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Multiple Credit Constraints and Time-Varying Macroeconomic Dynamics

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Abstract
I build a DSGE model where households face two occasionally binding credit constraints: a loan-to-value (LTV) constraint and a debt-service-to-income (DTI) constraint. From an estimation of the model, I infer when each constraint was binding over the 1975-2017 timespan. The LTV constraint often binds in contractions, when house prices are relatively low – and the DTI constraint mostly binds in expansions, when mortgage rates are relatively high. Moreover, both constraints unbind during robust expansions. I also infer that DTI standards were relaxed during the mid-2000s credit boom, going from a maximally allowed DTI ratio of 28 pct. in 1999 to 35 pct. in 2006. In the light of this, the boom could have been avoided by tighter DTI limits. A lower LTV limit could contrarily not have prevented the boom, since soaring house prices slackened this constraint. In this way, whether or not a constraint binds shapes its effectiveness as a macroprudential tool. The role of multiple credit constraints for the emergence of nonlinear dynamics is corroborated by county panel data.

Resume
Jeg bygger en DSGE model, hvori husholdningerne er underlagt to lånebegrænsninger: en belåningsgradsbegrænsning og en gældsydelsesbegrænsning. Ved en estimation af modellen identificerer jeg, hvornår hver begrænsning bandt i løbet af perioden 1975-2017. Belåningsgradsbegrænsningen binder ofte i lavkonjunkturer, når boligpriserne er relativt lave – og gældsydelsesbegrænsningen binder for det meste i højkonjunkturer, når realkreditrenterne er relativt høje. Ydermere bliver begge begrænsninger ikkebindende i kraftige højkonjunkturer. Jeg finder også, at gældsydelseskravene blev lempet i løbet af kreditboomet i midt-2000'erne. Set i lyset af dette kunne boomet have været undgået ved hjælp af strammere gældsydelseskrav. Et lavere belåningsgradskrav kunne modsat ikke have forhindret boomet, eftersom stærkt stigende boligpriser løsnede denne begrænsning. På den måde bliver lånebegrænsningernes effektivitet som makroprudentielle redskaber formet af, hvorvidt de binder eller ej. I slutningen af arbejdspapiret dokumenterer jeg med paneldata på tværs af amter lånebegrænsningernes relevans i at frembringe ikkelineære dynamikker.

Key words
Multiple credit constraints; Nonlinear estimation of DSGE models; State-dependent credit origination

JEL classification
C33; D58; E32; E44

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The author alone are responsible for any remaining errors.

Multiple Credit Constraints and Time-Varying Macroeconomic Dynamics*

Marcus Mølbak Ingholt†

May 23, 2019

Job Market Paper

Please find updated versions of the paper here.

Abstract

I build a DSGE model where households face two occasionally binding credit constraints: a loan-to-value (LTV) constraint and a debt-service-to-income (DTI) constraint. From an estimation of the model, I infer when each constraint was binding over the 1975-2017 timespan. The LTV constraint often binds in contractions, when house prices are relatively low – and the DTI constraint mostly binds in expansions, when mortgage rates are relatively high. Moreover, both constraints unbind during robust expansions. I also infer that DTI standards were relaxed during the mid-2000s credit boom, going from a maximally allowed DTI ratio of 28 pct. in 1999 to 35 pct. in 2006. In the light of this, the boom could have been avoided by tighter DTI limits. A lower LTV limit could contrarily not have prevented the boom, since soaring house prices slackened this constraint. In this way, whether or not a constraint binds shapes its effectiveness as a macroprudential tool. The role of multiple credit constraints for the emergence of nonlinear dynamics is corroborated by county panel data.

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1 Introduction

Numerous empirical and theoretical papers emphasize the role of the loan-to-value (LTV) limits on loan applicants in causing financial acceleration.[1] In these contributions, the supply of collateralized credit to households moves up and down proportionally to asset prices, thereby acting as an impetus that expands and contracts the economy. In reality, however, banks *also* impose debt-service-to-income (DTI) limits on loan applicants.[2] Given that LTV and DTI constraints generally do not allow for the same amounts of debt, households effectively face the single constraint that yields the lowest amount. In turn, endogenous switching between the two constraints can occur depending on various determinants of mortgage borrowing, such as house prices, incomes, and mortgage rates. This then raises some questions, all of which are fundamental to macroeconomics and finance. When and why have LTV and DTI limits historically restricted mortgage borrowing? Did looser LTV or DTI limits cause the credit boom prior to the Great Recession, and could regulation have limited the resulting bust? How, if at all, does switching between different credit constraints affect the propagation and amplification of macroeconomic shocks? The answers to these questions have profound implications for how we model the economy and implement macroprudential policies. For instance, if house price growth does not lead to a significant credit expansion when households' incomes are below a certain threshold, models with a single credit constraint will either overestimate the role of house prices or underestimate the role of incomes in enhancing booms. Consequently, macroprudential policymakers will misidentify the risks associated with house price and income growth.

In order to understand these issues better, I develop a tractable New Keynesian dynamic stochastic general equilibrium (DSGE) model with two occasionally binding credit constraints: an LTV constraint and a DTI constraint. With this setup, homeowners must fulfill a collateral requirement and a debt service requirement in order to qualify for a mortgage loan. The LTV constraint is the solution to a debt enforcement problem, as in Kiyotaki and Moore (1997). The DTI constraint is a generalization of the natural borrowing limit in Aiyagari (1994). I estimate the model by Bayesian maximum likelihood

[1] See, e.g., Kiyotaki and Moore (1997), Iacoviello (2005), Iacoviello and Neri (2010), Mendoza (2010), Jermann and Quadrini (2012), Liu, Wang, and Zha (2013), Liu, Miao, and Zha (2016), Justiniano, Primiceri, and Tambalotti (2015), Guerrieri and Iacoviello (2017), Jensen, Petrella, Ravn, and Santoro (2017), and Jensen, Ravn, and Santoro (2018).

[2] Appendix A reports the DTI limits that the ten largest U.S. retail banks specify on their websites. All mortgage issuing banks set front-end limits of 28 pct. or back-end limits of 36 pct. Greenwald (2018) shows that borrowers bunch around institutional DTI limits, in addition to institutional LTV limits. Johnson and Li (2010) aptly find that households with high DTI ratios are far more likely to be turned down for credit than comparable households with low ratios.

on time series covering the U.S. economy over the 1975-2017 timespan. The solution of the model is based on a piecewise first-order perturbation method, so as to handle the occasionally binding nature of the constraints (Guerrieri and Iacoviello, 2015, 2017). Using this framework, I present three main sets of results.

The first set relates to the historical evolution in credit conditions. The estimation allows me to identify when the two credit constraints were binding and which shocks caused them to bind. At least one constraint binds throughout most of the period, signifying that borrowers have generally been credit constrained. The LTV constraint often binds during and after recessions, when house prices, which largely determine housing wealth, are relatively low (e.g., 1975-1979, 1990-1998, and 2009-2017). The DTI constraint reversely mostly binds in expansions, when mortgage rates, which impact debt services, are relatively high, due to countercyclical monetary policy (e.g., 1980-1985, 1999-2002, and 2005-2008). Both constraints unbind during powerful expansions if both house prices and incomes rise sufficiently (e.g., 2003-2004).[3] In this way, like Guerrieri and Iacoviello (2017), I establish that the LTV constraint was slack in 1999-2007. However, in contrast to their findings, I also conclude that this did not imply that homeowners could borrow freely, because of DTI requirements.

Corbae and Quintin (2015) and Greenwald (2018) hypothesize a relaxation of DTI limits as the cause of the mid-2000s credit boom. My estimation corroborates this hypothesis, inferring that the maximally allowed debt service to income ratio was raised from 28 pct. in 1999 to 35 pct. in 2006. To my knowledge, this is the first evidence of a DTI relaxation obtained within an estimated model. Such a relaxation is consistent with Justiniano, Primiceri, and Tambalotti (2017, 2018), who find that looser LTV limits cannot explain the credit boom, and that the fraction of borrowers presenting full income documentation dropped substantially in 2000-2007. Justiniano et al. (2018) also argue that it was an increase in credit supply which caused the surge in mortgage debt. My results qualify these previous discoveries, together suggesting that the increase in credit supply translated into a relaxation of DTI limits. The results also show that credit standards were eased during the financial deregulation in the early-1980s and tightened following the Stock Market Crash of 1987, the Savings and Loan Crisis of the late-1980s, and the Great Recession, in line with narrative accounts (Campbell and Hercowitz, 2009; Mian, Sufi, and Verner, 2017) and VAR estimates (Prieto, Eickmeier, and Marcellino, 2016).

[3]Whether or not both constraints unbind following a given housing wealth and income appreciation depends on the patience of borrowers. Since this parameter is estimated, the model allows, but does not *a priori* impose, that both credit constraints should unbind during powerful expansions.

The second set of results relates to the optimal timing and implementation of macroprudential policy. Recent studies show that credit expansions predict subsequent banking and housing market crises (e.g., Mian and Sufi, 2009; Schularick and Taylor, 2012; Baron and Xiong, 2017). Motivated by this, I consider how mortgage credit would historically have evolved if LTV and DTI limits had responded countercyclically to deviations of credit from its long-run trend. I find that countercyclical DTI limits are effective at curbing increases in mortgage debt, since these increases typically occur in expansions, when the DTI constraint is binding. For instance, mortgage credit growth is halved during the mid-2000s boom in my policy simulation. The flip-side of this result is that countercyclical LTV limits cannot prevent mortgage debt from rising, since this constraint typically is slack in expansions. Tighter LTV limits would therefore not have been able to prevent the mid-2000s credit boom. Countercyclical LTV limits can, however, abate the adverse consequences of house price slumps on credit availability by raising credit limits. In this way, the lowest volatility in borrowing is reached by combining the LTV and DTI policies into a two-stringed policy entailing that *both* credit limits respond countercyclically. Macroprudential policy then takes into account that the effective policy tool changes over the business cycle, with an LTV tool in contractions and a DTI tool in expansions. Because this policy limits the deleveraging-induced flow of funds from borrowers to lenders in recessionary episodes, the policy efficiently redistributes consumption risk from borrowers to lenders. Thus, congruous with common definitions of value-at-risk, consumption-at-risk is lower for borrowers and higher for lenders under the two-stringed policy. Such theoretical guidance on how to combine multiple credit constraints for macroprudential purposes is scarce within the existing literature, as also noted by Jácome and Mitra (2015).[4]

The third set of results relates to how endogenous switching between credit constraints transmits shocks nonlinearly through the economy. Housing preference and credit shocks exert asymmetric effects on real activity, in that adverse shocks have larger effects than similarly sized favorable shocks. Adverse shocks are amplified by borrowers lowering their housing demand, which tightens the LTV constraint and forces borrowers to delever further. Favorable shocks are, by contrast, dampened by countercyclical monetary policy, which raises the mortgage rate and, *ceteris paribus*, tightens the DTI constraint. Housing preference and credit shocks also exert state-dependent effects, since these shocks have larger effects in contractions than in expansions. Thus, shocks that occur when the LTV constraint binds (typically in contractions) are amplified by housing demand moving in the same direction as the shock, while shocks that occur when the DTI constraint binds

[4] An exception to this is Greenwald (2018), who focuses on policy around the Great Recession.

(typically in expansions) are curbed by countercyclical monetary policy. These predictions of nonlinear responses fit with an emerging body of empirical studies.[5] Models with only an occasionally binding LTV constraint, in comparison, have difficulties in producing nonlinear dynamics. State-of-the-art models, such as Guerrieri and Iacoviello (2017) or Jensen et al. (2018), do capture some nonlinearity following *large favorable* shocks that unbind this constraint. However, the reactions of these models are linear up until the point where the LTV constraint unbinds.[6]

As a final contribution, I use a county-level panel dataset to test two key predictions of homeowners facing both an LTV constraint and a DTI constraint. The predictions are that (i) house price growth shall not allow homeowners to borrow more if incomes are sufficiently low, and (ii) income growth shall not allow homeowners to borrow more if house prices are sufficiently low. My identification strategy is based on Bartik-type house price and income instruments, along with county and state-year fixed effects. The specific test involves estimating the elasticities of mortgage loan origination with respect to house prices and personal incomes, importantly after partitioning the elasticities based on the detrended house price and income levels. The exercise confirms that both elasticities are highly state-dependent. The elasticity with respect to house prices is zero when incomes are below their long-run trend and 0.69 when they are above. Correspondingly, the elasticity with respect to incomes is zero when house prices are below their long-run trend and 0.43 when they are above. Thus, the exercise certifies that house price (income) growth does not increase credit origination when households' incomes (house prices) are low, in keeping with a simultaneous imposition of LTV and DTI constraints. These estimates are among the first, in an otherwise large micro-data literature, to suggest that house prices and incomes amplify each others' effect on credit origination.

The rest of the paper is structured as follows. Section 2 discusses how the paper relates to the existing literature. Section 3 presents the theoretical model. Section 4 performs the Bayesian estimation of the model. Section 5 highlights the nonlinear dynamics that the credit constraints introduce. Section 6 decomposes the historical evolution in credit conditions. Section 7 conducts the macroprudential policy experiment. Section 8 presents the panel evidence on state-dependent mortgage debt elasticities. Section 9 contains the concluding remarks.

[5] See, e.g., Engelhardt (1996), Skinner (1996), Davig and Hakkio (2010), Hubrich and Tetlow (2015), Kuttner and Shim (2016), Prieto et al. (2016), and Barnichon, Matthes, and Ziegenbein (2017).

[6] I verify this point by also building and estimating a model that only has an occasionally binding LTV constraint. The marginal data density massively favors the baseline model over the LTV model.

