{K}_{t+1}(j) R^k_{t+1} \bar{\omega}_{t+1}. \tag{4}$$

Entrepreneurs with $\omega_{t+1}(j) < \bar{\omega}_{t+1}$ declare bankruptcy and turn their capital to their creditors for foreclosure. In this case, the lender seizes the entrepreneurial assets and liquidates the physical capital at fire sale prices $FS_t \equiv s_t Q_t$. The determination of FS_t will be explained below. Thus, the return that a creditor makes on a unit of capital from a defaulting entrepreneur is given by:

$$R^{Def}_{t+1} \equiv \frac{(1-\tau^k)[u_{t+1} r^k_{t+1} - a(u_{t+1})]\Upsilon^{-(t+1)} P_{t+1} + (1-\delta) FS_{t+1} + \tau^k \delta Q_t}{Q_t}. \tag{5}$$

The ex-post $t+1$ payoff to an entrepreneur with net worth $N_t(j)$ is given by

$$\Pi^e_{t+1} = \int_{\bar{\omega}_{t+1}}^{\infty} [Q_t \bar{K}_{t+1}(j) R^k_{t+1} \omega - B_{t+1}(j) Z_{t+1}] dF(\omega) = [1 - \Gamma_t(\bar{\omega}_{t+1})] R^k_{t+1} \kappa_t N_t(j), \tag{6}$$

where

$$\kappa_t \equiv \frac{Q_t \bar{K}_{t+1}(j)}{N_t(j)},$$

$$\Gamma_t(\bar{\omega}_{t+1}) \equiv [1 - F(\bar{\omega}_{t+1})]\bar{\omega}_{t+1} + G(\bar{\omega}_{t+1}),$$

$$G(\bar{\omega}_{t+1}) \equiv \int_0^{\bar{\omega}_{t+1}} \omega dF(\omega).$$

and κ_t denotes leverage, from which we have dropped the index j in anticipation of the result that leverage is independent of net worth (see below).

Financial intermediaries collect deposits from the household, to which they promise a competitively determined, non-state contingent, nominal interest rate R_t. The financial intermediary diversifies his lending across a large number of entrepreneurs. Thus, its participation constraint can be written as:

$$[1 - F(\bar{\omega}_{t+1})]Z_{t+1}B_{t+1} + \int_0^{\bar{\omega}_{t+1}} \omega_{t+1} dF(\omega) R_{t+1}^{Def} Q_t \bar{K}_{t+1} = R_t B_{t+1}, \tag{7}$$

where the left-hand side of (7) is the expected return on the lending activity and the right-hand side is the opportunity cost of lending for the financial intermediary. The return from lending on the left-hand side consists of loan repayments from firms that do not default, and of the returns obtained from the resale of the assets of defaulting entrepreneurs. After substituting equation (4) into (7) and some manipulation, the participation constraint can be re-expressed as:

$$[1 - F(\bar{\omega}_{t+1})]\bar{\omega}_{t+1} R_{t+1}^k Q_t + (1 - \mu_{t+1}) G(\bar{\omega}_{t+1}) \bar{K}_{t+1} R_{t+1}^k Q_t = R_t [Q_t \bar{K}_{t+1} - N_t]. \tag{8}$$

In the last equation we have defined $1 - \mu_{t+1} \equiv \frac{R_{t+1}^{Def}}{R_{t+1}^k}$. The variable μ_{t+1} has the interpretation of liquidation costs and depends on the difference in the price of a regular and a foreclosed unit of capital:

$$\mu_{t+1} = \frac{R_{t+1}^k - R_{t+1}^{Def}}{R_{t+1}^k} = \frac{(1 - \delta)(Q_{t+1} - FS_{t+1})}{R_{t+1}^k Q_t}. \tag{9}$$

After entrepreneurs have sold their undepreciated capital, collected capital rental receipts, and settled their obligations to their mutual fund or defaulted at the end of period $t + 1$, a random fraction, $1 - \gamma_{t+1}$, of each entrepreneur's assets is transferred to their household. The complementary fraction, γ_{t+1}, remains in the hands of the entrepreneurs. In addition, each entrepreneur receives a lump-sum transfer, W_e , from the household. The objects, γ_{t+1} and

W_e, are exogenous. The entrepreneurial objective function is described by

$$\mathbb{E}_t \Bigg\{ \sum_{s=0}^{\infty} \Big[\big(\Pi_{i=0}^{s} \gamma_{t+i} \big) \Pi_{t+s}^{e} \Big] \Bigg\}. \tag{10}$$

The debt contract specifies a pair (B_{t+1}, Z_{t+1}) that maximizes the utility of the entrepreneur given by (10) subject to the participation constraint of lenders defined by (8). As it is evident, the problem of choosing B_{t+1} is equivalent to choosing κ_t, independently of net worth. Furthermore, using (4) we can re-express Z_{t+1} in terms of $\bar{\omega}_{t+1}$, so that our contract is described by the pair $(\kappa_t, \bar{\omega}_{t+1})$. Dmitriev and Hoddenbagh (2017) show that maximization of intertemporal utility with linear preferences is identical to the maximization of the next period expected payoff in (6) to a first-order approximation.

The participation constraint in (8) takes the same form as the constraint that arises in a set up with asymmetric information and monitoring costs à la Bernanke, Gertler, and Gilchrist (1999). The key difference is that, in their setup, $\mu_{t+1} = \mu$ is an exogenous fixed parameter that captures the liquidation costs associated with bankruptcies. In our case, μ_{t+1} is an endogenous object that depends on the resale value of liquidated assets. We now turn to the determination of this resale value.

Liquidation. At time t, after entrepreneurs have paid off or defaulted on their debt and the transfer between household and entrepreneurs has taken place, banks take over the undepreciated assets of defaulting entrepreneurs, $(1-\delta)G(\bar{\omega}_t)\bar{K}_t$. In the spirit of Shleifer and Vishny (1992), we assume that there is limited redeployability of these assets. In their framework, liquidated assets can be bought by two potential buyers: an insider or an outsider. These differ along two dimensions. First, insiders can generate a higher cash flow from the assets than outsiders because they face lower costs of managing the assets and putting them to good use. Second, while outsiders are financially unconstrained, insiders are subject to limited debt capacity due to financial frictions. In this environment, when insiders are in financial distress, the assets are sold at prices below their value in best use.

We assume that there is a market for assets in default where banks sell the capital of defaulting entrepreneurs at price FS_t. The natural potential buyers in our framework are the non-defaulting entrepreneurs. To parallel the idea that different agents can generate different cash flows from the asset, we assume that entrepreneur face idiosyncratic costs of redeploying liquidated capital, i.e. idiosyncratic costs of converting a unit of capital in default into newly usable capital. Specifically, entrepreneurs can convert a unit of liquidated capital into a unit of new physical capital to be sold to capital builders by paying a redeployment cost of $\Theta(\omega_t(j))Q_t$ units of final good, that depends on the individual entrepreneur's productivity in that period, $\omega_t(j)$. Thus, instead of having two potential buyers as in Shleifer and Vishny (1992), we exploit the idiosyncratic productivity of entrepreneurs to introduce a continuum of potential buyers.

To formalize the other key idea that financial conditions of potential buyers matter, we assume that surviving entrepreneurs cannot raise external finance to buy these assets, but can only use their current net worth. It can be shown that this scenario arises as an extreme case of a more general model where entrepreneurs can also use an intra-period loan but are subject to a sufficiently severe moral hazard/costly enforcement problem. Proceeding with this assumption allows us to maintain the tractability of the framework despite the heterogeneity in entrepreneurial net worth — and in returns from liquidation that the more general environment would entail — while at the same time capturing the essence of the idea in Shleifer and Vishny (1992).

