

# Household Leverage and the Recession<sup>\*</sup>

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## Abstract

We evaluate and partially challenge the household leverage view of the Great Recession. In the data, employment and consumption declined more in U.S. states where household debt declined more. We study a model of a monetary union composed of many regions in which liquidity constraints shape the response of employment and consumption to changes in debt. We estimate the model with Bayesian methods combining state and aggregate data. Changes in household credit explain 40% of the differential rise and fall of employment across states, but a small fraction of the aggregate employment decline in 2007-2010. Nevertheless, since household deleveraging was gradual, credit shocks greatly slowed the recovery.

*Keywords:* Great Recession, Household Debt, Regional Evidence, Zero Lower Bound.

*JEL classifications:* E2, E4, E5, G0, G01.

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# 1 Introduction

A salient feature of the Great Recession is that U.S. regions with the largest declines in household debt had the largest declines in employment and consumption. Figure 1 illustrates this pattern, originally documented in a series of papers by Mian and Sufi.<sup>1</sup> One interpretation of this evidence that has received a lot of attention is the *household leverage* view of the recession. According to this view, declines in household debt forced households to reduce consumption and, because of price rigidities and trade frictions, caused a reduction in employment.

Our goal in this paper is to quantitatively evaluate the household leverage view of the recession. We ask: how important were shocks to household credit in generating fluctuations in employment and consumption across regions and in the aggregate? The evidence in Figure 1 does not directly answer this question for at least two reasons. First, a variety of shocks, in addition to credit shocks, affect the economy. Second, the response of employment or consumption in an individual state to credit shocks may be very different than the response in the aggregate. Extrapolating from the cross-sectional to the aggregate elasticity requires a careful consideration of trade patterns and monetary policy.

We therefore use a model to isolate the effects of credit shocks and answer our question. We study a tractable model of a monetary union composed of many regions that trade. Households face liquidity constraints that restrict their ability to use the equity in their homes to finance consumption. These constraints generate a time-varying spread between the equilibrium interest rate and the households' rate of time preference. In our baseline model we assume that credit shocks affect loan-to-value constraints which limit the amount of housing equity that households can extract. In an extension we obtain similar results by assuming instead that household debt fluctuates in response to credit supply shocks. In addition to credit shocks, households in each region are subject to a number of additional disturbances to productivity and preferences.

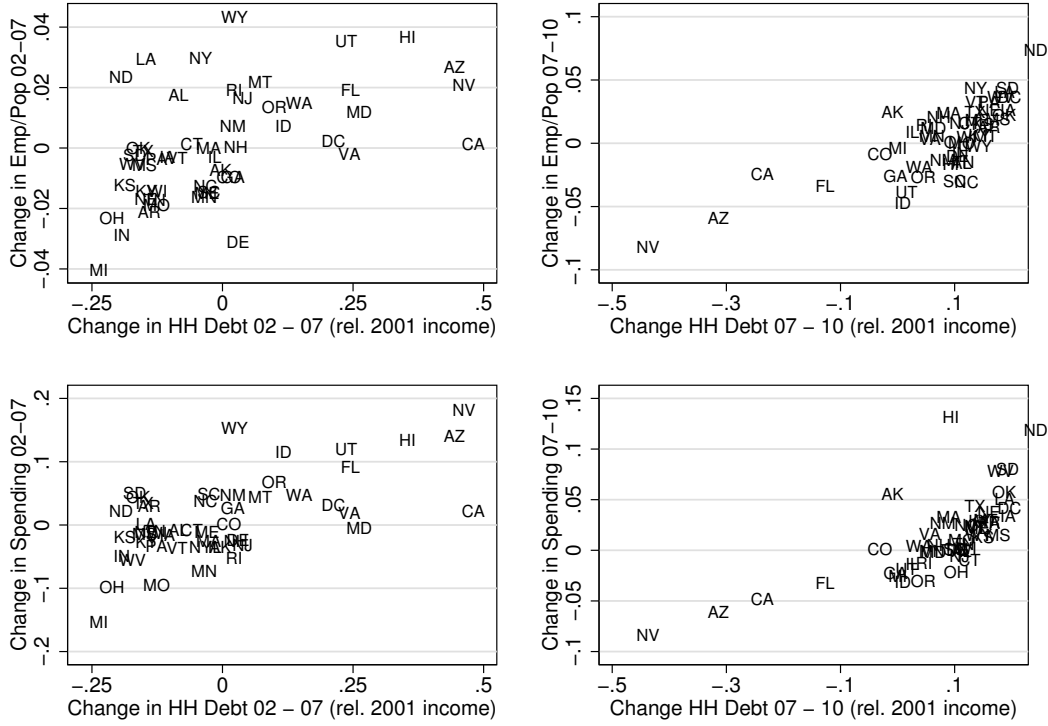
We estimate the model using Bayesian full-information methods and data on employment, consumption, wages, house prices and household debt at the regional and aggregate levels. An important challenge that arises in our estimation is that the policy interest rate was at the zero lower bound (ZLB) during part of our sample. We account for the non-linearities arising from this bound by using a piece-wise linear solution method.<sup>2</sup> Even with this approximation, a direct application of full-information methods is infeasible in our setting given the large number of regional and aggregate state variables. We therefore develop a methodology that allows us

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<sup>1</sup>See Mian and Sufi (2011); Mian et al. (2013); Mian and Sufi (2014) for additional evidence.

<sup>2</sup>See Eggertsson and Woodford (2003); Guerrieri and Iacoviello (2015); Jones (2017).

Figure 1: State Debt, Employment, and Spending



to combine regional and aggregate data to evaluate the likelihood function.

A popular approach to modeling household debt is to assume heterogeneity in agents' rate of time preference, as in [Iacoviello \(2005\)](#) and a large literature that follows.<sup>3</sup> These models feature a single financial asset, which impatient households use to borrow from patient households. A tightening of credit limits reduces the amount that impatient households borrow and translates into a dollar-for-dollar drop in their consumption, but, in the absence of changes in the equilibrium interest rate, leaves patient households unaffected. Such models thus predict that consumption in an individual region changes dollar-for-dollar with changes in household debt, regardless of how many agents are impatient, as long as the region is sufficiently small so it does not affect the economy-wide interest rate. One-asset models therefore imply counterfactually large comovements between consumption and credit across regions, at odds with the evidence in [Figure 1](#).<sup>4</sup>

Motivated by this observation, we pursue an alternative approach. We assume that house-

<sup>3</sup>See [Eggertsson and Krugman \(2012\)](#); [Justiniano et al. \(2015\)](#); [Guerrieri and Iacoviello \(2017\)](#) for the U.S., and [Martin and Philippon \(2014\)](#); [Gourinchas et al. \(2016\)](#) for the Eurozone.

<sup>4</sup>If there are few borrowers in a region, the percentage change in consumption can be much lower than the percentage change in debt. Notice, however, that in [Figure 1](#) we scale debt by the 2001 income in a region. Since income and consumption are of a similar magnitude, one-asset models would imply much larger percentage changes in consumption compared to the data.

holds are subject to idiosyncratic shocks to their liquidity needs which make it optimal to simultaneously hold liquid assets and borrow. A household can therefore respond to a tightening of credit by drawing on its liquid assets instead of cutting consumption. The extent to which it can do so depends on the volatility of idiosyncratic shocks. If these shocks are volatile, the household maintains its liquid asset position, thus reducing consumption sharply after a credit tightening. If, in contrast, the volatility of idiosyncratic shocks is low, households find it optimal to dip into their liquid assets to insulate consumption from credit shocks. Our model thus flexibly nests both one-asset models in which a region-specific tightening of credit leads to a large drop in consumption, as well as the frictionless model in which credit shocks have no effect on consumption. We view this framework as our main theoretical contribution: it is flexible enough to capture complex credit dynamics but simple enough to be estimated on a full panel of regional economic data.

We next explain why households in our model value liquidity. The typical approach to modeling the notion that housing equity is illiquid is to assume that agents must pay a fixed cost to refinance their mortgage, as in the work of [Kaplan et al. \(2020\)](#) and [Boar et al. \(2020\)](#). Since most homeowners who do not refinance are constrained,<sup>5</sup> they save in a liquid asset in order to smooth consumption. By contrast, considerations of computational tractability lead us to follow an alternative approach inspired by [Lucas \(1990\)](#). Agents in our model can costlessly rebalance their portfolios between periods, but they must do so prior to the realization of an idiosyncratic preference shock. We achieve tractability by assuming a family construct to eliminate the distributional consequences of asset market incompleteness.<sup>6</sup> These assumptions allow us to parsimoniously model an interest-elastic supply of liquid assets of the type that would arise in richer but less tractable models of mortgage refinancing. In particular, the larger the interest rate is relative to the rate of time preference, the more households save in their liquid accounts to smooth the impact of idiosyncratic shocks. Our notion of liquidity therefore closely resembles that in the work of [Shi \(2015\)](#), [Rocheteau et al. \(2018\)](#) and [Kiyotaki and Moore \(2019\)](#) in which liquidity is valued because of idiosyncratic investment opportunities or preference shocks.

Consider now the macroeconomic implications of a credit shock. At the economy-wide level, a tightening of credit leads to a reduction in the natural interest rate. The drop in the natural rate depends on the volatility of idiosyncratic preference shocks: more volatile shocks

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<sup>5</sup>See [Amromin et al. \(2007\)](#) and [Adelman et al. \(2010\)](#) for evidence on this.

<sup>6</sup>See also [Lucas and Stokey \(2011\)](#) who emphasize the role of liquidity frictions and [Challe and Ragot \(2016\)](#) who use a family construct to characterize an economy with uninsurable unemployment risk.

reduce the elasticity of liquid assets and imply a larger fall in the natural rate. If prices are sticky and monetary policy is unable to track movements in the natural rate, the credit shock leads to a decline in employment. The response to economy-wide credit shocks is therefore highly non-linear depending on how long the ZLB is expected to constrain monetary policy. At the regional level, a tightening of credit acts like a sudden stop by forcing an increase in the net foreign asset position, as in [Gourinchas et al. \(2016\)](#), but the extent of the increase in net foreign assets depends, once again, on the volatility of idiosyncratic shocks. Hence, the same parameter governing the elasticity of liquid assets determines both the economy-wide and regional implications of a tightening of credit, a feature that we exploit in estimation.

We estimate three structural parameters that play a key role in shaping the economy’s response to a credit shock: the degrees of wage and price stickiness, and the degree of idiosyncratic uncertainty. We also estimate the persistence and volatility of the regional and aggregate shock processes. To make full-information estimation feasible we exploit the structure of the model and express regional variables as deviations from the corresponding aggregates. Up to a first-order approximation, these deviations evolve according to a law of motion that is independent of monetary policy. This structure allows us to separate the likelihood function into independent state-level and aggregate components. Intuitively, our estimation exploits the differential rise and fall of individual states’ spending, employment, debt, wages and house prices, in addition to the aggregate comovement of these series, to identify the structural parameters.

We use the model to generate counterfactual series for employment and consumption by turning off all shocks other than credit shocks. We find that credit shocks alone account for 40 – 50% of the relative movements in state-level employment and consumption during the 2002 to 2010 period. Our findings are thus consistent with those of [Mian and Sufi \(2011, 2014\)](#) who argue that household credit played an important role at the regional level.

We next discuss the model’s economy-wide implications. We distinguish between two periods: the onset of the Great Recession from 2007 to 2010, and the recovery period up to the end of 2012. Given the non-linear nature of the responses at the ZLB, we provide bounds on the impact of credit shocks. The lower bound assumes no ZLB. The upper bound assumes that the ZLB binds and that the Fed does not pursue forward guidance. Under both bounds we find that household credit shocks have a relatively small impact on employment between 2007 and 2010. In the data, employment fell by 7% during this period. In contrast, the lower and upper bounds on the contribution of credit shocks to the decline in employment are 0.5% and 1.7%, respectively. Thus, even under the stark assumption that the Fed did not react to credit shocks

at all, household deleveraging explains at most a quarter of the drop in employment during the acute phase of the crisis. This result is a consequence of the gradual nature of household deleveraging which leads to a gradual decline in the natural rate and reflects the findings of [Kaplan et al. \(2020\)](#) who show that the duration of mortgages greatly matters for the effects of shocks to household credit.<sup>7</sup>

The results are different when we consider the period 2007 to 2012. Since household debt fell more over this longer period, so did the natural rate, and the model predicts a more important role for credit shocks. In the data, employment was 6.2% lower by the end of 2012 compared to 2007. Under the two bounds, employment declined by 1.3% and 4.8%, respectively. The model therefore predicts that credit shocks greatly delayed the recovery.<sup>8</sup> Our results are robust to a number of perturbations, including adding a construction sector, allowing for fiscal policy, lowering the duration of mortgage contracts, explicitly modeling mortgage default, credit supply shocks and heterogeneity in state responses to credit shocks.

Our goal in this paper is to quantify the role of credit shocks in accounting for regional and aggregate employment during the Great Recession. To keep our analysis as transparent as possible, we focus on the *household leverage* view of the Great Recession and do not explicitly model the other forces that arguably played an important role, such as bank and firm-level financing constraints, changes in uncertainty, demographics, increase in markups and risk premia. These factors are instead captured by our rich set of exogenous shocks. A limitation of our approach is that household credit may interact with a number of these forces in important ways.<sup>9</sup>

Our analysis also focuses on a representative agent economy, which, in general equilibrium, precludes us from capturing housing wealth effects on consumption. Introducing housing wealth effects, which [Kaplan et al. \(2020\)](#) argue were responsible for a large fraction of the expenditure drop during the Great Recession, requires explicitly modelling household heterogeneity and the resulting correlation between wealth effects and marginal propensities to consume across households. To keep our analysis tractable, we abstract from such heterogeneity and thus implicitly capture these forces using changes in the household's rate of time-preference.

**Related Work.** Our paper is related to [Eggertsson and Krugman \(2012\)](#) and [Guerrieri and Lorenzoni \(2017\)](#) who also study the responses of an economy to a household credit crunch. While they study a closed-economy setting, our model is that of a monetary union composed of

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<sup>7</sup>See also [Kiyotaki et al. \(2011\)](#).

<sup>8</sup>See the literature on the slow recovery discussed by [Fernald et al. \(2017\)](#).

<sup>9</sup>For example, a tightening of household credit that depresses income and home prices may trigger a wave of default that reduces the net worth of financial intermediaries. See [Faria-e-Castro \(2018\)](#) for such a model.

a large number of regions. Moreover, our focus is on estimating the model using state-level and aggregate data. Since we found that one-asset models cannot account for the comovement between state-level consumption and household debt, we explicitly introduce liquidity constraints which make it optimal for households to simultaneously borrow and save in the liquid asset, an ingredient which we argue is critical to match the regional data.

Our use of regional data to estimate the model is related to the work of [Beraja et al. \(2019\)](#). These researchers apply a limited-information approach to estimate the degree of wage stickiness using state-level data, and then use those estimates as a prior in a full-information estimation with only aggregate data. In contrast, we develop a methodology that allows one to simultaneously use regional and aggregate data in a full-information approach, despite the large number of state variables and non-linearities associated with the ZLB. This methodology can be fruitfully applied to other applications. Our emphasis on cross-sectional evidence is also shared by the work of [Nakamura and Steinsson \(2014\)](#). Finally, our work is related to the literature on financial intermediation, originating with [Bernanke and Gertler \(1989\)](#); [Kiyotaki and Moore \(1997\)](#); [Bernanke et al. \(1999\)](#) and more recently [Mendoza \(2010\)](#); [Gertler and Karadi \(2011\)](#); [Gilchrist and Zakrajšek \(2012\)](#).<sup>10</sup>

## 2 Model

We first describe the model economy. The economy consists of a continuum of ex-ante identical islands of unit mass that belong to a monetary union and trade among themselves. Consumers derive utility from a final good, leisure and housing. The final good is assembled using as inputs traded and non-traded goods. We assume that producers of intermediate goods are monopolistically competitive. Prices and wages are subject to Calvo adjustment frictions. Labor is immobile across islands and the housing stock on each island is in fixed supply.