2 Related Literature

The paper is, to my knowledge, the first to include both an occasionally binding LTV constraint and an occasionally binding DTI constraint in the same estimated general equilibrium model. A small theoretical literature already studies house price propagation through occasionally binding LTV constraints. Guerrieri and Iacoviello (2017) demonstrate that the macroeconomic sensitivity to house price changes is smaller during booms (when LTV constraints may unbind) than during busts (when LTV constraints bind). Jensen et al. (2018) study how relaxations of LTV limits lead to an increased macroeconomic volatility, up until a point where the limits become sufficiently lax and credit constraints generally unbind, after which this pattern reverts. Jensen et al. (2017) document that the U.S. business cycle has increasingly become negatively skewed, and explain this through secularly increasing LTV limits that dampen the effects of expansionary shocks and amplify the effects of contractionary shocks.

A growing empirical literature documents the presence of substantial asymmetric and state-dependent responses to house price and financial shocks. Barnichon et al. (2017) show that increments in the excess bond premium have large and persistent negative real effects, while reductions have no significant effects, using a nonlinear vector moving average model and U.S., U.K., and Euro area data. They also show that increments have larger and more persistent effects on real activity in contractions than in expansions. In a similar manner, Prieto et al. (2016) show that house price and credit spread shocks have larger impacts on GDP growth in crisis periods than in non-crisis periods, using a time-varying parameter VAR model and U.S. data. Finally, Engelhardt (1996) and Skinner (1996) show that consumption falls significantly following decreases in housing wealth, but does not rise following increases in housing wealth, using U.S. panel surveys. The existing piecewise linear models with LTV constraints cannot easily reproduce the nonlinear effects of house price and financial shocks. Within these frameworks, nonlinearities only arise if the LTV constraint unbinds, which presupposes that debt quantity limits expand to the extent that borrowing demand becomes saturated. For instance, Guerrieri and Iacoviello (2017) need to apply a 20 pct. house price increase in order for their LTV constraint to unbind. Such kinds of expansionary events occur more rarely than simple switching between an LTV constraint and a DTI constraint in yielding the lowest debt quantity. Thus, while the LTV constraint does provide some business cycle nonlinearity in expansions, the nonlinearities of the two constraint model apply to a much broader set of scenarios.

Greenwald (2018) complementarily studies the implications of LTV and DTI constraints for monetary policy and the mid-2000s boom.[7] He relies on a calibrated model with an always binding credit constraint which is an endogenously weighted average of an LTV and a DTI constraint, and considers linearized impulse responses. The present paper provides new insights into the implications of such multiple constraints. First, the estimation allows for a full-information identification of when the respective constraints were dominating over the long 1975-2017 timespan and the impact of stabilization policies.[8] Second, the discrete switching between the constraints generates asymmetric and state-dependent impulse responses, incompatible with linear models. Third, the occasionally binding constraints imply that borrowers may become credit unconstrained if both constraints unbind simultaneously, unlike in the case with always binding constraints.

The paper is finally, again to my knowledge, the first to examine the interacting effects of house price and income growth on equity extraction, using cross-sectional or panel data. A large literature already studies the effects of house price growth on equity extraction and real activity.[9] However, this literature mainly considers the effects of separate variation in house prices, rather than the interacted effects of changes in house prices and other drivers of credit. A notable exception to this is Bhutta and Keys (2016), who interact house price and interest rate changes, and find that they amplify each other considerably. This prediction fits with my theoretical model, as simultaneous expansionary shocks to house prices and monetary policy there relax both credit constraints directly.

3 Model

The model has an infinite time horizon. Time is discrete, and indexed by t. The economy is populated by two representative households: a patient household and an impatient household. Households consume goods and housing services, and supply labor. Goods are

[7] The heterogeneous agents models in Chen, Michaux, and Roussanov (2013), Gorea and Midrigan (2017), and Kaplan, Mitman, and Violante (2017) also impose both LTV and DTI constraints, but do not study their interactions over the business cycle. Moreover, while including rich descriptions of financial markets and risk, the models lack general equilibrium dynamics related to interactions between the constraints and housing demand and labor supply, output, and monetary and macroprudential policy. Focusing on firms' borrowing, Drechsel (2018) establishes a connection between corporations' current earnings and their access to debt, and formalizes this link through an earnings-based constraint.

[8] Formal identification is important, in that the relative dominance of the two constraints hinges on the magnitude and persistence of house price shocks relative to the magnitude and persistence of income and mortgage rate shocks. These moments, in turn, largely depend on the shock processes, which are difficult to calibrate accurately due to their reduced-form nature and cross-model inconsistency.

[9] See, e.g., Engelhardt (1996), Skinner (1996), Campbell and Cocco (2007), Mian and Sufi (2011), Mian, Rao, and Sufi (2013), Bhutta and Keys (2016), Guerrieri and Iacoviello (2017), Cloyne, Huber, Ilzetzki, and Kleven (2017), and Guren, McKay, Nakamura, and Steinsson (2018).

produced by a representative intermediate firm, by combining employment and nonresidential capital. Retail firms unilaterally set prices subject to downward-sloping demand curves. The time preference heterogeneity implies that the patient household lends funds to the impatient household. The patient household also owns and operates the firms and nonresidential capital. The housing stock is fixed, but housing reallocations take place between households. The equilibrium conditions are derived in the Online Appendix.

3.1 Patient and Impatient Households

Variables and parameters without (with) a prime refer to the patient (impatient) household. The household types differ with respect to their pure time discount factors, $\beta \in (0,1)$ and $\beta' \in (0,1)$, since $\beta > \beta'$. The economic size of each household is measured by its wage share: $\alpha \in (0,1)$ for the patient household and $1-\alpha$ for the impatient household.

The patient and impatient households maximize their utility functions,

$$\mathbb{E}_0\left\{\sum_{t=0}^{\infty}\beta^t s_{I,t}\left[\chi_C \log(c_t-\eta_C c_{t-1})+\omega_H s_{H,t}\chi_H\log(h_t-\eta_H h_{t-1})-\frac{s_{L,t}}{1+\varphi}l_t^{1+\varphi}\right]\right\}, \quad (1)$$

$$\mathbb{E}_0\left\{\sum_{t=0}^{\infty}\beta'^t s_{I,t}\left[\chi'_C \log(c'_t-\eta_C c'_{t-1})+\omega_H s_{H,t}\chi'_H\log(h'_t-\eta_H h'_{t-1})-\frac{s_{L,t}}{1+\varphi}l_t'^{1+\varphi}\right]\right\}, \quad (2)$$

where $\chi_C \equiv \frac{1-\eta_C}{1-\beta\eta_C}$, $\chi'_C \equiv \frac{1-\eta_C}{1-\beta'\eta_C}$, $\chi_H \equiv \frac{1-\eta_H}{1-\beta\eta_H}$, $\chi'_H \equiv \frac{1-\eta_H}{1-\beta'\eta_H}$,[10] c_t and c'_t denote goods consumption, h_t and h'_t denote housing, l_t and l'_t denote labor supply and, equivalently, employment measured in hours, $s_{I,t}$ is an intertemporal preference shock, $s_{H,t}$ is a housing preference shock, and $s_{L,t}$ is a labor preference shock. Moreover, $\eta_C \in (0,1)$ and $\eta_H \in (0,1)$ measure habit formation in goods and housing consumption, while $\omega_H \in \mathbb{R}_+$ weights the utility of housing services relative to the utility of goods consumption.[11]

Utility maximization of the patient household is subject to the budget constraint,

$$\begin{aligned} c_t + q_t(h_t-h_{t-1}) + \frac{1+r_{t-1}}{1+\pi_t}b_{t-1} + k_t + \frac{\iota}{2}\left(\frac{k_t}{k_{t-1}}-1\right)^2 k_{t-1} \\ = w_t l_t + div_t + b_t + (r_{K,t}+1-\delta_K)k_{t-1}, \end{aligned} \quad (3)$$

where q_t denotes the real house price, r_t denotes the nominal net interest rate, π_t denotes net price inflation, b_t denotes net borrowing, k_t denotes nonresidential capital, w_t denotes

[10] The scaling factors ensure that the marginal utilities of goods consumption and housing services are $\frac{1}{c}$, $\frac{1}{c'}$, $\frac{\omega_H}{h}$, and $\frac{\omega_H}{h'}$ in the steady state.

[11] It is not necessary to weight the disutility of labor supply, since its steady-state level only affects the scale of the economy, as in Justiniano et al. (2015) and Guerrieri and Iacoviello (2017).

the real wage, div_t denotes dividends from retail firms, and $r_{K,t}$ denotes the real net rental rate of nonresidential capital. $\iota \in \mathbb{R}_+$ measures capital adjustment costs, and $\delta_K \in [0,1]$ measures the depreciation of nonresidential capital.

Utility maximization of the impatient household is subject to the budget constraint,

$$c'_t + q_t(h'_t - h'_{t-1}) + \frac{1+r_{t-1}}{1+\pi_t} b'_{t-1} = w'_t l'_t + b'_t, \tag{4}$$

where b'_t denotes net borrowing, and w'_t denotes the real wage. Utility maximization of the impatient household is also subject to two occasionally binding credit constraints,

$$b'_t \leq (1-\rho)\frac{b'_{t-1}}{1+\pi_t} + \rho \xi_{LTV} s_{C,t} \mathbb{E}_t \big\{ (1+\pi_{t+1}) q_{t+1} h'_t \big\}, \tag{5}$$

$$b'_t \leq (1-\rho)\frac{b'_{t-1}}{1+\pi_t} + \rho \xi_{DTI} s_{C,t} \mathbb{E}_t \left\{ \frac{(1+\pi_{t+1}) w'_{t+1} l'_t}{\sigma + r_t} \right\}, \tag{6}$$

where $s_{C,t}$ is a credit shock which shifts the credit limits imposed by both constraints. Thus, following Kaplan et al. (2017), shocks to the two credit limits are perfectly correlated, implying that the shocks do not, on impact, influence which constraint that binds.[12] $\rho \in [0,1]$ measures the share of homeowners who refinance in a given period. This specification allows a share of homeowners, $(1-\rho)$, to roll over their existing mortgages without refinancing, as in Guerrieri and Iacoviello (2017). $\xi_{LTV} \in [0,1]$ measures the steady-state LTV limit, $\xi_{DTI} \in [0,1]$ measures the steady-state DTI limit, and σ measures the amortization rate on outstanding debt. The constraints require that homeowners fulfill the following collateral and debt service requirements on newly issued mortgage loans:

$$\tilde{b}'_t \leq \xi_{LTV} s_{C,t} \mathbb{E}_t \big\{ (1+\pi_{t+1}) q_{t+1} h'_t \big\} \quad \text{and} \quad (\sigma + r_t)\tilde{b}'_t \leq \xi_{DTI} s_{C,t} \mathbb{E}_t \big\{ (1+\pi_{t+1}) w'_{t+1} l'_t \big\},$$

where $\tilde{b}'_t$ denotes newly issued net borrowing. A similar LTV constraint can be derived as the solution to a debt enforcement problem, as shown by Kiyotaki and Moore (1997). Appendix B shows that the DTI constraint can be derived separately as an incentive compatibility constraint on the impatient household, and that it is a generalization of the natural borrowing limit in Aiyagari (1994). Finally, the assumption $\beta > \beta'$ implies that (5) or (6) always hold with equality in (but not necessarily around) the steady state.[13]

[12] Estimating uncorrelated credit shocks is unfeasible, because it is only the shocks to the constraint yielding the lowest debt quantity that are identified in the model estimation.

[13] The Online Appendix shows that the results in Sections 6-7 are robust to letting the employment of impatient workers drive the aggregate variation in hours worked, leaving the employment of patient workers constant at its steady-state level.

3.2 Firms

3.2.1 Intermediate Firm

The intermediate firm produces intermediate goods, by hiring labor from both households and renting capital from the patient household. The firm operates under perfect competition. The profits to be maximized are given by

$$\frac{Y_t}{M_{P,t}} - w_t l_t - w'_t l'_t - r_{K,t} k_{t-1}, \tag{7}$$

subject to the available goods production technology,

$$Y_t = k_{t-1}^{\mu} (s_{Y,t} l_t^{\alpha} l_t'^{1-\alpha})^{1-\mu}, \tag{8}$$

where Y_t denotes goods production, $M_{P,t}$ denotes an average gross price markup over marginal costs set by the retail firms, and $s_{Y,t}$ is a labor-augmenting technology shock. Lastly, $\mu \in (0,1)$ measures the goods production elasticity with respect to nonresidential capital.

3.2.2 Retail Firms

Retail firms are distributed over a unit continuum by product specialization. They purchase and assemble intermediate goods into retail firm-specific final goods at no additional cost. The final goods are then sold for consumption and nonresidential investment purposes. The specialization allows the firms to operate under monopolistic competition. All dividends are paid out to the patient household:

$$div_t \equiv \left(1 - \frac{1}{M_{P,t}}\right) Y_t. \tag{9}$$

The solution of the retail firms' price setting problem yields a New Keynesian Price Phillips Curve:

$$\pi_t = \beta \mathbb{E}_t\{\pi_{t+1}\} - \lambda_P \left(\log M_{P,t} - \log \frac{\epsilon_P}{\epsilon_P - 1} \right), \tag{10}$$

where $\lambda_P \equiv \frac{(1-\theta_P)(1-\beta\theta_P)}{\theta_P}$. Furthermore, $\epsilon_P > 1$ measures the price elasticity of retail firm-specific goods demand, and $\theta_P \in (0,1)$ measures the Calvo probability of a firm not being able to adjust its price in a given period.