The market for capital in default is competitive. It follows that only entrepreneurs with productivity $\omega_t(j) > \tilde{\omega}_t$ will find it profitable to buy liquidated assets, where the threshold is given by:

$$Q_t = FS_t - \Theta(\tilde{\omega}_t)Q_t. \tag{11}$$

Equation (11) equates the marginal revenue of a unit of liquidated capital to the marginal cost, which is the sum of the purchase price of a unit of capital and the cost of transforming the capital in default into new capital. It also shows that if marginal liquidation costs were zero the price of capital in default would be equal to the price of new capital, which is the implicit standard assumption in the literature. Recalling that we defined $FS_t = s_t Q_t$ the above condition can be written as $s_t = 1 - \Theta(\tilde{\omega}_t)$. To ensure that $0 < s_t < 1$ we use the following functional form for the cost function: $\Theta(\omega_t(j)) = \frac{b_1(\omega_t(j)/\tilde{\omega}_{ss})^{-b_2}}{1+b_1(\omega_t(j)/\tilde{\omega}_{ss})^{-b_2}}$, where b_1 is a parameter that relates to the steady of the model, and b_2 is related to the curvature of the redeployment cost function. The market clearing for the liquidated capital states that the market value of the units of capital to be liquidated must equal the total net worth available of entrepreneurs with $\omega_t(j) > \tilde{\omega}_t$ after debt repayment for the purchase of this capital:

$$(1-\delta)G(\bar{\omega}_t)\bar{K}_t FS_t = \gamma_t \int_{\tilde{\omega}_t}^{\infty} [Q_t \bar{K}_t R_t^k \omega - B_t Z_t] dF(\omega). \tag{12}$$

Making use of s_t and the definition of $\bar{\omega}_t$ in (4) we can rewrite the above condition as:

$$(1-\delta)G(\bar{\omega}_t)\bar{K}_t(1-\Theta(\tilde{\omega}_t))Q_t = \gamma_t Q_{t-1} R_t^k \int_{\tilde{\omega}_t}^{\infty} (\omega - \bar{\omega}_t) dF(\omega). \tag{13}$$

This equation determines the equilibrium value of $\tilde{\omega}_t$. Intuitively, when aggregate net worth falls, the fire sale price will fall to clear the market for liquidated capital. The fall in FS_t reflects the fact that now less productive entrepreneurs enter the liquidation market. Thus, in a recession, the deadweight loss associated with defaults, summarized by the variable μ_t in equation (9), increases.

3.2 Final Goods Producers

Perfectly competitive firms produce a homogeneous final good, Y_t, from a continuum of intermediate goods, $Y_{j,t}, j \in [0,1]$ using the following Dixit-Stiglitz aggregator

$$Y_t = \left(\int_0^1 Y_{j,t}^{\frac{1}{\lambda_{f,t}}} dj \right)^{\lambda_{f,t}}, \qquad 1 < \lambda_{f,t} < \infty \tag{14}$$

where $\lambda_{f,t}$ is a price markup shock. All the shocks processes will be described below. Maximization of profits, together with the zero-profit condition, implies that the price of the final good, P_t, is the familiar CES aggregate of intermediate goods' prices.

3.3 Intermediate Goods Producers

Each intermediate good j is produced by a monopolist using the following production function

$$Y_{j,t} = \max[\epsilon_t^z K_{j,t}^{\alpha}(z_t l_{j,t})^{1-\alpha} - \Phi z_t, 0], \tag{15}$$

where $K_{j,t}$ and $l_{j,t}$ denote the amount of effective capital and labor employed by firm j. ϵ_t^z is a stationary technology shock, while the variable z_t follows a process with a stationary growth rate. Φ is a fixed cost in production chosen so that profits are zero in steady state. Supplier j sets his price to maximize his profits subject to Calvo-style frictions (Calvo, 1983). In particular, in every period t a random subset ξ_p of suppliers cannot optimally set its price, but adjusts it according to $P_{j,t} = \tilde{\pi}_t P_{j,t-1}$, where the indexation follows $\tilde{\pi}_t = (\pi_t^{target})^{\iota}(\pi_{t-1})^{1-\iota}$ and $\pi_{t-1} \equiv P_{t-1}/P_{t-2}$. π_t^{target} represents a target inflation rate for the monetary policy rule, described below. The complementary set of suppliers $1 - \xi_p$ re-optimizes prices to maximize the profit function:

$$E_t \sum_{s=0}^{\infty} \beta^s \xi_p^s \frac{\Lambda_{t+s}}{\Lambda_t} \left[P_{j,t} \left(\prod_{k=1}^{s} (\pi_{t+k}^{target})^{\iota} (\pi_{t+k-1})^{1-\iota} \right) Y_{j,t+s} - W_{t+s} l_{j,t+s} - P_{t+s} r_{t+s}^k K_{j,t+s} \right], \tag{16}$$

where the demand for the intermediate product $Y_{j,t}$ comes from the final goods producers, W_t indicates the nominal wage and Λ_t is the marginal utility of nominal income for the representative household.

3.4 Capital Goods Producing Sector

Perfectly competitive firms purchase undepreciated capital from entrepreneurs and liquidated capital at price Q_t, and investment goods from the final good sector. They transform them into new capital that they sell back to the entrepreneurs. Therefore the aggregate law of motion for capital is given by:

$$\bar{K}_t = (1-\delta)\bar{K}_{t-1} + (1 - S(\zeta_{I,t} I_t / I_{t-1})) I_t. \tag{17}$$

The function $S(x)$ captures the presence of adjustment costs in investment, and is such that $S(x) = S'(x) = 0$ and $S''(x) = S''$, where x denotes the steady-state value of $\zeta_{I,t} I_t / I_{t-1}$ and S'' will be a model parameter. $\zeta_{I,t}$ is a shock to the marginal efficiency of investment (MEI) in producing capital goods.

3.5 Labor Market

The structure of the labor market follows Erceg, Henderson, and Levin (2000). The specialized labor types, $h_{i,t}$, are combined by perfectly competitive employment agencies into a homogenous labor input using the following technology:

$$l_t = \left(\int_0^1 (h_{i,t})^{\frac{1}{\lambda_w}} di \right)^{\lambda_w}, \qquad 1 < \lambda_w < \infty \tag{18}$$

The homogenous labor input is then sold to the intermediate firms. The wage paid by these firms for the homogenous labor input

$$W_t = \left(\int_0^1 (W_t^i)^{\frac{1}{1-\lambda_w}} di \right)^{1-\lambda_w}, \tag{19}$$

can be obtained by solving the profit maximization problem of the employment agencies.

3.6 Households

The representative household maximizes its lifetime utility by choosing the optimal path of consumption and labor input

$$E_t \sum_{s=0}^{\infty} \beta^s \zeta_{c,t+s} \left\{ \log(C_{t+s} - bC_{t+s-1}) - \Psi_L \int_0^1 \frac{h_{i,t+s}^{1+\sigma_L}}{1+\sigma_L} di \right\}, \qquad b, \sigma_L > 0 \tag{20}$$

where C_t denotes household consumption, b parameterizes the degree of consumption habits and $\zeta_{c,t}$ indicates a preference shock. The household provides a continuum of differentiated labor inputs, $h_{i,t} \in [0,1]$. We can write the flow budget constraint for the household as

$$(1+\tau^c)P_tC_t + B_{t+1} \leq (1-\tau^l)\int_0^1 W_t^i h_{i,t}di + R_tB_t + \Pi_t. \tag{21}$$

The left-hand side of the budget constraint encompasses the sources of expenditure. The household purchases consumption goods, C_t, that are taxed at a rate τ^c,at price P_t, and bonds, B_{t+1}. The household's sources of revenues are the earnings from labor and from bonds. Π_t denotes lump-sum payments to the household, including profits from intermediate goods, transfers from entrepreneurs, and lump-sum transfers from the government net of lump-sum taxes. Following Erceg, Henderson, and Levin (2000), we assume that there is a monopoly union for each type of labor input that sets the wage rate, W_t^i, according to a Calvo-style friction. Specifically, in every period a random subset of unions $1-\xi_w$ sets their wage optimally by maximizing

$$E_t\sum_{s=0}^{\infty}\beta^s\xi_w^s\left\{\Lambda_{t+s}W_t^ih_{i,t+s} - \zeta_{c,t+s}\Psi_L\frac{h_{i,t+s}^{1+\sigma_L}}{1+\sigma_L}\right\}, \tag{22}$$

subject to the labor demand function coming from the intermediate goods producers. The complementary set of unions adjusts their wage according to $W_t^i = (\mu_{z^*,t})^{\iota_\mu}(\mu_{z^*})^{1-\iota_\mu}\tilde{\pi}_{w,t}W_{t-1}^i$, where μ_{z^*} is the growth rate of z_t^* in the non-stochastic steady state and

$$\tilde{\pi}_{w,t} = (\pi_t^{target})^{\iota_w}(\pi_{t-1})^{1-\iota_w}, \quad 0 < \iota_w < 1. \tag{23}$$

3.7 The Government and Aggregation

A monetary authority sets the nominal interest rate, in linearized form, following the feedback rule:

$$R_t - R = \rho_p(R_{t-1} - R) + (1-\rho_p)\left[\alpha_\pi(\pi_{t+1} - \pi_t^{target}) + \alpha_{\Delta y}\frac{1}{4}(g_{y,t} - \mu_z)\right] + \frac{1}{400}\epsilon_t^p, \tag{24}$$

where ϵ_t^p is a shock to monetary policy in annual percentage points and ρ_p is a smoothing parameter in the policy rule. The monetary authority responds to deviations of expected inflation from target, $\pi_{t+1} - \pi_t^{target}$, and to deviations of quarterly growth in gross domestic product from its steady state, $g_{y,t} - \mu_z$.