We explicitly model the distinction between liquid and illiquid assets on households' balance sheets. In contrast to [Kaplan and Violante \(2014\)](#) and much of the segmented asset markets literature which assumes fixed costs of portfolio rebalancing, we follow instead an alternative approach due to [Lucas \(1990\)](#). We assume that consumers allocate their wealth between liquid and illiquid assets prior to the realization of an idiosyncratic preference shock. The more volatile this shock is, the stronger the precautionary savings motive in liquid assets, and the larger the response of consumption to credit shocks. Following [Lucas \(1990\)](#), we assume that consumers

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<sup>10</sup>See also the work [Lustig and Van Nieuwerburgh \(2005\)](#); [Garriga et al. \(2019\)](#); [Favilukis et al. \(2017\)](#); [Burnside et al. \(2016\)](#); [Landvoigt et al. \(2015\)](#) who study the determinants of house prices.

belong to families that share idiosyncratic risks.

Households face shocks to their ability to tap home equity, which we refer to as credit shocks. We also allow for shocks to the households' rate of time preference, disutility from work, preference for housing and productivity. Each shock has an island-specific and aggregate component. We also assume aggregate shocks to the interest rate rule and to the aggregate inflation equation. These additional shocks allow us to capture other channels that can explain movements in macroeconomic aggregates.

## 2.1 Households

**Securities.** Households borrow using mortgages which are long-term perpetuities with coupon payments that decay geometrically at a rate determined by a parameter  $\gamma$ . A seller of such a security issues one unit at a price  $q_t$  in period  $t$  and repays 1 unit of the good in period  $t + 1$ ,  $\gamma$  units in  $t + 2$ ,  $\gamma^2$  in  $t + 3$  and so on in perpetuity.<sup>11</sup> The household borrows from perfectly competitive financial intermediaries.

It is convenient to describe the outstanding mortgage debt of a household on island  $s$  by recording the amount of coupon payments  $b_t(s)$  it must make in period  $t$ . Letting  $l_t(s)$  denote the amount of newly issued mortgages in period  $t$ , the date  $t + 1$  coupon payments are

$$b_{t+1}(s) = \sum_{i=0}^{\infty} \gamma^i l_{t-i}(s) = l_t(s) + \gamma b_t(s). \quad (1)$$

Letting  $q_t$  denote the economy-wide price of one claim to such a perpetuity, the value of a household's mortgage liabilities is  $b_t(s)(1 + \gamma q_t)$ , reflecting the amount the household owes in coupon payments in period  $t$  and the market value of its outstanding debt. On the asset side, we assume that households save in a one-period nominal security at a rate  $i_t$ .<sup>12</sup>

**Preferences.** We introduce wage-setting frictions by assuming that households are organized in unions that set wages. We assume perfect risk-sharing across households that belong to different labor unions on a given island. Because of separability in preferences, risk-sharing implies that all households on an island make identical consumption, housing and savings choices, even though their labor supply differs depending on when the union they belong to last reset its wage. The preferences of a household on island  $s$  who belongs to a labor union  $\iota$  are

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \left( \prod_{\tau=0}^{t-1} \beta_{\tau}(s) \right) \left[ \int_0^1 v_{it}(\iota, s) \log c_{it}(\iota, s) di + \eta_t^h(s) \log h_t(\iota, s) - \frac{\eta_t^n(s)}{1 + \nu} n_t(\iota, s)^{1+\nu} \right], \quad (2)$$

<sup>11</sup>See Hatchondo and Martinez (2009) and Arellano and Ramanarayanan (2012).

<sup>12</sup>Since we solve the model using first-order perturbation methods, the assumption that assets have a different maturity structure than liabilities is inconsequential and we only use it to simplify the notation.

where  $c_{it}(\iota, s)$  denotes the consumption of a member  $i$  of household  $(\iota, s)$ ,  $h_t(\iota, s)$  denotes the total amount of housing owned by that household and  $n_t(\iota, s)$  denote the labor it supplies. The shifters  $\eta_t^h(s)$  and  $\eta_t^n(s)$  determine the preference for housing and the disutility from work, while  $\beta_t(s)$  is the household's one-period ahead discount factor. We assume that each of these preference shifters have an island-specific and aggregate component, all of which follow AR(1) processes with independent Gaussian innovations.

The term  $v_{it}(\iota, s) \geq 1$  is specific to each consumer  $i$  and denotes an idiosyncratic taste shifter, which is an i.i.d random variable drawn from a Pareto distribution over  $[1, \infty)$

$$\Pr(v_{it} \leq v) = F(v) = 1 - v^{-\alpha}. \quad (3)$$

The parameter  $\alpha > 1$  determines the amount of uncertainty about  $v$ . A lower  $\alpha$  implies more uncertainty. From now on we drop the dependence on  $\iota$  for notational simplicity.

**Budget and Credit Constraints.** Let  $x_t(s)$  denote the total amount of funds the household transfers to its members. We assume that  $x_t(s)$  is chosen prior to the realization of the idiosyncratic preference shock  $v_{it}(s)$ . Since individual members are ex-ante identical and of mass 1,  $x_t(s)$  also represents the amount of funds received by any individual member. We assume a *liquidity constraint* which limits each member's consumption by the amount of funds it has when entering the goods market:

$$p_t(s)c_{it}(s) \leq x_t(s), \quad (4)$$

where  $p_t(s)$  is the price of the final good on island  $s$ . The budget constraint is

$$x_t(s) + e_t(s)(h_{t+1}(s) - h_t(s)) = w_t(s)n_t(s) + q_t l_t(s) - b_t(s) + (1 + i_{t-1})a_t(s) + T_t(s), \quad (5)$$

where  $e_t(s)$  is the price of housing,  $w_t(s)$  is the wage rate the household faces,  $b_t(s)$  are the coupon payments on outstanding mortgage debt,  $a_t(s)$  are the liquid assets it enters the period with and  $T_t(s)$  collects the profits households earn from their ownership of intermediate goods firms, transfers from the government aimed at correcting the steady state markup distortion, as well as the transfers stemming from the risk-sharing arrangement. We assume that households on island  $s$  exclusively own firms on that island.

The household also faces a *borrowing constraint* which limits its ability to issue *new* loans:

$$q_t l_t(s) \leq m_t(s)e_t(s)h_{t+1}(s), \quad (6)$$

where the credit limit  $m_t(s)$  evolves as the product of an island-specific and aggregate component, both of which follow an AR(1) process. This formulation allows us to capture the slow

movement of debt in the data in which only a fraction of households obtain new mortgages in any given period, and so face the current credit conditions and house prices in determining mortgage limits.

We introduce housing preference shocks to capture movements in house prices that are otherwise difficult to rationalize.<sup>13</sup> Because housing is separable in the utility function and the housing stock is in fixed supply, movements in house prices only affect equilibrium allocations via their impact on the households' ability to borrow.<sup>14</sup>

**Savings.** A household's savings are the unspent funds of its shoppers in the goods market. The total amount of liquid assets the household has at the end of the shopping period is

$$a_{t+1}(s) = \left( x_t(s) - p_t(s) \int_0^1 c_{it}(s) di \right). \quad (7)$$

These funds are deposited with financial intermediaries and earn the nominal interest rate  $i_t$ .

Our model is reminiscent of cash-in-advance models, though there are several important differences. First, we assume that the household can access its date  $t$  labor income  $w_t(s)n_t(s)$  immediately. Second, we allow agents to save in interest-bearing assets at the conclusion of their shopping period. The only distortion we introduce is that arising from the household's inability to smooth the marginal utility of consumption *across* its members within a period.

**Timing.** Figure 2 summarizes our timing assumptions. The household's portfolio composition is described by the liquid assets  $a_t(s)$ , housing  $h_t(s)$  and mortgage obligations  $b_t(s)$ . All shocks – except  $v_{it}(s)$  – are realized at the beginning of the period. The household then chooses how much to work  $n_t(s)$ , its housing  $h_{t+1}(s)$ , borrowing  $b_{t+1}(s)$ , and transfers  $x_t(s)$ . The idiosyncratic preference shocks  $v_{it}(s)$  are then realized and individual members choose consumption  $c_{it}(s)$ . All unspent funds  $a_{t+1}(s)$  are then saved in the liquid asset.

## 2.2 Optimal Savings Choice

Let  $\lambda_t(s)$  denote the multiplier on the household's budget constraint (5) and  $\xi_{it}(s)$  denote the multiplier on the liquidity constraint (4). The optimal choice of  $x_t(s)$  satisfies

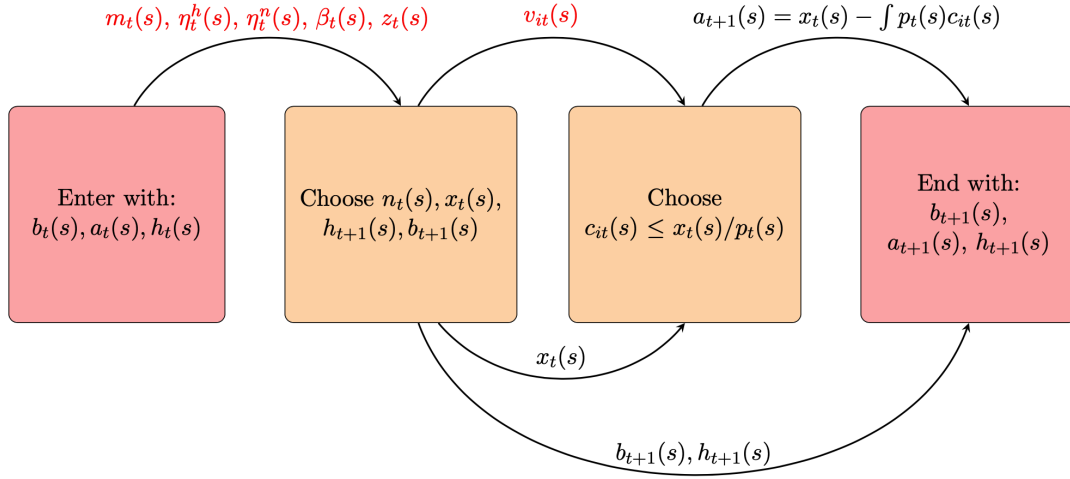
$$\lambda_t(s) = \beta_t(s)(1 + i_t)\mathbb{E}_t\lambda_{t+1}(s) + \int_0^1 \xi_{it}(s) di. \quad (8)$$

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<sup>13</sup>See Kiyotaki et al. (2011) for an illustration of the problem and Favilukis et al. (2017), Garriga et al. (2019), and Kaplan et al. (2020) for approaches to resolve it. We think of preference shocks as a parsimonious way of capturing changes in risk premia or beliefs that trigger changes in house prices in these richer models.

<sup>14</sup>In contrast, in partial equilibrium house price changes would have wealth effects on household consumption, as shown in Berger et al. (2018).

Figure 2: Timing of the Model



The transfer  $x_t(s)$  is valued at  $\lambda_t(s)$ , the shadow value of wealth. Since unspent funds can be saved at the conclusion of the shopping period, they are valued at  $\beta_t(s)(1 + i_t)\mathbb{E}_t\lambda_{t+1}(s)$ . The last term captures the liquidity services provided by  $x_t(s)$ , namely the average multiplier on the liquidity constraint of individual members.

Optimal consumption spending is equal to

$$p_t(s)c_{it}(s) = \min \left[ \frac{v_{it}(s)}{\beta_t(s)(1 + i_t)\mathbb{E}_t\lambda_{t+1}(s)}, x_t(s) \right] \quad (9)$$

and the multiplier on the liquidity constraint is

$$\xi_{it}(s) = \max \left[ 0, \frac{v_{it}(s)}{x_t(s)} - \beta_t(s)(1 + i_t)\mathbb{E}_t\lambda_{t+1}(s) \right]. \quad (10)$$

Integrating (10) across all members of a given household implies that

$$\int_0^1 \xi_{it}(s) di = \frac{1}{\alpha - 1} x_t(s)^{-\alpha} [\beta_t(s)(1 + i_t)\mathbb{E}_t\lambda_{t+1}(s)]^{1-\alpha}. \quad (11)$$

Let

$$\Delta_t(s) \equiv \frac{\lambda_t(s)}{(1 + i_t)\beta_t(s)\mathbb{E}_t\lambda_{t+1}(s)} - 1 \quad (12)$$

denote the wedge between the household's rate of time preference and the return on the liquid asset. Combining (8) and (11) allows us to express transfers as a decreasing function of  $\Delta_t(s)$ :

$$x_t(s) = \frac{1}{\beta_t(s)(1 + i_t)\mathbb{E}_t\lambda_{t+1}(s)} [(\alpha - 1)\Delta_t(s)]^{-\frac{1}{\alpha}}. \quad (13)$$

Since liquid savings are equal to the amount of unspent funds in the goods market,  $a_{t+1}(s) = x_t(s) - p_t(s) \int c_t(s) di$ , they can be also expressed as a decreasing function of the wedge:

$$\frac{a_{t+1}(s)}{p_t(s)c_t(s)} = \left( \frac{\alpha}{\alpha - 1} [(\alpha - 1)\Delta_t(s)]^{\frac{1}{\alpha}} - \Delta_t(s) \right)^{-1} - 1. \quad (14)$$

To understand this expression, note that when  $\Delta_t(s)$  is high, the household is relatively impatient. Idiosyncratic taste shocks generate a precautionary savings motive, in addition to the intertemporal substitution motive. When uncertainty about taste shocks is high ( $\alpha$  is low), the precautionary motive dominates so savings are relatively insensitive to the wedge  $\Delta_t(s)$ . In contrast, when the uncertainty about taste shocks is low ( $\alpha$  is high), the precautionary motive is weak and savings are sensitive to  $\Delta_t(s)$ . As  $\alpha \rightarrow \infty$ , the precautionary motive disappears and the supply of liquid assets is infinitely elastic.

The assumption that taste shocks are Pareto distributed, or that idiosyncratic uncertainty takes the form of preference, as opposed to income or expense shocks, is not critical to our arguments. In the Appendix we consider alternative types of shocks. Although these alternatives are not as tractable as our baseline formulation, their qualitative implications are similar.

### 2.3 Optimal Debt and Housing Choice

We next discuss the household's demand for mortgage debt and housing. Let

$$R_{t+1} = \frac{1 + \gamma q_{t+1}}{q_t} \quad (15)$$

denote the one-period return on mortgages. The first-order condition for  $b_{t+1}(s)$  is

$$\lambda_t(s) = \beta_t(s) \mathbb{E}_t \lambda_{t+1}(s) R_{t+1} + \mu_t(s) - \gamma \beta_t(s) \mathbb{E}_t \mu_{t+1}(s) \frac{q_{t+1}}{q_t}, \quad (16)$$

where  $\mu_t(s)$  is the multiplier on the borrowing constraint (6). The first-order condition for housing is

$$e_t(s) \lambda_t(s) - \beta_t(s) \mathbb{E}_t \lambda_{t+1}(s) e_{t+1}(s) = \beta_t(s) \mathbb{E}_t \frac{\eta_{t+1}^h(s)}{h_{t+1}(s)} + \mu_t(s) m_t(s) e_t(s). \quad (17)$$

The left hand side is the user cost of housing. The right hand side adds the marginal utility of housing services to the collateral value of housing.

