

Essays in Dynamic Macroeconomics:

From Structural Parameter Estimation to the Evaluation of Central Bank Policies

A dissertation submitted for assessment with a view
to obtaining the degree of Doctor of Philosophy at the
Department of Economics of the European University Institute

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- **Dynamic macroeconomics** is extremely useful to understand the effects of central bank / government policies
- Researchers typically use **two main approaches**:
 - * Empirical: identify these effects in the data, e.g. estimating impulse responses
 - * Theoretical: build structural models that are consistent with data to rationalize findings
- Empirics \Leftrightarrow (Quantitative) **Theory**
 - * Conclusions of a structural model depend on the estimated parameters
 - Chapter 1: Methodological contribution on how estimate models via minimum distance
 - * Empirical findings motivate the construction of models
 - Chapter 2: the rental market
 - Chapter 3: the mortgage interest fixation period

CHAPTER 1:

*Local Projections vs. VARs
for structural parameter estimation*

- Starting with Jordà (2005), **local projections** (LP) have become a common tool to understanding the dynamic effects of economic shocks
 - * An alternative to vector autorregresions (VARs) when estimating impulse responses
- Other studies analyze the performance of these two models when estimating impulse response functions (IRFs)
 - * VARs and LPs estimate the same impulse responses in population (Plagborg-Møller and Wolf, 2020)
 - * However, there is a bias-variance trade off in finite samples (Li et al., 2021)
- My focus is instead on the **structural parameters** of any DSGE model
 - * Follow Smith (1993) in estimating structural parameters through an indirect inference exercise in which the auxiliary model is a macro-econometric model
- How should we **choose between VARs and LPs** when estimating – via **minimum distance** – the structural parameters of our DSGE model?

MONTÉ-CARLO ANALYSIS

- The **log-linearized version of the Smets and Wouters (2007)** model is used to generate **S repeated samples** of macroeconomic aggregates
- The model is simulated each time at the estimated values from their paper using a sample of **T observations**
 - * $T = 300$ used as baseline
 - * $T = 100$ to address the issue of small sample bias of LPs (Herbst & Johansen, 2023)
- We concentrate in **8 structural parameters** of the model:

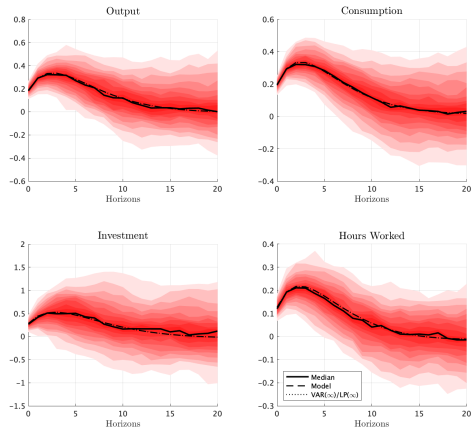
* σ_c : intertemporal elasticity of substitution	* φ : investment adjustment cost parameter
* h : habit parameter	* ξ_w, ξ_p : Calvo adjustment probabilities
* σ_l : elasticity of labor supply	* ι_w, ι_p : Degree of indexation to past inflation
- **Simulated series are 10 times larger** than the sample size during the optimization stage
- The importance of the coefficients used to summarize the data is **weighted** by a squared matrix **W**

* Identity matrix: I_m	* Diagonal matrix with $1/h$ elements: I_d
* Inverse of the VCM of the moments: Ω^{-1}	

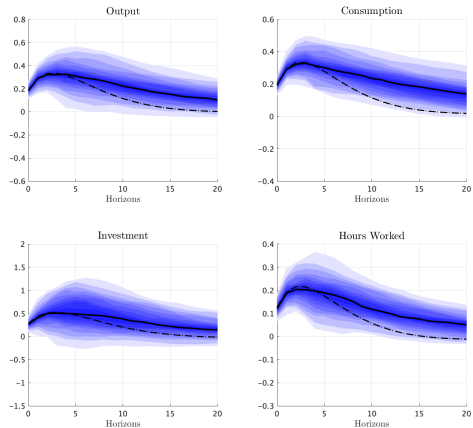
- We focus on the **estimated impulse responses of four variables**: *output, consumption, investment and hours worked* to one of **three main aggregate shocks**: *monetary policy, fiscal policy and technology*
- Shocks are treated by the econometrician as
 - * *observed*, i.e. $\tilde{x}_t = \eta_t^i$
 - * *inferred via recursive ordering*
 - * *observed with error*, i.e. $\tilde{x}_t = \eta_t^i + \sigma_v v_t$
- The IRFs are estimated using a **VAR** or a **Local Projections**.
 - * If the sample size is small ($T = 100$), we also consider the bias-corrected LP (Herbst & Johannsen, 2023) or the procedure by Killian (1998) for the SVAR
- In either case, the econometrician still needs to decide on at least two more things:
 - * The impulse response horizon, H . We set $H = 20$.
 - * The number of lags, p . We experiment with various p 's, i.e. $p \in \{2, 4, 8, 12\}$.

Targeted Impulse Responses ($S=100$, $T=300$, $p=4$)

Local Projection



SVAR



- When estimating a subset of the structural parameters Θ of any DSGE model by matching impulse responses, there are two approaches:

- * **Target empirical** responses but **match with model** impulse responses

$$J^{irf} = \min_{\Theta} (\beta - \text{IRF}(\Theta))' W (\beta - \text{IRF}(\Theta)) \quad (1)$$

- It doesn't require a simulated dataset, only structural IRFs

- * **Target and match with** empirical responses

$$J^{smm} = \min_{\Theta} (\beta - \beta(\Theta))' W (\beta - \beta(\Theta)) \quad (2)$$

- It uses the same econometric approach in the real and simulated data

- How does the **choice of the econometric model** affects parameter estimates?

- * J^{irf} speaks about potential misspecification of the model economy
- * J^{smm} relates to misspecification of both the model and the binding function

- Overall performance

$$J^* = (\text{IRF}(\Theta^*) - \text{IRF}(\hat{\Theta}))' (\text{IRF}(\Theta^*) - \text{IRF}(\hat{\Theta})) \quad (3)$$

$$J^{smm} = (\beta(\Theta^*) - \beta(\hat{\Theta}))' (\beta(\Theta^*) - \beta(\hat{\Theta})) \quad (4)$$

$$J^{irf} = (\beta(\Theta^*) - \text{IRF}(\hat{\Theta}))' (\beta(\Theta^*) - \text{IRF}(\hat{\Theta})) \quad (5)$$

- Parameter-by-parameter performance

$$\mathcal{L}_\omega(\hat{\Theta}_i, \Theta_i^*) = \omega \times \underbrace{(\mathbb{E} [\hat{\Theta}_i] - \Theta_i^*)^2}_{\text{bias}} + (1 - \omega) \times \underbrace{\text{Var}(\hat{\Theta}_i)}_{\text{variance}} \quad (6)$$

- Model fit

- * Similar to (3), compute the unweighted distance between the structural IRFs but to other non-targeted shocks in the economy
- * For example, if targeting monetary policy shocks, look at fiscal and technology

5 MAIN LESSONS

1. IRF matching is more **sensitive to bias** in targeted responses and hence using LP-IRFs is preferable, while Ind. Inf. is **robust to misspecification** and hence benefits from the lower variance of VAR-IRFs.
2. When the **lag length p is large**, then IRFs and estimated parameters are **similar** independently of the econometric model. On the other hand, when **p is small**, **LP-IRFs** are less biased and hence better for IRF matching, while **SVAR-IRFs** have a larger bias but lower variance and hence better for Ind. Inf.
3. **Small sample bias** worsens the performance of the estimation specially for IRF matching when bias correction partly offsets the problem.
4. **Incorrect recursive identifications** are not an issue for parameter estimation when employing Ind. Inf.. Not true for IRF matching.
5. **Measurement error** worsens the structural estimation outcome and unit normalization only ameliorates the problem.