Fiscal policy is fully Ricardian. Government consumption expenditure, G_t, is given by

$$G_t = z_t g_t, \tag{25}$$

where g_t follows a stationary stochastic process. The aggregate law of motion for entrepreneurial net worth is given by

$$N_t = \gamma_t\left\{[1 - \Gamma_{t-1}(\bar{\omega}_t)] + \int_{\tilde{\omega}_t}^{\infty}(\omega - \bar{\omega}_t)\frac{\Theta(\tilde{\omega}_t) - \Theta(\omega_t)}{(1 - \Theta(\tilde{\omega}_t))}dF(\omega)\right\} R_t^k Q_{t-1}\bar{K}_t + W_t^e, \tag{26}$$

where the last term in curly brackets reflects the aggregate profits made in the market for liquidated capital. Finally, the resource constraint can be written as

$$Y_t = D_t + G_t + C_t + I_t + a(u_t)\bar{K}_t. \tag{27}$$

The last term on the constraint indicates the output cost of adjusting capital utilization. D_t represents the resource cost associated with the liquidation of the assets of defaulting entrepreneurs

$$D_t = (1-\delta)G(\bar{\omega}_t)\bar{K}_t\int_{\tilde{\omega}_t}^{\infty}\Theta(\omega)dF(\omega). \tag{28}$$

3.8 Shock Processes

The model described above includes 9 aggregate shocks: $\epsilon_t^z, \mu_{z,t}, \lambda_{f,t}, \pi_t^*, \zeta_{c,t}, \zeta_{I,t}, \gamma_t, \epsilon_t^p$ and g_t. Each shock, x_t, is modeled as a first-order autoregressive process:

$$x_t = \rho_x x_{t-1} + \sigma_x \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma_x^2),$$

with the exception of the monetary policy shock, ϵ_t^p, whose autocorrelation is set to zero. All shocks are mean zero and uncorrelated over time and with each other. Thus, each shock process is fully characterized by two parameters: an autocorrelation and a standard deviation parameter.

4 Estimation

We partition the model parameters into two sets. The first set contains parameters related to the steady state of the model that we fix a priori. These parameters are summarized in Table 1 and are set to standard values that can be found, for instance, in Christiano, Motto, and Rostagno (2014). We set the capital's share, α, to 0.4, the Frisch elasticity of labor supply, σ_L to 1, and the depreciation rate for capital to 0.025. The mean growth rate of the unit root technology, μ_z, is fixed at 0.41 to be consistent with the average growth rate of per capita GDP over the sample period. We set the steady state value of g_t so that government expenditure is 20 percent of GDP in steady state, consistent with the data. Steady-state inflation is fixed at 2.4 percent on an annual basis. The household's discount factor is set to 0.9987. As in Christiano, Eichenbaum, and Evans (2005) we set the steady state markups in the product market λ_f and in the labor market λ_w to 1.2 and 1.05. The tax rates on consumption, capital and labor income follow CMR. We fix the habit formation parameter, b, to 0.74, the posterior mode from CMR.

For the part of the model that relates to financial frictions, we set the steady-state transfer of net worth from entrepreneurs to the households, $1-\gamma$, to $1-0.985$. Liquidation costs in steady state, μ, are set to 0.21 and the steady-state volatility of idiosyncratic productivity to 0.26. These values imply a steady-state leverage $\bar{K}/N$ of 2.015, an annualized default probability of 2.24 percent and a value of R^k/R of 1.0073 corresponding to annualized excess return to capital of 4 percent. Furthermore, our calibration implies a share of consumption and investment in GDP of 0.52 and 0.27, in line with the data. We set b_1 such that μ_t in steady state is equal to our chosen value of μ. This choice allows our model to fully nest a standard model with fixed liquidation cost, which can be retrieved by setting the elasticity of the liquidation cost function b_2 to zero. These parameters imply that the steady-state value of $\tilde{\omega}$ is 2.14, which implies that the top 0.11% of entrepreneurs is buying the liquidated assets in equilibrium.

4.1 Data and Priors

We estimate the rest of the parameters with Bayesian techniques as described in An and Schorfheide (2007). Our sample consists of quarterly observations for 9 variables covering the period, 1985:Q1-2008:Q4. We choose the end of the sample period to avoid the observed zero bound on the nominal rate. Seven of these variables are standard in empirical analyses with macroeconomic data: GDP, consumption, investment, inflation, the real wage, hours worked, and the federal funds rate. We use two financial variables in our analysis: the credit spread and the aggregate recovery rate. Specifically, we map the credit spread, $Z_t - R_t$, into the spread between BAA-rated corporate bonds and the ten-year US government bond rate. For aggregate recovery rates, we use the FDCI measure described in Section 2 that in our model corresponds to:

$$Recovery_t = \frac{(1-\mu_t)G(\bar{\omega}_t)}{\bar{\omega}_t F(\bar{\omega}_t)}.$$

We derive this formula in Appendix A. The description of all data transformations is available in Appendix B. Our priors follow CMR and are summarized in Tables 2 and 3. We estimate two versions of our model: one with time varying liquidation cost, which we label "endogenous liquidation" (EL), and one with fixed liquidation costs (FL), which is obtained by imposing

$b_2 = 0$. The latter is the model that we used to produce Figure 2.

The parameters ξ_p and ξ_w are given relatively tight priors around values that imply that prices and wages will remain unchanged on average for one-half and one year, respectively. For our new parameter in the endogenous liquidation model, b_2, we use a pretty wide Inverse Gamma distribution which captures our intent to let the data speak about its value.

We allow for a shock to the observation equation of the recovery rate variable, $\epsilon_t^{rec} \sim \mathcal{N}(0, \sigma_{rec}^2)$. We think of this shock as capturing both measurement error and model mis-specification. The prior for standard deviation σ_{rec} follows a uniform distribution that is sufficiently wide to allow this shock to explain the entire variation in recovery rates. We proceed in this way because we want to investigate how much more of the cyclical variation in the recovery rate our model can capture relative to the model with fixed liquidation costs without forcing either model to explain a certain fraction of it a priori. In other words, we want to assess whether our model is less mis-specified than a model with fixed liquidation costs. By allowing for the same prior on the two models we can also conduct a meaningful model comparison.

5 Quantitative Analysis

In this section we evaluate the new mechanism of endogenous liquidation costs. We find that the mechanism is supported by the data and examine its implications for the transmission of structural disturbances. We conclude by considering some options for policy intervention.

5.1 Posterior and Model Evaluation

Tables 2 and 3 report the posterior mean and standard deviation of the estimated parameters, along with the marginal likelihood of the two models. In most cases, there is a reasonable amount of information in the data about the parameters, indicated by the fact that the standard deviation of the posterior distribution is often less than half of the standard deviation of the prior distribution.

The marginal likelihood is a key statistic used in a Bayesian model comparison exercise, as it tells the econometrician how he would update his prior on which model is more likely to be the true one after having observed the data. The difference of 48 log points in between the model with endogenous liquidation costs and the model with fixed liquidation costs indicates that the data strongly prefers the former. This result is reflected in the fact that the key estimated parameter governing the endogenous liquidation costs has a mean estimate of 17.09, with a 90% posterior credible set that is sufficiently far away from the case of fixed liquidation costs (i.e., zero).

Many of the other parameter estimates are very similar across the two models, and within the range of the findings of the previous literature. A couple of differences are worth some comment. First, the estimated investment adjustment cost parameter is larger in the model with fixed liquidation than in the model with endogenous liquidation: 18.67 for the former and 8.92 for the latter. The level of adjustment costs has two contrasting effects. First, higher adjustment costs will mute the response of investment to aggregate shocks. Second, higher adjustment costs imply larger movements in the price of installed capital (Q_t) and thus larger financial accelerator effects in the standard Bernanke, Gertler, and Gilchrist (1999) model. Not surprisingly, the estimated model with fixed liquidation costs features high adjustment costs that amplify aggregate shocks. Second, the process for the net worth shock is estimated to be three times larger in the model with fixed liquidation costs relative to our benchmark model. As we show in Section 5.3, this is intuitive, because endogenous liquidation costs tend to amplify the effect of financial shocks, so that this model requires smaller shocks of this type.

