Learning Financial Shocks

and the Great Recession[*]

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Abstract: This paper develops a simple business-cycle model in which financial shocks have large macroeconomic effects when private agents are gradually learning their uncertain environment. When agents update their beliefs about the parameters that govern the unobserved process driving financial shocks to the leverage ratio, the responses of output and other aggregates under adaptive learning are significantly larger than under rational expectations. In our benchmark case calibrated using US data on leverage, debt-to-GDP and land value-to-GDP ratios for 1996Q1-2008Q4, learning amplifies leverage shocks by a factor of about three, relative to rational expectations. When fed with actual leverage innovations observed over that period, the learning model predicts a sizeable recession in 2008-10, while its rational expectations counterpart predicts a counter-factual expansion. In addition, we show that procyclical leverage reinforces the amplification due to learning and, accordingly, that macro-prudential policies enforcing countercyclical leverage dampen the effects of leverage shocks.

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1   Introduction

The 2007-2008 US financial crisis and the recession that followed have revived interest in alternative approaches to model how agents forecast economic variables. Several recent papers explore the macroeconomic implications of relaxing the assumption that people know the "true" data-generating process when making decisions in an economy that is subject to random disturbances. For example, Hebert, Fuster and Laibson [15] show that asset prices dynamics are more satisfactorily explained when forecasters use simple models that typically underestimate mean-reversion and overestimate the persistence of the impact of shocks. Ilut and Schneider [20] show that shocks driving the unknown mean level of productivity contribute significantly, under ambiguity aversion, to business cycles. In both contributions, the key assumption is that there is uncertainty about the "true" parameters (e.g. the mean and the autocorrelation) governing the random shocks that affect the economy.

In this paper, we contribute to this strand of literature by assuming that agents do not know the parameters of the stochastic process governing financial shocks. In our model agents learn their economic environment by estimating unknown parameters and by updating each period their beliefs about that process as new data arrive, following Marcet and Sargent [29] and Evans and Honkapohja [13] (see also the related discussion in Evans [12]). In a simple business-cycle model with collateral constraints, we theoretically show that learning amplifies financial shocks when agents overestimate either the persistence of financial shocks or the long-run level of financial variables. We then simulate the model using actual financial innovations and we report that our learning model delivers a sizeable recession in 2008-2010, in contrast to the rational expectations that predicts a counterfactual *expansion* when subjected with the same financial shocks. The key random variable in our analysis is the leverage ratio defined by how much one can borrow

out of the land market value. We show that when agents update their beliefs about the parameters that govern the unobserved process driving shocks to the leverage ratio, the responses of output and other aggregates under adaptive learning are significantly larger than under rational expectations. More specifically, we compare two settings: (i) the model with (full information) rational expectations, in which agents know the parameters governing the AR(1) process of shocks to leverage; (ii) the model with learning, in which agents are ignorant about the "true" AR(1) parameters and update their estimates as new data arrive.

Our results can be anticipated by looking at the two panels in Figure 1. Panel a) of Figure 1 plots the US quarterly households' leverage data (provided by Boz and Mendoza [5]) over the period 1996Q1-2010Q1 that covers the latest boom-bust behavior in the housing market. As explained in more details in Section 4, we take out of the raw data the endogenous component of leverage that has been (moderately) elastic to land prices prior to 2008 (Mian and Sufi [30]) and we estimate an AR(1) process on the residual (exogenous) component. Panel b) of Figure 1 reports the autocorrelation coefficient of the exogenous leverage component that is estimated under learning. The autocorrelation coefficient (solid red line) in panel b) is obtained through constant-gain recursive estimation in real-time, as new data is collected. Panel b) shows that when confronted with the data in panel a), learning agents think of the AR(1) leverage process as moving towards unit root at the end of the period. Essentially, the level of leverage shows a rapid increase after 2006, when the land price stops expanding and starts falling - panel a) - and this also when learning agents start increasing their estimate of autocorrelation, which ends up being very close to one prior in the last two quarters of 2008. As a result, both the observed mean level of leverage and its estimated persistence peak at the same time, in 2008Q4. On the other hand, the rational expectations estimate, obtained by ordinary least squares over the whole sample period, is lower than its learning counterpart

Figure 1: in Panel a) US Household Leverage Ratio 1996Q1-2010Q1 (Source: Boz and Mendoza [5]), in Panel b) Model Estimate of Leverage Autocorrelation 1996Q1-2010Q1.

Panel a): Leverage Data

Panel b): Estimate of Persistence
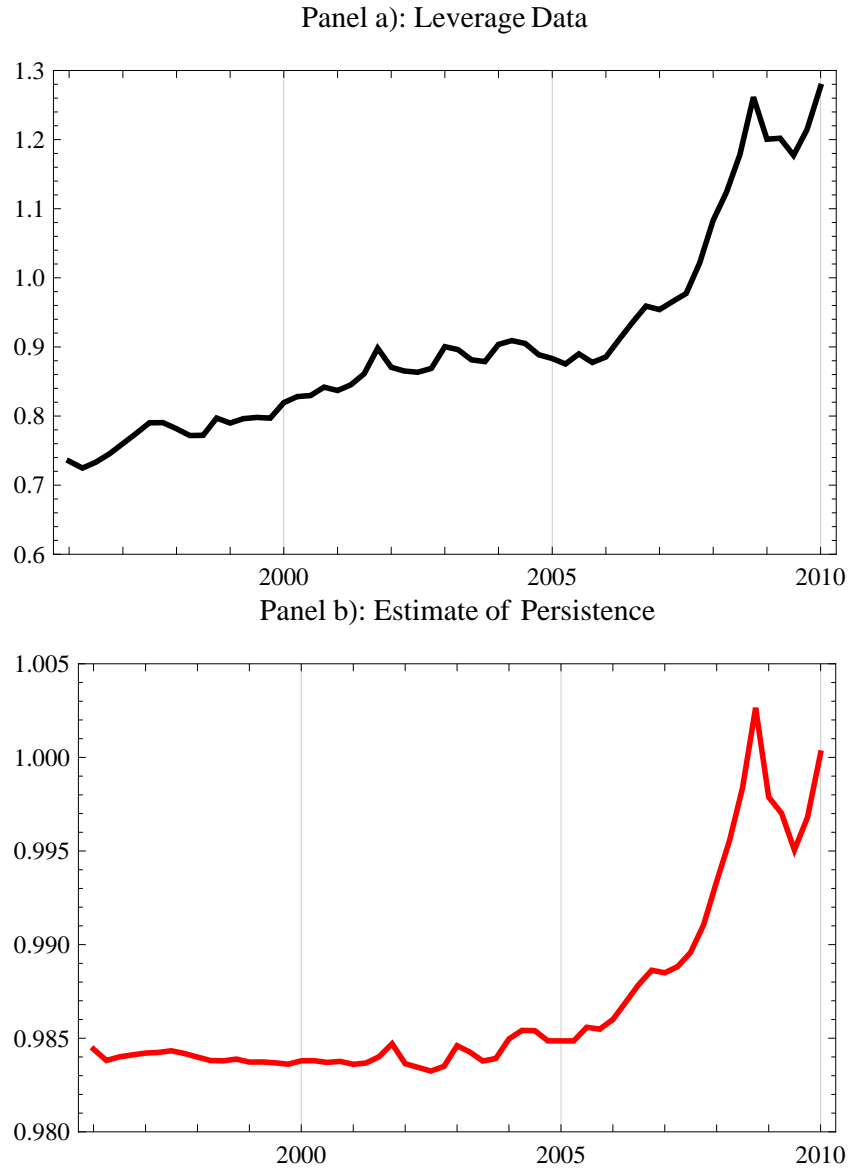
over the period shown in panel b) and it is around 0.976. Because the learning model generates the estimate shown in panel b) when fed with the actual leverage innovations, it predicts that the impact of the negative shock to leverage observed in 2008Q4 is three times bigger than under rational expectations. When believed under learning to be close to permanent, financial shocks have a larger effect on the economy, compared to rational expectations.

Our main findings are derived in a model that is a simple variant of Kiyotaki and Moore [24] based on Kocherlakota [25]. We focus on financial shocks that drive up and down the leverage ratio, which according to the data in panel a) of Figure 1 are very persistent. We first perform two theoretical experiments. The first one assumes that agents know the economy's steady state and, in particular, the mean level of leverage but not its autocorrelation, which is allowed to be time-varying. We calibrate the model using data on leverage, debt-to-GDP and land value-to-GDP ratios for the period 1996Q1-2008Q4 and we subject the economy to the large negative shock to leverage that was observed in 2008Q4 (see panel a) in Figure 1) under the assumption that learning agents overestimate the persistence of the leverage shock, which is believed to be close to unity (see panel b) in Figure 1). We compare the responses of the linearized economy under adaptive learning and under rational expectations. Our typical sample of results shows that learning amplifies leverage shocks by a factor of more than three (see Figure 2). More precisely, our model predicts, when fed with the negative leverage shock of about -5% observed in 2008Q4, that output falls by about 0.8%, which is roughly by how much US GDP dropped at that time. In addition, aggregate consumption and the capital stock fall by about 1.1% and 1.8%, respectively. Under rational expectations, however, output drops only by about 0.25% while the responses of consumption and investment are divided by more than two at impact. Consumption and investment go down by a significantly larger margin under learning because de-leveraging is more severe: land price and debt

are much more depressed after the negative leverage shock hits when its persistence is overestimated by agents who are constantly learning their environment and, because of recent past data, temporarily pessimistic. We next show that the magnitude of the consequent recession may in part be attributed to the high *level* of leverage (and the correspondingly high level of the debt-to-GDP ratio) observed in 2008Q4. When the same negative leverage shock occurs in the model calibrated using 1996Q1 data, when leverage was much lower, the impact on output's response is reduced by about two thirds. In this sense, our model points at the obvious fact that financial shocks to leverage originate larger aggregate volatility in economies that are more levered.

In addition, we also ask whether procyclical leverage may act as an aggravating factor and our answer is positive. The assumption that households' leverage responds to land price is motivated by the recent evidence provided by Mian and Sufi [30] (see also the discussion in Midrigan and Philippon [31]). The counter-factual experiment with countercyclical leverage shows dampened effects of leverage shocks, with responses of aggregate variables under learning that are close to their rational expectations counterpart. One possible interpretation of this finding is that macro-prudential policies enforcing countercyclical leverage have potential stabilizing effects on the economy in the face of financial shocks, at small cost provided that non-distortionary policies are implemented (e.g. through regulation).

Our second theoretical experiment is carried out under the assumption that learning agents do not know the steady state of the economy and, in particular, that they do not know the long-run level of leverage. This is our preferred model in the sense that it is arguably a more realistic description of the difficulties that forecasting agents/econometricians face when trying to figure out the parameters governing the data generating process. In such a setting, we again feed the model with the negative leverage shock of about -5% observed in 2008Q4 and we show that the responses of the economy are further amplified

under learning when agents' belief about the mean level of leverage is overestimated (see Figure 6). Summing up the results from our two model experiments, our main conclusion is that in a world where agents overestimate the persistence of financial shocks and/or the mean level of leverage, learning amplifies the disturbances to borrowing capacity.

We next derive our set of quantitative results about the model-generated recession for 2008-10. In line with the literature (see Kiyotaki, Michaelides, Nikolov [23], Liu, Wang, Zha [27], Justiniano, Primiceri, Tombalotti [22], among others), we show that replicating the observed boom-bust pattern of land prices over the 2000s requires another source of shocks in addition to leverage shocks. We introduce a land investment wedge that we calibrate to ensure that the behavior of the endogenous land price matches its observed counterpart. We also feed the model with the actual innovations to leverage and show that the model predicts a sizeable fraction of the output fall observed during the Great Recession. More precisely, we do that in a setting where agents do not know the steady state of the economy and the autocorrelation matrix, that they have to estimate using constant-gain learning. When we let agents revise their estimates in reaction to the actual leverage innovations observed up to 2008, the learning model predicts a boom that is followed by a sizeable recession in 2008-10 (see Figure 10). In sharp contrast, in the 2000s the rational expectations model predicts a long recession that is followed by an expansion, which are both at odds with the data.

To summarize, our main finding is that leverage shocks are amplified when agents gradually update their beliefs about the process driving financial shocks. We believe it is important to acknowledge that, as Figure 1 suggests, nonstationary leverage (either because it is subject to permanent shocks or because of its time-varying steady state level) may have played an important role in favoring conditions that worsened the Great Recession. Looking back in time at the data in Figure 1, there is a sense in which everybody should have foreseen that leverage could not possibly increase forever. However,

figuring out when leverage would stop rising was a much harder task. Our paper stresses that when such a change comes, its macroeconomic impact when agents adaptively learn differs much from what happens under rational expectations. Moreover, on the policy side, our analysis gives an example of a macro-prudential policy that dampens the impact of financial shocks to the macroeconomy under learning by ensuring that leverage goes down when asset prices spike up.

Related Literature: Our paper connects to several strands of the literature. The macroeconomic importance of financial shocks has recently been emphasized by Jermann and Quadrini [21], among others, and our paper contributes to this literature about credit shocks by showing how learning matters. Closest to ours are the papers by Adam, Kuang and Marcet [1], who focus on interest rate changes, and by Boz and Mendoza [5], who show how changes in the leverage ratio have large macroeconomic effects under Bayesian learning and Markov regime switching. As in Boz and Mendoza [5], we focus on leverage shocks but our setting is different. First, our model with adaptive learning is easily amenable to simulations and we solve for equilibria through usual linearization techniques. Because we assume that agents are adaptively learning through VAR estimation, it is possible to enrich the model by adding capital accumulation and endogenous production. Most importantly, our model predicts large output drops when the economy is hit by negative leverage shocks. In contrast, absent TFP shocks, output remains constant after a financial regime switch in Boz and Mendoza [5]. Our paper also relates to some of the insights in Howitt [18], Hebert, Fuster and Laibson [15, 16]. Contrary to Hebert, Fuster and Laibson [15, 16] who assume that agents use a misspecified model, in our case the overestimated persistence of shocks arises endogenously under adaptive learning when agents face the sequence of financial innovations that was observed in the run-up to the crisis.[1] In addition, our paper stresses that endogenous

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[1]Along this dimension, we address some concerns raised by Evans [12].

changes in the beliefs about the long-run level of leverage may also matter for explaining why shocks get amplified under adaptive learning. This is also where our paper departs from Ilut and Schneider [20], who do not consider learning in their setting with exogenously driven ambiguity about TFP shocks.