3.3 Monetary Policy

The central bank sets the nominal net interest rate according to a Taylor-type monetary policy rule,

$$r_t = \tau_R r_{t-1} + (1 - \tau_R) r + (1 - \tau_R) \tau_P \pi_{P,t} + \varepsilon_{M,t}, \tag{11}$$

where r denotes the steady-state nominal net interest rate, and $\varepsilon_{M,t}$ is a monetary policy innovation. Moreover, $\tau_R \in (0, 1)$ measures deterministic interest rate smoothing, and $\tau_P > 1$ measures the policy response to price inflation.[14]

3.4 Equilibrium

The model contains a goods market, a housing market, and a loan market, in addition to two redundant labor markets. The market clearing conditions are

$$c_t + c'_t + k_t - (1 - \delta_K) k_{t-1} + \frac{\iota}{2} \left[\frac{k_t}{k_{t-1}} - 1 \right]^2 k_{t-1} = Y_t, \tag{12}$$

$$h_t + h'_t = \mathcal{H}, \tag{13}$$

$$b_t = -b'_t, \tag{14}$$

where $\mathcal{H} \in \mathbb{R}_+$ measures the fixed aggregate stock of housing.

3.5 Stochastic Processes

All stochastic shocks except the monetary policy innovation follow AR(1) processes. The monetary policy innovation is a single-period innovation, so that any persistence in this policy is captured by interest rate smoothing, as in Christiano, Motto, and Rostagno (2014). All six stochastic innovations are normally independent and identically distributed, with a constant standard deviation.

[14] I do not model a zero lower bound on the nominal interest rate, since my interest rate measure is the 30-year fixed rate mortgage average, which did not reach zero following the Great Recession. The federal funds rate realistically exercises a large influence on the 30-year mortgage rate through the yield curve. For instance, the correlation between the two rates was 94 pct., on average across 1975-2017. The Online Appendix shows that the results in Sections 6-7 are robust to measuring the interest rate by the effective federal funds rate.

4 Solution and Estimation of the Model

4.1 Methods

I solve the model with the perturbation method from Guerrieri and Iacoviello (2015, 2017). This allows me to account for the two occasionally binding credit constraints and handle the associated nonlinear solution when implementing the Bayesian maximum likelihood estimation. The model economy will always be in one of four regimes, depending on whether the LTV constraint binds or not and whether the DTI constraint binds or not. The solution method performs a first-order approximation of each of the four regimes around the steady state of a reference regime (one of the four regimes). In the regime where both constraints are binding, the borrowing limits imposed by the two constraints are, as a knife-edge case, identical.[15] Outside this regime, the borrowing limits may naturally differ, causing discrete switching between which of the three other regimes that applies. As a reference regime, I choose the regime where both constraints are binding, in order to treat the constraints symmetrically.[16] The calibrations of ξ_{LTV} and ξ_{DTI} must consequently ensure that the right-hand sides of (5) and (6) are identical in the steady state. However, this restriction on the parameterization of the model does not entail that it is not possible to calibrate the model realistically. Instead, as will be evident in Subsection 4.3, a highly probable calibration can be reached. Once a constraint unbinds, the households will expect it to bind again at some forecast horizon.[17] The households therefore base their decisions on the expected duration of the current regime, which, in turn, depends on the state vector. As a result, the solution of the model is nonlinear in two dimensions. First, it is nonlinear *between* regimes, depending on which regime that applies. Second, it is nonlinear *within* each regime, depending on the expected duration of the regime.

When estimating the model, one cannot use the Kalman filter to retrieve the estimates of the innovations. This is because the policy functions depend nonlinearly on which constraint that binds, which, in turn, depends on the innovations. Instead, I recursively solve for the innovations, given the state of the economy and the observations, as in Fair and Taylor (1983).

[15] This complication is not present in Guerrieri and Iacoviello (2017), since their two constraints (an LTV constraint and a zero lower bound) restrict two variables (borrowing and the nominal interest rate).

[16] I avoid specifying a reference regime where only one constraint binds, since this could bias the model towards that regime. The regime where both constraints are slack is unfeasible as a reference regime, in that the time preference heterogeneity is inconsistent with both households being credit unconstrained in the steady state.

[17] The expectation that both credit constraints eventually will bind results from an expectation that the economy eventually returns to its reference regime, where both constraints are binding.

Borrowing is an observed variable in the estimation. It is mainly the credit shock which ensures that the theoretical borrowing variable matches its empirical measure. When a credit constraint is binding, the credit shock has an immediate effect on borrowing through the binding constraint, leading to a direct econometric identification of the shock. When both constraints are slack, this direct channel is switched off, since the credit constraints no-longer contemporaneously predict borrowing. Despite this, the model will not suffer from stochastic singularity (i.e., fewer shocks than observed variables), since the credit shock also has an effect on borrowing when both constraints are slack. This effect, only now, works through the first-order condition of the impatient household with respect to net borrowing:

$$\begin{aligned} u'_{c,t} + \beta'(1-\rho)\mathbb{E}_t\bigg\{ s_{I,t+1}\frac{\lambda_{LTV,t+1}+\lambda_{DTI,t+1}}{1+\pi_{t+1}}\bigg\} \\ = \beta'\mathbb{E}_t\bigg\{ u'_{c,t+1}\frac{1+r_t}{1+\pi_{t+1}}\bigg\} + s_{I,t}(\lambda_{LTV,t}+\lambda_{DTI,t}). \end{aligned}$$

Through recursive substitution v periods ahead, this condition can be restated as

$$\begin{aligned} u'_{c,t} = {} & \beta'^{v}\mathbb{E}_t\bigg\{ u'_{c,t+v}\prod_{j=0}^{v-1}\frac{1+r_{t+j}}{1+\pi_{t+j+1}}\bigg\} \\ & + \sum_{i=1}^{v-1}\beta'^{i}\mathbb{E}_t\bigg\{ s_{I,t+i}(\lambda_{LTV,t+i}+\lambda_{DTI,t+i})\prod_{j=0}^{i-1}\frac{1+r_{t+j}}{1+\pi_{t+j+1}}\bigg\} \\ & \qquad - \sum_{i=1}^{v-1}\beta'^{i+1}(1-\rho)\mathbb{E}_t\bigg\{ s_{I,t+i+1}\frac{\lambda_{LTV,t+i+1}+\lambda_{DTI,t+i+1}}{1+\pi_{t+i+1}}\prod_{j=0}^{i-1}\frac{1+r_{t+j}}{1+\pi_{t+j+1}}\bigg\} \\ & + s_{I,t}(\lambda_{LTV,t}+\lambda_{DTI,t}) - \beta'(1-\rho)\mathbb{E}_t\bigg\{ s_{I,t+1}\frac{\lambda_{LTV,t+1}+\lambda_{DTI,t+1}}{1+\pi_{t+1}}\bigg\}, \end{aligned}$$

for $v \in \{\mathrm{v} \in \mathbb{Z} | \mathrm{v} > 1\}$. According to the expression, the current levels of consumption and (via the budget constraint) borrowing are pinned down by the current and expected future Lagrange multipliers for $v \to \infty$. The current multipliers are zero ($\lambda_{LTV,t} = \lambda_{DTI,t} = 0$) when both constraints are slack. The expected future multipliers will, however, be positive at some forecast horizon, due to the model being stable with zero mean stochastic innovations. The current credit shock can thereby (along with any other shock) – through its persistent effects on future credit limits – have an effect on the expected future Lagrange multipliers and ultimately consumption and borrowing in the current period. As a result, when both constraint are slack, the credit shock is identified via the constraint that allows for the lowest amount of borrowing, hence is the closest to binding.

4.2 Data

The estimation sample covers the U.S. economy in 1975Q1-2017Q4, at a quarterly frequency.[18] The sample contains the following six time series: 1. Real personal consumption expenditures per capita. 2. Real home mortgage loan liabilities per capita. 3. Real house prices. 4. Real disposable personal income per capita. 5. Aggregate weekly hours per capita. 6. Quartered 30-year fixed rate mortgage average.

Series 1-5 are normalized relative to 1975Q1 and then log-transformed. They are lastly detrended by a one-sided HP filter (with a smoothing parameter of 100,000) in order to remove their low-frequency components, following Guerrieri and Iacoviello (2017). This filter produces plausible trend and gap estimates for the variables. For instance, the troughs of consumption and mortgage debt following the Great Recession lie 7 pct. and 23 pct. below the trend, in 2009Q3 and 2012Q4, according to the filter. Furthermore, the one-sided filter preserves the temporal ordering of the data, as the correlation of current observations with subsequent observations is not affected by the filter (Stock and Watson, 1999). Series 6 is demeaned. Data sources and time series plots are reported in the Online Appendix.

4.3 Calibration and Prior Distribution

A subset of the parameters are calibrated using information complementary to the estimation sample. Table 1 reports the calibrated parameters and information on their calibration. I set the steady-state DTI limit ($\xi_{DTI} = 0.36$), so that debt servicing relative to labor incomes *before taxes* may not exceed 28 pct., as in Greenwald (2018).[19] This value is identical to the typical front-end (i.e., excluding other recurring debts) DTI limit set by mortgage issuing banks in the U.S., according to Appendix A. The number is also corroborated by the U.S. Consumer Financial Protection Bureau, which in its home loan guide writes: "A mortgage lending rule of thumb is that your total monthly home payment should be at or below 28% of your total monthly income before taxes." (see Consumer Financial Protection Bureau (2015, p. 5)). Since there are no taxes in the model, the labor incomes the households receive should be treated as after tax incomes. The average labor tax rate was 23.1 pct. in the postwar U.S., according to Jones (2002). The DTI limit accordingly becomes $\frac{0.28}{1-0.231} = 0.36$ for incomes *after taxes*.

Given the calibration of the DTI limit, a steady-state LTV limit of 77 pct. ensures that the borrowing limits imposed by the two constraints are identical in the steady state

[18] The Online Appendix shows that the results in Sections 6-7 are robust to estimating the model on a sample covering the 1985Q1-2017Q4 period (i.e., starting after the Great Moderation).

[19] Kaplan et al. (2017) similarly set their DTI limit to 25 pct.

Table 1: CALIBRATED PARAMETERS

Description		Value	Source or Steady-State Target
Time discount factor, pt. hh.	β	0.99	Annual net real interest rate: 4 pct.
Housing utility weight	ω_H	0.31	Steady-state target[a]
Steady-state LTV limit	ξ_{LTV}	0.769	See text
Steady-state DTI limit	ξ_{DTI}	0.364	See text
Amortization rate	σ	1/104.2	Average original loan term[b]
Depreciation rate, non-res. cap.	δ_K	0.025	Standard value
Capital income share	μ	0.33	Standard value
Price elasticity of goods demand	ϵ	5.00	Standard value
Calvo price rigidity parameter	θ	0.80	Galí and Gertler (1999), Sbordone (2002)
Stock of housing (log. value)	$\mathcal{H}$	1.00	Normalization

[a]The model is calibrated to match the average ratio of owner-occupied residential fixed assets to durable goods consumption expenditures (37.8) over the sample period.
[b]The model is calibrated to match the average loan term (104.2 quarters) on originated loans weighted by the original loan balance during 2000-2016 in Fannie Mae's Single Family Loan Acquisition Data.

(cf., the discussion on the solution of the model in Subsection 4.1). This LTV limit is well within the range of typically applied limits (e.g., Liu et al. (2013) and Liu et al. (2016) use 0.75, Kydland, Rupert, and Šustek (2016) use 0.76, Justiniano et al. (2018) use 0.80, and Iacoviello and Neri (2010) and Justiniano et al. (2015) use 0.85).

Table 2 reports the prior distributions of the estimated parameters. The prior means of the wage share parameter ($\alpha = 0.66$), the impatient time discount factor ($\beta' = 0.984$), the habit formation parameters ($\eta_C = \eta_H = 0.70$), and the debt inertia parameter ($\rho = 0.25$) follow the prior means in Guerrieri and Iacoviello (2017). The prior mean of the elasticity of the marginal disutility of labor supply ($\varphi = 5.00$) implies a real wage elasticity of labor supply of $\frac{1}{5}$, consistent with the micro-estimates in MaCurdy (1981) and Altonji (1986). The prior means of the remaining estimated parameters follow the prior means of the corresponding parameters in Iacoviello and Neri (2010).

4.4 Posterior Distribution

Table 2 reports two posterior distributions: One from the baseline model with two occasionally binding credit constraints and one from a model with only an occasionally binding LTV constraint. Apart from not featuring a DTI constraint, this latter model is identical to the baseline model. The difference in marginal data densities across the two models implies a posterior odds ratio of exp(30.8) to 1 in favor of the baseline model, suggesting that the data massively favor the baseline model.