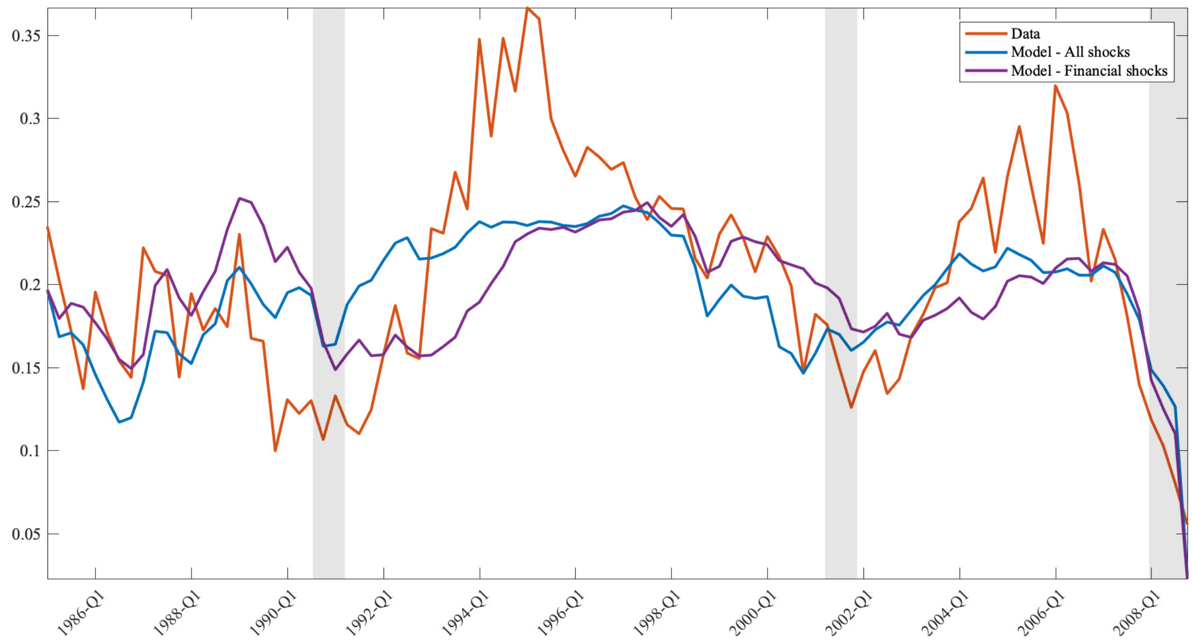
5.2 The Drivers of Recovery Rates

In Section 2, we have already shown that the estimated model with fixed liquidation costs fails to explain the volatility of recovery rates found in the data. This finding is corroborated by the variance decomposition for the estimated model with fixed liquidation costs reported in Table 4, which shows that this model attributes 99.71% of the variation in recovery rates to the shock in the observation equation of recovery rates itself. In other words, structural shocks explain only 0.29% of the variation of this variable inside the model.

In Figure 3, the orange line shows the recovery rates in the data. The blue line is the model counterpart of the orange line. It is the smoothed series of recovery rates obtained by simulating the model at the posterior mode using the estimated initial conditions and structural shocks. The Figure shows that the smoothed series not only displays an amount of variation that is more comparable to the data, but also a reasonable cyclicality. Recovery rates rise and fall over the cycle in a way that is similar to the data, and the model is able to capture the sharp fall associated with the beginning of the Great Recession. These findings contrast sharply with those of models with fixed liquidation costs such as the one evaluated in Section 3, where recovery rates are essentially flat. Table 5, which reports the variance decomposition for the model with endogenous liquidation costs, shows that our model can endogenously account for 44.18% of the variance in recovery rates observed in the data. The shock to the observation equation to recovery rates is still needed to explain the fact that recovery rates in the data rise in booms more than what our model predicts. A closer look at the data reveals a certain asymmetry in recovery rates over the cycle, in that they tend to rise more in booms than they fall in recessions. Clearly, the first-order approximation of model cannot capture this feature of the data, but it is possible that higher-order approximations that take into account other moments of the distribution of entrepreneurial productivity could. We leave this question for future research. Finally, we note that part of the variation in recovery rates observed in the data is likely due to true measurement error. This measurement error is likely to be more severe in booms, when there are naturally fewer default observations underlying our aggregate series.

The comparison of the smoothed series in the model with endogenous and fixed liquidation cost shows that the borrowing constraint on buyers of liquidated assets are important for explaining recovery rates, but it does not tell us which shocks are the drivers of recovery rates. To shed further light on this question, the purple line in Figure 3 contrasts the actual recovery rates in the data with the smoothed series of recovery rates implied by the estimated

Figure 3: Recovery rates - Data versus Model



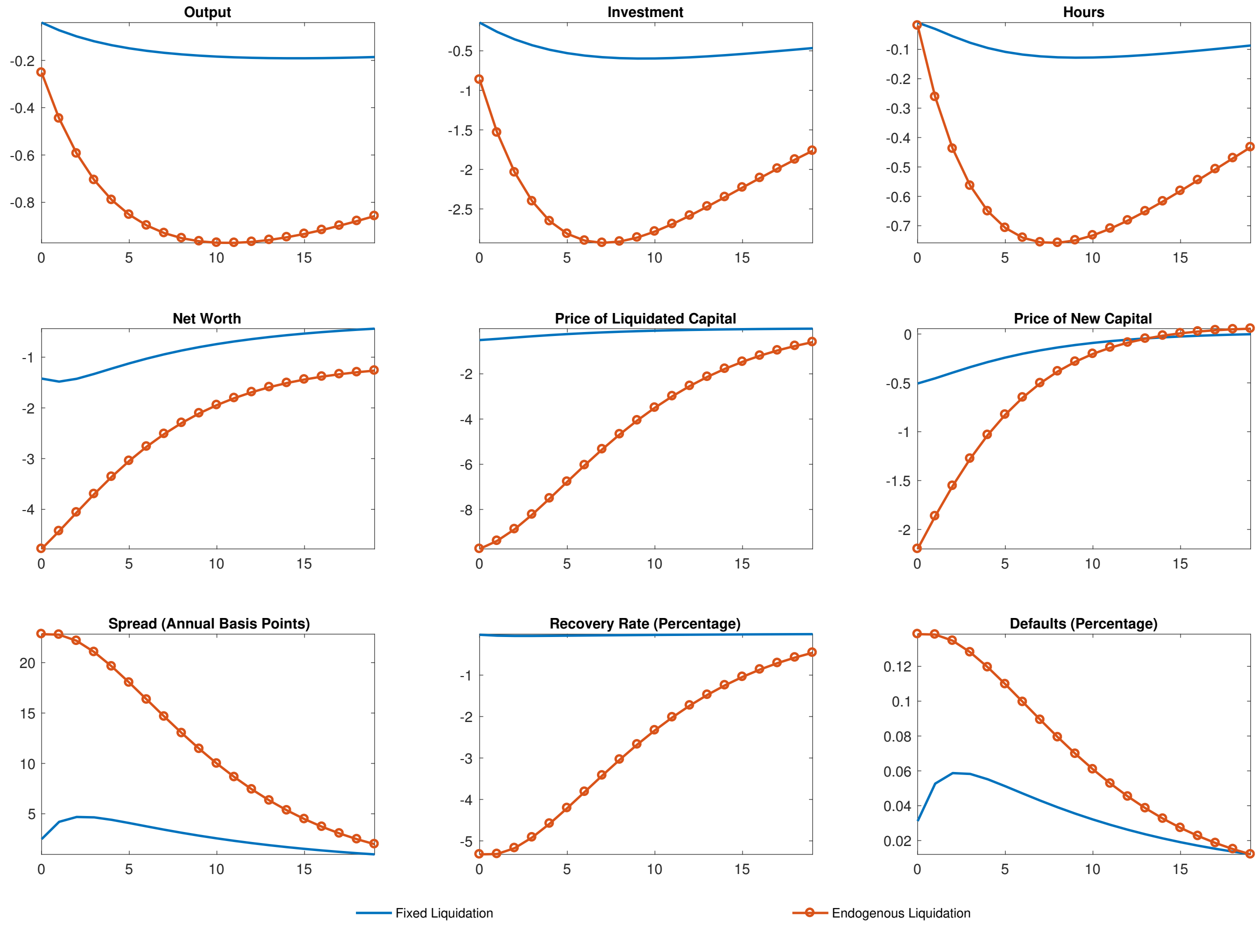
Notes: The figure depicts the FDCI recovery rate data (orange) and the smoothed recovery rates (blue) implied by the estimated model of Section 3 under the assumption of endogenous liquidation costs. The purple line represents the smoothed series of recovery rates implied by the model when only financial shocks are fed through the system.

model at the posterior mode *when only smoothed financial shocks are fed through the system*. In other words, we obtain the purple line by simulating the model at the posterior mode, feeding through only the financial shock γ_t. The notable feature is how close the dotted and black lines are to each other. This shows that it is financial shocks that are largely responsible for the movements in recovery rates. Taken together, these findings suggest that endogenous liquidation costs coupled with financial shocks are essential to rationalize the empirical pattern of recovery rates over the business cycle. In the next section, we explain the reasons behind these two key results by means of impulse response analysis.

