

Essays in Macroeconomics and Finance



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Doctor of Philosophy in Economics
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Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university.

I confirm that chapter one was jointly co-authored with Dr William Tayler and chapter two was jointly co-authored with Prof. Efthymios Pavlidis. I moreover confirm that chapter two was accepted for publication in the Journal of International Money and Finance (Volume 109, December 2020).

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Abstract

This thesis comprises three essays in macroeconomics and finance. In the first chapter we investigate the business cycle, property-price and investment dynamics when there is competition between households and firms for real estate. We introduce a construction sector into a RBC framework, which uses land, capital and labour to produce both commercial and residential real estate. This market structure activates a ‘real estate substitution channel’, where economic disturbances which alter the demand for one type of real estate, by affecting the overall costs of real estate production, endogenously create a substitution with its counterpart. For example, an increase in demand for residential real estate, also increases the cost of producing commercial structures which reduces the amount demanded by firms. In turn, this crowds out commercial real estate which affects the goods market in a similar way to an adverse aggregate supply shock. The estimated model reveals that housing preference shocks explain the largest part of the variation in property prices and residential investment, while commercial real estate prices are primarily driven by technology shocks.

The second topic proposes a novel approach for testing for rational speculative bubbles in segmented capital markets. The basic idea is that, under capital controls, heterogeneity of speculative expectations across international equity markets causes financial assets with identical cash flow promises to trade at different prices. Because these deviations from the law of one price inherit the properties of the speculative bubble process, they display periods of explosive dynamics and have predictive power for future movements in equity prices in sample. These two hypotheses can be examined empirically using sequential unit root tests and predictive regressions. An

attractive feature of this approach for bubble detection is that it does not require the specification of a model for market fundamentals, thus mitigating the well-known joint hypothesis problem. The focus of the paper is on mainland Chinese companies that cross list shares in Hong Kong. China is an ideal setting for our analysis because of the significant restrictions on capital movements imposed by the authorities and the turbulent behaviour of its stock market over the last decades.

Finally, the third chapter investigates the causal effect of consumer confidence on the housing market dynamics, using narrative evidence. We adopt an external instrument approach that is using mass fatalities to identify exogenous variations in consumer confidence. We find that adverse sentiment shocks can negatively affect housing demand with a strong and prolonged reduction of house prices and new houses sold. The deterioration of sentiments worsens homeownership conditions, causes a response of monetary policy, and exacerbates real consumption spending. In a counterfactual experiment, we assess the importance of the housing market by restricting the response of the housing market variables to sentiment shock to be zero. We find that, the housing market can propagate the effect of the sentiment shock to the rest of the economy. The effect becomes particularly evident in longer horizons, specifically after one year, where the deviation from the unrestricted model becomes substantial.

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Chapter 1

Real Estate and Construction Sector Dynamics in the Business Cycle

Joint with William Tayler

1.1 Introduction

Real estate is a significant component of the economy's capital stock and households' wealth, which serves as both a crucial input for producers and provider of residence for households. Investment in real estate can be categorised according to its use as either commercial or residential,¹ with commercial real estate (henceforth CRE) typically accounting for around half of business assets (Nelson et al., 2000) and residential real estate (henceforth RRE) constituting one-third of household net worth. Moreover, the

¹Commercial investment consists of new construction and improvements to existing structures in commercial and health care buildings, manufacturing buildings, power and communications structures, and other structures. Residential investment includes new construction of single-family homes and multifamily homes and spending on other residential structures (Lally, 2009) - BEA Briefing

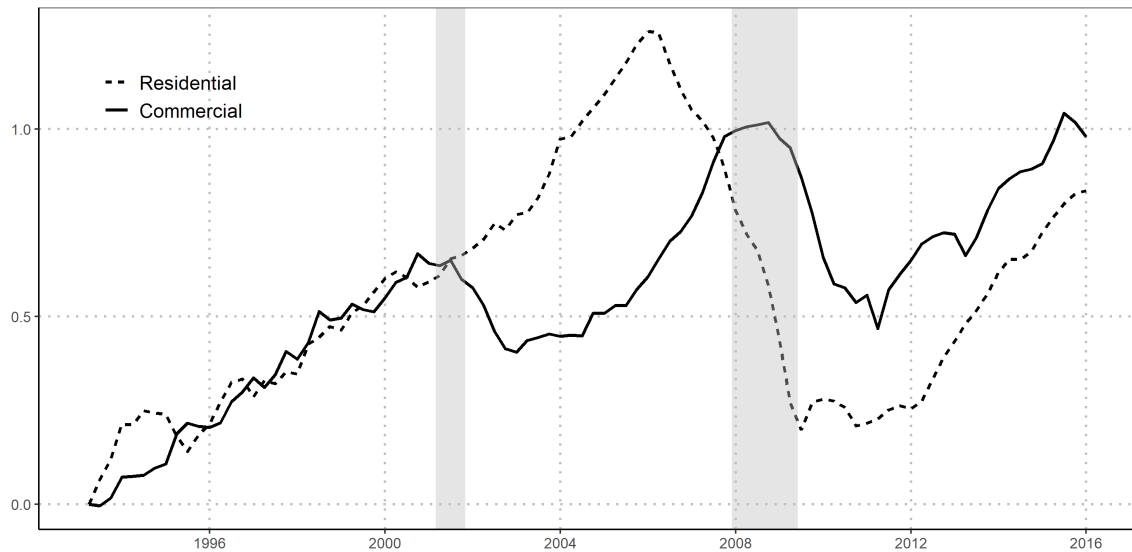
construction sector lies in a unique and influential position as a major contributor to the business cycle (Case et al., 2000; Head et al., 2014; Leamer, 2015).

In this paper, we argue that the inclusion of a construction sector as a producer of both commercial and residential real estate is pivotal when evaluating the driving forces behind property prices and economic activity. Firstly, CRE creation is an important indicator of macroeconomic activity since it constitutes a significant factor of production at the firm level. Secondly, the construction sector, as a creator of RRE, responds directly to the demand for residential housing over the business cycle. As a consequence, the competition for inputs that arise in the construction sector, such as land, labour and capital creates direct spillovers between the two types of real estate.

A closer look into the construction sector and the disaggregated construction spending for the US (Figure 1.1) reveals that despite both commercial and residential spending growing in a similar way until 2001, they behave quite differently following the two recession periods. After the *2001 dot.com* crisis there was a fall in commercial spending, while residential spending continued its upward trend until the onset of the *2007 financial crisis* when it dived sooner and greater than commercial spending. Thus, depending on the source of macroeconomic fluctuation, these two types of real estate can potentially display quite different cyclical behaviours. More recently, the move away from conventional office based work towards home working due to the Covid-19 pandemic has only further emphasised the importance of understanding the properties and mechanisms behind these real estate co-movements.

The level of construction activity is one of the key mechanisms through which changes in real estate prices are transmitted to the wider economy. Since construction spending tracks the overall investment in real estate, i.e. the creation of new structures, investment seems to follow a very similar path. Figure 1.2 plots the property and land prices, alongside real estate investment. As was the case with construction spending, different types of real estate investment have quite different cyclic behaviours (Wheaton, 1999); this can be particularly evident prior to the financial crisis. Analogous periods can also be considered, for example, the *2nd energy crisis of 1982*, where the demand

Fig. 1.1 Construction Spending



Notes: Commercial construction spending (solid line) and residential construction spending (dotted line). Variables are in log units and normalised to the origin of the sample. The shaded bars mark the NBER recession dates. Private construction spending covers the dollar construction work done on new structures or improvements to existing structures. Data estimates include the cost of labour and materials, cost of architectural and engineering work, overhead costs, interest and taxes paid during construction, and contractor's profits. Source: data.gov

for commercial real estate boomed and reached a speculative point in many markets followed by an immediate fall in commercial real estate prices and investment, and the aftermath of the early 1990s recession.

In line with the evidence of Roback (1982); Rosen (1979), and Gyourko (2009), property and land prices appear to comove contemporaneously and have similar time-series patterns. In particular, during the 2007-2008 financial crisis, all three series displayed a sharp fall followed by a more gradual recovery. Finally, land prices have followed a steady upward trend during the whole sample, which appears to drive both commercial and residential real estate prices (Davis and Heathcote, 2007; Glaeser and Ward, 2009; Gyourko et al., 2013).

We further investigate the dynamics of residential and commercial real estate empirically. We consider the partial derivatives of RRE and CRE investment, and CRE price at various horizons with respect to innovation in the RRE price shock. Figure 1.3 displays the estimated impulse response of RRE price, RRE investment,

Fig. 1.2 Real Estate Dynamics



Notes: Real commercial property price (solid line), real land price (dotted line) and real house price (dashed line). All variables are in log units and normalized to the origin of the sample. The shaded bars mark the NBER recession dates.

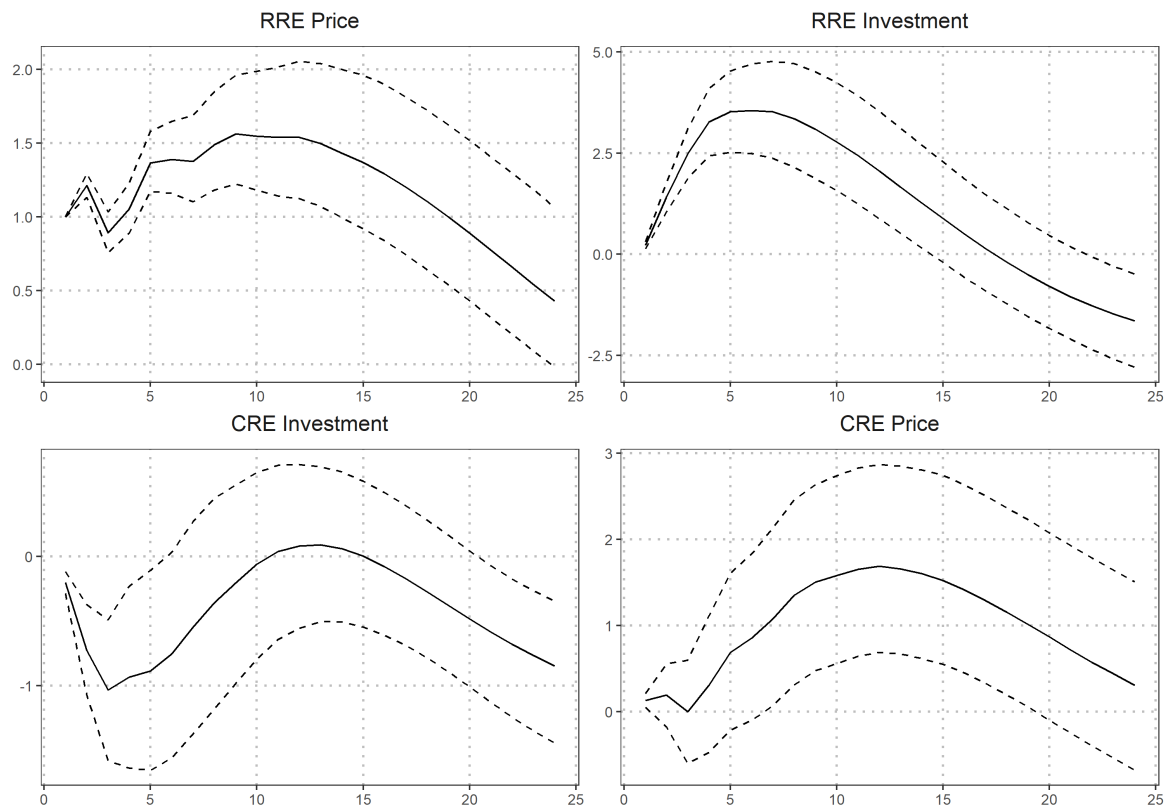
CRE investment, and CRE price following a shock to the RRE price series.² The impulse responses are estimated in a four-variable Bayesian Vector Autoregressive (BVAR) model with the flat prior. We generate IRFs for an RRE price shock using recursive identification, where we order RRE prices first. Although the identification of the model may appear unguided by theory, it can approximate the effects of a housing demand shock in a DSGE framework that represents an exogenous shift to housing preferences.³

A positive shock to the RRE price leads to a positive response of the RRE investment. On the other hand, CRE investment has the opposite response, which indicates a substitution between the two real estate sectors, i.e. residential and commercial. Since

²In Appendix 1 there is a comprehensive explanation of the data and the data-manipulations used in this paper.

³Innovations in RRE price may simply reflect information already contained in other variables innovations. To address this possibility, we reorder the variables in the system such that RRE price is orthogonalized with respect to other variables (RRE price is ordered last). We find that, whether or not is first orthogonalized with respect to CRE, the shape of the impulse responses remain identical. For robustness, we perform the same estimation with the Minnesota prior (Doan et al., 1984; Litterman, 1986). Results are available in the Appendix.

Fig. 1.3 RRE Price Shock



Notes: Impulse response to a positive shock to the residential real estate price from a recursive BVAR model with Diffuse Prior. Identification is achieved through Cholesky decomposition with the following ordering {RRE Price, RRE Investment, CRE Investment, CRE Price}, all in real terms. Solid lines represent the median estimated responses and dotted lines the 68% probability bands.

property prices co-move, the CRE price will increase following a positive shock to RRE prices.

The aim of this paper is to shed light on the mechanism behind the relationship between the price of residential and commercial real estate, and the substitution between residential and commercial investment outlined in Figure 1.3. To do so, we introduce a construction sector into a DSGE model, which undertakes the production of both commercial and residential real estate. Specifically, we introduce sectoral heterogeneity as in Iacoviello and Neri (2010), by differentiating between two groups of entrepreneurs - consumption good and construction sector. To achieve this multi-sector entrepreneur structure, we disaggregate the capital stock (Davis and Heathcote, 2005) into three

components: consumption good, residential and commercial real estate. Whilst there is a growing literature whereby residential housing production allows households to consume both housing and nonhousing goods (Benhabib et al., 1991; Chang, 2000; Davis and Heathcote, 2005; Fisher, 2007; Greenwood and Hercowitz, 1991), we also allow the construction sector to facilitate the production of new commercial structures. In this way, we can analyse the interplay between commercial and residential real estate when there is both competition for land in the construction sector and competition for real estate between households and consumption good entrepreneurs.

According to Davis and Heathcote (2007), fluctuations in real estate values are primarily driven by changes in land prices, and land provides important collateral value for business investment spending. As a result, we assume entrepreneurs in both groups face credit constraints in the spirit of Kiyotaki and Moore (1997), where firms finance investment spending by using the value of their inputs (besides labour) as collateral. By doing so, there are positive co-movements between land prices and business investment, as in (Liu et al., 2013). However, the additional requirement of commercial and residential investment for construction means that the dynamics and level of real estate prices can differ between commercial and residential production.

Our model is able to capture the substitution between commercial and residential investment, which is evident in the BVAR model in Figure 1.3. We refer to this mechanism as the “real estate substitution channel”. The channel we address encapsulates the land reallocation channel as was initially established by Liu et al. (2013), however, we claim that land does not equate real estate investment. Land has a unique quality; it is fixed on aggregate, however, real estate investment clearly follows its own law of motion. By introducing a construction sector where investment decisions depend upon not only land but all of the inputs of real estate production, we are able to connect the dynamics of the two series. Our results indicate that in general, the residential/commercial land allocation acts as an anchor for the allocation of its real estate investment counterpart. However, this is by no means always the case and, in particular following recession periods, there is a notable divergence between the movements of land and real estate

investment which has non-trivial implications for both real estate dynamics and real economic activity.

The paper proceeds as follows. The next chapter describes the theoretical model. Section 3 reports the calibration and estimation details. Section 4 explains the properties of the model. Section 5 describes the importance of land. Finally, Section 6 concludes.

1.2 Model

We consider an economy that consists of two types of agents: a representative household and an entrepreneur. The entrepreneur chooses to produce either consumption goods or build new property structures for residential or commercial purposes. The representative household's utility depends on consumption goods, housing, and leisure, while the entrepreneur's utility depends only on consumption goods. Consumption goods production requires labour, capital, and commercial real estate as inputs. Real estate investments require labour, capital, and land as inputs. Furthermore, the entrepreneur in both of these sectors needs external financing for investment spending. Imperfect contract enforcement implies that the entrepreneur's borrowing capacity is constrained by the value of their collateral assets. Because these assets vary depending upon the sector, collateral differs according to the type of production. Borrowing in the consumption good sector is constrained by the value of non-construction capital and the value of the commercial real estate, while the construction sector is constrained by the value of capital and land.

1.2.1 Households

There is a continuum of households indexed by $d \in [0, 1]$. The representative household seeks to maximize its discounted, time separable lifetime utility. The utility function is given by

$$E_t \sum_{t=0}^{\infty} \beta_d^t z_t \left\{ \ln(C_{d,t} - \gamma_d C_{d,t-1}) + \chi_t \ln(H_{d,t}) - \frac{\psi_t}{1+\eta} \left(N_{c,t}^{1+\xi} + (N_{hc,t} + N_{hd,t})^{1+\xi} \right)^{\frac{1+\eta}{1+\xi}} \right\}, \quad (1.1)$$

where $C_{d,t}$ denotes consumption, $H_{d,t}$ denotes residential housing stock, $N_{c,t}$, $N_{hc,t}$ and $N_{hd,t}$ denote labour hours in consumption good, commercial and residential real estate production, respectively. The parameter $\beta_d \in (0, 1)$ is a discount factor, the parameter γ_d measures habits in consumption and parameters ξ and η measure, the labour mobility among the different types of production and the inverse of the Frisch elasticity, respectively. The terms z_t and ψ_t capture shocks in intertemporal preference and labour supply respectively. Housing preference shock χ_t shifts preferences away from consumption and leisure towards housing. The shocks follow

$$\ln z_t = \rho_z \ln z_{t-1} + \sigma_z \epsilon_{z,t}, \quad \ln \psi_t = \rho_\psi \ln \psi_{t-1} + \sigma_\psi \epsilon_{\psi,t},$$

$$\ln \chi_t = (1 - \rho_\chi) \ln \bar{\chi} + \rho_\chi \ln \chi_{t-1} + \sigma_\chi \epsilon_{\chi,t},$$

where σ_z , σ_ψ , σ_χ are the standard deviations of the innovation, and $\epsilon_{z,t}$, $\epsilon_{\psi,t}$, $\epsilon_{\chi,t}$ are independent and identically distributed (i.i.d) normal processes.

The disutility of labour, follows Horvath (2000) and Iacoviello and Neri (2010) specification that allows for imperfect labour mobility among sectors. The household allocate labour resources to the productive activities, for $\xi \geq 0$, hours worked are not perfect substitutes between sectors. Specifically, labour in the consumption and real estate sectors in sectors are imperfect substitutes which gives rise to sectoral wage differentials. In contrast, labour can freely move from commercial to residential real estate production and vice versa within the construction sector and they face the same wage.

The households consume, accumulate houses, work for the consumption good and construction sector, and use bonds to smooth consumption. The flow of funds constraint

for the household is given by

$$C_{d,t} + q_{hd,t}H_{d,t} + \frac{S_t}{R_t} \leq q_{hd,t}(1 - \delta_{hd})H_{d,t-1} + w_{c,t}N_{c,t} + w_{h,t}N_{hc,t} + w_{h,t}N_{hd,t} + S_{t-1} + q_{l,t}L_{hd,t}^{ep} \quad (1.2)$$

where $q_{hd,t}$ is the price of residential homes, R_t is the gross real loan rate, and $w_{c,t}$, w_h the real wage of the consumption good and construction sector respectively. S_t is the loanable bond that the household buys in period t which pays off in period $t + 1$. Finally, $L_{hd,t}^{ep}$ is the amount of land that the household is left with after the depreciation of the housing stock where $q_{l,t}$ is the land price. The household chooses C_d , H_d , N_c , N_{hc} , N_{hd} and S_t to maximize (1.1) subject to (1.2).

1.2.2 The Entrepreneur

We model the entrepreneurial sector with borrowing constraints *à la* Iacoviello (2005), where entrepreneurs consume in every period and can raise their net worth by lowering their consumption. To introduce sectoral heterogeneity we consider a representative entrepreneur that operates in two sectors - consumption good and construction sector, where residential and commercial real estate comprise the construction sector. The entrepreneur faces the utility function

$$E_t \sum_{t=0}^{\infty} \beta_e^t \left(\log(C_{i,t} - \gamma_e C_{i,t-1}) \right), \quad i = c, h \quad (1.3)$$

where c and h define the respective consumption good and construction good sectors. $C_{i,t}$ denotes the entrepreneur's consumption and γ_e is the habit persistence parameter. We ensure that the parameter $\beta_e \in (0, 1)$ is smaller than the households discount factor $\beta_e < \beta_d$, so that the credit constraint is binding in a neighborhood of the steady state (Iacoviello, 2005). The entrepreneur owns all inputs beside labour, i.e. capital, land and commercial real estate.

1.2.3 The Consumption Good Sector

The entrepreneur in the consumption good sector produces goods using non-construction capital, labour and commercial real estate as inputs. The production function is given

$$Y_t = K_{c,t-1}^{\alpha_c} H_{c,t-1}^{\mu_c} (A_{c,t} N_{c,t})^{1-\alpha_c-\mu_c} \quad (1.4)$$

where Y_t denotes output, $K_{c,t-1}$, $H_{c,t-1}$, $N_{c,t}$, $A_{c,t}$, denote non-construction capital, commercial real estate, labour and labour productivity respectively. The entrepreneur is endowed with $K_{c,t-1}$ units of initial non-construction capital stock and $H_{c,t-1}$ of commercial real estate stock. Production functions in both sectors are subject to an exogenous labour-augmenting productivity shock. The shocks follow

$$\ln A_{c,t} = \rho_{Ac} \ln A_{c,t-1} + \sigma_{Ac} \epsilon_{Ac,t},$$

where σ_{Ac} is the standard deviations of the innovation, and $\epsilon_{Ac,t}$ is an independent and identically distributed (i.i.d) normal process. The entrepreneur faces the flow of funds constraint

$$\begin{aligned} C_{c,t} + K_{c,t} + q_{hc,t} H_{c,t} + w_{c,t} N_{c,t} + B_{c,t-1} \\ = Y_t + (1 - \delta_{kc}) K_{c,t-1} + (1 - \delta_{hc}) q_{hc,t} H_{c,t-1} + \frac{B_{c,t}}{R_t} + q_{l,t} L_{hc,t}^{ep} - \phi_{c,t}^4 \end{aligned} \quad (1.5)$$

where $q_{hc,t}$ denotes the price of commercial real estate, the variable $\phi_{c,t}$ describes capital adjustment costs and δ_{kc} and δ_{hc} are the depreciation rates of non-construction capital and commercial real estate respectively. The value of land that the entrepreneur is left with after the depreciation of the housing stock is $q_{l,t} L_{hc,t}^{ep}$. Finally, $B_{c,t}$ is the amount of debt used to finance investments in the non-construction sector which is subject to

$${}^4\phi_{c,t} = \frac{\phi_{kc}}{2} \left(\frac{k_{c,t}}{k_{c,t-1}} - 1 \right)^2 k_{c,t-1}$$

the credit constraint

$$B_{c,t} \leq \rho_b B_{c,t-1} + (1 - \rho_b) \theta_c E_t (q_{hc,t+1} H_{c,t} + K_{c,t}), \quad (1.6)$$

where θ_c can be interpreted as a steady state loan-to-value (LTV) ratio, and ρ_b measures the inertia in the borrowing limit Iacoviello (2015). Following Kiyotaki and Moore (1997) there is a limit on the obligations of entrepreneurs. The amount the creditor can borrow to invest is bounded by a fraction of the value of the collateral assets i.e. the commercial real estate and the non-construction capital. The entrepreneur in the consumption good sector chooses $\{C_{c,t}, K_{c,t}, H_{c,t}, N_{c,t}, B_{c,t}\}$ to maximize (1.3) subject to (1.4) - (1.6).

1.2.4 The Construction Sector

The entrepreneur in the construction sector produces new commercial and residential real estate using capital, labour and land as inputs. The production function for the former is given by

$$IH_{c,t} = K_{hc,t-1}^{\alpha_h} L_{hc,t-1}^{\mu_h} (A_{hc,t} N_{hc,t})^{1-\alpha_h-\mu_h}, \quad (1.7)$$

where $IH_{c,t}$ denotes the commercial real estate. Subscript hc and hd define the commercial and residential real estate sectors such that $K_{hc,t-1}$, $N_{hc,t}$, $L_{hc,t-1}$, denote the inputs; commercial real estate capital, labour and land that is used for commercial real estate, respectively. The production function for residential real estate is

$$IH_{d,t} = K_{hd,t-1}^{\alpha_h} L_{hd,t-1}^{\mu_h} (A_{hd,t} N_{hd,t})^{1-\alpha_h-\mu_h}, \quad (1.8)$$

where $IH_{d,t}$ denotes new homes, and $K_{hd,t-1}$, $N_{hd,t}$ and $L_{hd,t-1}$, are the corresponding inputs. $A_{hc,t}$ and $A_{hd,t}$ measure the productivity of commercial and residential

construction and follow the processes

$$\ln A_{hc,t} = \rho_{A_{hc}} \ln A_{hc,t-1} + \sigma_{A_{hc}} \epsilon_{A_{hc},t}$$

$$\ln A_{hd,t} = \rho_{A_{hd}} \ln A_{hd,t-1} + \sigma_{A_{hd}} \epsilon_{A_{hd},t}$$

where $\sigma_{A_{hc}}$ and $\sigma_{A_{hd}}$ are the standard deviations of the innovation, and $\epsilon_{A_{hc}}$ and $\epsilon_{A_{hd},t}$ are two independent and identically distributed (i.i.d) normal processes. Construction sector entrepreneurs face the following flow of funds constraint

$$\begin{aligned} C_{h,t} + K_{hc,t} + K_{hd,t} + q_{l,t}(L_{hc,t} + L_{hd,t}) + w_{h,t}(N_{hc,t} + N_{hd,t}) + B_{h,t-1} = q_{hc,t}IH_{c,t} \\ + q_{hd,t}IH_{d,t} + (1 - \delta_{kh})K_{hc,t-1} + (1 - \delta_{kh})K_{hd,t-1} + \frac{B_{h,t}}{R_t} - \phi_{h,t}^5, \end{aligned} \quad (1.9)$$

where $B_{h,t}$ is the debt for financing investments in the construction sector and is subject to the credit constraint

$$B_{h,t} \leq \rho_b B_{h,t-1} + (1 - \rho_b)\theta_h E_t (q_{l,t+1}(L_{hc,t} + L_{hd,t}) + K_{hc,t} + K_{hd,t}). \quad (1.10)$$

The amount the entrepreneur can borrow in the constructions sector is limited by the total value of land and construction capital in the production of real estate. The entrepreneur in the construction sector chooses $\{C_{h,t}, K_{hc,t}, K_{hd,t}, L_{hc,t}, L_{hd,t}, N_{hc,t}, N_{hd,t}, B_{h,t}\}$ to maximize (1.3) subject to (1.7) - (1.10).

$$\phi_{h,t}^5 = \frac{\phi_{hc}}{2} \left(\frac{k_{hc,t}}{k_{hc,t-1}} - 1 \right)^2 k_{hc,t-1} + \frac{\phi_{hd}}{2} \left(\frac{k_{hd,t}}{k_{hd,t-1}} - 1 \right)^2 k_{hd,t-1}$$

1.2.5 Market Clearing Conditions and Equilibrium

The goods market produces consumption and business investment. The clearing condition implies that

$$Y_t - \phi_t = C_t + IB_t, \quad (1.11)$$

where $C_t = C_{d,t} + C_{c,t} + C_{h,t}$ is the aggregate consumption and IB_t is the business investment. Business investment is described as

$$IB_t = IK_{c,t} + IK_{h,t} + \bar{q}_{hc}IH_{c,t},$$

where $IK_{c,t} = K_{c,t} - (1 - \delta_{kc})K_{c,t-1}$ can be described as investment in nonresidential equipment and intellectual property products. The second part of business investment $IK_{h,t} = K_{hc,t} - (1 - \delta_{kh})K_{hc,t-1} + K_{hd,t} - (1 - \delta_{kh})K_{hd,t-1}$ denotes the investment in construction machinery, which is a small part of the total machinery. CRE is used as an intermediate input in the production of consumption good output and built into the capital stock of the sector in the economy, hence the last term $\bar{q}_{hc}IH_{c,t}$ describes the value of new RRE. $H_{c,t}$ evolves according to the law of motion

$$IH_{c,t} = H_{c,t} - (1 - \delta_{hc})H_{c,t-1}. \quad (1.12)$$

The construction sector produces new homes $IH_{d,t}$

$$IH_{d,t} = H_{d,t} - (1 - \delta_{hd})H_{d,t-1}, \quad (1.13)$$

where $H_{d,t}$ is the stock of residential real estate. The GDP is the sum of the value added of the consumption good and residential real estate, that is

$$GDP_t = Y_t + \bar{q}_{hd}IH_{d,t}. \quad (1.14)$$

Available land does not evolve over time (without loss of generality we can assume land to fixed at $\bar{L}_h = 1$). In the spirit of Liu et al. (2013), we assume land market clearing with the following condition

$$\bar{L}_h = L_{hc,t} + L_{hd,t}. \quad (1.15)$$

We define ex post land, L_{hd}^{ep} and L_{hc}^{ep} as the land which is owned by the respective household and entrepreneur following the depreciation of their housing stock. This is then purchased the construction entrepreneur who uses it as an input. Since all land has a positive value it is always built upon when it becomes available, thus it follows that $L_{hc}^{ep} + L_{hd}^{ep} = \bar{L}_h$ with the following shares applied to each sector

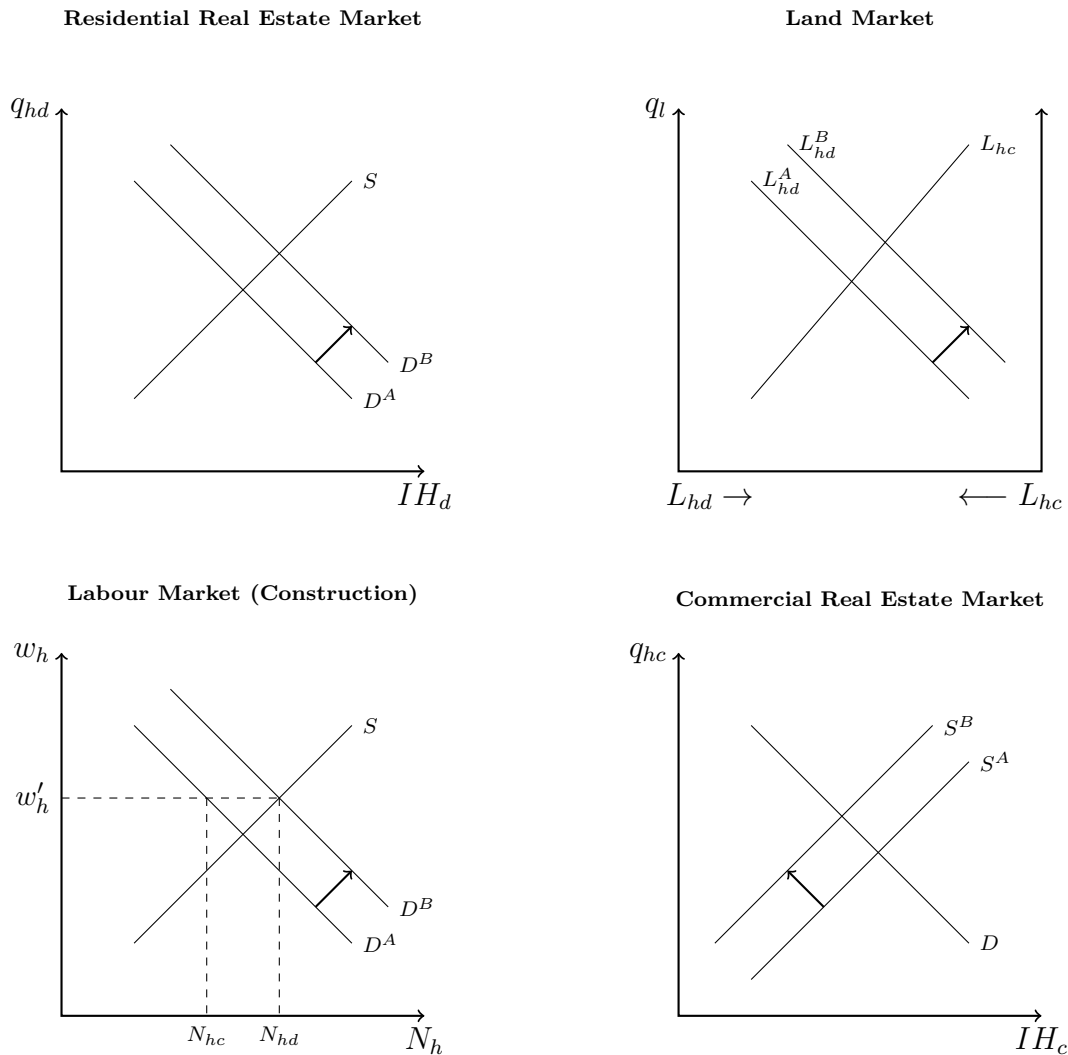
$$L_{hc,t}^{ep} = \frac{\delta_{hc}H_{c,t-1}}{\delta_{hc}H_{c,t-1} + \delta_{hd}H_{d,t-1}}\bar{L}_h \quad L_{hd,t}^{ep} = \frac{\delta_{hd}H_{d,t-1}}{\delta_{hc}H_{c,t-1} + \delta_{hd}H_{d,t-1}}\bar{L}_h. \quad (1.16)$$

1.2.6 Real Estate Substitution

In this section, we use a static model to explain the mechanism of real estate substitution in the presence of a housing demand shock. Figure 1.4 includes the four markets we consider in our analysis, residential real estate (top left), land market (top right), labour market (bottom left) and commercial real estate (bottom right).