### 2.4 Technology

We next discuss the assumptions we make on the technology with which final and intermediate goods are produced.

**Final Goods Producers.** Final goods producers on island  $s$  produce  $y_t(s)$  units of the final good using  $y_t^N(s)$  units of non-tradable goods produced locally and  $y_t^M(s)$  units of imported

goods. Imported and non-tradable goods are combined using a CES aggregator with elasticity of substitution  $\sigma$ ,

$$y_t(s) = \left( \omega^{\frac{1}{\sigma}} y_t^N(s)^{\frac{\sigma-1}{\sigma}} + (1-\omega)^{\frac{1}{\sigma}} y_t^M(s)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \quad (18)$$

where  $\omega$  determines the share of non-traded goods. The imported good is a CES composite of imports from all islands with elasticity of substitution  $\kappa$ :

$$y_t^M(s) = \left( \int_0^1 y_t^M(s, s')^{\frac{\kappa-1}{\kappa}} ds' \right)^{\frac{\kappa}{\kappa-1}}. \quad (19)$$

We assume that there are no trade costs, so all islands face the same import price index

$$p_t^T = \left( \int_0^1 p_t^T(s')^{1-\kappa} ds' \right)^{\frac{1}{1-\kappa}},$$

where  $p_t^T(s)$  is the price of imports from island  $s$ . Letting  $p_t^N(s)$  denote the price of non-tradable goods, the final goods price on an island is

$$p_t(s) = \left( \omega p_t^N(s)^{1-\sigma} + (1-\omega) (p_t^T)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}. \quad (20)$$

The demand for non-tradable goods produced on an island is

$$y_t^N(s) = \omega \left( \frac{p_t^N(s)}{p_t(s)} \right)^{-\sigma} y_t(s), \quad (21)$$

while demand for its exports is the sum of purchases from all islands:

$$y_t^X(s) = (1-\omega) \left( \frac{p_t^T(s)}{p_t^T} \right)^{-\kappa} \left( \int_0^1 \left( \frac{p_t^T}{p_t(s')} \right)^{-\sigma} y_t(s') ds' \right). \quad (22)$$

**Intermediate Goods Producers.** Tradable and non-tradable goods are themselves CES composites of varieties of differentiated intermediate inputs with an elasticity of substitution  $\vartheta$ . Technology is linear in labor and subject to a productivity disturbance  $z_t(s)$  that is common to both the tradable and non-tradable sectors:

$$y_{kt}^j(s) = z_t(s) n_{kt}^j(s), \text{ for } j \in \{X, N\}.$$

Producers of intermediate goods are subject to Calvo pricing frictions and can only reset prices with probability  $1 - \theta_p$  each period. A firm that resets its price maximizes the present discounted flow of profits weighted by the probability that the price it chooses at  $t$  will still be in effect at any particular date. The government levies a production subsidy  $\tau_p = \frac{\vartheta-1}{\vartheta}$  which eliminates the steady state markup distortion and is financed with lump-sum taxes.

**Wage Setting.** Individual households are organized in unions that supply differentiated varieties of labor with elasticity of substitution  $\psi$ . Unions reset their wages with probability  $1 - \theta_w$  each period. We assume that the government offsets the steady-state wage markup distortion using a subsidy  $\tau_w = \frac{\psi-1}{\psi}$  financed with lump-sum transfers.

## 2.5 Monetary Policy

Let  $y_t = \int_0^1 p_t(s)y_t(s)/p_t ds$  be total output in this economy,  $p_t = \int_0^1 p_t(s)ds$  be the aggregate price level and  $\pi_t = p_t/p_{t-1}$  denote the rate of inflation. Aggregating the prices of individual producers in all islands implies, up to a first-order approximation,

$$\log(\pi_t/\bar{\pi}) = \bar{\beta}\mathbb{E}_t \log(\pi_{t+1}/\bar{\pi}) + \frac{(1-\theta_p)(1-\theta_p\bar{\beta})}{\theta_p} (\log(w_t) - \log(z_t)) + \eta_t^\pi,$$

where  $w_t = \int w_t(s)ds$  is the average wage in the economy,  $\eta_t^\pi$  is an AR(1) disturbance to individual firms' desired markups, common to all islands,  $\bar{\beta}$  is the steady state discount factor and  $\bar{\pi}$  is the steady-state rate of inflation.<sup>15</sup>

We follow [Smets and Wouters \(2007\)](#) and assume that monetary policy follows a Taylor rule when the ZLB does not bind:

$$1 + i_t = (1 + i_{t-1})^{\alpha_r} \left[ (1 + \bar{i}) (\pi_t/\bar{\pi})^{\alpha_\pi} \hat{y}_t^{\alpha_y} \right]^{1-\alpha_r} (\hat{y}_t/\hat{y}_{t-1})^{\alpha_x} \eta_t^i,$$

where  $\bar{i}$  is the steady state nominal interest rate,  $\eta_t^i$  is an i.i.d. monetary policy shock,  $\alpha_r$  determines the persistence and  $\alpha_\pi$ ,  $\alpha_y$  and  $\alpha_x$  determine the extent to which monetary policy responds to deviations of inflation from the target  $\bar{\pi}$ , the output gap  $\hat{y}_t$ , and the growth rate of the output gap, respectively. The output gap is the ratio of actual output to its flexible price level,  $\hat{y}_t = y_t/y_t^*$ . When the ZLB binds, the Fed sets  $i_t = 0$ .

The Fed may set an interest rate of zero not only when the ZLB binds, but also when it follows its *forward guidance*. In particular, we assume that in periods in which the ZLB binds the Fed can commit to keeping  $i_t$  at zero for longer than the duration prescribed by the Taylor rule. We thus implicitly assume that the Fed can manipulate expectations of how the path of interest rates evolves when the economy hits the ZLB, as in [Eggertsson and Woodford \(2003\)](#) and [Werning \(2011\)](#). In our estimation we use survey data from the New York Federal Reserve to discipline the expected duration of the zero interest rate regime between 2009 and 2015.

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<sup>15</sup>We assume in our quantitative analysis that  $\bar{\pi}$  is equal to 2% per year. We implicitly eliminate the steady-state costs of positive inflation by assuming that all prices and wages are automatically indexed to  $\bar{\pi}$ . See [Coibion and Gorodnichenko \(2015\)](#) and [Blanco \(2019\)](#) who study the size of these costs in the absence of indexation.

## 2.6 Asset Market

The monetary union is closed so savings in the liquid asset equals aggregate mortgage debt:

$$\int_0^1 a_{t+1}(s)ds = \int_0^1 b_{t+1}(s)ds. \quad (23)$$

In contrast, individual states can run current account imbalances. An island's net foreign asset position evolves over time according to

$$a_{t+1}(s) - q_t b_{t+1}(s) = (1 + i_{t-1})a_t(s) - (1 + \gamma q_t)b_t(s) + p_t^T(s)y_t^X(s) - p_t^T y_t^M(s).$$

Perfectly competitive risk-neutral financial intermediaries borrow liquid assets from households and lend in the mortgage market. Perfect competition implies that the expected return to holding mortgages is equal to the interest rate on the liquid asset:

$$\mathbb{E}_t R_{t+1} = 1 + i_t.$$

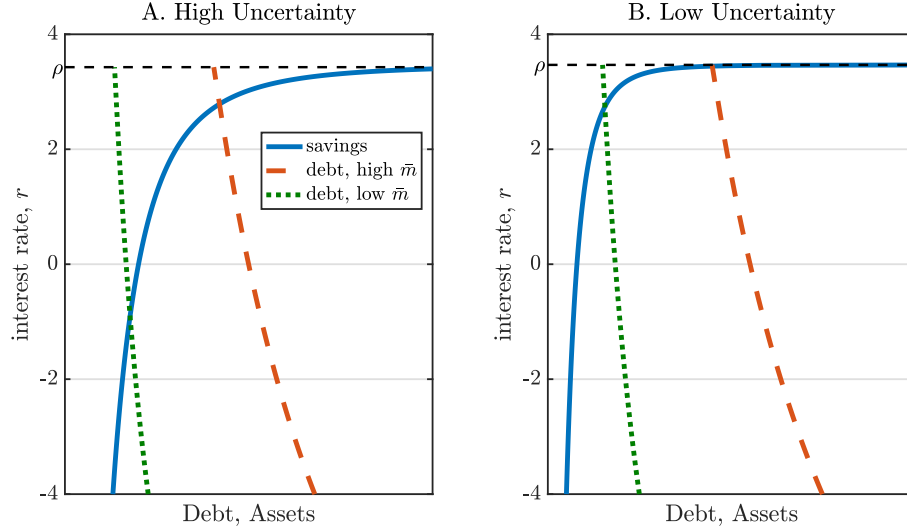
We next discuss the role of liquidity constraints in determining the equilibrium interest rate in the steady state of the model. Recall that the household's liquid savings are given by (14). In steady state the wedge between the discount rate and the interest rate is equal to  $\Delta = \frac{1}{\bar{\beta}} / \frac{1+i}{\pi} - 1 \approx \rho - r$ , where  $\rho = 1/\bar{\beta} - 1$  is the discount rate and  $r = \frac{1+i}{\pi} - 1$  is the real interest rate. The upward-sloping curves in Figure 3 illustrate the households' optimal savings choices as a function of the real interest rate. The two panels of the Figure correspond to two scenarios, one with a relatively high idiosyncratic uncertainty (low  $\alpha$ ), and another with a relatively low uncertainty (high  $\alpha$ ).

To derive the demand for assets, we note that the borrowing limit binds at all times. This is because taste shocks are unbounded, which implies that the multiplier on the liquidity constraint  $\xi_{it}(s)$  is positive for a positive mass of household members. A comparison of (8) and (16), together with the no-arbitrage condition  $\mathbb{E}_t R_{t+1} = 1 + i_t$ , implies that the multiplier on the borrowing constraint  $\mu_t(s)$  is also positive. Intuitively, since the household anticipates that a fraction of its members will end up liquidity constrained, and since the expected return on the mortgage is equal to the liquid interest rate, it borrows as much as possible. The result that all households are constrained, though stark, is consistent with Boar et al. (2020) who find that four-fifths of homeowners are debt-constrained.<sup>16</sup>

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<sup>16</sup>In reality, the observation that households are constrained in how much they borrow may reflect higher returns on other assets, such as equity, and not necessarily liquidity constraints.

Figure 3: Equilibrium Real Interest Rate in Steady State



Since the credit limit binds, mortgage debt is proportional to the value of houses,

$$qb = \frac{\bar{m}}{1-\gamma} eh = \frac{\bar{m}}{1-\gamma} \frac{\bar{\eta}^h}{\lambda} \frac{1}{\left(1 - \frac{\bar{m}}{1-\beta\gamma}\right) \rho + \frac{\bar{m}}{1-\beta\gamma} r}, \quad (24)$$

where the last equation follows from the Euler equation for housing (17). The value of housing is given by the marginal utility of housing,  $\bar{\eta}^h/\lambda$ , discounted by a weighted average of the rate of time preference  $\rho$  and the interest rate  $r$ , with a weight that depends on how much the household can borrow. As long as  $\rho > r$ , an increase in the loan-to-value ratio  $\bar{m}$  reduces the effective discount rate, raising house prices.

The downward sloping curve in Figure 3 super-imposes the demand for mortgages (24) and illustrates how the equilibrium interest rate is determined in steady state. A tightening of the debt limit mechanically reduces the demand for debt, thus reducing the equilibrium interest rate. The extent to which the equilibrium interest rate falls depends on the degree of idiosyncratic uncertainty. As the two panels of the figure show, the larger the uncertainty, the less elastic the supply of liquid assets, and therefore the larger the reduction in the equilibrium interest rate.

## 2.7 The Workings of the Model

We next provide some intuition for how the model works. The key parameters in the model are those that determine the degree of idiosyncratic uncertainty,  $\alpha$ , and those governing the degree of price and wage stickiness,  $\theta_p$  and  $\theta_w$ . We illustrate the role of each of these sets of parameters by perturbing them and describing the impulse responses to shocks to the credit limit  $m_t(s)$ .

**Impulse Response to a State-Level Credit Shock.** Figure 4 reports impulse responses to a state-level credit shock. To build intuition, we first report, in the left column, the responses under flexible prices and wages. Panel A of the figure shows that the shock leads to a gradual decline in debt because of the long-term nature of mortgage contracts. Households cannot borrow as much as they used to, and they respond in three ways. They reduce their liquid asset holdings, which limits their ability to smooth idiosyncratic shocks. They also reduce consumption and increase labor supply. Prices and wages fall, employment rises, and the island runs a current account surplus.

The middle column of Figure 4 illustrates how price rigidities affect the response of an island to a credit shock. We refer to this parameterization as the “Baseline” because it relies on the parameters from our estimation below. Wage and price rigidities reverse the response of employment. Price stickiness limits the increase in exports so the increase in the current account takes place via a compression of domestic demand. The fall in employment reduces income and consumption further. Wage rigidities act as a tax on labor supply, while price rigidities increase firms’ markups, and both effects reduce employment.<sup>17</sup>