The estimates of the wage share parameter ($\alpha = 0.58$), the impatient time discount

Table 2: Prior and Posterior Distributions

	Prior Distribution			Posterior Distribution					
				Baseline			Only LTV Constraint		
	Type	Mean	S.D.	Mode	5 pct.	95 pct.	Mode	5 pct.	95 pct.
Structural Parameters									
α	B	0.66	0.10	0.5833	0.5605	0.6062	0.2991	0.2943	0.3038
β'	B	0.984	0.006	0.9892	0.9892	0.9893	0.9871	0.9868	0.9874
η_C	B	0.70	0.10	0.6218	0.5915	0.6521	0.4890	0.4664	0.5116
η_H	B	0.70	0.10	0.6591	0.6319	0.6864	0.6699	0.6500	0.6898
φ	N	5.00	0.15	3.9298	3.4829	4.3767	2.0905	1.9524	2.2287
ρ	B	0.25	0.10	0.2029	0.1847	0.2211	0.4102	0.3878	0.4325
ι	N	10.0	2.00	20.805	18.965	22.645	18.586	16.867	20.306
τ_R	B	0.75	0.05	0.7264	0.7054	0.7473	0.6026	0.5803	0.6249
τ_P	N	1.50	0.15	2.0568	1.4940	2.6195	1.7722	1.2840	2.2605
Persistence of Shock Processes									
IP	B	0.50	0.20	0.7829	0.7551	0.8107	0.7939	0.7756	0.8121
HP	B	0.50	0.20	0.9628	0.9487	0.9769	0.9966	0.9943	0.9989
CC	B	0.50	0.20	0.9911	0.9872	0.9950	0.9753	0.9702	0.9803
AY	B	0.50	0.20	0.9701	0.9636	0.9765	0.9643	0.9579	0.9707
LP	B	0.50	0.20	0.9817	0.9778	0.9855	0.9677	0.9613	0.9741
Standard Deviations of Innovations									
IP	IG	0.01	0.10	0.0622	0.0512	0.0733	0.0174	0.0109	0.0240
HP	IG	0.01	0.10	0.0636	0.0524	0.0748	0.0198	0.0129	0.0268
CC	IG	0.01	0.10	0.0144	0.0081	0.0208	0.0088	0.0037	0.0139
AY	IG	0.01	0.10	0.0399	0.0306	0.0492	0.0260	0.0183	0.0337
LP	IG	0.01	0.10	0.0016	0.0001	0.0048	0.0015	0.0001	0.0046
MP	IG	0.01	0.10	0.0094	0.0040	0.0148	0.0096	0.0043	0.0148
Measures of Fit at the Posterior Mode (absolute log values)									
Posterior Kernel					4045.11			4009.95	
Marginal Data Density					4296.98			4266.21	

Distributions: N: Normal. B: Beta. IG: Inverse-Gamma.
Shocks: IP: Intertemporal preference. HP: Housing preference. CC: Credit. AY: Labor-augmenting technology. LP: Labor preference. MP: Monetary policy.
Note: The bounds indicate the confidence intervals surrounding the posterior mode. The prior distribution of β' is truncated with an upper bound at 0.9899.

factor ($\beta' = 0.9892$), and debt inertia ($\rho = 0.20$) in the baseline model are similar to the estimates of the corresponding parameters in Guerrieri and Iacoviello (2017). This is comforting considering that these parameters are decisive in determining when the credit constraints bind. The confidence bounds surrounding the three estimates are considerably smaller than in Guerrieri and Iacoviello (2017). One plausible explanation for this higher precision is that the mortgage debt series, which is intimately related to these parameters, is included in my estimation sample, but not in Guerrieri and Iacoviello's (2017) sample.

Another explanation for this is that, while there is the same number of variables and 64 more observations in my estimation sample, as compared to Guerrieri and Iacoviello's (2017) sample, there are two fewer estimated structural parameters.

5 Asymmetric and State-Dependent Dynamics

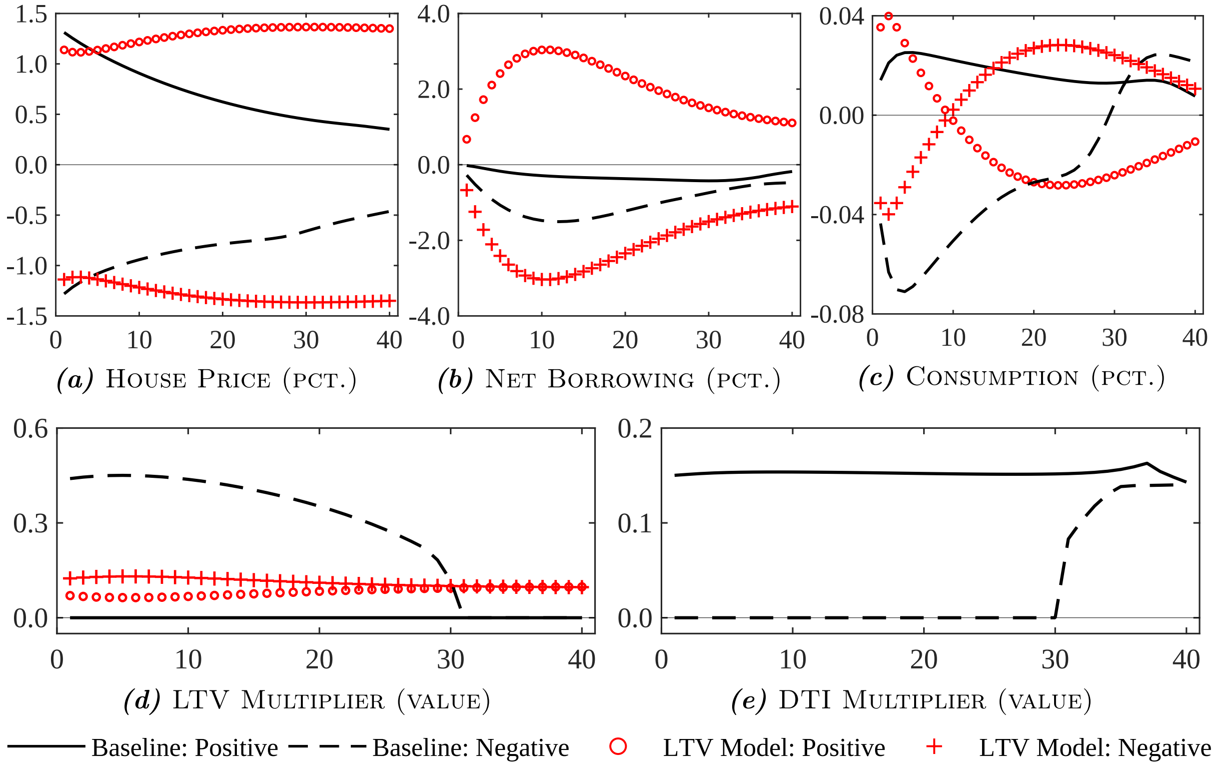
This section illustrates how endogenous switching between the credit constraints generates asymmetric and state-dependent responses to housing preference and credit shocks. The section also illustrates that the responses of the model with only an LTV constraint are radically different from the baseline responses. In the LTV model, nonlinearities only arise if the LTV constraint unbinds, which presupposes that borrowing demand is saturated. As we will see, this type of event occurs much more rarely than simple switching between the constraints. Thus, while the LTV constraint might provide some business cycle nonlinearity in expansions, the nonlinearities of the two constraint model apply to a much broader set of scenarios.

Figure 1 plots the effects of unit standard deviation positive and negative housing preference shocks, in the baseline model and in the LTV model. The responses of borrowing and consumption are highly asymmetric in the baseline model and completely symmetric in the LTV model. The asymmetries in the baseline model arise from differences in the constraint that binds. Following a positive shock, the house price increases. The concurrent increase in borrowers' wealth allows them to consume more goods, leading to a small increase in aggregate consumption. The central bank raises the interest rate, which tightens the DTI constraint, thereby suppressing borrowing and limiting the increase in consumption. Following the negative shock, instead, the house price falls, and the LTV constraint is tightened, inducing the impatient household to reduce consumption, in order to delever proportionally to the drop in housing wealth. The symmetry in the consumption responses match with Engelhardt (1996) and Skinner (1996), showing statistically significant consumption responses to falls in housing wealth, but not to increases.

5.1 Responses to Housing Preference Shocks

Next, Figure 2 plots the effects of positive unit standard deviation housing preference shocks, which occur in low and high house price states, in the baseline model and in the LTV model. The house price states are simulated by lowering or raising the housing preference of both households permanently by one standard deviation, before applying

Figure 1: Asymmetric Impulse Responses to Housing Preference Shocks



(a) House Price (pct.) *(b)* Net Borrowing (pct.) *(c)* Consumption (pct.)

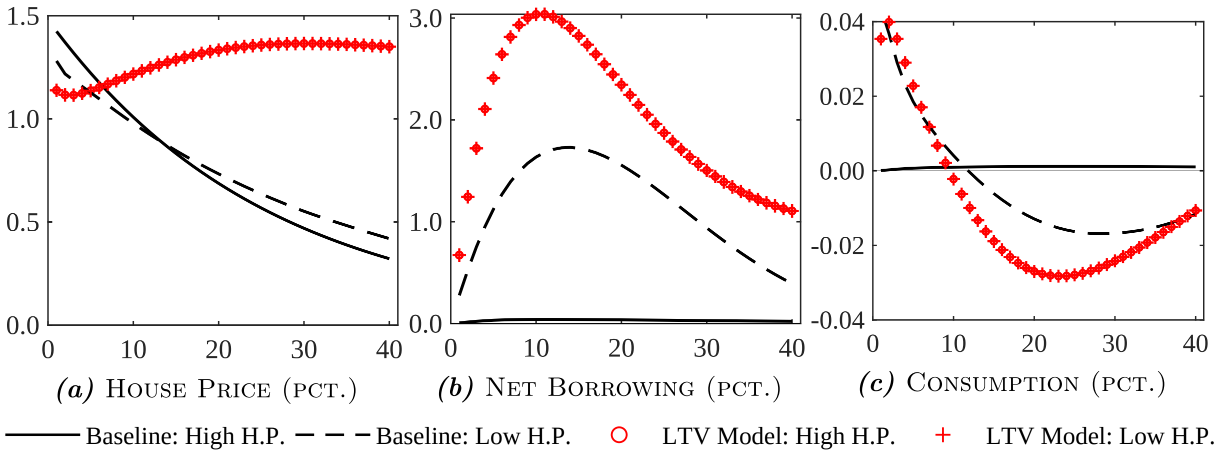
(d) LTV Multiplier (value) *(e)* DTI Multiplier (value)

Note: The models are calibrated to their respective posterior modes. Vertical axes measure deviations from the steady state (Figures 1a-1c) or utility levels (Figures 1d-1e), following positive and negative unit standard deviation shocks.

the shock impulses. In the baseline model, the housing preference shock only expands borrowing and consumption in the low house price state. This is in contrast to the LTV model, where the housing preference shock expands borrowing and consumption in both states. The responses in the baseline model are caused by differences across the business cycle in the constraint that binds. When the house price is relatively low and the LTV constraint binds, this constraint forcefully propagates the house price appreciation onto borrowing and consumption. When the house price is already high and the DTI constraint binds, this amplification channel is switched off, significantly muting the effects of the housing preference shock. The state-dependence is in keeping with Guerrieri and Iacoviello (2017), who show that economic activity is considerably more sensitive to house prices in low house price states than in high house price states, and Prieto et al. (2016), who show the same thing for crisis and non-crisis periods.

The symmetric and state-invariant responses in the LTV model, shown in Figures 1-2, arise, since its LTV constraint does not stop binding following the impulses. As a result, borrowing always moves in tandem with housing wealth, leaving the model completely linear. If the constraint were to stop binding, nonlinearities would arise, but they would,

Figure 2: State-Dependent Impulse Responses to Housing Preference Shocks



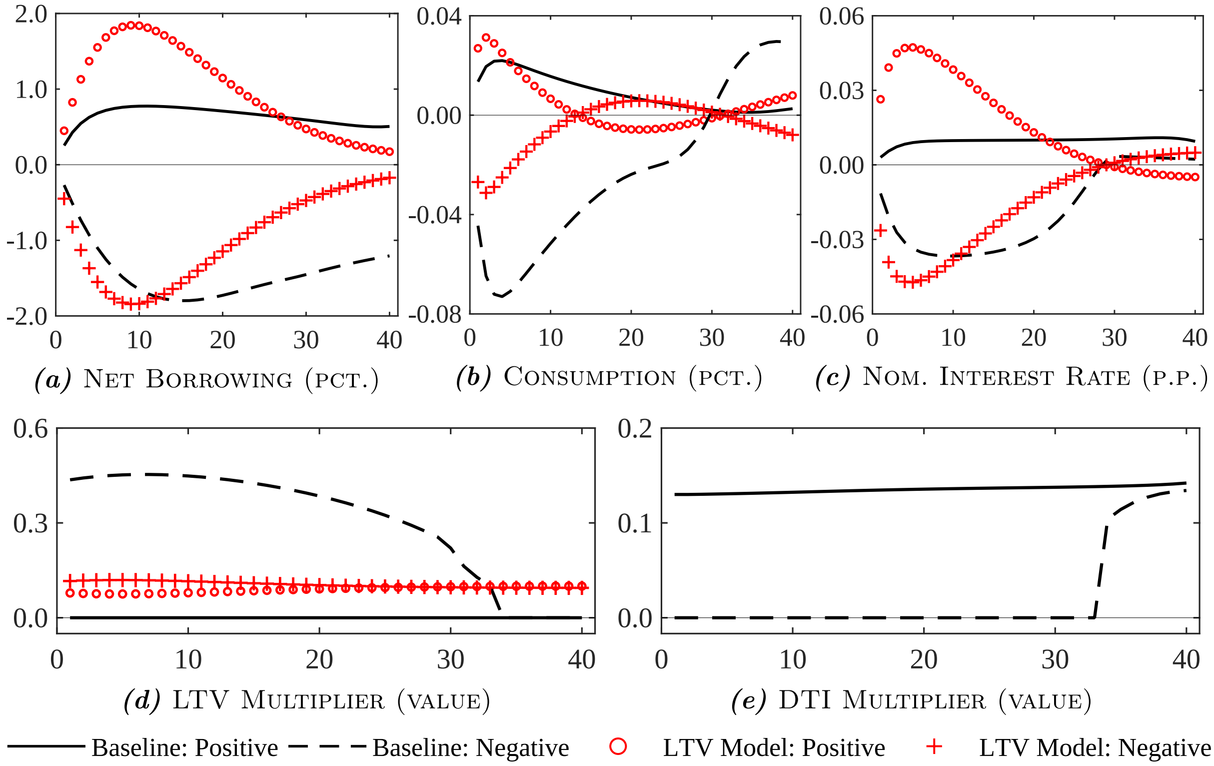
Note: The models are calibrated to their respective posterior modes. The housing preference of both households is permanently one standard deviation below (above) its steady-state level in the low (high) house price state in the absence of the housing preference shocks. Vertical axes measure deviations from these house price states that are caused by the housing preference shocks.

in general, be smaller than in the baseline model. The differences between the two models suggest that frameworks with only an LTV constraint misidentify the propagation from lone housing preference shocks.