Consider a positive RRE price shock that shifts the demand curve in the RRE market from D_A to D_B . Higher demand for houses will increase RRE prices (q_{hd}) and cause RRE investment to rise. To facilitate this increase in production, demand for construction machinery, labour in the construction sector, and land will also increase. In the land market, the residential land demand curve will shift from L_{hd}^A to L_{hd}^B , increasing competition for the available land, which leads to an increase in land prices and a substitution towards RRE land use. Similarly, the increased demand for labour for residential construction will raise construction sector wages. This hike in construction costs generates a vertical shift in the supply of commercial real estate,

Fig. 1.4 Housing Demand Shock



Notes: The figure displays the residential real estate market (top left), the land market (top right), the labour market (bottom left) and the commercial real estate market (bottom right), following a housing demand shock.

displayed by the shift from S^A to S^B , which increases the CRE price, q_{hc} and causes a fall in CRE investment.

Thus "real estate substitution" following a RRE demand shock is driven by cost push pressures which acts to crowd out the CRE market in the same way as an adverse aggregate supply shock.⁶ As can be seen in Figure 1.4, the overall effects of real estate

⁶There is a strand of literature in urban economics that indicates that the demand for both residential and commercial real estate are similar. In this framework introduced by Rosen (1979)

substitution on both real estate prices and investment depend upon the price elasticities of supply and demand in the real estate, land and labour markets. To shed further light upon the quantitative and state-contingent behaviour of this channel, we fully estimate the model in the following section.

1.3 Estimation

We use Bayesian methods to estimate our model. The posterior density is constructed by simulation using the Metropolis-Hastings algorithm (with 200,000 draws) as described in An and Schorfheide (2007).⁷ The model due to the innate characteristics of the RBC, can only allow for a limited number of shocks, which in this case amount to six. Since we can not accommodate more than six shocks in the model we are restricted to six observables: consumption, residential real estate investment, residential real estate price, commercial real estate investment, commercial real estate prices and total hours. All variables are denoted in real terms. All the data have been gathered from freely available sources such as BEA, BLS and FRED. We demean the hours and detrend the logarithm of the rest of the variables independently using a quadratic trend.⁸ The detrended and demeaned data are plotted in Figure 1.5 The sample covers the period from 1975:Q1 to 2016:Q4.

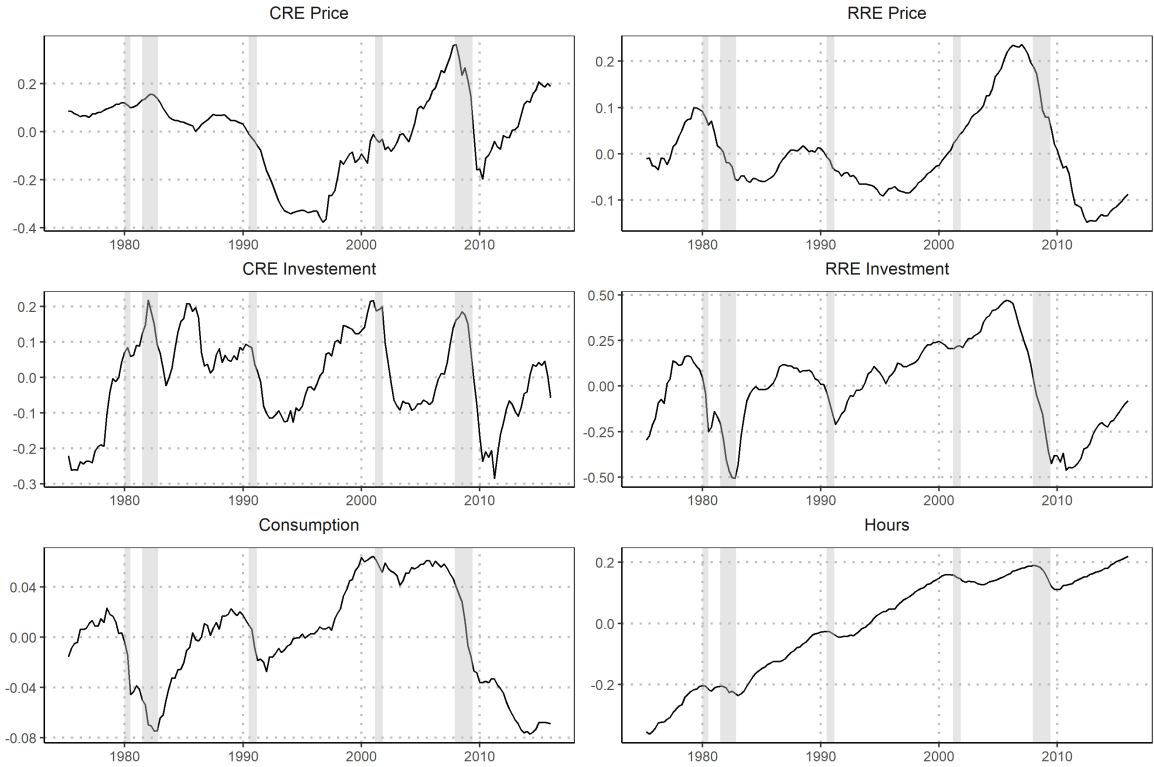
Due to the low number of observables we are unable to estimate a wide range of structural parameters, hence we focus our estimation strategy primarily to the shocks' processes.

and Roback (1982) land prices is the entry fee that households and firms must pay to access the productivity and the amenities of a labour market area. Because land is substitutable between uses, the price of both residential and commercial property will move together.

⁷Appendix C plots the prior and posterior densities, details on the estimation strategy and tests of convergence for the stability of the estimated parameters

⁸Appendix A describes further details of the data construction

Fig. 1.5 Detrended Data



Notes: Prices, investment and consumption have been detrended using a quadratic trend and normalized to the beginning of the sample. Hours are demeaned. The model parameters are estimated using data from 1975Q1-2016Q4. Shaded regions indicate the NBER recession periods.

1.3.1 Calibrated Parameters

To calibrate, we use data on the US market. Table 1.1 summarizes our calibration. We set the discount factor for households $\beta_d = 0.9925$, that corresponds to a annual 3% bank prime loan rate. We fix the discount factor for entrepreneurs at $\beta_e = 0.975$, which makes the credit constrain binding in the steady state (Iacoviello, 2005). Since entrepreneurs can use bonds to smooth consumption we assume a higher degree of habit persistence $\gamma_e = 0.65$ than households $\gamma_d = 0.5$. The depreciation rates for residential real estate, non construction capital, commercial real estate, and capital in the construction sector are set to $\delta_{hd} = 0.01$, $\delta_{kc} = 0.025$, $\delta_{hc} = 0.025$ and $\delta_{kh} = 0.04$ (Iacoviello and Neri, 2010). Parameter χ is calibrated to 0.2 to set the steady state of the ratio of residential investment to output.

Real estate also typically accounts for about half of business assets, so we set $\alpha_c = 0.20$ for the capital share and $\mu_c = 0.20$ for the real estate share (Liu et al., 2013). It is important to note that the construction sector is more labour-intensive, hence the labour share ought to be larger than the consumption good sector, thus the construction factor shares are set to $\alpha_h = 0.20$ for the capital share and $\mu_h = 0.1$ for the land share (Davis and Heathcote, 2005).

Finally, the LTV ratios have to take values less than 0.75, since commercial mortgage-backed securities loans permit maximum LTV of 75%. Grovenstein et al. (2005) measures LTV ratios to be 71.01% in five major commercial real estate property types originating from 10547 loans. Downing et al. (2008) report an average LTV of 67.40% for over 14,000 commercial mortgages between 1996 and 2005. Arsenault et al. (2013) finds a mean of 66% for the period of 1991 to 2011. For our purpose we set consumption good LTV to 70% ($\theta_c = 0.70$), while real estate firms correspond to an aggregate loan-to-value ration to 50% (Gyourko, 2009), thus we set $\theta_h = 0.5$.

Table 1.2 shows the steady state ratios of the model. The sum of the consumption share (68%) and the business investment (22%) is the consumption good share, which amounts to 90%. The remaining 10% is the residential real estate share. We split the business investment share into three sub-components. The commercial real estate share accounts for 34% of business investment or 7% of GDP. The other two components

Table 1.1 Calibrated Parameter Values

Households			Entrepreneur		
β_d	Discount factor	0.9925	β_e	Discount factor	0.975
χ	Housing services	0.2	γ_e	Habit persistence	0.65
γ_d	Habit persistence	0.5	ρ_b	Borrowing inertia	0.8
Entrepreneur: Consumption Good			Entrepreneur: Construction		
α_c	Non-construction capital share	0.2	α_h	Construction capital share	0.2
μ_c	Commercial real estate share	0.2	μ_h	Land share	0.1
δ_{kc}	Depreciation of non-construction capital	0.025	δ_{hd}	Depreciation residential real estate	0.01
δ_{hc}	Depreciation of commercial real estate	0.025	δ_{kh}	Depreciation of construction capital	0.04
θ_c	LTV consumption good sector	0.70	θ_h	LTV construction sector	0.5

Table 1.2 Steady State Ratios

C/GDP	Consumption share	68%
IB/GDP	Business investment share	22%
$- IK_c/IB$	Software and non-construction equipment share	53%
$- IK_h/IB$	Construction equipment share	11%
$- q_{hc}IH_c/IB$	Commercial structure share	34%
$q_{hd}IH_d/GDP$	Residential structure share	10%
$q_{hd}H_d/(4 \times GDP)$	Residential real estate wealth	2.46
$(q_cH_c + K_c)/(4 \times GDP)$	Consumption good capital	3.1
$(K_{hc} + K_{hd})/(4 \times GDP)$	Construction capital	0.16

are software and non-construction capital and construction capital that constitute the largest part of business investment 53% and 11% respectively. To calculate the business capital in the consumption good sector, we sum the capital used in the production of the consumption good and the commercial real estate wealth. The business capital for the construction good is 25% higher than the residential housing wealth, while the business capital of the construction is only 4% of the business capital stock. This means that construction firms possess only a small part of the total capital.

1.3.2 Prior & Posterior Distributions

Table 1.3 summarizes the estimation of the model. We report the estimates of shock and structural parameters at the posterior mean, median and mode, along with the 90% posterior probability intervals. For the shock processes, we use Beta distribution for the persistence with prior mean of 0.8 and a standard deviation of 0.1, and Inverse-Gamma distribution for the standard errors with prior mean 0.001 and standard deviation 0.01. For labour supply elasticity (η) we use a normal distribution centred around 0.5, and we observe a moderate response of labour supply to wages with a median estimate to 0.64. Also, agents exhibit little preference for labour mobility with a median estimate of 0.89.

Table 1.3 Prior and Posterior Distribution

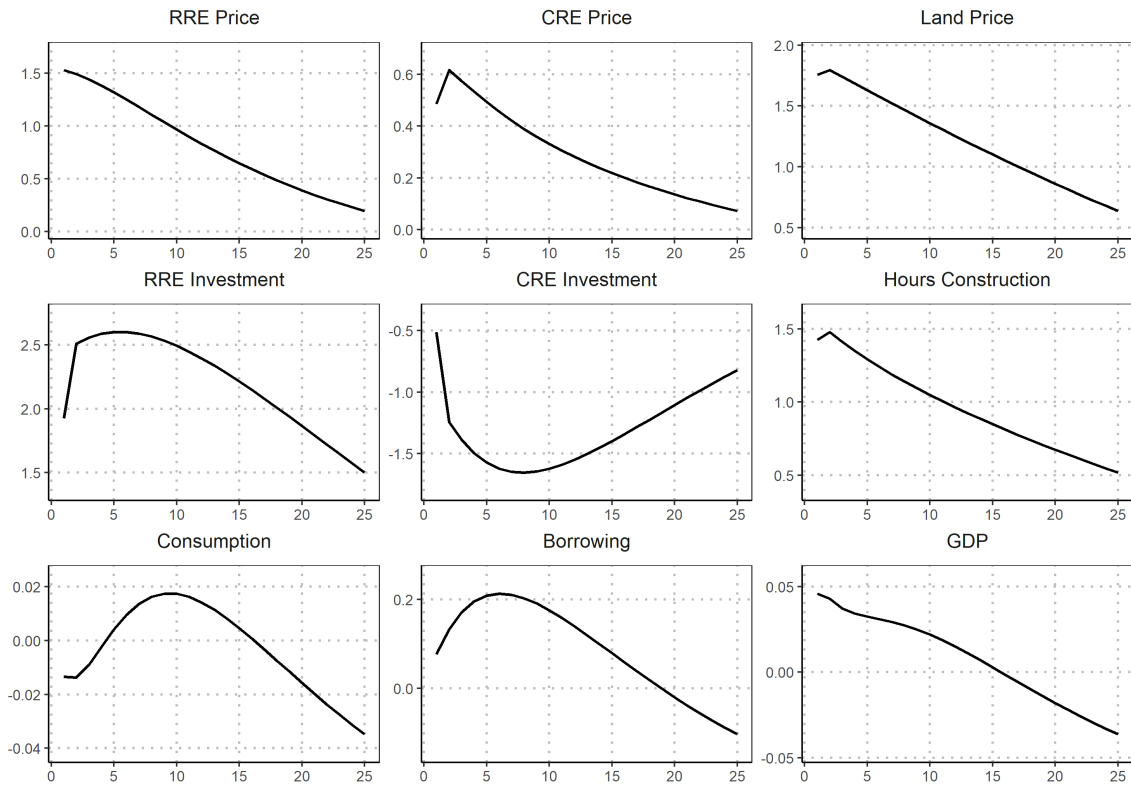
Parameter	Prior Distribution			Posterior Distribution				
	Density	Mean	SD	Mean	2.5%	Median	Mode	97.5%
σ_z	Inv Gamma	0.00	0.00	0.069	0.061	0.069	0.068	0.077
σ_χ	Inv Gamma	0.00	0.00	0.081	0.063	0.08	0.08	0.099
σ_ψ	Inv Gamma	0.00	0.00	0.017	0.016	0.017	0.017	0.019
σ_{Ac}	Inv Gamma	0.00	0.00	0.02	0.017	0.02	0.02	0.023
σ_{Ahc}	Inv Gamma	0.00	0.00	0.03	0.028	0.03	0.03	0.033
σ_{Ahd}	Inv Gamma	0.00	0.00	0.031	0.028	0.031	0.031	0.035
ρ_z	Beta	0.80	0.01	0.78	0.75	0.79	0.79	0.82
ρ_χ	Beta	0.80	0.01	0.95	0.93	0.95	0.95	0.96
ρ_ψ	Beta	0.80	0.01	0.98	0.98	0.98	0.98	0.99
ρ_{Ac}	Beta	0.80	0.01	0.98	0.97	0.98	0.98	0.99
ρ_{Ahc}	Beta	0.80	0.01	0.98	0.97	0.98	0.98	0.99
ρ_{Ahd}	Beta	0.80	0.01	0.96	0.95	0.96	0.96	0.97
ξ	Beta	1	0.1	0.89	0.84	0.89	0.9	0.94
η	Normal	0.5	0.1	0.64	0.41	0.64	0.65	0.88
ϕ_c	Gamma	10.00	6.25	13	10	13	13	17
ϕ_h	Gamma	10.00	6.25	14	8.9	14	10	19

In the construction sector, we observe that the autoregressive terms are relative high, indicating a persistent and prolonged effect on the construction technology, consistent with Iacoviello and Neri (2010). The standard errors are close 0.03 and 0.031 for commercial and residential, respectively.

1.4 Properties of the Model

For the central part of the analysis, we focus on two shocks: an RRE preference shock and a technology shock to the consumption good sector. All impulse responses plots

Fig. 1.6 Housing Preference Shock



Notes: Impulse responses to a positive (one standard deviation) shock to housing preferences. The y -axis measures percent deviation from the steady state.

correspond to a one standard deviation shock. The y -axis measures the deviation from the steady state.

1.4.1 Estimated IRFs

Figure 1.6 shows IRFs for the housing preference shock. As explained in section 2.6, the housing preference shock, causes RRE prices and investment to increase.⁹ Increases in the production of residential real estate requires more inputs, thus increasing the land prices, wages in the construction sector, and therefore RRE investment itself. However, CRE production also requires these inputs, and it is the rise of these input prices that activate the *real estate substitution* channel and causes a fall in CRE investment.

⁹Alternatively this could be considered a "housing demand shock" as in Iacoviello and Neri (2010)

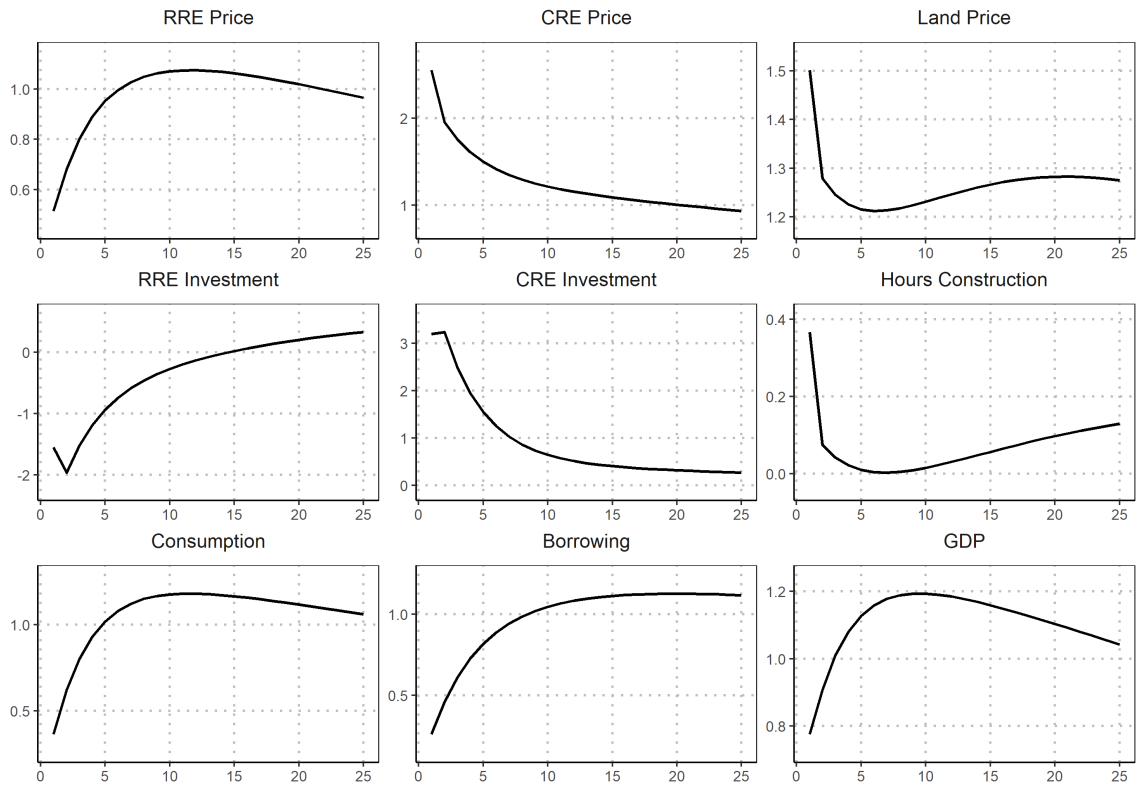
In Iacoviello and Neri (2010) a positive housing preference shock creates a rise in capital in the construction sector and a decrease in capital in the consumption sector. This shift in resources between sectors cause a small but negative response to business investment. In our model, CRE investment by definition is included in the business investment; therefore with a reduction in CRE investment, business investment will follow. However, rather than the shift of resources between construction and non-construction capital, the redistribution takes place within the construction sector between the two types of real estate producers.

The increase in land prices also raises the collateral capacity of the entrepreneurs in the construction sector, allowing them to increase borrowing and consumption. On the other hand, the increase in RRE prices and the fall in CRE investment reduces the household consumption and the collateral capacity of entrepreneurs in the consumption good sector, respectively. The behaviour of consumption resembles the case of heterogeneous households (Iacoviello, 2005; Iacoviello and Neri, 2010), where the assumption of constrained-households produces positive co-movement between consumption and house prices. However, in our model, we generate this co-movement, by utilising the borrowing characteristic of entrepreneurs in the construction sector.

Figure 1.7 shows the IRF for a technology shock in the consumption good sector. For a technology shock, investment and output go up on impact. However, with the separation of investment, we can observe that it is CRE investment that drives business investment, which in turn increases production and output, while RRE investment declines, by a smaller proportion, and overall output still increases.

Specifically, a positive productivity shock increases the demand and price of the inputs required to produce consumption good, that is consumption good capital, CRE capital and commercial land. In turn, the increase in demand for CRE increase CRE investment, wages in the construction sector and land prices. Higher input prices set up the real estate substitution mechanism, which generates a cost-push increase in residential prices and reduces residential investment. Thus what we initially considered a positive supply shock to the consumption good, instigates the equivalent of a positive

Fig. 1.7 Consumption Good Technology Shock



Notes: Impulse responses to a positive (one standard deviation) shock to consumption-good technology. The y-axis measures percent deviation from the steady state.

demand shock to CRE and, in turn, an adverse supply shock to residential property. Borrowing increases stem from the higher value of CRE and the increase in land prices. Consumption follows residential house prices very closely since household utility retains the same relative weights on housing and consumption.

1.4.2 Relative Importance of the shocks

Table 1.4 reports variance decomposition for the key macroeconomic variables across the 6 type of structural shocks at forecasting horizons between the impact period (1Q) and the five years after the initial shock (20Q).

It is clear that the largest variation in RRE prices stems from the housing preference shocks, especially at short horizons. Indeed over longer horizons changes in household

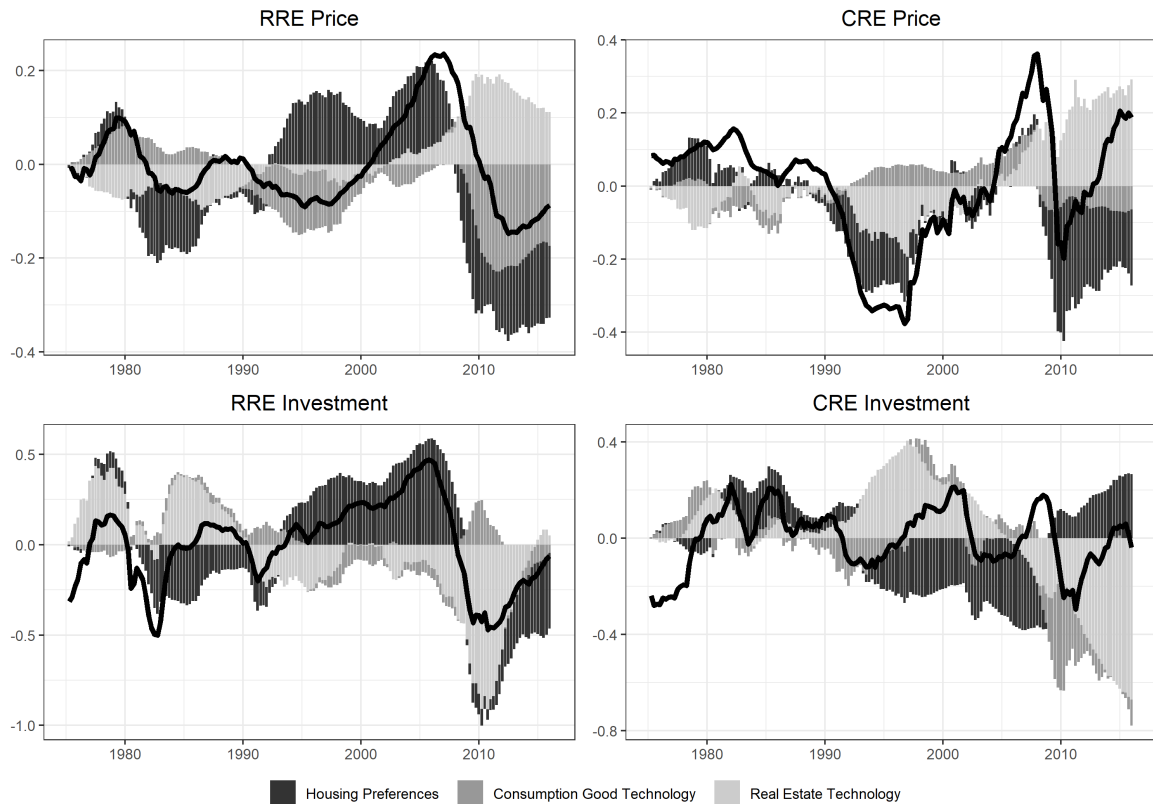
Table 1.4 Variance Decomposition

Horizon	Shocks					
	Discount	Housing Preferences	Labour Supply	Consumption Technology	CRE Technology	RRE Technology
RRE Prices						
1Q	8.37	62.91	0.26	7.16	7.44	13.87
5Q	12.76	56.94	0.47	16.99	2.17	10.67
10Q	12.34	49.58	0.59	25.54	2.11	9.85
20Q	9.33	38.91	0.76	36.82	2.46	11.73
CRE Prices						
1Q	7.71	1.71	2.41	46.92	39.55	1.70
5Q	14.48	2.86	1.42	35.34	43.01	2.88
10Q	12.61	2.81	1.15	33.44	47.06	2.93
20Q	9.14	2.39	0.99	33.70	51.21	2.57
RRE Investment						
1Q	0.40	16.29	1.47	10.57	2.02	69.26
5Q	1.77	21.33	1.50	7.72	0.73	66.94
10Q	1.01	23.25	2.14	4.51	1.34	67.75
20Q	1.12	23.66	2.96	2.65	3.69	65.91
CRE Investment						
1Q	4.28	1.69	18.77	66.54	7.50	1.22
5Q	11.18	9.21	11.81	36.12	23.51	8.17
10Q	5.97	11.21	8.50	19.18	44.35	10.78
20Q	2.93	10.02	6.34	9.65	60.52	10.55
Consumption						
1Q	83.12	0.02	2.68	14.15	0.00	0.02
5Q	65.68	0.00	5.12	28.99	0.21	0.01
10Q	44.26	0.01	7.95	46.97	0.80	0.01
20Q	25.06	0.01	10.68	63.07	1.18	0.01

income are spread across both the consumption good and house prices which also explains why the two components of household utility are highly correlated. CRE prices react in a similar way, over short horizons most of the variation is attributed to demand (consumption technology shock), while more weight is allocated to supply (CRE technology) as you go in longer horizons. Additionally, discount shocks play a non-trivial role in determining property prices, which further highlights the importance of treating real estate separately to consumption.

More than half of the RRE investment variation is attributed to the technology shock to the residential construction, and around a quarter of the variation is driven by a housing demand shock. On the other hand CRE investment, on impact is primarily explained by a technology shock to the consumption good, i.e. CRE demand shock,

Fig. 1.8 Historical Decomposition of Structural Shocks



Notes: The solid line represents the data. Housing preferences and consumption good technology include only their corresponding shock. Real estate technology shock includes both CRE and RRE technology shocks. All series are in deviation from the estimated trend.

and secondarily by the technology shock to the commercial construction. However, the effect of the shock in the end changes and allocates more weight into the supply shock and less to the demand shock.

Figure 1.8 displays the historical decomposition of the prices and investment in residential and commercial real estate. The solid lines display the detrended historical data, obtained by applying a quadratic filter on the observed series. The filled regions show the historical contribution of the four shocks under our estimated parameters. In order to observe the technology shock across the whole construction sector, we combine residential and commercial real estate technology as real estate technology.

The sum of these four shocks accounts for most of the variation in the filtered observed series. The *real estate substitution* channel indicates that a positive shock

in either the housing preferences or consumption good technology will increase real estate prices, however, the response of each element of investment will be contingent on the source and the dominance of the shock. A positive housing preference shock boosts residential investment and diminishes commercial investment, while consumption good technology works in the opposite way where residential investment drops and commercial investment increases. However, in the bottom two graphs of Figure 1.8 that display the property quantities (investments) the two shock work against each other, a result that is attributed to the real estate substitution channel. Thus to fully comprehend these investment cycles it is crucial that the demands for the two types of real estate are not considered in isolation, but rather that the relative strength of the disturbances that drive them are considered.

The housing preference shock seems to be the main driver of the 2007 financial crisis, which is evident in all variables besides the CRE prices. Significantly, in the build-up to the financial crises the increase in RRE are not offset by a fall in CRE investment and following the financial crisis both types of investment fall, a result in contrast to the *real estate substitution* channel. In the following section, we detail how the construction sector and its interaction with both land, and the two types of real estate, can give rise to both of these investment co-movements.

1.5 The role of Land

1.5.1 Land as a unique input

Land, while not *directly* useful as an input for consumption good producers or as a product for households, is a unique factor of production. Competition for land, stems from the fact that not only land is finite¹⁰, but also both households and firms need it *indirectly* through their demands for new RRE and CRE respectively. Liu et al. (2013) were the first to introduce competition for land and the “land reallocation channel” in

¹⁰Land can grow at a very small rate if we consider the land zoning restriction lifts, that enable the commercial and residential building to overtake farmlands or previously unzoned territories

a DSGE framework. In their novel paper, there was no need for real estate production since land prices are able to capture the largest part of the business cycle fluctuations (Davis and Heathcote, 2007). With the abstraction of real estate production and the construction sector, land prices are identical to property prices, and guarantee that the land reallocation channel will always be present and dominant. However, the price and the quantity of land has very different time-series properties to the price and quantity of land in commercial use (Davis, 2009).

To understand more clearly the relationship between land and real estate in our framework, consider construction sector's demand for land, which for RRE and CRE production is given by

$$q_{l,t} = \beta_e E_t \frac{u_{ch,t+1}}{u_{ch,t}} \left(\mu_h \frac{q_{hc,t} I H_{c,t+1}}{L_{hc,t}} \right) + \lambda_{bh,t} (1 - \rho_b) \theta_h q_{l,t+1} \quad (1.17)$$

and

$$q_{l,t} = \beta_e E_t \frac{u_{ch,t+1}}{u_{ch,t}} \left(\mu_h \frac{q_{hd,t} I H_{d,t+1}}{L_{hd,t}} \right) + \lambda_{bh,t} (1 - \rho_b) \theta_h q_{l,t+1} \quad (1.18)$$

respectively. The term u_{ch} is the marginal utility of consumption and λ_{bh} defines the shadow value of the construction sectors existing loans in consumption units. Like Liu et al. (2013) according to equations (1.17) and (1.18) the cost of a unit of land depends upon the marginal utility of land services and the discounted resale value of land. However, the marginal product of land, $(\mu_h \frac{I H_{d,t+1}}{L_{hd,t}}$ and $\mu_h \frac{I H_{c,t+1}}{L_{hc,t}}$) depends upon the real estate demands of the construction sector and not directly on the consumption good producers or households.

At the extreme when $\mu_h \rightarrow 1$ in production functions of RRE and CRE ((1.7) and (1.8) respectively), the construction of real estate requires only depends land, so that the construction sector becomes redundant. The supply of new structures is constant, and land and real estate are equivalent, so that akin Liu et al. (2013) the change in RRE investment perfectly offsets the change in CRE investment, to equates marginal product of land in each sector.

In our framework, the land reallocation channel is encapsulated through a broader definition of competition in the construction sector, where the competition between households and firms is not for land use but for the two types of real estate. Land reallocation is always present, but in comparison with Liu et al. (2013) it is not always dominant. A critical motivation behind a more flexible version of “real estate substitution” is that the two types of real estate do not always follow an opposing path, so an assumption of complete substitution would be unreasonable. The recent global Covid-19 pandemic has further underscored the importance of this model feature. The restrictions of workers to attend offices and hospitality venues has had severe implications for both the supply of labour, the value of commercial premises, and in-turn commercial real estate investment. On the other hand, the implications for residential real estate investment depend upon changes in both the demand for residential property and *all* of the inputs required for production in the construction sector. To shed further light on this issue we consider a labour supply shock.