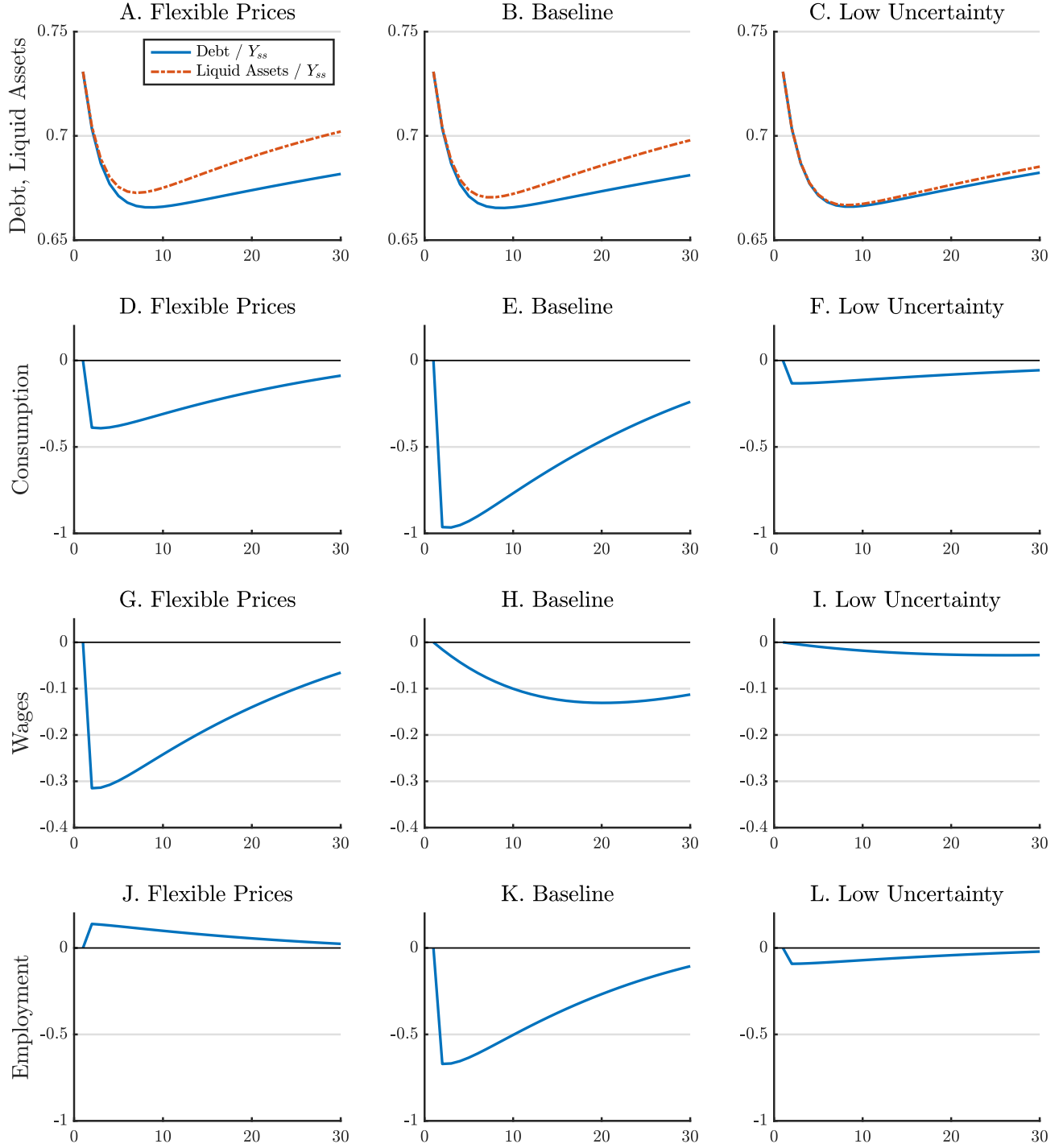
The last column of Figure 4 illustrates how liquidity constraints and liquidity demand affect the response of an island to a credit shock. We reduce the volatility of idiosyncratic shocks by increasing the parameter  $\alpha$ . With less need to smooth large liquidity risks, households are more willing to reduce their liquid asset holdings in response to a tightening of their borrowing limit. As a result, consumption barely falls and the impact on employment and wages is small. These effects are captured in equation (14) which shows that liquid asset holdings are more sensitive to the wedge between the discount rate and the interest rate when  $\alpha$  is high. The discount rate  $\frac{\lambda_t(s)}{\beta_t(s)\mathbb{E}_t\lambda_{t+1}(s)}$  increases in response to the credit tightening, while the interest rate is constant since the island is atomistic. When idiosyncratic uncertainty is low, it is relatively costless to reduce liquid asset holdings. Both sides of the household’s balance sheet thus contract, with little impact on other variables. In this case credit is a veil with little impact on macroeconomic aggregates. In contrast, when idiosyncratic uncertainty is high, reducing liquid assets is costly. Households therefore find it optimal to respond to the credit tightening by cutting consumption.

A tightening of debt constraints thus distorts allocations in two ways: it prevents households from smoothing the marginal utility of consumption both *across members* as well as *across time*. Households face a tradeoff: they can respond to a tightening of credit by either reducing overall consumption, distorting the intertemporal allocations, or by reducing liquid assets, distorting

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<sup>17</sup>See Kehoe et al. (2016) for cross-sectional evidence from the U.S. Great Recession that both of these margins account for the drop in employment in states that have experience the largest declines in household credit.

Figure 4: Impulse Response to State-Level Credit Shock



the intrafamily allocations. The more dispersed idiosyncratic shocks are, the more the household reduces the overall level of consumption to limit variation in the marginal utility of consumption across its members.

**Impulse Response to an Aggregate Credit Shock.** To understand the effect of an aggregate credit shock, we note first that the shadow value of wealth  $\lambda_t$  is approximately inversely proportional to nominal consumption spending,  $\lambda_t \sim 1/p_t c_t$ . Up to a first-order approximation, the Euler equation that determines the growth rate of  $\lambda_t$  is given by

$$(1 + \Delta_t)(1 + i_t)\beta\mathbb{E}_t\frac{\lambda_{t+1}}{\lambda_t} = 1.$$

where

$$\left(\frac{\alpha}{\alpha-1}[(\alpha-1)\Delta_t]^{\frac{1}{\alpha}} - \Delta_t\right)^{-1} - 1 = \frac{q_t b_{t+1}}{y_t} \quad (25)$$

follows from asset market clearing. A tightening of debt limits reduces the right-hand side of (25) and increases the wedge  $\Delta_t$ , thus reducing the natural rate.

The first column of Figure 5 shows the response to an aggregate credit shock in an economy with flexible prices. The shock reduces the equilibrium interest rate (Panel A), and has a negligible effect on employment (Panel D). Employment falls slightly because a tightening of credit magnifies the consumption-leisure distortions, as in cash-in-advance economies. As in those economies, the impact of these distortions is small.<sup>18</sup>

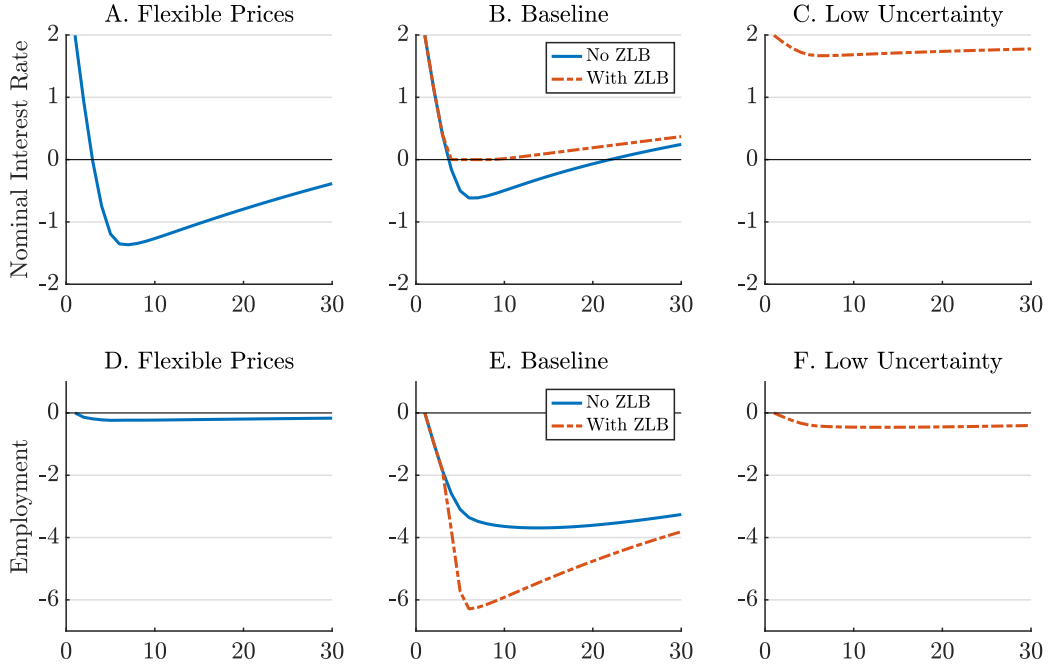
We next turn to our baseline parameterization with sticky prices. As is well understood, the extent to which changes in the natural rate affect macroeconomic aggregates depends on the stance of monetary policy. We illustrate this point in the second column of Figure 5 by contrasting the responses to the same credit shock under two scenarios: one in which we impose the ZLB and another one in which we do not. Clearly, the ZLB magnifies the reduction in employment because it prevents the monetary authority from accommodating the decline in the natural rate.

As in the case of island-level responses, the volatility of idiosyncratic shocks is critical in determining how the economy reacts to a credit shock. As the last column of Figure 5 shows, if idiosyncratic uncertainty is low, interest rates and employment fall little. In this case liquid asset holdings are sensitive to interest rates, so a small reduction in the equilibrium rate is required to clear the asset market. The natural rate of interest thus falls little, leading to a negligible impact on macroeconomic outcomes.

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<sup>18</sup>See Cooley and Hansen (1989).

Figure 5: Impulse Response to an Aggregate Credit Shock



This exercise shows that the parameters that shape the responses of island-level variables to credit shocks also determine the aggregate-level responses. These parameters govern the slopes of two curves: that of the Phillips curve that relates inflation to changes in marginal costs and that of the savings curve which relates liquid asset holdings to the gap between the discount rate and the interest rate. Since these are both functions of the primitive parameters, they are identical in the aggregate and at the state level. In contrast, the equilibrium responses of, say, employment to credit shocks are determined by factors such as a state's openness to trade and the stance of monetary policy and one cannot extrapolate state-level elasticities to draw conclusions about the aggregate. Indeed, if monetary policy were to perfectly track the natural rate, it would eliminate employment fluctuations in the aggregate, yet would be unable to respond to disturbances on an individual island. We can therefore use state-level data to identify the parameters that determine the slopes of these curves, but need to use the structure of the model to identify the impact of credit shocks in the aggregate.

Our modeling of how households allocate their wealth between housing, liquid assets and mortgage debt is purposefully simple and designed to capture aggregate comovements, not the behavior of individual households. Just as the Calvo pricing protocol is a crude description of how individual firms price, our family construct is a crude description of how individual households save. Fully micro-founding household portfolio choices would require a rich three-state model of the housing market similar to that studied by [Kaplan et al. \(2020\)](#) and [Boar et](#)

al. (2020). Such a model would entail significant micro-level non-convexities that would make full-information estimation infeasible. Since our goal is to use state-level data to isolate the impact of monetary policy in stabilizing the response of real variables to credit shocks, our conjecture is that our simplification provides a useful approximation, analogous to the Calvo pricing approach in modeling the dynamics of inflation.

## 2.8 Solution Method

To use Bayesian techniques in estimation, we need an efficient solution method. We thus use a piece-wise linear approximation method developed by Eggertsson and Woodford (2003), Guerrieri and Iacoviello (2015) and Jones (2017) to deal with the ZLB. We next describe the method, which we adapt for our application combining state-level and aggregate variables.

The linearized system of equations defining the equilibrium of the model is

$$\mathbf{A}\mathbf{x}_t(s) = \mathbf{B}\mathbf{x}_{t-1}(s) + \mathbf{D}\mathbb{E}_t\mathbf{x}_{t+1}(s) + \mathbf{F}\epsilon_t(s) + \bar{\mathbf{A}}^r\mathbf{x}_t + \bar{\mathbf{B}}^r\mathbf{x}_{t-1} + \bar{\mathbf{D}}^r\mathbb{E}_t\mathbf{x}_{t+1} + \bar{\mathbf{F}}^r\epsilon_t, \quad (26)$$

where  $\mathbf{x}_t(s)$  is a vector that collects state-level variables,  $\epsilon_t(s)$  are the state-level shocks,  $\mathbf{x}_t$  are the aggregate variables,  $\epsilon_t$  are the aggregate shocks, and the bold matrices are functions of the parameters of the model.

The economy may be in one of two regimes. We let  $r = 0$  correspond to periods when the ZLB does not bind, and  $r = 1$  to periods when it does. Because each individual island is atomistic, whether the ZLB binds does not, up to a first-order approximation, affect the dependence of an island's variables on its own lagged or future variables, or its shocks. Thus the matrices  $\mathbf{A}$ ,  $\mathbf{B}$ ,  $\mathbf{D}$ , and  $\mathbf{F}$  are not regime-dependent.

Integrating over the individual states under the normalization  $\int \epsilon_t(s)ds = 0$ , and adding the Taylor rule, we derive an expression that determines the dynamics of aggregate variables,

$$\mathbf{A}^r\mathbf{x}_t = \mathbf{C}^r + \mathbf{B}^r\mathbf{x}_{t-1} + \mathbf{D}^r\mathbb{E}_t\mathbf{x}_{t+1} + \mathbf{F}^r\epsilon_t, \quad (27)$$

where  $\mathbf{x}_t$  collects all the aggregate variables,  $\int \mathbf{x}_t(s)ds$ , and the nominal interest rate  $i_t$ . Once again, notice that the coefficient matrices depend on the monetary policy regime.

The algorithm is based on a piece-wise linear solution of the equilibrium conditions in the two monetary policy regimes  $r = \{0, 1\}$ , under the assumption that agents observe all shocks in each period, but believe that no other shocks are possible in the future. Under the regime when the ZLB does not bind, we use standard methods to derive the time-invariant VAR representation that describes the evolution of the aggregate variables

$$\mathbf{x}_t = \mathbf{J}^0 + \mathbf{Q}^0\mathbf{x}_{t-1} + \mathbf{G}^0\epsilon_t. \quad (28)$$

When the ZLB binds, we iterate on the date  $T(\mathbf{x}_{t-1}, \epsilon_t, f_t)$  at which the ZLB will stop binding conditional on no further aggregate shocks hitting the economy. Here  $f_t$  encodes forward guidance announcements, if any. For periods after  $T$ , the economy evolves following (28). Prior to  $T$ , the solution of the model is

$$\mathbf{x}_t = \mathbf{J}_t + \mathbf{Q}_t \mathbf{x}_{t-1} + \mathbf{G}_t \epsilon_t, \quad (29)$$

where the reduced-form matrices are updated iteratively according to the following recursion

$$\begin{aligned} \mathbf{Q}_t &= [\mathbf{A}^1 - \mathbf{D}^1 \mathbf{Q}_{t+1}]^{-1} \mathbf{B}^1 \\ \mathbf{J}_t &= [\mathbf{A}^1 - \mathbf{D}^1 \mathbf{Q}_{t+1}]^{-1} (\mathbf{C}^1 + \mathbf{D}^1 \mathbf{J}_{t+1}) \\ \mathbf{G}_t &= [\mathbf{A}^1 - \mathbf{D}^1 \mathbf{Q}_{t+1}]^{-1} \mathbf{E}^1, \end{aligned} \quad (30)$$

These recursions are the same as those in [Guerrieri and Iacoviello \(2015\)](#) and [Kulish and Pagan \(2017\)](#). In short, we iterate backwards from the conjectured date of exit from the ZLB regime by using the equilibrium conditions consistent with  $i_t = 0$ . Notice that by changing the structural matrices corresponding to the regimes in (30) we allow for the possibility that a shock at date  $t$  triggers the ZLB at some *future* period even though it does not bind at  $t$ . We iterate on the conjectured date  $T$  until convergence.<sup>19</sup>

Having solved for the aggregate outcomes we then solve for the island-level variables,

$$\mathbf{x}_t(s) = \underbrace{\mathbf{Q} \mathbf{x}_{t-1}(s) + \mathbf{G} \epsilon_t(s)}_{\text{state-level component}} + \underbrace{\bar{\mathbf{J}}_t + \bar{\mathbf{Q}}_t \mathbf{x}_{t-1} + \bar{\mathbf{G}}_t \epsilon_t}_{\text{aggregate component}}. \quad (31)$$

The matrices  $\bar{\mathbf{J}}_t$ ,  $\bar{\mathbf{Q}}_t$ , and  $\bar{\mathbf{G}}_t$  encode how an island responds to aggregate-level variables and vary over time because of the ZLB. In contrast, the matrices  $\mathbf{Q}$  and  $\mathbf{G}$  which determine how an island's variables depend on their own lags and island-specific shocks are time-invariant. Intuitively, since each island is of measure zero, shocks to an individual island do not change the expected date at which the ZLB will stop binding for the rest of the economy. Moreover, agents on each island take aggregate prices, including the interest rate, as given. Therefore, conditional on the aggregate state variables, the ZLB regime does not affect the evolution of island-level relative variables. From the perspective of agents on a given island, the presence of the ZLB acts like any other aggregate shock which, up to a first-order approximation, does not change how that island responds to its own history of idiosyncratic shocks.