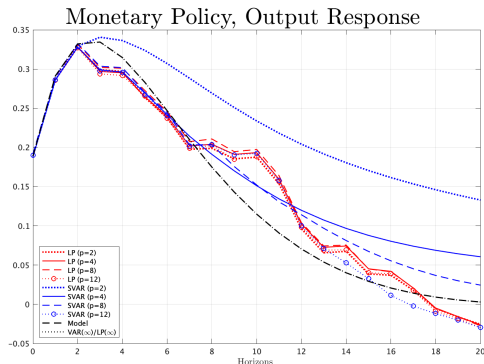
- Simplifying assumptions for comparison:
 - * Observed shock assumption
 - * Target IRFs estimated with a LP or SVAR model and $T = 300$ observations
 - * Weight all responses equally during the estimation stage, i.e. $W = I$
- **Overall performance measures** are averaged across estimations using different lag lengths ($p \in \{2, 4, 8, 12\}$) and shocks (TFP, fiscal, monetary)

	IRF matching				Indirect Inference			
	J_{irf}	J^*	Time	J_{unt}^*	J_{smm}	J^*	Time	J_{unt}^*
<i>Local Projection</i>	35.10	0.27	3.49 min	18.70	32.54	0.39	42.88 min	17.91
<i>Structural VAR</i>	35.23	0.41	3.93 min	17.93	33.87	0.33	14.47 min	18.39

- In the IRF matching estimator we are minimizing a distance that can be decomposed as:

$$\underbrace{[\beta(p, T|\Theta) - \beta(p, T = \infty|\Theta)]}_{\text{small sample bias}} + \underbrace{[\beta(p, T = \infty|\Theta) - IRF(\Theta)]}_{\text{lag truncation bias}} \quad (7)$$

- *Small sample bias* is common to both Local Projections and VARs
- *Lag truncation bias* only matter for VARs!
 - * Local Projection IRFs are independent of the lag length when the shock is observed
 - * VAR IRFs are heavily biased at short lag lengths and this truncation bias shrinks as we increase p

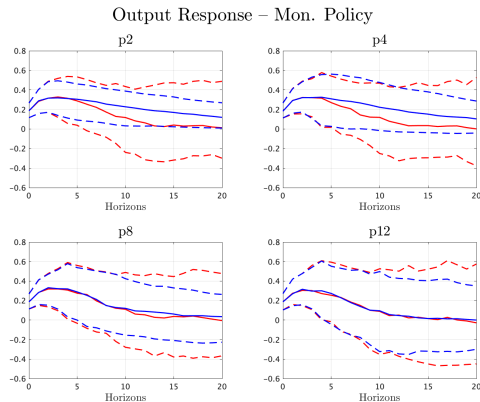


- Point estimates

- * Local Projection IRFs are independent of the lag length when the shock is observed
- * SVAR IRFs approximately agree with LP IRFs up to horizon p , then extrapolates using the first p sample autocovariances

- Confidence Intervals

- * Local Projection IRFs have a much wider bands, specially at long horizons
- * SVAR IRFs converge towards the sample uncertainty of LPs as p gets large



	IRF matching				Indirect Inference			
	J_{irf}	J^*	Time	J_{unt}^*	J_{smm}	J^*	Time	J_{unt}^*
p=2								
Local Projection	35.75	0.24	3.30 min	18.97	25.47	0.34	18.93 min	18.02
Structural VAR	34.61	0.61	4.32 min	17.00	26.25	0.16	11.88 min	19.32
p=4								
Local Projection	35.68	0.25	3.40 min	18.74	30.26	0.37	28.99 min	17.95
Structural VAR	36.01	0.39	3.89 min	17.75	31.49	0.26	15.35 min	18.26
p=8								
Local Projection	34.69	0.28	3.83 min	18.47	35.91	0.44	45.06 min	17.69
Structural VAR	34.92	0.34	3.85 min	18.36	37.26	0.49	13.35 min	18.01
p=12								
Local Projection	34.27	0.29	3.44 min	18.63	38.52	0.41	78.53 min	17.98
Structural VAR	35.39	0.30	3.67 min	18.61	40.47	0.41	17.29 min	17.98

KEY MESSAGE

*(Indirect Inference > IRF Matching)**

** LPs + IRF Matching can still be the most accurate option
conditional on correct identification and a sufficiently long sample*

CHAPTER 2:

The Aggregate and Distributional Implications of Credit Shocks on Housing and Rental Markets

Jointly with: **Andrew Hannon (ECB) & Gonzalo Paz-Pardo (ECB)**

- Housing ...
 - * is the most important **asset** for the majority of households
 - * represents a large share of household's **consumption** basket (non-homeowners must rent)
- After the GFC, there was an increasing focus on housing and the macroeconomy
 - * Link between credit, house prices and the business cycle
 - * Policy interventions related to mortgage credit
- But welfare effects on households depend also on rental markets
 - * Credit shocks → house prices and **rents** → household's decisions and welfare

AN EQUILIBRIUM MODEL OF THE HOUSING & RENTAL MARKETS

- Final Good Producer

- * Linear technology: $Y_c = A_c N$, where A_c is a parameter and N is labor
- * Profit maximization: $wage = A_c$

- Housing Good Producer

- * Cobb-Douglas technology: $Y_h = A_h \bar{L}^{\alpha_L} S^{1-\alpha_L}$ where $\{A_h, \alpha_L\}$ are parameters, \bar{L} land permits and S structures
- * Profit maximization: $Y_h = A_h^{1/\alpha_L} ((1 - \alpha_L) p_h)^{(1-\alpha_L)/\alpha_L} \bar{L}$ (housing investment function)
- * *Housing stock* is composed by houses of two different qualities: $H = \tilde{h}_1 H_1^{sh} + \tilde{h}_2 H_2^{sh}$ where \tilde{h}_i denotes quality and H_i^{sh} is its share in the aggregate stock
 - Final transaction price depends on type: $p(\tilde{h}_i)$
 - Conversion between types is costly for the firm
 - Households will need to buy and sell to adjust their stock

$$V(a, \underbrace{\{h, \tilde{h}\}}_{=s}, y, j) = \max_{c, a', s'} \left\{ \frac{(c f(\tilde{h}))^{1-\gamma}}{1-\gamma} + \sigma_\varepsilon \varepsilon(s) + \beta \mathbb{E} V(a', s', y', j+1) \right\} \quad (8)$$

s.t.

$$c + a' + p(\tilde{h}')h' + \mathbb{1}_{sell} \tau^h p(\tilde{h})h + \mathbb{1}_{buy} \tau^h p(\tilde{h}')h' + \delta^h p(\tilde{h})h \leq y + (1 + r(1 + \mathbb{1}_{a' < 0} \kappa))a + p(\tilde{h})h + p_r(h-1) \quad (9)$$

$$a' \geq \begin{cases} \max \{ -\lambda_{LTV} p(\tilde{h}') h', -\lambda_{LTI} y \} & \text{if } h' > h \\ a(1 + r(1 + \kappa)) - m(j) & \text{if } h > 0 \text{ and } a < 0 \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

$$\varepsilon(s) \sim F, \text{ extreme value type I dtb} \quad (11)$$

$$m(j) = \frac{r(1 + \kappa)(1 + r(1 + \kappa))^{J-j}}{(1 + r(1 + \kappa))^{J-j} - 1} \quad (12)$$

- r is fixed \rightarrow small open economy
- **Housing market**
 - * houses bought = houses produced + houses sold - depreciation
- **Rental market**
 - * Competitive: renters meet landlords
 - * p_r is determined using household's equilibrium distribution, $\mathcal{D}(a, s, y, j)$

$$\underbrace{\sum_{j=1}^J \int \int \mathcal{D}(a, s_1, y, j) da dy}_{\text{renters}} = \underbrace{\sum_{j=1}^J \int \int \mathcal{D}(a, s_4, y, j) da dy}_{\text{landlords w/ 1 btl property}} + 2 \underbrace{\sum_{j=1}^J \int \int \mathcal{D}(a, s_5, y, j) da dy}_{\text{landlords w/ 2 btl properties}}$$