5.3 Impulse Responses

We now shed further light on the results about the fit of the models of Section 5.1 by examining the role of endogenous liquidation costs for the transmission of shocks on key macroeconomic indicators. Figure 4 outlines the dynamic effect of a positive shock to entrepreneurial

Figure 4: Effect of Net Worth Shocks



Notes: The figure depicts the impulse response functions to a one standard deviation net worth shock in the model with fixed (blue) and endogenous (orange) liquidation costs using the estimated parameter values for each model and normalizing the standard deviation of the shock to the endogenous liquidation cost model estimate.

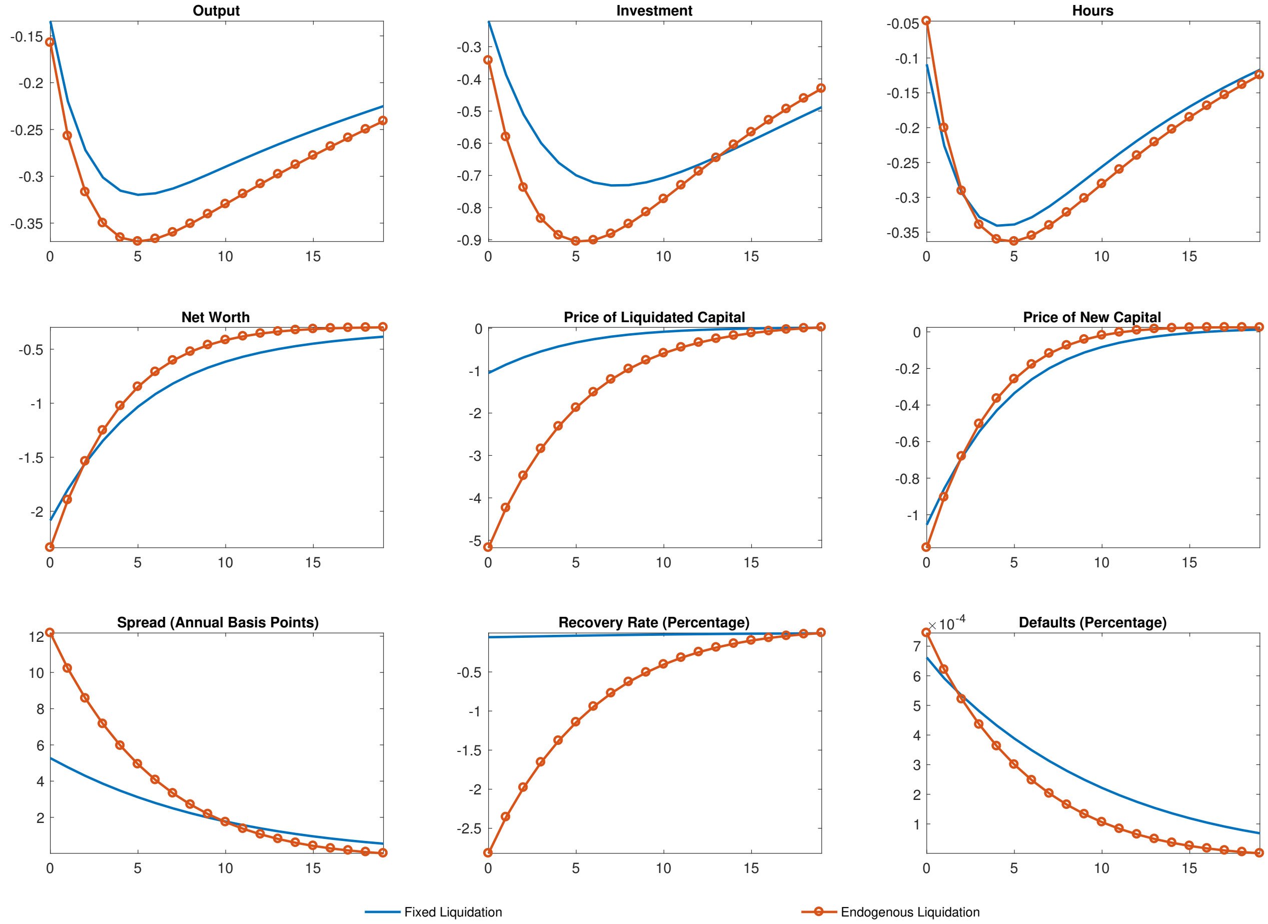
net worth, γ_t. The orange line is the response in our benckmark model and the blue line is the economy with fixed liquidation costs. To make the shocks comparable, the size of the impulse is set to the estimated standard deviation under our benchmark model. Following the shock, the fall in net worth constrains the entrepreneurs' ability to borrow. Consequently investment decreases, driving asset prices, output and hours down. Lower asset prices decrease aggregate returns, which leads to a larger fall in net worth and a spike in defaults. This is an example of the standard financial accelerator mechanism, and it holds both in the model with fixed and endogenous liquidation costs.

Despite these similarities, the two models generate very different dynamics of recovery rates. While in the basic model the recovery rate stays practically flat, in the model with the liquidity channel the recovery rate increases by about 5 percentage points. This sharper decrease in recovery follows from the fact that the aggregate fall in net worth reduces the resources available in the economy to buy defaulted assets, leading to the entry of less efficient entrepreneurs into the liquidation process. As a result, the price for liquidated assets falls more, and financial intermediaries incur larger losses from defaulting entrepreneurs. The deterioration in recovery rates increases the cost of lending, which in turn drives investment, net worth, output and asset prices further down. The endogenous movement in the price of liquidated capital thus generates a vicious spiral that magnifies the financial accelerator and results in much larger effects of financial shocks on output and investment. The variance decomposition in Table 5 confirms previous findings in the literature that financial shocks are important drivers of the business cycle, accounting for roughly 38% and 18% of the volatility in investment and output. Additionally it shows that financial shocks are essentially the unique drivers of premia and defaults.

The mechanism outlined above is similar for a contractionary monetary shock, illustrated in Figure 5. The negative demand shock causes a contraction in investment and asset prices. This initial effect translates into net worth losses and leads to the next round of financial tightening, decreasing investment, prices, and net worth and leading to a surge in defaults. The sharp decline in the price of liquidated assets that follows from the rise in default and the fall in aggregate net worth generates a stronger decline in recovery rates relative to the model with fixed liquidation costs, where it essentially stays at the steady state level. The additional fall in the recovery rate makes external financing more costly and causes investment and asset prices to go down, which again leads to the deterioration of net worth and strengthens the recession.