Labour supply shocks have been shown to be a significant driver of the fall in labour hours during the Covid-19 pandemic (Brinca et al., 2020).¹¹ We argue that such a fall in labour supply will unmistakably leads to a fall in CRE investment as the marginal product of CRE falls. However the implications for RRE investment are ambiguous and contingent upon the weight that land has relative to the other inputs required for the construction of real estate. With a construction sector, where the creation of structures is given by equations (1.7) and (1.8), we have that land, capital and labour all contribute to the formation of new real estate. As a result, the fall in the supply of labour in Figure 1.9 with low values of μ_h not only reduces the demand for $IH_{c,t}$ from consumption good producers but also the supply of both labour and capital to the whole of the construction sector. This creates a separation of real estate investment

¹¹For tractability we assume that the labour supply shock falls uniformly across our sectors. As argued by Dingel and Neiman (2020), the extent to which work in a sector can be carried out at home would have implications for our model, both for the sectoral response of hours, but also because it creates a separation between labour and CRE in production. In our model this would create a cushioning of the falls in labour supply alongside an amplification of the fall in CRE investment and real estate substitution

from land use which can be seen by equating (1.17) and (1.18) to give

$$IH_{c,t+1} = \frac{L_{hc,t} q_{hd,t}}{L_{hd,t} q_{hc,t}} IH_{d,t+1} \quad (1.19)$$

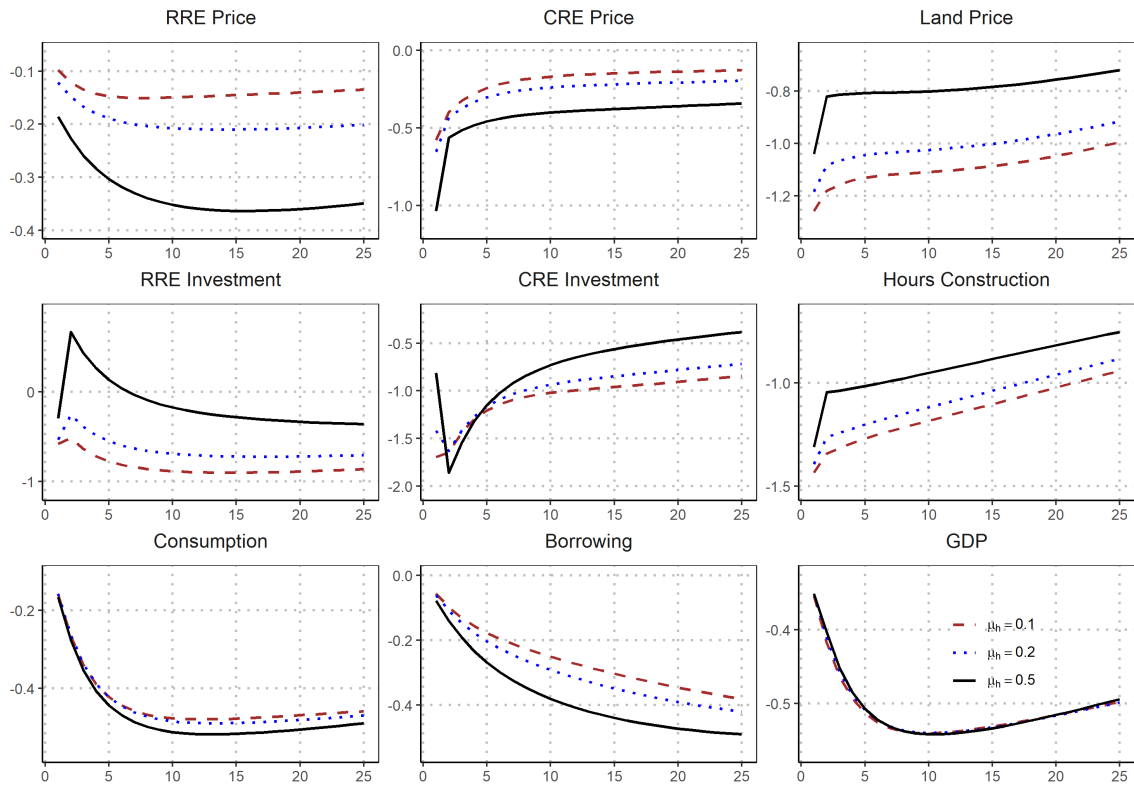
In (1.19) commercial real estate investment dynamics are not only determined by the ratio of land use, but also by the demands for residential real estate. This separation of $IH_{d,t}$ from $L_{hd,t}$ allows $IH_{c,t}$ to potentially fall which allows for both CRE and RRE investment to co-move such that the aggregate supply of real estate falls. Moreover, as can be seen in equations (1.17) and (1.18) and in Figure 1.9, with lower values of μ_h the falls in the land price has less influence on construction costs and the real estate substitution channel is weakened which suppresses some of the falls RRE and CRE prices. Meanwhile, driven by the reduction in labour hours, spending on both RRE and CRE ($q_{hc,t}IH_{c,t+1}$ and $q_{hd,t}IH_{d,t+1}$ respectively) falls whilst, by assumption, the supply of land is fixed. This reduces the marginal product of land, such that land prices become more volatile. In contrast for higher values of μ_h the real estate substitution channel dominates and the two series take opposing paths.

1.5.2 Land Shares

To investigate the role of land as input in the construction sector and its implications for the real estate cycle, we examine the simulated path of investment and land share for both residential and commercial real estate. Figure 1.10 displays the simulated path of RRE investment and residential land in the top panel, and the CRE investment and commercial land in the bottom panel. Land and investment cycles seem to be in synchronisation for most of the sample, however, there are significant divergences, in particular following recession periods.

For example, after the office overbuilding of the 1980s and the consequent collapse, demand for residential land followed a steady upward trend which peaks in 2007. However, post-2007 there is large shift that changes the composition of land share towards the commercial side. Due to the model flexibility, we can observe movements

Fig. 1.9 Labour Supply Shock Sensitivity

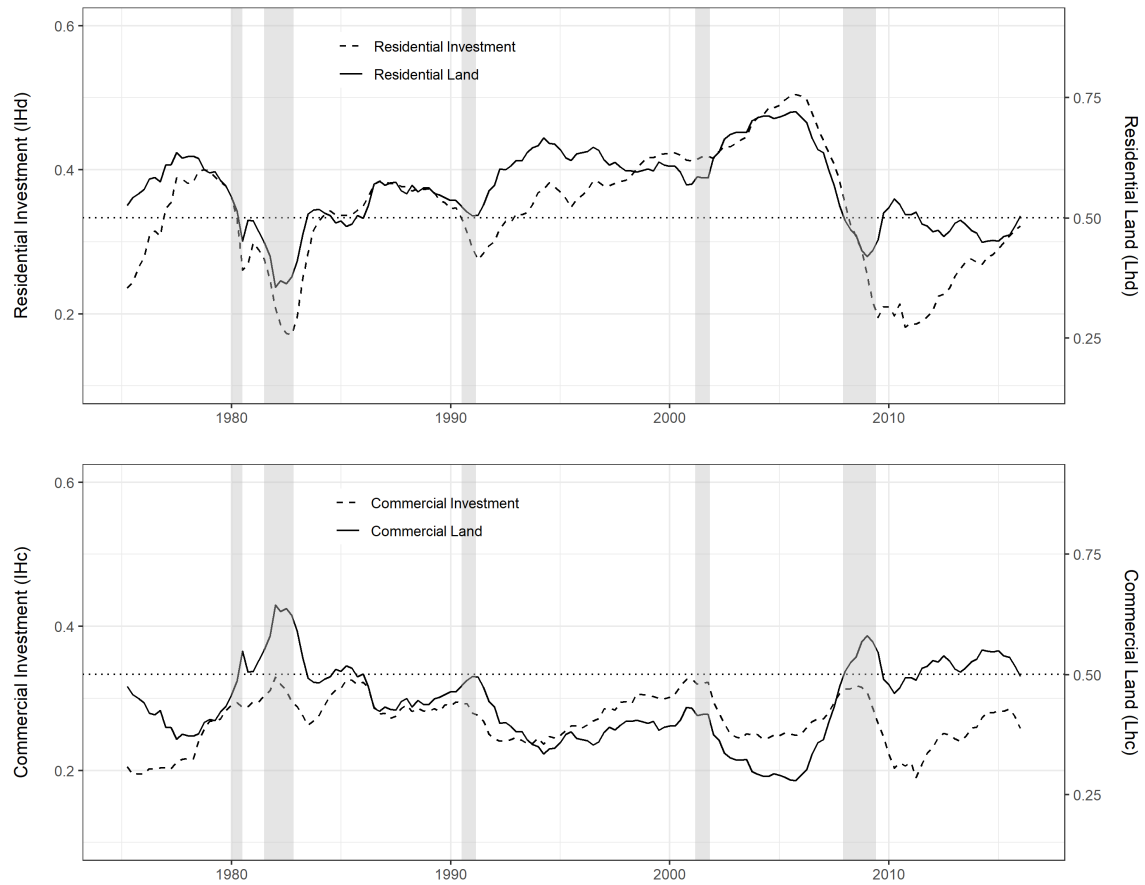


Notes: Impulse responses to a positive (one standard deviation) shock to labour supply. The y-axis measures percent deviation from the steady state.

in investment that is not simply equivalent to the supply of land. Moreover, in the post-financial crisis period, we see a significant fall in both RRE and CRE investment that is not attributed to the substitution of land. By ignoring the construction sector, and using land as the only input, the supply land would be significantly overestimated. Eventually, towards the end of the sample where RRE demand begins to recover, residential investment converges towards its land counterpart.

Finally, we compare our estimate of land share with the estimate derived from Davis and Palumbo (2008). Figure 1.11 plots model estimate of residential land share (dotted line), the aggregate residential land shares (solid line) along with the 68% error bands (dashed lines) that correspond to the bottom 16% and top 84% percentile of the MSA land shares. According to Davis and Heathcote (2007), land values can also

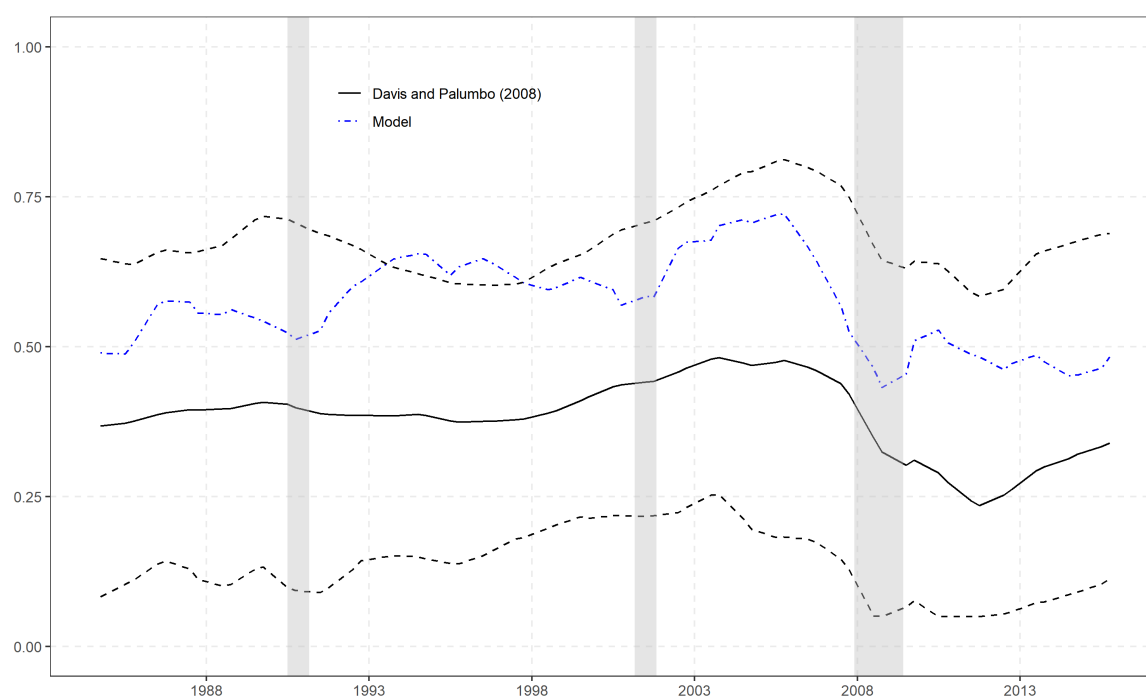
Fig. 1.10 Investment and Land



Notes: Top figure display the residential investment (solid line) and the residential land (dashed line). The bottom figure display the the commercial investment (solid line) and the commercial land (dashed line). The sum of land should always be one. Investment is measured on the left axis and land on the right. The shaded bars mark the NBER recession dates.

be conceptualised as the value of the real estate when you exclude the cost of the structures. Thus the mentioned estimate does not correspond to land measurement, but instead as the ratio of residential real estate value to residential land value. Consistent with Davis and Palumbo (2008), our model estimate shows an upward trend which indicates that residential housing is much more land-intensive than it used to be. Both estimates capture the upward trend and subsequent fall of the land shares after 2007. The crisis in 2007 reverts this trend to 1980s levels.

Fig. 1.11 Land Shares



Notes: Empirical land shares are calculated as the ratio of land value over the home value from Davis and Palumbo (2008). The dashed bands indicate the top and bottom decile of the MSA areas land share. The shaded bars mark the NBER recession dates. *Source* www.aei.org/housing/land-price-indicators/

1.6 Conclusion

This paper has shown both the existence and potential mechanism behind the real estate substitution channel as well as captured the way it manifests. Notably, the inputs of the construction sector play a significant role in explaining the detail and scale of the processes that create this effect. The channel is reciprocal, meaning that it can either originate in residential or the commercial real estate. However, the magnitude and dynamics are not symmetrical, which highlights that even though construction has many commonalities in the production of the two types of real estate, the specificity of each type is non-trivial.

We give a unique interpretation to the housing preference shock, where it does not merely generate a shift in the preference for housing, instead it is shown to have of a structural connection with commercial real estate. In turn, this relationship explains

how demand shocks in the residential real estate can easily crowd out commercial real estate, which affects the goods market in a similar way to an adverse aggregate supply shock.

The Bayesian estimation of the model reveals that housing preference shocks determine much of the movements in aggregate variables. Moreover, the historical decomposition reveals that whilst movements in housing demand drives all variables; it was the collapse in CRE prices that was particularly dominant in the 2007 crisis, which stemmed from a fall in productivity in the consumption good sector. As a result, whilst the co-movements of RRE and CRE prices are somewhat anchored our results reveal that there are different mechanisms at play which are very important for explaining the short-run dynamics in both the construction sector and economy as a whole.

Chapter 2

Speculative Bubbles in Segmented Markets: Evidence from Chinese Cross-Listed Stocks

Joint with Efthymios Pavlidis

2.1 Introduction

China's stock market: A crazy casino (The Economist, May 26th 2015)

Since the re-opening of the Shanghai stock exchange (SSE) and the foundation of the Shenzhen stock exchange (SZSE) in the early 1990s, the Chinese stock market has experienced a remarkable growth. Starting from just a handful of listed companies in 1990 and a tiny market capitalization, it expanded to over three thousand firms in 2017 and a market capitalization of seven trillion dollars, ranking second worldwide behind the United States (Carpenter and Whitelaw, 2017). While the Chinese stock market has grown rapidly over the last decades, movements in Chinese share prices have been anything but tranquil, with spectacular price rallies followed by severe

market crashes occurring in the 1990s, 2000s, and 2010s. Such extreme financial events appear difficult to explain using observed market fundamentals and have led to a consensus that speculative forces are in action in the Chinese stock market. Notably, in his 2001 speech, the preeminent Chinese economist Wu Jinglian compared China's stock market to a *casino*, that is manipulated by speculators and lacks a strong link to fundamentals. The *casino* term has since been adopted by the popular press to describe the overall behaviour of Chinese share prices. Given China's leading role in global economic growth and investment, the presence of speculative dynamics, bubbles, in the country's capital allocation system constitutes a topic of increasing significance.

In general, testing for speculative bubbles in financial markets is confounded by the fact that the fundamental value of financial securities is unobserved. Early studies have attempted to address this issue by utilizing observed variables, such as dividends, to estimate intrinsic values. A major drawback of such direct approaches is that they depend crucially on the strong and, in most cases, unrealistic assumption that the true data generating process for fundamentals is known. As argued by several researchers, model misspecification or omitted variables can lead to false inference in favour of bubbles, rendering direct approaches invalid (Flood and Garber, 1994; Gürkaynak, 2008; Hamilton and Whiteman, 1985; West, 1987). To circumvent this problem, more recent studies have employed indirect approaches that exploit information about market fundamentals incorporated in derivative prices or survey data (Pavlidis et al., 2017, 2018). These studies show that periodically collapsing bubbles create a wedge between actual realizations of future spot prices and market expectations which, under general conditions, depends solely on the bubble process. As an implication, rather than using estimates of intrinsic asset values to assess the presence of speculative bubbles, researchers can examine the dynamics of the difference between actual future spot prices and market expectations. Unfortunately, indirect approaches based on future prices or survey data cannot be applied in the case of China because derivative markets

are at an early stage of development and survey data on market expectations that cover periods long enough to allow a proper econometric analysis do not exist.¹

In this paper, we propose an alternative approach for testing for rational speculative bubbles that makes use of the unique trading features of Chinese cross-listed securities. There is a large number of companies incorporated in mainland China that simultaneously issue A shares on SSE or SZSE, and H shares on the Stock Exchange of Hong Kong (SEHK). For a given issuer, these two types of shares have identical voting rights and exchange-rate-adjusted dividend payments (i.e., they have the same fundamentals) but differ in terms of their accessibility by different groups of investors. Prior to the introduction of the Stock Connect scheme, Chinese mainland investors could easily access A but not H shares, while international and Hong Kong investors could readily access H but not A shares because of strict government regulations. The segmentation of A- and H-share markets implied that price valuations of the same security could differ across geographical locations without giving rise to arbitrage opportunities (Chen and Knez, 1995; Froot and Dabora, 1999; Lamont and Thaler, 2003). The main idea of the present paper is that, in this setting with limits to arbitrage, differences in speculative trading in Chinese mainland and Hong Kong can lead to distinct bubbles processes in A- and H-share markets. As a consequence, share prices of cross-listed companies can diverge despite having the same underlying fundamentals.

To demonstrate the theoretical implications of different speculative dynamics in A- and H-share markets, we adopt a standard asset-pricing model with rational, risk-neutral investors and consider a periodically collapsing bubble process in the market for A but not for H shares. We show that, in this framework, the A-H price differential displays two characteristic properties when the bubble erupts. First, the price differential grows (in expectation) at an exponential rate, thus displaying explosive dynamics and, second, it has predictive content for future changes in A-share prices.

¹Equity warrants were briefly introduced in China in 2005–8 (Liu et al., 2014). By examining the behaviour of the warrants market during this period, Xiong and Yu (2011) provide strong evidence in favour of speculative dynamics. Specifically, they show that the price of many put warrants with long maturities exceeded both the upper bound given by the strike price and the more conservative fundamental value implied by the Black and Scholes model.

These two properties can be examined empirically to test for speculative bubbles by exploiting recent advances in recursive unit root tests and in predictive regression tests with persistent regressors.

For our empirical application, we use data on the Hang Seng AH Premium Index and on a panel of 26 cross-listed companies spanning the period from January 2006 to December 2018. By employing the popular Generalized Supremum Augmented Dickey Fuller (GSADF) of Phillips et al. (2015a,b) and its panel version, we show that A-H price differentials display episodes of explosive dynamics. These episodes are relative short and coincide with periods commonly considered to be characterized by speculative bubbles. Namely, the Chinese stock market *frenzy* of 2007 and the Chinese stock market *crash* of 2014-2015. A similar conclusion is reached by looking at the predictive regression results, which indicate periods of in-sample predictability, again, during 2007 and 2014-15. Thus, in line with the *casino* hypothesis, our findings support the presence of speculative dynamics in the Chinese stock market prior to 2015. On the contrary, we find no evidence of speculative bubbles after the 2014-15 market crash. As we discuss in more detail in the empirical results section, during this latter period mutual stock market connectivity was established between mainland China and Hong Kong through the Shanghai- and Shenzhen-Hong Kong Stock Connect programs. By raising the degree of financial integration of China into the global economy, these programs gradually increased capital flows across markets.

The presence of distinct bubble processes in mainland China and Hong Kong provides a possible explanation for one of the most intriguing puzzles in finance: the large and highly persistent share price deviations of Chinese cross-listed companies (Carpenter and Whitelaw, 2017; Fernald and Rogers, 2002). A number of factors have been put forth in the literature as determinants of foreign share discounts, such as different attitudes toward risk, information asymmetries, changes in exchange rate expectations, liquidity and transaction costs (Chan et al., 2008; Chung et al., 2013; Wang and Jiang, 2004). As a final exercise, we use a dynamic panel probit methodology to investigate whether such factors can explain the identified episodes of exuberance in

A-H price differentials. The estimation results suggest that the likelihood of bubble formation is associated with a proxy for credit and a measure of the degree of public dissemination of information.

The rest of the paper is structured as follows. Section 2.2 provides an overview of the institutional background of Chinese stock markets. Section 2.3 outlines the theoretical framework and describes the proposed bubble detection methods. The following section deals with the empirical application of these methods to A-H cross-listed shares. The same section provides a robustness exercise based on American Depository Receipts, discusses the Stock Connect program and its impact on the time-series behaviour of A-H price differentials, and presents the results of the dynamic panel probit analysis. The final section summarizes our findings and provides concluding remarks.

2.2 Institutional Background

China's modern stock market opened only in the early 1990s with the re-establishment of SSE on November 26, 1990 and the foundation of SZSE on December 1, 1991. Upon their opening, SSE listed eight companies and had a market capitalization of 1.2 billion renminbi (RMB), and SZSE listed six companies with a total share capital of 273 million RMB. In 2016, the number of listings in SSE and SZSE increased to 3,134 firms and their combined market capitalization reached 51 trillion RMB, which corresponded to 68 percent of the country's gross domestic product.

There are two types of tradable shares issued by Chinese firms listed on SSE and SZSE, the so-called A and B shares. The market for A shares is by far the largest, accounting for the lion's share of trading volume and market capitalization. A shares are quoted in domestic currency (RMB) and, until recently, were primarily traded by mainland Chinese citizens due to strict capital controls imposed by the Chinese authorities.² B shares, on the other hand, are traded in foreign currency (US dollars in

²During our sample period, China implemented a number of schemes aiming to gradually open its capital market to overseas investors. In 2002, the Qualified Foreign Institutional Investor (QFII) program was launched, which allowed overseas financial institutions that met a set of admission requirements to invest in China's securities markets subject to quotas. In 2011, a second scheme,

Shanghai and Hong-Kong dollars in Shenzhen) and were limited to foreign investors until February 2001, when China Securities Regulatory Commission (CSRC) permitted their purchase by mainland citizens via the secondary market.

Since 1993, Chinese firms can also list shares on stock exchanges outside mainland China to raise capital from abroad. Due to its geographical proximity and extensive socio-economic links to the mainland, the most popular location is Hong Kong. Compared to SSE and SZSE, the Stock Exchange of Hong Kong (SEHK) constitutes a more advanced financial market, it has adopted financial reporting standards that are in alignment with the IFRS since 2005, and it is open to foreign investors. In 2016, 241 Chinese firms issued shares in SEHK with a market capitalization exceeding 24 trillion Hong-Kong dollars. This type of shares, referred to as H, is subject to the Hong Kong Exchanges and Clearing Limited listing requirements, and are quoted and traded in Hong Kong dollars. Analogously to the market for A shares, investors residing in mainland China had very limited access to the market for H shares until 2015 due to tight restrictions on capital movements.³

A key feature for our analysis is that a number of Chinese companies issue both A shares in mainland China and H shares in Hong Kong. Apart from their trading location, these cross-listed securities are identical. They have the same legal rights and the same claims to exchange-rate adjusted dividends. Moreover, cross-listed Chinese companies are required to disclose the same information to local and overseas investors (Jia et al., 2017). Thus, in the absence of market frictions, A and H shares should trade for the same price. However, due to the segmentation of A and H markets, deviations from the law of one price are typical, with A shares usually trading at a premium.

the Renminbi QFII (RQFII), was jointly established by the CSRC, the People's Bank of China, and the State Administration of Foreign Exchange (SAFE). The scheme allowed subsidiaries of domestic financial institutions in Hong Kong to invest in mainland stock markets. As of February 2016, 279 foreign institutions had been granted QFII licenses and 158 institutions RQFII licenses. The total QFII and RQFII quotas were 80.795 billion US dollars and 471.425 billion RMB, respectively, which represented a small fraction of total market capitalization.

³In 2006, the Qualified Domestic Institutional Investor (QDII) program was launched which provided limited opportunities for mainland investors to access overseas markets, including Hong Kong, via CSRC approved financial institutions. As of December 2015, 132 institutions had been granted QDII qualification, and SAFE had approved investment quotas of 90 billion US dollars.

Table 2.1 Distribution of cash market trading volume by investor type and origin

	2006-07	2007-08	2008-09	2009-10	2010-11	2011-12	2012-13	2013-14	2014-15	2016	2018	Full Sample
Retail Total	32%	29%	29%	25%	26%	21%	23%	25%	27%	23%	16%	25%
- Local Retail	28%	26%	25%	21%	22%	17%	18%	20%	19%	16%	10%	20%
- Overseas Retail	4%	3%	4%	4%	4%	4%	5%	5%	8%	7%	6%	5%
Institutional Total	64%	65%	62%	65%	62%	63%	61%	58%	50%	53%	55%	60%
- Local Institutional	25%	27%	24%	23%	20%	21%	20%	24%	19%	20%	20%	22%
- Overseas Institutional	39%	38%	38%	42%	42%	42%	41%	34%	31%	20%	20%	35%
Other	4%	6%	8%	10%	12%	15%	16%	16%	22%	24%	29%	15%
US+Europe	71%	74%	70%	69%	69%	69%	67%	64%	56%	57%	51%	65%
Asia	22%	22%	26%	27%	22%	21%	24%	29%	36%	36%	42%	28%

Source: Hong Kong Exchanges and Clearing Limited Cash Market Transaction Surveys from 2007 to 2016.

A potential explanation for the documented A-H price disparities is investor heterogeneity between markets. On the one hand, the market for A shares is dominated by local, retail investors. These investors account for more than 80 percent of the trading volume and, as survey evidence suggests, are less experienced than US investors and younger, with more than half being under 45 years of age (see, Gan et al., 2014, Feng and Seasholes, 2003, and the 2013 CSRC securities report). On the other hand, retail investors comprise only a small part of the Hong Kong market (25 percent during our sample period), with most of the trading volume being generated by institutional investors (60 percent). Trading from overseas investors (mainly from the United States and Europe) is also substantial, accounting for 40 percent of the total volume (see Table 2.1). Mei et al. (2005), among others, argue that, because of their type and age composition, stock market investors in mainland China are more likely to engage in intense speculative trading.

As we discuss in Section 2.4, a factor that may magnify the effect of speculative trading on A-H prices disparities is differences in the institutional features of short selling across markets. While short selling has been permitted in Hong Kong since January 1994, it was not until March 2010 that China launched a pilot program allowing 90 constituent stocks of the SSE and SZSE composite indices to be sold short and purchased on margin.⁴ The main objective of the program was to improve information

⁴The CSRC also conducted a few small pilot programs in 2007 and 2008.

efficiency, thus facilitating the price discovery process, and to generate trading liquidity. In 2011, the CSRC announced that the pilot scheme would become routine practice, and in subsequent years, the list of eligible stocks was revised and expanded several times. By December 2016, the number of eligible stocks increased to 950, representing one-third of the total number of firms issuing A shares. Despite the gradual removal of the ban on margin trading and securities lending in mainland Chinese markets, the associated margin financing and shorting costs are higher by an order of magnitude compared to more developed financial markets (see, e.g., Chang et al., 2014).

2.3 Speculative Bubbles: Theory and Econometric Tests

We begin our analysis with a standard endowment economy in which rational, infinitely-lived investors derive utility from personal consumption (Diba and Grossman, 1988; Gürkaynak, 2008). In this economy, the representative investor's objective is to

$$\max E_t \sum_{\tau=t}^{\infty} \beta^{\tau-t} u(C_\tau), \quad (2.1)$$

where C_τ denotes the level of consumption at period τ , E_t is the rational expectations operator conditional on all available information at time t , and β is a discount factor that is restricted to take values in $(0,1)$ so that time preferences are positive. The instantaneous utility function, $u(\cdot)$, is assumed to be concave, increasing in C_τ , and continuously differentiable.

At each time period, τ , the investor is faced with a budget constraint. She receives an endowment y_τ which can be instantly consumed or used to purchase dividend-paying shares, s_τ , in order to smooth future consumption. Letting P_τ denote the price of a share in units of the consumption good and D_τ the dividend payment, the budget

constraint faced by the investor is given by

$$C_\tau \leq y_\tau + (s_{\tau+1} - s_\tau)P_\tau + D_\tau s_\tau. \quad (2.2)$$

The first order condition for the investor's utility maximization problem specified by (2.1) and (2.2) is given by

$$P_t u(C_t) = \beta E_\tau [(P_{t+1} + D_{t+1}) u'(C_{t+1})]. \quad (2.3)$$

Intuitively, the above Euler equation states that for a time-path of s to be optimal, an investor cannot become better off by selling or buying a share at time t and reversing the transaction at time $t + 1$. By assuming that financial and goods markets clear and normalizing the number of existing shares to unity, Equation (2.3) can be rewritten as

$$E_t[q_{t+1}] - \beta^{-1}q_t = -E_t[u'(y_{t+1} + D_{t+1})D_{t+1}], \quad (2.4)$$

where $q_t \equiv P_t u'(y_t + D_t)$. The general solution to this first order stochastic difference equation is given by

$$q_t = F_t + B_t, \quad (2.5)$$

where the first term of the RHS is referred to as the market fundamentals component because it depends on the present value of all future dividends and the marginal utilities of consumption, $F_t = \sum_{j=1}^{\infty} \beta^j E_t[u'(y_{t+j} + D_{t+j})D_{t+j}]$; while, the second term is a rational bubble component that satisfies the condition

$$E_t[B_{t+1}] = \beta^{-1}B_t. \quad (2.6)$$

In the empirical literature on rational bubbles, B_t is usually viewed to be driven by variables that are exogenous to the valuation process. Moreover, it is often assumed that utility is linear, which implies risk neutrality and constant marginal utility. Under this latter assumption, the general solution to (2.4) simplifies to the textbook asset

pricing equation

$$P_t = F_t + B_t = \sum_{j=1}^{\infty} \beta^j E_t[D_{t+j}] + B_t, \quad (2.7)$$

which links the current stock price to the bubble process B_t and to a market-fundamentals component that equals the discounted value of expected future dividends.

The above analysis has important implications for econometric tests for rational speculative bubbles. By condition (2.6), if a bubble exists then it will grow, in expectation, geometrically at the rate of $\beta^{-1} - 1$. It follows from Equation (2.7) that the stock price will display explosive dynamics and diverge from its fundamental value over time.⁵ This prediction has motivated a plethora of studies that employ non-stationarity tests to examine the presence of speculative bubbles in financial markets. Some studies have applied unit root tests to stock prices and price-to-fundamentals ratios (such as stock prices to dividends). Others have examined the existence of cointegrating relationships between prices and observed market fundamentals. The main drawback of such direct approaches is that they rely on strong assumptions about the data generating process for market fundamentals which are difficult to verify in practice. Specifically, tests on raw prices implicitly assume that the fundamental component in (2.7) does not display explosive dynamics in sample. Whilst, tests that control for market fundamentals by using observed economic and financial variables are subject to model misspecification and omitted-variable problems. As argued by several researchers, these deficiencies can lead to false inference (Gürkaynak, 2008).

2.3.1 Cross-Listed Securities

Consider an extension of the above framework to two segmented, but otherwise identical economies, A and H, in which investors trade shares of the same storable asset locally.

⁵The increasing difference between actual and intrinsic asset values arises because of investors' expectation to sell the asset at an even higher price in a future date. Note, however, that these large, expected capital gains do not imply arbitrage opportunities since they are already priced in the market. That is, the evolution of asset prices satisfies the requirement of market efficiency by construction.

In this setting, there is an asset pricing equation for each economy given by

$$P_t^i = F_t^i + B_t^i, \quad (2.8)$$

with $i = A, H$. Because investors are entitled to the same stream of dividend payments irrespective of their location, their valuations for the market fundamental components of A- and H-share prices satisfy $F_t^A = F_t^H$. However, there are no forces that guarantee equality of the bubble components B_t^A and B_t^H . This is so because arbitrage between markets is not feasible and market efficiency dictates that $\{B_t^i\}_{t=0}^\infty$ can be any sequence of random variables that satisfies condition (2.6). Thus, allowing for speculative bubbles in financial markets gives rise to the possibility of non-unique asset price paths for A and H shares,

$$P_t^A - P_t^H = B_t^A - B_t^H, \quad (2.9)$$

and can lead to violations of the law of one price. The above expression lies in the heart of our analysis. It suggests that the price differential between A and H shares, first, does not depend on market fundamentals and, second, it displays the same behaviour as the difference in bubble sequences. As long as B_t^A and B_t^H are not co-explosive, the price differential will exhibit explosive dynamics (see Nielsen, 2010). Therefore, one can test for the presence of distinct speculative bubbles, while remaining agnostic about the intrinsic value of the asset, by simply running right-tailed unit root tests on $P_t^A - P_t^H$.