5.2 Responses to Credit Shocks

Figure 3 now plots the effects of unit standard deviation positive and negative credit shocks, in the baseline model and in the LTV model. A positive shock causes borrowing and consumption to increase, while a negative shock causes borrowing and consumption to fall, in both models. However, the size of the responses is highly asymmetric to the sign of the shock in the baseline model and completely symmetric in the LTV model. More precisely, in the baseline model, borrowing and consumption move over three times more when a negative shock occurs, as compared to a positive one, measured at the peak of the responses. This degree of asymmetry is commensurate to Barnichon et al. (2017), who show that the effects of adverse bond premium shocks are four times larger than the effects of favorable shocks. Moreover, the asymmetry is consistent with Kuttner and Shim (2016), who find significant negative effects of LTV and DTI tightenings on household credit and insignificant positive effects of relaxations, using a sample of 57 economies across 1980-2012. The asymmetries in the baseline model again result from differences in the constraint that binds. Following the positive shock, consumption and housing demand rise, along with house prices and inflation. However, the ensuing rise in the interest rate tightens the DTI constraint, thus moderating the increase in credit and

Figure 3: Asymmetric Impulse Responses to Credit Shocks



(a) Net Borrowing (pct.) ***(b)*** Consumption (pct.) ***(c)*** Nom. Interest Rate (p.p.)

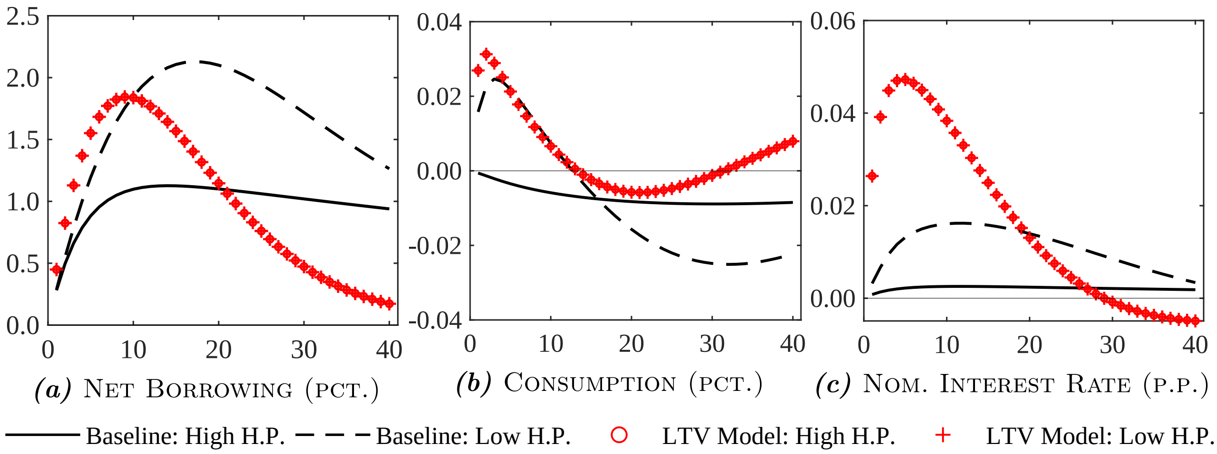
(d) LTV Multiplier (value) ***(e)*** DTI Multiplier (value)

Note: The models are calibrated to their respective posterior modes. Vertical axes measure deviations from the steady state (Figures 3a-3c) or utility levels (Figures 3d-3e), following positive and negative unit standard deviation shocks.

consumption. Following the negative shock, the impatient household is conversely forced to delever, leading it to cut consumption and housing demand. This latter response and the associated drop in house prices tighten the LTV constraint, and amplify the contraction in credit and consumption.

Finally, Figure 4 plots the effects of positive unit standard deviation credit shocks, which occur in low and high house price states, in the baseline model and the LTV model. The house price states are again generated by permanent housing preference shocks. In the baseline model, the responses are state-dependent, with the sign of the consumption response varying between states. Once again, these baseline responses are qualitatively comparable to Barnichon et al. (2017), who find that favorable bond premium shocks have positive effects on output in contractions and no effects in expansions. These responses again contradict the LTV model, in which borrowing and consumption expand by the same amount between states. The state-dependent responses are caused by differences, across the house price cycle, in the constraint that binds. A positive credit shock always increases consumption, inflation, and thus leads the central bank to hike the interest rate. Furthermore, the impatient household always increases its housing demand. When the

Figure 4: State-Dependent Impulse Responses to Credit Shocks



(a) Net Borrowing (pct.) *(b)* Consumption (pct.) *(c)* Nom. Interest Rate (p.p.)

Note: The models are calibrated to their respective posterior modes. The housing preference of both households is permanently one standard deviation below (above) its steady-state level in the low (high) house price state. Vertical axes measure deviations from these house price states that are caused by the credit shocks.

house price is relatively low and the LTV constraint binds, the concurrent house price appreciation amplifies the leveraging process, leading to a further increase in aggregate consumption. By contrast, when the house price is high and the DTI constraint binds, the higher interest rate curbs the increase in borrowing and consumption of the impatient household to the extent that aggregate consumption falls.

As for the LTV model, we again observe symmetric and state-invariant responses, due to the LTV constraint not becoming slack.

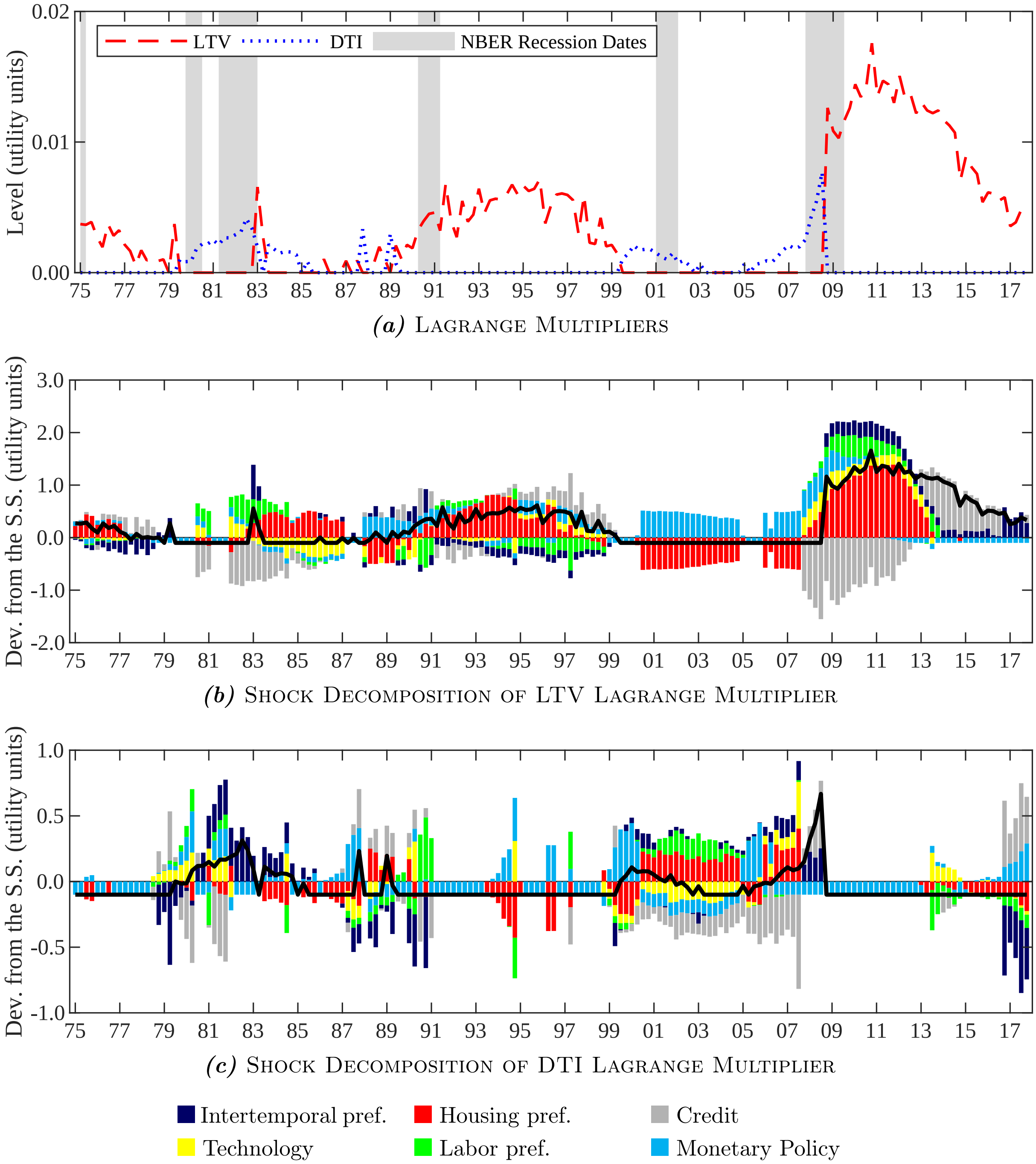
6 The Historical Evolution in Credit Conditions

This section gives a historical account of the evolution in credit conditions. The first subsection focuses on when each credit constraint restricted mortgage borrowing, and the circumstances that led them to do so. The second subsection zooms in on the importance of credit shocks in exogenously shifting LTV and DTI limits.

6.1 LTV vs. DTI Constraints

Figure 5a superimposes the smoothed posterior Lagrange multipliers of the two credit constraints onto shaded NBER recession date areas. The LTV constraint binds when $\lambda_{LTV} > 0$, while the DTI constraint binds when $\lambda_{DTI} > 0$. Figures 5b-5c plot the histori-

Figure 5: Smoothed Posterior Variables



(a) Lagrange Multipliers

(b) Shock Decomposition of LTV Lagrange Multiplier

(c) Shock Decomposition of DTI Lagrange Multiplier

Note: The decomposition is performed at the baseline posterior mode. Each bar indicates the contribution of a given shock to a certain variable. The shocks were marginalized in the following order: (1) housing preference, (2) labor-augmenting technology, (3) monetary policy, (4) labor preference, (5) credit, and (6) intertemporal preference. The results are robust to alternative orderings.

cal shock decomposition of the Lagrange multipliers in deviations from the steady state.[20] At least one Lagrange multiplier is positive through most of the 1975-2017 period. Borrowers have thus been credit constrained through most of the considered timespan. The

[20]The steady-state values of the Lagrange multipliers are positive and identical, since both constraints are binding in the steady state.

LTV constraint often binds during and after recessions, and the DTI constraint mostly binds in expansions. This pattern largely reflects that house prices are more volatile than personal incomes, so that, in recessions, the LTV constraint is tightened more than the DTI constraint. This latter point is accentuated by a negative skewness in the house price growth rate, signifying that, once house prices have fallen, they do not rise quickly again.[21] Lastly, the pattern is also due to countercyclical monetary policy, which, *ceteris paribus*, relaxes the DTI constraint in recessions and vice versa in expansions.

In the end-1970s, the oil crises and the resulting stagflation depressed the real house price to the extent that the LTV constraint was binding. Starting from 1980, the DTI constraint became binding, partly as the tight monetary policy of Paul Volcker dramatically increased interest payments, and partly as low productivity growth, poor employment prospects, and depressed consumer sentiments (negative intertemporal preference shocks) curtailed goods demand and cut incomes. Eventually, however, from around 1983, the DTI constraint was gradually relaxed. This relaxation broadly stemmed from the mid-1980s boom and the onset of the Great Moderation, which led to economic optimism (antecedent negative intertemporal preference shocks disappearing) and lower mortgage rates, in addition to increased productivity growth. As a result, both constraints ended up periodically not binding in 1985-1986. Thus, the U.S. entered the first period in recent history where mortgage issuance was determined by the loan demand of the borrowers, rather than by credit restrictions. Later on, from 1989 and through the early-1990s recession, the LTV constraint again started to lastingly bind, as mortgage rates were hiked, house prices fell, and credit limits were tightened. Then, from 1999 and into the mid-2000s economic boom, the DTI constraint became binding. Initially, a more hawkish monetary policy and weak employment opportunities increased interest payments and lowered incomes, while a gradual house price growth simultaneously relaxed the LTV constraint. From 2003, however, the U.S. would enter the second period where mortgage issuance was demand-determined, as booming productivity growth, along with lax credit limits and a dovish monetary policy, also caused the DTI constraint to unbind. Later, from 2005, the DTI constraint would again bind, due to a dwindling wage and house price growth, in addition to depressed consumer sentiments. With the onset of the Great Recession, the LTV constraint started to bind, and continued doing so for the remaining part of the sample, as house prices plummeted and credit conditions gradually deteriorated.

The shock decomposition echoes the result of Guerrieri and Iacoviello (2017) that the

[21] The volatilities of the detrended house price and personal income series are 0.091 and 0.019. The skewness of the growth rate of the detrended house price series is -0.88.

LTV constraint was slack in 1999-2007, due to soaring house prices. However, in contrast to their findings, the decomposition also shows that this did not imply that homeowners were free to borrow. Instead, they remained constrained by debt service requirements, with the exception of 2003-2004.