In the literature, the idea that procyclical leverage has adverse consequences on the macroeconomy is forthfully developed in Geanakoplos [17] (see also Cao [7]). Although our formulation of elastic leverage is derived in an admittedly simple setup, it allows us to examine its effect in a full-fledged macroeconomic setting. Last but not least, the notion that learning is important in business-cycle models when some change in the shock process occurs has been discussed by, e.g., Bullard and Duffy [6] and Williams [36]. More recently, Eusepi and Preston [11] have shown that learning matters in a standard RBC model when the economy is hit by shocks to productivity growth (see also the related paper by Edge, Laubach, Williams [10]). Our paper adds to this literature by focusing on financial shocks under collateral constraints. As mentioned before, part of the paper's motivation also comes from the growing micro-evidence about the importance of households' and firms' leverage for understanding consumption and investment behaviors (e.g. Mian and Sufi [30], Chaney, Sraer and Thesmar [9]).

The paper is organized as follows. Section 2 presents the model and derives its rational expectations equilibria. Section 3 relaxes the assumption that agents form rational expectations in the short run and it shows how financial shocks are amplified under learning when agents update their estimates about the parameters of the stochastic process driving financial shocks. Section 4 shows that such a setting predicts a sizeable recession in 2008-10 while its rational expectations counterpart does not. Section 5 gathers concluding remarks and all proofs are exposed in the appendices.

2 The Economy with Financial Shocks

2.1 Model

The model is essentially an extension of Kocherlakota's [25] to partial capital depreciation and adaptive learning. A representative agent solves:

$$\max E_0 \sum_{t=0}^{\infty} \beta^t \frac{C_t^{1-\sigma} - 1}{1-\sigma} \tag{1}$$

where $C_t \geq 0$ is consumption and $\sigma \geq 0$ denotes relative risk aversion, subject to both the budget constraint:

$$C_t + K_{t+1} - (1-\delta)K_t + T_t Q_t (L_{t+1} - L_t) + (1+R)B_t = B_{t+1} + A K_t^{\alpha} L_t^{\gamma} \tag{2}$$

and the collateral constraint:

$$\tilde{\Theta}_t E_t[Q_{t+1}] L_{t+1} \geq (1+R)B_{t+1} \tag{3}$$

where K_{t+1}, L_{t+1} and B_{t+1} are the capital stock, the land stock and the amount of new borrowing, respectively, all chosen in period t, Q_t is the land price, R is the exogenous interest rate, and A is the total factor productivity (TFP thereafter). In the model, leverage $\tilde{\Theta}_t$ is subject to random shocks whereas both the interest rate and TFP are constant over time. As we focus on financial shocks, we ignore TFP disturbances and simply notice that similar results hold when learning agents do not know the parameters governing the technological shock process. We also introduce a land investment wedge shock T, essentially because the model with only leverage disturbances can hardly replicate the land price behavior that has been observed in the 2000s. In line with the literature (see e.g. Kiyotaki, Michaelides, Nikolov [23], Liu, Wang, Zha [27], Justiniano, Primiceri, Tombalotti [22] among others), we find that the model with both shocks does a better job along this dimension. Although the wedge formulation we use is rather

agnostic, it is easy to show that it is essentially equivalent to land preference shocks or other "political" shocks that push the demand for land and the land price up or down. We assume that the wedge process is $T_t = T_{t-1}^{1-\rho_\tau} \Psi_t$ and absent shocks there it does not cause any distortions to the steady state. We present first the results obtained under the collateral constraint (3), which follows Kiyotaki and Moore [24]. However, quantitatively similar results hold under the margin requirement timing stressed in Aiyagari and Gertler [3] (see Section 3.3 for robustness analysis).

Denoting Λ_t and Φ_t the Lagrange multipliers of constraints (2) and (3), respectively, the borrower's first-order conditions with respect to consumption, land stock, capital stock, and loan are given by:

$$C_t^{-\sigma} = \Lambda_t \tag{4}$$

$$T_t Q_t \Lambda_t = \beta E_t[T_{t+1} Q_{t+1} \Lambda_{t+1}] + \beta \gamma E_t[\Lambda_{t+1} Y_{t+1}/L_{t+1}] + \Phi_t \tilde{\Theta}_t E_t[Q_{t+1}] \tag{5}$$

$$\Lambda_t = \beta E_t[\Lambda_{t+1}(\alpha Y_{t+1}/K_{t+1} + 1 - \delta)] \tag{6}$$

$$\Lambda_t = \beta(1 + R)E_t[\Lambda_{t+1}] + (1 + R)\Phi_t. \tag{7}$$

Following the "shadow price learning" approach proposed by Evans and Mc Gough [14], we keep track of the Lagrange multipliers in our learning procedure. We also incorporate into the model the feature that leverage responds to changes in the land price, which accords with the US micro data evidence documented by Mian and Sufi [30]. More precisely, we posit that:

$$\tilde{\Theta}_t \equiv \Theta_t \left\{ \frac{E_t[Q_{t+1}]}{Q} \right\}^\varepsilon \tag{8}$$

where Q is the steady-state value of land price and the log of Θ_t follows an AR(1) process, that is, $\Theta_t = \overline{\Theta}^{1-\rho_\theta} \Theta_{t-1}^{\rho_\theta} \Xi_t$. In Appendix A.2, we show how (8) can be derived in a simple setting with ex-post moral hazard and costly monitoring. One can think of (8) as a decomposition of leverage into an exogenous component Θ_t and an endogenous component $\{E_t[Q_{t+1}]/Q\}^\varepsilon$. While we set the parameter ε to a positive value in our

benchmark calibration, in accord with Mian and Sufi [30], we also study the predictions of our model with a counterfactual, countercyclical leverage.

In what follows, we assume that while Θ_t and T_t are observed, the innovations Ξ_t and Ψ_t are not. We compare two cases regarding what agents know about the data generating process underlying leverage and wedge shocks:

(i) rational expectations (with full information): agents know with certainty the "true" values of ρ_τ, ρ_θ and $\overline{\Theta}$,

(ii) learning (with incomplete information): ρ_τ, ρ_θ and $\overline{\Theta}$ are unknown and agents have to estimate those parameters based on available data. We consider two experiments which are reported in Sections 3.1 and 3.4. In Section 3.1, we first assume that the steady state is known but that learning agents do not know (and have to estimate) the persistence parameter ρ_θ. Next, in Section 3.4, we assume that agents are uncertain about the steady state level of leverage $\overline{\Theta}$ as well. Before turning to that, we present the benchmark case of rational expectations equilibria.

2.2   Rational Expectations Equilibria

A rational expectations competitive equilibrium is a sequence of positive prices $\{Q_t\}_{t=0}^\infty$ and positive allocations $\{C_t, K_{t+1}, L_{t+1}, B_{t+1}\}_{t=0}^\infty$ such that, given the exogenous sequence $\{\Theta_t, T_t\}_{t=0}^\infty$ of the leverage and price wedges, and the exogenous interest rate $R \geq 0$:

(i) $\{C_t, K_{t+1}, L_{t+1}, B_{t+1}\}_{t=0}^\infty$ satisfies the first-order conditions (4)-(7), the transversality conditions, $\lim_{t\to\infty} \beta^t \Lambda_t L_{t+1} = \lim_{t\to\infty} \beta^t \Lambda_t K_{t+1} = 0$, and the complementarity slackness condition $\Phi_t \left[\tilde{\Theta}_t E_t[Q_{t+1}]L_{t+1} - (1+R)B_{t+1} \right] = 0$ for all $t \geq 0$, where $\tilde{\Theta}_t \equiv \Theta_t \{E_t[Q_{t+1}]/Q\}^\varepsilon$, given the initial endowments $L_0 \geq 0, B_0 \geq 0, K_0 \geq 0$;

(ii) The good and asset markets clear for all t, that is, $C_t + K_{t+1} - (1-\delta)K_t + (1+R)B_t =$

$B_{t+1} + A_t K_t^\alpha$ and $L_t = 1$, respectively.

The above definition assumes that the interest rate is exogenous. Therefore, a natural interpretation of the model is that it represents a small, open economy. Appendix A.3 presents a closed-economy variant based on Iacoviello [19], in which borrowers and lenders meet in a competitive credit market subject to collateral constraints and a constant debtor interest rate. Our findings reported below can be replicated in the closed-economy model when the economy is hit by negative financial and TFP shocks that occur simultaneously. As our focus is on how borrowers adaptively learn how the economy settles after financial shocks, we abstract both from TFP shocks and from further details regarding the lender's side, and we focus on the small-open-economy setting, as in Adam, Kuang and Marcet [1], Boz and Mendoza [5].

There is a unique (deterministic) stationary equilibrium such that the credit constraint (3) binds, provided that the interest factor $1 + R \equiv 1/\mu$ is such that $\mu \in (\beta, 1)$, that is, if lenders are more patient than borrowers. This follows from the steady-state version of (7), $\Phi = \Lambda(\mu - \beta) > 0$. The steady state is characterized by the following great ratios, that fully determine the linearized dynamics around the steady state. From (5) and (6), it follows that the land price-to-GDP and capital-to-GDP ratios are given by $Q/Y = \gamma\beta/[1 - \beta - \overline{\Theta}(\mu - \beta)]$ and $K/Y = \alpha\beta/[1 - \beta(1 - \delta)]$, respectively. Finally, (3) yields the debt-to-GDP ratio $B/Y = \mu\overline{\Theta}Q/Y$ and (2) yields the consumption-to-GDP ratio $C/Y = 1 - \delta K/Y - (1/\mu - 1)(B/Y)$.

Appendix A.2 provides a log-linearized version in levels of the set of equations (2)-(7) defining, together with (8) and the laws of motion $\Theta_t = \overline{\Theta}^{1-\rho_\theta}\Theta_{t-1}^{\rho_\theta}\Xi_t$ and $T_t = T_{t-1}^{1-\rho_\tau}\Psi_t$, intertemporal equilibria. The linearized expectational system can be written as:

$$X_t = \mathbf{A}X_{t-1} + \mathbf{B}E_{t-1}[X_t] + \mathbf{C}E_t[X_{t+1}] + \mathbf{N} + \mathbf{D}\xi_t + \mathbf{F}\psi_t \tag{9}$$

where $X_t' \equiv (c_t, q_t, \lambda_t, \phi_t, b_t, k_t, \theta_t, \tau_t)$ is observed whereas ξ_t and ψ_t are not, and all variables in lowercase letters denote variables in log (e.g. $k_t \equiv \log(K_t)$). The derivation

and the expressions of the 8-by-8 matrices $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$, $\mathbf{D}$, $\mathbf{F}$, $\mathbf{N}$ as functions of parameters are given in Appendix A.2.

Anticipating our results on E-stability, we now use the fact that the linearized rational expectations equilibrium around steady state can be obtained as the unique E-stable Minimal-State-Variable solution (MSV thereafter) such that

$$E_t[X_t] = \mathbf{H}^{\mathbf{re}} + \mathbf{M}^{\mathbf{re}} X_{t-1}, \tag{10}$$

where $\mathbf{M}^{\mathbf{re}}$ and $\mathbf{H}^{\mathbf{re}}$ solve

$$\mathbf{M} = [\mathbf{I}_8 - \mathbf{CM}]^{-1}[\mathbf{A} + \mathbf{BM}], \tag{11}$$

$$\mathbf{H} = [\mathbf{I}_8 - \mathbf{CM}^{\mathbf{re}}]^{-1}[\mathbf{BH} + \mathbf{CH} + \mathbf{N}], \tag{12}$$

and $\mathbf{I}_8$ is the 8-by-8 identity matrix.

It is important to underline that all parameters, including both the autocorrelation of the leverage shock process, that is, ρ_θ, and the leverage level, that is $\overline{\Theta}$, are known under rational expectations. In contrast, the next sections relax such an assumption and assume instead that agents have to form estimates about ρ_θ and $\overline{\Theta}$ using the available data.

3 Adaptive Learning

Following Marcet and Sargent [29] and Evans and Honkapohja [13], we now relax the assumption that agents form rational expectations in the short-run. We first assume that the steady state of the economy is known, which implies that the level of leverage is common knowledge. However, the parameters governing the dynamics of the economy are not known. In particular, ρ_θ is not known with certainty by agents. We can still use

the linearized dynamic system in log levels, which is now:

$$X_t = \mathbf{A}X_{t-1} + \mathbf{B}E^*_{t-1}[X_t] + \mathbf{C}E^*_t[X_{t+1}] + \mathbf{N} + \mathbf{D}\xi_t + \mathbf{F}\psi_t \tag{13}$$

where the operator E^*_t indicates expectations that are taken using all information available at t but that are possibly nonrational. More precisely, agents behave as econometricians by embracing the following perceived law of motion (PLM thereafter):

$$X_t = \mathbf{M}X_{t-1} + \mathbf{H} + \mathbf{D}\xi_t + \mathbf{F}\psi_t \tag{14}$$

which agents use for forecasting. In particular, (14) yields $E_t[X_{t+1}] = \mathbf{M}_{t-1}X_t + \mathbf{H}_{t-1}$ and $E_{t-1}[X_t] = \mathbf{M}_{t-2}X_{t-1} + \mathbf{H}_{t-2}$. The actual law of motion (ALM thereafter) results from combining (13) and (14) which gives:

$$[\mathbf{I}_8 - \mathbf{C}\mathbf{M}_{t-1}]X_t = [\mathbf{A} + \mathbf{B}\mathbf{M}_{t-2}]X_{t-1} + [\mathbf{B}\mathbf{H}_{t-2} + \mathbf{C}\mathbf{H}_{t-1} + \mathbf{N}] + \mathbf{D}\xi_t + \mathbf{F}\psi_t. \tag{15}$$

When $\mathbf{M}$ and $\mathbf{H}$ coincide with $\mathbf{M^{re}}$ and $\mathbf{H^{re}}$ (as derived in Section 2.2) then agents hold rational expectations. However, beliefs captured in $\mathbf{M}$ and $\mathbf{H}$ may differ from rational expectations. Following Evans and Honkapohja [13], we assume they are updated in real time using recursive learning algorithms which means that the belief matrices $\mathbf{M}$ and $\mathbf{H}$ are time-varying. The coefficients are updated according to

$$\mathbf{\Omega}_t = \mathbf{\Omega}_{t-1} + \nu_t(X_t - \mathbf{\Omega}_{t-1}Z_{t-1})Z'_{t-1}\mathbf{R}^{-1}_t \tag{16}$$

$$\mathbf{R}_t = \mathbf{R}_{t-1} + \nu_t(Z_{t-1}Z'_{t-1} - \mathbf{R}_{t-1}) \tag{17}$$

where $Z'_t = [1, X'_t]$ and $\mathbf{\Omega} = [\mathbf{H} \quad \mathbf{M}]$. $\mathbf{R}$ is the estimate of the variance-covariance matrix and ν_t is the gain sequence (which equals $1/t$ under ordinary least squares and ν under constant gain, respectively OLS and CG thereafter). One difference with rational expectations that is key to our results is that agents' estimates may differ from true parameter values. For example, agents may overestimate the autocorrelation parameter ρ_θ or overestimate the steady state level of leverage $\bar{\Theta}$.