Recursive Unit Root Tests The property that $P_t^A - P_t^H$ is explosive when B_t^A and B_t^H do not co-explode holds irrespective of the type of speculative bubble. The simplest scenario is that of a linear AR(1) process for B_t^A

$$B_{t+1}^A = \beta^{-1} B_t^A + \epsilon_{t+1}, \quad (2.10)$$

where $\epsilon_{t+1} \sim \text{iid}(0, \sigma_\epsilon^2)$, and no bubbles in the market for H shares, $B_t^H = 0$. For the case of the Chinese market, it is more realistic to presume that bubbles, if they exist,

are periodically collapsing. For expositional purposes, we focus on the periodically-collapsing bubble proposed by Blanchard (1979)

$$B_{t+1}^A = \begin{cases} \frac{1}{\beta\pi} B_t^A + \epsilon_{t+1}, & \text{with prob. } \pi \\ \epsilon_{t+1}, & \text{with prob. } 1 - \pi. \end{cases} \quad (2.11)$$

This process switches between two states. In the first state, it grows geometrically at the higher than average rate of $1/(\beta\pi) - 1$, whilst in the second state it collapses to a white noise. In expectation, the growth rate of B_t^A equals $\beta^{-1} - 1$ and, therefore, Equation (2.11) satisfies (2.6). By resembling the behaviour of the bubble process, the price differential

$$P_t^A - P_t^H = B_t^A, \quad (2.12)$$

also alternates between an explosive and a stationary state. As will be shown in the following section, this behaviour is in line with the price rallies and subsequent collapses that have characterized the A-H premium index over the last decades.

From an empirical perspective, the presence of boom-bust dynamics in $P_t^A - P_t^H$ implies that standard unit root tests based on linear, time-invariant regression equations may display extremely low power to detect bubbles. A number of studies illustrate that such tests frequently lead to finding spurious stationarity even though asset prices driven by periodically-collapsing bubbles are inherently explosive (see, e.g., Evans, 1991). To deal with this shortcoming, in this paper we employ the GSADF test of Phillips et al. (2015a,b) and its panel version proposed by Pavlidis et al. (2016). The GSADF test has a number of attractive features. First, due to its recursive nature, it is consistent with multiple changes in regime. Second, it displays accurate size and good power properties and in many cases is superior to alternative tests for periodically-collapsing bubbles (for simulation evidence, see Phillips et al., 2015a, and Homm and Breitung, 2012). And third, it permits identification of the periods during which the series under examination displays explosive dynamics. The panel version, on the other hand, introduces a rich specification, that captures the heterogeneity and

cross-sectional dependencies of constituent series, in order to test for overall exuberance. By doing so, it can lead to substantial power gains in comparison to univariate unit root procedures applied to aggregate series (Pavlidis et al., 2019). A description of the GSADF and panel GSADF tests can be found in Appendix B.1.

Rolling Predictive Regressions The presence of distinct asset price bubbles has also implications for predictability tests on stock prices. Consider the following predictive regression

$$P_{t+1}^A - P_t^A = \alpha_0 + \alpha_1(P_t^A - P_t^H) + u_{t+1}, \quad (2.13)$$

where α_0 and α_1 are regression coefficients, and the error term $u_{t+1} \sim \text{iid}(0, \sigma_u^2)$. In the absence of speculative bubbles and under risk neutrality, the efficient market hypothesis postulates that movements in stock prices are unpredictable and, therefore, the value of the slope coefficient in (2.13) is continuously equal to zero. However, this prediction may fail in the presence of distinct bubbles. To illustrate this point most simply, let fundamentals follow a random walk process, $F_{t+1} = F_t + v_{t+1}$, and consider again the case of an ongoing bubble in the market for A shares but no bubble in the market for H shares. The least squares estimate for the slope coefficient in regression (2.13) is

$$\hat{\alpha}_1 = \frac{\widehat{\text{cov}}(P_{t+1}^A - P_t^A, P_t^A - P_t^H)}{\widehat{\text{var}}(P_t^A - P_t^H)}. \quad (2.14)$$

We have already obtained an expression for the regressor in (2.14), see Equation (2.12). Using Equation (2.11), we can also obtain the following expression for the regressand

$$P_{t+1}^A - P_t^A = \frac{1 - \pi}{\beta\pi} B_t^A + \epsilon_{t+1} + v_{t+1}. \quad (2.15)$$

Substituting (2.12) and (2.15) into the formula for the least-squares coefficient yields

$$\hat{\alpha}_1 = \frac{1 - \pi}{\beta\pi} + \frac{\widehat{\text{cov}}(\epsilon_{t+1}, B_t^A)}{\widehat{\text{var}}(B_t^A)} + \frac{\widehat{\text{cov}}(v_{t+1}, B_t^A)}{\widehat{\text{var}}(B_t^A)}.$$

Because the vector of future shocks $(\epsilon_{t+1}, v_{t+1})$ is orthogonal to B_t^A , the plim of $\widehat{cov}(\epsilon_{t+1}, B_t^A)/\widehat{var}(B_t^A)$ and of $\widehat{cov}(v_{t+1}, B_t^A)/\widehat{var}(B_t^A)$ are zero. Therefore, as the bubble erupts

$$\text{plim } \hat{\alpha}_1 = \frac{1 - \pi}{\beta\pi} > 0, \quad (2.16)$$

and price movements in A shares become predictable. Note, however, that this *ex post* predictability cannot be exploited in real time by investors, who rationally price A shares by attaching a non-zero probability to the bubble bursting, and therefore it does not imply rejection of market efficiency. Note also that, in the absence of bubbles, explosive fundamentals cannot cause α_1 to deviate from zero since in this case the regressor will be fixed at $P_t^A - P_t^H = 0$.

The above analysis suggests that, if the null of non-explosive dynamics in $P_t^A - P_t^H$ is rejected, then researchers can further examine the presence of speculative bubbles by sequentially testing the hypothesis of no predictability, $H_0 : \alpha_1 = 0$, against the one-sided alternative $H_1 : \alpha_1 > 0$. An issue of concern in this framework is that the predictor in regression (2.13) is highly persistent under the alternative hypothesis. As a consequence, the slope coefficient α_1 follows a non-standard limiting distribution, and results based on conventional inference methods can be misleading (Phillips, 2014). Several methods have been proposed in the literature to draw valid statistical inference in this setting, such as the efficient Q -test of Campbell and Yogo (2006), the conditional likelihood approach of Jansson and Moreira (2006), the nearly optimal test of Elliott et al. (2015), and the bootstrap procedures of Kilian (1999) and Kilian and Taylor (2003). We adopt a rolling-window approach that consists of sequentially estimating predictive regressions and drawing statistical inference using the IVX instrumentation method of Phillips and Magdalinos (2009), Phillips and Lee (2013), and Kostakis et al. (2015). The IVX method is particularly attractive in this setting because it allows robust chi-square inference for a wide range of AR processes, from stationary to mildly explosive. For a description of the IVX testing procedure, the interested reader is referred to Appendix B.2.

2.4 Empirical Results

In this section, we apply the above bubble detection methods to data on Chinese A-H twin shares. We also provide a robustness check, which examines Chinese American Depository Receipts traded in the New York Stock Exchange, and discuss the effect of the Stock Connect program on A-H price differentials. Finally, we explore the ability of a number of factors, that have been put forth in the literature as potential determinants of foreign share discounts, to explain episodes of exuberance in A and H share price differences.

2.4.1 A and H Shares

Data For our main empirical analysis, we employ the Hang Seng AH premium index, and a balanced panel of 26 Chinese companies simultaneously listed on SEHK and SSE or SZSE. The data are downloaded from Thomson Reuters Datastream and cover the period from the first week of January 2006 to the last week of December 2018.⁶ The reason for setting the start date at January 2006 is twofold. On the one hand, this choice allows us to examine the Chinese stock market frenzy of 2007 and, on the other, we avoid potential biases related to, first, the A-share market reforms that occurred in April 2005 and, second, the change in the exchange-rate regime that took place in July of the same year.⁷ With regard to the data frequency, the use of weekly prices enables us examine a large sample size ($T = 678$ observations), which may lead to

⁶The entire population of companies that listed both A and H shares throughout our sample period is 29. We have discarded three companies, Luoyang Glass and Hisense Kelon Electrical Holdings, due to the large number of missing observations, which exceeds 15% of the sample size, and Shenji Group Kunming Machine Tool Company Limited due to cancellation of listing. For the remaining companies, for which the percentage of missing data is small (less than 6%), we have replaced missing data with the latest available observation.

⁷On the 29th of April 2005, the Chinese government implemented the Split Share Structure Reform which led to a substantial reduction in the number of state owned non-tradable shares. On the 21st of July 2005, China abandoned its peg to the US dollar, which caused an immediate appreciation to 8.11 RMB per US dollar. Since then, China has adopted a managed floating exchange rate with reference to a basket of foreign currencies.

Table 2.2 Chinese Cross-listed Companies

Company Name	Abbreviation	Sector	A-Ticker	H-Ticker	ADR-Ticker
Angang Steel	Angang	Materials	000898.SZ	0347.HK	
Anhui Conch Cement	Anhui Conch	Materials	600585.SS	0914.HK	
Anhui Expressway	Anhui Express	Industrials	600012.SS	0995.HK	
Guangzhou Baiyunshan Pharmaceutical Holdings	Baiyunshan	Health Care	600332.SS	0874.HK	
China Eastern Airlines	China East Air	Industrials	600115.SS	0670.HK	CEA
China Petroleum & Chemical	China Petroleu	Energy	600028.SS	0386.HK	SNP
COSCO Shipping Energy Transportation	Cosco Shipping	Industrials	600026.SS	1138.HK	
CSSC Offshore & Marine Engineering Group	CSSC Marine En	Industrials	600685.SS	0317.HK	
Dongfang Electric	Dongfang Elec	Industrials	600875.SS	1072.HK	
Huadian Power International	Huadian Power	Utilities	600027.SS	1071.HK	
Huaneng Power International Inc	Huaneng Power	Utilities	600011.SS	0902.HK	HNP
Jiangsu Expressway	Jiangsu Exp	Industrials	600377.SS	0177.HK	
Jiangxi Copper	Jiangxi Copper	Materials	600362.SS	0358.HK	
Beijing Jingcheng Machinery Electric	Jingcheng Mach	Industrials	600860.SS	0187.HK	
Maanshan Iron & Steel	Maanshan Iron	Materials	600808.SS	0323.HK	
Nanjing Panda Electronics	Nanjing Panda	Information Technology	600775.SS	0553.HK	
Northeast Electric Development	Northeast Elec	Industrials	000585.SZ	0042.HK	
Sinopec Shanghai Petrochemical	S Sh Pechem	Materials	600688.SS	0338.HK	SHI
Sinopec Oilfield Service	Sinopec Oilfie	Energy	600871.SS	1033.HK	
China Southern Airlines	Southern Air	Industrials	600029.SS	1055.HK	ZNH
Shenzhen Expressway	Sz Expressway	Industrials	600548.SS	0548.HK	
Tianjin Capital Environmental Protection Group	Tianjin Cap	Industrials	600874.SS	1065.HK	
Tsingtao Brewery	Tsingtao Brew	Consumer Staples	600600.SS	0168.HK	
Shandong Xinhua Pharmaceutical	Xinhua Pharm	Health Care	000756.SZ	0719.HK	
Yanzhou Coal Mining	Yanzhou Coal	Energy	600188.SS	1171.HK	
ZTE	ZTE	Information Technology	000063.SZ	0763.HK	

Notes: SS, SZ, and HK indicate shares listed on the Shanghai Stock Exchange, the Shenzhen Stock Exchange, and the Stock Exchange of Hong Kong, respectively. All American Depository Receipts (ADRs) are traded on the New York Stock Exchange.

substantial power gains in detecting periodically-collapsing bubbles, especially if these are short-lived.

Table 2.2 reports the list of companies together with their stock ticker, the stock exchange on which they are listed, and the corresponding market sector. As can be seen from the table, the majority of shares (22 out of 26) are traded on SSE, which accounts for the largest share of total market capitalization in mainland China. Furthermore, the sample spans all but three stock market sectors, from energy and materials to utilities, health care and information technology. From this perspective, the sample is quite representative of the market.

The three sectors not covered in our analysis are communications, financial, and real estate. Regarding the latter, China has experienced a spectacular real estate boom

during the last decades. Fang et al. (2016) show that real estate prices in the four most developed metropolitan areas (Beijing, Shanghai, Shenzhen, and Guangzhou) grew by 13 percent per annum from 2003 to 2013; and Wu et al. (2015) find that real land prices in 35 major Chinese cities increased by a factor of five for a sample period similar to ours. The sheer magnitude of these price changes makes the Chinese real estate boom even more spectacular than the one experienced by the US in the 2000s, and has raised concerns about the presence of speculative dynamics in the sector (Chen and Wen, 2017; Glaeser et al., 2017). In line with these concerns, several studies provide evidence in favour of bubble-type dynamics in China's real estate market (Mao and Shen, 2019; Zhi et al., 2019). Hence, if anything, the omission of real estate from our analysis may bias the results in favour of the no-bubble null hypothesis.

Summary Statistics Table 2.3 presents descriptive statistics (means, standard deviations, minimum and maximum values, and AR(1) coefficient estimates) of the A- to H-share price ratios for the 26 cross-listed companies. To allow meaningful comparisons between markets, A-share prices are converted to Hong-Kong dollars. Two stylized facts about the size and the dynamics of A-H price disparities emerge. The first is that A shares typically sell at a premium relative to H shares. As is evident from Columns 2 and 4 of Table 2.3, for the vast majority of companies, this premium is on average substantial, and can reach extreme values in parts of the sample. A prime example is *Sinopec Oilfie*, whose A shares traded at almost three times the price of H shares on average, and at slightly less than nine times the price of H shares in October 2008. The second fact that emerges is that A-H price ratios are highly persistent, with AR(1) coefficient estimates very close to unity. The above well-documented facts are difficult to reconcile with standard asset-pricing models, giving rise to the so-called A-H premium puzzle.

The two stylized facts are also apparent when looking at the aggregate behaviour of A- and H-share prices. Figure 2.1 shows the evolution of the Hang Seng A share and AH premium indices over time. The latter index measures the price premium/discount

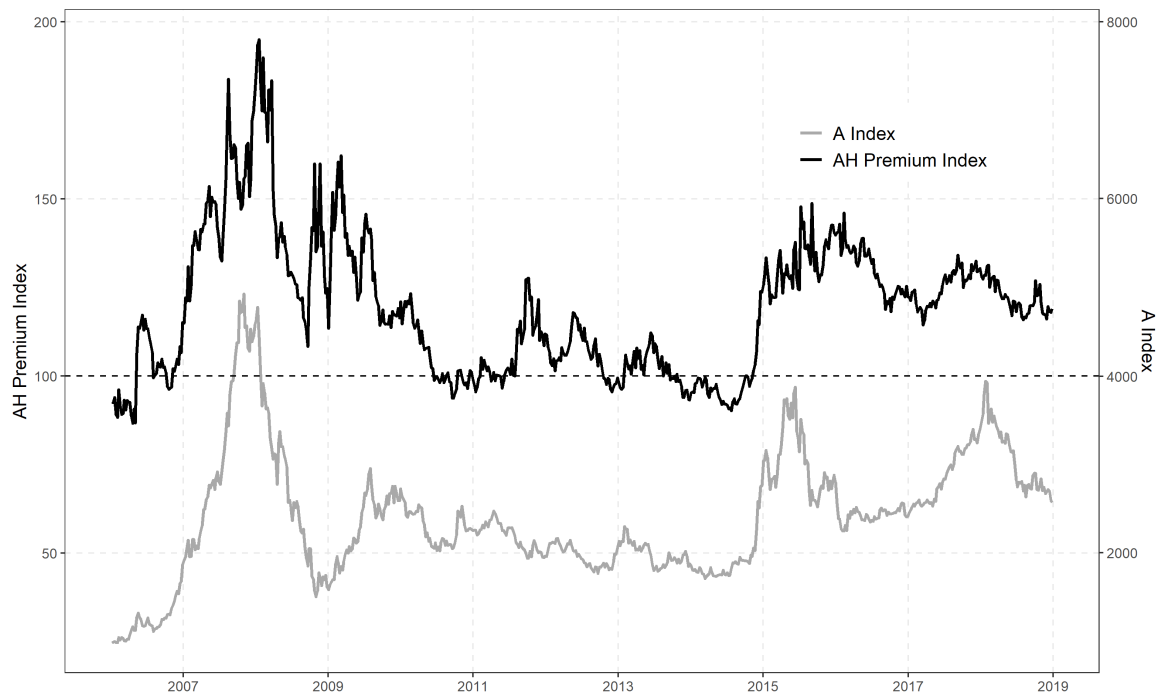
Table 2.3 Descriptive Statistics of A- to H-share price ratios

Company	Mean	SD	Min	Max	AR(1)
Angang	1.077	0.261	0.704	2.312	0.953
Anhui Conch	0.927	0.134	0.603	1.491	0.929
Anhui Express	1.549	0.538	0.863	3.184	0.982
Baiyunshan	1.875	0.515	1.200	3.559	0.972
China East Air	2.131	0.842	1.128	5.949	0.972
China Petroleu	1.343	0.398	0.838	2.553	0.979
Cosco Shipping	1.467	0.363	0.866	2.768	0.956
CSSC Marine En	1.972	0.680	0.816	3.843	0.978
Dongfang Elec	1.493	0.344	0.861	2.772	0.959
Huadian Power	1.882	0.646	0.816	3.950	0.977
Huaneng Power	1.410	0.327	0.787	2.184	0.968
Jiangsu Exp	1.027	0.151	0.706	1.554	0.931
Jiangxi Copper	1.852	0.471	1.047	3.589	0.957
Jingcheng Mach	3.322	0.813	1.571	7.375	0.942
Maanshan Iron	1.418	0.442	0.838	3.530	0.963
Nanjing Panda	3.503	1.057	1.673	6.180	0.975
Northeast Elec	3.428	0.808	1.404	7.344	0.947
S Sh Pechem	2.696	0.959	1.208	5.070	0.978
Sinopec Oilfie	3.626	1.182	1.273	8.851	0.967
Southern Air	1.886	0.639	1.008	4.258	0.973
Sz Expressway	1.474	0.278	0.892	2.610	0.945
Tianjin Cap	3.019	0.866	1.430	6.569	0.968
Tsingtao Brew	1.115	0.193	0.808	1.824	0.949
Xinhua Pharm	2.839	0.614	1.559	4.647	0.960
Yanzhou Coal	1.828	0.566	0.870	3.591	0.965
ZTE	1.238	0.237	0.825	2.316	0.930

Note: The table presents means, standard deviations, minimum and maximum values, and AR(1) coefficient estimates for A-H price ratios.

of A shares over H shares for the largest and most liquid cross-listed Chinese companies. Similarly to individual companies, the index typically takes values above its parity value of 100, averaging around 120 and reaching a maximum of 195 in 2008. The index is also highly persistent, displaying extraordinary long swings. Interestingly, the most notable AH premium rallies coincide with the two Chinese stock market ‘bubbles’: the market frenzy of 2007 and the period preceding the market crash of 2015. Given that

Fig. 2.1 Hang Seng Indices



the AH premium reflects deviations of asset prices from fundamentals, Figure 2.1 hints that the boom episodes in mainland China were driven by speculative trading.

Econometrics Results To formally examine the existence of speculative bubbles in the Chinese stock market, we run standard ADF and GSADF tests on the AH premium index and on the A-H price differentials for the 26 cross-listed companies. Following the recommendation of Phillips et al. (2015a,b), we choose a short lag length, $k = 1$, and set the minimum window size in the recursive GSADF procedure by using the rule of thumb $r_0 = 0.01 + 1.8/\sqrt{T}$. Overall, the unit root test results provide several new insights about the integration properties of the series.

Looking at the GSADF test statistic for the AH index and the panel GSADF statistic for the group of companies, presented in Table 2.4., we observe that the null hypothesis of no explosive behaviour can be rejected by both tests at all conventional significance levels. Thus, there is strong evidence of speculative bubbles in A-H share price differentials at the aggregate level. Although informative about the overall

Table 2.4 Bubble Detection Tests: A-H Shares

Company	ADF	GSADF	Company	ADF	GSADF
Angang	-3.593	3.197***	Jingcheng Mach	-3.391	4.339***
Anhui Conch	-3.765	1.004	Maanshan Iron	-3.247	3.386***
Anhui Express	-2.313	7.012***	Nanjing Panda	-4.568	4.233***
Baiyunshan	-4.188	1.670	Northeast Elec	-3.001	3.432***
China East Air	-2.859	5.718***	S Sh Pechem	-2.655	3.722***
China Petroleu	-2.148	3.835***	Sinopec Oilfie	-2.856	5.640***
Cosco Shipping	-3.141	3.033***	Southern Air	-2.952	4.230***
CSSC Marine En	-3.132	4.722***	Sz Expressway	-3.796	4.606***
Dongfang Elec	-4.310	2.348**	Tianjin Cap	-3.435	8.663***
Huadian Power	-3.243	3.078***	Tsingtao Brew	-3.378	3.002***
Huaneng Power	-2.800	3.411***	Xinhua Pharm	-3.066	4.703***
Jiangsu Exp	-3.570	2.447**	Yanzhou Coal	-3.878	3.552***
Jiangxi Copper	-2.986	4.530***	ZTE	-3.369	1.450
AH Premium Index	-2.977	3.225***	Panel		1.829***

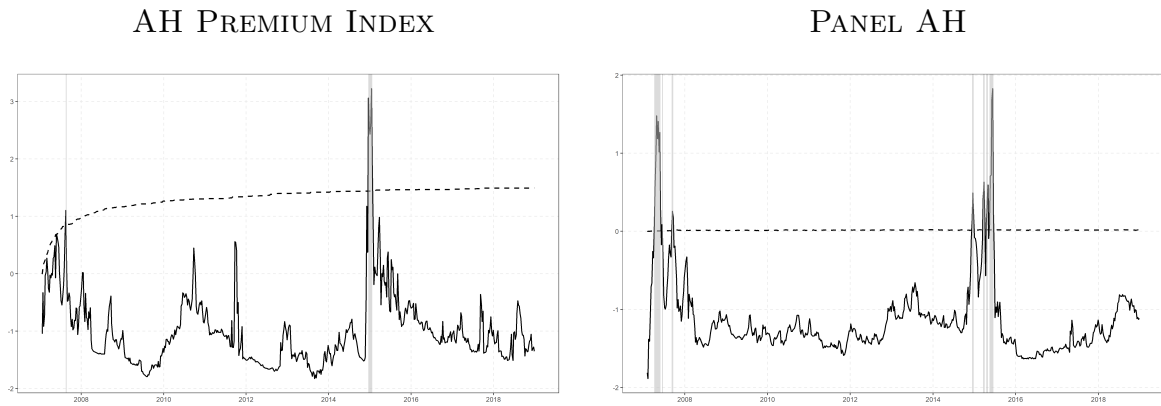
Notes: The table reports ADF, GSADF, and panel GSADF test statistics for the AH premium index and the 26 cross-listed companies. *, ** and *** denote statistical significance at the ten, five, and one percent levels, respectively. The minimum window size for the GSADF and panel GSADF test is set equal to 53 weeks. Finite sample critical values are obtained from using 2000 simulations.

behaviour of the Chinese stock market, this finding does not shed light on whether bubbles are widespread across cross-listed companies. This is so because both the univariate and the panel GSADF tests can, in principle, reject the null even if a single constituent series displays exuberance.⁸ However, the results for the disaggregate data suggest that this is not the case. From the 26 cross-listed securities, 21 have statistically significant GSADF statistics at the one percent significance level and 23 at the five percent. The conclusion that emerges is that speculative bubbles are prevalent across companies.

Another point that is worth noting is that, although the majority of GSADF statistics exceed the 95 percent critical value, the ADF statistics fail to do so. These findings are not inconsistent. As aforementioned, standard unit root tests, including the ADF, have extremely low power in detecting speculative bubbles which collapse

⁸For the univariate GSADF test, this property follows from the fact that the combination of the explosive constituent series with other unit root and/or stationary processes results in an explosive AH index, and for the panel test, it is a direct implication of the alternative hypothesis of at least one of the elements of the panel displaying explosive dynamics.

Fig. 2.2 Date-stamping Periods of Market Exuberance

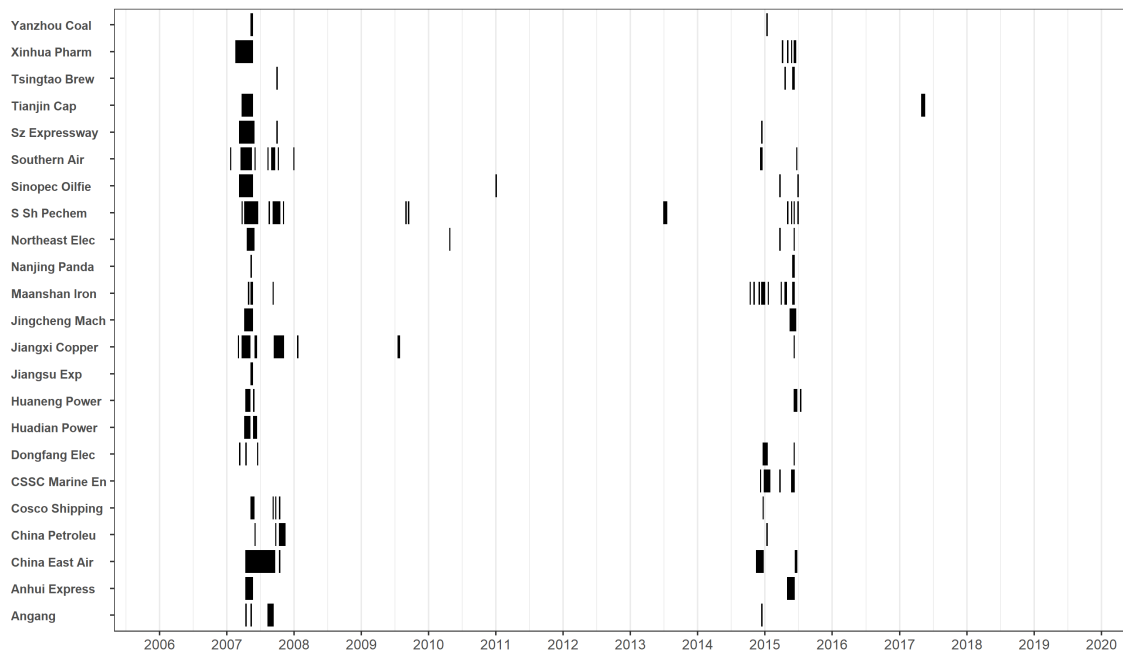


Notes: The plots display the sequence of BSADF statistics (solid line) together with the corresponding 95 percent critical value sequence (dotted line) for the AH premium index (left) and the panel of 26 cross-listed companies (right). Critical values are obtained using 2000 simulations. The minimum window is 53 weeks. The shaded areas indicate periods of exuberance.

in sample. Hence, taken together, the ADF and GSADF test results imply that A-H price differences display explosive dynamics during parts of, but not the entire, sample.

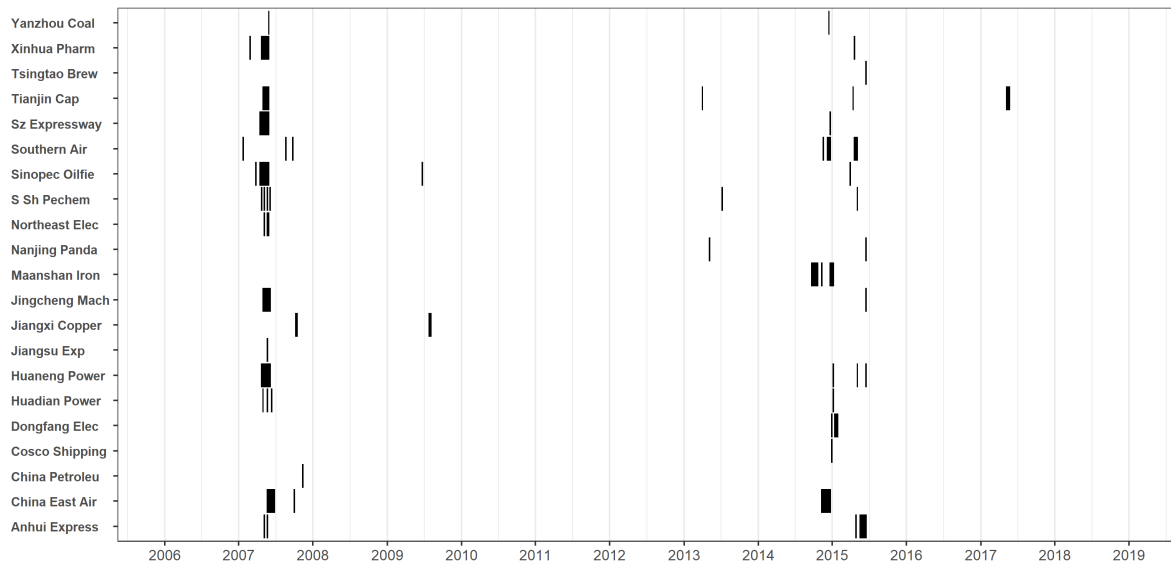
To identify these periods of exuberance, we start by plotting the Backward Supremum ADF (BSADF) statistics for the A-H premium index, and the panel BSADF statistics for the 26 cross-listed companies together with their corresponding 95 percent critical value sequence in Figure 2.2. A comparison of the test statistics with their critical values indicates that speculative bubbles occurred in 2007 and 2014-15. This conclusion is supported further by the results for individual companies. Figure 2.3 shows the periods of exuberance for each of the 23 cross-listed securities that have statistically significant GSADF statistics at the five percent level. As is evident from the figure, the episodes of exuberance are clustered around 2007-08 and 2014-15. The fact that bubble episodes are highly synchronised across companies points to the existence of a market-wide speculative factor that drove A-share prices to diverge from their fundamental values, and led to the stock market frenzy of 2007 and the market crash of 2014-15. The presence of such a factor is also in accordance with previous studies which show that changes in foreign share discounts are highly correlated with movements in the market they trade (Froot and Dabora, 1999).

Fig. 2.3 Date-stamping Periods of Exuberance in A-H Price Differentials



Notes: The figure shows the periods of exuberance in A-H share price differentials identified by the BSADF date-stamping strategy. 95 percent critical values are obtained using 2000 simulations. The minimum window size is 53 weeks.

Fig. 2.4 Date-stamping Periods of In-Sample Predictability



Notes: The figure shows the periods of in-sample predictability of A-share price movements identified by IVX rolling-predictive regressions. The regressor in Equation (2.13) is the A-H price differential. The window size is 53 weeks.

Having established the presence of explosive dynamics in A-H twin share prices, we run rolling predictive regressions of the form given by Equation (2.13). To allow direct comparisons with the unit root test results, the rolling window size is set equal to the minimum window size r_0 . Figure 2.4 shows the periods of predictability for each of the cross-listed securities in our sample. In accordance with the pattern of the BSADF statistics, we observe that the majority of IVX statistics become positive and statistically significant in 2007 and in 2014-15. Thus, as suggested by the theoretical analysis of Section 2.3, A-H price differences have predictive content for future movements in A-share prices during periods of exuberance. Overall, the above results provide novel evidence in support of speculative bubbles in China's stock market.

2.4.2 Chinese American Depository Receipts

As a robustness check, we repeat the above analysis using a subset of our sample of Chinese companies for which American Depository Receipts (ADRs) are traded on the New York Stock Exchange. An ADR represents a bundle of H shares held in trust by a U.S. depository bank. On the one hand, these securities make it easier for U.S. investors to trade shares of companies incorporated outside the U.S. and, on the other, they provide a source of capital for China. Like A and H shares, ADRs entitle investors to the same exchange-rate-adjusted dividend payments and capital gains. However, contrary to A and H shares, limits to arbitrage between Hong Kong and the U.S. market are far less constraining. If an ADR sells at a premium, a financial intermediary can purchase H shares in Hong Kong, create a new ADR, and make an instant profit (Lamont and Thaler, 2003). Thus, arbitrage should restrict ADR and H-share prices from diverging due to speculation, but not ADR and A-share prices.