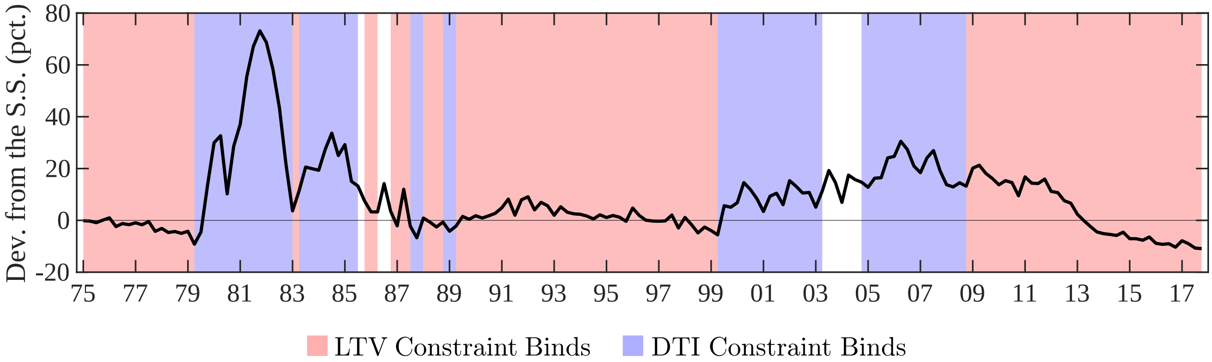
6.2 Credit Limit Cycles

This subsection focuses on how historical events have shifted LTV and DTI limits exogenously. Figure 6 superimposes the smoothed posterior credit shock ($s_{C,t}$) onto shaded areas indicating when each credit constraint has been binding. The U.S. economy has undergone two credit boom-busts in the past 43 years.

The first credit cycle started in the early-1980s. Credit limits were raised 53 pct. above their steady-state levels, on average across 1981-1982. This implies that the binding DTI limit was raised from its steady-state limit of 28 pct. before taxes in 1979 to 43 pct. This relaxation likely resulted from the first major financial deregulation since the Great Depression. The Depository Institutions Deregulation and Monetary Control Act of 1980 and the Garn-St. Germain Depository Institutions Act of 1982 deregulated and increased the competition between banks and thrift institutions, according to Campbell and Hercowitz (2009). In addition, state deregulation allowed banks to expand their branch networks within and between states, further increasing bank competition, as emphasized by Mian et al. (2017). Due to these changes in legislation, greater access to alternative borrowing instruments (e.g., adjustable-rate loans) reduced effective down payments and allowed households to delay repayment through cash-out refinancing. This process continued until the Black Monday Stock Market Crash of 1987 and the Savings and Loan Crisis, after which credit limits returned to their steady-state levels.

The second credit cycle started in 1999. This time, credit limits were raised 26 pct. above their steady-state levels, by 2006. This implies that the DTI limit, which was binding in 1999-2002 and 2005-2008, was raised to 35 pct. These observations are consistent with Justiniano et al. (2017, 2018), who find that looser LTV limits cannot explain the recent credit boom, and that the fraction of borrowers presenting full income documentation dropped substantially in 2000-2007. Justiniano et al. (2018) also argue that it was an increase in credit supply which caused the surge in mortgage credit. They mention the pooling and tranching of mortgage bonds into mortgage-backed securities and the global savings influx into the U.S. mortgage market following the late-1990s Asian financial crisis. These discoveries are consistent with my result that the DTI limit was relaxed, since it

Figure 6: Smoothed Credit Shock



Note: The historical credit shock is identified at the baseline posterior mode. At a given point in time, the shock is identified through the constraint that allows for the lowest amount of borrowing, as discussed in Subsection 4.1.

suggests that the increase in credit supply translated into a relaxation of the DTI limit.[22] Later on, from the eruption of the Subprime Crisis in 2007 and into the ensuing recession, credit limits were gradually tightened, and eventually fell below their steady-state levels. The absence of a rapid tightening around 2009 possibly reflects the introduction of the Home Affordable Refinance Program and the Home Affordable Modification Program in March 2009. These programs lowered the debt services for homeowners who had high LTV ratios or were in delinquency, via an exemption from mortgage insurance, interest rate and principal reductions, forbearance, and term extensions. Waves of mortgage defaults were thereby avoided, according to Agarwal, Amromin, Chomsisengphet, Landvoigt, Piskorski, Seru, and Yao (2015) and Agarwal, Amromin, Ben-David, Chomsisengphet, Piskorski, and Seru (2017), allowing for a more gradual subsequent deleveraging.

The overall validity of the shock estimates in Figure 6 is corroborated by Prieto et al. (2016), who also find traces of two credit cycles, using a VAR approach.

7 Macroprudential Policy Implications

Recent studies show that credit expansions predict subsequent banking and housing market crises with severe economic consequences (e.g., Mian and Sufi, 2009; Schularick and Taylor, 2012; Baron and Xiong, 2017). Motivated by this, I will now examine how mortgage credit would historically have evolved if LTV and DTI limits had responded countercyclically to deviations of credit from its long-run trend. Figure 7a plots the reaction

[22]Credit constraints are, in the model, the only wedges between the credit supply of the patient household and the credit demand of the impatient household. Hence, the credit shock, in a reduced form, captures all exogenous shocks to both credit supply and credit demand.

of borrowing to the estimated sequence of shocks under four different macroprudential regimes. In the first regime, there is no active macroprudential policy, so the credit limits are only shifted by the credit shock, as in the estimated model. Thus, the observed variables in the model, by construction, match the data. In the three other regimes, the following policies apply: a countercyclical LTV limit, a countercyclical DTI limit, and countercyclical LTV and DTI limits. Figures 7b-7c plot the credit limits implied by the policies. I introduce the countercyclical debt limits by augmenting the credit constraints in (5) and (6) with two macroprudential stabilizers:

$$b'_t \leq (1-\rho)\frac{b'_{t-1}}{1+\pi_t} + \rho\xi_{LTV} s_{C,t} s_{LTV,t} \mathbb{E}_t\{(1+\pi_{t+1})q_{t+1}h'_t\},$$
$$b'_t \leq (1-\rho)\frac{b'_{t-1}}{1+\pi_t} + \rho\xi_{DTI} s_{C,t} s_{DTI,t} \mathbb{E}_t\left\{\frac{(1+\pi_{t+1})w'_{t+1}l'_t}{\sigma+r_t}\right\},$$

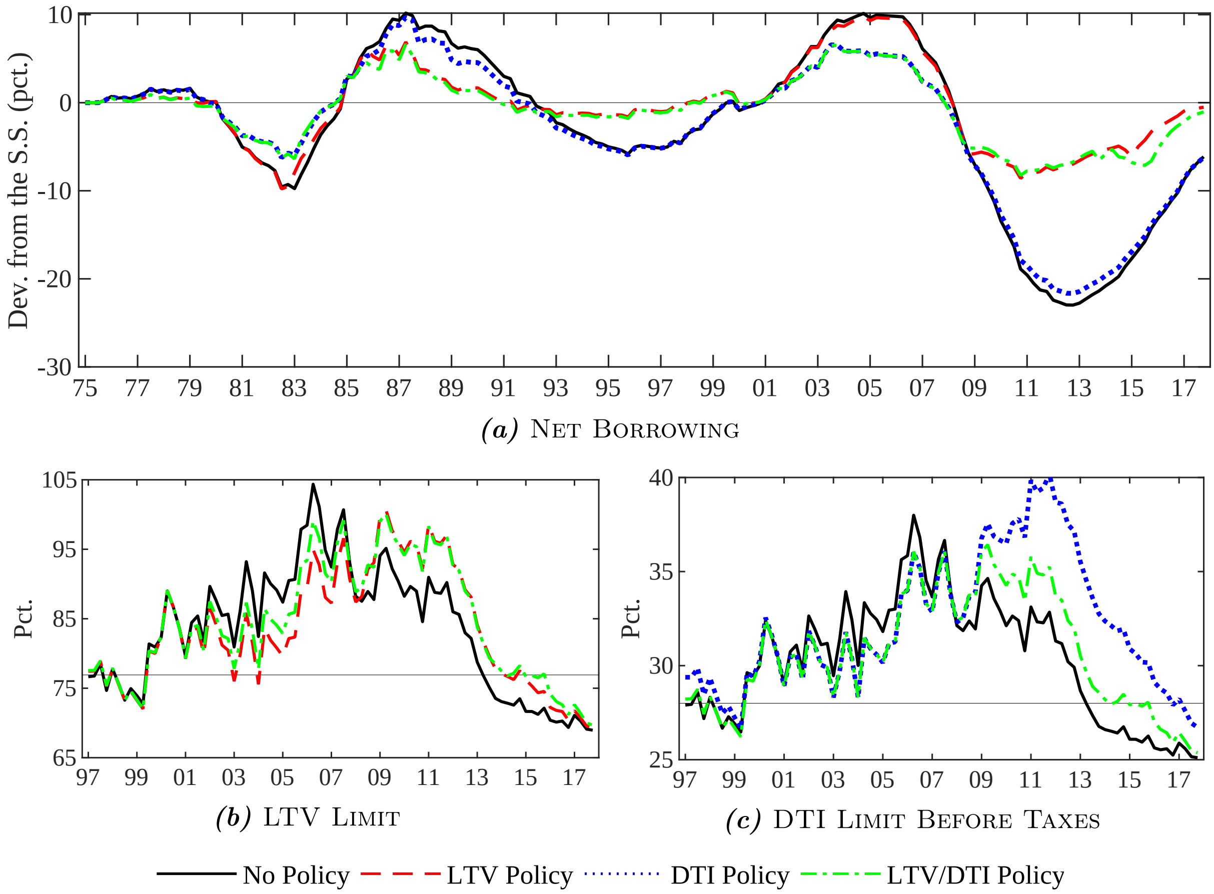
where $s_{LTV,t}$ is an LTV stabilizer, and $s_{DTI,t}$ is a DTI stabilizer. As the simplest imaginable policy rule to stabilize credit, the stabilizers respond negatively with a unit elasticity to deviations of borrowing from its steady-state level:

$$\log s_{LTV,t} = -(\log b'_t - \log b') \qquad \text{and} \qquad \log s_{DTI,t} = -(\log b'_t - \log b'), \qquad (15)$$

where b' denotes steady-state net borrowing. Numerous other functional forms than the ones in (15) are, in principle, conceivable to capture countercyclical macroprudential policy. In the Online Appendix, I try a rule that also has some persistence, as well as a rule that responds negatively to the quarterly year-on-year growth in borrowing. The policy considerations provided in the text below also apply in these alternative cases.

The historical standard deviation of borrowing is 8.9 pct. The LTV policy reduces this standard deviation to 4.7 pct., i.e., by 48 pct. relative to the historical benchmark. It does so mostly by mitigating the adverse effects of house price slumps on credit availability when the LTV constraint is binding. For instance, following the Great Recession, the LTV limit is, on average, 6.6 p.p. higher under (15) than in the benchmark simulation, which considerably limits the credit bust. The flip-side of this result is that the LTV policy often cannot curb credit expansions during house price booms, since the LTV constraint is slack there. Thus, even though the LTV limit, on average across 2003-2006, is 7.7 p.p. lower with the LTV policy, as compared to the benchmark simulation, macroprudential policy does not prevent the mid-2000s boom in credit. The DTI policy is, by contrast, able to curb credit during house price booms by enforcing stricter DTI limits. In the above simulations, this policy reduces the standard deviation of borrowing to 7.8 pct.,

Figure 7: Alternative Macroprudential Regimes



(a) Net Borrowing

(b) LTV Limit

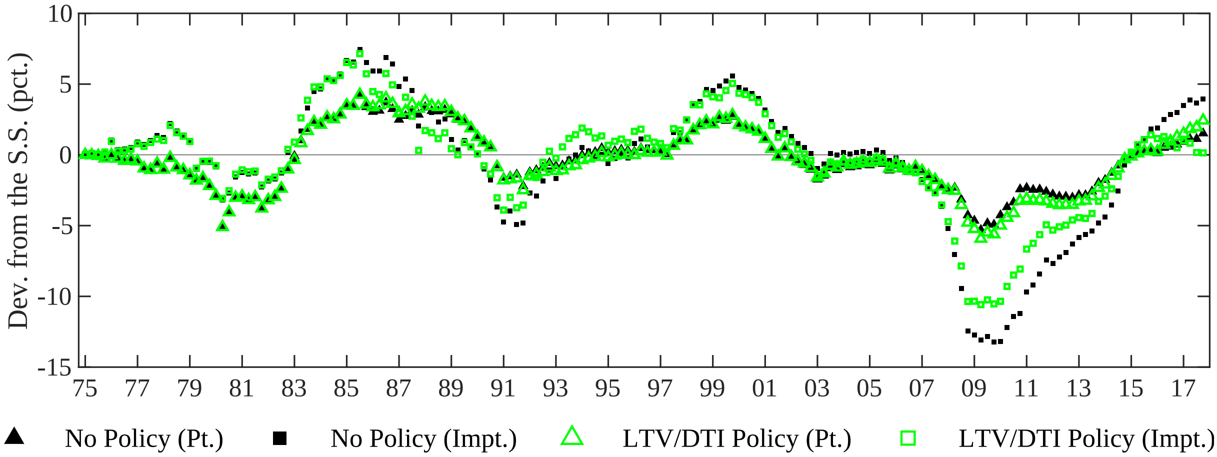
(c) DTI Limit Before Taxes

Note: The simulations are performed at the baseline posterior mode. Figures 7b-7c plot $\xi_{LTV} s_{C,t} s_{LTV,t}$ and $\xi_{DTI} s_{C,t} s_{DTI,t}$, with horizontal lines indicating ξ_{LTV} and ξ_{DTI}.

i.e., by 12 pct. relative to the benchmark. In this way, while the DTI policy has a smaller quantitative effect on mortgage borrowing than the LTV policy, the fact that it curtails credit expansions makes it particularly useful. Zooming in on the mid-2000s credit boom, the DTI policy dictates that the DTI limit should have been 1.8 p.p. lower, again on average across 2003-2006. This would roughly have halved the expansion in credit from 1999 to 2006. The lowest volatility in borrowing is reached by combining the LTV and DTI policies. This reduces the standard deviation of borrowing to 3.8 pct., i.e., by 58 pct. relative to the benchmark. In this case, macroprudential policy takes into account that the effective policy tool changes over the business cycle, mostly with a DTI tool in expansions and an LTV tool in contractions. The implementation of such a policy does not require that the policymaker in real time knows when either constraint binds. Rather, it merely presupposes that the policymaker conducts a two-stringed policy entailing that *both* LTV and DTI limits respond countercyclically to credit growth.