THE 2015 MACRO-PRUDENTIAL REFORM IN IRELAND

- *Loan-to-Value (LTV) requirements:*

- * *General limit: 80%*
- * *For first time buyers (FTB): 90% if property value is below €220,000*
- * *For buy-to-let (BTL): 70%*
- * *15% of new lending can be above limit*

- *Loan-to-Income (LTI) requirements:*

- * *3.5 times household income (only for FTB)*
- * *20% of bank lending can be above limit*

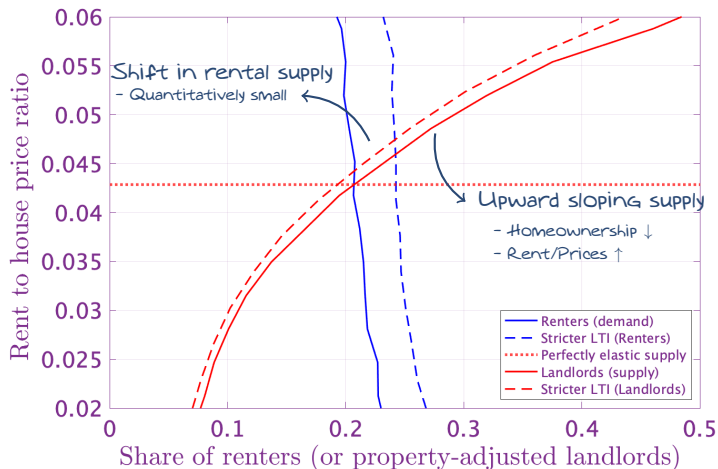
- We replicate Acharya et al. (2020) empirical strategy using also **data on rents**:

$$\Delta HP_i = \beta_0 + \beta_1 \text{Distance}_i + \epsilon_i \quad (13)$$

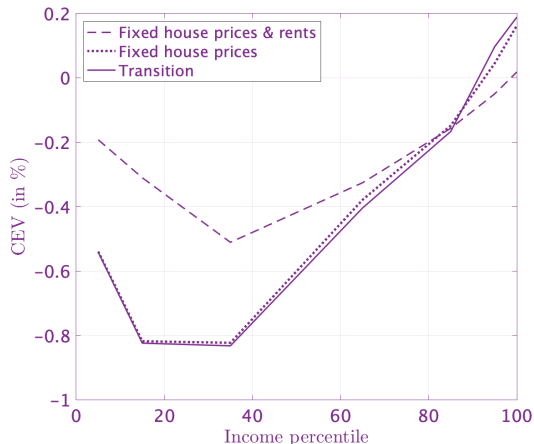
$$\Delta HR_i = \gamma_0 + \gamma_1 \text{Distance}_i + \nu_i \quad (14)$$

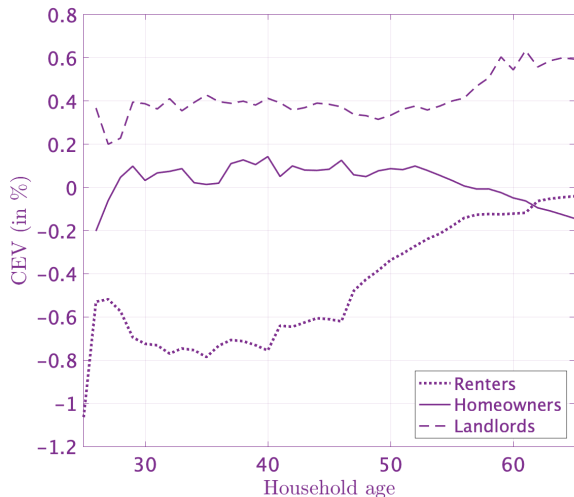
where i is county, Δ is change between 2014Q3 and 2016Q4

	Δ House prices	Δ Rents
Distance	0.289 (0.068)	-0.171 (0.039)
Obs.	52	52
R^2	0.34	0.31



- **Tighter LTV & LTI limits** affects potential (constrained) homebuyers in the **middle** of the income distribution
- **Increase in rental prices** hurts those at the **bottom**: more likely to be renters, harder to save for downpayment
- Limited role for house prices





- **Renters are the biggest losers:** harder to access homeownership + they pay higher rental prices
- **Homeowners are indifferent**
- **Landlords benefit:** higher cash flows from their housing portfolio

A PERMANENT RISE IN THE REAL INTEREST RATE

- Similarly to before: harder to access credit (mortgages)
- Unlike before: higher rate of return on financial assets
 - * *Substitution effect*: financial assets more attractive than houses
 - * *Income effect*: cheaper to save for downpayment
- Implications:
 - * Homeownership drops (0.92 p.p.)
 - * Large increase in rents (12.7 %)
 - * Sizable drop in house prices (-1.62 %)
- These effects would have been larger without macro-prudential policies

KEY MESSAGES

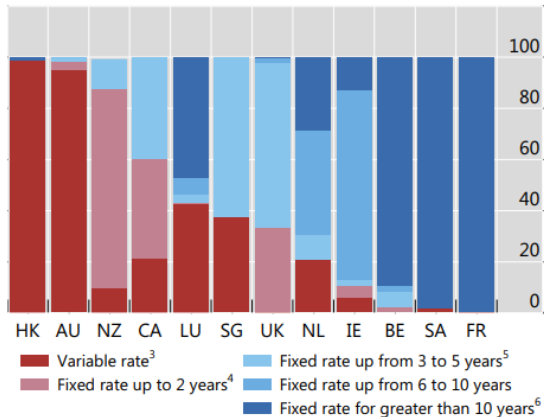
- 1. Borrower based macro-prudential policies have unintended and overlooked consequences through the rental market as they increase rents and reduce welfare for renters and prospective buyers*
- 2. Real interest rises have a direct impact on rents that can dampen the cooling effect of monetary policy on inflation as rents form part of households' consumption baskets*

CHAPTER 3:

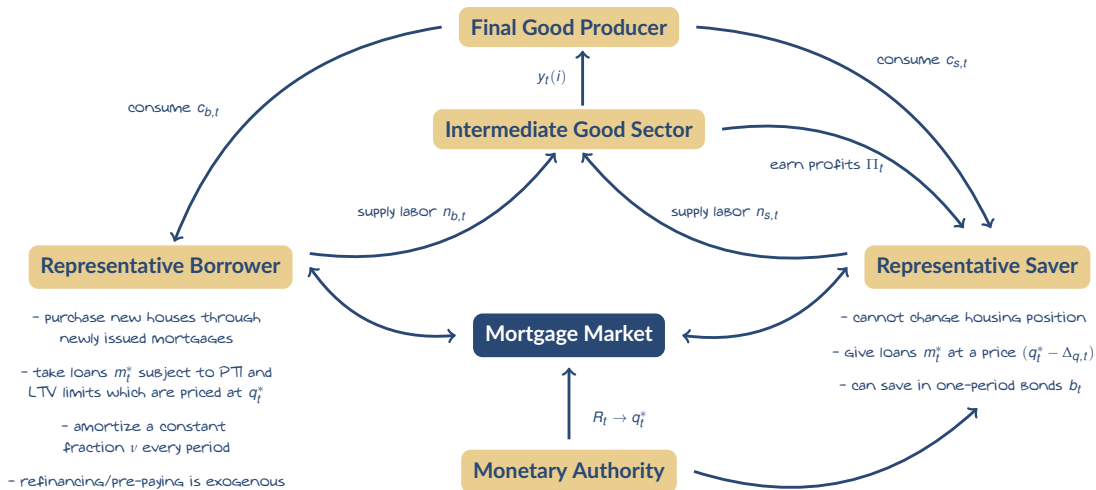
The Role of Interest Fixation Periods for Macro-Prudential & Monetary Policies