The mapping from the PLM (14) into the ALM (15) is given by:

$$T_{\mathbf{M}}(\mathbf{M}, \mathbf{H}) \;=\; [\mathbf{I}_8 - \mathbf{CM}]^{-1}[\mathbf{A} + \mathbf{BM}] \tag{18}$$

$$T_{\mathbf{H}}(\mathbf{M}, \mathbf{H}) \;=\; [\mathbf{I}_8 - \mathbf{CM}]^{-1}[\mathbf{BH} + \mathbf{CH} + \mathbf{N}]. \tag{19}$$

Adapting Proposition 10.3 from Evans and Honkapohja [13], we check that all eigenvalues of $DT_{\mathbf{M}}(\mathbf{M}, \mathbf{H})$ and $DT_{\mathbf{H}}(\mathbf{M}, \mathbf{H})$ have real parts less than 1 when evaluated at the fixed-point solutions of the T-map (18), that is, $\mathbf{M} = \mathbf{M}^{\mathbf{re}}$ and $\mathbf{H} = \mathbf{H}^{\mathbf{re}}$. Using the rules for vectorization, we get:

$$
\begin{aligned}
DT_{\mathbf{M}}(\mathbf{M}^{\mathbf{re}}, \mathbf{H}^{\mathbf{re}}) \;=\;& ([\mathbf{I}_8 - \mathbf{CM}^{\mathbf{re}}]^{-1}[\mathbf{A} + \mathbf{BM}^{\mathbf{re}}])' \otimes [\mathbf{I}_8 - \mathbf{CM}^{\mathbf{re}}]^{-1}\mathbf{C} \\
& + \mathbf{I}_8 \otimes [\mathbf{I}_8 - \mathbf{CM}^{\mathbf{re}}]^{-1}\mathbf{B} \\
DT_{\mathbf{H}}(\mathbf{M}^{\mathbf{re}}, \mathbf{H}^{\mathbf{re}}) \;=\;& [\mathbf{I}_8 - \mathbf{CM}^{\mathbf{re}}]^{-1}[\mathbf{B} + \mathbf{C}].
\end{aligned}
$$

All MSV solutions that we consider from now on are said to be locally E-stable when all eigenvalues of both $DT_{\mathbf{M}}(\mathbf{M}^{\mathbf{re}}, \mathbf{H}^{\mathbf{re}})$ and $DT_{\mathbf{H}}(\mathbf{M}^{\mathbf{re}}, \mathbf{H}^{\mathbf{re}})$ lie within the interior of the unit circle. In practice, we numerically compute the E-stable solutions by iterating the T-map (18)-(19), as described in Evans and Honkapohja [13, p.232].

3.1 Learning the Persistence of Leverage Shocks

In this section, we show that learning amplifies leverage shocks when agents' beliefs about the model parameters are allowed to differ from rational expectations. In particular, we assume that learning agents incorrectly believe that ρ_θ is closer to one than the "true" value. This is meant to capture the trend in leverage that is observed in the run-up to the 2008Q4 crisis. On the other hand, we make our theoretical experiment more transparent by subjecting the model to a single source of shock and we shut down the wedge shock, that is, $T_t = 1$ for all t.

The quaterly data on households's debt, land holdings, land price and leverage we use is borrowed from Boz and Mendoza [5]. The model is calibrated to deliver average values for leverage, debt-to-GDP and land value-to-GDP ratios observed over the housing market "bubble" period 1996Q1-2008Q4, that is $\overline{\Theta} \approx 0.88$, $B/Y \approx 0.52$ and $QL/Y \approx 0.59$, see Table 1 for all parameter values. To calibrate those ratios, we fix the quarterly interest rate to 1% (that is, $\mu = 0.99$) and $\beta = 0.98\mu$, consistently with the literature on heterogeneous discount rates; e.g. Krusell and Smith [26], and then pick the land share γ to target the land price-to-GDP ratio $QL/Y \approx 0.59$. Setting the leverage mean level $\overline{\Theta} \approx 0.88$ ensures that the debt-to-GDP is $B/Y \approx 0.52$ as in the data. In addition, we choose $\varepsilon = 0.5$, which is consistent with the estimates of Mian and Sufi [30].[2] Finally, the standard deviation of the innovations to leverage, that is, σ_ξ, comes from the OLS estimate over the whole sample period. In all the simulations reported below, we have checked numerically that the borrowing constraint is always binding.

Table 1. Parameter Values (1996Q1-2008Q4)

μ	β	δ	α	γ	$\overline{\Theta}$	σ	ε	ν	σ_ξ
0.99	0.98μ	0.025	0.45	0.0075	0.88	1	0.5	0.013	0.034

The experiment that produces our first set of results is the following. We assume that in the period preceding the financial collapse of 2008Q4, the agents in our model economy have learned that ρ_θ was close to one, reflecting the leverage trend that starts in the early 1990s. This means that agents' beliefs encapsulated in matrix $\mathbf{M}$ of the PLM (14) reflect that $\rho_\theta \approx 1$. Then in 2008Q4 a large negative shock to leverage of about -5% happens (see Figure 1). The (pseudo-)impulse response functions in Figure 2 report the reaction of the economy's aggregates under the assumptions that agents wrongly believe

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[2]The value we set ε to implies, for instance, that a 10% increase in land price triggers a 5% increase in leverage, which under our calibration would raise leverage from 0.88 to about 0.92.

that $\rho_\theta \approx 0.998$ whereas the true value is 0.976. Such a calibration is consistent with both the CG and OLS estimates in 2008Q4 obtained from the data, as shown in panel b) of Figure 1 (see also Figure 9 in Section 4). More precisely, panel b) in Figure 1 shows that $\rho_\theta \approx 0.998$ in 2008Q3, which is the value that learning agents use to forecast 2008Q4. To initialize the model, we simulate a million times the RE model calibrated according to Table 1, estimate the variance-covariance matrix $\mathbf{R}$, compute the matrices $\mathbf{M}^{CG}$, $\mathbf{H}^{CG}$ and use them as initial values to generate the responses under learning. The blue dotted line in Figure 2 represents the RE equilibrium with $\rho_\theta = 0.976$. The solid red curve in Figure 2 occurs when agents gradually learn using (16)-(17) under the initial belief that $\rho_\theta = 0.998$, with the true value being 0.976. Although Figure 2 assumes CG learning with $\nu = 0.013$, similar results would occur under larger gains (which would imply similar effects at impact but faster recovery).[3] Such a low value for the gain parameter implies that learning agents regress past data using a forgetting half-length of about 13 years, that is, data older than 13 years are weighted less than 50%.

Figure 2 shows that the negative leverage shock is significantly amplified under learning. In particular, the impact on output and capital is roughly three times larger and the consumption drop is multiplied by about four compared to the rational expectations outcome. This follows from the fact that deleveraging is much more severe under learning: the fall in land price is more than four times larger and the debt decrease is multiplied by more than two compared to RE.[4]

In summary, because agents incorrectly believe that the negative leverage shock will be

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[3]Our chosen value for the gain parameter falls within the lower range of estimates reported in Branch and Evans [4], Chakraborty and Evans [8], Milani [32, 33] and it is consistent with the estimates of Malmendier and Nagel [28] for younger generations. Although there seems to be no empirical estimate of the gain parameter corresponding to actual forecasts of housing or land prices, the dataset exploited in Pancrazi and Pietrunti [34] could be used to that purpose.

[4]In Figure 2, debt falls by much more than output. This implies that the debt-to-GDP ratio - a common definition of aggregate leverage - falls by a large amount as well.

very persistent, they expect a much larger fall in land price and a much tighter borrowing constraint than under rational expectations. We can say that agents are pessimistic due to incorrect beliefs. This pessimism depresses the consumption, the investment and the output more than under rational expectations.

Figure 2: Responses (in Percentage Deviations from Steady State) to a -5% Leverage Shock under Learning (Red Solid Line) and Rational Expectations (Blue Dotted Line); Parameter Values in Table 1.
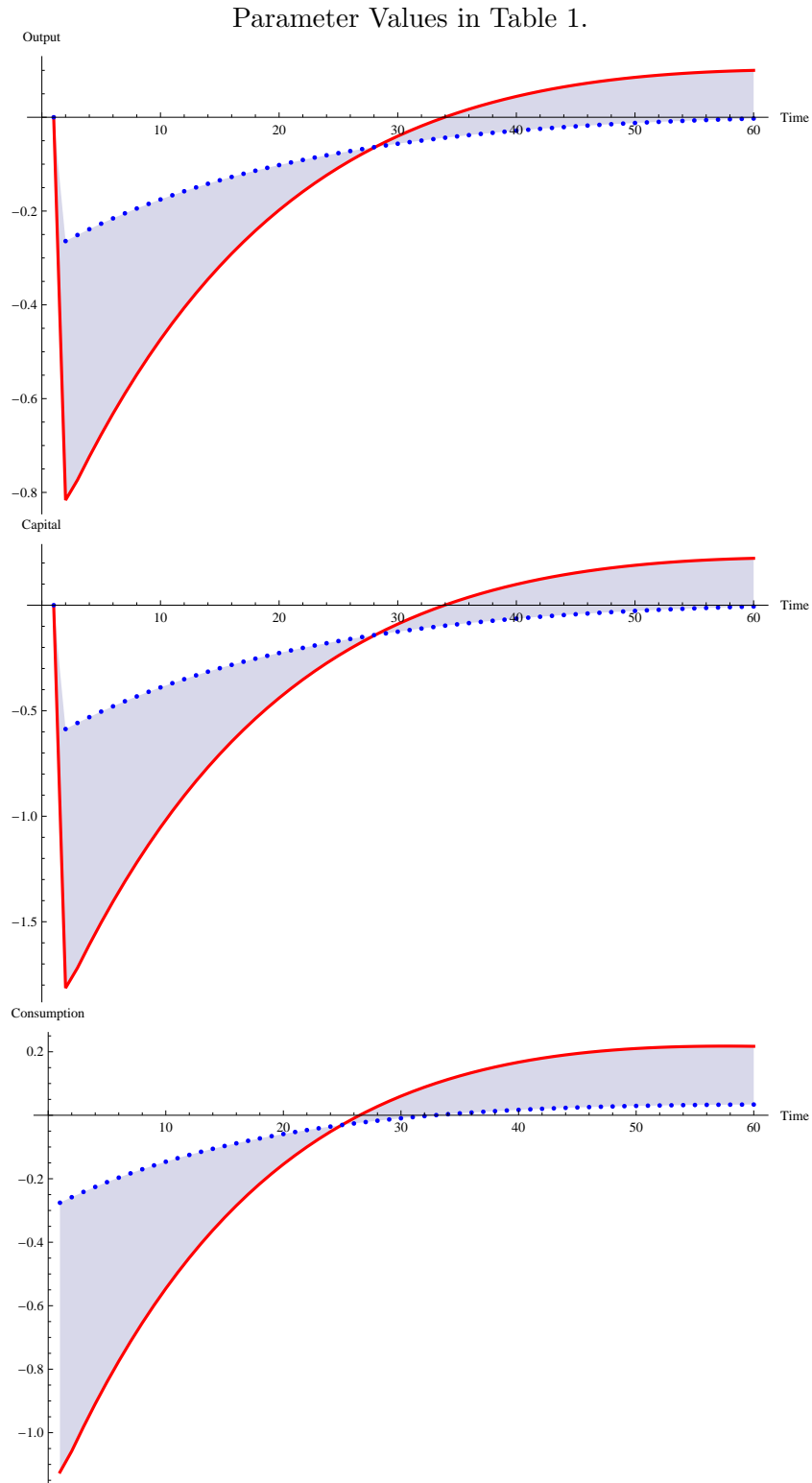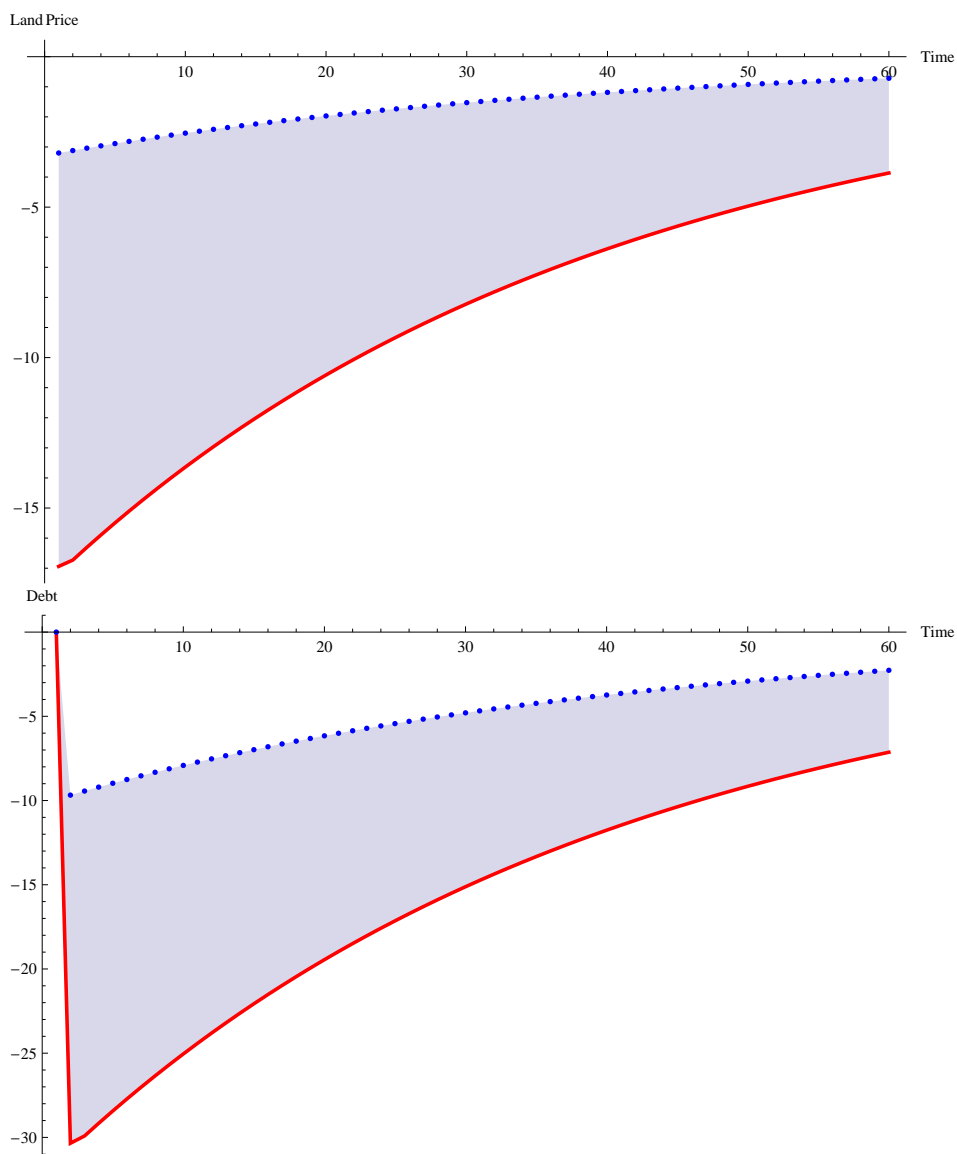
To measure how the leverage level matters for the response to a financial shock, we now calibrate the model using data from the first quarter of 1996 and set $\overline{\Theta} \approx 0.73$ (the other values are as in Table 1), which leads to $B/Y \approx 0.34$ and $QL/Y \approx 0.48$. According to most measures, this corresponds to the starting point of the housing price "bubble". The lower level of leverage implies that both the debt-to-GDP and the land value-to-GDP are correspondingly lower than their averages over the 1996Q1-2008Q4 period. Figure 3 replicates the same experiment as above, when a -5% shock to leverage