The underlying objective of a macroprudential policy that stabilizes credit fluctuations

Figure 8: Alternative Macroprudential Regimes: Household Consumption



Note: The simulations are performed at the baseline posterior mode.

is arguably to minimize the probability of large drops in consumption. For this reason, I now compute a measure of consumption-at-risk in the no-policy scenario and under the two-stringed policy. I define consumption-at-risk as the maximum negative deviation of consumption from its steady-state level occurring within the top 95 pct. of the distribution of consumption observations. Such a definition is congruous with the value-at-risk measure commonly used within finance and the output-at-risk measure of Nicolò and Lucchetta (2013) and Jensen et al. (2018). Historical consumption-at-risk is 3.7 pct. of steady-state consumption for the patient household and 11.1 pct. for the impatient household. Under the two-stringed policy, consumption-at-risk increases to 4.1 pct. for the patient household, and decreases to 8.1 pct. for the impatient household. Figure 8 sheds some light on these changes by plotting the paths of household consumption in the two scenarios. Under the active policy, deleveraging in busts is significantly curtailed, as was previously shown by Figure 7. This dampens the redistribution of funds from the impatient to the patient household in these episodes, leaving borrowers able to consume more and lenders necessitated to consume less. As a result, the left tail of the consumption distribution is lower for the patient household and higher for the impatient household. The two-stringed policy thus redistributes consumption *risk* from the impatient household to the patient household, while roughly maintaining average household consumption levels.[23] Aggregate consumption and output are roughly unaffected by the policy, because the responses of borrowers and lenders "wash out in the aggregate", as coined by Justiniano et al. (2015).

The benefits of a two-stringed macroprudential policy are not well-documented within

[23]Consumption is 0.06 pct. lower in the patient household and 0.21 pct. higher in the impatient household, on average across 1975-2017.

economics. With the exception of Greenwald (2018), who focuses on policy counterfactuals around the Great Recession, there is little theoretical guidance on how to combine the two limits, as also noted by Jácome and Mitra (2015). Instead, the existing literature focuses on stabilization through countercyclical LTV limits.[24] The ineffectiveness of LTV limits in expansions and DTI limits in contractions underscores the necessity of models with both constraints in order to determine the optimal implementation of macroprudential policy.

8 Evidence on State-Dependent Credit Origination

The credit constraints predict that house price (income) growth shall not allow homeowners to take on additional debt if incomes (house prices) are below a certain threshold. In this section, I test this prediction by estimating the elasticities of mortgage loan origination with respect to house prices and personal incomes, importantly after partitioning the house price (income) elasticity based on the detrended income (house price) level.

8.1 Data

The dataset contains data on the amount of originated mortgage loans, house prices, and personal incomes, across U.S. counties in all 50 states and the District of Columbia at an annual longitudinal frequency. The data on originated mortgage loans is from the Home Mortgage Disclosure Act (HMDA) dataset of the U.S. Consumer Financial Protection Bureau. This dataset is also used by Mondragon (2018) and Gilchrist, Siemer, and Zakrajšek (2018) to study the effects of credit supply shocks to households. I consider originated mortgage loans that are secured by a first or subordinate lien in an owner-occupied principal dwelling, consistent with the theoretical measure of credit in the DSGE model. The results are robust to broader credit measures, such as total originated mortgage loans. A limitation of the HMDA data is its inability to exactly identify equity extraction. However, as shown by Mondragon (2018), the behavior of aggregate mortgage origination is similar to that of aggregate equity extraction. Coverage of the online HMDA dataset starts in 2007. The house price data is from the All-Transactions House Price Index of the U.S. Federal Housing Finance Agency, and is available from 1975. The income and population data is from the Personal Income, Population, Per Capita Personal Income (CA1)

[24] See, e.g., the Committee on the Global Financial System (2010), the IMF (2011), Lambertini, Mendicino, and Teresa Punzi (2013), and Jensen et al. (2018). In addition to these contributions, Gelain, Lansing, and Mendicino (2013) show that loan-to-income constraints are more effective than LTV constraints at stabilizing mortgage borrowing in both booms and busts, using a linear model with a single always binding constraint.

Table 3: SUMMARY STATISTICS OF GROWTH RATES (2008-2016)

Counts, Means, and Standard Deviations by Year							
Variable	Obs.	Loan Origination		House Price		Disp. Personal Income	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
2008	2643	-0.339	0.258	0.043	0.038	0.043	0.038
2009	2656	0.193	0.216	-0.030	0.038	-0.030	0.038
2010	2657	-0.118	0.128	0.030	0.026	0.030	0.026
2011	2667	-0.092	0.108	0.058	0.028	0.058	0.028
2012	2666	0.345	0.140	0.046	0.033	0.046	0.033
2013	2663	-0.085	0.120	0.013	0.025	0.013	0.025
2014	2664	-0.297	0.124	0.050	0.026	0.050	0.026
2015	2649	0.253	0.104	0.048	0.026	0.048	0.026
2016	2631	0.152	0.086	0.023	0.021	0.023	0.021
All years	23896	0.003	0.275	0.031	0.039	0.031	0.039

Correlations across all Years			
	Loan Origination	House Price	Disp. Personal Income
Loan Origination	1.00		
House Price	0.22	1.00	
Disp. Personal Income	-0.06	0.31	1.00

Note: The observations are weighted by the county population in a given year.

table in the Regional Economic Accounts of the U.S. Bureau of Economic Analysis, and is available from 1966. Since I am regressing log-differences, which entails me to lose the first year of observations, the merged sample effectively covers the 2008-2016 timespan. The dataset is unbalanced, since observations on loan originations and house prices are sporadically missing if the transaction volume in a given county and year was insufficient.

Panel 3 reports summary statistics of the data. The dataset contains $23,896$ unique county-year observations on population size and the growth rates of mortgage loan origination, house prices, and incomes. Across the years, there is a substantial variation in both the central tendency and the dispersion of the growth rates of mortgage loan origination, house prices, and incomes. Loan origination growth has a positive correlation with house price growth and a tiny negative correlation with income growth, while house price and income growth are themselves positively correlated.

8.2 Identification Strategy

The goal of the analysis is to identify the causal effects of house price growth, income growth, and interactions between house price and income growth on loan origination growth. A challenge to doing this is that house prices and incomes are endogenously determined by each other, along with forces determining home credit. For instance, a favorable credit or productivity shock may increase loan origination, house prices, and incomes without any causal relationship between these variables. In that case, would not only the house price and income elasticities be positively biased, but the interacting effect of house price and income growth would also be positively biased.

In order to overcome the described identification challenge, I rely on an instrumental variable strategy, in combination with a rich set of fixed effects. The instrumental variable strategy uses systematic differences in the sensitivity of local house prices (incomes) to the nationwide house price (income) cycle to instrument house price (income) variation. This strategy is inspired by the commonly used "Bartik instrument", which in labor economics involves using nationwide employment to instrument local labor demand (e.g., Blanchard and Katz, 1992). Guren et al. (2018) similarly use regional house price cycles to instrument local house prices, in their study of the effect of local house prices on retail employment. For each county i, I perform the following first-stage time series estimations:

$$\Delta \log hp_{i,t} = \gamma_{i,hp} + \beta_{i,hp} \Delta \log hp_{-i,t} + v_{i,t,hp}, \tag{16}$$

$$\Delta \log inc_{i,t} = \gamma_{i,inc} + \beta_{i,inc} \Delta \log inc_{-i,t} + v_{i,t,inc}, \tag{17}$$

where $\mathbb{E}\{v_{i,t,hp}\} = \mathbb{E}\{v_{i,t,inc}\} = 0$. $\Delta \log hp_{i,t}$ and $\Delta \log inc_{i,t}$ denote the log-change in house prices and personal incomes in county i in year t. Moreover, $\Delta \log hp_{-i,t}$ and $\Delta \log inc_{-i,t}$ denote the log-change in the nationwide house prices and personal incomes in year t after weighing out the contribution of county i to the nationwide indices.[25] I use the predicted values from (16) and (17) as instruments for the growth rates of house prices and personal incomes across counties.

In addition to instrumenting house price and income growth, I rely on county and state-year fixed effects, in order to control for potential confounders, as in Cloyne et al. (2017). County fixed effects control for fixed differences in the propensity to originate loans, while state-year fixed effects control for time-varying state shocks to loan origination. Identification hence arises from time-varying differences in credit originations across counties that cannot be explained by the average originations within a county's state. With these controls, e.g., state fiscal or credit shocks will not threaten identification, as they will be captured by the state-year effects.

Under the following two assumptions, a regression of the house price and income in-

[25] This weighing-out is meant to remove the mechanical contribution of county i to the nationwide indices. I use the county population shares as weights. For all practical purposes, the transformed indices are identical to the nationwide indices, as the population shares of even large counties are tiny. The results are thereupon robust to simply using the nationwide indices as instruments.

struments on credit originations identifies the causal effects of local house price and income growth on local credit originations. First, the nationwide house price and income cycles must yield predictive power over local house prices and incomes, so that the instruments are relevant.[26] Second, the nationwide house price and income cycles must not be influenced by *local* shocks to credit originations conditional on the fixed effects, implying that the instruments are exogenous.

8.3 Results

The baseline second-stage regression specification is given by

$$\begin{aligned}\Delta \log d_{i,t} = \delta_i + \zeta_{j,t} + \beta_{hp}\Delta \widehat{\log hp}_{i,t-1} + \beta_{inc}\Delta \widehat{\log inc}_{i,t-1} \\ + \tilde{\beta}_{hp}\mathcal{I}^{inc}_{i,t}\Delta \widehat{\log hp}_{i,t-1} + \tilde{\beta}_{inc}\mathcal{I}^{hp}_{i,t}\Delta \widehat{\log inc}_{i,t-1} + u_{i,t},\end{aligned} \tag{18}$$

where $\mathbb{E}\{u_{i,t}\} = 0$. $\Delta \log d_{i,t}$ denotes the log-change in the amount of originated mortgage loans in county i in year t. Moreover, δ_i denotes the county fixed effect in county i, and $\zeta_{j,t}$ denotes the state-year fixed effect in state j in year t. Finally, $\Delta \widehat{\log hp}_{i,t}$ and $\Delta \widehat{\log inc}_{i,t}$ denote the predicted values from (16) and (17). (18) uses lagged house price and incomes variables, so as to prevent any confounding shocks that have not already been instrumented out or are captured by the fixed effects from biasing the results, as in Guerrieri and Iacoviello (2017). The results below are qualitatively robust to a number of alternative econometric assumptions, such as not using the Bartik-instruments, as well as using current house price and income variables. They are also robust to omitting the county fixed effects or replacing the state-year fixed effects with year fixed effects.

In my baseline specification, I let $\mathcal{I}^{hp}_{i,t}$ and $\mathcal{I}^{inc}_{i,t}$ denote level indicators for house prices and personal incomes in county i in year t. The indicators take the value "1" if the log-level of their input variable is above its long-run county-specific time trend, and the value "0" if it is below:

$$\mathcal{I}^{hp}_{i,t} \equiv \begin{cases} 0 & \text{if } \log hp_{i,t} \leq \overline{\log hp_{i,t}} \\ 1 & \text{else,} \end{cases} \qquad \mathcal{I}^{inc}_{i,t} \equiv \begin{cases} 0 & \text{if } \log inc_{i,t} \leq \overline{\log inc_{i,t}} \\ 1 & \text{else,} \end{cases} \tag{19}$$

where $\overline{\log hp_{i,t}}$ and $\overline{\log inc_{i,t}}$ denote separately estimated county-specific log-linear time trends. With this specification, the level indicators partition the house price and income

[26] In (16)-(17), the restrictions $\beta_{i,hp} = 0$ or $\beta_{i,inc} = 0$ are rejected at a one percent confidence level in 84 pct. of all counties for house prices and 97 pct. for incomes, indicating that the instruments are broadly relevant. The average t-statistic is 5.28 for house prices and 9.69 for incomes across all counties.

Table 4: DETERMINANTS OF CREDIT ORIGINATION: LEVEL SHIFTERS (2008-2016)

	$\Delta \log b_t$					
Sample Period for Trends	N/A	1975-2016		2000-2016		N/A
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log \widehat{hp}_{i,t-1}$	0.410***	0.392***	0.383***	0.135		0.292**
	(0.108)	(0.107)	(0.107)	(0.124)		(0.120)
$\Delta \log \widehat{inc}_{i,t-1}$	-0.159	-0.143		-0.0509		0.0871
	(0.253)	(0.251)		(0.251)		(0.291)
$\mathcal{I}^{inc}_{i,t} \Delta \log \widehat{hp}_{i,t-1}$		0.804***	0.818***	0.670***	0.687***	
		(0.285)	(0.284)	(0.108)	(0.102)	
$\mathcal{I}^{hp}_{i,t} \Delta \log \widehat{inc}_{i,t-1}$		0.415**	0.406**	0.419***	0.425***	
		(0.204)	(0.205)	(0.109)	(0.107)	
$\Delta \log \widehat{hp}_{i,t-1} \Delta \log \widehat{inc}_{i,t-1}$						4.998**
						(2.129)
Observations	23896	23896	23896	23896	23896	23896
Adjusted R^2	0.843	0.844	0.844	0.845	0.845	0.844

Note: County and state-year fixed effects are always included. The observations are weighted by the county population in a given year. Standard errors are clustered at the county level, and reported in parentheses. ***, **, and * indicate statistical significance at 1 pct., 5 pct., and 10 pct. confidence levels.

elasticities in (18) based on the prevailing detrended income and house price levels. The house price elasticity given that incomes are low is β_{hp}, while the house price elasticity given that incomes are high is $\beta_{hp} + \tilde{\beta}_{hp}$. Consistently, the income elasticity given that house prices are low is β_{inc}, and the income elasticity given that house prices are high is $\beta_{inc} + \tilde{\beta}_{inc}$. More forces than just multiple credit constraints could, in principle, cause house price and income growth to amplify each other.[27] Nonetheless, this partitioning does provide a test of whether the state-dependent credit dynamics imposed by the LTV and DTI constraints are present in the data. If homeowners must fulfill a DTI requirement and incomes are currently low, then the house price elasticity should likely be lower than if incomes are high. Likewise, if homeowners must fulfill an LTV requirement and house prices are currently low, then the income elasticity should likely be lower than if house prices are high.