Jointly with: **Stephen Millard (NIESR) & Alexandra Varadi (BoE)**

- Mortgages represent about 80% of the outstanding stock of UK household debt
- The **mortgage interest fixation period** is a crucial element as it affects the **pass-through** from the nominal policy rate to mortgage rates, and in turn affects key economic variables
- *How does the strength of monetary policy depend on the mortgage interest fixation period? And how it is affected by credit conditions?*



A TANK MODEL WITH LONG TERM NOMINAL DEBT AND MORTGAGE CREDIT LIMITS



- Mortgage debt is constrained by two credit limits – **payment-to-income (PTI)** & **loan-to-value (LTV)** – and its aggregate level is given by

$$m_t^* \leq \bar{m}_t = \underbrace{(\theta^{PTI} w_t n_{t,i} e_{t,i}) / q_t^*}_{=\bar{m}_t^{PTI}} \int^{\bar{e}_t} e_i d\Gamma_e(e_i) + \underbrace{\theta^{LTV} p_t^h h_{i,t}^*}_{=\bar{m}_t^{LTV}} (1 - \Gamma_e(\bar{e}_t))$$

- **Fixed, Adjustable and Hybrid Rate Mortgage** economies **only differ** in the evolution of *mortgage promised payments*

$$x_{b,t}^{HRM} = \sum_{\tau=0}^{T-1} \left[\rho ((1-\rho)(1-\nu))^{\tau} \left(\prod_{i=0}^{\tau-1} \pi_{t-i}^{-1} \right) q_{t-\tau}^* m_{t-\tau}^* \right] + ((1-\rho)(1-\nu))^T \left(\prod_{i=0}^{T-1} \pi_{t-i}^{-1} \right) q_{t-T}^* m_{t-T}^*$$

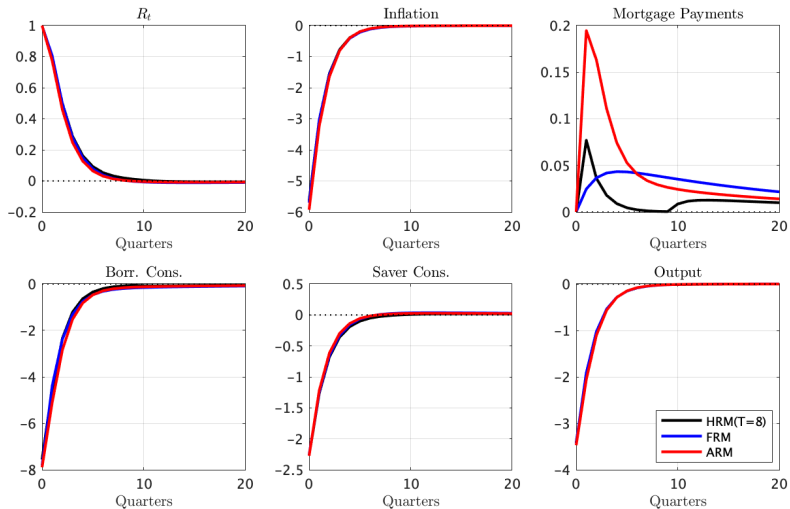
$$* \quad T = 0 \implies x_{b,t}^{ARM} = q_t^* m_t^*$$

$$* \quad T \rightarrow \infty \implies x_{b,t}^{FRM} = \rho q_t^* m_t^* + (1-\rho)(1-\nu) \pi_t^{-1} x_{b,t-1}$$

- * Same logic applies in the saver's promised payments law of motion

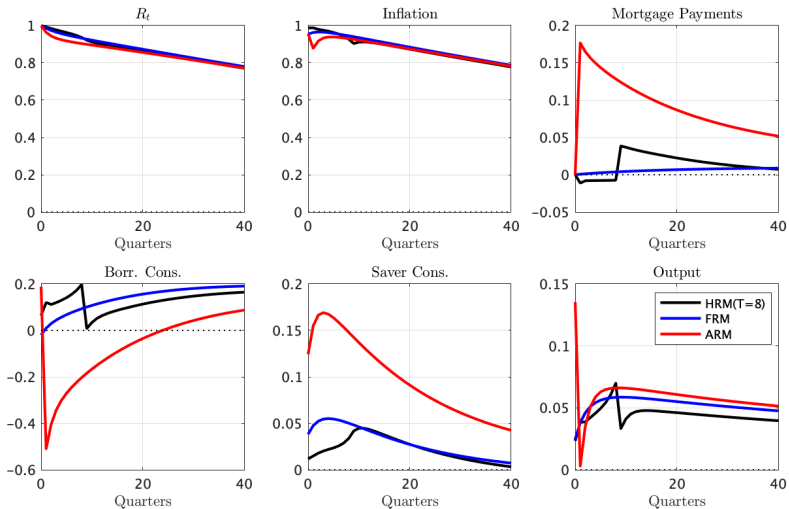
RESULT # 1:

*The mortgage interest fixation period and
the tightness of credit conditions **do not matter**
when the monetary policy shock is **transitory**.*



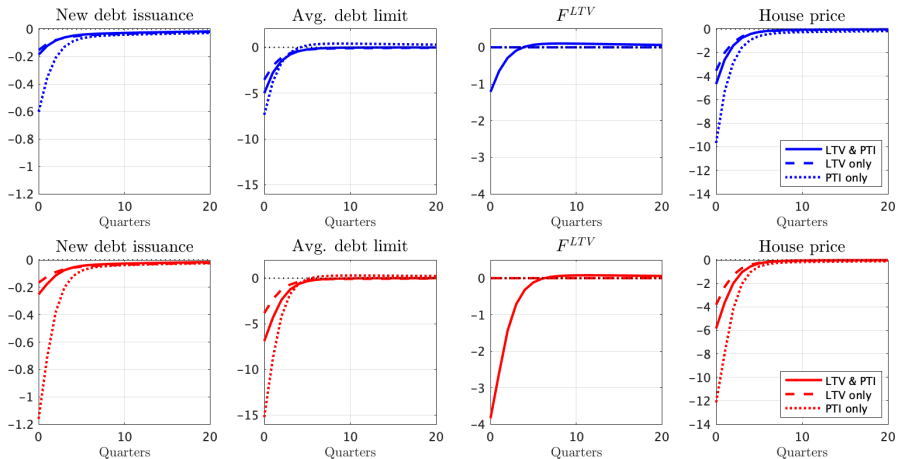
RESULT # 2:

*Looser credit conditions and **shorter** interest fixation periods **amplify** the redistributive effects of shocks that lead to **persistent** changes in the nominal rate.*



RESULT # 3:

LTV limits act as a backstop to the high sensitivity of PTI limits to monetary policy, especially when the interest fixation period is short.



KEY MESSAGES

- 1. The persistence in the nominal rate response determines if the mortgage interest fixation period matters or not for the transmission of monetary policy*
- 2. The set of credit tools in place (LTV and/or PTI) interact with the interest fixation period in affecting the strength of the monetary policy transmission*

APPENDIX TO CHAPTER 1

- Some notation:

- * Let $\tilde{y}_t \in \{y_t, c_t, i_t, hw_t\}$ denote one of response variables of interest.
- * Let $\tilde{x}_t \in \{\eta_t^a, \eta_t^g, \eta_t^m\}$ denote the innovation of one of the three aggregate shocks.
- * Define the vector of contemporaneous r_t and lagged controls $w_t = \{\tilde{x}_t, \tilde{y}_t\}$

- Then, consider for each horizon $h = 0, 1, 2, \dots, H$ the *linear projections*:

$$\tilde{y}_{t+h} = \mu_h + \beta_h \tilde{x}_t + \gamma_h' r_t + \sum_{\ell=1}^p \delta_{h,\ell}' w_{t-\ell} + \zeta_{h,t} \quad (15)$$

where $\zeta_{h,t}$ is the projection residual and $\mu_h, \beta_h, \gamma_h, \{\delta_{h,\ell}'\}_{\ell=1}^p$ are the projection coefficients.

- **Definition.** The LP - IRFs of \tilde{y}_t with respect to \tilde{x}_t is given by $\{\beta_h\}_{h \geq 0}$ in the equation above.