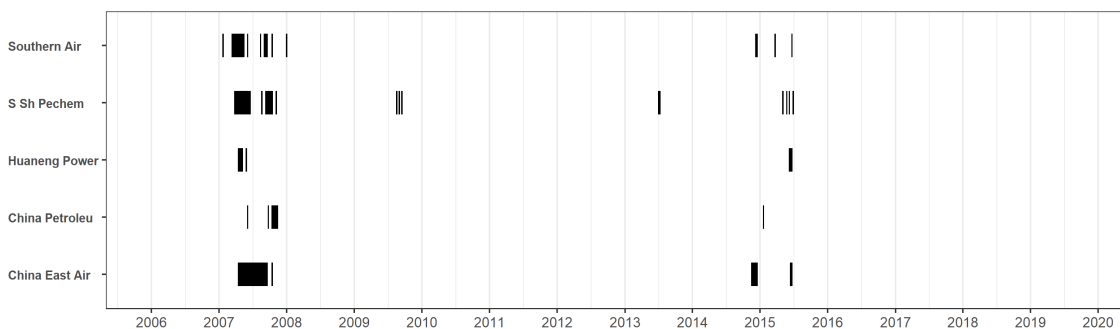
Our empirical results are in line with this hypothesis. Starting with the unit root test statistics presented in Table 2.5, we observe that the univariate GSADF and panel GSADF tests always fail to reject the null of non-explosive dynamics in ADR-H price differentials. On the contrary, there is strong evidence in favour of explosive dynamics

Table 2.5 Bubble Detection Tests: American Depository Receipts

Company	ADR-H		A-ADR	
	ADF	GSADF	ADF	GSADF
China East Air	-17.911	-0.729	-2.874	5.597***
China Petroleu	-17.381	-3.035	-2.155	3.964***
Huaneng Power	-15.837	-1.190	-2.830	3.131***
S Sh Pechem	-15.579	-2.142	-2.646	3.660***
Southern Air	-16.252	-0.523	-2.942	4.068***
Panel		-3.043		2.251***

Notes: The table reports GSADF test statistics for the difference between the prices of A shares and ADRs, as well as the difference between the prices of ADRs and H shares. *, ** and *** denote statistical significance at the ten, five, and one percent levels, respectively. The minimum window size for the GSADF and panel GSADF test is set equal to 53 weeks. Finite sample critical values are obtained from using 2000 simulations.

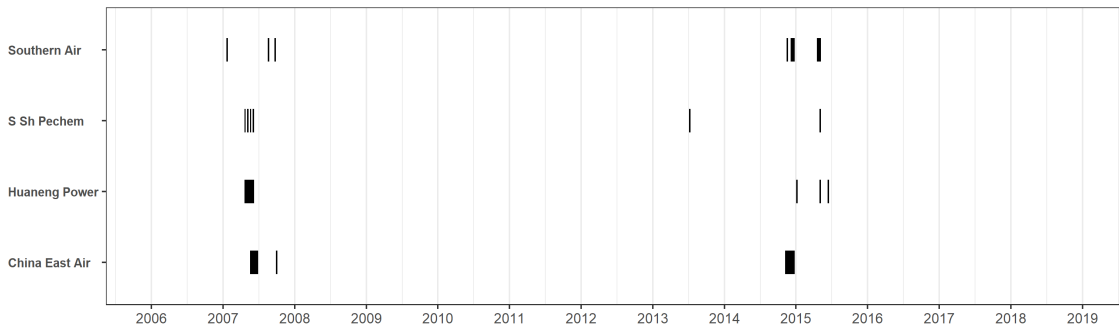
Fig. 2.5 Date-stamping Periods of Exuberance in A-ADR Price Differentials



Notes: The figure shows the periods of exuberance in A-ADR price differentials identified by the BSADF date-stamping strategy. 95 percent critical values are obtained using 2000 simulations. The minimum window size is 53 weeks.

for A-ADR price pairs, with all test statistics being significant at the one percent significance level. The results for the BSADF statistics, summarized in Figure 2.5, indicate that the periods of exuberance in the latter series are again synchronised, taking place in 2007 and 2014-15. Thus, they coincide with those for A-H share prices. Similarly, the IVX predictive regressions, presented in Figure 2.6, suggest that A-ADR price differentials contain valuable information for predicting A-share price movements during these periods.

Fig. 2.6 Date-stamping Periods of In-Sample Predictability



Notes: The figure shows the periods of in-sample predictability of A-share price movements identified by IVX rolling-predictive regressions. The regressor in Equation (2.13) is the A-ADR price differential. The window size is 53 weeks.

2.4.3 The Stock Connect Programs

Two major developments for China's integration into global capital markets took place in the last part of our sample period. In November 2014, the Shanghai-Hong Kong Stock Connect program was launched and a similar program, the Shenzhen-Hong Kong Stock Connect, was put into operation in December 2016. Under the Stock Connect programs, SSE/SZSE and SEHK established mutual order-routing connectivity which enabled mainland Chinese and international/Hong-Kong investors to trade, specific securities listed in SEHK and SSE/SZSE, respectively, subject to daily and aggregate quotas. The two programs are open to exchange participants, who satisfy certain eligibility requirements, and cover all cross-listed shares.

Although the Stock Connect landmark programs established mutual stock market access between mainland China and Hong Kong, they did not eliminate A-H price disparities. There are two reasons for this empirical observation. The first reason is that cross-listed shares remained non-fungible under the Stock Connect scheme. The fact that investors cannot purchase 'cheap' H shares in Hong Kong and sell them onshore implies that A-H price differentials continued to not constitute pure arbitrage opportunities. The second reason is that Stock Connect is a long-term initiative whose aim is to gradually increase the degree of financial integration of China into the global economy. Upon its inception, there were several issues in terms of rules and operations

(such as legal ownership rights, investor protection, settlement arrangements and trading limits) which acted as impediments to capital flows. Due to these issues, the take up of the programs' investment quota was anaemic in the first year of operation, representing less than one percent of trades in the entire market. Since then, regulators have introduced a number of enhancements to address these issues and to improve operational efficiencies. For instance, real-time delivery versus payment was introduced to address concerns about the absence of real-time settlement, Hong Kong Exchanges and Clearing Limited started offering special segregated account services to remove some of the obstacles presented by pre-delivery requirements, aggregate quotas were removed, and daily quotas were raised. These improvements were associated with a steady increase in the average daily northbound and southbound turnover over time, from less than 1% of equity total to 2% (SZSE/northbound), 3.5% (SSE/northbound), and 8% (southbound) in 2018. As can be seen from Figure 2.1, the increase in turnover coincides with a small but evident reduction in A-H price disparities, with the AH premium index dropping from 150 in 2015 to around 120 at the end of 2018. Furthermore, our empirical analysis shows that, even though A-H price differentials are still substantial, there is no statistical evidence in favour of speculative bubbles since the 2014-15 stock market crash (see Figures 2.2, 2.3 and 2.4).

2.4.4 Sources of AH Premia

Several studies have attempted to explain the AH premium puzzle by looking at market and firm-specific factors which, under segmented markets, can cause price valuations of the same asset to differ across geographical locations (Cai et al., 2011; Chung et al., 2013; Seasholes and Liu, 2011; Wang and Jiang, 2004). In this section, we explore whether changes in such factors are linked to periods of exuberance in A-H price differentials. For doing so, we employ a dynamic panel probit (DPP).

Let $b_{i,t}$ denote a binary bubble indicator, which takes the value of unity when the BSADF statistic for firm i exceeds its critical value at time t , and zero otherwise. The

DPP model can be defined in reference to a theoretical relationship of the form

$$b_{i,t}^* = X'_{i,t}\beta + \epsilon_{i,t}, \quad (2.17)$$

where $b_{i,t}^*$ is an unobservable variable that determines the occurrence of a bubble in the share price of firm i at time t , $X_{i,t}$ is a vector of covariates that includes a constant, the lag value of $b_{i,t}$, and market and firm-specific variables, β is a coefficient vector, and $\epsilon_{i,t}$ is a normally distributed error term. The binary bubble indicator $b_{i,t}$ is related to the latent variable $b_{i,t}^*$ according to

$$b_{i,t} = \begin{cases} 1, & \text{if } b_{i,t}^* > 0 \\ 0, & \text{otherwise,} \end{cases} \quad (2.18)$$

and the corresponding DPP model is given by

$$\Pr(b_{i,t} = 1|X_{i,t}) = \Phi(X'_{i,t}\beta), \quad (2.19)$$

where $\Phi(\cdot)$ denotes the cumulative Gaussian distribution function. This model can be estimated via partial maximum likelihood, and the corresponding pooled probit estimator is consistent and asymptotically normal (Wooldridge, 2001, Ch. 13).

In line with previous literature, we consider the following potential sources of AH premia:

- *Risk Appetite.* The differential risk hypothesis postulates that A shares may sell at a premium because investors in mainland China are less risk averse in comparison to overseas investors and therefore demand a lower compensation for bearing risk (Ma, 1996). We proxy differences in risk appetite (*risk*) by the ratio of variances of A- and H-share returns (Chung et al., 2013; Wang and Jiang, 2004). Similarly to Wang and Jiang (2004), we measure the variance of returns using the squared residuals of a regression of returns on their one-period lagged values and local market index returns.

- *Liquidity.* According to the liquidity hypothesis, investors require compensation in the form of lower prices for purchasing assets which are relatively less liquid and have higher transaction costs (Amihud and Mendelson, 1986). We employ two proxies to capture differences in liquidity between markets. The first is given by the ratio of trading volumes (*volume*). The second is a transaction cost-based liquidity measure, defined as the difference between the bid–ask spreads of A and H shares (*spread*).
- *Changes in Exchange Rate Expectations.* Because firms incorporated in mainland China pay dividends in RMB, an expected depreciation of the Chinese currency implies a reduction in the expected future payoffs received by overseas investors from holding H shares. By altering the present value of H shares, movements in exchange rate expectations can cause A- and H-share prices to diverge. A natural way to capture this effect is to include changes in (log) forward exchange rates (*forward*) in the DPP model. Unfortunately, forward exchange rates are only available for the period beginning in June 2009, which does not cover the first bubble episode in Chinese stock markets. To deal with this shortcoming, we use spot exchange rate returns (*spot*) in our main analysis. The results for forward rates, which are reported in Appendix B.3, are qualitatively similar.
- *Aggregate Market Conditions.* Previous studies show that aggregate market conditions are correlated with AH premia (Chung et al., 2013; Ma, 1996; Wang and Jiang, 2004). The findings of these studies suggest that when mainland Chinese stock markets are more bullish than the Hong Kong market, A-H price differentials tend to widen and vice versa. Though typically this behaviour is attributed to investor sentiment (see, e.g., Stambaugh et al., 2012, and the references therein) it is also consistent with the presence of a market-wide bubble that drives the prices of individual Chinese securities (as suggested by the IVX and BSADF results). Irrespective of whether the mechanism generating security prices involves bubbles or sentimental investors, differences in aggregate market

conditions constitute a speculative source of AH premia and, in this aspect, differ from the factors outlined above which fall in the category of market fundamentals.⁹ To proxy for relative market conditions, we follow Chung et al. (2013) and use the logarithm of the A-share price index over the H-share price index (*market*).

- *Public Dissemination of Information.*¹⁰ Another factor related to speculative trading is the degree of public dissemination of information. A number of theoretical models predict that, in the presence of short-sale constraints, heterogeneous beliefs can give rise to price overvaluation (Harrison and Kreps, 1978; Scheinkman and Xiong, 2003). In these models, investors are willing to pay a price that exceeds the intrinsic value of an asset because they expect to profit from selling the asset to a more ‘optimistic’ investor in the future. By reducing the dispersion of beliefs across agents and, thereby, lowering the probability of future transactions with more optimistic investors, public dissemination of information lowers the magnitude of bubbles.

A popular measure of the degree of public dissemination of information is the number of financial analysts covering a stock, *analyst coverage* (Brennan et al., 1993; Duarte et al., 2008; Hong and Kacperczyk, 2010; Hong et al., 2000; Kelly and Ljungqvist, 2012). Financial analysts gather information from a variety of formal sources, such as financial disclosures, news, and earnings conference calls, but also via informal channels, such as discussions with firms’ management, brokerage clients, and investors, to produce reports assessing the performance of financial assets (Bradshaw, 2011). These reports can coordinate beliefs by aggregating complex information and presenting it in an easily understandable manner to less sophisticated investors (Chang et al., 2007). Thereby, an increase

⁹It should be noted that behavioural models establish a link between bubbles, transaction volume, and volatility (Scheinkman, 2014; Scheinkman and Xiong, 2003), which makes the distinction between fundamental and non-fundamental factors even less clear.

¹⁰We are grateful to a referee for motivating the examination of public dissemination of information, short-sale constraints, and margin trading in our empirical analysis.

in the number of analysts covering a stock can raise the rate of information flow to market participants and lead to a higher degree of belief coordination.

A substantial empirical literature indicates that analyst coverage conveys information to the market (Ayers and Freeman, 2003; Hong et al., 2000; Lys and Sohn, 1990; Womack, 1996). In a study closely related to ours, Andrade et al. (2013) use several measures of overvaluation and show that Chinese stocks covered by a greater number of analysts were much less affected by the spectacular boom-bust episode of 2007. Furthermore, the authors provide evidence in favour of the hypothesis that analyst coverage reduced bubble intensity by lowering the dispersion of beliefs. We collect data on analyst coverage from IBES.

- *Short-Sale Constraints.* Short sale constraints are widely believed to impact on the functioning of capital markets. From a theoretical perspective, their effect on asset prices is ambiguous (Beber and Pagano, 2013). In a highly cited paper, Miller (1977) hypothesizes that short-sale constraints can result in overpricing as they prevent the information held by bearish investors, who do not own a stock, from being impounded into market prices. This prediction is in line with the conventional view that short-sale impediments act as a limit-to-arbitrage, restricting investors from exploiting and eliminating overpricing and making bubble formation more likely. Diamond and Verrecchia (1987) show, however, that Miller's prediction does not hold under rationality and risk neutrality because rational agents factor in their valuations the fact that short-sale constraints restrain investors with negative information from trading. Chang et al. (2006) propose a model in which rational, risk averse investors trade to share risks and to speculate on private information. In this framework, short-sale constraints can actually cause securities to sell below fundamental values. On the one hand, short-sale constraints induce a slower price discovery, which increases the risk perceived by less informed investors and makes them require higher returns, thus causing market prices to decline. On the other hand, limiting short sales related to risk sharing raises the demand for assets and, thereby, their price. Depending

on whether the information or risk-sharing effect dominates, the introduction of a short-sale constraint can lead to systematically lower or higher prices compared to fundamentals. Bhojraj et al. (2009) also demonstrate that short sellers may not eliminate overpricing when there is ‘synchronisation risk’ so that arbitrageurs cannot predict each others trading strategies (see also Abreu and Brunnermeier, 2002, 2003).¹¹

Most of the empirical literature finds positive effects of short selling on stock market efficiency and the process of price discovery (e.g. Alexander and Peterson, 2008; Autore et al., 2011; Boehmer et al., 2013; Chang et al., 2007; Diether et al., 2009). By employing either short interest or shorting flow data, the majority of empirical studies suggest that short sales are based on value-relevant information and reduce overvaluation (see, e.g. Asquith and Meulbroek, 1995; Asquith et al., 2005; Boehmer et al., 2008b; Christophe et al., 2004; Curtis and Fargher, 2014; Dechow et al., 2001; Diether et al., 2008) However, there are also studies that fail to find a significant relationship between short-sale constraints and asset prices (e.g. Battalio and Schultz, 2006; Boehmer et al., 2008a; Diether et al., 2009; Kaplan et al., 2013) or provide evidence against the overvaluation hypothesis (Doukas et al., 2006).

Following previous literature, we use differences in short-interest ratios (shares sold short over total shares outstanding) as a relevant instrument for differences in short-sale constraints across markets.¹² Our null hypothesis is that an increase in the short-interest ratios for A shares with respect to those for their H counterparts is associated with a relative decline in A-share prices, and thus with a lower

¹¹A number of papers show that short selling can also cause price manipulation and amplify price declines, thereby increasing the severity of a market crash (e.g. Allen and Gale, 1992; Brunnermeier and Oehmke, 2013; Goldstein and Guembel, 2008; Hong and Stein, 2003).

¹²In addition to short interest ratios, indirect proxies for short-sale constraints include breadth of ownership (Chen et al., 2002), institutional ownership (Hirshleifer et al., 2011; Nagel, 2005), and rebate rates (Drechsler and Drechsler, 2014; Geczy et al., 2002; Jones and Lamont, 2002). In our analysis, we focus on short interest ratios because weekly lending data are readily available at the stock level. On the contrary, rebate rates are not publicly available. As a consequence, empirical studies have been limited to proprietary databases over short time periods. With regard to institutional ownership, Nagel (2005) and Asquith et al. (2005), find that this proxy is highly correlated with short interest.

probability of a bubble occurring. To construct the *short interest* variable, we download data on SSE and SZSE securities lending from the China Stock Market & Accounting Research (CSMAR) database provided by GuoTaiAn, and obtain short-selling data for H shares from the Historical Data Service of the Hong Kong Exchanges and Clearing Market website.

- *Margin Trading.* Academics and policy makers have long argued that the interaction of credit and speculation is an essential component of booms and crises (Borio et al., 2002; Fisher, 1933; Jordà et al., 2016; Mishkin, 2009; Mishkin et al., 2008). This view is supported by recent theoretical work which links bubble formation to the expansion of credit (Barlevy, 2014; Martin and Ventura, 2016; Miao and Wang, 2018), and also by several empirical papers that provide strong evidence in favour of credit-fuelled bubbles in asset markets (Jordà et al., 2015; Wachter, 2015).

In mainland China, trading on margin, like short selling, was strictly prohibited until March 2010. In the following years and especially during the 2014-15 stock market boom, the volume of margin trading surged. Between June 2014 and June 2015, outstanding margin loans quintupled from 403 billion RMB to 2.27 trillion, which comprised around 12 percent of the combined free float of the Shanghai and Shenzhen stock markets - the highest level of margin to free float in the history of global equity markets.¹³ In line with the academic literature on *leveraged* bubbles, this unprecedented expansion in credit is generally viewed as a prime cause of the 2014-15 stock market rally and the subsequent crash. However, to the best of our knowledge, there is still no formal statistical evidence to support this hypothesis. To fill this gap in the literature, as a final explanatory variable,

¹³The evolution of margin financing in mainland China and its impact on equity prices was extensively covered by the financial press. See, for instance, *Untameable Market* (The Economist, 3 July 2015).

we employ a *margin* proxy: the volume of margin trading as a percentage of the total volume of shares outstanding for securities traded in mainland China.¹⁴

The above set of covariates does not account for two potential determinants of AH premia: *macroeconomic conditions* and *information asymmetries* between local and overseas investors. The reason for not examining the former determinant is twofold. First, because macroeconomic variables are observed at a low frequency (monthly or quarterly), their use requires temporal aggregation of the high-frequency financial variables and, most importantly, of the bubble indicator process $b_{i,t}$. This change in frequency can induce non-random measurement error in the left hand side variable of the probit model (especially given that the identified episodes of exuberance are relatively short) and thereby result in biased and inconsistent regression estimates (Hausman, 2001). Second, as shown by previous literature, macroeconomic variables do not appear to have a statistically significant relationship with movements in AH premia so that their omission should not have a substantial impact on our results (Chung et al., 2013). With regard to information asymmetries between local and overseas investors, a proxy for this factor is given by market capitalization. However, market capitalization is itself a function of share prices and, as such, is directly influenced by the presence of speculative bubbles. Consequently, this proxy cannot shed light on whether episodes of exuberance in A-H price differentials are due to asymmetric information or speculation.

Having specified the set of explanatory variables, we turn to the DPP estimation results. Table 2.6 presents coefficient estimates, marginal effects, standard errors, likelihood ratio (LR) statistics, and McFadden R^2 s for two specifications, DPP1 and DPP2. In DPP1, the set of covariates is restricted to an intercept, the lagged value of

¹⁴It should be noted that our margin proxy suffers from two limitations. First, it is based solely on data for mainland China since margin trading data is not available for the Hong Kong market and, second, it does not account for other types of leveraged financing available to retail investors. The latter limitation is likely more important for our analysis. Before the 2015 crash, grey-market margin lending thrived in mainland China, with estimates placing it as high as 1 to 1.5 trillion RMB (for a discussion of unregulated margin borrowing in mainland China, see *So you're a leveraged stock market investor with poor timing in China?* (Financial Times, 15 July 2015) and the May 2015 report of Credit Suisse). As a consequence, our empirical results may understate the strength of the relationship between total financing and speculative bubbles.

Table 2.6 Estimation results for the Dynamic Panel Probit model

	DPP1		DPP2	
	Coefficient Estimate	Marginal Effects	Coefficient Estimate	Marginal Effects
lagged exuberance	2.682*** (0.089)	0.519*** (0.035)	2.679*** (0.089)	0.516*** (0.036)
market	2.229*** (0.281)	0.033*** (0.004)	2.273*** (0.284)	0.033*** (0.004)
analyst coverage	-0.035*** (0.008)	-5.2e - 04*** (1.2e - 04)	-0.036*** (0.008)	-5e - 04*** (1.3e - 04)
short interest	-0.086 (0.074)	-0.001 (0.001)	-0.068 (0.076)	-0.001 (0.001)
margin	0.008*** (0.002)	1.2e - 04*** (2.6e - 05)	0.008*** (0.002)	1.2e - 04*** (2.8e - 05)
risk			-3.6e - 08 (7.1e - 07)	-5.3e - 10 (1.0e - 08)
volume			-0.004 (0.006)	-5.7e - 05 (8.6e - 05)
spread			-1.008 (0.754)	-0.015 (0.011)
spot			-0.989 (9.615)	-0.015 (0.141)
Constant	-2.915*** (0.112)		-2.883*** (0.118)	
McFadden R^2	0.518		0.519	
LR Statistic (p -value)			2.619(0.623)	

Notes: The table presents coefficient estimates, marginal effects, standard errors, and McFadden R^2 s for a restricted (DPP1) and an unrestricted (DPP2) model specification. It also reports the likelihood ratio (LR) statistic and the corresponding p -value for the restriction that the coefficients on risk, liquidity, spread, and spot are equal to zero. *, ** and *** denote statistical significance at the ten, five, and one percent levels, respectively.

the bubble indicator, the measure of relative market conditions, the proxy for short-sale restrictions, analyst coverage and the proxy for margin trading in mainland China, i.e., $X_{i,t} = (1, b_{i,t-1}, \text{market}, \text{analyst coverage}, \text{short interest}, \text{margin})$. While, in DPP2, we also include the four variables that account for fundamental sources, i.e., $X_{i,t} = (1, b_{i,t-1}, \text{market}, \text{analyst coverage}, \text{short interest}, \text{margin}, \text{risk}, \text{volume}, \text{spread}, \text{spot})$.

Overall, the estimation results for the two DPP models suggest that fundamental sources cannot explain episodes of exuberance in A-H price differentials. The coefficients

on risk, volume, spread and spot are individually statistically insignificant, and the LR test fails to reject the joint null hypothesis that all four coefficients are equal to zero with a p -value of 0.623. Furthermore, the difference between the McFadden R^2 s of the restricted and unrestricted models is minimal.

On the other hand, the coefficient estimates for the variables related to speculation are correctly signed and statistically significant at the one percent level with only one exception, the instrument for short-sale constraints. Starting with the market variable, which captures differences in market-wide speculation, we observe that this proxy is positively associated with the likelihood of bubble formation. This implies that as mainland Chinese markets become more bullish in comparison to the Hong-Kong market, there is a higher probability of an episode of exuberance in A-H price differentials occurring. According to the marginal effect estimates for DPP1 and DPP2, the magnitude of this relationship is substantial, with a one percent increase in the log difference between the A- and H-share price indices being associated with a three percentage points increase in the probability of exuberance. This finding provides support to the claim that the divergence of A-share prices from their fundamental values is related to market-wide speculation.

Our results are also broadly consistent with real option theories which predict that the public dissemination of information reduces overpricing through the coordination of investors' beliefs. Specifically, our results indicate that as the number of analysts covering a stock (analyst coverage) increases the likelihood of bubble formation in A-H price differentials declines -though the marginal effect is smaller compared to the market variable. The relationship between public dissemination of information and exuberance has policy implications. It implies that micro-level policies can contribute toward financial stability by enhancing the information flow to Chinese markets. Such policies may consist of regulating information disclosure by firms, subsidising analyst coverage and coordinating the matching process of analysts and firms (for a detailed discussion, see Andrade et al., 2013).

The relation between credit and asset price exuberance has also policy relevance. In line with the theoretical and empirical literature on leveraged bubbles, we find that credit expansion, approximated by margin, is associated with an increase in the likelihood of bubble formation. Since margin trading was prohibited in mainland China prior to 2010, this finding supports the commonly held view that credit played a significant role in the development of the stock market bubble of 2014-15. This conclusion justifies the actions of the Chinese authorities in 2015 which, although long-delayed, aimed at limiting speculative trading by i) enforcing stricter regulations on margin trading and ii) by cracking down on grey-market lending (Huang et al., 2019). In a wider policy context, the 2014-15 Chinese stock market crash forms part of a series of financial events that highlight the need for a robust system of regulation and financial supervision that prevents credit excesses (see, e.g., Yellen, 2011).

With regard to the short-sale proxy, we observe that the estimated coefficient on this variable is negative, in line with Miller's hypothesis that short selling reduces overpricing, but statistically insignificant. The fact that short sellers did not lean against the 2014-15 bubble is also evident by the relatively low short-selling volume in Chinese markets, which prior to the market crash did not exceed 10.3 billion RMB. A potential explanation for this behaviour is provided by theoretical models with 'noise-trading' or 'synchronisation' risk (Brunnermeier and Oehmke, 2013). In the former models, rational arbitrageurs with finite horizons refrain from trading against the bubble because noise traders may widen the mispricing. While, in the latter, bursting the bubble requires synchronised action by arbitrageurs, who are however unable to coordinate. The uncertainty about the timing of the price correction, makes it optimal for rational agents to ride rather than trade against the bubble.

2.5 Conclusion

In the presence of limits to arbitrage, speculative bubbles can cause financial assets with the same market fundamentals to trade at different prices in different locations.

These deviations from the law of one price display, like the bubble process, explosive dynamics and have predictive content for equity price movements. Based on these two predictions, we proposed a new approach for bubble detection in segmented markets that utilizes recursive unit root tests and predictive regressions. By applying these methods to data on Chinese cross-listed shares, we found strong evidence in favour of speculative dynamics. Interestingly, for the vast majority of cross-listed securities, the identified periods of exuberance coincide with the Chinese stock market frenzy of 2007 and the market crash of 2014-15. These findings point to a market-wide speculative factor driving Chinese share prices. Finally, we employed a dynamic panel probit model to shed light on the determinants of exuberance. The estimation results suggest that the likelihood of exuberance in A-H price differentials is associated with a proxy for credit expansion and a measure of public dissemination of information. This highlights the importance of micro-level and macroprudential policies for financial stability.

Chapter 3

Sentimental Housing Markets

3.1 Introduction

Since the 2006 housing market collapse in the US that triggered the financial meltdown, housing dynamics have attracted a lot of attention amongst academics and practitioners. House prices in the US exhibited unprecedented volatility (Glaeser et al., 2014), and significant momentum (Case and Shiller, 1989; Piazzesi and Schneider, 2009) that reached levels far above what economic fundamentals could reasonably support (Shiller, 2015). While there are many popular approaches that are trying to explain the recent developments in the housing market, one prominent view is the role of sentiment. Conventional models work under the premise of rational expectations; however, this notion is challenged when individual expectations deviate from the rationality assumption. Home price expectations can play an important role in housing dynamics (Armona et al., 2019) and shifts in beliefs can be a substantial driver of movements in house prices, and rents (Kaplan et al., 2015). ‘Animal spirits’ or irrational expectations in the housing market, can lead to substantial house price appreciation (Case et al., 2003; Shiller, 2014), that drive the price away from market fundamentals.

We study the role of expectations and the influence of sentiment in the housing markets through survey evidence on consumer behaviour. We extract data about expectations through the Michigan survey, which offers a comprehensive dataset on

consumer buying and savings decisions. From a selection of consumer confidence indices, we use the Index of Consumer Expectations (ICE), which focuses on the prospects of the economy and households' financial situation, that are inherently more forward-looking. However, consumer confidence indices "are mostly a reflection of what's going on rather than a cause" (Friedman, 1992), which means that consumer confidence indices cannot appropriately represent sentiment, since innovations in consumer confidence carry information which reflects both fundamentals and noise and cannot be easily disentangled.¹

In order to reconcile for the existence of the fundamental component in consumer confidence, we adopt the novel identification approach of Lagerborg et al. (2018), where fatalities from mass shootings are used to identify exogenous variations to consumer sentiment. Mass public shootings draw a lot of public and media attention because they are a significant emotional event that involves "innocent victims and offenders who seemingly went 'berserk' in a public setting" (Duwe, 2000, p. 391). The occurrence of these tragic events and the subsequent media coverage to the wider public can potentially create a wave of fear and pessimism that can affect the behaviour of the consumers, which can impact on the whole economy. Although mass shootings incur a substantial cost to society, individual events are unlikely to induce direct economic costs and have been shown to be unrelated to economic fundamentals (Pappa et al., 2019). However, they have been shown to directly affect consumer confidence (Lagerborg et al., 2018).

We investigate the role of expectations on the housing market dynamics by examining exogenous variations to consumer sentiment. To identify consumer sentiment shocks, we implement the proxy SVAR estimation procedure and use mass fatalities in the US as an instrument to consumer confidence index (Lagerborg et al., 2018). The instrument diagnostics show rejection of instrument irrelevance, but evidence of

¹Barsky and Sims (2012) decompose the two contradicting views on consumer confidence into the 'animal spirits' and the 'news' approach. The 'animal spirits' approach represents autonomous (self-fulfilling) fluctuations in beliefs, while the 'news' approach refers to the sentiment that depicts present and future beliefs about fundamentals.

weak instrument. To face problem caused by weak instrumentation, we use the robust inference approach of Montiel Olea et al. (2020), that constructs confidence sets for impulse response coefficients that are valid under weak-instrument asymptotics; thus, we are able to correct for potential small-sample bias and size distortions.

Our analysis uses monthly data for the sample period of 1963 to 2016. Our benchmark model consists of the ICE, industrial production, unemployment rate, consumer price index, house prices, and new houses sold. We introduce negative sentiment shocks that correspond to an increase of pessimism. As agents become pessimistic, households experience increase uncertainty about future income, which means the consumer is increasing their precautionary savings, causing the savings rate to go up (Angeletos et al., 2018). Households reduce consumption, and firms cut down on employment and investment; which reduce aggregate consumption, industrial production and increase unemployment. We also find that the CPI marginally increases and interest rates decline. Decreased confidence levels affect the household's demand for housing which is reflected through a fall in house prices and new houses sold. Finally, the adverse effect on housing demand deteriorates the housing affordability and increases the mortgage spreads, which adversely affects homeowners.

We isolate the effect of the housing market by conducting a counterfactual experiment that restricts the effect of the house prices and new houses sold. We evaluate the quantitative effect of the housing market by measuring the difference between the restricted and the unrestricted model. In the presence of a consumer sentiment shock, the inclusion of the housing market enhances the responsiveness of the savings rate, monetary policy and consumption. Declining house prices reduce the households' spending capabilities and lead to a further increase in the savings rate. Monetary policy takes into account potential changes in house price expectations, which exacerbate the fall of the interest rates. Finally consumption falls more than the unrestricted model, the reasons attributed to this additional reduction in consumption is twofold i) increased savings reduce durable consumption, while ii) the decrease in house prices are creating negative wealth effects on non-durable and service consumption. The

influence of the housing market becomes particularly evident after one year, where the deviation from the unrestricted model becomes substantial.

Our results are consistent with macroeconomic models where housing play a driving role in belief formation (Burnside et al., 2016; Glaeser and Nathanson, 2017; Piazzesi and Schneider, 2009). Our work is also related to a growing literature that is focusing on the relationship between the housing market with consumer confidence. Kaplan et al. (2016) investigates how consumers' home price expectations respond to past home price growth, and how they impact investment decisions. Soo (2018) reveals that housing media sentiment has significant predictive power for future house prices. Makridis (2018) shows that housing price growth is associated with a rise in perceptions about the current state of the economy. Finally, Khan et al. (2019) find that household investment increases and follow a persistent response after a positive confidence shock, and confidence shocks account for a substantial share of variation in household investment.

The rest of the paper is organised as follows. Section 2 discusses the data. Section 3 describes the empirical methodology. Section 4 presents the empirical results, while section 5 provides the robustness checks. Finally, section 5 concludes.

3.2 Data and preliminaries

In this section, we provide a detailed description of the variables. We discuss the data and their unique characteristics, with a focus on the construction of the mass fatalities index.

Consumer Confidence To study consumer confidence, we use data from the Surveys of Consumers, which is published monthly by the University of Michigan². Responders are asked questions regarding their personal and family finances, business and buying conditions. For all question, answers are categorised into 'favourable', 'neutral', and

²The survey is based on at least 500 telephonic household interviews that are conducted nationally, statistically designed to be representative of all American households. Michigan has adopted a rotating panel design for this survey, in which the majority of individuals (approximately 60%) are first-time respondents from whom re-interviews will be attempted six months thereafter.

‘unfavourable’. The ‘relative score’ is calculated as the difference between the percentage of responders that are giving a favourable response and the percentage of responders that are giving an unfavourable response, plus 100. Thus, a relative score of 100 would indicate parity between favourable and unfavourable responses. appendix:data offers a more detailed description of the index, accompanied by the questions comprising it.