Figure 3: Responses (in Percentage Deviations from Steady State) to a -5% Leverage

Shock (Learning: Red Solid Line; Rational Expectations: Blue Dotted Line) when

$\overline{\Theta} = 0.73$ (Other Parameter Values in Table 1)
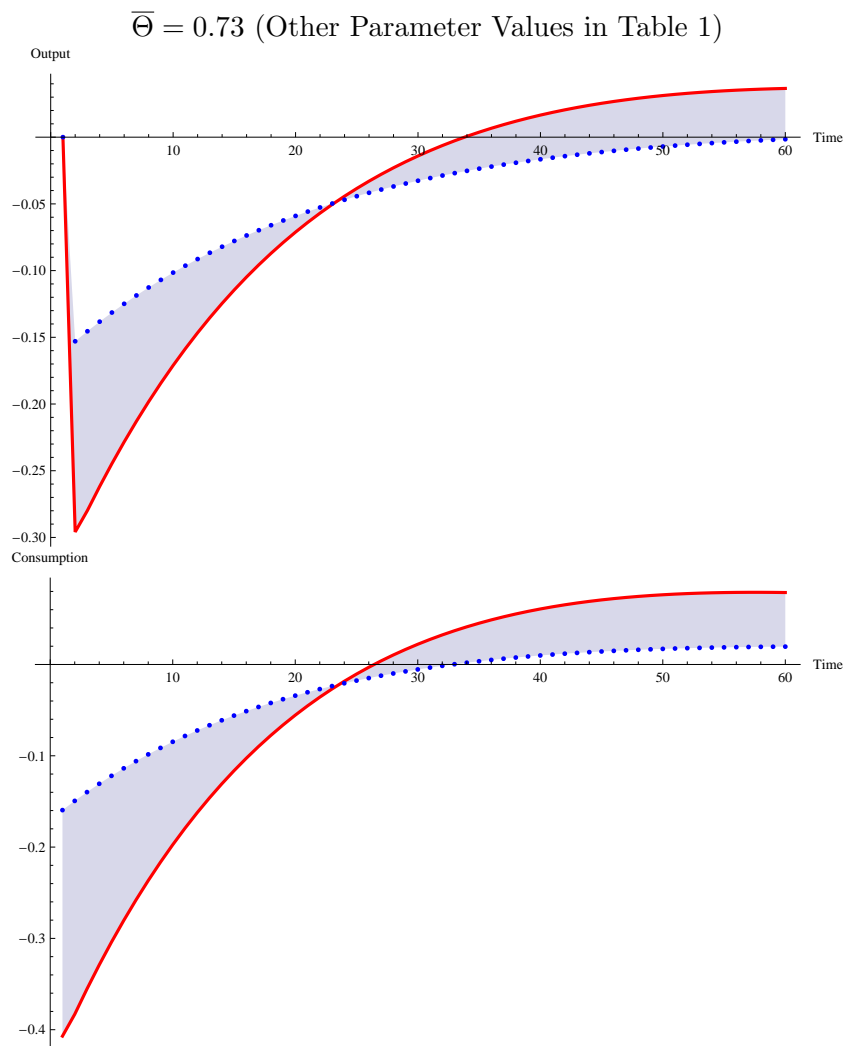
hits the economy and ρ_θ is believed to equal 0.998 while its true value is 0.976. Direct

comparison of Figures 2 and 3 reveals that higher leverage increases the effect of the

shock on aggregates by about 150% at impact under learning. In this sense, the larger

the level of leverage the deeper the recession that follows after a negative financial shock.[5]

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[5]Output's response and capital's response are proportional so we report only the former and not the

latter.
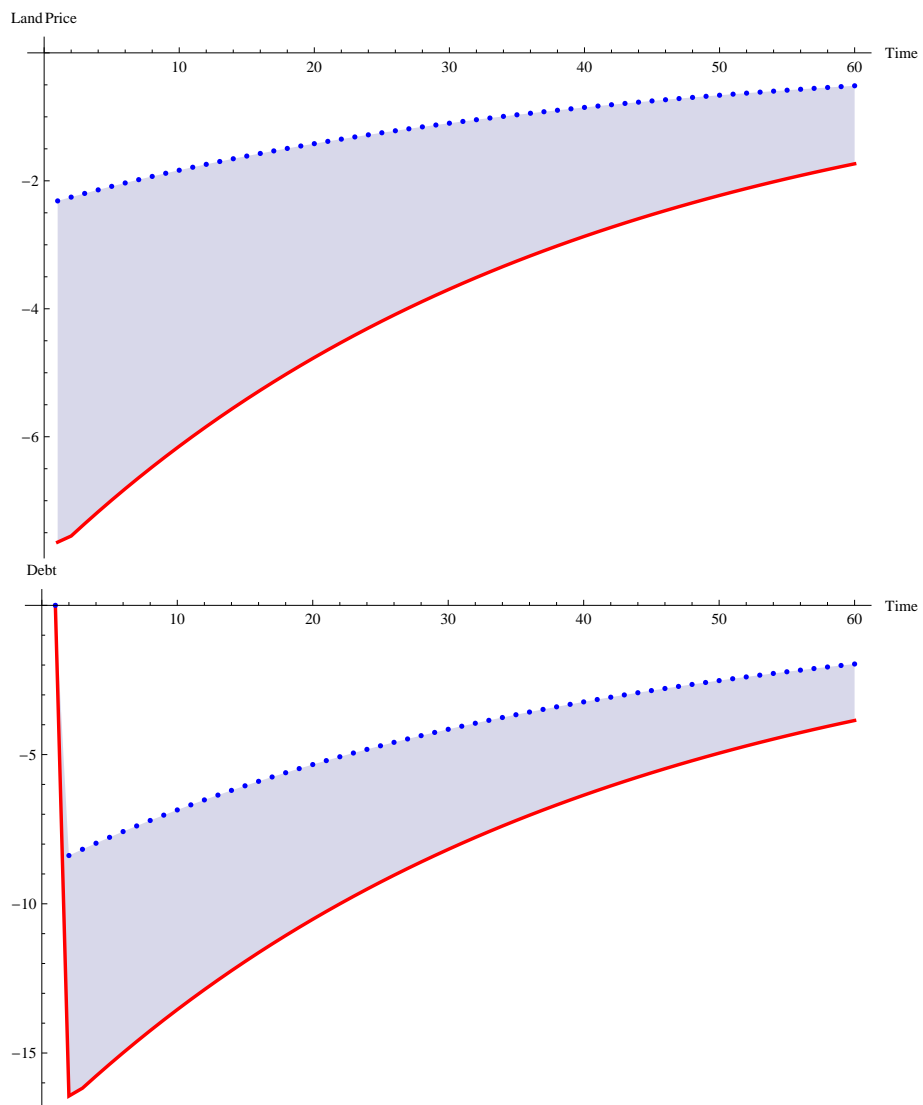
It is important to stress that the economy's responses to a leverage shock are larger under learning because the land price forecast interacts with the borrowing constraint. To illustrate this fact, we now report the responses of a subset of the same variables when the land price is assumed to be fixed in the borrowing constraint, that is, when (3) is replaced by:

$$\Theta_t QL_{t+1} \geq (1+R)B_{t+1} \tag{20}$$

while it is allowed to respond according to the Euler condition (5). Figure 4 reports the responses of output and consumption, which are about the same under learning and

under rational expectations, in contrast to Figure 2. This unambiguously shows that it is the interaction of land price expectations with the borrowing constraint that generates our results under learning.

Figure 4: Responses (in Percentage Deviations from Steady State) to a -5% Leverage Shock with Fixed Land Price (Learning: Red Solid Line; Rational Expectations: Blue Dotted Line); Parameter Values in Table 1.
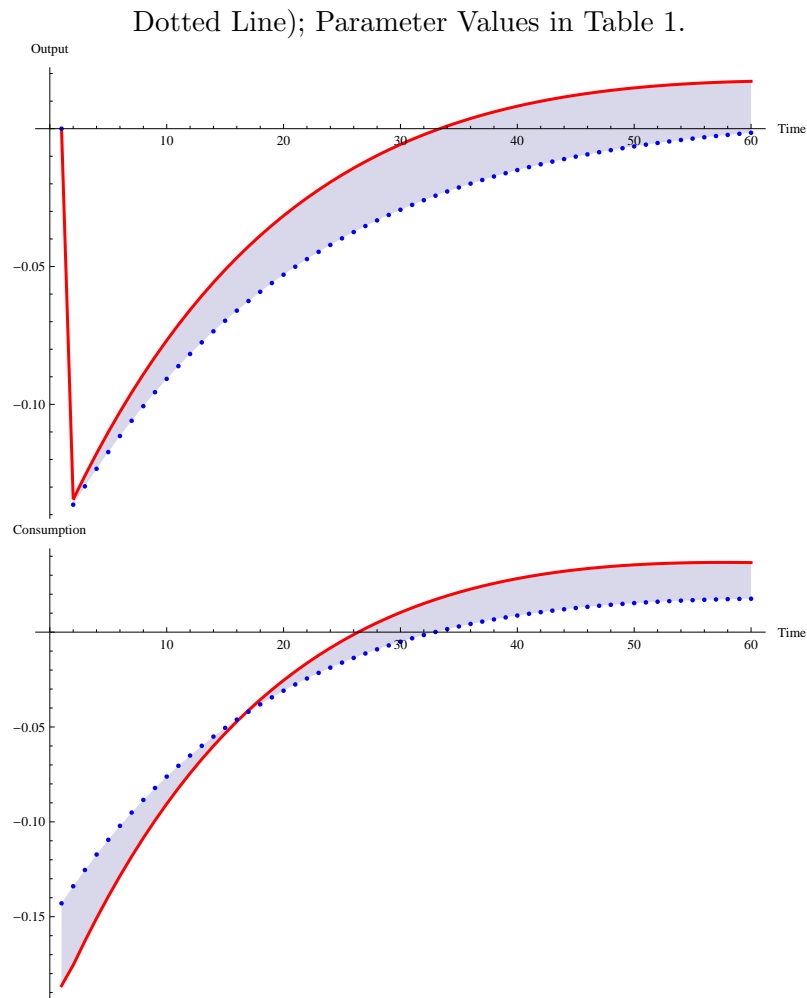
3.2 Macroprudential Policy

In this section, we show that countercyclical leverage dampens the impact of leverage shocks under learning. We now ask the counter-factual question: what would be the reaction of the economy to the same shock, under the same parameter values but with the leverage being now mildly countercyclical?[6] More precisely, we assume that $\varepsilon = -0.5$ while the other parameters are kept unchanged and set as in Table 1. The economy's responses are reported in Figure 5. Comparing Figures 2 and 5 shows that countercyclical leverage dampens by a significant margin the responses to financial shocks and it brings learning dynamics closer to its rational expectations counterpart. As a consequence, a much smaller recession follows a negative leverage shock: though agents anticipate a too large deleveraging effect because they overestimate the persistence of the adverse leverage shock, the land price fall now triggers an *increase* in countercyclical leverage, which dampens the impact of the negative shock. In other words, the negative shock to the exogenous component of leverage is now dampened by an increase of the endogenous part, which is itself triggered by a fall in land price. As a consequence, borrowing falls only moderately and the resulting recession is much smaller and similar under learning and under RE.

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[6]This feature could possibly be enforced by appropriate regulation of credit markets. Alternatively, Appendix A.2 shows how it arises if government uses procyclical taxes.