- Consider the multivariate linear VAR(p) projection:

$$w_t = c + \sum_{\ell=1}^p A_{\ell} w_{t-\ell} + u_t \quad (16)$$

where u_t is the projection residual and $c, \{A_{\ell}\}_{\ell=1}^p$ are the projection coefficients.

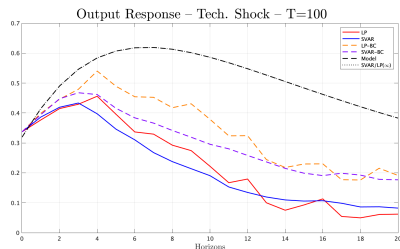
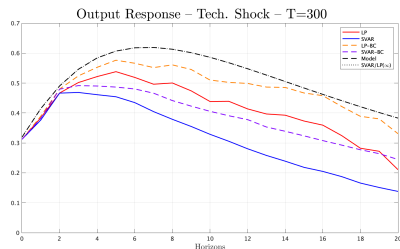
- Let $\Sigma_u \equiv \mathbb{E}[u_t u_t']$ and define the Cholesky decomposition $\Sigma_u = BB'$ where B is lower triangular with positive diagonal entries.
- Consider the corresponding recursive SVAR representation:

$$A(L)w_t = c + B\eta \quad (17)$$

where $A(L) = I - \sum_{\ell=1}^p A_{\ell} L^{\ell}$ and $\eta = B^{-1} u_t$. Define the lag polynomial $\sum_{\ell=0}^p C_{\ell} L^{\ell} = C(L) = A(L)^{-1}$.

- **Definition.** The SVAR - IRFs of \tilde{y}_t with respect to \tilde{x}_t is given by $\{\theta_h\}_{h \geq 0}$ with $\theta_h \equiv C_{2,\bullet,h} B_{\bullet,1}$ where $\{C_{\ell}\}$ and B are defined above.

- P-M & W (2023) show that $LP(p)$ exactly agree with true responses and that $SVAR(p)$ agrees up to lag p
- However, **sample uncertainty** matters!
 - * In finite samples, e.g. $T = 300$, both LP and SVAR are biased after horizon p , with SVARs having a more severe bias as long as the response is persistent
 - * The sample size typically found in empirical applications is even shorter and around $T=100$ (H&J, 2023), which makes these biases worse.
- **Bias correction** partially offsets the small sample bias, but two questions arise in our context
 - * Q1: Does Indirect Inference improves upon IRF matching when this bias is severe?
 - * Q2: Does targeting bias corrected responses improve the model estimation?

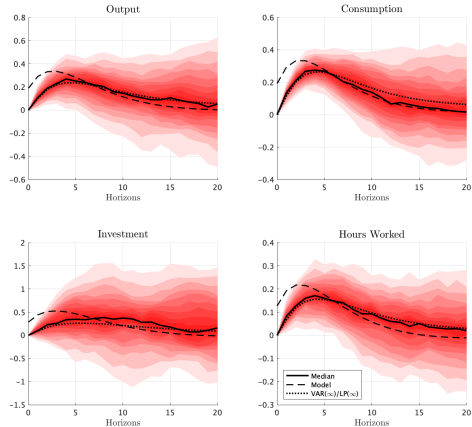


- Higher sample uncertainty associated with fewer observations ($T = 100$) leads to a **worse fit** of the model **for both estimation strategies**
- IRF matching suffers more its consequences as **Ind. Inf. is robust to misspecification** of the binding function
- For the same reason, applying **bias correction** to the targeted IRFs is more useful for IRF matching

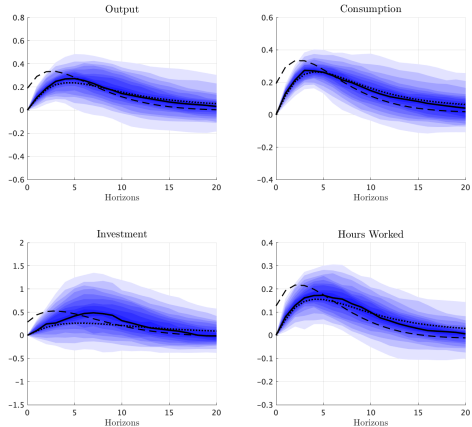
	IRF matching				Indirect Inference			
	J_{irf}	J^*	Time	J_{unt}^*	J_{simm}	J^*	Time	J_{unt}^*
T=300								
Local Projection	35.10	0.27	3.49 min	18.70	32.54	0.39	42.88 min	17.91
Structural VAR	35.23	0.41	3.93 min	17.93	33.87	0.33	14.47 min	18.39
T=100								
Local Projection	29.71	0.53	3.56 min	18.13	22.00	0.46	18.46 min	19.03
Structural VAR	31.62	0.47	3.33 min	17.98	25.16	0.36	9.78 min	19.50
Bias Corrected LP	31.55	0.32	3.26 min	19.18	23.29	0.35	20.48 min	19.50
Bias Corrected SVAR	33.48	0.32	3.42 min	18.65	26.06	0.33	11.02 min	20.11

Real variables respond at $t = 0$ in the Sm & Wo model

Local Projection



SVAR



- When *identification assumption* are incorrect, then **Ind. Inf. is robust to such misspecification**
- * Targeting consistently wrong responses helps with parameter identification as long as they have low variance

	IRF matching				Indirect Inference			
	J_{irf}	J^*	Time	J_{unt}^*	J_{smm}	J^*	Time	J_{unt}^*
<i>Observed Shock</i>								
<i>Local Projection</i>	50.65	0.07	3.46 min	9.36	48.46	0.31	41.39 min	9.40
<i>Structural VAR</i>	54.07	0.11	4.38 min	9.26	53.60	0.30	14.65 min	9.44
<i>Recursive Shock</i>								
<i>Local Projection</i>	48.11	0.29	3.34 min	9.60	56.91	0.18	78.57 min	9.34
<i>Structural VAR</i>	47.09	0.34	3.78 min	9.31	58.70	0.12	11.44 min	9.34

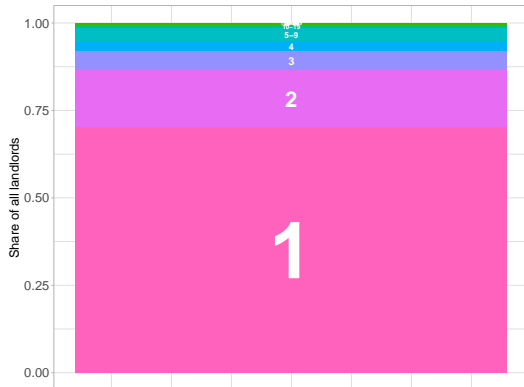
- Unit normalization corrects the attenuation bias in estimated responses through rescaling.
- Great fix for the structural estimation as well, specially for *IRF matching*.

	IRF matching				Indirect Inference			
	J_{irf}	J^*	Time	J_{unt}^*	J_{smm}	J^*	Time	J_{unt}^*
	True Monetary policy shock (η_t^m)							
Local Projection	50.65	0.07	3.46 min	9.36	48.46	0.31	41.39 min	9.40
Structural VAR	54.07	0.11	4.38 min	9.26	53.60	0.30	14.65 min	9.44
	Proxied monetary policy shock ($\eta_t^{a,obs} = \eta_t^a + \sigma_v v_t$)							
Local Projection	1.79	1.25	3.05 min	34.30	1.35	1.40	40.23 min	33.31
Structural VAR	3.41	1.70	2.80 min	33.47	1.70	1.18	13.74 min	34.39
	A 1% increase in r_0 (Stock and Watson (2018) normalization)							
Local Projection	50.77	0.08	3.83 min	19.34	49.49	0.52	49.84 min	17.85
Structural VAR	53.41	0.32	4.04 min	18.86	51.23	0.42	12.49 min	17.93

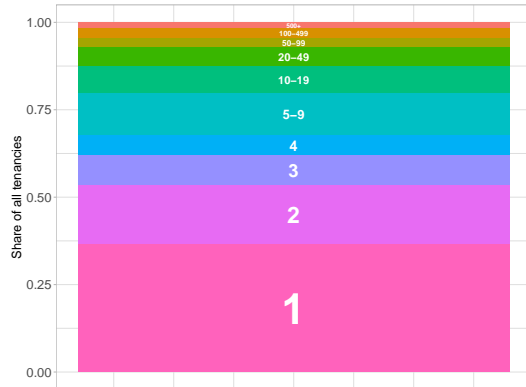
APPENDIX TO CHAPTER 2

Why we only model small landlords?