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<sup>19</sup>See [Kulish and Pagan \(2017\)](#) and [Jones \(2017\)](#) for more details on the recursion underlying this solution. [Jones \(2017\)](#) contrasts this method with fully non-linear ones in smaller scale models and shows that the piece-wise linear method we use here is accurate. [Lepetyuk et al. \(2017\)](#) contrast these perturbation-based methods with fully non-linear projection methods in larger-scale models and reach similar conclusions regarding their accuracy.

Equation (31) reveals that our model has a special structure. First, the mapping from state-level histories of shocks to state-level outcomes is time-invariant and common to all states. Second, the mapping from aggregate histories of shocks to state-level variables, though time-varying, is also common to all states. We exploit this structure to construct the likelihood function, as we describe below.

### 3 Estimation

We next explain how we chose parameters for our model. We first discuss the parameters we assign values to, and then the ones we estimate.

The parameters that we estimate are those that are critical in determining the model's responses to a credit shock: the degree of wage and price stickiness,  $\theta_w$  and  $\theta_p$ , as well as the volatility of idiosyncratic taste shocks,  $\alpha$ . We refer to these parameters as our *structural parameters*. In addition, we estimate the AR(1) processes characterizing the island-specific and aggregate components of the various shocks. We next describe the parameters we have assigned, the construction of the likelihood function, and then our results.

#### 3.1 Assigned Parameters

We report the parameter values we assign in Table 1. The period is one quarter. We assume a Frisch elasticity of labor supply of 1/2. We set  $\gamma$ , the parameter governing the duration of debt, to 0.985, so that the Macaulay duration of debt in our model is equal to that of 30-year mortgages, approximately 13 years.<sup>20</sup> We follow the trade literature in setting the weight on non-traded goods in an island's consumption basket,  $\omega$ , equal to 0.7; the elasticity of substitution between tradable and non-tradable goods,  $\sigma$ , equal to 0.5; and the elasticity of substitution between varieties of tradable goods produced in different islands,  $\kappa$ , equal to 4, the estimate of [Simonovska and Waugh \(2014\)](#). We follow [Christiano et al. \(2005\)](#) in choosing  $\psi$  to ensure a wage markup of 5%.<sup>21</sup> We use the [Justiniano et al. \(2011\)](#) estimates of the parameters characterizing the Taylor rule.

We pin down three additional parameters using steady state considerations. The steady state discount factor  $\bar{\beta}$  is chosen so that the steady state real interest rate is equal to 2% per year. The steady state weight of housing in preferences  $\bar{\eta}^h$  is chosen so that the aggregate

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<sup>20</sup>The Macaulay duration is the weighted average maturity of the flows, with weights given by the present value of the flows accruing at each date. In our model with geometrically decaying perpetuities this duration is given by  $(1+r)/(1+r-\gamma)$ .

<sup>21</sup>We show in our Robustness section that our conclusions are not sensitive to alternative values of  $\psi$ .

Table 1: Assigned Parameters

Parameter	Value	Description	Source/Target
$\nu$	2	Inverse labor supply elasticity	
$\gamma$	0.985	Persistence coupon payments	13 year mortgage debt duration
$\omega$	0.7	Weight on non-traded goods	
$\sigma$	0.5	Elasticity traded/non-traded	
$\kappa$	4	Elasticity traded goods	<a href="#">Simonovska and Waugh (2014)</a>
$\psi$	21	Elasticity labor aggregator	<a href="#">Christiano et al. (2005)</a>
$\alpha_r$	0.86	Taylor rule persistence	<a href="#">Justiniano et al. (2011)</a>
$\alpha_\pi$	1.71	Taylor coefficient inflation	<a href="#">Justiniano et al. (2011)</a>
$\alpha_y$	0.05	Taylor coefficient output	<a href="#">Justiniano et al. (2011)</a>
$\alpha_x$	0.21	Taylor coefficient output growth	<a href="#">Justiniano et al. (2011)</a>
Parameters chosen to match steady-state target			
$-\ln(\beta)$	2.46%	Annual discount rate	2% real rate
$\eta$	0.084	Weight on housing	Housing-to-income ratio of 2.5
$\bar{m}$	0.0044	Credit limit	Debt-to-housing ratio of 0.29

housing to (annual) income ratio is equal to 2.5, a number that we compute using the 2001 Survey of Consumer Finances (SCF). Finally, the steady state LTV ratio is chosen so that the aggregate debt to housing ratio is equal to 0.29, a number once again computed from the SCF. Since the debt constraint binds in the model, these two last two targets imply an aggregate debt to (annual) income ratio of  $2.5 \times 0.29 = 0.725$ .

## 3.2 Estimation Procedure

Our goal is to simultaneously use regional and aggregate data to estimate the model and identify the impact of credit shocks on real activity. In contrast to [Nakamura and Steinsson \(2014\)](#) and [Beraja et al. \(2019\)](#), who also use regional data to understand the effect of various shocks on macroeconomic aggregates, our approach simultaneously uses state and aggregate-level data in a full-information estimation. One important technical challenge we need to overcome in order to compute the likelihood function is the presence of the occasionally binding ZLB, which renders conventional methods infeasible due to the very large number of island-level state variables and the resulting curse of dimensionality. We therefore exploit the special structure of our model and develop an efficient algorithm that circumvents these difficulties. We first describe the details of our approach, and then report our results.

### 3.2.1 The Data

**Regional Data.** We use a panel of employment, household spending, wages, household debt and house prices in the cross-section of 51 U.S. states from 1999 to 2015. The household debt

information is from the FRB New York Consumer Credit Panel.<sup>22</sup> Since the measure of debt in the data is the book value of outstanding debt, we construct a corresponding series for our model using

$$\text{debt}_t(s) = \gamma \text{debt}_{t-1}(s) + q_t l_t(s),$$

where  $q_t l_t(s)$  is the market value of mortgage debt issued in period  $t$  and  $\gamma \text{debt}_{t-1}(s)$  is the book value of outstanding debt. We found that our results are unchanged if we instead use the market value of debt  $q_t b_{t+1}(s)$  to proxy for household credit in the data.

We use data on house prices from the FHFA, and data on employment, consumption expenditures and wages from the BEA. Our measure of employment is the employment-population ratio in a given state. Our measure of wages is total employee compensation divided by the number of workers. Since we do not model the construction sector, we subtract construction employment and compensation in computing measures of employment and wages.<sup>23</sup>

**Aggregate Data.** We use aggregate data on employment, household consumption expenditures, wages, household debt, house prices, inflation and the Fed Funds rate from 1984 to 2015. We construct this data in a similar way to the state-level data. An additional critical input in the estimation is the sequence of expected durations of the ZLB between 2009 and 2015, which we take from the Blue Chip Financial Forecasts survey from 2009 to 2010 and the New York Federal Reserve’s Survey of Primary Dealers from 2011 to 2015.<sup>24</sup>

### 3.2.2 The Likelihood Function

The conventional approach to estimating the model would be to write down a likelihood function that directly combines state and aggregate data. This approach is computationally infeasible because of the non-linearity induced by the ZLB and the curse of dimensionality which arises from our use of 51 regions, each of which has 11 individual state variables.

We thus use the structure of our model to formulate an alternative approach to constructing the likelihood function, one that exploits *relative* variation across individual states’ outcomes. Intuitively, our approach recognizes that, up to a first-order approximation, the difference between employment in, say, Nevada and in the aggregate is a linear function of the Nevada state

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<sup>22</sup>We include credit card debt, auto loans and student loans, in addition to mortgage debt in our measure of household credit. Since mortgage debt makes up a large fraction of household debt, our results are virtually unchanged when we only use mortgage debt in our estimation.

<sup>23</sup>See our Robustness section for an extension that explicitly models the construction sector and uses data on construction employment in estimation. Our results are robust to this modification.

<sup>24</sup>See the Appendix for a more detailed description of the data we use.

variables only. This observation allows us to separate the likelihood into state-level components and an aggregate component.

To understand our approach, recall that the evolution of variables in any given state is given by (31), which we reproduce here for convenience:

$$\mathbf{x}_t(s) = \mathbf{Q}\mathbf{x}_{t-1}(s) + \mathbf{G}\epsilon_t(s) + \bar{\mathbf{J}}_t + \bar{\mathbf{Q}}_t\mathbf{x}_{t-1} + \bar{\mathbf{G}}_t\epsilon_t.$$

Since the last three reduced-form matrices are time-varying functions of the underlying structural parameters whenever the ZLB binds, computing them for each parameter draw in the estimation is infeasible. The special structure of the model allows us, however, to write the deviation of island-level variables from their economy-wide averages,

$$\hat{\mathbf{x}}_t(s) = \mathbf{x}_t(s) - \int \mathbf{x}_t(s)ds, \quad (32)$$

as a time-invariant function of island-level variables alone:

$$\hat{\mathbf{x}}_t(s) = \mathbf{Q}\hat{\mathbf{x}}_{t-1}(s) + \mathbf{G}\epsilon_t(s). \quad (33)$$

This structure allows us to significantly speed up the computation of the likelihood function.

We therefore use the representation in (29) and (33) to estimate the model using state-level and aggregate U.S. data. To do so, we first express each state's observable variable as deviations from its aggregate counterpart by subtracting a full set of time effects, one for each year and each variable. We also subtract a state-specific fixed effect and time trend for each observable since in our model all islands are ex-ante identical.<sup>25</sup> Since the island-level shocks in (33) are independent and do not affect aggregate outcomes, we can write the log-likelihood of the model as the sum of each individual state's likelihood, computed from (33) and the aggregate likelihood, computed from (29):

$$\log \mathcal{L} = \sum_{s=1}^{51} \bar{\omega}(s) \log \mathcal{L}(s) + \log \mathcal{L}^a,$$

where  $\mathcal{L}(s)$  is the contribution to the likelihood of an individual state's data,  $\mathcal{L}^a$  is the contribution to the likelihood of the aggregate data, and  $\bar{\omega}(s)$  is the relative weight of state  $s$ . This additive structure follows from the block exogeneity implied by our representation (33) which allows us to express the determinant of the variance-covariance matrix of the forecast errors as the product of the determinants of the variance-covariance matrices of the individual states.

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<sup>25</sup>In practice, subtracting the state-specific fixed effects only, as we have done in an earlier version of the paper, does not change our substantive results.

To see how we construct the likelihood for an individual state, denote by  $\bar{N} = 5$  the number of observable variables and  $\bar{T} = 17$  (1999 to 2015) the number of years of data that are available. With Gaussian errors, the log-likelihood function for any individual state is

$$\log \mathcal{L}(s) = - \left( \frac{\bar{N}\bar{T}}{2} \right) \log 2\pi - \frac{1}{2} \sum_{t=1}^{\bar{T}} \log \det \mathbf{S}_t - \frac{1}{2} \sum_{t=1}^{\bar{T}} \tilde{\mathbf{x}}_t'(s) \mathbf{S}_t^{-1} \tilde{\mathbf{x}}_t(s).$$

where  $\tilde{\mathbf{x}}_t(s)$  is the vector of forecast errors, calculated using the Kalman filter and the structural matrices  $\mathbf{Q}$  and  $\mathbf{G}$  from (33), and  $\mathbf{S}_t$  is the covariance matrix of  $\tilde{\mathbf{x}}_t(s)$ . We compute the aggregate likelihood component in a similar fashion, taking into account that the sequence of forecast errors and their covariance matrices are functions of the underlying time-varying reduced-form matrices  $\mathbf{Q}_t$  and  $\mathbf{G}_t$  from (29) (see the Appendix for details).

To summarize, our estimation exploits the differential rise and fall of individual states' spending, debt, wages, house prices and employment, in addition to the aggregate comovement of these series, to identify the structural parameters of the model. Notice that by simultaneously using state and aggregate data to construct the likelihood, our approach differs from that of [Beraja et al. \(2019\)](#). These researchers first apply limited information methods to estimate the degree of wage stickiness using state-level data. They then use that estimate to form a prior in a second step, which uses only aggregate data to form the likelihood function.

The state-level data is observed at an annual frequency, while the model is quarterly, so we conduct a *mixed-frequency* estimation, by computing forecast errors every four quarters for state-level variables. The aggregate data, in contrast, is observed quarterly and for a longer time-period, from 1984 to 2015. To account for differences in the size of different states and ensure that smaller states exert a relatively smaller influence on the shape of the likelihood, we weight the likelihood contribution of each state by their 1999 population shares.<sup>26</sup> In a robustness exercise reported below, we also compute the likelihood without weighting individual states. In our baseline estimation, we assign an equal weight to the aggregate likelihood and the combined state-level likelihood.

### 3.3 Parameter Estimates

Table 2 reports moments of the prior and posterior distributions of the structural parameters we estimate. We use diffuse priors. We find, consistent with the work of [Del Negro et al. \(2015\)](#), that wages and prices are sticky, with a modal estimate of  $\theta_p$  of 0.97 and a modal estimate of  $\theta_w$

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<sup>26</sup>See [Agostinelli and Greco \(2012\)](#) who show that this simple weighting scheme preserves the asymptotic properties of the true likelihood function.

Table 2: Estimated Structural Parameters

Parameter	Prior				Posterior		
	Dist	Median	10%	90%	Mean	10%	90%
$\lambda_p$	B	0.5	0.2	0.8	0.97	0.94	0.98
$\lambda_w$	B	0.5	0.2	0.8	0.86	0.83	0.89
$\alpha$	N	2.5	1.2	3.8	3.45	3.01	3.90

of 0.86. As is well known, accounting for the stability of inflation around the Great Recession requires a great deal of price stickiness. We show below that estimating the model using state-level data alone implies a much lower degree of price stickiness, consistent with the evidence in [Beraja et al. \(2019\)](#). We explore the implications of this alternative set of parameter estimates in our Robustness section below.

The mean estimate of the Pareto tail parameter  $\alpha$  is equal to 3.45, implying a 0.47% spread between the subjective discount rate and the interest rate at the annual frequency. Notice that this parameter is well identified with a relatively tight posterior distribution. The 10th and 90th percentiles are 3.0 and 3.9, respectively. This estimate implies that the fraction of household members who are liquidity constrained is relatively low, 0.3% in steady-state. Moreover, as we show in the Appendix, the model’s implications for the marginal propensity to consume out of a transitory income shock are also very similar to those of the frictionless model. In this sense, our results do not rely on assuming severe liquidity constraints.

We report in the Appendix the posterior estimates of the parameters governing the persistence and volatility of state and aggregate shocks, and the full time series of shocks.

### 3.4 Identification of $\alpha$

We next provide intuition for how the key parameter  $\alpha$  is identified from the comovement of state-level household debt, consumption, and employment. Table 3 reports coefficient estimates from univariate regressions of changes in employment and consumption on changes in household debt in the boom (2002 to 2007) and the bust (2007 to 2010). As pointed out by [Mian and Sufi \(2014\)](#), state-level data show a strong correlation between these variables. For example, as the first column of the table shows, an increase in debt-to-income of 100 percent is associated with a 7 percent increase in employment and 15 percent increase in consumption from 2002 to 2007.