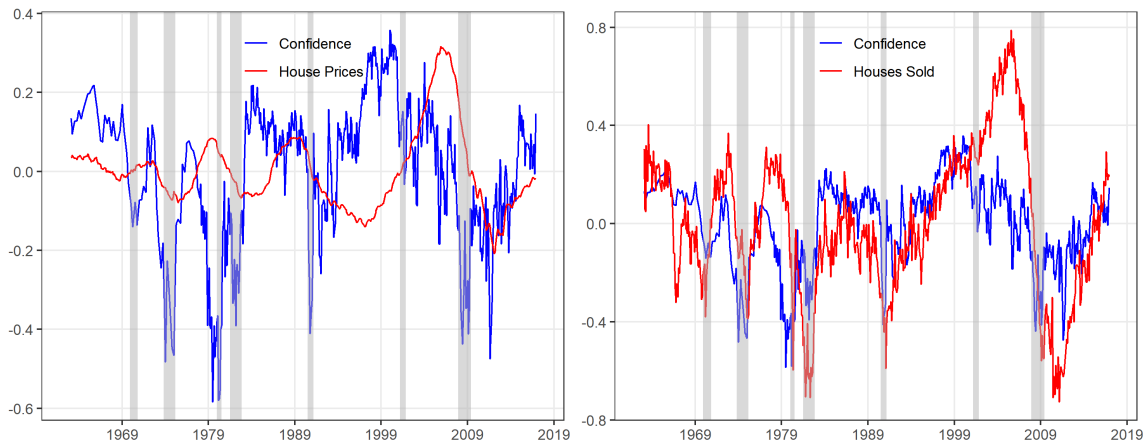
The most popular index from the consumer survey is the Index of Consumer Sentiment (ICS), which is a broad index covering respondents’ views about both current and expected future conditions. For our empirical analysis, we are only interested in views about future conditions, so we focus on the Index of Consumer Expectation (ICE) as the measure of consumer confidence, which is constructed from three out of five questions from ICS. The questions comprising ICE focus on how consumers view prospects for their financial situation, the general economy over the near term, and the economy over the long term; thus ICE is inherently more forward-looking and more suitable to proxy expectations change in consumer behaviour.

To investigate the causal effect of consumer sentiment on the housing market, we analyse the relationship between consumer confidence and both house prices and new houses sold. To measure house price appreciation, we use the historical home price index of Case & Shiller. The Case & Shiller index is a national home price index for single-family homes that are available since 1890 and are updated monthly. In order to study the housing volume cycle (supply), we use new houses sold, since residential investment is not available at monthly frequencies. The reason we prefer new houses sold to housing starts, or permits is that there is a discrepancy among these variables that derives from the fact that not all new single-family houses are measured as part of the residential sales series. There are several categories to residential construction series, but only those that are built for sale are included in the residential sales series.³

Even though there is a growing literature on how consumer confidence relates to macroeconomic conditions, there is little evidence on the relationship of consumer confidence with the housing market. Figure 3.1 plots the detrended series — consumer

³We also include housing starts in our sensitivity analysis, which produces similar results.

Fig. 3.1 Housing Market and Consumer Confidence



Note: The graph presents the consumer confidence with the house prices (left panel) and the consumer confidence with the houses sold (right panel).

confidence with house prices (left panel) and consumer confidence with the new houses sold (right panel). Although confidence does not display significant contemporaneous correlation with house prices, there is substantial cross-correlation. According to Makridis (2018), housing price growth affects beliefs about the economy almost half as much as employment growth and is associated with a 0.65sd rise in perceptions about the current economic conditions. As for the new houses sold we can say that it exhibits very strong comovement with confidence. Khan et al. (2019) also investigate the relationship of the housing market with consumer confidence, where confidence leads household investment by two quarters, and housing starts by one quarter. Finally, housing displays a strong price and volume cycle, especially around the 2007-financial crisis, that can be explained by the preceding years of low short-term interest rates and relaxed lending standards (Leamer, 2015; Taylor, 2007).

Mass Fatalities As aforementioned, we use fatalities from mass shootings to proxy autonomous changes in consumer sentiment. Mass shootings are a terminological antecedent of mass murder and have been identified as a novel American crime problem. They are driven by mass public shootings, which include gun-related mass murder that takes place at a public location in the absence of other criminal activity; thus it can be

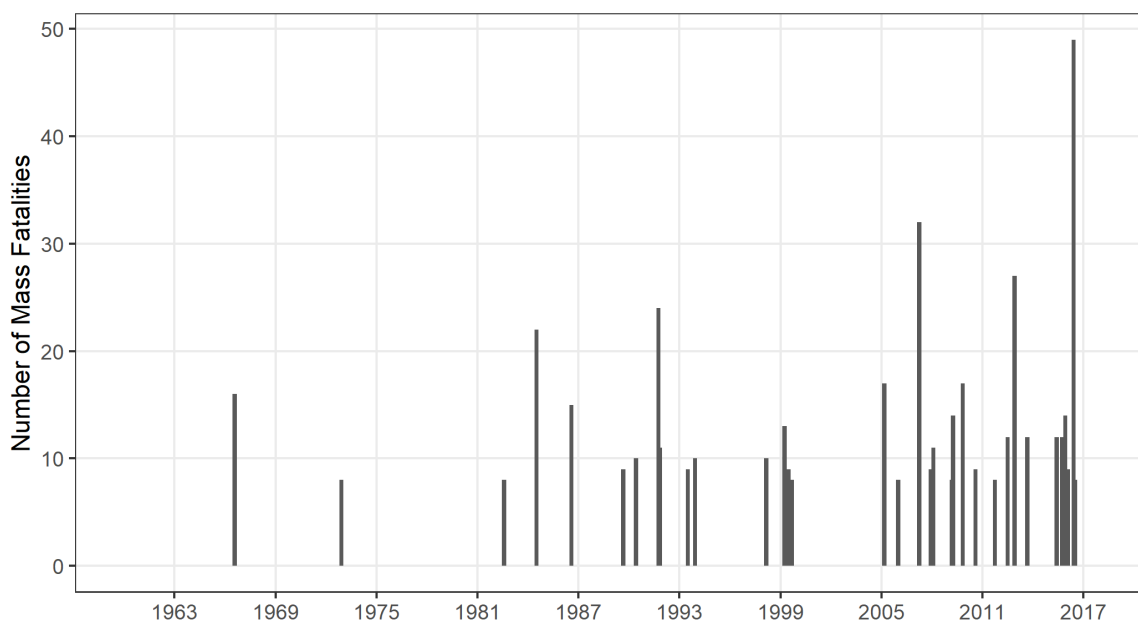
seen not only as a type of mass murder but also as a specific type of mass shooting (Duwe, 2020). There is a clear relationship between mass public shootings and mental illness, where perpetrators demonstrated signs of severe mental illness prior to the attack or have been diagnosed with a mental disorder.

To construct the US mass fatalities series, we use two data sources, Wikipedia (Wikipedia, 2020) for the period 1963 to 1985 and MotherJones' open-source database of (Follman et al., 2015) from 1985 to the end of 2016. The selection criteria include crimes that were committed in a public place by a single perpetrator that acted alone, and the perpetrator killed more than seven people. According to Duwe (2000), even though almost all mass murders are newsworthy, familicides and felony-related massacres are among the least newsworthy. So in order to capture the sentiment that resonates to the whole country, we exclude familicides, crimes connected to domestic violence or felony-related massacres such as burglary, gang wars, or contract killings.⁴

Figure 3.2 shows the chronology of mass shootings with incidents that exceed seven fatalities from 1963:1 to 2016:12. During this period, there were 32 incidents, with 395 people injured and 447 fatalities. Between 1963 and 2005, a mass shooting occurred roughly once every 78 days. However, between 2005 and 2016, that rate has accelerated greatly, with at least one mass shooting every 16 days, almost three times more. In the years following 2016, the number of fatalities has increased substantially, caused not only by the increased mass shooting frequency but also because the death count per shooting rose dramatically. Eight of the twenty most deadly mass shootings in American history occurred in the last five years, including the deadliest incident of 2017 Las Vegas shooting that claimed 58 lives. More than half of the cases involved school or workplace shootings; the other cases occurred in locations including shopping malls, restaurants, and religious and government buildings. During our sample period, the three most lethal shootings were (1) the Orlando nightclub massacre with 49 fatalities, (2) the Sandy Hook Elementary massacre with 25 fatalities, and (3) the Virginia Tech massacre with 37 fatalities. At the later stage of our analysis, we exclude

⁴MortherJones' database includes cases known as "spree killings"—killings occurred in more than one location, but still over a short period.

Fig. 3.2 Mass Fatalities



Note: The graph presents the chronology of mass shooting with incidents that exceed 7 fatalities from 1960:1 to 2016:12.

these observations from our variable to check our instrument robustness on single extreme events.

It is crucial to stress mass fatalities' unique characteristics that depend on the US locality and the frequency of these events. The idiosyncrasy of the US market enables the construction of an irregular time series that depends on the occurrence of mass fatalities. However, these events may be non-existent to most of the countries of the world, or the recurrence of this event is so rare that it can hardly proxy validly the consumer confidence. Furthermore, the housing market is usually examined at the quarterly frequency, which allows the presence for a variety of prices and quantities for the housing market. However, mass fatalities are better represented with the monthly frequency, since aggregating fatalities in lower frequencies would create extreme observations of fatalities that could influence the validity the instrument; thus reduce the instrument's information and make it irrelevant concerning consumer confidence.

3.3 Methodology

In this section we give an overview of the proxy SVAR methodology. We describe the important parameters, the identification, the scale parameterization, the weak instrument diagnostics and robust inference when the instrument strength is weak.

3.3.1 Proxy Structural Vector Autoregression

The proxy SVAR was firstly introduced by Stock and Watson (2012) and Mertens and Ravn (2013). We adopt the notation of Montiel Olea et al. (2020), which formalize the theory for inference in a proxy SVAR setting. The model is a standard finite-order structural vector autoregression. Let Y_t be an $n \times 1$ vector of observables, with the reduced form representation,

$$Y_t = \sum_{j=1}^p A_j Y_{t-j} + u_t, \quad (3.1)$$

where $A_j, j = 1, \dots, p$ are $n \times n$ coefficient matrices, and u_t is a vector of reduced form residuals with covariance matrix $\Sigma_{uu'}$. The reduced form innovations are related to a vector of structural shock, ε_t , via

$$u_t = \Theta_0 \varepsilon_t, \quad (3.2)$$

where Θ_0 is invertible. The structural shocks are assumed to be serially and mutually uncorrelated, with $E(\varepsilon_t) = 0$, $E(\varepsilon_t \varepsilon_t') = I_n$, $E(\varepsilon_t \varepsilon_s') = 0$ for $s \neq t$ where I is the identity matrix. Under the stationarity assumption, the structural moving average representation is given by

$$Y_t = \sum_{k=0}^{\infty} C_k(A) \Theta_0 \varepsilon_{t-k}, \quad (3.3)$$

where the notation $C_k(A)$ emphasizes the dependence of the MA coefficients on the AR coefficients in $A = (A_1, A_2, \dots, A_p)$.⁵ From (3.3), we derive the structural impulse response coefficients, which is the response of $Y_{i,t+k}$ to a one-unit change in $e_{j,t}$

$$\frac{\partial Y_{i,t+k}}{\partial \varepsilon_{j,t}} = e_i' C_k(A) \Theta_0 e_j, \quad (3.4)$$

where e_j denotes the j^{th} column of the identity matrix I_n .

In our analysis, we focus on the identification of the consumer sentiment shock, which without loss of generality, it can be ordered first. To proceed with the identification we need to partition the structural shock into $\varepsilon_t = (\varepsilon'_{1,t}, \varepsilon'_{2,t})'$, where $\varepsilon_{1,t}$ is the $n \times 1$ vector that contains the structural shocks of interest and $\varepsilon_{2,t}$ is the $n \times (n-1)$ vector that contains the other shocks. Similarly, we consider the following partition of Θ_0 :

$$\Theta_0 = \begin{bmatrix} \Theta_{0,1} & \Theta_{0,2} \\ n \times 1 & n \times (n-1) \end{bmatrix}, \quad \Theta_{0,1} = \begin{bmatrix} \Theta'_{0,11} & \Theta'_{0,21} \\ 1 \times 1 & 1 \times (n-1) \end{bmatrix}', \quad \Theta_{0,2} = \begin{bmatrix} \Theta'_{0,12} & \Theta'_{0,22} \\ (n-1) \times 1 & (n-1) \times (n-1) \end{bmatrix}'$$

where $\Theta_{0,1}$ is the $n \times 1$ matrix of coefficients that correspond to the structural shocks of interest, and $\Theta_{0,2}$ is the $n \times (n-1)$ matrix of coefficients that corresponds to other shocks.

Let z_t be a k vector of instrumental (proxy) variables for the target shock, that are correlated with the structural shock of interest (relevance) but orthogonal to other shocks (exogeneity).

$$E[z_t \varepsilon'_{1t}] = \phi \neq 0 \quad (\text{relevance}) \quad (3.5)$$

$$E[z_t \varepsilon'_{it}] = 0, i > 1 \quad (\text{exogeneity}), \quad (3.6)$$

where ϕ is an unknown scalar.

⁵Specifically: $C_k(A) = \sum_{m=1}^k C_{k-m}(A) A_m$, $k = 1, 2, \dots$, where $C_0(A) = I_n$ and $A_m = 0$ for $m > p$.

The impulse responses with respect the shock of interest are determined by $\Theta_0 e_1 = \Theta_{0,1}$. The econometric problem arises in Equation 3.2, where $\Theta_{0,1}$ cannot be identified because $\varepsilon_{1,t}$ is not observable. Since $\varepsilon_{1,t}$ and $\Theta_{0,1}$ are not separately identified, we use (3.5) and (3.6) to normalise the scale of the target shock $\varepsilon_{1,t}$. Then $\Theta_{0,1}$ can be identified up to scale convention with

$$\Gamma = E(z_t u_t) = E(z_t \Theta_0 \varepsilon_t) = \phi \Theta_{0,11}. \quad (3.7)$$

We normalize the size of target shock to have a one unit contemporaneous effect on a pre-specified variable Y_{i^*} , that is $\partial Y_{i^*,t} / \partial \varepsilon_{1,t} = -1$, in order to generate a negative consumer sentiment shock. Using the unit effect normalisation $\Theta_{0,11} = 1$, $\Gamma_{11} = E(z_t u_t') = \phi$, so that

$$\Theta_{0,1} = \frac{E(z_t u_{1,t})}{E(z_t u_{i,t})} = \frac{\Gamma}{\Gamma_{11}} = \frac{\Gamma}{e_1' \Gamma}. \quad (3.8)$$

Thus, the structural impulse response with respect to $\varepsilon_{1,t}$ follows directly from (3.4):

$$\lambda_{k,i} = \frac{\partial Y_{i,t+k}}{\partial \varepsilon_{1,t}} = \frac{e_1' C_k(A) \Gamma}{e_1' \Gamma}. \quad (3.9)$$

Implementation and the plug-in estimator The plug-in estimator for $\lambda_{k,i}$ replaces A and Γ in Equation 3.9 with the corresponding estimators

$$\hat{\lambda}_{k,i}(\hat{A}_T, \hat{\Gamma}_T) = \frac{e_1' C_k(\hat{A}_T) \hat{\Gamma}_T}{e_1' \hat{\Gamma}_T}, \quad (3.10)$$

where \hat{A}_T is the least squares estimator of the VAR coefficients, and $\hat{\Gamma}_T$ is the sample covariance between z_t and u_t .

When z_t is a strong instrument, confidence sets for impulse responses can be formed in a way that leads to the $100\ddot{O}(1-a)\%$ large sample confidence set for $\lambda_{k,i}$:

$$CS^{Plug-in} = \left\{ \lambda_{k,i} \left| \frac{T(\hat{\lambda}_{k,i}(\hat{A}_T, \hat{\Gamma}_T) - \lambda_{k,i})^2}{\sigma_{T,k,i}^2} \leq \chi_{1,1-a}^2 \right. \right\}, \quad (3.11)$$

where $\chi_{1,1-a}^2$ is the $1 - a$ percentile of the χ_1^2 distribution and $\hat{\sigma}_{T,k,i}^2$ is a consistent estimator for $\sigma_{k,i}^2$. The presence of $e1'\hat{\Gamma}$ in the denominator of (3.10) suggests that the large-sample normal approximation of the distribution of the plug-in estimator may be poor when $e1'\hat{\Gamma}$ is small, leading to poor coverage of the resulting $CS^{Plug-in}$ confidence set. Montiel Olea et al. (2020) also propose an inference approach that is valid under weak-instrument asymptotics.

3.3.2 PSVAR: Weak Instrument and Robust Confidence sets

When instruments are weak, the plug-in estimator in Equation 3.11 is biased toward the probability limit of the estimator of the impulse response coefficient. To allow for models which the correlation between the external instrument and the target structural shock can be arbitrarily close to zero, consider $E(z_t \varepsilon_{1,t}) = \phi_T$, where $\phi_T \rightarrow \phi$, and $\phi = 0$ is allowed. This framework allows, for strong instruments, but also weak instruments as in Staiger and Stock (1997), where an instrument is valid but potentially weak (and exogeneity holds). Montiel Olea et al. (2020) create confidence bands robust towards weak instrument on the inverted Anderson-Rubin (AR) test (Anderson and Rubin, 1949), which yields

$$CS^{AR} = \left\{ \lambda_{k,i} \mid AR(\lambda_{k,i}) \leq \chi_{1,1-a}^2 \right\}, \quad (3.12)$$

which are asymptotically valid and have strong-instrument asymptotic equivalence with the $CS^{plug-in}$.

Weak Instrument Diagnostics When there is a single instrument, i.e. $k = 1$ we can detect weak instruments with the heteroskedasticity-robust first-stage F-statistic. An alternative diagnostic arises from noting that, with $\Theta_{0,11}$ normalised to equal 1, ϕ equals Γ_{11} . Because, $\sqrt{T}(\Gamma_t - \Gamma) \xrightarrow{d} \mathcal{N}(0, W_\Gamma)$, the Wald Statistic is equal to

$$\xi_1 = \frac{T\hat{\Gamma}_{T,1}^2}{\hat{W}_{\Gamma,11}} \quad (3.13)$$

and also is a measure of instrument strength, where $\hat{W}_{\Gamma,11}$ is the estimated asymptotic variance of the estimator $\hat{A}_T, \hat{\Gamma}_t$ and Σ_T . Under weak instrument asymptotics, ξ_1 has the same non-centrality parameter as the heteroskedasticity-robust first-stage F and will tend to be smaller in finite samples than the first-stage F. Both statistics can be compared to the Stock and Yogo (2005) critical values or to some rule of thumb, such as $\xi_1 > 10$. Additionally, the statistic ξ_1 has the feature that the 100%(1 - a) AR confidence set is a bounded interval if and only if $\xi_1 > \chi_{1,1-a}^2$.

3.4 Empirical Results

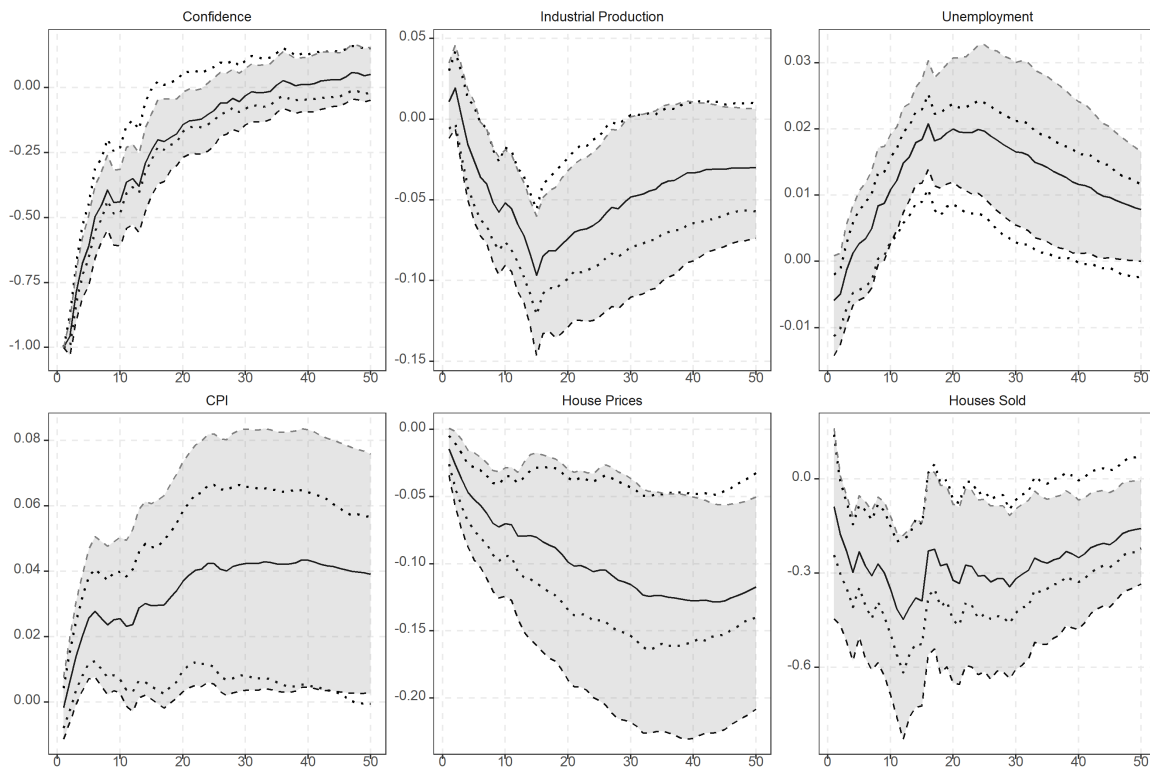
In this section, we apply the proxy SVAR with the proposed identification in the benchmark model. We assess our instrument strength, and we apply robust inference for weak instruments. We examine the effect of the housing market by conducting a counterfactual, where variables are not allowed to respond to the housing market. Finally, we provide an array of robustness checks which examine the sensitivity of the specification.

3.4.1 Benchmark Model

Data We analyse monthly data over the period of January of 1963 to December 2016. For our benchmark model, we use a six-variable specification which consists of the confidence index (ICE), the industrial production, the unemployment rate, the consumer price index (CPI), the house prices and the new houses sold. All variables except the unemployment-rate enter the VAR in log-levels, we use a quadratic trend to detrend all variables, and we use 18 lags for our specification. `appendix:data` offers a detailed description of the data.

To properly evaluate our identification validity, it is crucial to investigate the strength of the instrument since instruments that are weakly correlated with endogenous regressors render conventional methods for estimation and inference unreliable (Andrews et al., 2019). We find that the heteroskedasticity-robust first stage F-statistic is 7.75,

Fig. 3.3 Benchmark Model Identified with IV



Note: Impulse response to a negative sentiment shock from proxy SVAR model. Identification is achieved by using mass fatalities as an instrumental variable to Confidence. Solid lines represent the estimated responses and shaded areas represent the 68% probability bands generated with the AR confidence bands. Dotted lines represent the 68% probability bands obtained from a wild-bootstrap procedure with 500 repetitions.

and the ξ_1 Wald statistic is 4.46. Both statistics exceed the 5% critical value ($\chi_{1,0.05}^2 = 3.84$) for rejecting instrument irrelevance, but they are below the Stock and Yogo (2005) rule of thumb cutoff of 10, suggesting that the instrument is weak. Thus we need to apply the Anderson-Rubin confidence sets, in order to make our setting robust to the low-strength instrument. Finally, because $\xi_1 < \chi_{1,0.05}^2$, the 95% AR weak-instrument confidence sets for the impulse response coefficients are bounded intervals.

Figure 3.3 shows the IRFs of the benchmark model to a negative sentiment shock, which corresponds to a 1% decline in consumer confidence. The impulse responses are identified using a proxy SVAR with mass fatalities as the instrument for the full sample. The shaded areas represent the 68% weak-instrument robust CS^{AR} confidence

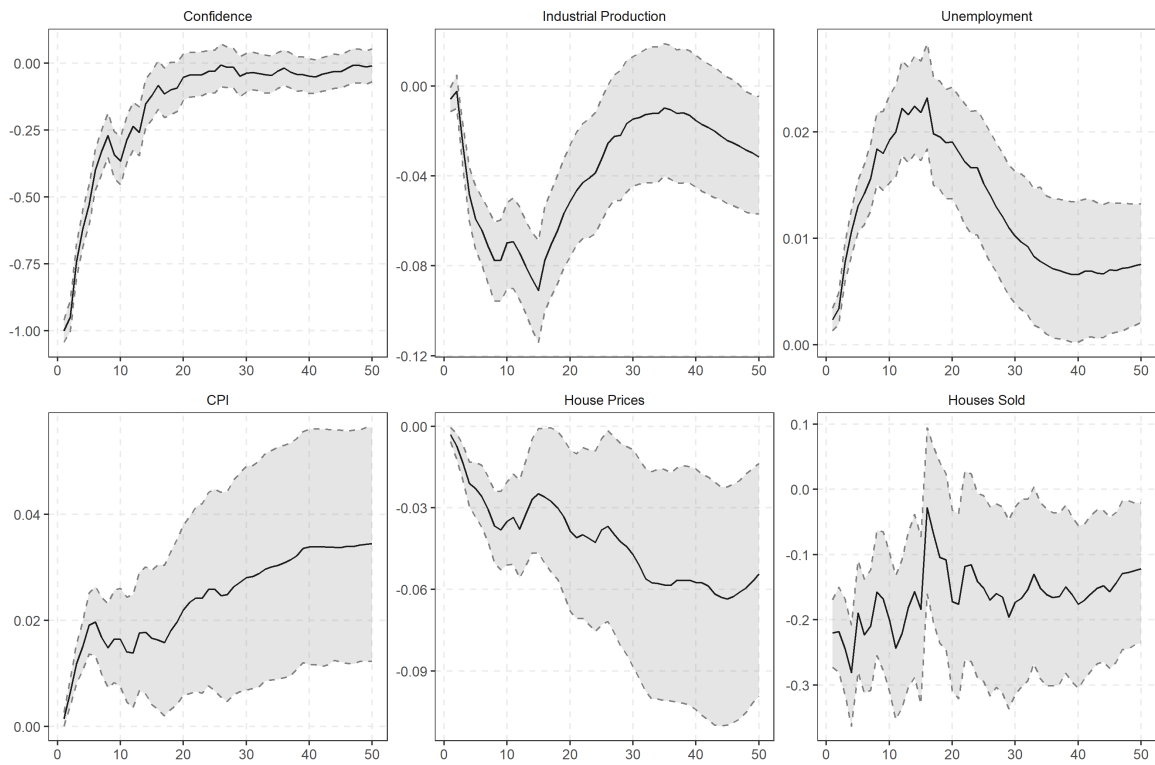
sets, and the dotted lines show the 68% confidence intervals that are obtained through a wild-bootstrap procedure with 500 repetitions. Robust confidence sets take into consideration the low strength of the instrument and increase the uncertainty for all variable by producing broader confidence bands. Specifically, we can observe a large deviation in house prices confidence bands, where the lower bound reaches 0.2 with the AR bands in comparison to 0.15 with band obtained from a wild-bootstrap procedure. However, for the most part, it seems that weak instrument confidence sets roughly coincide with the strong instrument confidence sets, and our results are significant. From this point onward, we only calculate robust confidence sets in the proxy SVAR model.

A 1% negative shock in the sentiment that is caused by innovation to consumer confidence does not have any substantial implication on impact for most of the variables. It is followed by a persistent and significant response to confidence itself that dies approximately after two years. Industrial production follows a declining path that reaches almost 1% at its' lowest point, while unemployment follows an upward path that rises up to 2%. Both measures of economic activity exhibit a similar pattern that gradually reaches the maximum deviation from the trend around the 14-16 months and eventually take three years to fully recover. CPI has a much slower and persistent response that can not be considered significant for the majority of horizons.⁶ Regarding our housing market variables, houses sold resemble the shape of the response of industrial production; however, the magnitude is almost four times stronger. Finally, house prices exhibits a persistent and almost permanent response that reaches -1.3%.

Lagerborg et al. (2018) indicate that sentiment shocks identified with a triangular covariance matrix are not orthogonal to fundamentals, as it specified by total factor productivity, thus extracting a composite signal of news and animal spirits. To investigate this alternative identification, we compare our benchmark specification with

⁶The FOMC focused on inflation as measured by the price index for personal consumption expenditures (PCE) rather than consumer price index (CPI) because that measure is less dominated than is the CPI by the imputed rent of owner-occupied housing and for other technical reasons. To that end, we use the PCE price index as an alternative measure of price inflation in our analysis. Our results remain identical.

Fig. 3.4 Benchmark Model identified with Cholesky Decomposition



Note: Impulse response to a negative sentiment shock from a recursive VAR model. Identification is achieved through Cholesky decomposition with Confidence ordered first. Solid lines represent the estimated responses and shaded areas represent the 68% probability bands obtained through bootstrap with 500 repetitions.

an SVAR model identified with Cholesky decomposition (Figure 3.4). Although there are no qualitative differences, we can observe disparities on the magnitude, the impact size and the statistical significance of the responses. The effect on industrial production and unemployment appears to be very similar in both identification schemes. CPI is more persistent without exhibiting a reversion to the trend, and the confidence bands indicate that the effect is statistical significance for all horizons. Houses sold exhibit a significant difference in the size of the response on impact, which is almost four times larger. Finally, house prices response is contracted almost 50% less than our benchmark identification.. In a similar study, Khan et al. (2019) use a 4-variable VAR model identified with Cholesky decomposition ordered as {ICE, House Price, Household Investment and Output}, that shows a 1% response of house prices and 2%

to household investment (residential investment plus consumer durables) response to a unit shock to confidence. The results from the Cholesky decomposition significantly underestimate the responses of the housing market, cutting both house prices and houses sold response to half.

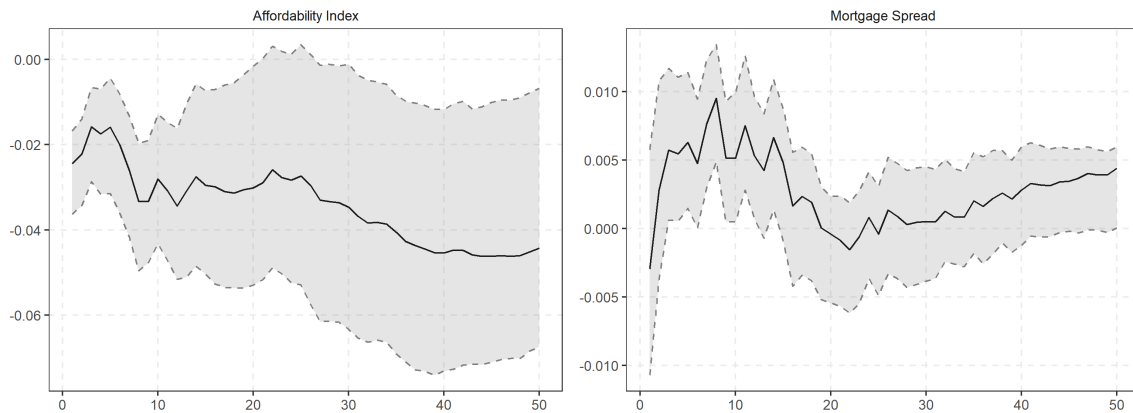
3.4.2 The Impact of the Housing Market on the Augmented Model

In order to investigate additional variables that are related to the housing market conditions, we augment our benchmark specification. To achieve that we include one variable at a time, while we only report the additional variables under the condition that the model remains almost identical. This way, we can study a set of variables without altering the benchmark model. Our first variables expand on the housing market model and are associated with home buying conditions and homeownership.

Homeownership affects household decisions including savings, consumption, labour supply and other socio-economic aspects of consumer decisions. Affordability could constitute a good predictor of the current level of homeownership or the direction of near-future changes in the homeownership rate. In the benchmark model, a sharp drop in consumer confidence would adversely affect house prices and income levels. However, to fully grasp the cost of owner-occupied housing, we need to use a basic definition for housing affordability, which is calculated as the ratio of house price to disposable income (Weicher, 1977). Figure 3.5 illustrates a significant decline in housing affordability (left panel), which indicates that the cost of owning a house becomes burdensome. Even though the reversal of industrial production could replenish income, house prices are declining at a faster rate than household income, which creates a prolonged and persistent burden to housing affordability and homeownership.

The same time, prospective homeowners weighs the cost of borrowing to finance the purchase, which can be represented by mortgage spreads. In our definition, the mortgage spread corresponds to the difference of 30-year mortgage rate with the mean of the five- and ten-year government bond (Walentin, 2014). Figure 3.5 shows

Fig. 3.5 Affordability and Home Buying Conditions



Note: Impulse response to a negative sentiment shock from proxy SVAR model. Identification is achieved by using mass fatalities as an instrumental variable to Confidence. Solid lines represent the estimated responses and shaded areas represent the 68% probability bands generated with the AR confidence bands.

the mortgage spreads (right panel), which indicates that borrowing conditions for new homebuyers will worsen, making the home purchase more costly. However, the response seems to be relatively short-lived that dies out in less in a year. In general, the effect of sentiment is negatively existing homeowner in the long-term, and discouraging potential homeowners in the short-term.