We turn to another shock that has been considered to be an important driver of business cycles. Figure 6 considers the effect of a marginal efficiency of investment (MEI) shock. The MEI shock perturbs the supply curve of capital, which is derived from the capital builder problem discussed in Section 3.4. The demand for capital comes from entrepreneurs. Therefore,

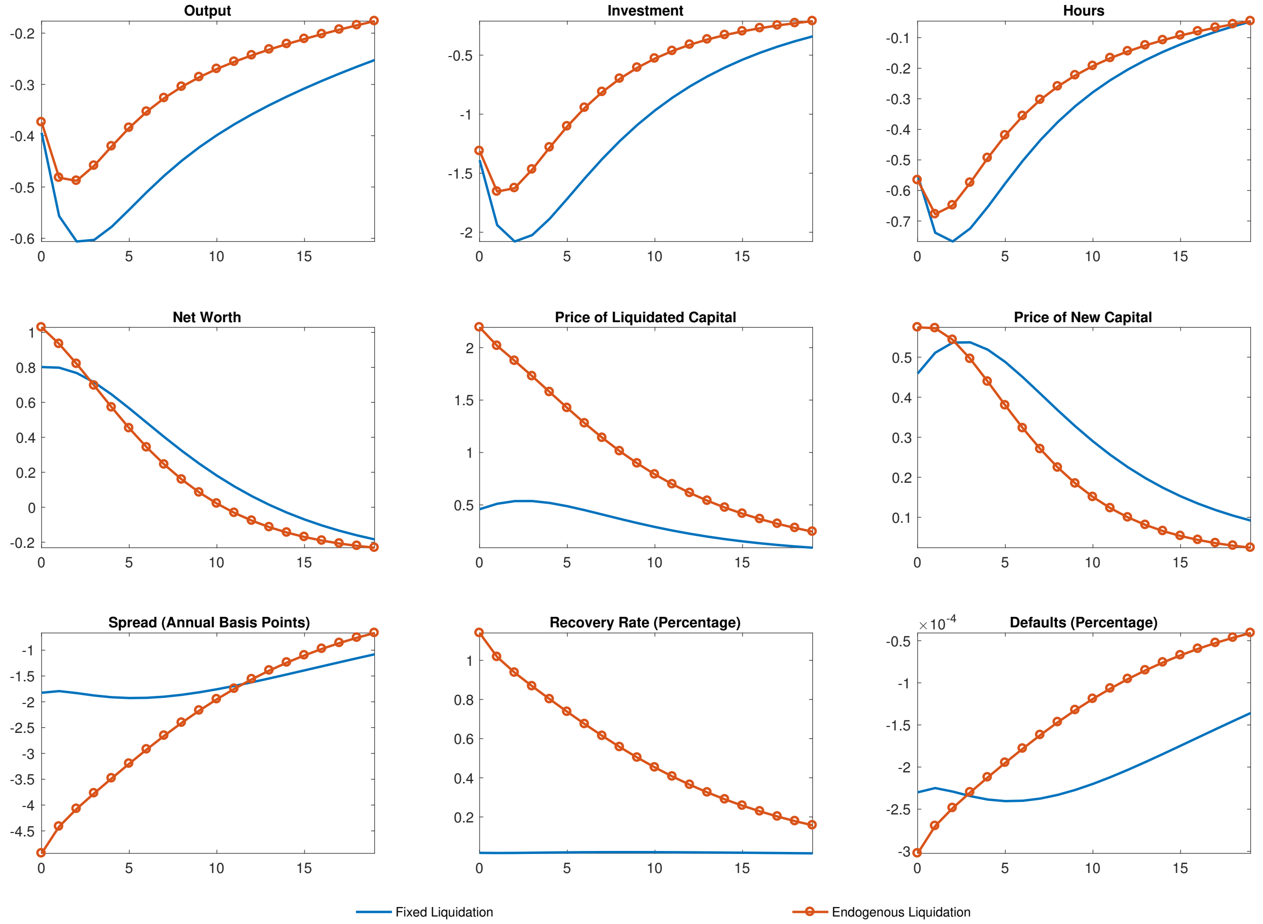
Figure 5: Effect of Monetary Shocks



Notes: The figure depicts the impulse response functions to a one standard deviation monetary policy shock in the model with fixed (blue) and endogenous (orange) liquidation costs using the estimated parameter values for each model and normalizing the standard deviation of the shock to the endogenous liquidation cost model estimate.

a positive MEI shock leads to a fall in the price of capital and a rise in investment and, via aggregate demand, output. The fall in the price of capital lowers entrepreneurs' net worth which has been remarked to be at odds with the data by Christiano, Motto, and Rostagno (2014), and it is the reason why financial shocks displace MEI shocks as drivers of business cycles in their model. Here the fall in net worth has additional consequences, as it reduces the resources available to non-defaulting entrepreneurs to buy liquidated capital. The ensuing fall in the price of liquidated capital leads to countercyclical recovery rates that are also at odds with the data. The variance decompositions of Tables 4 and 5 indeed confirm that the model with endogenous liquidation costs, which generates more realistic movements in re-

Figure 6: Effect of Marginal Efficiency of Investment Shocks

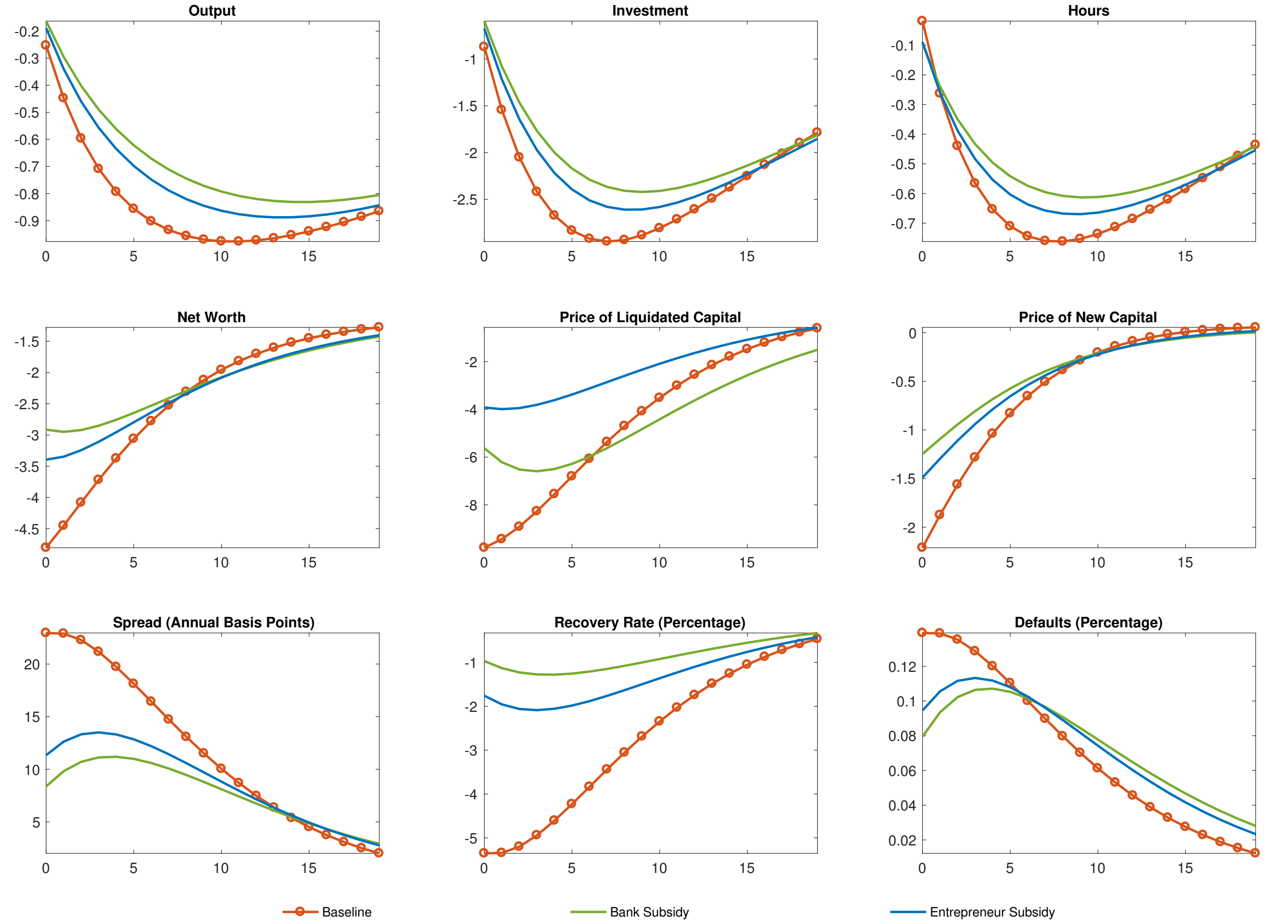


Notes: The figure depicts the impulse response functions to a one standard deviation marginal efficiency of investment shock in the model with fixed (blue) and endogenous (orange) liquidation costs using the estimated parameter values for each model and normalizing the standard deviation of the shock to the endogenous liquidation cost model estimate.

covery rates, attributes a smaller fraction of output variation to these types of shocks relative to the model with fixed liquidation costs.

Taken together, our key findings suggest that the presence of endogenous liquidation cost is essential to explain the dynamics of recovery rates. These countercyclical liquidation costs in turn magnify the effect of financial disturbances, confirming their importance in explaining fluctuations in financial *and* real variables over the business cycle.

Figure 7: Policy Intervention



Notes: The figure depicts the impulse response functions to a one standard deviation net worth shock in the baseline model (orange), the model with the government subsidy to the banks (blue) and to the entrepreneurs (green).