Share of landlords by number of registered tenancies (RTB)

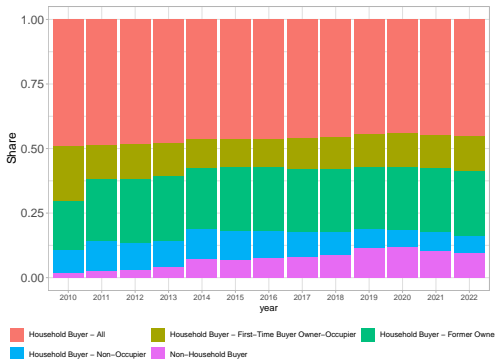


Share of tenancies owned by landlords



Corporate vs. individual landlords

Share of all property transactions, by type of buyer and year (CSO data)



Share of all property transactions, by type of buyer and year (CSO data), excluding owner-occupiers.



- Life cycle model

- * Working age from $j = 1, \dots, J^{ret} \rightarrow$ supply labor inelastically and receive idiosyncratic income
- * Retirement age from $j = J^{ret} + 1, \dots, J \rightarrow$ receive fix fraction of their last period income
- * After age $J \rightarrow$ they die with certainty

- Preferences

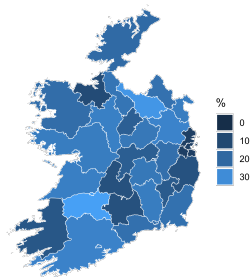
$$u(c, \tilde{h}) = \frac{(c f(\tilde{h}_i))^{1-\gamma}}{1-\gamma} \quad \text{where} \quad f'(\cdot) > 0, f''(\cdot) < 0$$

- Assets and liabilities

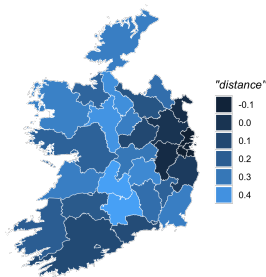
- * Financial assets $\rightarrow r$
- * Real estate $\rightarrow p_r/p(\tilde{h})$
- * Mortgages $\rightarrow r(1 + \kappa)$

- **Housing state:** quantity and quality of housing $s := \{h, \tilde{h}\} \in \mathcal{H}$, $\dim(\mathcal{H}) = 5$
 - * Renter: doesn't own ($h = 0$), lives in a small rented house $\{\tilde{h}_1\}$, and pays rent p_r
 - * Homeowner: owns ($h = 1$) and lives in a house of either quality $\{\tilde{h}_1, \tilde{h}_2\}$
 - * Landlord: owns multiple houses ($1 < h \leq 3$), lives in the best quality $\{\tilde{h}_2\}$ and rents the remaining low quality $\{\tilde{h}_1\}$ at a rate p_r each
- Houses are **illiquid** (proportional transaction costs, τ_h) and **costly to maintain**, δ_h
- Mortgages ($a < 0$) are limited by two **financial constraints** that can only *bind at origination*:
$$a' \geq -\lambda_{LTV} p_h(\tilde{h}') h'$$
$$a' \geq -\lambda_{LTI} y$$
- Households must at least **pay interests** and **amortize** a minimum amount per period for the remaining life of the mortgage

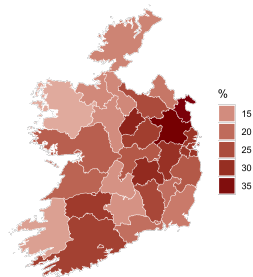
- Data on **house prices and rents** obtained from **daft.ie** property website (Lyons, 2022)
 - * 54 housing markets (26 counties + cities + all postcodes in Dublin)
- **Distance measure** computed at borrower level (Acharya et al., 2022)
 - * Look at households who obtain a mortgage in year 2014
 - * Compute the distance of their mortgage from the new limits
 - * Group over 26 counties and over the income distribution
 - * Take averages



(a) House price growth



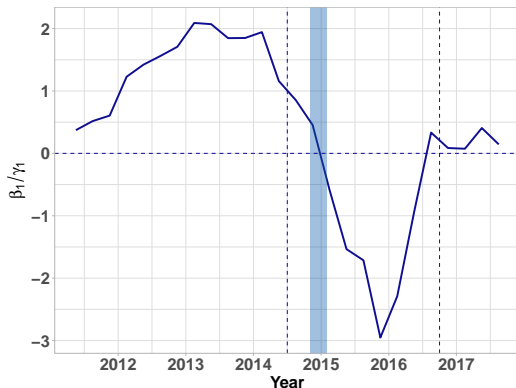
(b) Distance measure



(c) Rental price growth

- Counties where borrowers are close to the borrowing limits (low distance), e.g. around Dublin, experience *lower house price growth* (positive correlation) and *higher rental growth* (negative correlation).

- Run placebo regressions (6) - (7) using 9-quarter rolling windows to compute growth rates
- Plot ratio of regression coefficients
 - * $\beta_1/\gamma_1 > 0 \implies \text{cov}(\Delta HP, \Delta HR) > 0$
 - * $\beta_1/\gamma_1 < 0 \implies \text{cov}(\Delta HP, \Delta HR) < 0$
- Sign changes around the reform ...
 - * Rents do not longer co-move with house prices as a result of the credit shock

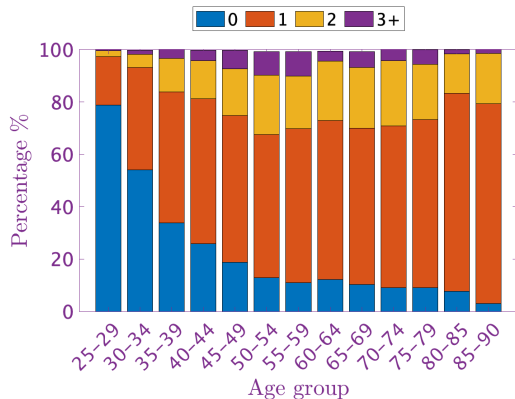


Parameter	Interpretation	Value
J^{ret}	Working life (years)	41
J	Length of life (years)	71
γ	Risk aversion coefficient	2.0
σ_ε	Taste shock scale parameter	0.05
$\{\tilde{h}_1, \tilde{h}_2\}$	Housing qualities	$\{0.905, 1.1095\}$
α^h	Curvature in utility premium function	0.5
δ^h	Housing depreciation rate	0.012
τ^h	Proportional transaction cost	0.03
λ_{LTV}	Maximum loan-to-value ratio	1.0
λ_{LTI}	Maximum loan-to-income ratio	6.0
r_s	Risk-free rate	0.02
r_b	Mortgage rate	0.04
A_c	Aggregate labor productivity	1.2055
\bar{L}	Amount of buildable land	1.0
α_L	Share of land in production	0.33
ξ	Adjustment cost scale in housing production	0.16

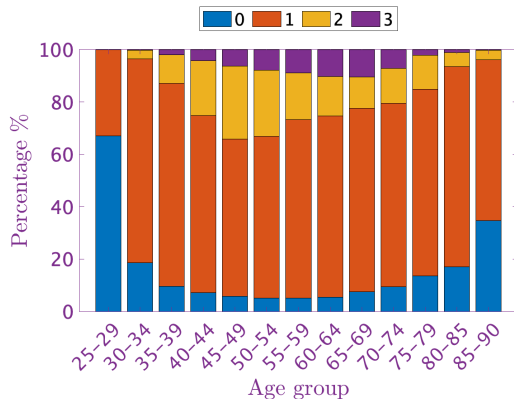
- The discount factor $\beta = 0.9656$, the ownership utility premium $f(\tilde{h}_1) = 1.3378$, and the scaling factor in housing production $A_h = 0.121$ are jointly chosen to match four moments of the data:

Moment	Model	Data	Source
<i>Targeted:</i>			
Wealth to income ratio	5.89	6.78	HFCS
Homeownership rate	79.42%	80%	EU-SILC
Avg. house price to income ratio	4.93	5.0	CSO
House price to rents ratio	22.73	22.58	RTB/CSO
<i>Untargeted:</i>			
Rents to avg. income ratio	0.196	0.2216	RTB/CSO
Share of households with 3+ properties	4.29%	5.11%	HFCS

Life-cycle patterns: number of properties

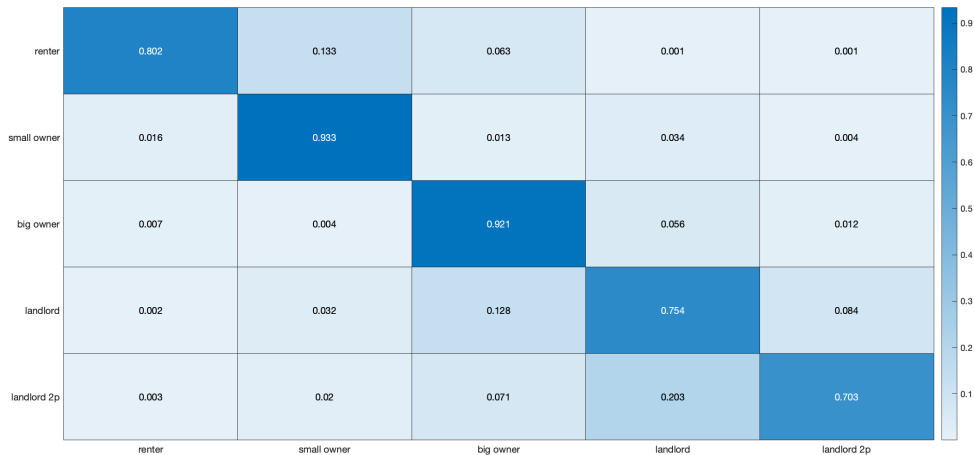


(a) Data

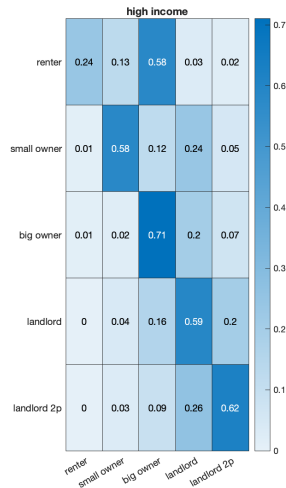
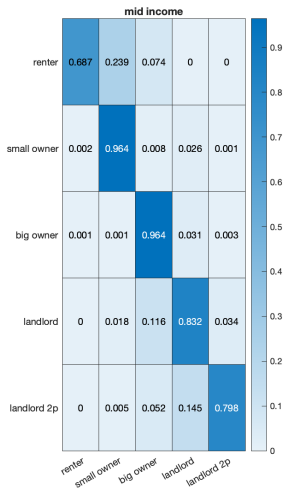
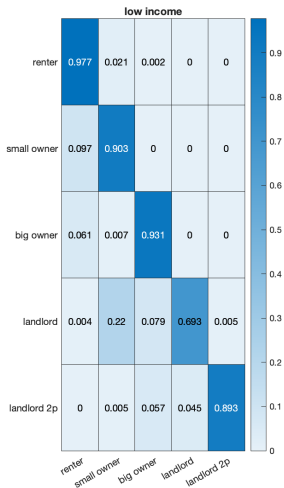


(b) Model

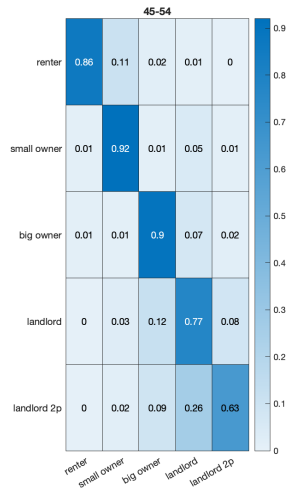
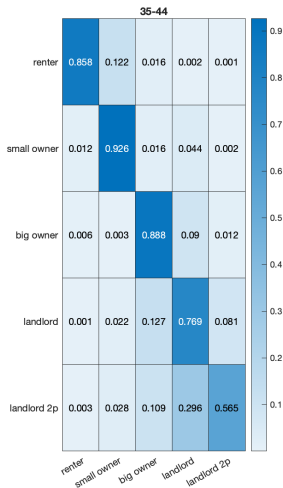
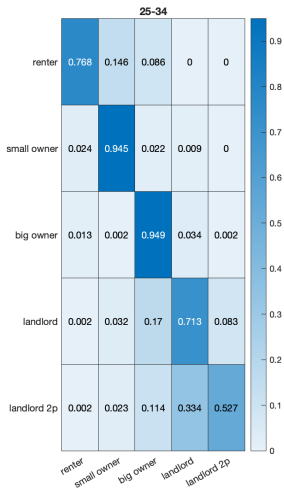
Housing Tenure Transition Matrix



Housing Tenure Transition Matrix: Income Level



Housing Tenure Transition Matrix: Age Group



	Pre-Reform	Post-Reform
	LTV = 100%, LTI = 6	LTV = 80%, LTI = 3.5
Rent-to-Price	3.98 %	4.09 %
Average house price to income	4.930	4.925
Rent to Income	0.196	0.201
Homeownership rate	79.42 %	77.59 %
Share of HHs living in big house	50.41 %	50.03 %
Share of households with 3 properties	4.29 %	4.51 %

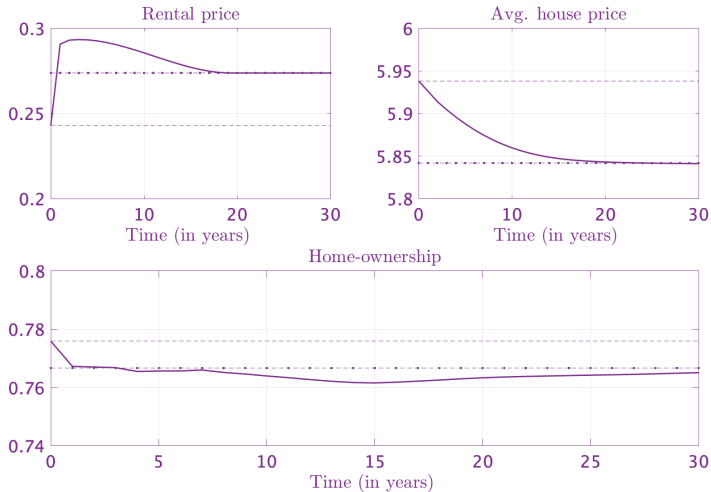
- Rent/Price $\rightarrow 2.82\% \uparrow = \begin{cases} \text{Prices} \rightarrow 0.01\% \downarrow \\ \text{Rents} \rightarrow 2.73\% \uparrow \end{cases}$
 - Homeownership rate $\rightarrow 1.83\text{pp} \downarrow$
 - Share of HHs living in big $\rightarrow 0.38\text{pp} \downarrow$
- Increased rental demand is met by owners starting the landlord business (1.39pp) rather than by landlords purchasing extra units ($0.22 \times 2 = 0.44\text{pp}$)