We continue by performing a counterfactual experiment where we impose zero restriction on the IRFs on the house prices and new houses sold for all horizons. We achieve that by applying the methodology applied by Bachmann and Sims (2012) and Bassetto et al. (2016), that restricts the coefficients of the underlying VAR in such a way as to force the response of the housing market variables to sentiment shock to be zero, and then compare the restricted impulse responses with the unrestricted ones. The difference between both impulse response functions identifies the quantitative importance of the housing market for the propagation of the sentiment shocks. The variables that we are going to investigate are associated with savings decisions, monetary policy and consumption expenditure choices.

To study the monetary policy response, we look at the period preceding the housing bubble collapse, which has been characterised by exceptionally low short-term interest

Fig. 3.6 Savings Rate

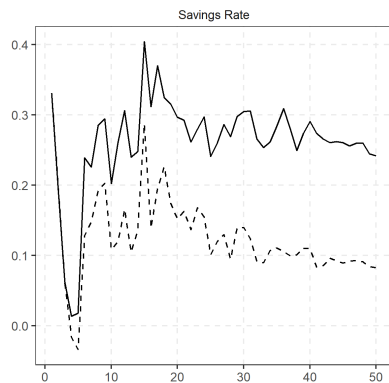
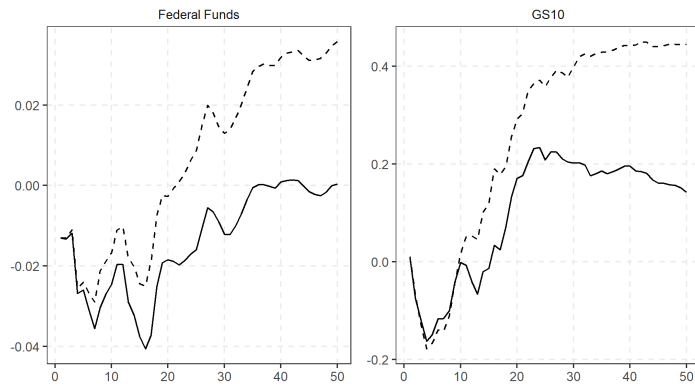


Fig. 3.7 Monetary Policy



Note: Impulse response to a negative sentiment shock from proxy SVAR model. Identification is achieved by using mass fatalities as an instrumental variable to Confidence. Solid lines represent the estimated responses from the unrestricted mode, while dashed lines represent the estimated response from the restricted model.

rates and relaxed lending conditions that may have contributed to factors that influence the demand for housing (Taylor, 2007), which ultimately lead to a boom in housing starts and soaring house prices. There is evidence that the Federal Reserve has systematically responded to conditions in the housing market (Bachmann and R uth, 2020), taking into account potential systematic monetary policy reactions to changes in house price expectations. The housing market is also known for its spillover mechanism that can potentially affect other sectors of economic activity. For example, a change in housing wealth is often considered as a mechanism through which monetary policy can affect consumer spending and other aspects of the individual's balance sheet (Attanasio et al., 2009; Browning et al., 2013; Campbell and Cocco, 2007; Carroll et al., 2011; Mian et al., 2013).

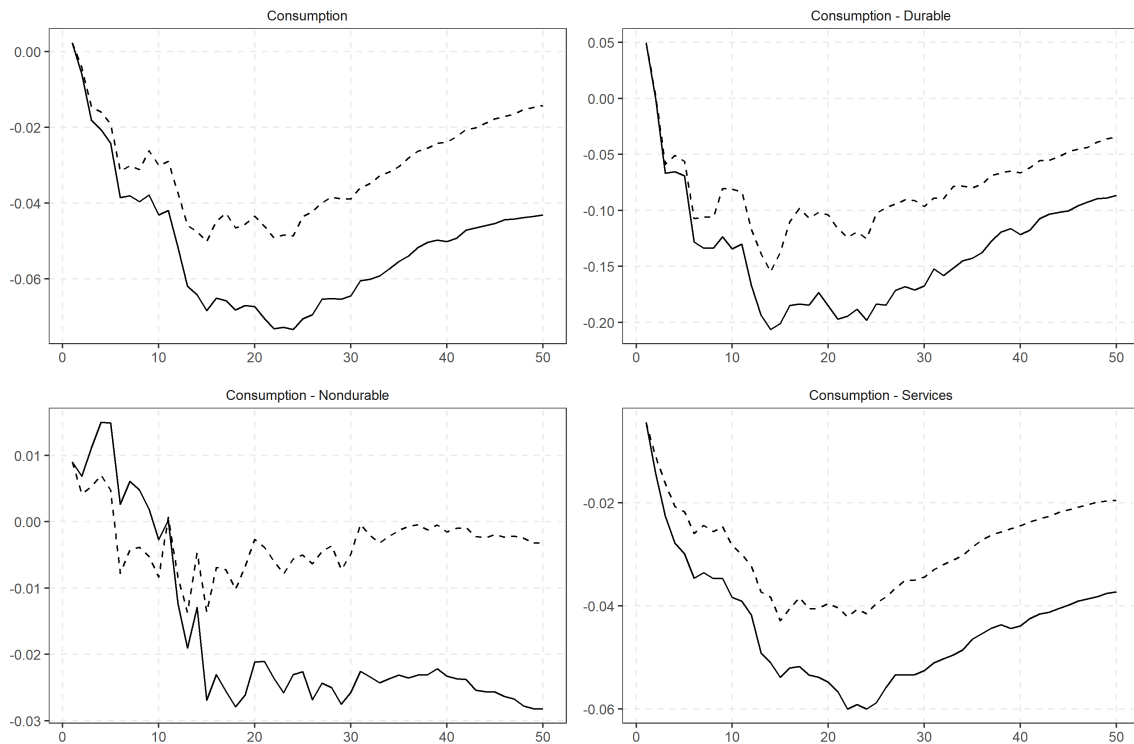
We examine the monetary policy reaction in a negative sentiment shock, through the response of federal funds rate. Figure 3.7 illustrates the policy rate and long-term interest rate. A negative sentiment shock will lead to a decline in the federal fund rate as a response to the labour market and inflation. Consumers respond to the uncertainty created by the deterioration of confidence by increasing their precautionary savings (Figure 3.6). The response of the policy rate counter the effects of the sentiment in the economy, which in return, creates a trade-off with inflation. The absence of the housing

market as it displayed by the restricted IRFs, shows that the reaction of the interest rate and the savings decision would have been exacerbated. Corroborated by previous literature, the response of the short-term rate indicates that the Fed systematically reacts to the housing market conditions when conducting monetary policy.

The sample period includes the recent crisis, a period where the short-term interest rate reached the zero lower bound; thus, we need to consider alternative ways to investigate the effect of monetary policy. So, in addition to the federal funds rate, which is the main instrument that the central bank is conducting monetary policy implementations, we also include the shadow rate of Wu and Xia (2016). The shadow rate is a new measure for the monetary policy stance that can be negative when the short-term rate is bounded below by zero. We find that even when we adjust for the zero-lower bound period with the shadow rate, we attain the same results (Appendix Figure C.1). As short-term interest rates stay close to zero, we also include the long-term interest rate in order to capture movements in unconventional monetary policy. All interest rates exhibit the same pattern, where the effect of the housing market becomes more prominent after one year, where the restricted IRFs seem to deviate more from the unrestricted model.

An approach to aggregate consumer expenditures behaviour relates to the existence of ‘animal spirits’ (Eppright et al., 1998), such that other sources of information like extraordinary circumstances (e.g. wars), or socio-political environment may be responsible for the aggregate consumer expectation changes. Confidence indicators reflect consumers’ private information, so uncertainty about future income can lead households to cut consumption and increase their stock of precautionary savings (Acemoglu and Scott, 1994), to counteract the fall in their income (Carroll and Dunn, 1997; Carroll et al., 1992; Zeldes, 1989). There is a plethora of evidence to support that measures of consumer confidence are highly correlated with real consumption (Carroll et al., 1994; Pistaferri, 2016), and their role of the housing market to propagate this effect.

Fig. 3.8 Personal Consumption Expenditure



Note: Impulse response to a negative sentiment shock from proxy SVAR model. Identification is achieved by using mass fatalities as an instrumental variable to Confidence. Solid lines represent the estimated responses from the unrestricted mode, while dashed lines represent the estimated response from the restricted model.

Housing is an important component of household wealth and a source of collateral for securing loans. Rising house prices may stimulate consumption by relaxing borrowing constraints or by increasing households' perceived wealth. Case et al. (2003) explore a panel of developed countries from the late 1970s through the late 1990s and find a strong correlation between house prices and aggregate consumption. According to Jarociński and Smets (2008), in the US a one per cent increase in real house prices leads to a 0.075 per cent increase in real consumption after four quarters. In addition, house price expectations are able to predict household expenditure decisions (Bover, 2015).

Consumption is comprised of three categories: durables, non-durables and services. Conventionally models examine consumption by looking at the effect on durables⁷ and non-durables, while services are usually disregarded or included in the non-durables calculation (Barsky and Sims, 2012). However, since housing constitutes an important component of services⁸, it would be interesting to examine each part of consumption independently and observe the individual contributions to consumption.

Figure 3.8 displays the response of aggregate (top-left panel) consumption, as well as the response of durables (top right panel), non-durables (bottom-left) and services (bottom-right). Following a negative sentiment shock, consumption drops, where eventually starts to recover after two years. When we examine the three sub-components, we can see that the biggest effect occurs in durables, which is almost three times more than non-durables and four times bigger than services. One possible explanation behind this proliferated effect of durable consumption can be, that unemployment risk is an important factor in the timing of the purchase of durable goods (Dunn, 1998). The counterfactual analysis shows that the contribution of the housing market after one year becomes substantial, where the difference regarding the unrestricted model reaches approximately to 2% . Furthermore, the response of the industrial production to the negative sentiment shock may be largely attributed to consumption; however, consumption is slightly more persistent, which may be indicative of the influence of the housing market.

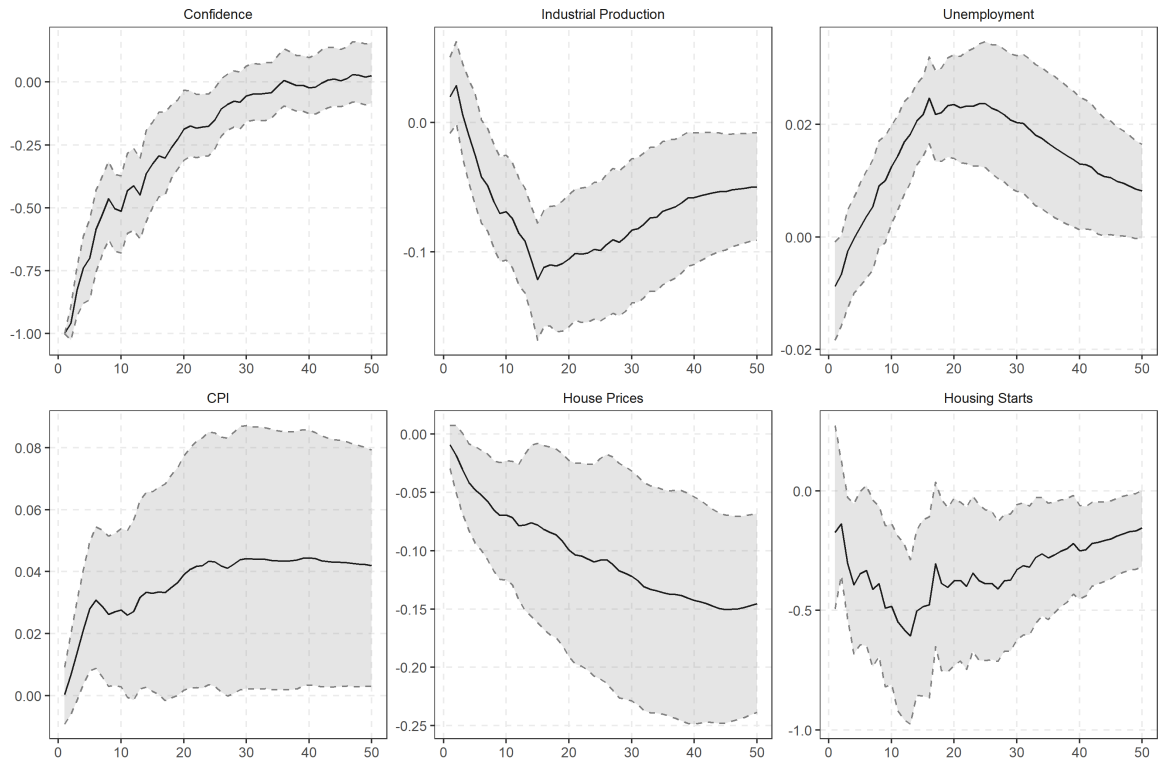
3.5 Sensitivity Analysis

In this section, we conduct a variety of robustness checks; however, we only report the figures of a few salient robustness checks and provide the rest in an online appendix.

⁷The central SNA framework explicitly excludes consumer durables acquired by households from its concept of assets. This exclusion occurs because the services they provide to households are not treated as being within the SNA's production boundary.

⁸Household consumption expenditures: Housing includes rental and imputed rental of owner-occupied nonfarm housing and other.

Fig. 3.9 Specification with Housing Starts



Note: Impulse response to a negative sentiment shock from proxy SVAR model. Identification is achieved by using mass fatalities as an instrumental variable to Confidence. Solid lines represent the estimated responses and shaded areas represent the 68% probability bands generated with the AR confidence bands.

Housing starts is very prevalent measure of housing activity in the literature. Although in our analysis, we favoured new houses sold against alternative measures of housing volume, we apply an alternative specification to our benchmark model as a sensitivity check, where we substitute new house sold with housing starts. Figure 3.9 shows the results from this alternative specification. Even though there are some quantitative differences in housing starts, our overall conclusions remain unchanged. The inclusion of housing starts has a 50% larger response on itself than houses sold, which in its turn reinforce the size of the response of house prices, unemployment and industrial production by 25%.

Next, we focus on the validity of the instrument by exploring its' relationship with the confidence index. It can be argued that due to the innate nature of mass

fatalities that depict a series of tragic events, it can only convey information about the pessimistic emotions of the economy; thus, mass fatalities cannot proxy the overall sentiment of the economy. For that reason, we do an exercise where we construct two additional indices from the Michigan Survey that are trying to capture the pessimism (unfavourable) and the optimism (favourable) aspect of the consumer behaviour. We extract all the responses from questionnaires that are included in the construction of the ICE index. Then, we split these responses into favourable and unfavourable, and we aggregate them into two distinct sub-indices that follow the same construction principles with ICE.

Figure C.2 illustrates the two unfiltered sub-indices. As expected, the two indices mirror each other almost perfectly, i.e. the decline of favourable responses is accompanied by an increase of unfavourable response and vice versa. A potential interpretation could be that the lack of pessimism in the survey's questionnaire can be represented as optimism, which fits our instrument's disposition. We continue by applying the instrumental variable identification in a proxy-SVAR model for both the favourable and the unfavourable ICE sub-indices. However, since the two indices depict different sentiment, in order to produce a negative sentimental unit-shock to both cases, instead of a negative, we deliver a positive unit-shock to the unfavourable index. Figure C.3 shows that mass fatalities can successfully identify the autonomous changes in consumer confidence in both cases, with almost no distinct differences. Thus mass fatalities can constitute a valid instrument to identify the overall sentiment of the economy.

To further ensure our instrument's robustness, we perform some additional checks on our instrument's initial inclusion conditions. First, we use a different rule to calculate our instrument, where instead of seven, we use three or more fatalities (*fatalities3*), to show that our instrument is not sensitive to our selection criteria. (Figure C.4) illustrates the benchmark model, where *fatalities3* is used as an instrument for the identification. The results remain identical.

Furthermore, since *fatalities* is a zero-inflated instrument, the location of non-zero observations could be very critical to the identification. We assure that this is not the

case, by applying random reshuffling of the instrument, which will indicate whether the identification is coincidental. Figure C.5 shows that random allocation of the fatalities cannot identify the confidence correctly. Additionally, mass fatalities are relatively sparse that happen in an irregular rate, thus could be sensitive to minor alternations of the information they convey. Results that are sensitive to the deletion of one or two clusters of observations highlight the degree to which significant results depend upon sensitive coefficient, and standard error estimates (Young, 2020). We make sure that the instrument is not sensitive to the exclusion of observations by removing the three most lethal events individually (Figure C.6). The exclusion of the events is slightly mitigating the effect of the sentiment as expected since the number of total fatalities is reduced; however, it does not affect the identification.

Finally, we conduct a battery of checks to further assess the robustness of the model. We focus on the initial lag specification and the detrending filter assumptions. We use 12 lags (Figure C.7) and 24 lags (Figure C.8), and we detrend all variables with 4th order polynomial (Figure C.9). All sensitivity checks show that the model is robust.

3.6 Conclusions

In this paper, we investigate the role of consumer sentiment shocks on the housing market variables. We implement an identification approach that uses mass fatalities as instrumental variables to identify autonomous movements to consumer confidence. Mass fatalities have been shown to be exogenous to economic activity; however, they constitute a unique instrument to proxy the overall sentiment of the economy, since it can explain developments in consumer confidence. We find that adverse sentiment shocks are associated with a reduction in house prices and houses sold.

We augment our benchmark specification with additional variables in order to explore the influence of the sentiment shocks on other aspects of the economy. We find that negative shocks worsen homeownership conditions, induce the response of monetary policy in order to counter the dampening effects on economic activity, and exacerbate

real consumption spending. In a counterfactual experiment, we find that the presence of the housing market in a consumer sentiment shock enhances the responsiveness of the market variables. The role of the housing market becomes especially prominent on longer horizons, usually after one year, where we observe increasing divergence from the unrestricted model.

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Appendix A

Real Estate and Construction Sector Dynamics in the Business Cycle

A.1 Data and Sources

Aggregate Consumption: Real Personal Consumption Expenditure (seasonally adjusted, chain-type quantity index, base year 2009, table 1.1.3) divided by the Civilian Noninstitutional Population (CNP16OV, source: Bureau of labour Statistics). Source: Bureau of Economic Analysis (BEA)

Business Investment: Real Private Nonresidential Fixed Investment (seasonally adjusted, chain-type quantity index, base year 2009, table 1.1.3) divided by CNP16OV. Source: BEA

Residential Investment Real Private Residential Fixed Investment (seasonally adjusted, chain-type quantity index, base year 2009, table 1.1.3) divided by CNP16OV. Source: BEA

Commercial Real Estate Investment Real Private Nonresidential Structures Fixed Investment (seasonally adjusted, chain-type quantity index, base year 2009, table 1.1.3) divided by CNP16OV. Source: BEA

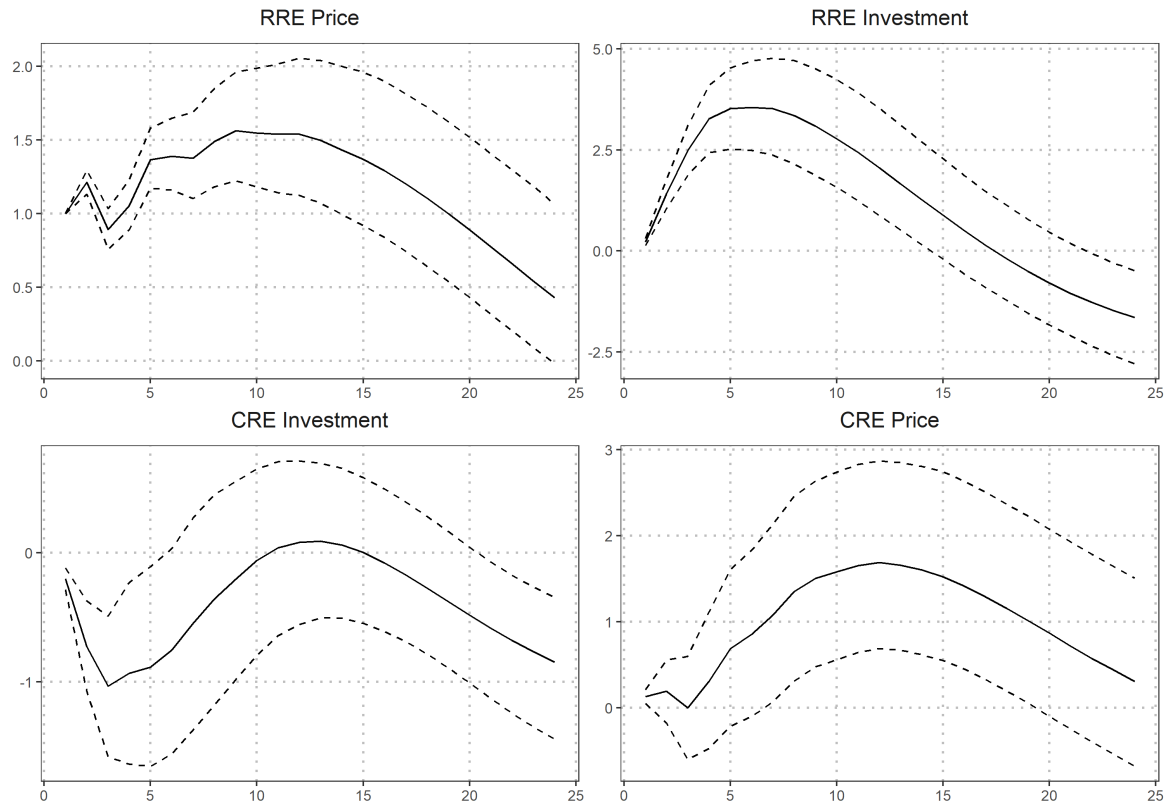
Residential Real Estate Prices : Real House Price Index, United States (NSA) deflated with the implicit price deflator for the nonfarm business sector (table 2 , source: BLS). Source: Census Bureau

Commercial Real Estate Prices : Real Commercial Real Estate Price Index, United States (NSA) deflated with the implicit price deflator for the nonfarm business sector (table 2 , source: BLS). Source: Federal Reserve System

Hours: Hours of Wage and Salary Workers on Nonfarm Payrolls: Private(seasonally adjusted, Billions of Hours, Series ID: PRSCQ). Source: FRED

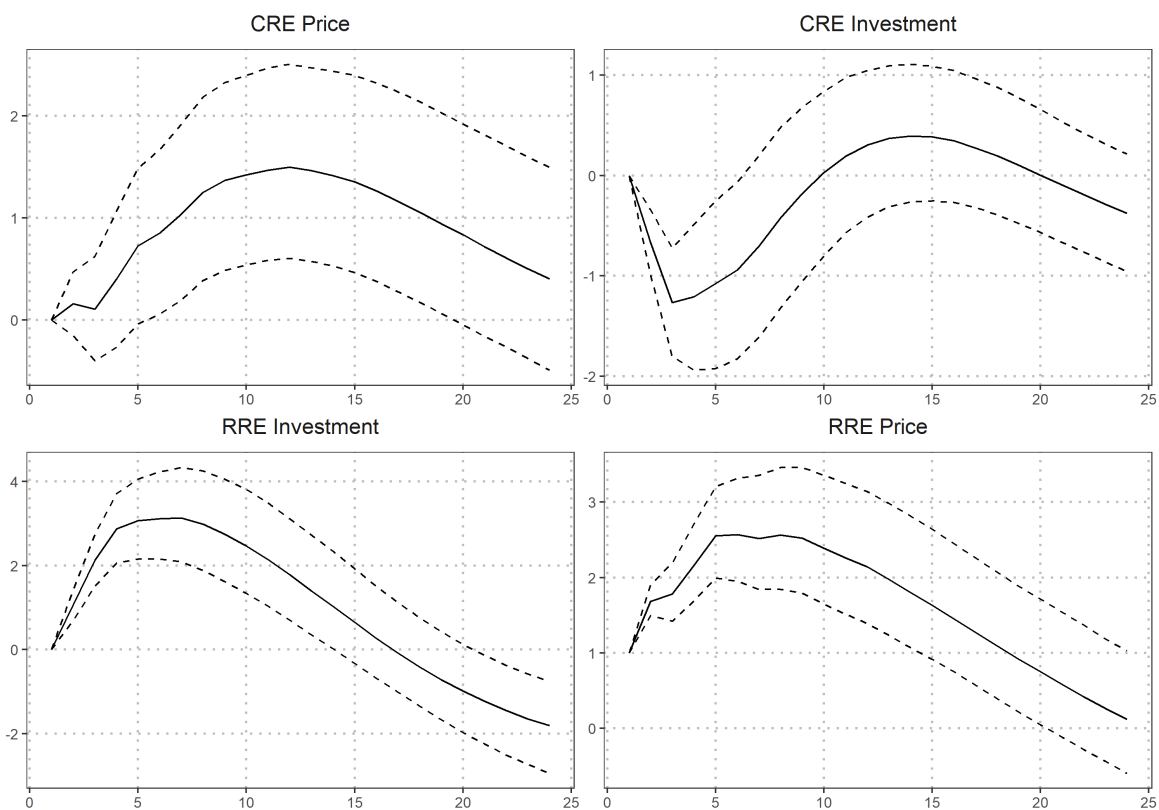
A.2 BVAR

Fig. A.1 RRE Price Shock - Minnesota Prior



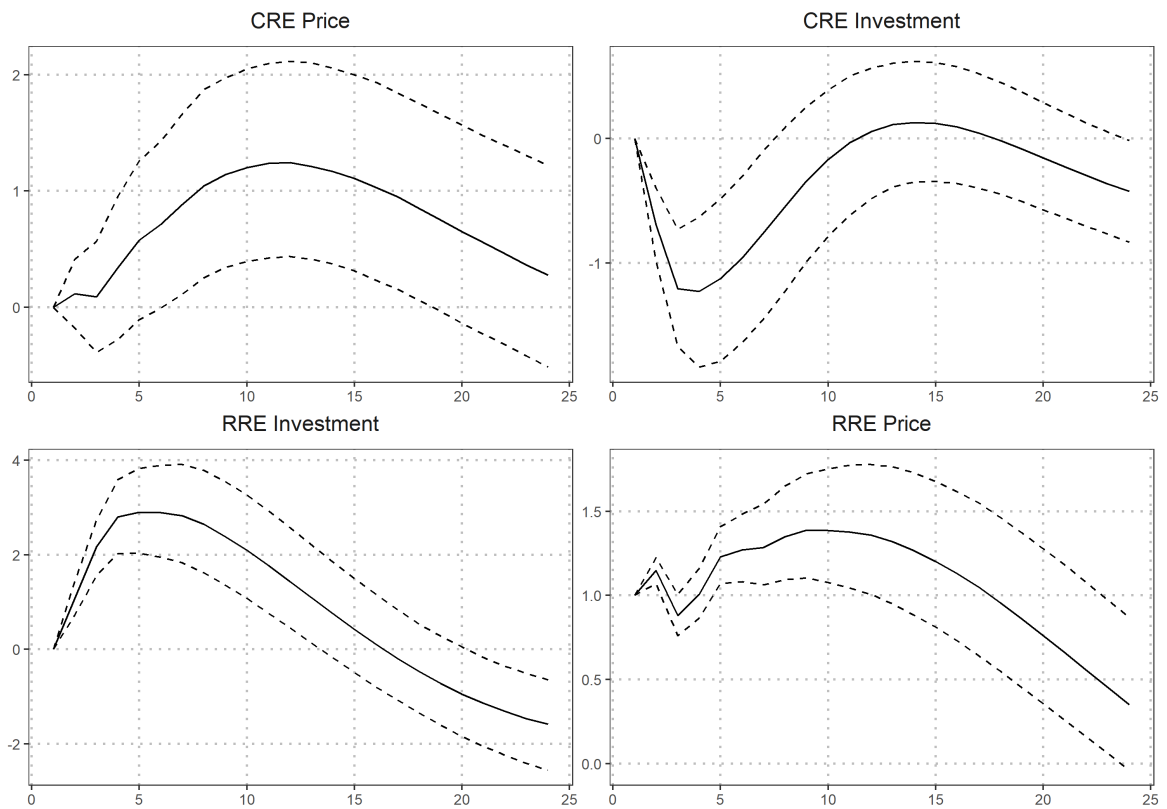
Notes: Impulse response to a positive shock to the residential real estate price from a recursive BVAR model with Minnesota Prior. Identification is achieved through Cholesky decomposition with the following ordering {RRE Price, RRE Investment, CRE Investment, CRE Price }, all in real terms. Solid lines represent the median estimated responses and dotted lines the 68% probability bands.

Fig. A.2 RRE Price Shock - RRE Price Ordered Last



Notes: Impulse response to a positive shock to the residential real estate price from a recursive BVAR model with Diffuse Prior. Identification is achieved through Cholesky decomposition with the following ordering {CRE Price, CRE Investment, RRE Investment, RRE Price}, all in real terms. Solid lines represent the median estimated responses and dotted lines the 68% probability bands.

Fig. A.3 RRE Price Shock - RRE Price Ordered Last - Minnesota Prior



Notes: Impulse response to a positive shock to the residential real estate price from a recursive BVAR model with Minnesota Prior. Identification is achieved through Cholesky decomposition with the following ordering {RRE Price, RRE Investment, CRE Investment, CRE Price }, all in real terms. Solid lines represent the median estimated responses and dotted lines the 68% probability bands.

A.3 Model Equations

$$C_{d,t} + q_{hd,t}H_{d,t} + \frac{S_t}{R_t} \leq q_{hd,t}(1 - \delta_{hd})H_{d,t-1} + w_{c,t}N_{c,t} + w_{h,t}N_{hc,t} + w_{h,t}N_{hd,t} + S_{t-1} + q_{l,t}L_{hd,t}^{ep}.$$

The first-order conditions for households are:

$$u_{cd,t}w_{c,t} = z_t\psi_t(N_{c,t}^{1+\xi} + (N_{hc,t} + N_{hd,t})^{1+\xi})^{\frac{\eta-\xi}{1+\xi}}N_{c,t}^\xi, \quad (\text{A3.1})$$

$$u_{cd,t}w_{h,t} = z_t\psi_t(N_{c,t}^{1+\xi} + (N_{hc,t} + N_{hd,t})^{1+\xi})^{\frac{\eta-\xi}{1+\xi}}(N_{hc,t} + N_{hd,t})^\xi, \quad (\text{A3.2})$$

$$u_{cd,t} = \beta_d R_t u_{cd,t+1}, \quad (\text{A3.3})$$

$$u_{cd,t}q_{hd,t} = \frac{\chi_t z_t}{H_{d,t}} + \beta_d E_t(u_{cd,t+1} + (1 - \delta_{hd})q_{hd,t+1}) \quad (\text{A3.4})$$

$$u_{cd,t} = z_t \left(\frac{1}{C_{d,t} - \gamma_d C_{d,t-1}} - E_t \frac{\beta_d \gamma_d}{C_{d,t+1} - \gamma_d C_{d,t}} \right). \quad (\text{A3.5})$$

The budget and borrowing constraint for consumption-good entrepreneur are:

$$C_{c,t} + K_{c,t} + q_{hc,t}H_{c,t} + w_{c,t}N_{c,t} + B_{c,t-1} \quad (\text{A3.6})$$

$$= Y_t + (1 - \delta_{kc})K_{c,t-1} + (1 - \delta_{hc})q_{hc,t}H_{c,t-1} + \frac{B_{c,t}}{R_t} + q_{l,t}L_{hc,t}^{ep} - \phi_{c,t}$$

$$B_{c,t} \leq \rho_b B_{c,t-1} + (1 - \rho_b)\theta_c E_t \left[q_{hc,t+1}H_{c,t} + \frac{K_{c,t}}{A_{kc,t}} \right]. \quad (\text{A3.7})$$

the production technology is:

$$Y_t = K_{c,t-1}^{\alpha_c} H_{c,t-1}^{\mu_c} (A_{c,t}N_{c,t})^{1-\alpha_c-\mu_c}. \quad (\text{A3.8})$$

and the first order conditions are:

$$(1 - \alpha_c - \mu_c)Y_t = w_{c,t}N_{c,t}, \quad (\text{A3.9})$$

$$\begin{aligned} u_{cc,t} \left(1 + \frac{\partial \phi_{c,t}}{\partial K_{c,t}} \right) \\ = \beta_e E_t u_{cc,t+1} \left(\alpha_c \frac{Y_{t+1}}{K_{c,t}} + (1 - \delta_{kc}) - \frac{\partial \phi_{c,t+1}}{\partial K_{c,t}} \right) + \lambda_{bc,t}(1 - \rho_b)\theta_c, \end{aligned} \quad (\text{A3.10})$$

$$\begin{aligned} u_{cc,t} q_{hc,t} \\ = \beta_e E_t u_{cc,t+1} \left(\mu_c \frac{Y_{t+1}}{H_{c,t}} + (1 - \delta_{hc})q_{hc,t+1} \right) + \lambda_{bc,t}(1 - \rho_b)\theta_c q_{hc,t+1}, \end{aligned} \quad (\text{A3.11})$$

$$u_{cc,t} = \beta_e R_t u_{cc,t+1} + \lambda_{c,t} - \rho_b \beta_e \lambda_{c,t-1}, \quad (\text{A3.12})$$

$$u_{cc,t} = \left(\frac{1}{C_{c,t} - \gamma_e C_{c,t-1}} - E_t \frac{\beta_e \gamma_e}{C_{c,t+1} - \gamma_e C_{c,t}} \right), \quad (\text{A3.13})$$

where $\lambda_{bc,t}$ denotes the multiplier on the borrowing constraint, which is greater than zero in a neighbourhood of the equilibrium.