5.4 Policy Intervention

We now consider two types of policy interventions that could limit the impact of fire-sale prices of foreclosed assets on the size of the recession: a subsidy to the banking and entrepreneurial sectors, i.e. the supply and demand side of the market for assets in default. We assume that the government subsidizes the transactions that take place in the liquidation market. The subsidy is therefore paid in any given period after this market has closed. We model the subsidy to the banking sector in the following way: for every dollar of of assets in default that the financial intermediaries sell, they receive $\tau_t^B - 1$ dollars from the government, where τ_t^B represents the gross subsidy. Thus, effectively the financial intermediaries' cash flow for a unit of asset in default is $\tau_t^B FS_t$.

For the entrepreneurial subsidy, the entrepreneur buys a unit of capital in default at price FS_t and then obtains $(\tau_t^E - 1)FS_t$ dollars from the government. Thus, in this case the entrepreneur with productivity $\tilde{\omega}_t$ who is indifferent between entering and not entering the liquidation market is given by $Q_t = \tau_t^E FS_t - \Theta(\tilde{\omega}_t)Q_t$. Both subsidies are financed by households via lump-sum taxes, which implies that they have only second-order effects on the household's budget constraint. We assume that the government implements a cyclical policy for the subsidy so that the subsidy responds to the spread $\tau_t = a(Z_t/R_t)^{\varphi}$. In the bank subsidy case, we choose φ such that the fall in the price of liquidated capital at the time the shock hits is only 40% of the drop of the same price in our baseline model. We then choose φ in the entrepreneurial subsidy case such that the present value of the subsidy measured in consumption units is equal in the two cases.[1]

Figure 7 shows the impulse response functions to a net worth shock for the two subsidies considered above, along with the response in our baseline model. By limiting the drop in the price of liquidated capital, the subsidy contains the fall in recovery rates relative to our benchmark case. The smaller losses incurred by banks on defaulting entrepreneurs result in a spread that rises only by 8 and 11 annual basis points in the bank and entrepreneur subsidy cases respectively, compared to 23 basis points in the baseline scenario. The more moderate rise in the spread results in a smaller decline in investment and output.

As the picture shows, while the two subsidies are of equal sizes in net present value, the bank subsidy is more effective than the entrepreneurial subsidy. Investment on impact falls only by 0.59% in the bank subsidy case, compared to the 0.67% and 0.87% in the entrepreneur subsidy and baseline cases, respectively. The gap between the impulse responses grows wider in the 3 years following the shock. If the market for liquidated capital were frictionless, the two subsidies should lead to the same allocation. This does not happen in our model because entrepreneurs are financially constrained. Paying the subsidy to entrepreneurs ex-post allows less efficient ones to buy assets in default. The resulting upward pressure on the price of liquidated capital ex-ante also reduces the purchasing power of the most efficient

[1] The present value of the subsidy is $V_t = (1-\tau_t)(1-\delta)G(\bar{\omega}_t)\frac{FS_t}{P_t}\bar{K}_t + \beta E_t V_{t+1}$.

entrepreneurs. As a result, total liquidation costs increase. Conversely, when the subsidy is directed to financial intermediaries, it directly increases their recovery value from defaults, thereby allowing them to charge lower interest rates on existing debt obligations. Lower debt repayments increase the wealth of non-defaulting entrepreneurs, allowing the most efficient ones to redeploy a larger share of foreclosed assets. The resulting lower liquidation costs generate a smaller deadweight loss and a stronger stabilizing effect on the economy.

6 Conclusions

Recovery rates from defaults in the United States are very volatile and pro-cyclical. Despite their importance as key indicators of financial frictions, recovery rates have received relatively little attention in the macroeconomic literature. In this paper, we aim to fill this gap. We show that current models of financial frictions significantly underpredict the volatility of recovery rates observed in the data. We resolve the puzzle by introducing the idea of limited capital redeployability and liquidity constraints on potential buyers into an otherwise standard model with agency frictions. These assumptions result in countercyclical liquidation costs that allow us to jointly account for the behavior of standard business cycle variables and recovery rates. Our estimated model indicates that the effect of financial shocks on output and asset prices is strongly amplified in the presence of countercyclical liquidation costs. These shocks turn out to be the unique drivers of financial variables and remain critical in explaining business cycle fluctuations.

Our findings show that the balance-sheet channel in models with financial frictions represents a limited view of market incompleteness. Our results suggest that the interaction of assets specificity and liquidity constraints can paralyze financial markets and increase spreads beyond the standard effect of balance sheet deterioration. In this paper, we make a first step towards modeling the inefficiencies in the process of liquidation that arise from the interaction of financial intermediaries and liquidity-constrained buyers.

The empirical success of the limited redeployability of capital and liquidity constraints of potential buyers suggests several avenues of future research. First, it calls for more detailed modeling of financial intermediaries, which are still perfectly competitive in our model. Second, our model features one-period contracts and a market for liquidated assets that clears within the period. In reality, defaults represent a stock of assets and contracts have a long-term nature. Third, limited redeployability of capital calls for an industry-specific analysis. Whether defaults are concentrated in one industry or spread out across the economy is irrelevant in standard models where capital is easily redeployable. Instead, under limited redeployability bankruptcies are likely to be more harmful to the economy when they are concentrated in one industry because they imply lower valuations of collateral at default.

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Appendix

A. Expression for Recovery Rates

A continuum of entrepreneurs, indexed by (j) purchase raw capital, $\bar{K}$, at a unit price of Q. The entrepreneur j uses his net worth, $N(j)$, and a one-period loan $B(j)$ from a financial intermediary to purchase his desired level of capital. The entrepreneur is subject to an aggregate return, R^k, and an idiosyncratic return, ω, where $\log(\omega) \sim \mathcal{N}(-\frac{1}{2}\sigma_\omega^2, \sigma_\omega^2)$ so that the mean of ω is equal to 1. We denote by $f(\omega)$ and by $F(\omega)$ the probability density function and cumulative distribution function of ω, respectively. Thus, the value of the entrepreneur's assets ex-post is $Q\bar{K}(j)R^k\omega$. The loan obtained by the entrepreneur takes the form of a standard debt contract, where Z denotes the promised gross rate of return on the loan. Let, $\bar{\omega}$, be the value of ω below which an entrepreneur is not able to repay the principal and the interest on the loan. This cutoff is defined by

$$B(j)Z = Q\bar{K}(j)R^k\bar{\omega}. \tag{29}$$

Entrepreneurs with $\omega < \bar{\omega}$ are not able to refinance and, hence, declare bankruptcy. Due to bankruptcy costs, the financial intermediary is only able to recover a fraction $(1-\mu)$ of the entrepreneur's asset. Thus the average recovery rate, conditional on default is given by:

$$R_c = \int_0^1 \int_0^\infty \frac{(1-\mu)\omega Q\bar{K}(j)R^k}{F(\bar{\omega})B(j)Z} dF(\bar{\omega})dj. \tag{30}$$

Now multiply both the numerator and denominator by $\bar{\omega}$, and substitute out for $B(j)Z$ using (29) to obtain

$$R_c = \int_0^1 \int_0^\infty \frac{(1-\mu)\omega}{F(\bar{\omega})\bar{\omega}} dF(\bar{\omega})dj = \frac{(1-\mu)G(\bar{\omega})}{F(\bar{\omega})\bar{\omega}}, \tag{31}$$

where $G(\bar{\omega}) \equiv \int_0^\infty \omega dF(\omega)$.

B. Data

The following series are used in the estimation of the DSGE model:

1. *Growth rate of real GDP per capita*. GDP is divided by its implicit price deflator and converted in per capita term by dividing by the population over 16. (Annual population data obtained from the Organization for Economic Cooperation and Development were linearly interpolated to obtain quarterly frequency.) The data provided by the FRED database are annualized, so we divide the series by four to obtain quarterly values for the measures of interest.

2. *Growth rate of real consumption per capita*. Real consumption is the sum of household purchases of nondurable goods and services, each deflated by its own implicit price deflator. We use the same transformations as before to obtain the real per-capita counterpart.

3. *Growth rate of investment per capita*. Investment is the sum of gross private domestic investment plus household purchases of durable goods, each deflated by its own price deflator. We use the same transformations as before to obtain the real per-capita counterpart.

4. *Growth rate of investment per capita*. Investment is the sum of gross private domestic investment plus household purchases of durable goods, each deflated by its own price deflator. We use the same transformations as before to obtain the real per-capita counterpart.

5. *Hours worked*. The aggregate labor input is an index of non-farm business hours of all persons. We use the same transformations as before to obtain the real per-capita counterpart.