Table 4 reports the ordinary least squares estimates of the second-stage regression in (18) under (19). In specification 1, I do not allow for state-dependent elasticities, in which case only the house price elasticity is significantly positive. In specification 2, I

[27]For instance, income growth might cause homeowners to be more optimistic about their personal finances, leading them to borrow more as house price growth relaxes LTV constraints.

partition the elasticities as explained above, based on trends that were estimated over the 1975-2016 period, consistent with the DSGE sample. While the point estimates of the unconditional elasticities do not change to any considerable extent, the estimates of both newly introduced conditional elasticities are significantly positive and, as compared to the unconditional elasticities, sizable. In particular, in the parsimonious specification 3, the house price elasticity is three times greater when incomes are high (1.20) than when they are low (0.38), while the income elasticity (0.41) is only positive when house prices are high. In specifications 4-5, I rerun the estimation, using trends that were computed over the shorter 2000-2016 period. These trends plausibly better capture the true trends in house price and income growth around the time that is covered by the full panel sample (2008-2016), since the trend growth rates are unlikely to have been constant over the entire 1975-2016 period.[28] The previous results on state-dependent elasticities now appear even more distinctly. In specification 4, both unconditional elasticities shrink markedly towards zero, and become statistically insignificant, so that only house price growth conditional on high incomes and income growth conditional on high house prices increase loan origination. I arrive at the parsimonious specification 5 after sequentially having restricted the most insignificant term out and reestimated the model. Here, the house price elasticity is 0.69 if incomes are high, and the income elasticity is 0.43 if house prices are high. Lastly, in specification 6, I add a continuous interaction term. If positive house price and income growth amplify each other, then this might also show up as a continuous interaction, something that I find to be the case.

The LTV and DTI constraints tie the borrowing ability of homeowners to the *levels* of their housing wealth and incomes. Nevertheless, if homeowners must fulfill such constraints, then we should also expect that low *growth rates* of house prices (incomes) eventually lead homeowners to become LTV (DTI) constrained. If this is true and the growth rate of incomes (house prices) was low in the previous year, then the house price (income) elasticity should likely be lower than if the growth rate was high. I now test this prediction by letting $\mathcal{I}_{i,t}^{hp}$ and $\mathcal{I}_{i,t}^{inc}$ denote *growth* indicators for house prices and personal incomes in county i in year t. The indicators concretely take the value "1" if the growth rate of their input variable was above a certain threshold in the previous year, and the

[28]For instance, shifts in total factor productivity growth, relative sectoral productivity levels, labor market participation, or migration patterns could affect the trend growth rates.

value "0" if it fell below:

$$\mathcal{I}_{i,t}^{hp} \equiv \begin{cases} 0 & \text{if } \Delta \log hp_{i,t-1} \leq \kappa_{hp} \\ 1 & \text{else,} \end{cases} \qquad \mathcal{I}_{i,t}^{inc} \equiv \begin{cases} 0 & \text{if } \Delta \log inc_{i,t-1} \leq \kappa_{inc} \\ 1 & \text{else,} \end{cases} \tag{20}$$

where $\kappa_{hp} \in \mathbb{R}$ and $\kappa_{inc} \in \mathbb{R}$ measure the growth thresholds. Under this specification, the growth indicators partition the house price and income elasticities based on the growth rates of incomes and house prices in the previous year. It is not *a priori* obvious what value the growth thresholds should take, i.e., what defines "low" growth rates of house prices and incomes. I therefore allow the data to choose the thresholds by simulating these in the following way. First, I divide the observations of house price and income growth rates, respectively, into ten percentiles, thus obtaining nine quantiles as potential thresholds for each variable. I then estimate (18) under (20), tentatively trying each of the $9 \cdot 9 = 81$ possible quantile pair combinations. As the final threshold, I choose the quantile pair that minimizes the root mean square error of the regression. This combination is $(\kappa_{hp}, \kappa_{inc}) = (0.0269, 0.0131)$, which is the 60 pct. house price growth quantile and the 20 pct. income growth quantile.

Table 5 reports the ordinary least squares estimates of the second-stage regression in (18) under (20), with $(\kappa_{hp}, \kappa_{inc}) = (0.0269, 0.0131)$. I again obtain the parsimonious specification 3 by sequentially restricting insignificant terms out and reestimating the model. According to this specification, the house price elasticity is only positive if the income growth was above 1.3 pct. in the previous year, and the income elasticity is only positive if the house price growth was above 2.7 pct. in the previous year. Thus, only house price growth conditional on high income growth and income growth conditional on high house price growth increase loan origination. In specifications 4-5, I sequentially test these results on state-dependent elasticities. The results continue to hold. After introducing *either* a conditional house price elasticity *or* a conditional income elasticity, the corresponding unconditional elasticity is insignificant. Furthermore, the newly introduced conditional elasticity is significant with a point estimate similar to the ones in specifications 2-3. Lastly, in specification 6, I check that the statistical significance of the conditional elasticities is not singularly driven by the growth indicators, $\mathcal{I}_{i,t}^{inc}$ and $\mathcal{I}_{i,t}^{hp}$. I find this not to be the case, in that the estimates in front of the growth indicators are largely insignificant, signifying that it is the interactions which drive the significance.

As a final robustness check provided in the Online Appendix, I use the alternative threshold, $(\kappa_{hp}, \kappa_{inc}) = (0, 0)$, where the estimates are partitioned based on whether house

Table 5: Determinants of Credit Origination: Growth Rate Shifters (2008-2016)

	$\Delta \log b_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log \widehat{hp}_{i,t-1}$	0.410***	0.0443		0.116	0.309***	0.0116
	(0.108)	(0.139)		(0.141)	(0.113)	(0.136)
$\Delta \log \widehat{inc}_{i,t-1}$	-0.159	-0.0824		-0.0339	-0.202	-0.136
	(0.253)	(0.278)		(0.270)	(0.260)	(0.291)
$\mathcal{I}^{inc}_{i,t} \Delta \log \widehat{hp}_{i,t-1}$		0.437**	0.451***	0.470***		0.447***
		(0.171)	(0.149)	(0.169)		(0.168)
$\mathcal{I}^{hp}_{i,t} \Delta \log \widehat{inc}_{i,t-1}$		0.423***	0.423***		0.460***	0.462***
		(0.117)	(0.114)		(0.113)	(0.173)
$\mathcal{I}^{inc}_{i,t}$						0.00870*
						(0.00523)
$\mathcal{I}^{hp}_{i,t}$						-0.00257
						(0.00808)
Observations	23896	23896	23896	23896	23896	23896
Adjusted R^2	0.843	0.844	0.844	0.844	0.844	0.844

Note: County and state-year fixed effects are always included. The observations are weighted by the county population in a given year. Standard errors are clustered at the county level, and reported in parentheses. ***, **, and * indicate statistical significance at 1 pct., 5 pct., and 10 pct. confidence levels.

prices and incomes fell or grew in the previous year. I find that the house price elasticity is zero if incomes just fell, and that the income elasticity is zero if house prices just fell. All in all, it emerges that the process through which growth in house prices and incomes leads to growth in mortgage credit is not a linear process. Instead, house prices and incomes discretely amplify each others' effect on credit origination, as would be implied by the presence of multiple credit constraints.

9 Concluding Remarks

Across the business cycle, banks impose both LTV and DTI limits on loan applicants. However, because house prices and mortgage rates are low in recessions and high in expansions, LTV limits tend to dominate in recessions, and DTI limits tend to dominate in expansions. This – until now, unexplored – systematic discrete switching between credit constraints has fundamental implications for macroeconomics and finance. The switching causes a sizable asymmetric and state-dependent variation in the transmission of housing preference and credit shocks onto real activity. Adverse shocks have larger effects than similarly sized favorable shocks, and a given shock has the largest effects in contractions. The switching also implies that the effective macroprudential tool changes over the business cycle. As a consequence, LTV policies should focus on supporting borrowing in contractions, and DTI policies should focus on constraining borrowing in expansions.

Looking ahead, numerous avenues for future research remain within the macro-housing literature. From an empirical micro perspective, existing studies on the housing net worth, household credit, and firm credit channels mainly consider separate variation in determinants of credit, such as house prices or banks' balance sheets. Future avenues include both how multiple determinants interact within one channel and how the three channels themselves interact. From a time series perspective, a better understanding of the nonlinear transmission of house price shocks remains. For instance, a local projection instrumental variable approach would address concerns about both the functional form of the response and endogeneity of house prices. From a macro-theory perspective, a large number of models deliver different predictions for how the housing boom-bust cycle affects real activity; e.g., via credit supply constraints (Justiniano et al., 2018), firm LTV constraints (Liu et al., 2013), and bank runs (Gertler and Kiyotaki, 2015), in addition to household LTV and DTI constraints. While some of these predictions may not be mutually exclusive, further work is needed in order to assess the relative importance of each channel. Lastly, from a heterogeneous agents perspective, an avenue includes a better understanding of the implications of heterogeneity in LTV and DTI constrained individuals, related to, e.g., life-cycle variation in credit restrictions or heterogeneous effects of house price and income drops on housing demand and labor supply or the choice to default.

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Appendix

A Evidence on the DTI Limits of Banks

Table 6 reports the DTI limits that the ten largest U.S. retail banks specify on their websites. All banks that issue mortgage loans require loan applicants to fulfill a DTI requirement contingent on obtaining the loan. The banks either set front-end limits of 28 pct. or back-end limits of 36 pct.[29]

Table 6: DTI Limits of the Ten Largest U.S. Retail Banks

Rank	Name	Domestic Assets (million $)	DTI Limit Front-end	DTI Limit Back-end
1	JPMorgan Chase Bank	1,676,806	28 pct.	36 pct.
2	Wells Fargo Bank	1,662,311	–	36 pct.
3	Bank of America	1,661,832	–	36 pct.
4	Citibank	821,805	–	36 pct.
5	U.S. Bank	442,844	28 pct.	–
6	PNC Bank	364,084	28 pct.	36 pct.
7	TD Bank	294,830	28 pct.	36 pct.
8	Capital One	289,808	–	–
9	Branch Banking and Trust Company	214,817	28 pct.	–
10	SunTrust Bank	199,970	28 pct.	36 pct.

Note: The Online Appendix quotes the specific statements on DTI limits that the banks post on their websites. No DTI limits are available from Capital One, since this bank stopped issuing mortgage loans in 2017. All websites were accessed on September 23, 2018. The banks are ranked by the size of their domestic assets as of March 31, 2018, see Federal Reserve Statistical Release (2018).

B Derivation of the DTI Constraint

This appendix demonstrates that the DTI constraint can be derived as an incentive compatibility constraint imposed by the patient household on the impatient household, and that it is a generalization of the natural borrowing limit in Aiyagari (1994). The derivation is separate from the LTV constraint in the sense that the patient household does not internalize the LTV constraint when imposing the DTI constraint.

The impatient household faces the choice of whether or not to default in period $t+1$ on the borrowing issued to it in period t. Suppose that if the impatient household defaults, the patient household obtains the right to repayment through a perpetual income stream commencing at period $t+1$. The payments in the income stream are based on the amount

[29] The front-end limit only includes debt services on mortgage loans. The back-end limit also includes debt services on other kinds of recurring debt, such as credit card debt, car loans, and student debt.

$\mathbb{E}_t\{(1+\pi_{t+1})w'_{t+1}l'_t\}$, and decrease by the amortization rate, reflecting a gradual repayment of the loan. Hence, from a period t perspective and assuming that the patient household discounts the future by r_t, the net present value of the perpetual income stream is

$$S_t = \mathbb{E}_t\left\{\frac{(1+\pi_{t+1})w'_{t+1}l'_t}{1+r_t} + (1-\sigma)\frac{(1+\pi_{t+1})w'_{t+1}l'_t}{(1+r_t)^2} + (1-\sigma)^2\frac{(1+\pi_{t+1})w'_{t+1}l'_t}{(1+r_t)^3} + \dots\right\}.$$

Since the income stream is a converging infinite geometric series ($\frac{1-\sigma}{1+r_t} < 1$ applies), its net present value can be expressed as

$$S_t = \mathbb{E}_t\left\{\frac{(1+\pi_{t+1})w'_{t+1}l'_t}{\sigma + r_t}\right\}.$$

Suppose next that it is uncertain whether or not the patient household will receive the income stream to which it is entitled in the case of default. With probability ξ_{DTI}, the household will receive the full stream, and with complementary probability $1-\xi_{DTI}$, the household will not receive anything. The DTI constraint now arises as an incentive compatibility constraint that the patient household imposes on the impatient household in period t. Incentive compatibility requires that the value of the loan about to be lent is not greater than the expected income stream in the event of default:

$$\tilde{b}'_t \leq \xi_{DTI}\mathbb{E}_t\left\{\frac{(1+\pi_{t+1})w'_{t+1}l'_t}{\sigma + r_t}\right\} + (1-\xi_{LTV})\cdot 0.$$

This constraint is a generalization of the natural borrowing limit in Aiyagari (1994). In his seminal paper, he assumed that households may borrow up to the discounted sum of all their future minimum labor incomes, giving him the following constraint: $\tilde{b}'_t \leq \frac{wn_{min}}{r}$. Thus, in the phrasing of the present paper, Aiyagari (1994) assumed that stream payments are certain ($\xi_{DTI} = 1$) and not amortized ($\sigma = 0$).

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