Figure 5: Responses (in Percentage Deviations from Steady State) to a -5% Leverage Shock under Countercyclical Leverage (Learning: Red Solid Line; Rational Expectations: Blue Dotted Line); $\varepsilon = -0.5$ and other Parameter Values in Table 1.
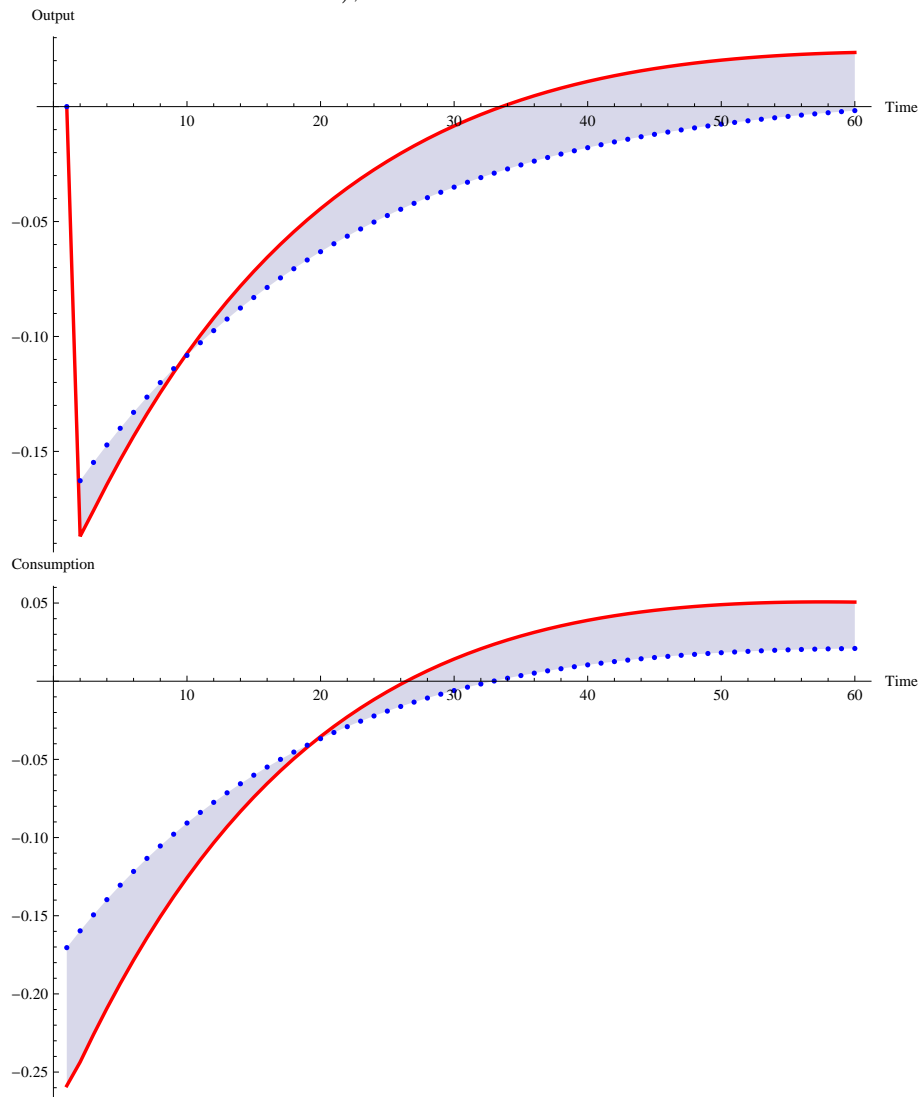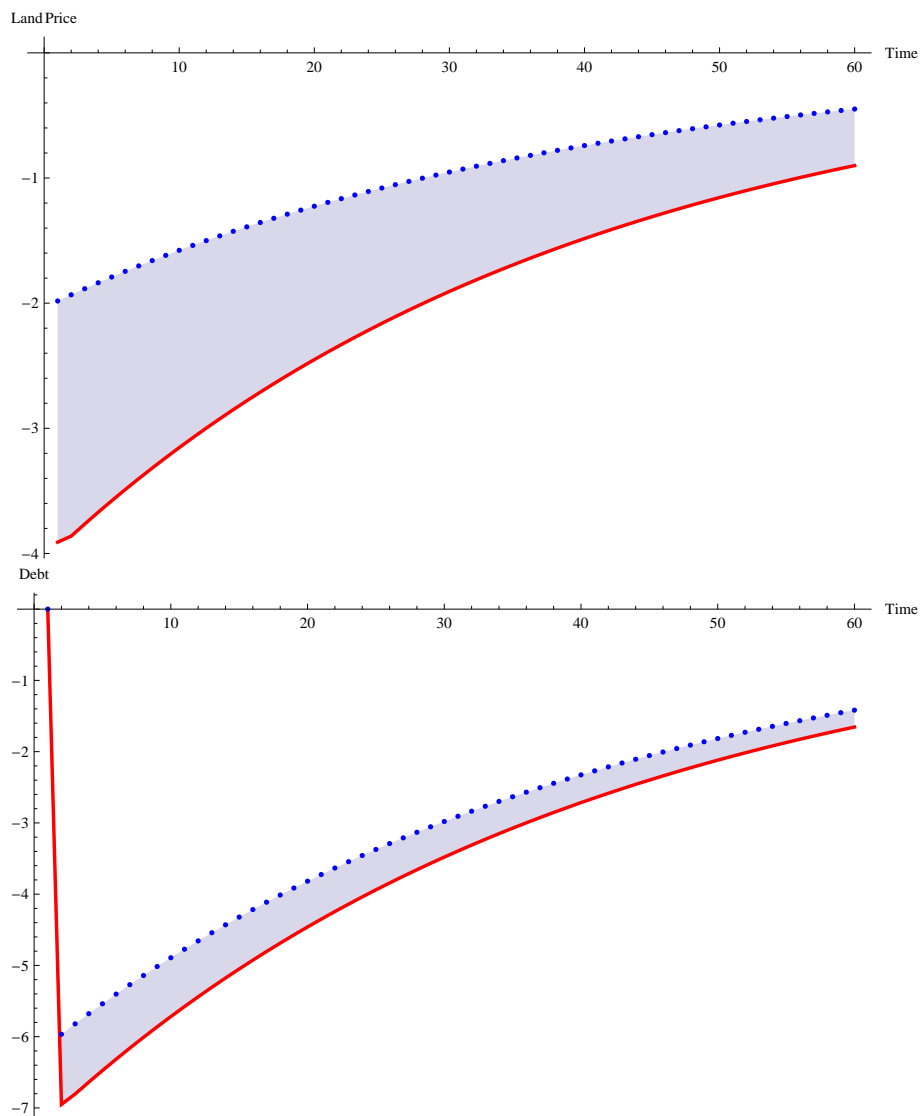
3.3 Robustness Under Alternative Assumptions

To assess the robustness of the findings reported in Section 3.1, we now relax two assumptions. First, we depart from logarithmic utility and we allow σ to take on values that are larger or smaller than one. Second, we adopt the timing assumption that is implied by the margin requirement interpretation of the borrowing constraint (Aiyagari and Gertler [3]). That is, borrowing is limited to the current market value of collateral, as opposed to tomorrow's market value. In other words, we replace both (3) by $\tilde{\Theta}_t Q_t L_{t+1} \geq$

$(1 + R)B_{t+1}$ and (8) by $\tilde{\Theta}_t \equiv \Theta_t \{Q_t/Q\}^{\varepsilon}$.

In Table 2, we report the output amplification that obtains under learning, as a fraction of that with rational expectations. For example, the impact of a -5% leverage shock on output's deviation (from its steady-state value, in percentage terms) is about -0.82% under learning and -0.27% under RE (see Figure 2) when parameters are set according to Table 1. Therefore, the first column of Table 2 reports that the ratio is about $3.09 \approx 0.82/0.23$. Similarly, the second and third columns of Table 2 report such a ratio when all parameter values are set according to Table 1, except for risk aversion σ which equals 0.5 and 3, respectively. Finally, the last column in Table 2 reports the ratio in the margin requirement model.

Table 2. Output Amplification Factor Under Learning

| Benchmark	$\sigma = 0.5$	$\sigma = 3$	Margin Model
3.09	3.08	3.12	3.05

Direct inspection of Table 2 shows that our main findings are robust both to changes in the utility function's curvature and to an alternative timing assumption. Output amplification is quantitatively similar across all different models and this turns out to be the case for the other variables (not reported) as well. In addition, how the numbers change in Table 2 accords with intuition. First, under the timing assumed in (3), incorrect beliefs about the economy further amplify shocks because land price forecasts are temporarily deviating from RE. In the margin model where the borrowing limit depends on today's collateral market values so that forecast errors are slightly less important during deleveraging episodes. In addition, smaller risk aversion implies that consumption will fall by more and, therefore, that investment will fall by less at impact, which means that output will also fall by (slightly) less under learning compared to rational expectations.

3.4 Learning the Mean Level of Leverage

The purpose of this section is to report the outcome of our second experiment. We now subject the economy to the same shock that was considered in Section 3.1 but we now assume that agents overestimate both the leverage level $\overline{\Theta}$ and the leverage shocks' persistence. That is agents believe that $\rho_\theta = 0.998$ while the true value is 0.976. We also RE value $\overline{\Theta} = 0.88$ just as in Table 1, but assume learning agents believe that $\overline{\Theta} = 0.966$, the value of leverage in the data at the peak of the land price "bubble" in 2007Q2.

Figure 6: Responses (in Percentage Deviations from the RE Steady State) to a -5%

Leverage Shock (Learning: Red Solid Line; Rational Expectations: Blue Dotted Line);

Parameter Values as in Table 1 and Belief set to $\overline{\Theta} = 0.966$
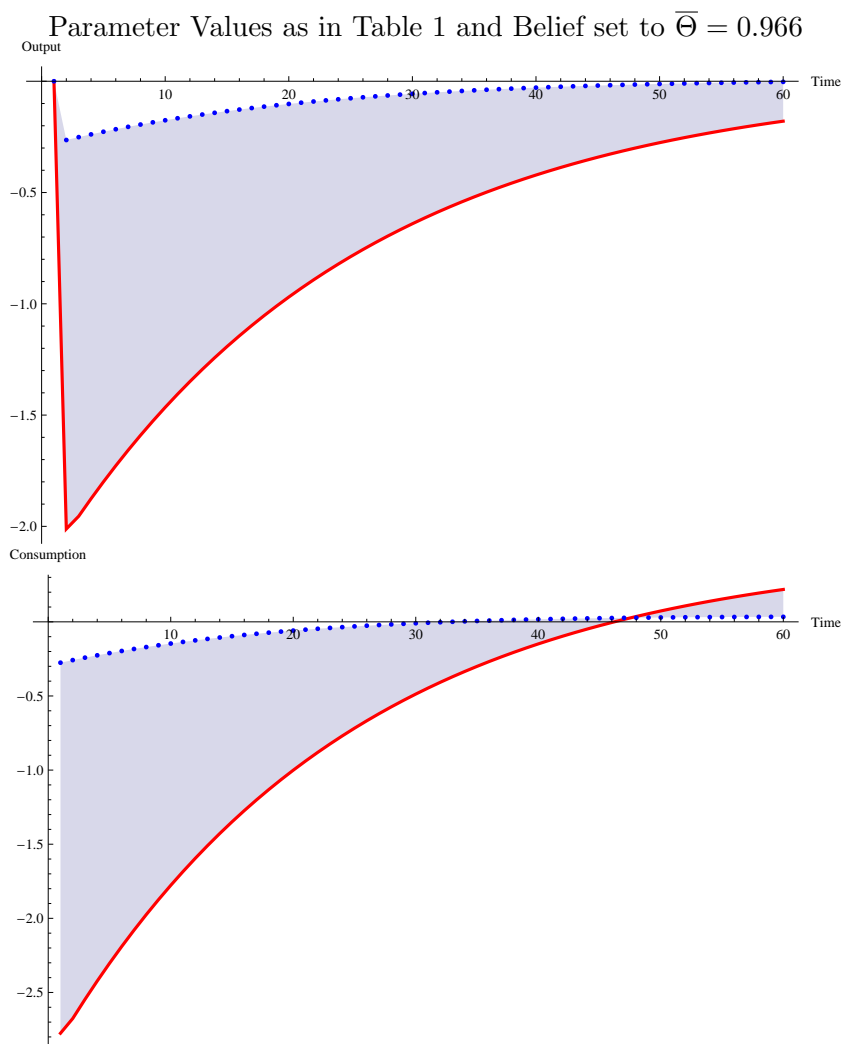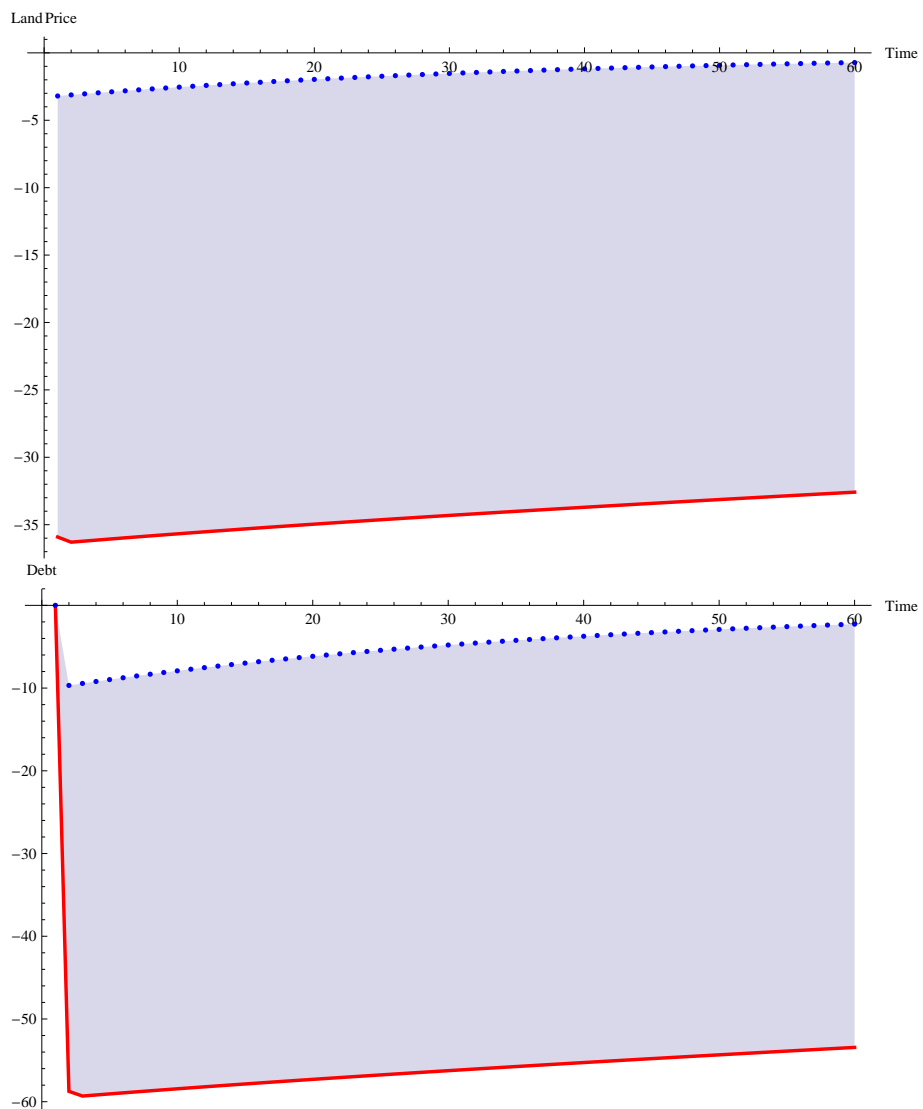
The responses of our set of variables to a -5% shock to leverage are reported in Figure 6, which features substantially larger deviations under CG learning compared to the RE benchmark. The fall in output under CG learning is more than 7 times larger than that under RE, compared to 3 times in Figure 2. Overestimating the mean level of leverage on top of its persistence adds a extra kick to the amplification mechanism that arises under learning. Taken together, our two experiments suggest that learning amplifies negative shocks to leverage such as the one observed in 2008Q4. A natural question that we now ask is whether or not the learning model accords better with the actual path followed by