We next discuss the model’s predictions for these comovements. We use our mean estimates in Table 2 to simulate a large panel of states and run identical regressions in the model. As the

Table 3: Regressions with Simulated Panel Datasets From Model

	Data	Baseline	$\alpha = 2^\dagger$	$\alpha = 10^\dagger$	$\alpha = 10^\ddagger$
A. Dependent Variable: $\Delta$ Debt. Boom, 2002 to 2007					
$\Delta$ Employment	0.07 (0.01)	0.06 (0.01)	0.22 (0.01)	0.02 (0.01)	0.02 (0.01)
$\Delta$ Consumption	0.15 (0.03)	0.11 (0.01)	0.31 (0.01)	0.02 (0.01)	0.02 (0.01)
B. Dependent Variable: $\Delta$ Debt. Bust, 2007 to 2010					
$\Delta$ Employment	0.10 (0.01)	0.06 (0.01)	0.22 (0.01)	0.03 (0.01)	0.01 (0.01)
$\Delta$ Consumption	0.17 (0.02)	0.10 (0.01)	0.31 (0.01)	0.03 (0.01)	0.02 (0.01)
$\dagger$ : Other parameters as in baseline. $\ddagger$ : Other parameters reestimated. Standard errors in parentheses					

second column of Table 3 shows, our baseline model reproduces the correlations in the data very well. Consider next what happens if we simulate data from the model using higher and lower values of  $\alpha$ . When idiosyncratic uncertainty is high ( $\alpha = 2$ ), employment and consumption comove much more strongly with changes in household debt than in the data. For example, a 100 percent increase in household debt-to-income is associated with a 22 percent increase in employment and 31 percent increase in consumption. In contrast, when idiosyncratic uncertainty is low ( $\alpha = 10$ ), employment and consumption comove little with changes in household debt. For example, a 100 percent increase in household debt-to-income is associated with a 2 percent increase in employment and consumption.

In the Appendix, we also report the predictions of our model for the comovement between employment, consumption, and household debt for longer leads and lags using local projections. We show that simulated series from the model with too high or too low values of  $\alpha$  generate impulse responses that greatly differ from those computed in the data. We also report in the Appendix results from a GMM-based procedure which produces similar estimates.

### 3.5 Separating Credit Shocks from Other Household Demand Shocks

How does our framework identify the separate contribution of shocks that change household credit limits from that of discount factor shocks, which also lead to comovements between consumption and household savings? To see this, recall that we assume that there is no spread between the rate at which households save in the liquid asset and the mortgage interest rate.

Since liquid assets provide liquidity services, agents find it optimal to always borrow up to the limit.<sup>27</sup> Thus, though both shocks to credit limits and discount factor shocks lead to comovements between consumption and household net asset positions, only shocks to the credit limit affect the amount households borrow. Discount factor shocks lead to changes in liquid asset holdings, but leave mortgage debt unchanged.

The result that all homeowners are against their borrowing limit is admittedly extreme, but it is broadly consistent with the data. To see this, notice that the majority of household debt in the data is mortgage debt, which is refinanced infrequently. The vast majority of households are therefore against the limit implicitly built-in their mortgage contract, namely the requirement that they make the minimum principal and interest payments on the mortgage. As is well-known, most households in the data do not exceed these minimum payments. For example [Amromin et al. \(2007\)](#) and [Adelman et al. \(2010\)](#) show that only approximately 15–20% of borrowers have ever made mortgage payments greater than the minimum required ones. [Boar et al. \(2020\)](#) use this and other evidence and a rich model of the housing market to show that the majority of homeowners are indeed borrowing constrained.

Nevertheless, to the extent to which some shocks indeed lead unconstrained households to cut the amount they borrow, say for precautionary reasons, our estimation will interpret them as credit shocks. Our exercise thus allows one to disentangle the relative contribution of household demand shocks that manifest themselves through changes in the amount borrowed, as opposed to other shocks that manifest themselves through changes in liquid savings.

### 3.6 Variance Decompositions

To interpret the estimates of the persistence and volatility of shocks, we report in Table 4 the theoretical forecast error variance decompositions of state and aggregate observables into the various shocks at the infinite horizon.

Consider first Panel A of Table 4 which reports this variance decomposition for state-level variables, expressed as deviations from their aggregate counterparts. State-level credit shocks account for 7% of the variation of *relative* employment and 30% of the variation in relative household spending. State-level productivity shocks account for about 10% of the variation in relative employment and a negligible fraction of the volatility of consumption. Shocks to the disutility from work account for about 71% of the volatility of employment and 35% of the volatility of consumption. Finally, shocks to the individual states' discount rates account

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<sup>27</sup>We relax this assumption in the robustness section when studying a model with default and show that our results are unchanged.

Table 4: Unconditional Variance Decomposition, Infinite Horizon

Shock Variable	Collateral	Housing	Productivity	Leisure	Discount	Policy	Markup
A. State-level							
Spending	30.3	0.4	0.0	34.6	34.7	-	-
Employment	7.1	0.1	9.6	71.1	12.2	-	-
Wages	1.9	0.0	0.0	97.9	0.1	-	-
Debt-to-income	98.8	1.1	0.0	0.1	0.0	-	-
House prices	2.3	95.0	0.0	2.5	0.2	-	-
B. Aggregate-level							
Consumption	1.5	0.1	22.7	8.8	47.6	10.7	8.7
Employment	1.8	0.1	4.0	10.9	59.2	13.2	10.8
Wages	0.3	0.0	3.7	69.6	3.0	0.3	23.1
Debt-to-income	78.8	5.9	0.5	2.4	12.0	0.1	0.4
House prices	0.0	87.3	3.3	1.2	5.3	1.6	1.3
Fed Funds rate	3.4	0.3	11.2	2.6	76.5	3.6	2.2
Inflation	0.8	0.1	2.9	12.2	2.6	0.2	81.3

for 12% percent of the volatility of relative employment and 35% of the volatility of relative consumption, while shocks to the preference for housing have a negligible impact on state-level real variables. The variance decompositions for wages, household debt-to-income, and house prices show that these series are explained by leisure shocks, credit shocks, and housing preference shocks respectively. We also report in the Appendix the variance decompositions at shorter horizons. At shorter horizons, productivity shocks are a more important determinant of employment, while discount factor shocks are a more important determinant of relative consumption fluctuations across states. For example, at a one-year horizon productivity shocks account for 39% of the relative variation in employment, while discount factor shocks account for 77% of the relative variation in consumption.

Consider next Panel B of Table 4 which reports a similar decomposition for aggregate variables. Unconditionally, absent the ZLB, household credit shocks account for only 1.5% and 1.8% of the volatility of aggregate employment and consumption, respectively. Intuitively, credit shocks matter much more at the state-level than in the aggregate because individual states are part of a monetary union and cannot use monetary policy to offset their effects. Productivity shocks account for about 4% of the employment volatility and 23% of the volatility of consumption. Discount rate shocks account for a substantial fraction of movements in employ-

ment and consumption, while shocks to the disutility from work or preference for housing have little effect. Monetary policy shocks account for about 10% of the variation in employment and consumption and a negligible amount of the variation in other observables. Consistent with the variance decompositions obtained using the model of [Smets and Wouters \(2007\)](#), as reported in the Appendix, we find that the behavior of inflation is mostly explained by markup shocks, while wages are accounted for by labor disutility shocks.

### 3.7 Additional Implications

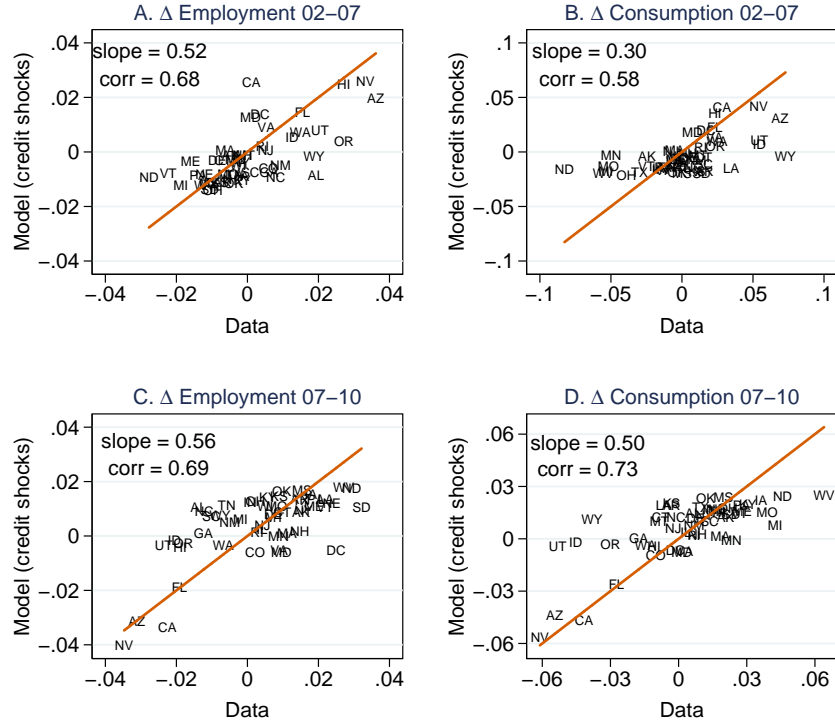
We report in the Appendix our model’s ability to reproduce several additional variables that we have not directly used in estimation. We find that most of the decline in state-level employment was due to declines in non-tradable employment, consistent with Mian and Sufi. Our model also reproduces well the medium term movements in mortgage rates.

## 4 Credit Shocks in the Great Recession

We next study the role of household credit shocks in shaping the dynamics of employment and consumption in the cross-section and in the aggregate during the Great Recession. Recall that in our model the credit limit always binds, so household credit fluctuates due to exogenous changes in the credit limit  $m_t(s)$ , and house prices,  $e_t(s)$ . The latter fluctuate mostly due to shocks to the preference for housing. Since housing is in fixed supply and separable in preferences, housing preference shocks only affect equilibrium outcomes through their effect on the credit limit. We thus refer to both shocks to the credit limit  $m_t(s)$  and housing preferences  $\eta_t^h(s)$  as *credit shocks*.

We first show that state-level credit shocks account for a large fraction of the differential rise and fall in state-level employment and consumption during the boom and the bust years. Our findings thus reinforce the conclusions of [Mian et al. \(2013\)](#) and [Mian and Sufi \(2014\)](#) who argue that household credit played an important role in accounting for the heterogeneity in state-level outcomes during the Great Recession. We then study the aggregate implications of credit shocks. We show that aggregate credit shocks alone generate a modest decline in the natural interest rate during the Great Recession and are not sufficient to trigger the ZLB on their own. Absent other shocks, aggregate credit shocks would therefore have had a relatively small effect on employment. We finally study how the effect of credit shocks on employment is magnified when additional shocks render monetary policy constrained, as was the case during the Great Recession.

Figure 6: Effect of Credit Shocks on State Employment and Consumption



#### 4.1 Role of Credit Shocks at the State Level

We report the effects of state-level credit shocks on employment and consumption in Figure 6. The horizontal axes show the actual data we used to extract the state-level component of the shocks. We construct a counterfactual series for each variable by shutting down all of the shocks other than those to credit, and plot the changes in these series on the vertical axes. The solid line in each of these plots is the 45 degree line.

Consider first the 2002 to 2007 period, which we label the *boom*. The upper panels of Figure 6 show that credit shocks account for a substantial fraction of the differential changes in employment and consumption during the boom. The correlation between the change in the counterfactual series driven by credit shocks only and the change in the data is 0.68 for employment and 0.58 for consumption. The slope coefficient of a regression of these counterfactual changes against the data is 0.52 for employment and 0.30 for consumption. Credit shocks thus account for about one-half of the relative movements in employment and one-third of the relative movements in consumption across states during the boom.

The lower panels of Figure 6 illustrate the corresponding patterns during the 2007 to 2010 recession, which we term the *bust*. Credit shocks account for an even larger fraction of the

Table 5: Contribution of Individual Shocks to Observed Change

	Credit Limit	Housing	Productivity	Leisure	Discount
$\Delta$ Employment					
– 2002 to 2007	0.47	0.05	−0.09	−0.09	0.58
– 2007 to 2010	0.52	0.04	0.14	−0.08	0.38
$\Delta$ Consumption					
– 2002 to 2007	0.27	0.03	0.00	−0.08	0.74
– 2007 to 2010	0.48	0.03	0.00	−0.03	0.55

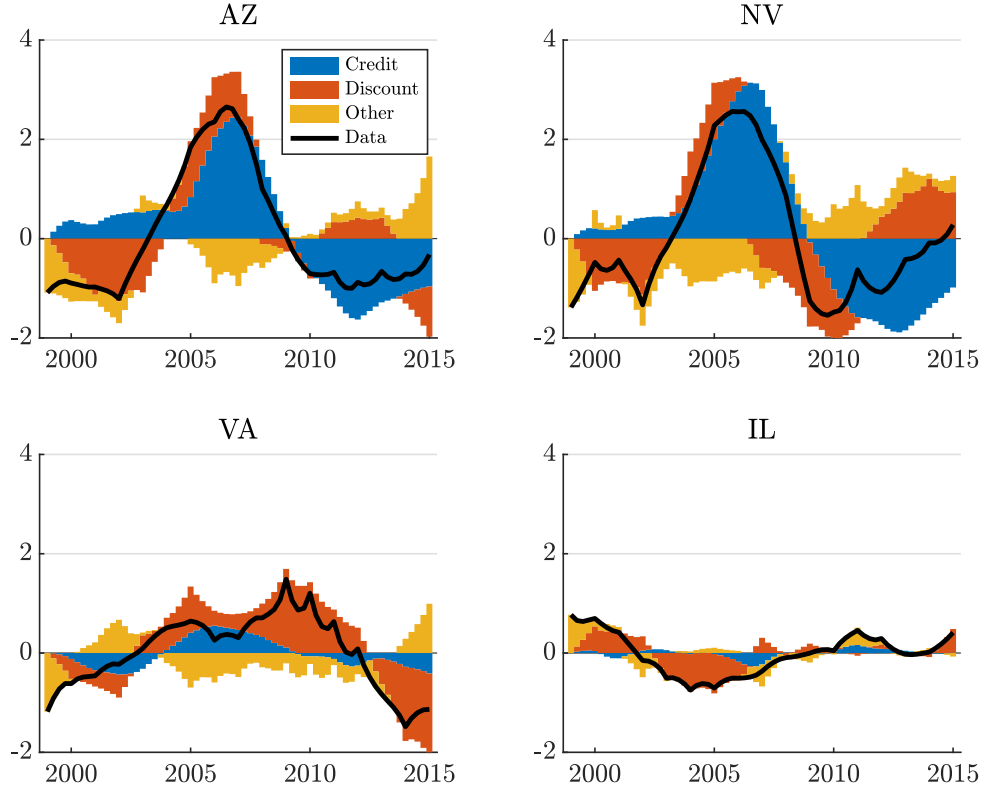
differential change in employment and consumption during the bust. The slope coefficients are 0.56 for employment and 0.50 for consumption, implying that credit shocks account for one-half of the differential decline in employment and consumption across states. We emphasize that these results are not simply an artefact of the modeling choices we have made, but rather a result of the estimation and the path for shocks extracted by the Kalman smoother from the data. If instead we used a higher value of  $\alpha$  in simulating the model, credit shocks would have had much smaller effects, as we report in the Robustness section.

Table 5 illustrates the role of all additional shocks in explaining the relative changes in employment and consumption during these two periods. We use the Kalman smoother to extract the shocks and construct counterfactual employment and consumption panels by turning on one shock at a time. Table 5 reports the slope coefficients of the projection of the counterfactual series on the actual data.<sup>28</sup> In addition to the credit shocks, discount factor shocks account for the bulk of the remaining fluctuations in employment and consumption. These shocks capture other sources of state-level movements in consumption, such as perhaps heterogeneity in fiscal transfers across states, expectations of future growth, precautionary savings motives, and other factors. In our Robustness section, we show that explicitly introducing differential changes in government spending across states reduces the contribution of discount factor shocks, but leaves the contribution of credit shocks unchanged.