	Low Int. Rate	Decomposition	High Int. Rate
	$r^s = 0.02, r^b = 0.04$	$r^s = 0.03, r^b = 0.04$	$r^s = 0.03, r^b = 0.05$
Rent-to-Price	4.09 %	4.58 %	4.69 %
Average house price to income	4.925	4.899	4.846
Rent to Income	0.201	0.224	0.227
Homeownership rate	77.59 %	76.99 %	76.67 %
Share of HHs living in big houses	50.03 %	47.74 %	43.02 %

- $\uparrow r^s$ has large portfolio effects on landlords, substitute away from housing
 - * $SE > IE \rightarrow$ homeownership $\downarrow 0.6p.p.$, $p_r \uparrow 11.38\%$, $p_h^{avg} \downarrow 0.50\%$
- $\uparrow r^b$ generates a large downsizing effect, choose smaller mortgages
 - * homeownership $\downarrow 0.33p.p.$, $p_r \uparrow 1.22\%$, $p_h^{avg} \downarrow 1.1\%$

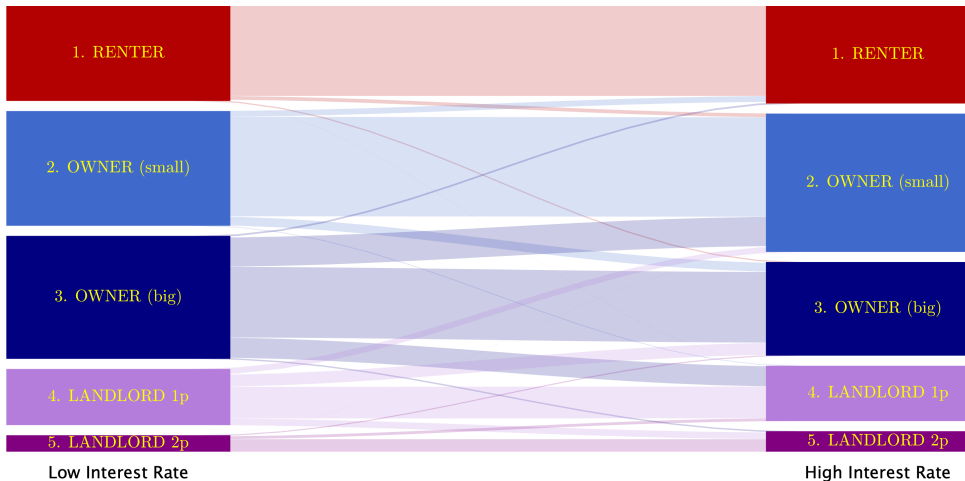
- Macro-prudential policies help cushion the effects of other shocks
- Larger fall in the home-ownership rate and the average house price
- Similar rise in the rental price

	Loose Credit Conditions			Tight Credit Conditions		
	Higher r	Higher r^b	Higher r^s	Higher r	Higher r^b	Higher r^s
Average house price to income	-1.93 %	-0.93 %	-1.01 %	-1.62 %	-1.1 %	-0.5 %
Rent to Income	12.84 %	1.13 %	11.57 %	12.70 %	1.22 %	11.38%
Homeownership rate	-1.07 p.p.	-0.58 p.p.	-0.49 p.p.	-0.92 p.p.	-0.33 p.p.	-0.6 p.p.



- The increase in the **return on savings** is welfare improving and **gains** are (monotonically) **increasing on income**
- The higher **borrowing rates** negatively impact welfare. **Losses** are larger for those at the **middle** of the income distribution (potential home-buyers)
- Adjustments in the **rental market** (higher rents) lead to **winners (top half)** and **losers (bottom half)** from the overall increase in real rates
- Limited role for house prices





APPENDIX TO CHAPTER 3

- The optimality of new debt, m_t^* , determines the mortgage coupon rate, q_t^*
- **Borrower optimality:**

$$1 = \Omega_{b,t}^m + \Omega_{b,t}^x q_t^* + \mu_t$$

where μ_t is the multiplier on the aggregate credit limit, and $\Omega_{b,t}^m$ and $\Omega_{b,t}^x$ are the marginal continuation costs to the borrower of taking an additional dollar of face value debt and of promising an additional dollar of initial payments

- **Saver optimality:**

$$1 = \Omega_{s,t}^m + \Omega_{s,t}^x (q_t^* - \Delta_{q,t})$$

where $\Omega_{s,t}^m$ and $\Omega_{s,t}^x$ are the marginal continuation benefits of an additional unit of face value debt and an additional dollar of promised initial payments

- **Borrower (saver) marginal continuation costs (benefits) differ depending on the contract type:**
(a) ARM, (b) FRM, (c) HRM

- **FRM & HRM economies** have the same marginal continuation cost of *face value debt* $\Omega_{b,t}^m$, but different marginal continuation cost of an *additional dollar of promised payments*:

$$\begin{aligned}\Omega_{b,t}^m &= \mathbb{E}_t \left[\Lambda_{t,t+1}^b \pi_{t+1}^{-1} \left(\nu + (1 - \nu) \rho + (1 - \nu)(1 - \rho) \Omega_{b,t+1}^m \right) \right] \\ \Omega_{b,t}^{x,FRM} &= \mathbb{E}_t \left[\Lambda_{t,t+1}^b \pi_{t+1}^{-1} \left((1 - \tau_y) + (1 - \nu)(1 - \rho) \Omega_{b,t+1}^x \right) \right] \\ \Omega_{b,t}^{x,HRM} &= \sum_{\tau=1}^T (1 - \rho)^{\tau-1} (1 - \nu)^{\tau-1} \mathbb{E}_t \left[\left(\prod_{j=0}^{\tau-1} \Lambda_{t+j,t+j+1}^b \pi_{t+j+1}^{-1} \right) (1 - \tau_y) \right]\end{aligned}$$

- As *mortgage payments* is not a state variable in the **ARM economy**, its marginal continuation cost is zero: $\Omega_{b,t}^{x,ARM} = 0$. And the marginal cost of an *additional unit of debt* also includes a term that capture the cost of current mortgage payments:

$$\Omega_{b,t}^{m,ARM} = \mathbb{E}_t \left[\Lambda_{t,t+1}^b \pi_{t+1}^{-1} \left((1 - \tau_y) q_t^* + \nu + (1 - \nu) \rho + (1 - \nu)(1 - \rho) \Omega_{b,t+1}^{m,ARM} \right) \right]$$

- Similarly to the borrower's problem, the marginal continuation benefit of an *additional unit of debt* is identical in **FRM & HRM economies**. However, the marginal continuation benefit of an *additional dollar of promised payments* is different

$$\Omega_{s,t}^m = \mathbb{E}_t \left[\Lambda_{t,t+1}^s \pi_{t+1}^{-1} (\rho (1 - \nu) + (1 - \rho)(1 - \nu) \Omega_{s,t+1}^m) \right] \quad (18)$$

$$\Omega_{s,t}^{x,FRM} = \mathbb{E}_t \left[\Lambda_{t,t+1}^s \pi_{t+1}^{-1} \left(1 + (1 - \rho) (1 - \nu) \Omega_{s,t+1}^{x,FRM} \right) \right] \quad (19)$$

$$\Omega_{s,t}^{x,HRM} = \sum_{\tau=1}^T (1 - \rho)^{\tau-1} (1 - \nu)^{\tau-1} \mathbb{E}_t \left[\left(\prod_{j=0}^{\tau-1} \Lambda_{t+j+1,t+j}^s \pi_{t+j+1}^{-1} \right) \right] . \quad (20)$$

- In the **ARM economy**, as $x_{s,t}^{ARM}$ is not a state variable, the marginal benefit of an *additional dollar of payments* is again zero $\Omega_{s,t}^{x,ARM} = 0$, and the marginal benefit of an *additional unit of debt* includes a term on the current mortgage payment benefit

$$\Omega_{s,t}^{ARM} = \mathbb{E}_t \left[\Lambda_{t,t+1}^s \pi_{t+1}^{-1} \left((q_t^* - \Delta_{q,t}) + \rho (1 - \nu) + (1 - \nu)(1 - \rho) \Omega_{s,t+1}^{ARM} \right) \right] . \quad (21)$$