Figure 7: Land Price Response Over Time (Percentage Deviations From 2007Q4)

Actual Data (Green Line) and Model Generated Data (Red Line)
Land Price
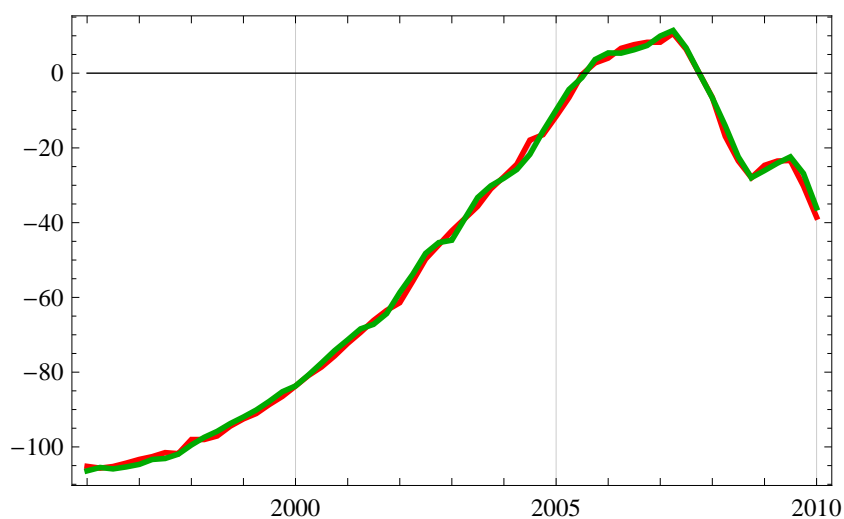
the US output over the Great Recession than its rational expectations counterpart.

4   Does Learning Help Account For The Great Recession?

The purpose of this section is to argue that learning is a plausible mechanism that helps explaining the magnitude of the Great Recession. More precisely, we now show that the learning model predicts both a boom in the early 2000s and a sizeable recession beginning 2007Q3, while the model with rational expectations generates a fall in output up to 2007Q3 followed by an expansion which are both at odds with the data. All parameter values are set according to Table 1 and we calibrate the land investment wedge i.i.d. shocks so as to replicate the observed path for land price, as shown in Figure 7.[7]

To derive leverage shocks, we use the data provided by Boz and Mendoza [5] for the period 1975Q1-2010Q1 to decompose the exogenous and endogenous components of lever-

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[7]Although we set ρ_τ to zero, similar results obtain when the wedge process has some autocorrelation.

Figure 8: Leverage Innovations (Constant-Gain Learning: Red Solid Line; Rational

Expectations: Blue Dotted Line)

Shocks
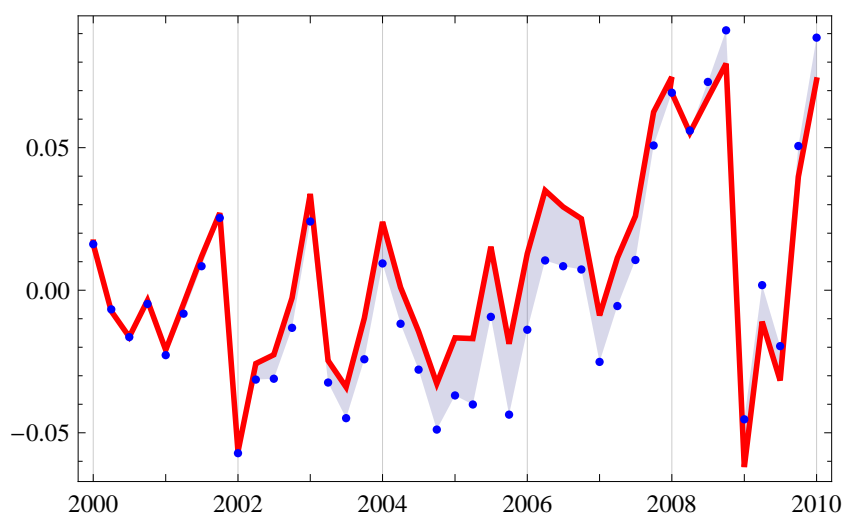
age using definition (8). That is, we obtain the exogenous component Θ_t by removing the part of the leverage that is explained by land price. We then estimate AR(1) processes on the log of Θ_t both under CG and under OLS and we compute the residuals from such estimated processes that we use to feed our model with.[8] The resulting innovations are reported in Figure 8.

Figure 8 makes clear why the model is unable to explain the Great Recession when fed with only the actual leverage innovations: the fall in land price that starts in early 2007 generates positive shocks in 2007 and 2008 that produce a large expansion that is hardly reversed when the negative shock happens in 2008Q4. Consistent with the literature, we find that the model requires another source of disturbance to accord with the data and this is why we use i.i.d. land investment wedge shocks to replicate the observed land price behavior as shown in Figure 7.

Figure 9 reports the OLS and CG estimates of ρ_θ for the period 2000Q1-2010Q1. The OLS estimate is obtained from a univariate regression using the data over sample period

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[8]We have also checked that ARMA processes do not better describe our ε-adjusted data on leverage.

Figure 9: Estimates of Leverage Persistence ρ_θ Over Time (Constant-Gain Learning:

Red Solid Line; Rational Expectations: Blue Dotted Line)
Persistence
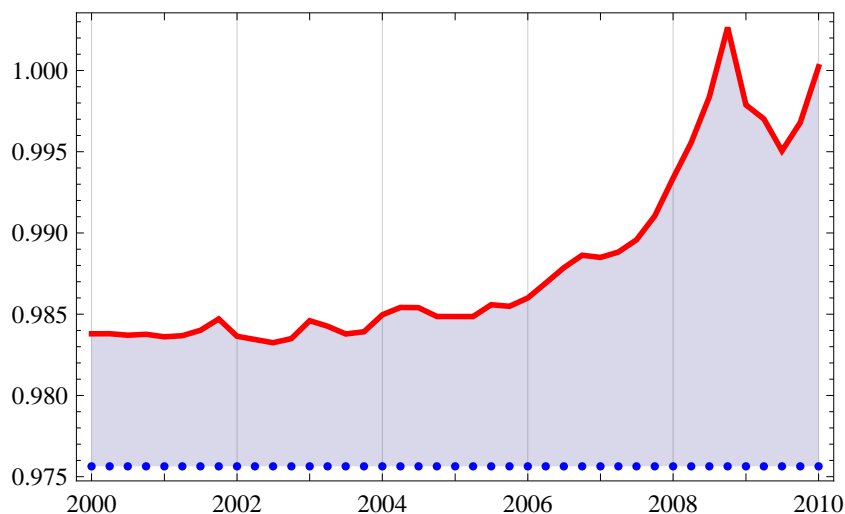
1975Q1-2010Q1. This is consistent with the notion that RE agents know the process governing leverage. The CG estimate is obtained from the VAR estimation when learning agents use the full model to forecast and update their beliefs in real time. Figure 9 partly replicates panel b) of Figure 1, to which we also add the OLS estimate which is $\rho_\theta \approx 0.976$.

Figure 9 shows that learning agents overestimate the autocorrelation parameter consistently over the 2000s and, more importantly, that their estimate drifts toward unit root. In particular, the model predicts that the VAR estimate of ρ_θ is around 0.998 in 2008Q3 (which is the value agents are assumed to use in Section 3.1 to make forecast about 2008Q4) and 1.002 in 2008Q4, before falling slightly below one. This means that when the negative leverage shock of 2008Q4 occurs, learning agents think of leverage as essentially having unit root and they expect any innovations at that time to be close to permanent. As a consequence, deleveraging is much more severe than what would happen under RE and the resulting outcome is reported in Figure 10.

Figure 10 shows that the model predicts a sizeable recession during the Great Reces-

Figure 10: Model-Generated Great Recession (Constant-Gain Learning: Red Solid Line; Rational Expectations: Blue Dotted Line)

Output, Consumption and Debt Responses Over Time (% Deviations From 2007Q4)

Output

Consumption

Borrowing
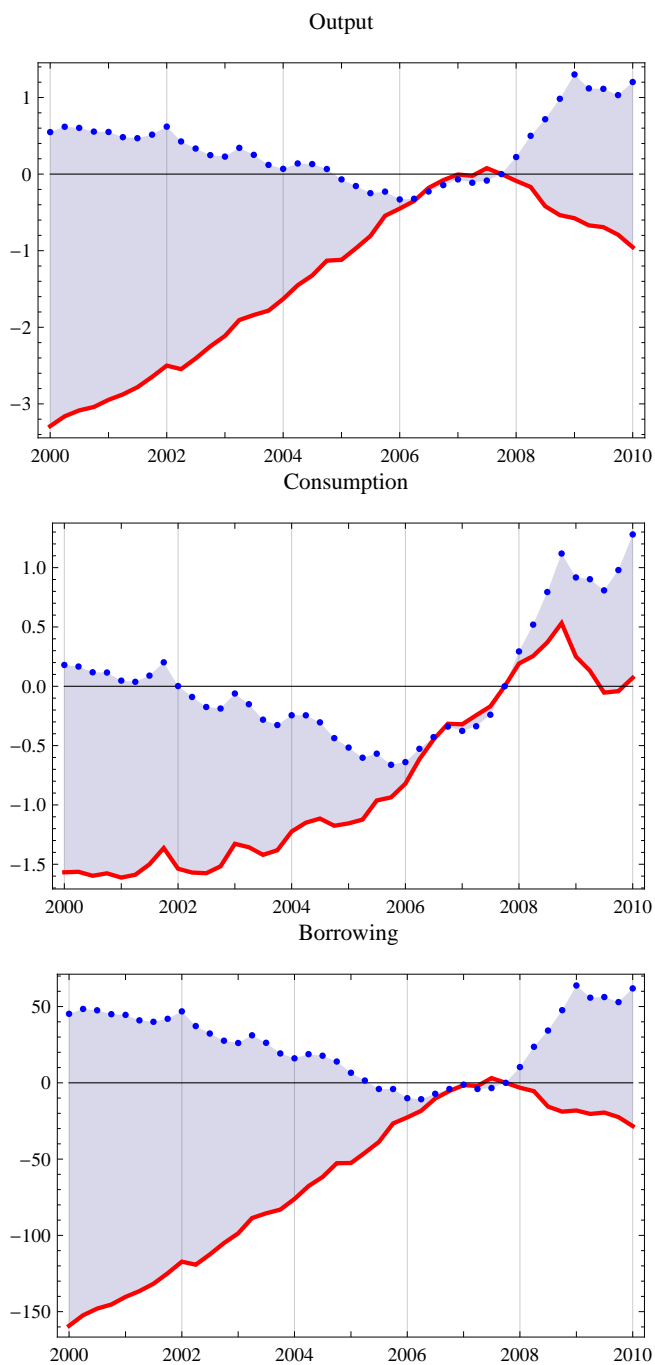
sion period, with a fall in output about 1% between 2007Q3 and 2010Q1 and a significant boom prior to that. Although the learning model explains only about 20% of the actual output drop reported by the NBER to be about 5%, it does much better than the RE model. The latter predicts a continuous fall in output from 2000 to 2007 followed by a significant expansion over the 2007-2010 period, both features being at odds with the data. The major reason behind such a stark contrast is that the RE model does not allow for belief revision, while the latter feature precisely explains why learning agents were overestimating the impact of the negative leverage shock in 2000Q4 and why this leads to a sizeable output fall at that time in the model. We should also stress that setting $\nu = 0.013$ is a rather conservative assumption and that choosing a larger value for the gain parameter would imply a bigger recession in the learning model. Given that the model is overly too simple to fully account for the data, our main claim here is that the learning model explains a sizeable fraction of the Great Recession, while the RE model does not.

In view of our theoretical results on countercyclical leverage reported in Section 3.2, it is natural to ask whether the fact that leverage is procyclical aggravates the recession, which is what intuition suggests. As a counter-factual, Figure 11 reports the output response that occurs under mildly countercyclical leverage, with $\varepsilon = -0.5$ (implying that a 10% fall in land price increases leverage by 5%). Comparing Figures 10 and 11 suggests that a simple macroprudential policy may substantially attenuate leverage shocks under learning. In Figure 11, output is in 2010Q1 at about the same level than that in 2007Q4.

Figure 11: Counter-factual Model-Generated Expansion (Constant-Gain Learning: Red Solid Line; Rational Expectations: Blue Dotted Line)

Output Response Over Time when $\varepsilon = -0.5$ (Percentage Deviations From 2007Q4)

Output
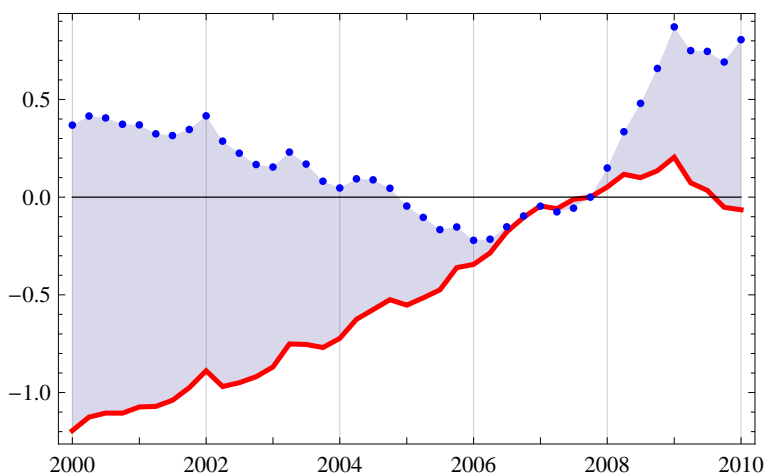
5 Conclusion

A large part of business-cycle theory relies on the assumption that agents know all parameters governing the stochastic process underlying the disturbances that hit the economy. This paper has shown how relaxing such an assumption in a simple model predicts that the economy's aggregates respond very differently to financial shocks when agents are gradually learning their environment, compared to rational expectations. More specifically, our theoretical experiments with a calibrated model suggest that reasonable parameter configurations can lead to much larger amplification of the impact of shocks to leverage. This is for instance the case when learning agents overestimate either the autocorrelation parameter governing the persistence of leverage shocks or the long-run level of leverage. We have provided evidence that both cases are not inconsistent with the US data prior to the Great Recession, when borrowers probably believed that credit collateralized by real estate assets was being extended by the financial sector. In ad-

dition, the more empirically oriented counterparts of our two theoretical experiments are informative about which assumption better stands against the data. Our preferred model with agents updating their estimates of the long-run level of leverage and of leverage persistence as new data arrive is not unsuccessful in that respect. In particular, it predicts a sizeable fall in output from peak to trough, as reported by the NBER, whereas the rational expectations model predicts a continued, counter-factual expansion in 2008 and 2009.