We next zoom in on several states and show in Figure 7 how the time-series of relative employment is shaped by credit, discount factor, and other shocks. The top row of the figure plots relative employment for two states – Arizona and Nevada – that experienced large changes in credit and employment. The bottom row of the figure shows two contrasting states – Virginia and Illinois – that experienced mild fluctuations. The figure reinforces the point that credit

<sup>28</sup>These coefficients do not sum to one because part of the variation of the observable series is attributed to initial conditions.

Figure 7: State Level Decomposition, Employment: Four States



shocks were an important driver of the relative change in employment across states over this period. In the Appendix, we show similar decompositions for all states, along with the full time series of shocks.

Our findings thus corroborate the conclusion of [Mian and Sufi \(2014\)](#) that credit shocks were an important determinant of the variation in employment and consumption across U.S. regions in the years before and after the Great Recession. Two caveats are in order. First, even though in our model changes in household credit are driven by shocks to the credit limit, in reality a tightening of household credit may have been induced by lower credit supply, as emphasized by [Justiniano et al. \(2019\)](#). Our approach is unable to differentiate between these sources of the decline in household leverage: changes in credit limits in our framework thus implicitly capture both supply and demand-side considerations. What is critical for our study is the comovement between changes in household credit and consumption, which our model reproduces well. We show in our Robustness section that our results are robust to modeling changes in household credit as arising from credit supply shocks.<sup>29</sup>

<sup>29</sup>Additional factors that may have contributed to the observed correlation between changes in household credit and real variables include wealth effects from changes in house prices, as in [Berger et al. \(2018\)](#), or a precautionary motive associated with the rise in uncertainty in this period. Our focus on a representative agent framework and our use of first-order solution methods implicitly abstracts from these effects.

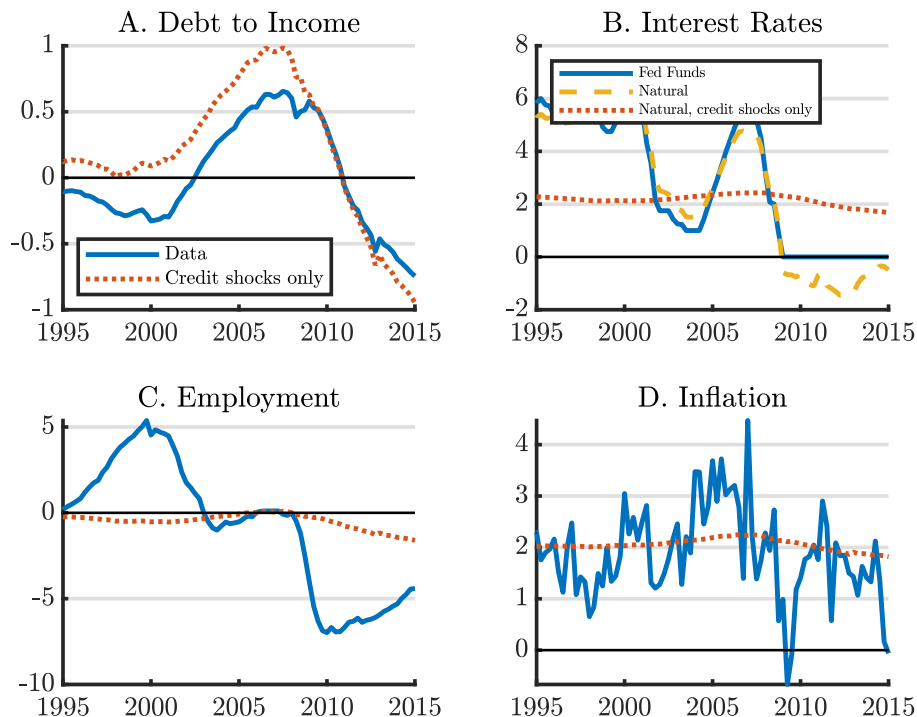
Second, our model attributes all relative changes in state-level variables to idiosyncratic state-level shocks. In practice, as pointed out by [Mian and Sufi \(2014\)](#), an important source of state-level variation was the asymmetry with which individual states responded to aggregate shocks. The approach we pursue is motivated by tractability considerations: if the matrices  $\bar{\mathbf{J}}_t$ ,  $\bar{\mathbf{Q}}_t$  and  $\bar{\mathbf{G}}_t$  of equation (31) that determine how an individual island responds to aggregate shocks were state-specific, say due to heterogeneity in housing supply elasticities, the likelihood function would not be additively separable into individual state-level likelihood contributions. Our estimates of the state-level shocks should therefore be interpreted more broadly as capturing not only state-specific idiosyncratic disturbances, but also heterogeneity in the extent to which state-level variables responded to aggregate shocks. In our Robustness section, we relax the assumption that all states react in an identical way to state and aggregate shocks by separating states into three groups that differ in their housing supply elasticities. In this extension we can only use state-level data to estimate the parameters, but find that our estimates of the key structural parameters and the model’s implications for the relative importance of credit shocks are similar to those in the baseline.

## 4.2 Role of Credit Shocks at the Aggregate Level

We next turn to discussing the model’s implications for the role of credit shocks in explaining fluctuations in the aggregate. Figure 8 presents the dynamics of the key aggregate time series during the 1995 to 2015 period in the data. We HP-filter the debt-to-income series and report it as deviations from the trend in Panel A. Panel B reports the evolution of the Fed Funds Rate and the implied natural rate predicted by the model. Panel C reports the data on employment, measured as the total number of employees on non-farm payrolls, scaled by the U.S. population and expressed as percent deviations from a linear trend. Panel D shows the time series for inflation. We used these series, together with aggregate data on wages, house prices and consumption, to extract the aggregate component of the exogenous shocks used in estimation.

We construct a counterfactual series for each of these variables by shutting down all shocks other than credit shocks. Panel A of Figure 8 shows that credit shocks drive most of the movements in household credit. As Panel B shows, however, credit shocks alone generate modest movements in the natural rate of interest. Specifically, our estimates imply that the natural rate declined from 4.7% at the beginning of 2007 to -1.4% by the end of 2012. Credit shocks account for only one-tenth of this decline: the natural rate would have fallen from 2.4% to 1.8% in the absence of other shocks.

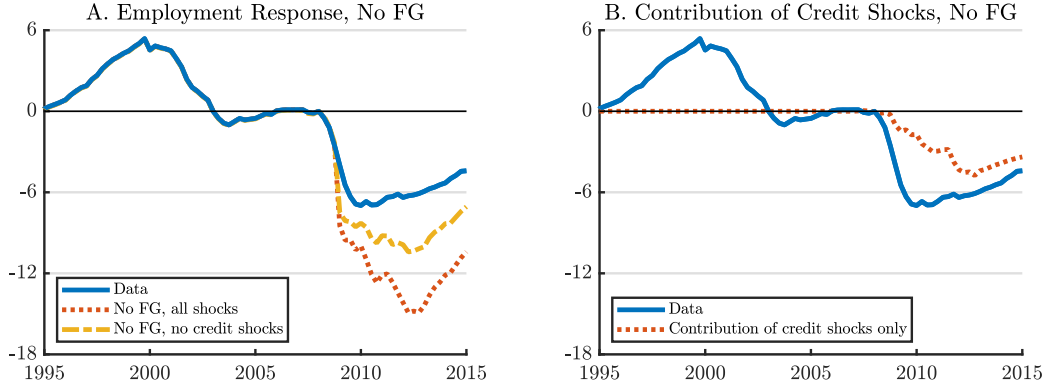
Figure 8: Effect of Credit Shocks Alone on Aggregate Variables



Consider next how employment responds to credit shocks. As the lower-left panel of Figure 8 and Table 6 shows, the Great Recession was associated with a nearly 6.2% drop in the employment-population ratio from 2007 to 2012. Credit shocks alone account for a modest 1.3% drop, one-fifth of the actual decline. Employment falls little because credit shocks generate a small decline in the natural rate, insufficient to trigger the ZLB. Absent additional shocks monetary policy is unconstrained and mimics the dynamics of the natural rate well, implying minor movements in employment and inflation. As is well-understood, however, the ZLB brings about important non-linearities in how aggregate variables respond to shocks. If household credit shocks are accompanied, as they were in the data, by other shocks that reduce the Fed’s ability to cut interest rates because of the ZLB, the resulting effects on output can be much greater. How much greater?

Answering this question is challenging because of the Fed’s pursuit of *forward guidance* policies. In our estimation we have taken the Fed’s forward guidance announcements as given, by setting the expected ZLB duration each quarter equal to the expectations in the data. Since these announcements were responding to the path of all shocks, including credit shocks, we cannot isolate the effect of credit shocks alone without taking a stand on how forward guidance would have been conducted absent such shocks. In short, the pursuit of forward guidance poses an identification challenge, one of decomposing the expected ZLB durations into an endogenous

Figure 9: Effect of Credit Shocks on Aggregate Employment



component due to shocks, and one due to forward guidance policies.<sup>30</sup>

We address this challenge by providing bounds on the role of credit shocks under two extreme sets of assumptions. The lower bound discussed above is that arising in the absence of the ZLB. We compute the upper bound by considering a counterfactual experiment in which the Fed *does not* pursue forward guidance. This is an upper bound because the Fed provides no additional monetary stimulus once interest rates hit zero. We compute this upper bound by first calculating two counterfactual series shown in Panel A of Figure 9. The dotted line shows that the recession would have been twice more severe in the absence of forward guidance. The dashed line turns off the credit shocks and computes the impact of all other shocks on employment. The difference between these series provides a measure of how credit shocks would have shaped employment outcomes in the absence of forward guidance. We plot this difference as the dotted line in Panel B of Figure 9 and summarize it in the last column of Table 6.

As the table shows, even under the extreme assumption of no forward guidance, credit shocks would have caused a modest 1.7% drop in employment from 2007 to 2010, one-fifth of the 7.1% decline in the data. In contrast, the contribution of credit shocks to employment is substantially larger by the end of 2012. Credit shocks would have generated a 4.8% drop in employment from 2007 to 2012 in the absence of forward guidance, three-fifths of the actual drop.

Credit shocks contribute little to employment at the onset of the recession because they are relatively modest initially, reflecting the gradual adjustment of household debt in the first years of the recession. For example, household debt-to-income fell by only 0.19 from 2007 to 2010. In contrast, it experienced a much larger 0.57 drop from 2007 to 2012, leading to a larger decline in the natural rate of interest. We thus conclude that credit shocks may have played a substantial role in delaying the recovery in the aftermath of the recession, but had a modest impact in the

<sup>30</sup>See Jones (2017) for a more detailed discussion of this identification problem and a solution to it.

Table 6: Aggregate Effects of Credit Shocks in the Bust

		Credit Shocks Only	
		No ZLB	No FG
Model and Data			
2007Q1 to 2010Q1			
– $\Delta$ HH Debt to Income	–0.19	–0.24	–0.20
– $\Delta$ Employment, %	–7.09	–0.47	–1.72
2007Q1 to 2012Q4			
– $\Delta$ HH Debt to Income	–0.57	–0.63	–0.57
– $\Delta$ Employment, %	–6.20	–1.34	–4.76

years immediately following 2007.

To summarize, we find that credit shocks account for a large fraction of the relative variability in consumption and employment across U.S. states, but had a modest impact in the first few years of the Great Recession. Does this result reflect differences in how credit shocks are transmitted to employment in the cross-section as opposed to the aggregate, or differences in the size of these shocks? We answer this question in Tables 6 and 7, in which we compare the response of employment to credit shocks in the aggregate and in two states – Arizona and Nevada – that have experienced relatively large boom and bust cycles in credit and employment.

Consider first Arizona. As Table 7 shows, this state experienced a 0.95 drop in the relative debt-to-income ratio from 2007 to 2010, and an even larger 1.6 drop from 2007 to 2012. This decline was much larger than the corresponding decline in the aggregate debt-to-income ratio and led to a sizable drop in relative employment. As the third column of the table shows, credit shocks generate a 3.1 percent drop in employment in Arizona from 2007 to 2010, and a 3.7 percent drop from 2007 to 2012. The patterns in Nevada are similar.

A comparison of the aggregate and state-level outcomes in Tables 6 and 7 reveals that credit shocks generate larger movements in employment in the cross-section of U.S. states compared to the aggregate because they were much larger. For example, from 2007 to 2013, the elasticity of credit shocks to employment in the aggregate was 2.1% (–1.34%/–0.63) at our lower bound estimate which assumes away the ZLB and 8.4% (–4.76%/–0.57) at our upper bound estimate which imposes the ZLB and assumes away forward guidance. In contrast, the corresponding ratio in Arizona is 2.2% (–3.73%/1.71), similar to the 2.1% in Nevada (–4.84%/–2.29). Thus, the transmission of credit shocks to employment is similar in the cross-section as in the aggregate. The larger contribution of credit shocks to cross-sectional variation reflects their larger size in the cross-section.

Table 7: Relative State-Level Effects of Credit Shocks in the Bust

	Model and Data		Credit Shocks Only	
	Arizona	Nevada	Arizona	Nevada
2007 to 2010				
– $\Delta$ HH Debt to Income	–0.95	–1.39	–1.01	–1.46
– $\Delta$ Employment, %	–3.11	–3.47	–3.13	–4.02
2007 to 2013				
– $\Delta$ HH Debt to Income	–1.60	–2.15	–1.71	–2.29
– $\Delta$ Employment, %	–3.07	–2.41	–3.73	–4.84

## 5 Robustness

We conclude by considering a number of robustness checks. For brevity, here we only report the various models’ implications for the importance of credit shocks in accounting for state-level and aggregate movements in employment and consumption. In the Appendix we report the parameter estimates. Table 8 reports the various models’ implications for the contribution of state-level credit shocks to the relative changes of state-level employment and consumption. Table 9 reports the models’ aggregate implications.

**No Population Weighting.** In this robustness exercise, we estimate the model’s parameters without population-weighting the contribution of individual states to the likelihood function. As Tables 8 and 9 show, our results are unaffected.

**Remove 5 Largest States.** One concern is that shocks to large states may have important aggregate consequences, invalidating our approach of assuming independent state-level and aggregate shocks. To address this concern, we examined the robustness of our results to removing the five largest states from the estimation. Specifically, we re-estimated the model without data on California, Texas, New York, Florida, and Illinois. As Tables 8 and 9 report, the estimated model’s implications for the contribution of credit shocks at both the state and aggregate level are similar to those in our baseline.

**State Data Only.** Here we estimate the model’s structural parameters using regional data alone. We then fix these parameters and use the aggregate data to only estimate the parameters of the aggregate shock processes. As we show in the Appendix, using state-level data only we estimate a much lower degree of wage and price stickiness. Intuitively, as [Beraja et al. \(2019\)](#)

Table 8: Contribution of State Credit Shocks to State-Level Variables

	Boom, 2002 to 2007		Bust, 2007 to 2010	
	Employment	Consumption	Employment	Consumption
Baseline Estimates	0.52	0.30	0.56	0.50
No Population Weighting	0.51	0.29	0.54	0.48
Remove 5 Largest States	0.63	0.36	0.60	0.55
State Data Only	0.25	0.23	0.39	0.40
Low Uncertainty ( $\alpha = 5$ )	0.10	0.05	0.09	0.08
High Uncertainty ( $\alpha = 2$ )	1.68	0.96	2.17	2.01
Lower Debt Duration ( $\gamma = 0.965$ )	0.63	0.35	0.64	0.59
One-period Debt ( $\gamma = 0$ )	0.38	0.21	0.30	0.28
Lower Labor Elasticity ( $\psi = 5$ )	0.57	0.33	0.63	0.56
Construction Sector	0.34	0.19	0.35	0.31
Heterogeneous Housing Elasticities	0.20	0.22	0.36	0.40
Government Spending	0.77	0.45	0.89	0.78
Option to Default	0.29	0.15	0.24	0.23
Estimated Taylor Rule	0.53	0.30	0.56	0.50

point out, state-level wages are quite volatile. In contrast, aggregate inflation has changed little during the Great Recession. Reproducing the aggregate data thus requires a greater degree of nominal stickiness, while reproducing the regional data requires a lower one. Our baseline estimates that use both aggregate and regional data thus fall somewhere in between. These results are consistent with the idea that prices respond more to large shocks than to small shocks, as in economies with menu costs (Alvarez et al., 2016) and rational inattention (Mackowiak and Wiederholt, 2009). We emphasize regional differences, but similar evidence exists at the sectoral level (Boivin et al., 2009).