6. *Growth rate of real wages*. The real wage is hourly compensation of all employees in non-farm business divided by the GDP implicit price deflator.

7. *Inflation*. Inflation is measured as the logarithmic first difference of the GDP deflator.

8. *Short term nominal interest rate*. The short-term risk-free interest rate is the three-month average of the daily effective federal funds rate.

9. *Spread*. The spread, $Z_t - R_t$ is measured by the difference between the interest rate on BAA-rated corporate bonds and the ten-year US government bond rate.

10. *Recovery rate*. The recovery rate is the ratio of recoveries to gross charge-offs for commercial banks from the FDIC database.

Tables

Table 1: Calibration - Parameters Related to the Steady State

Name	Description	Value
β	Discount rate	0.9987
σ_L	Inverse Frisch elasticity of labor supply	1
Ψ_L	Disutility weight on labor	0.7705
b	Habit formation	0.74
λ_w	Steady-state mark-up for suppliers of labor	1.05
λ_f	Steady-state mark-up for intermediate goods firms	1.2
μ_z	Mean growth rate of unit root technology process	0.41
δ	Capital depreciation rate	0.025
α	Share of capital in production function	0.4
γ	Fraction of entrepreneurial net worth retained	0.985
μ	Steady-state monitoring costs	0.21
σ	Steady-state standard deviation of idiosyncratic productivity	0.26
W^e	Transfers received by entrepreneurs	0.005
η_g	Share of government spending in GDP in steady state	0.2
π^{target}	Steady-state inflation rate (APR)	2.43
τ^c	Tax rate on consumption	0.05
τ^k	Tax rate on capital income	0.32
τ^l	Tax rate on labor income	0.24

Table 2: Estimated Parameters

		Prior			Posterior			
					Endogenous Liquidation		Fixed Liquidation	
Name	Description	Distr.	Mean	STD	Mean	STD	Mean	STD
ξ_w	Calvo wage stickiness	Beta	0.75	0.10	0.7887	0.0391	0.8025	0.0309
σ_a	Curvature, utilization cost	Gaussian	1.00	1.00	2.3924	0.6969	1.9625	0.7066
S''	Curvature, investment adjustment cost	Gaussian	5.00	3.00	8.9200	2.1428	18.6765	1.8644
ξ_p	Calvo price stickiness	Beta	0.50	0.10	0.7009	0.0353	0.7526	0.0373
α_π	Policy weight on inflation	Gaussian	1.50	0.25	2.0743	0.1813	1.9178	0.1845
ρ_p	Policy smoothing parameter	Beta	0.75	0.10	0.8387	0.0175	0.8705	0.0137
ι	Price indexing weight on inflation target	Beta	0.50	0.15	0.7720	0.0980	0.7107	0.1140
ι_w	Wage indexing weight on inflation target	Beta	0.50	0.15	0.5391	0.1383	0.5918	0.1353
Υ	Wage indexing weight on technology shock	Beta	0.50	0.15	0.9234	0.0298	0.9232	0.0310
$\alpha_{\Delta y}$	Policy weight on output growth	Gaussian	0.25	0.10	0.3759	0.1000	0.3357	0.0959
b_2	Redeployment cost curvature	Inv. Gamma	10.0	5.00	17.0902	3.7272	—	—
ρ_{λ_f}	Autocorrelation, price markup shock	Beta	0.50	0.20	0.9607	0.0230	0.9255	0.0385
ρ_g	Autocorrelation, government spending shock	Beta	0.50	0.20	0.9059	0.0272	0.9115	0.0316
ρ_{μ_z}	Autocorrelation, persistent technology	Beta	0.50	0.20	0.1790	0.0680	0.2008	0.0698
ρ_ϵ	Autocorrelation, transitory technology	Beta	0.50	0.20	0.8321	0.0775	0.8635	0.0674
ρ_γ	Autocorrelation, net worth shock	Beta	0.50	0.20	0.4689	0.2051	0.4750	0.0866
ρ_{ζ_c}	Autocorrelation, preference shock	Beta	0.50	0.20	0.9029	0.0379	0.9093	0.0311
ρ_{ζ_I}	Autocorrelation, MEI shock	Beta	0.50	0.20	0.5426	0.0975	0.5500	0.0984
Marginal Likelihood					3142.93		3095.73	

Table 3: Estimated Parameters (continued)

		Prior			Posterior			
					Endogenous Liquidation		Fixed Liquidation	
Name	Description	Distribution	Mean	STD	Mean	STD	Mean	Std
σ_{λ_f}	Price markup shock	Inv. Gamma	0.0023	0.0033	0.0083	0.0012	0.0112	0.0021
σ_g	Government spending shock	Inv. Gamma	0.0023	0.0033	0.0229	0.0016	0.0226	0.0015
σ_{μ_z}	Persistent technology shock	Inv. Gamma	0.0023	0.0033	0.0072	0.0006	0.0073	0.0006
σ_γ	Survival probability shock	Inv. Gamma	0.0023	0.0033	0.0104	0.0038	0.0337	0.0054
σ_{ϵ^z}	Temporary technology shock	Inv. Gamma	0.0023	0.0033	0.0049	0.0003	0.0051	0.0003
σ_{ϵ^p}	Monetary policy shock	Inv. Gamma	0.5833	0.8250	0.5114	0.0391	0.4888	0.0384
σ_{ζ_c}	Preference shock	Inv. Gamma	0.0023	0.0033	0.0256	0.0089	0.0250	0.0039
σ_{ζ_I}	MEI shock	Inv. Gamma	0.0023	0.0033	0.0203	0.0029	0.0204	0.0019
σ_{rec}	Shock to obs. equation for recovery	Uniform	0.250	0.1443	0.2517	0.0187	0.3428	0.0241

Table 4: Variance Decomposition - Fixed Liquidation

	ϵ^z	g	γ	λ_f	μ_z	ϵ^p	ζ_c	ζ_I	ϵ^{rec}
Y	0.89	17.78	35.25	7.48	5.40	2.94	6.99	23.25	0.00
I	0.15	0.00	56.25	3.00	0.33	1.50	0.31	38.45	0.00
C	3.07	0.80	13.91	15.56	3.95	5.19	55.33	2.16	0.00
π	13.10	1.33	34.02	31.90	1.83	3.04	9.86	4.49	0.00
W	4.34	0.24	5.19	15.01	73.82	0.19	0.25	0.95	0.00
H	3.07	3.50	56.57	12.85	1.46	3.44	5.54	13.55	0.00
r	4.82	1.08	54.85	13.03	3.52	5.21	13.63	3.65	0.00
$Spread$	0.08	0.05	97.65	0.07	0.08	1.10	0.24	0.72	0.00
$Recovery$	0.00	0.00	0.28	0.00	0.00	0.00	0.00	0.00	99.71
$Defaults$	0.08	0.05	97.66	0.07	0.08	1.09	0.24	0.72	0.00

Notes: For each variable indicated in the first column, variance decompositions are generated by model with fixed liquidation costs evaluated at the mode of the posterior distribution. The table does not display results for the shock π_t^* whose contribution is less than 1/2 of 1 percent to any of the variables.

Table 5: Variance Decomposition - Endogenous Liquidation

	ϵ^z	g	γ	λ_f	μ_z	ϵ^p	ζ_c	ζ_I	ϵ^{rec}
Y	1.05	24.82	18.01	14.82	6.93	5.53	7.61	21.21	0.00
I	0.28	0.01	37.59	9.71	0.59	5.81	1.13	44.87	0.00
C	2.92	1.29	4.06	20.13	3.98	3.85	62.36	1.39	0.00
π	25.00	2.99	12.02	29.26	2.70	5.12	16.29	5.91	0.00
W	6.24	0.44	1.32	13.73	76.61	0.31	0.39	0.96	0.00
H	4.76	6.15	19.94	40.25	2.59	5.79	6.74	13.75	0.00
r	10.49	3.01	22.73	14.13	6.56	6.98	30.89	4.78	0.00
$Spread$	0.67	0.34	84.91	0.79	0.44	8.24	0.91	3.66	0.00
$Recovery$	0.30	0.15	37.58	0.34	0.20	3.59	0.42	1.59	55.82
$Defaults$	0.68	0.35	84.82	0.79	0.44	8.26	0.94	3.68	0.00

Notes: For each variable indicated in the first column, variance decompositions are generated by the model with endogenous liquidation costs evaluated at the mode of the posterior distribution. The table does not display results for the shock π_t^* whose contribution is less than 1/2 of 1 percent to any of the variables.