We believe that the main results of this paper may also be relevant for studying other settings. For example, they are suggestive about how one could try to measure to what extent unemployment variations are driven by beliefs formed by firms about either the persistence of demand shocks or the steady-state level of demand, or both. Monetary policy perhaps provides still another example in which the beliefs formed by the private sector about the persistence or about the long-run stance of monetary policy matter, as they could change the effects of policy on the economy. These are but a few examples for which extensions of the setting used in this paper could lead to fruitful research. In the same vein, another potential avenue for future research would be to model how perceptions about the process driving uncertainty shocks affect how those shocks propagate in the real economy. This requires solving higher-order approximations of nonlinear models and we believe this calls for further inquiries.

A   Appendix

A.1   Elastic Leverage: Simple Micro-Foundations

This section derives some simple micro-foundations for the assumption of elastic leverage captured in (8). The case when leverage is procyclical (that is, $\varepsilon > 0$) obtains in

a setting with ex-post moral hazard and costly monitoring similar to Aghion et al. [2, p.1391]. Suppose that the borrower has wealth QL and has access to investment opportunities, which can be financed by credit in the amount B. If the borrower repays next period, his income is $I - (1+R)B$, where I is whatever income was generated by investing. If the borrower defaults next period, his income is now $I - pQL$, assuming that he loses his collateral with some probability p, which represents for example the frequency of foreclosures. Strategic default is avoided provided that $I - (1+R)B \geq I - pQL$, that is, if $pQL \geq (1+R)B$. The lender incurs a cost $C(p)L$ when collecting collateral, with $C'(p) > 0$ and $C''(p) > 0$, and he chooses the optimal monitoring policy by solving:

$$\max_p pQL - C(p)L \tag{21}$$

which gives $Q = C'(p)$. The higher the land price, the larger the incentives to increase effort to collect collateral. Assuming now that the cost function is $C(p) = \phi p^{1+1/\varepsilon}/(1+1/\varepsilon)$, with $\varepsilon > 0$, gives that $p = (Q/\phi)^\varepsilon$. Setting the scaling parameter $\phi = Q^* \Theta^{-1/\varepsilon}$, where Q^* is steady-state land value and Θ is leverage, gives (8). Therefore, ex-post moral hazard leads to procyclical leverage.

In contrast, countercyclical leverage obtains if government implements procyclical taxes as follows. Suppose now that the lender gets $(1 - \tau)pQL - C(p)L$ when monitoring, where $1 \geq \tau \geq 0$ is the tax rate. Under the assumption that the cost function is isoelastic, the optimal p is now $p = ((1 - \tau)Q/\phi)^\varepsilon$. If the government sets time-varying taxes such that $1 - \tau = (Q/\phi)^{-\eta/\varepsilon-1}$, for some $\eta \geq 0$, then it follows that $p = (Q/\phi)^{-\eta}$ and that leverage is countercyclical. Note that this happens provided that the tax rate goes up when the land price goes up.

A.2 Log-Linearized Model in Levels

We now derive the log-linearized version of the set of equations (2)-(7) defining, together with the laws of motion of leverage $\Theta_t = \overline{\Theta}^{1-\rho_\theta}\Theta_{t-1}^{\rho_\theta}\Xi_t$ and of land investment wedge $T_t = T_{t-1}^{\rho_\tau}\Psi_t$, intertemporal equilibria near steady state. In all equations below, lower-case letters denote logs and $\tilde{x}_t$ denotes the log of X_t/X, where X is the steady-state value of X_t. For example, $\tilde{k}_t \equiv k_t - k$, with $k_t = \log(K_t)$ and $k = \log(K)$, so that variables without time subscript are steady-state levels in log. Eliminating from the other equations Φ_t by using (7), one gets the following linearized equations corresponding to (2)-(7), respectively:

$$\tfrac{K}{Y}\tilde{k}_t - \tfrac{B}{Y}\tilde{b}_t = -\tfrac{C}{Y}\tilde{c}_{t-1} - \tfrac{(1+R)B}{Y}\tilde{b}_{t-1} + \left(\alpha + (1-\delta)\tfrac{K}{Y}\right)\tilde{k}_{t-1} \tag{22}$$

$$\tilde{b}_t = (1+\varepsilon)E_{t-1}[\tilde{q}_t] + \tilde{\theta}_{t-1} \tag{23}$$

$$\tilde{c}_t = -\tilde{\lambda}_t/\sigma \tag{24}$$

$$\begin{aligned}
\tilde{q}_t + \tilde{\tau}_t + \tilde{\lambda}_t(1 - \mu\overline{\Theta}) ={}& \beta E_t[\tilde{\tau}_{t+1}] + E_t[\tilde{q}_{t+1}]\left(\beta + \overline{\Theta}(1+\varepsilon)(\mu - \beta)\right) \\
&+ E_t[\tilde{\lambda}_{t+1}]\left(\beta(1 - \overline{\Theta}) + \gamma\beta\tfrac{Y}{Q}\right) \\
&+ \alpha\gamma\beta\tfrac{Y}{Q}E_t[k_{t+1}] + \theta_t\overline{\Theta}(\mu - \beta)
\end{aligned} \tag{25}$$

$$\tilde{\lambda}_t = E_t[\tilde{\lambda}_{t+1}]\left(\beta(1-\delta) + \alpha\beta\tfrac{Y}{K}\right) + \alpha\beta(\alpha - 1)\tfrac{Y}{K}E_t[\tilde{k}_{t+1}] \tag{26}$$

$$(\mu - \beta)\tilde{\phi}_t = \mu\tilde{\lambda}_t - \beta E_t[\tilde{\lambda}_{t+1}] \tag{27}$$

$$\tilde{\theta}_t = \rho_\theta\tilde{\theta}_{t-1} + \xi_t \tag{28}$$

$$\tilde{\tau}_t = \rho_\tau\tilde{\tau}_{t-1} + \psi_t \tag{29}$$

where $\tilde{\tau}_t = \log(T_t) = \tau_t$ as the steady state value of T_t is one by assumption.

Define $P'_t \equiv (b_t, k_t, \theta_t, \tau_t)$ and $S'_t = (c_t, q_t, \lambda_t, \phi_t)$ the vectors of predetermined and jump variables in log, respectively. Then equations (22)-(28) can be decomposed into

two subsystems, each pertaining to P_t and S_t. The first block composed of (22), (23), (28) and (29) can be written:

$$M_0 P_t = M_1 S_{t-1} + M_2 E_{t-1}[S_t] + M_3 P_{t-1} + N_0 + V_1 \xi_t + V_2 \psi_t \tag{30}$$

where:

$$M_0 = \begin{pmatrix} 1 & 0 & 0 & 0 \\ -\frac{B}{Y} & \frac{K}{Y} & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}, \; M_1 = \begin{pmatrix} 0 & 0 & 0 & 0 \\ -\frac{C}{Y} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}, \; M_2 = \begin{pmatrix} 0 & 1+\varepsilon & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix},$$

$$M_3 = \begin{pmatrix} 0 & 0 & 1 & 0 \\ -(1+R)\frac{B}{Y} & \alpha + (1-\delta)\frac{K}{Y} & 0 & 0 \\ 0 & 0 & \rho_\theta & 0 \\ 0 & 0 & 0 & \rho_\tau \end{pmatrix}, \; N_0 = \begin{pmatrix} b - (1+\varepsilon)q - \theta \\ \frac{K}{Y}k + \frac{RB}{Y}b + \frac{C}{Y}c - (\alpha + \frac{(1-\delta)K}{Y})k \\ (1-\rho_\theta)\theta \\ 0 \end{pmatrix}$$

and $V_1' = (0,0,1,0)$, $V_2' = (0,0,0,1)$.

The second block (24)-(27) can be written:

$$M_4 S_t = M_5 E_t[S_{t+1}] + M_6 P_t + M_7 E_t[P_{t+1}] + N_1 \tag{31}$$

where:

$$M_4 = \begin{pmatrix} 0 & 1 & 1-\mu\overline{\Theta} & 0 \\ 0 & 0 & 1 & 0 \\ \sigma & 0 & 1 & 0 \\ 0 & 0 & -\mu & \mu - \beta \end{pmatrix}, \; M_5 = \begin{pmatrix} 0 & \beta + \overline{\Theta}(1+\varepsilon)(\mu-\beta) & \beta(1-\overline{\Theta}) + \gamma\beta\frac{Y}{Q} & 0 \\ 0 & 0 & \beta(1-\delta) + \alpha\beta\frac{Y}{K} & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & -\beta & 0 \end{pmatrix},$$

$$M_6 = \begin{pmatrix} 0 & 0 & \overline{\Theta}(\mu-\beta) & -1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}, \; M_7 = \begin{pmatrix} 0 & \alpha\gamma\beta\frac{Y}{Q} & 0 & \beta \\ 0 & \alpha\beta(\alpha-1)\frac{Y}{K} & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix},$$

$$N_1 = \begin{pmatrix} q(1-\beta-\overline{\Theta}(1+\varepsilon)(\mu-\beta)) + \lambda(1-\overline{\Theta}\mu-\beta(1-\overline{\Theta})-\beta\gamma\frac{Y}{Q}) - \alpha\beta\gamma\frac{Y}{Q}k - \overline{\Theta}(\mu-\beta)\theta \\ \lambda(1-\beta(1-\delta)-\alpha\beta\frac{Y}{K}) - \alpha(\alpha-1)\beta\frac{Y}{K}k \\ c + \frac{\lambda}{\sigma} \\ (\mu-\beta)(\phi-\lambda) \end{pmatrix}.$$

Finally, substituting the expression of P_t from (30) in (31) and piling up the resulting two blocks of equations allows one to rewrite the system as:

$$X_t = \mathbf{A}X_{t-1} + \mathbf{B}E_{t-1}[X_t] + \mathbf{C}E_t[X_{t+1}] + \mathbf{N} + \mathbf{D}\xi_t + \mathbf{F}\psi_t \tag{32}$$

where $X_t' = \text{vec}(S_t', P_t')$ and:

$$\mathbf{A} = \begin{pmatrix} M_4^{-1}M_6M_0^{-1}M_1 & M_4^{-1}M_6M_0^{-1}M_3 \\ M_0^{-1}M_1 & M_0^{-1}M_3 \end{pmatrix}, \mathbf{B} = \begin{pmatrix} M_4^{-1}M_6M_0^{-1}M_2 & O_3 \\ M_0^{-1}M_2 & O_3 \end{pmatrix},$$

$$\mathbf{C} = \begin{pmatrix} M_4^{-1}M_5 & M_4^{-1}M_7 \\ O_3 & O_3 \end{pmatrix}, \mathbf{D} = \begin{pmatrix} M_4^{-1}M_6M_0^{-1}V_1 \\ M_0^{-1}V_1 \end{pmatrix}, \mathbf{F} = \begin{pmatrix} M_4^{-1}M_6M_0^{-1}V_2 \\ M_0^{-1}V_2 \end{pmatrix},$$

$$\mathbf{N} = \begin{pmatrix} M_4^{-1}N_1 + M_4^{-1}M_6M_0^{-1}N_0 \\ M_0^{-1}N_0 \end{pmatrix}$$

where O_4 is a 4-by-4 zeroes matrix.

A.3 Closed-Economy Model with Constant Interest Rate

The purpose of this appendix is to show that, similar to the open-economy model developed in Section 2, the debtor interest rate is constant over time in a closed-economy version with domestic borrowers and lenders, when the preferences of the latter are appropriately chosen.

Let us now assume that lenders are domestic agents (instead of foreign countries as in Section 2), whose unique role is to provide loans to borrowers. Following Iacoviello [19], lenders derive utility from consumption and land holdings, and they get interest income

from last period's loan payments. As discussed in Pintus and Wen [35], lenders may be interpreted as financial intermediaries. The representative lender solves:

$$\max E_0 \sum_{t=0}^{\infty} \mu^t \left\{ \frac{(C_t^l)^{1-\sigma_c} - 1}{1 - \sigma_c} + \psi \frac{(L_t^l)^{1-\sigma_l} - 1}{1 - \sigma_l} \right\} \tag{33}$$

with σ_c, σ_l, ψ all strictly greater than zero and $\mu \in (0,1)$, subject to the budget constraint:

$$C_t^l + Q_t(L_{t+1}^l - L_t^l) + B_{t+1} = (1 + R_t)B_t \tag{34}$$

where C_t^l and L_t^l denotes the lender's consumption and land holdings, respectively, Q_t is the land price, B_{t+1} is the new loan. The interest rate R_t is now endogenous and it is determined by the equality between the demand and supply of loans.

The first-order conditions obtained from (33)-(34) with respect to consumption, land, and lending are, respectively:

$$\left(C_t^l\right)^{-\sigma_c} = \chi_t \tag{35}$$

$$\chi_t Q_t = \mu E_t[\chi_{t+1} Q_{t+1}] + \mu \psi (L_{t+1}^l)^{-\sigma_l} \tag{36}$$

$$\chi_t = \mu E_t[\chi_{t+1}(1 + R_{t+1})] \tag{37}$$

where χ_t is the Lagrange multiplier of constraint (34) in period t.

Assuming that lenders' utility is linear in consumption (that is, $\sigma_c = 0$), one gets from (35) that in any rational expectations equilibrium $\chi_t = 1$ for all $t \geq 0$ so that, in view of (37), the interest factor is constant and given by $1 + R = 1/\mu$. As in the small-open economy model developed in Section 2, the interest rate is constant over time.