Table 8 shows that the model now predicts a smaller role for credit shocks in generating fluctuations in employment and consumption across U.S. states. For example, credit shocks account for 0.25 of the variability of employment during the boom and 0.39 during the recession. A similar pattern emerges for consumption. Table 9 shows that the contribution of aggregate credit shocks to aggregate employment is also smaller.

**Aggregate Data Only.** We also estimated the model with aggregate data only. Our estimate of  $\alpha$  was lower (3.1). As Table 9 shows, ignoring regional data increases the importance of credit shocks for aggregate employment.

Table 9: Contribution of Aggregate Credit Shocks to Aggregate Employment

	2007Q1 to 2010Q1		2007Q1 to 2012Q4	
	No ZLB	No FG	No ZLB	No FG
Baseline Estimates	−0.47	−1.72	−1.34	−4.76
No Population Weighting	−0.47	−1.67	−1.35	−4.62
Remove 5 Largest States	−0.62	−2.03	−1.77	−5.07
State Data Only	−0.31	−1.44	−0.63	−4.49
Aggregate Data Only	−0.33	−2.61	−1.81	−7.00
Low Uncertainty ( $\alpha = 5$ )	−0.08	−0.23	−0.20	−0.69
High Uncertainty ( $\alpha = 2$ )	−1.55	−4.93	−5.83	−8.02
Lower Debt Duration ( $\gamma = 0.965$ )	−1.10	−3.62	−3.33	−6.60
One-period Debt ( $\gamma = 0$ )	−1.50	−1.38	−4.25	−7.59
Lower Labor Elasticity ( $\psi = 5$ )	−0.52	−1.92	−1.52	−5.20
Construction Sector	0.32	−1.26	−0.14	−3.30
Government Spending	−0.38	−1.95	−1.73	−3.07
Option to Default	−0.60	−0.45	−1.38	−3.00
Estimated Taylor Rule	−0.25	−1.00	−0.79	−3.28

**High and Low Uncertainty.** Here we illustrate the role played by the volatility of idiosyncratic taste shocks. We first reduce the volatility of taste shocks by increasing  $\alpha$  to 5 and re-estimating all other parameters. As Table 8 shows, credit shocks now produce much smaller relative movements in employment and consumption across states. When idiosyncratic uncertainty is low, agents in a state subject to a credit tightening consume out of their liquid assets, so consumption and employment change little. Similarly, as Table 9 shows, credit shocks alone generate virtually no employment decline in the aggregate even at our upper bound that assumes no forward guidance.

We next increase the volatility of taste shocks by lowering  $\alpha$  to 2. The model now attributes a significantly larger role to credit shocks in explaining state-level movements in real variables. As Table 8 shows, credit shocks generate twice more volatile series for employment and consumption during the bust compared to the data. The model also ascribes a much more important role to credit shocks in explaining the aggregate employment decline. Even in the absence of the ZLB, the model predicts an almost 6 percent decline in employment from 2007 to 2012.

**Lower Debt Duration and One-period Debt.** So far we have imposed a value of  $\gamma$ , the parameter determining the decay rate of coupon payments in the mortgage contract, equal to 0.985, consistent with the maturity of mortgage contracts in the data. One could argue, however, that the effective duration of mortgages in the data is lower, due to households' ability

to refinance their mortgages or take on home equity loans. Here we reduce  $\gamma$  to 0.965, implying a duration of mortgages about half that in our baseline (6 years versus 13 years) and reestimate the model. Table 8 shows that credit shocks now generate somewhat larger relative movements in employment and consumption across U.S. states. Similarly, Table 9 shows that credit shocks now account for a larger drop in aggregate employment during the recovery. For example, credit shocks alone predict a 3.3% drop in employment from 2007 to 2012 even in the absence of the ZLB and a 6.6% drop at the ZLB and in the absence of forward guidance.

We have also considered a version of the model with one-period debt, by setting  $\gamma = 0$ . To help match the slow-moving debt and house prices, we now assume that the shocks to credit and preference for housing are themselves AR(1) processes. As Table 8 reports, the model’s implications for the role of credit shocks in the cross-section are very similar to those in our Benchmark parameterization. Mechanically, the persistence and volatility of credit shocks adjusts when we change  $\gamma$  so as to match the comovement of credit and real variables in the data, with little consequence for the behavior of other variables. At the aggregate-level, as Table 9 shows, the implications of credit shocks over the 2007 to 2010 period are unchanged compared to our baseline estimates. However, with one-period debt, credit shocks are more important over the 2007 to 2012 period.

We note that these results indicate a non-monotonic relationship between the duration of mortgage contracts and the contribution of credit shocks to employment and consumption. The reason for the non-monotonicity is that, regardless of the value of  $\gamma$  we use, we always reestimate the model and extract the series for shocks to match the same observed debt series. Since all of the parameters of the model adjust as we change  $\gamma$ , the model does not predict a one-for-one relationship between  $\gamma$  and the relative contribution of credit shocks.

**Lower Labor Elasticity.** In our baseline estimation, we assigned a value of this elasticity,  $\psi$ , equal to 21, following Christiano et al. (2005). This parameter acts like a real rigidity, in that it prevents reset wages from responding too much to a given shock. Here we reduce this parameter to 5, and re-estimate all other parameters of the model. As we report in the Appendix, the estimation now favors an even greater degree of nominal wage and price stickiness to compensate for the removal of the real rigidity. As Tables 8 and 9 show, the model’s implications for the importance of credit shocks in both the cross-section and the aggregate are virtually unchanged.

**Construction Sector.** In our baseline model, we assumed that the housing stock is in fixed supply and for consistency have removed construction employment from the state and aggregate

data. Here we introduce a construction sector and add construction employment as an additional observable in the estimation. We assume that the housing stock evolves according to

$$h_{t+1}(s) = (1 - \delta_h) h_t(s) + y_t^H(s),$$

where  $\delta_h$  is the rate at which housing depreciates and  $y_t^H(s)$  is housing investment, produced with a decreasing returns technology that uses a construction employment,  $n_t^H(s)$ ,

$$y_t^H(s) = z_t^H(s) (n_t^H(s))^\chi,$$

where  $z_t^H(s)$  is the productivity of the construction sector on island  $s$ . The problem of a firm in the the construction sector is to maximize profits, given by

$$e_t(s) z_t^H(s) (n_t^H(s))^\chi - w_t(s) n_t^H(s) - w_t(s) \frac{\xi}{2} (n_t^H(s) - \bar{n}^H)^2,$$

where the last term is an adjustment cost that capture frictions that prevent the movement of labor across sectors.

We set  $\chi = 0.37$  as in [Garriga and Hedlund \(2020\)](#) and  $\delta_h = 0.012$  to match the 4.9% share of construction employment in total employment. We estimate the process for  $z_t^H(s)$  and the other parameters of the model using state and aggregate data on construction employment, in addition to the original variables. As we show in the Appendix, our posterior estimates of the structural parameters are very similar to those in the baseline model. As Table 8 shows, credit shocks now explain a smaller fraction, approximately one-third, of the variation in consumption and non-construction employment across states. As Table 9 shows, the contribution of credit shocks to the drop in aggregate non-construction employment declines as well.

**Heterogeneous Housing Elasticities.** Motivated by the evidence in [Mian and Sufi \(2014\)](#) that individual states respond differentially to aggregate credit shocks due to heterogeneity in housing supply elasticities, we allow for such heterogeneity in our model. Owing to the computational complexity of integrating state and aggregate-level data in computing the likelihood function, here we are only able to use state-level data to conduct inference. We separate states in the U.S. into three equally-sized groups depending on how closely household debt in a given state comoves with household debt in the aggregate. We then calculate changes in all state-level variables relative to the average within each group and allow the housing supply elasticity  $\xi$  to vary across groups in an attempt to isolate the state-specific shocks from heterogeneity in elasticities. Table 8 shows that the model produces smaller fluctuations in employment in response to state-specific credit shocks during the boom but its implications for consumption and

the relative importance of credit shocks in explaining the drop in employment and consumption during the bust is similar to our baseline model with ex-ante identical states.

**Government Spending.** A crucial component of the government’s response to the Great Recession was fiscal policy, which we have so far abstracted from. Here, we allow for changes in government spending both at the state-level and in the aggregate and argue that our results are robust to this modification. Specifically, we now assume that the final good in each state is used for both consumption and government spending, with government spending following an AR(1) process subject to exogenous state-specific and aggregate shocks. We augment the estimation with state and aggregate-level data on government spending. As Table 8 shows, credit shocks imply larger movements in employment and consumption across states compared to our baseline estimates. In contrast, as Table 9 shows, the model’s aggregate implications are similar to our baseline.

**Option to Default.** We have also considered an alternative model in which households have the option to default on their mortgages and fluctuations in household credit are driven by credit supply shocks as opposed to changes in LTV limits. We assume that mortgages are one-period contracts here, to avoid the multiplicity of equilibria that arise in versions of this model with long-term debt.

Specifically, we follow [Landvoigt \(2017\)](#) and [Faria-e-Castro \(2018\)](#) in assuming that in addition to idiosyncratic preference shocks, individual household members experience shocks to the quality of the houses they own,  $\omega_{it}$ . Each member has housing wealth  $\omega_{it}e_th_t$  and is responsible for an equal share of the family’s debt  $b_t$ . The member has the option to default on its debt and does so whenever the value of its home is less than the amount owed,  $\omega_{it}e_th_t < b_t$ . We also assume that financial intermediaries face an ad-valorem transaction cost  $\tau_t$  of issuing new loans. Letting  $\Delta_t$  denote the spread between the discount rate and the rate of time preference, perfect competition between financial intermediaries drives their expected profits to zero, which gives the following debt-elastic schedule for the price of debt that incorporates the probability of default:

$$q_t = \frac{1 + \Delta_t}{1 + (1 + \Delta_t)\tau_t} \beta \mathbb{E}_t \frac{\lambda_{t+1}}{\lambda_t} \left( 1 - G(\hat{\omega}_{t+1}) + \frac{\theta}{\hat{\omega}_{t+1}} \int_0^{\hat{\omega}_{t+1}} \omega dG(\omega) \right),$$

where  $q_t$  is the price of one unit of mortgage debt,  $G(\omega) = (\omega/\bar{\omega})^\chi$  is the Beta distribution of housing quality shocks, which we assume are i.i.d,  $\theta$  is the fraction of the housing stock that

the lender can recover upon default, and

$$\hat{\omega}_t = \frac{b_t}{e_t h_t}$$

is the loan-to-value ratio which determines the cutoff quality below which the agent defaults.

Though the household does not face an explicit borrowing limit, it recognizes that borrowing more entails a larger spread between the interest rate on mortgages and the return on liquid assets. Its optimal choice of debt therefore satisfies

$$q_t = \beta \mathbb{E}_t \frac{\lambda_{t+1}}{\lambda_t} \left[ 1 - \left( 1 - \chi \left( 1 - \frac{\theta}{\bar{\omega}} \right) \frac{1 + \Delta_t}{1 + (1 + \Delta_t) \tau_t} \right) \left( \frac{\hat{\omega}_{t+1}}{\bar{\omega}} \right)^\chi \right].$$

This expression implies that household debt decreases with the transaction cost  $\tau_t$  which generates a spread between mortgage rates and the liquid rate of return even in the absence of default. We refer to changes in  $\tau_t$  as *credit supply* shocks.

We estimate this model using the same approach as earlier. Though we do not explicitly use data on default rates in our estimation, we show in the Appendix that the model matches the time-series of default rates during the boom and the bust cycle well. As Table 8 shows, shocks to  $\tau_t$  and housing preferences generate smaller movements in employment and consumption in the cross-section compared to our baseline, with credit shocks contributing about 30% and 24% of the relative variation in employment during the boom and bust, respectively. As Table 9 shows, the model's aggregate implications are similar to those of our baseline model.

**Estimated Taylor Rule.** In our baseline estimates we used the parameters of the Taylor rule estimated by Justiniano et al. (2011) using pre-Great Recession data. We have also estimated these policy parameters ourselves using a longer sample inclusive of the 2009 to 2015 period. As reported in the Appendix, our estimates of the Taylor Rule are similar to those of Justiniano et al. (2011), so our model's implications are largely unchanged.

## 6 Conclusions

A popular account of the U.S. Great Recession is that declines in households' ability to borrow led to a reduction in consumption and employment due to price rigidities and constraints on monetary policy. This view is motivated, in part, by the observation that employment co-moves strongly with changes in household debt in the cross-section of U.S. regions. This paper asks: what are the *aggregate* implications of these regional correlations?

We develop a model that captures this view by introducing a role for credit in alleviating household liquidity constraints. The more uncertain households are about their individual

liquidity needs, the stronger their precautionary savings motive is and the more sensitive their consumption is to credit shocks. Aggregating across households implies that the natural interest rate fluctuates more in response to changes in credit limits when idiosyncratic uncertainty is higher. We use both state-level and aggregate data on the comovement between consumption and household credit to identify the parameter governing the strength of the precautionary savings motive and thus the sensitivity of macroeconomic variables to credit shocks.

To make full-information Bayesian estimation feasible, we propose a novel methodology that exploits the structure of the model and identifies parameters from the relative variation of state-level variables, in addition to fluctuations in the aggregate. Our approach allows us to efficiently calculate the likelihood function in an economy with a large number of aggregate and regional state variables and with non-linear dynamics caused by the ZLB constraint on monetary policy.

Our estimates imply that credit shocks account for about 40% of the differential rise and fall in *state-level* employment and consumption during the boom and bust years of the past decade. In contrast, credit shocks alone generate modest movements in *aggregate* employment from 2007 to 2010, about one-fifth of the observed decline, even though monetary policy was constrained by the ZLB. This result reflects the gradual nature of household deleveraging, which caused a gradual decline in the natural interest rate.

The persistent nature of household deleveraging implies, however, that credit shocks became more important over time as the quantity of household debt continued to decline and the natural rate fell even further. Our estimates suggest that credit shocks account for a sizable fraction of the employment gap in 2012. The tightening in household-level credit limits thus helps account for the slow recovery of employment in the aftermath of the Great Recession.

A caveat is in order. We have focused on the *household leverage* view of the Great Recession and have abstracted from other forces, such as constraints on financial intermediaries, that played an important role during the acute phase of the crisis. A limitation of our approach is that we cannot estimate the *interactions* between household credit risk and the net worth of intermediaries. Though beyond the scope of this paper, explicitly modeling such interactions is an important area for future research. In the U.S. this played an important role at the aggregate level, and a more limited one across regions. In Europe, by contrast, the interaction of credit risk and financial intermediation created strong regional dynamics as sovereign and financial spreads widened and inter-state banking liquidity provision collapsed at least until the establishment of the banking union in 2012.

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