The borrower side of the model is still described by (1), (2) and (3), as in Section 2, with the addition that the total amount of land is now divided between lenders and borrowers according to:

$$L_t + L_t^l = \bar{L}.$$

where $\bar{L}$ is the fixed supply of land. How exactly is land divided depends on both the sequence of land price and the lender's preferences, as reflected in the first-order

condition (36). In addition, the representative borrower's first-order conditions are given by (4)-(7). As in Section 2, if $\mu \in (\beta, 1)$, then the borrower's credit constraint (3) is binding. Therefore, the main difference is that the closed-economy model allows some reallocation of land from lenders to borrowers when a shock hits the economy. Under our calibration (see Table 1), however, the effect of land reallocation is quantitatively unimportant because the land share γ is reasonably small. We have run simulations for the rational expectations versions of the open and closed economies and we have confirmed that the impulse-response functions of the variables involved in Section 2 are quantitatively similar under TFP shocks. In particular, the land price and debt behave in the same way in both economies.

A.4 Learning Procedure of VAR Model

A.4.1 VAR Estimation

Denoting $X_t' = \text{vec}(S_t', P_t')$ the system can be written as before:

$$X_t = \mathbf{A}X_{t-1} + \mathbf{B}E_{t-1}[X_t] + \mathbf{C}E_t[X_{t+1}] + \mathbf{N} + \mathbf{D}\xi_t + \mathbf{F}\psi_t \tag{38}$$

where $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$, $\mathbf{D}$, $\mathbf{F}$ and $\mathbf{N}$ are given in Appendix A.2. The rational expectations solution has a VAR form:

$$X_t = \mathbf{M}X_{t-1} + \mathbf{H} + \mathbf{G}\xi_t + \mathbf{J}\psi_t. \tag{39}$$

Given this form of equilibrium, the law of motion of endogenous variables can be represented using $E_{t-1}X_t = \mathbf{M}X_{t-1} + \mathbf{H}$ and $E_tX_{t+1} = \mathbf{M}X_t + \mathbf{H}$ as:

$$X_t = \mathbf{A}X_{t-1} + \mathbf{B}\left[\mathbf{M}X_{t-1} + \mathbf{H}\right] + \mathbf{C}\left[\mathbf{M}X_t + \mathbf{H}\right] + \mathbf{N} + \mathbf{D}\xi_t + \mathbf{F}\psi_t, \tag{40}$$

or

$$X_t \;=\; [\mathbf{I} - \mathbf{CM}]^{-1} [\mathbf{A} + \mathbf{BM}] X_{t-1} + [\mathbf{I} - \mathbf{CM}]^{-1} [\mathbf{BH} + \mathbf{CH} + \mathbf{N}]$$
$$+\; [\mathbf{I} - \mathbf{CM}]^{-1} [\mathbf{D}\xi_t + \mathbf{F}\psi_t] ,$$

Matrices $\mathbf{M}$ and $\mathbf{H}$ are given by:

$$\mathbf{M} \;=\; [\mathbf{I} - \mathbf{CM}]^{-1} [\mathbf{A} + \mathbf{BM}] \tag{41}$$

$$\mathbf{H} \;=\; [\mathbf{I} - \mathbf{CM}]^{-1} [\mathbf{BH} + \mathbf{CH} + \mathbf{N}] . \tag{42}$$

To estimate the VAR we represent the model as

$$X_t = \mathbf{\Omega} Z_{t-1} + \Sigma_t, \tag{43}$$

where $Z'_{t-1} = [1', X'_{t-1}]$ and $\mathbf{\Omega} = [\mathbf{H} \quad \mathbf{M}]$.

The estimator for Ω equals

$$\hat{\mathbf{\Omega}} = X Z' (Z Z')^{-1}, \tag{44}$$

and its time T estimates, $\hat{\mathbf{\Omega}}_T$, can be computed from

$$\hat{\mathbf{\Omega}}_T = \left(\frac{1}{T} \sum_{t=2}^{T} X_t Z'_{t-1} \right) \left(\frac{1}{T} \sum_{t=2}^{T} Z_{t-1} Z'_{t-1} \right)^{-1} . \tag{45}$$

The recursive OLS updating takes form of

$$\hat{\mathbf{\Omega}}_{T+1} \;=\; \hat{\mathbf{\Omega}}_T + \frac{1}{T+1} \left(X_{T+1} - \hat{\mathbf{\Omega}}_T Z_T \right) Z'_T \mathbf{R}_{T+1}^{-1} \tag{46}$$

and

$$\mathbf{R}_{T+1} \;=\; \mathbf{R}_T + \frac{1}{T+1} \left(Z_T Z'_T - \mathbf{R}_T \right) . \tag{47}$$

Equations (47) and (46) show how the estimates of matrix $\mathbf{\Omega}$ are updated as new data become available. In the above expression, $X_{T+1} - \hat{\mathbf{\Omega}}_T Z_T$ corresponds to a forecast error made using last period estimates. Under constant gain updating, the weight $1/(T+1)$ is replaced by the gain parameter ν.

A.4.2   Learning

Assume agents re-estimate the consistency with the RE model each period and use their estimates to make forecasts. These forecasts affect the behavior of the economy through equation (38).

Agents' perceived low of motion is

$$X_t = \mathbf{M}X_{t-1} + \mathbf{H} + \Sigma_t = \mathbf{\Omega}Z_{t-1} + \Sigma_t. \tag{48}$$

The forecasts agents make use the estimates of this PLM over available data. Since X_t depends on agents' forecasts (so it is not available at time t regression) at time t agents have run the regression:

$$E_t X_{t+1} \;=\; \mathbf{M}_{t-1}X_t + \mathbf{H}_{t-1} = \mathbf{\Omega}_{t-1}Z_t \tag{49}$$

$$E_{t-1} X_t \;=\; \mathbf{M}_{t-2}X_{t-1} + \mathbf{H}_{t-2} = \mathbf{\Omega}_{t-2}Z_{t-1} \tag{50}$$

where now we allow agents to depart from running simply OLS regression (least-squares learning) and use constant gain,

$$\mathbf{R}_t \;=\; \mathbf{R}_{t-1} + \nu_t \left(Z_{t-1}Z'_{t-1} - \mathbf{R}_{t-1} \right)$$

$$\mathbf{\Omega}_t \;=\; \mathbf{\Omega}_{t-1} + \nu_t \left(X_t - \mathbf{\Omega}_{t-1}Z_{t-1} \right) Z'_{t-1}\mathbf{R}_t^{-1}.$$

Substituting in agents' expectations, we can write the actual law of motion as

$$X_t = \mathbf{A}X_{t-1} + \mathbf{B}\left[\mathbf{M}_{t-2}X_{t-1} + \mathbf{H}_{t-2} \right] + \mathbf{C}\left[\mathbf{M}_{t-1}X_t + \mathbf{H}_{t-1} \right] + \mathbf{N} + \mathbf{D}\xi_t + \mathbf{F}\psi_t \tag{51}$$

or

$$
\begin{aligned}
X_t \;=\;& \left[\mathbf{I} - \mathbf{C}\mathbf{M}_{t-1} \right]^{-1} \left[\mathbf{A} + \mathbf{B}\mathbf{M}_{t-2} \right] + \left[\mathbf{I} - \mathbf{C}\mathbf{M}_{t-1} \right]^{-1} \left[\mathbf{C}\mathbf{H}_{t-1} + \mathbf{B}\mathbf{H}_{t-2} + \mathbf{N} \right] \\
& + \left[\mathbf{I} - \mathbf{C}\mathbf{M}_{t-1} \right]^{-1} \left[\mathbf{D}\xi_t + \mathbf{F}\psi_t \right]
\end{aligned}
\tag{52}
$$

There is a mapping $\{\mathbf{M}, \mathbf{H}\} = T(\mathbf{M}, \mathbf{H})$ from PLM to ALM,

$$T_{\mathbf{M}}(\mathbf{M}, \mathbf{H}) \;=\; [\mathbf{I} - \mathbf{CM}]^{-1}[\mathbf{A} + \mathbf{BM}] \tag{53}$$

$$T_{\mathbf{H}}(\mathbf{M}, \mathbf{H}) \;=\; [\mathbf{I} - \mathbf{CM}]^{-1}[\mathbf{BH} + \mathbf{CH} + \mathbf{N}]. \tag{54}$$

Rational expectations equilibrium is a fixed-point of this mapping:

$$\mathbf{M}^{\mathbf{re}} \;=\; [\mathbf{I} - \mathbf{CM}^{\mathbf{re}}]^{-1}[\mathbf{A} + \mathbf{BM}^{\mathbf{re}}]. \tag{55}$$

Conditional on $\mathbf{M}^{\mathbf{re}}$ we can solve for $\mathbf{H}^{\mathbf{re}}$:

$$\mathbf{H}^{\mathbf{re}} \;=\; \left[\mathbf{I} - [\mathbf{I} - \mathbf{CM}^{\mathbf{re}}]^{-1}(\mathbf{B} + \mathbf{C})\right]^{-1}[\mathbf{I} - \mathbf{CM}^{\mathbf{re}}]^{-1}\mathbf{N}. \tag{56}$$

References

[1] Adam, K., Kuang, P., Marcet, A. (2012). House price booms and the current account. In Acemoglu, D., Woodford, M., (Eds.), *NBER Macroeconomics Annual 2011* 26: 77-122.

[2] Aghion, P., Banerjee, A., Piketty, T. (1999). Dualism and macroeconomic volatility. *Quarterly Journal of Economics* 114: 1359-1397.

[3] Aiyagari, R., Gertler, M. (1999). "Overreaction" of asset prices in general equilibrium. *Review of Economic Dynamics* 2: 3-35.

[4] Branch, W., Evans, G. (2006). A simple recursive forecasting model. *Economics Letters* 91: 158-166.

[5] Boz, E., Mendoza, E. (2010). Financial innovation, the discovery of risk, and the U.S. credit crisis. NBER Working Paper 16020.

[6] Bullard, J., Duffy, J. (2004). Learning and structural change in macroeconomic data. St Louis Fed Working Paper 2004-016.

[7] Cao, D. (2011). Collateral shortages, asset price and investment volatility with heterogeneous beliefs. Mimeo Georgetown University.

[8] Chakraborty, A., Evans, G. (2008). Can perpetual learning explain the forward-premium puzzle? *Journal of Monetary Economics* 55: 477-490.

[9] Chaney, T., Sraer, D., Thesmar D. (2012). The collateral channel: how real estate shocks affect corporate investment. *American Economic Review* 102: 2381-2409.

[10] Edge, R., Laubach, T., Williams, J. (2007). Learning and shifts in long-run productivity growth. *Journal of Monetary Economics* 54: 2421-2438.

[11] Eusepi, S., Preston, B. (2011). Expectations, learning and business cycle fluctuations. *American Economic Review* 101: 2844-72.

[12] Evans, G., (2012). Comment on "Natural expectations, macroeconomic dynamics, and asset pricing". In Acemoglu, D., Woodford, M., (Eds.), *NBER Macroeconomics Annual 2011* 26: 61-71.

[13] Evans, G., Honkapohja, S. (2001). *Learning and expectations in macroeconomics*. Princeton University Press.

[14] Evans, G., Mc Gough, B. (2012). Learning to optimize. Mimeo University of Oregon.

[15] Fuster, A., Hebert, B., Laibson, D. (2012a). Natural expectations, macroeconomic dynamics, and asset pricing. In Acemoglu, D., Woodford, M., (Eds.), *NBER Macroeconomics Annual 2011* 26: 1-48.

[16] Fuster, A., Hebert, B., Laibson, D. (2012b). Investment dynamics with natural expectations. *International Journal of Central Banking* 8: 243-265.

[17] Geanakoplos, J. (2010). The leverage cycle. In Acemoglu, D., Rogoff, K., Woodford, M., (Eds.), *NBER Macroeconomic Annual 2009* 24: 1-65.

[18] Howitt, P. (2001). Learning, leverage and stability. Brown University mimeo.

[19] Iacoviello, M. (2005). House prices, borrowing constraints, and monetary policy in the business cycle. *American Economic Review* 95: 739-764.

[20] Ilut, C., Schneider, M. (2013). Ambiguous business cycles. Forthcoming *American Economic Review*.

[21] Jermann, U., Quadrini, V. (2012). Macroeconomic effects of financial shocks. *American Economic Review* 102: 238-71.

[22] Justiniano, A., Primiceri, G., Tambalotti, A. (2012). Household leveraging and deleveraging. Northwestern University and New York Fed mimeo.

[23] Kiyotaki, N., Michaelides, A., Nikolov, K. (2011). Winners and losers in housing markets. *Journal of Money, Credit and Banking* 43: 255-296.

[24] Kiyotaki, N., Moore, M. (1997). Credit cycles. *Journal of Political Economy* 105: 211-248.

[25] Kocherlakota, N. (2000). Creating business cycles through credit constraints. *Federal Reserve Bank of Minneapolis Quarterly Review* 24: 2-10.

[26] Krusell, P., Smith, A. (1998). Income and wealth heterogeneity in the macroeconomy. *Journal of Political Economy* 106: 867-896.

[27] Liu, X., Wang, P., Zha, T. (2013). Land-price dynamics and macroeconomic fluctuations. *Econometrica* 81: 1147-1184.

[28] Malmendier, U., Nagel, S. (2012). Learning from inflation experiences. Stanford University mimeo.

[29] Marcet, A., Sargent, T. (1989). Convergence of least squares learning mechanisms in self-referential linear stochastic models. *Journal of Economic Theory* 48: 337-368.

[30] Mian, A., Sufi, A. (2011). House prices, home equity-based borrowing, and the U.S. household leverage crisis. *American Economic Review* 101: 2132-2156.

[31] Midrigan, V., Philippon, T. (2011). Household leverage and the recession. NBER Working Paper 16965.

[32] Milani, F. (2007). Expectations, learning and macroeconomic persistence. *Journal of Monetary Economics* 54: 2065-2082.

[33] Milani, F. (2011). Expectations shocks and learning as drivers of the business cycle. *Economic Journal* 121: 379-401.

[34] Pancrazi, R., Pietrunti, M. (2013). Natural expectations and home equity extraction. Mimeo Warwick University.

[35] Pintus, P., Wen, Y. (2013). Leveraged borrowing and boom-bust cycles. *Review of Economics Dynamics* 16: 617-633.

[36] Williams, N. (2003). Adaptive learning and business cycles. Princeton University mimeo.