The budget and borrowing constraint for construction-sector entrepreneur are:

$$\begin{aligned} C_{h,t} + K_{hc,t} + K_{hd,t} + q_{l,t} (L_{hc,t} + L_{hd,t}) + w_{h,t} (N_{hc,t} + N_{hd,t}) + B_{h,t-1} \\ = q_{hc,t} I H_{c,t} + q_{hd,t} I H_{d,t} + (1 - \delta_{kh})K_{hc,t} + (1 - \delta_{kh})K_{hd,t} + q_{l,t} (L_{hc,t} + L_{hd,t}) + \frac{B_{h,t}}{R_t}, \end{aligned} \quad (\text{A3.14})$$

$$B_{h,t} \leq \rho_b B_{h,t-1} + (1 - \rho_b) \theta_h E_t [q_{l,t+1} (L_{hc,t} + L_{hd,t}) + K_{hc,t} + K_{hd,t}]. \quad (\text{A3.15})$$

The production technologies are:

$$IH_{c,t} = K_{hc,t-1}^{\alpha_{hc}} L_{hc,t-1}^{\mu_h} (A_{h,t}, N_{hc,t})^{1-\alpha_{hc}-\mu_h} \quad (\text{A3.16})$$

$$IH_{d,t} = A_{hd,t} K_{hd,t-1}^{\alpha_{hd}} L_{hd,t-1}^{\mu_h} (A_{hd,t}, N_{h,t})^{1-\alpha_{hd}-\mu_h} \quad (\text{A3.17})$$

and the first order conditions are:

$$(1 - \alpha_{hc} - \mu_h) q_{hc,t} IH_{c,t} = w_{h,t} N_{hc,t}, \quad (\text{A3.18})$$

$$(1 - \alpha_{hd} - \mu_h) q_{hd,t} IH_{d,t} = w_{h,t} N_{hd,t}, \quad (\text{A3.19})$$

$$\begin{aligned} & u_{ch,t} \left(1 + \frac{\partial \phi_{hc,t}}{\partial K_{hc,t}} \right) \quad (\text{A3.20}) \\ & = \beta_e E_t u_{ch,t+1} \left(\alpha_{hc} \frac{q_{hc,t} IH_{c,t+1}}{K_{hc,t}} + (1 - \delta_{k_{hc}}) - \frac{\partial \phi_{hc,t+1}}{\partial K_{hc,t}} \right) + \lambda_{bh,t} (1 - \rho_b) \theta_h, \end{aligned}$$

$$\begin{aligned} & u_{ch,t} \left(1 + \frac{\partial \phi_{hd,t}}{\partial K_{hd,t}} \right) \quad (\text{A3.21}) \\ & = \beta_e E_t u_{ch,t+1} \left(\alpha_{hd} \frac{q_{hd,t} IH_{d,t+1}}{K_{hd,t}} + (1 - \delta_{k_{hd}}) - \frac{\partial \phi_{hd,t+1}}{\partial K_{hd,t}} \right) + \lambda_{bh,t} (1 - \rho_b) \theta_h, \end{aligned}$$

$$u_{ch,t} q_{l,t} = \beta_e E_t u_{ch,t+1} \left(\mu_h \frac{q_{hc,t} IH_{c,t+1}}{L_{hc,t}} \right) + \lambda_{bh,t} (1 - \rho_b) \theta_h q_{l,t+1}, \quad (\text{A3.22})$$

$$u_{ch,t} q_{l,t} = \beta_e E_t u_{ch,t+1} \left(\mu_h \frac{q_{hd,t} IH_{d,t+1}}{L_{hd,t}} \right) + \lambda_{bh,t} (1 - \rho_b) \theta_h q_{l,t+1}, \quad (\text{A3.23})$$

$$u_{ch,t} = \beta_e R_t u_{ch,t+1} + \lambda_{bh,t} - \rho_b \beta_e \lambda_{bh,t-1}, \quad (\text{A3.24})$$

$$u_{ch,t} = \left(\frac{1}{C_{h,t} - \gamma_e C_{h,t-1}} - E_t \frac{\beta_e \gamma_e}{C_{h,t+1} - \gamma_e C_{h,t}} \right). \quad (\text{A3.25})$$

The market-clearing conditions are:

$$Y_t - \phi_t = C_t + IB_t, \quad (\text{A3.26})$$

$$GDP_t = Y_t + q_{hd} IH_{d,t}. \quad (\text{A3.27})$$

The evolution of commercial and residential real estate are:

$$IH_{c,t} = H_{c,t} - (1 - \delta_{hc}) H_{c,t-1}, \quad (\text{A3.28})$$

$$IH_{d,t} = H_{d,t} - (1 - \delta_{hd}) H_{d,t-1}. \quad (\text{A3.29})$$

The land is fixed and equal to:

$$\bar{L}_h = (L_{hc,t} + L_{hd,t}). \quad (\text{A3.30})$$

The aggregate consumption and business investment are:

$$C_t = C_{d,t} + C_{c,t} + C_{h,t}, \quad (\text{A3.31})$$

$$IK_{c,t} = K_{c,t} - (1 - \delta_{kc}) K_{c,t-1}. \quad (\text{A3.32})$$

Construction capital is equal to

$$IK_{h,t} = K_{hc,t} - (1 - \delta_{kh}) K_{hc,t-1} + K_{hd,t} - (1 - \delta_{kh}) K_{hd,t}. \quad (\text{A3.33})$$

Non-construction capital is equal to

$$IK_t = IK_{c,t} + IK_{h,t}. \quad (\text{A3.34})$$

Business Investment

$$IB_t = IK_t + \bar{q}_c IH_{c,t}; \quad (\text{A3.35})$$

Ex-post land equations are:

$$L_{hc}^{ep} = \frac{H_{c,t}}{(H_{c,t} + H_{c,t})} \bar{L}, \quad (\text{A3.36})$$

$$L_{hd}^{ep} = \frac{H_{d,t}}{(H_{c,t} + H_{c,t})} \bar{L}. \quad (\text{A3.37})$$

A competitive equilibrium consists of a sequence of allocation $\{C_{d,t}, H_{d,t}, N_{c,t}, N_{hc,t}, N_{hd,t}, S_t, C_{c,t}, K_{c,t}, H_{c,t}, B_{c,t}, C_{h,t}, IH_{c,t}, K_{hc,t}, L_{hc,t}, IH_{d,t}, K_{hd,t}, L_{hd,t}\}_{t=0}^{\infty}$ and prices $\{w_{c,t}, w_{hc,t}, w_{hd,t}, q_{hd,t}, q_{hd,t}, q_{l,t}, R_t\}_{t=0}^{\infty}$ such that

(i) given the $\{w_{c,t}, w_{hc,t}, w_{hd,t}, q_{hd,t}, R_t\}_{t=0}^{\infty}$ the sequence $\{C_{d,t}, H_{d,t}, N_{c,t}, N_{hc,t}, N_{hd,t}, S_t\}_{t=0}^{\infty}$ solves the household's problem,

(ii) given the $\{w_{c,t}, q_{hc,t}, R_t\}_{t=0}^{\infty}$ the sequence $\{C_{c,t}, K_{c,t}, H_{c,t}, N_{c,t}, B_{c,t}\}_{t=0}^{\infty}$ solves the entrepreneur in the consumption good sector problem,

(iii) given the $\{w_{hc,t}, q_{hc,t}, w_{hd,t}, q_{hd,t}, q_{l,t}, R_t\}_{t=0}^{\infty}$ the sequence $\{C_{h,t}, IH_{c,t}, K_{hc,t}, L_{hc,t}, N_{hc,t}, B_{h,t}, IH_{d,t}, K_{hd,t}, L_{hd,t}, N_{hd,t}\}_{t=0}^{\infty}$ solves the entrepreneur in the construction sector problem,

(iv) all markets clear.

A.4 Steady State

From the Euler equation we can derive that:

$$R = \frac{1}{\beta_d}.$$

The ratio of the Lagrange multipliers to the marginal utility of consumption is equal to:

$$\frac{\lambda_c}{u_{ce}} = \frac{\beta_d - \beta_e}{1 - \rho_b \beta_e} \quad \& \quad \frac{\lambda_h}{u_{ce}} = \frac{\beta_d - \beta_e}{1 - \rho_b \beta_e}.$$

The ratio of the construction capital for commercial structures to commercial real estate is:

$$\frac{K_{hc}}{q_{hc}IH_c} = \frac{\alpha_{hc}\beta_e}{1 - \beta_e(1 - \delta_{khc}) - \frac{\lambda_{hc}}{u_{ce}}(1 - \rho_b)\theta_{hc}},$$

and investment for commercial structures is:

$$\frac{I_{hc}}{q_{hc}IH_c} = \delta_{khc} \frac{K_{hc}}{q_{hc}IH_c}.$$

The ratio of the construction capital for residential structures to residential real estate is:

$$\frac{K_{hd}}{q_{hd}IH_d} = \frac{\alpha_{hd}\beta_e}{1 - \beta_e(1 - \delta_{khd}) - \frac{\lambda_{hd}}{u_{ce}}(1 - \rho_b)\theta_{hd}}$$

and investment for residential structures is:

$$\frac{I_{hd}}{q_{hd}IH_d} = \delta_{khd} \frac{K_{hd}}{q_{hd}IH_d}.$$

Land to both type of real estate are:

$$\frac{q_l L_{hc}}{q_{hc}IH_c} = \frac{\mu_h \beta_e}{1 - \beta_e - \frac{\lambda_{hc}}{u_{ce}}(1 - \rho_b)\theta_{hc}},$$

$$\frac{q_l L_{hd}}{q_{hd} I H_d} = \frac{\mu_h \beta_e}{1 - \beta_e - \frac{\lambda_{hd}}{u_{ce}} (1 - \rho_b) \theta_{hd}}.$$

From the FOC in the consumption good we can derive that:

$$\frac{K_c}{Y} = \frac{\alpha_c \beta_e}{1 - \beta_e (1 - \delta_{kc}) - \frac{\lambda_c}{u_{ce}} \theta_c (1 - \rho_b)},$$

$$\frac{I_c}{Y} = \delta_{kc} \frac{K_c}{Y},$$

$$\frac{q_{hc} H_c}{Y} = \frac{\mu_c \beta_e}{1 - \beta_e (1 - \delta_{hc}) - \frac{\lambda_c}{u_{ce}} \theta_c (1 - \rho_b)},$$

$$\frac{q_{hc} I H_c}{Y} = \delta_{hc} \frac{q_{hc} H_c}{Y},$$

$$\frac{B_c}{Y} = \theta_c \left(\frac{q_{hc} H_c}{Y} + \frac{K_c}{Y} \right),$$

and from the budget constraint in the consumption good

$$\frac{C_c}{Y} = \alpha_c + \mu_c - \delta'_{kc} \frac{K_c}{Y} - \delta'_{hc} \frac{q_{hc} H_c}{Y} + R' \frac{B_c}{Y}.$$

From the marginal marginal utility for residential real estate we can derive that:

$$\frac{q_{hd} H_d}{C_d} = \frac{\chi}{(1 - \beta_d (1 - \delta_{hd}))},$$

and then we use the auxiliary variables x_1 and x_2 to help us with the calculations.

We derive that:

$$\begin{aligned} x_1 &= \alpha_{hc} + \mu_h - \frac{I_{hc}}{q_{hc}IH_c} + \theta_h * \left(\frac{q_l L_{hc}}{q_{hc}IH_c} + \frac{K_{hc}}{q_{hc}IH_c} \right), \\ x_2 &= \alpha_{hc} + \mu_{hha} - \frac{I_{hc}}{q_{hc}IH_c} + \theta_h * \left(\frac{q_l L_{hc}}{q_{hc}IH_c} + \frac{K_{hc}}{q_{hc}IH_c} \right), \end{aligned}$$

$$\frac{C_d}{Y} = \frac{1 - \left(\frac{C_c}{Y} + \frac{I_c}{Y} \right) - \frac{q_{hc}IH_c}{Y} \left(1 - \frac{I_{hc}}{q_{hc}IH_c} + x_1 \right)}{1 + \delta_{hd} \frac{q_{hd}IH_d}{C_d} \left(\frac{I_{hd}}{q_{hd}IH_d} + x_2 \right)},$$

$$\frac{q_{hd}H_D}{Y} = \frac{q_{hd}H_d}{C_d} \frac{C_d}{Y},$$

$$\frac{q_{hd}IH_d}{Y} = \delta_{hd} \frac{q_{hd}H_d}{Y}.$$

To calculate the individual hours we need to combine the labour demand for consumption good, commercial and residential real estate:

$$\frac{N_{hd}}{N_{hc}} = \frac{(1 - \alpha_{hd} - \mu_h) q_{hd}IH_d}{(1 - \alpha_{hc} - \mu_h) q_{hc}IH_c},$$

$$\frac{N_{hc}}{N_c} = \left(\frac{\left(\frac{(1 - \alpha_{hc} - \mu_h) q_{hc}IH_c}{(1 - \alpha_c - \mu_c) Y} \right)^{\frac{1}{1+\xi}}}{\left(1 + \frac{N_{hd}}{N_{hc}} \right)^\xi} \right),$$

$$\frac{N_{hd}}{N_c} = \frac{N_{hd}}{N_{hc}} \frac{N_{hc}}{N_c},$$

and then we can find the levels of individual hours with:

$$N_c = \left(\frac{(1 - \alpha_c - \mu_c) \frac{Y}{C_d}}{\left(1 + \left(\frac{N_{hc}}{N_c} + \frac{N_{hd}}{N_c}\right)^{1+\xi}\right)^{\frac{\eta-\xi}{1+\xi}}} \right)^{\frac{1}{1+\eta}},$$

$$N_{hc} = \frac{N_{hc}}{N_c} N_c \quad \& \quad N_{hd} = \frac{N_{hd}}{N_c} N_c.$$

From the demand for land for commercial and residential use we can find that:

$$\frac{q_l L_{hc}}{Y} = \frac{q_l L_{hc}}{q_{hc} I H_c} \frac{q_{hc} I H_c}{Y},$$

$$\frac{q_l L_{hd}}{Y} = \frac{q_l L_{hd}}{q_{hd} I H_d} \frac{q_{hd} I H_d}{Y}.$$

From land supply we know that $\bar{L}_h = 1$, so:

$$\frac{q_l}{Y} = \frac{q_l L_{hc}}{Y} + \frac{q_l L_{hd}}{Y}$$

And then we can find the individual levels of land with

$$L_{hc} = \frac{q_l L_{hc}}{Y} + \frac{q_l}{Y},$$

$$L_{hd} = \frac{q_l L_{hd}}{Y} + \frac{q_l}{Y}.$$

From the production technologies we find that:

$$q_{hc}^{\frac{\mu_c}{1-\alpha_c-\mu_c}} Y = \left(\frac{K_c}{Y}\right)^{\frac{\alpha_c}{1-\alpha_c-\mu_c}} \left(\frac{q_{hc} H_c}{Y}\right)^{\frac{\mu_c}{1-\alpha_c-\mu_c}} N_c,$$

$$q_{hc}^{-\frac{\alpha_{hc}}{1-\alpha_{hc}}} I H_c = \left(\frac{K_{hc}}{q_{hc} I H_c}\right)^{\frac{\alpha_{hc}}{1-\alpha_{hc}}} L_{hc}^{\frac{\mu_h}{1-\alpha_{hc}}} N_c^{\frac{1-\alpha_{hc}-\mu_h}{1-\alpha_{hc}}}.$$

Combining these two we can find the levels:

$$q_{hc} = \left(\frac{\frac{\frac{\mu_c}{1-\alpha_c-\mu_c} Y}{q_{hc}} \frac{q_{hc} I H_c}{Y}}{\frac{\frac{\alpha_{hc}}{1-\alpha_{hc}} I H_c}{q_{hc}}} \right)^{1 + \frac{\mu_c}{1-\alpha_c-\mu_c} + \frac{\alpha_{hc}}{1-\alpha_{hc}}}$$

$$Y = \left(\frac{K_c}{Y} \right)^{\frac{\alpha_c}{1-\alpha_c-\mu_c}} \left(\frac{q_{hc} H_c}{Y} \right)^{\frac{\mu_c}{1-\alpha_c-\mu_c}} \frac{\frac{\mu_c}{1-\alpha_c-\mu_c}}{q_{hc}} N_c$$

$$I H_c = \left(\frac{K_{hc}}{q_{hc} I H_c} \right)^{\frac{\alpha_{hc}}{1-\alpha_{hc}}} \frac{\frac{\alpha_{hc}}{1-\alpha_{hc}}}{q_{hc}} L_{hc}^{\frac{\mu_h}{1-\alpha_{hc}}} N_{hc}^{\frac{1-\alpha_{hc}-\mu_h}{1-\alpha_{hc}}}$$

$$I H_d = \left(\frac{K_{hd}}{q_{hd} I H_d} \right)^{\alpha_{hc}} \left(\frac{q_{hd} I H_d Y}{Y} \right)^{\alpha_{hd}} L_{hd}^{\alpha_{hd}} N_{hd}^{1-\alpha_{hd}-\mu_h}.$$

Having solved for $Y, I H_c, q_{hc}, I H_d, q_{hd}$ we can substitute and solve for the rest of the variables $q_l, H_d, H_c, C_d, C_c, C_h, K_c, K_{hc}, K_{hd}, B_c, B_h, w_c, w_h \dots$

A.5 Estimation Details

The parameters of the model are estimated using Bayesian methods. We use Bayesian methods because they allow incorporating a priori information on the parameters of the model and also because pure maximum likelihood tends to produce fragile results, particularly in situations in which some parameters are weakly identified.

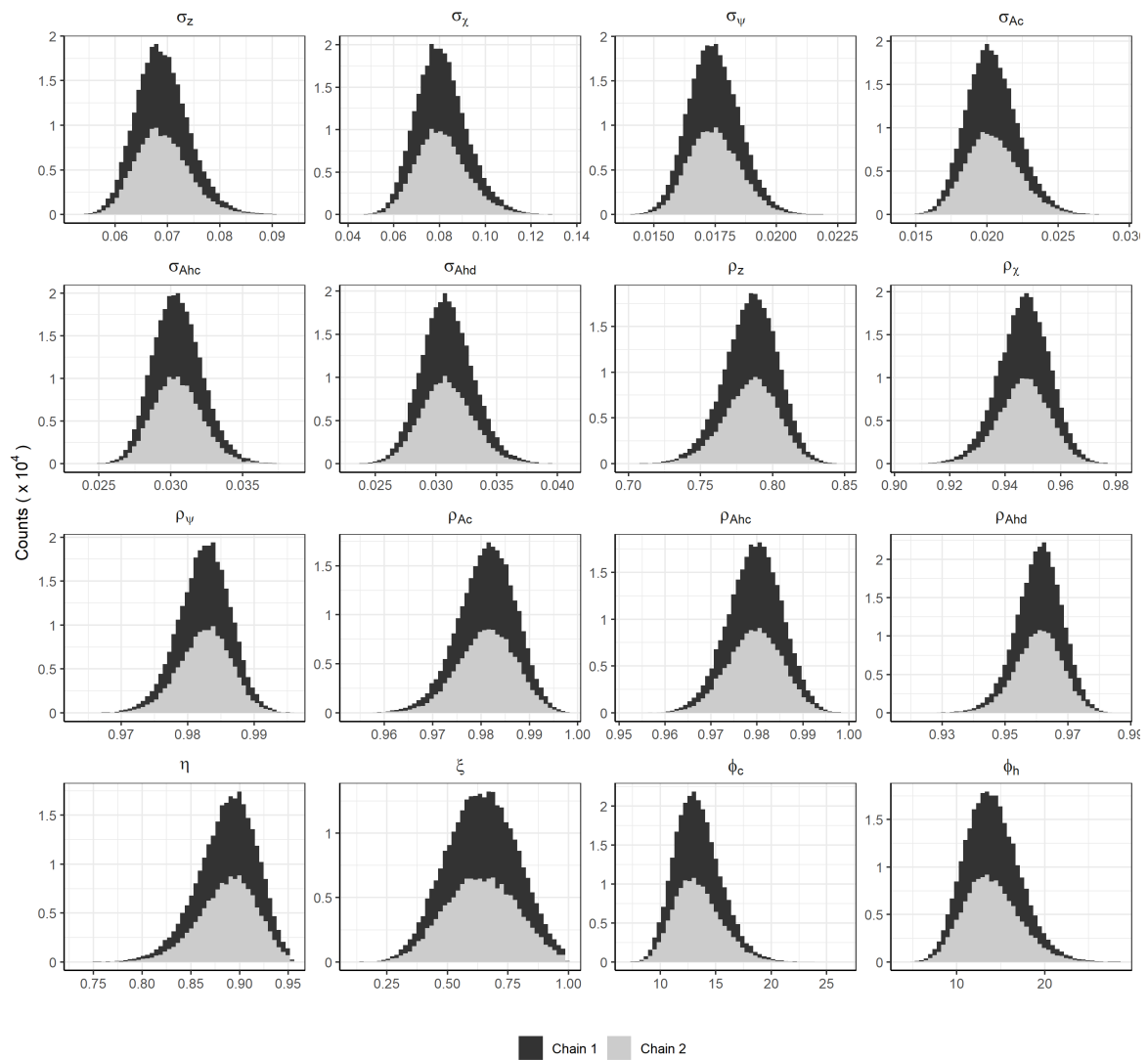
A.5.1 The Output of the Metropolis

The parameters of the model are estimated using Bayesian methods. We use Bayesian methods because they allow incorporating a priori information on the parameters of the model. Convergence of the algorithm is assessed by looking at the plots of the draws, the Brooks and Gelman (1998) statistics, and by computing recursively the mean of the marginal posterior distribution of each parameter.

A.5.2 Posterior Densities

In the following graphs we report the posterior densities of selected parameters for both chains. The posterior ones are based on 200,000 draws from the Metropolis algorithm.

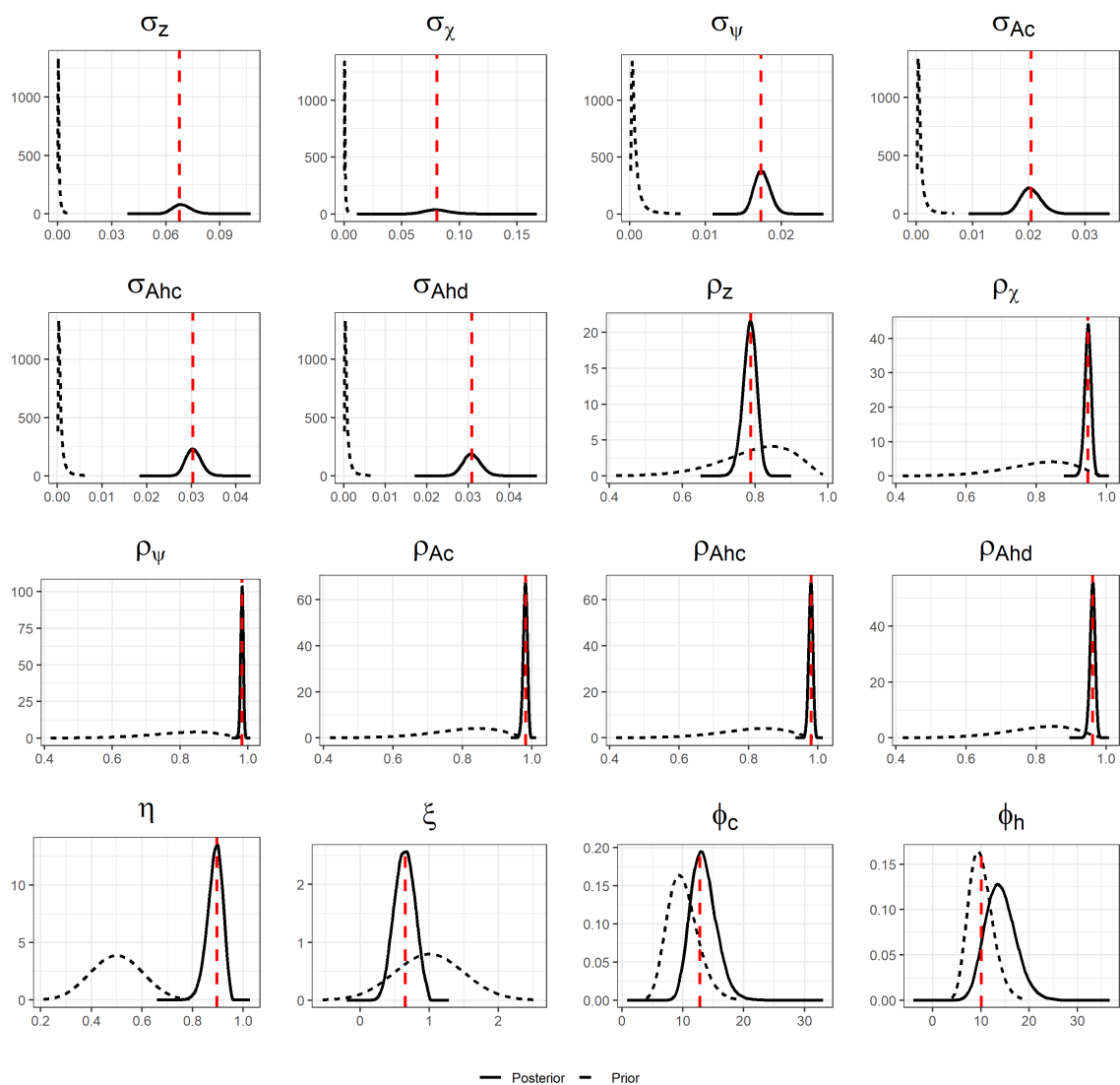
Fig. A.4 Posterior Densities



A.5.3 Prior and posterior densities

In the following graphs we report the prior and posterior densities of selected parameters. The posterior ones are based on 200,000 draws from the Metropolis algorithm and are estimated using a Gaussian kernel.

Fig. A.5 Prior & Posterior Densities



Notes: Solid lines denote the posterior density while the dashed lines denote the prior density. Vertical red lines correspond to the posterior mode.

A.5.4 The output of the Metropolis

The following graphs report the time series of the draws from the posterior distribution generated by the Metropolis algorithm.

Fig. A.6 Posterior Density Traceplot

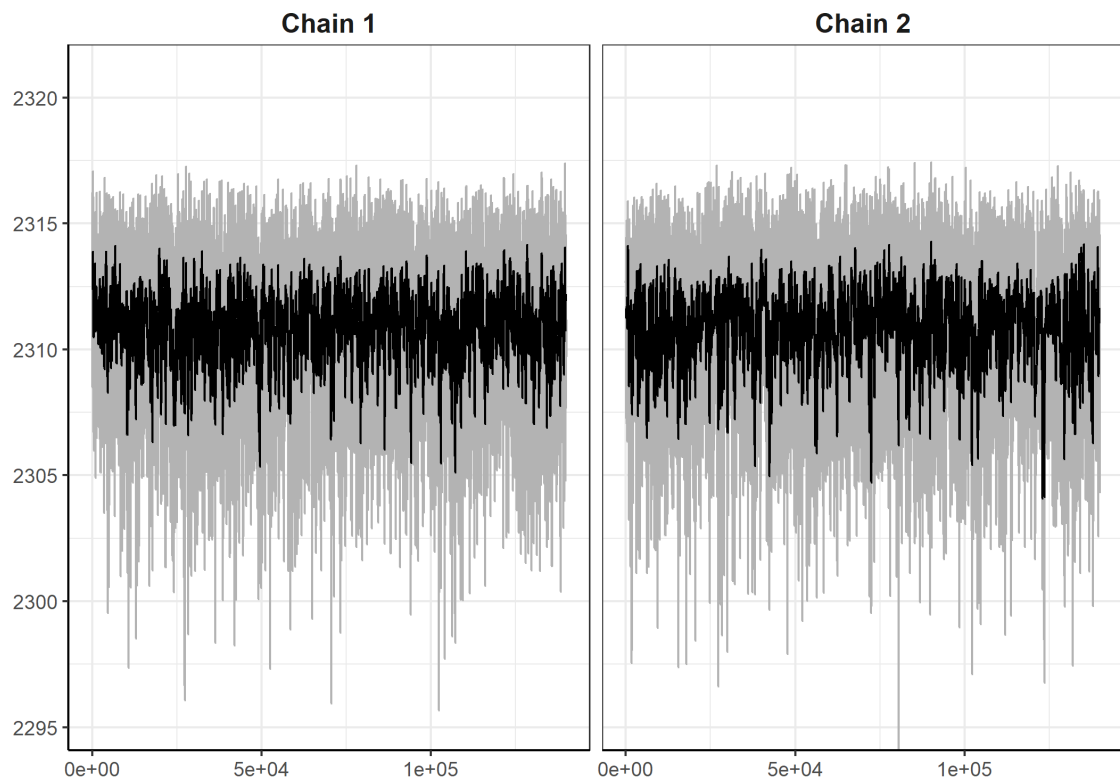


Fig. A.7 Structural Shock Traceplot - Chain 1

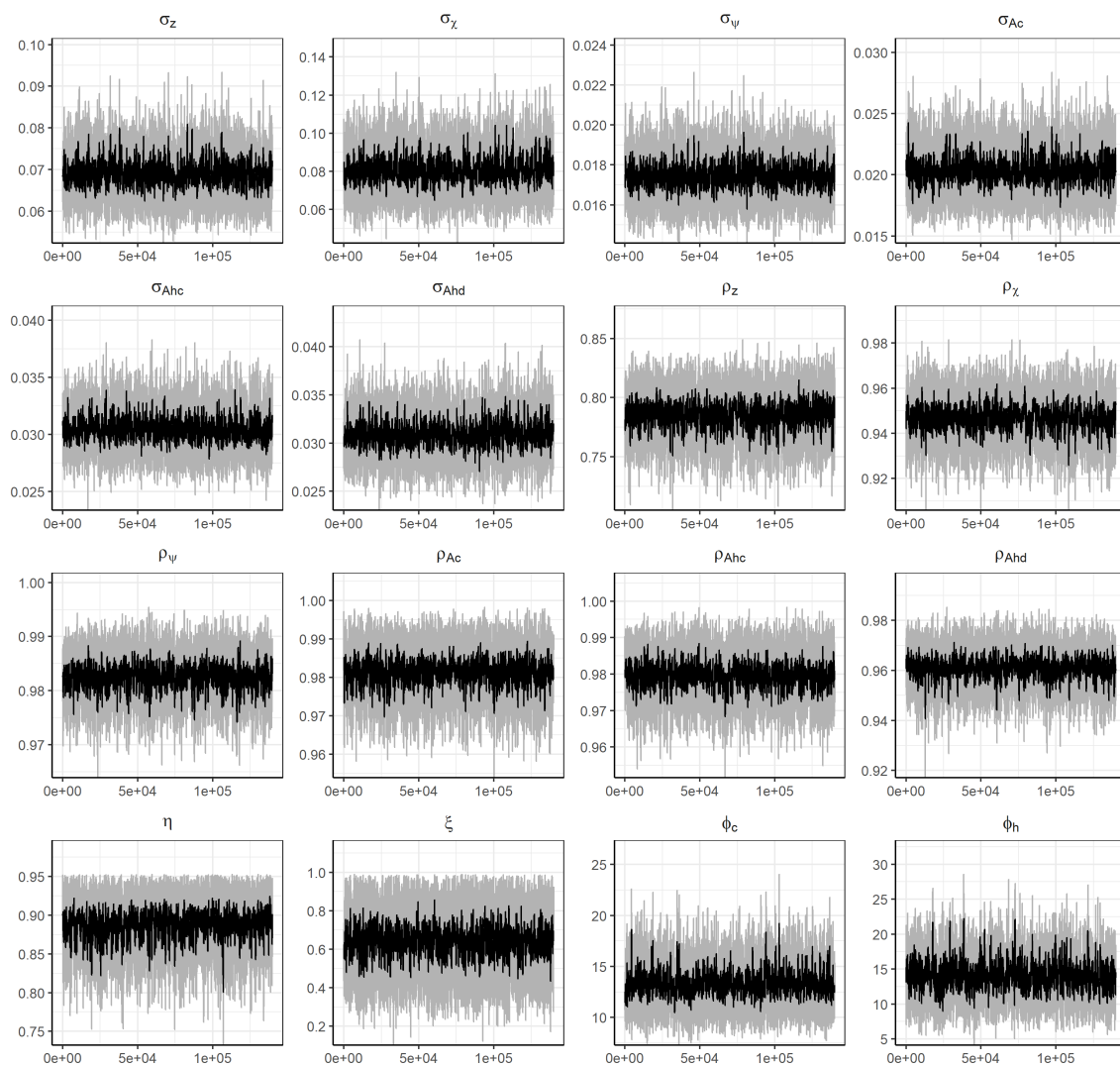
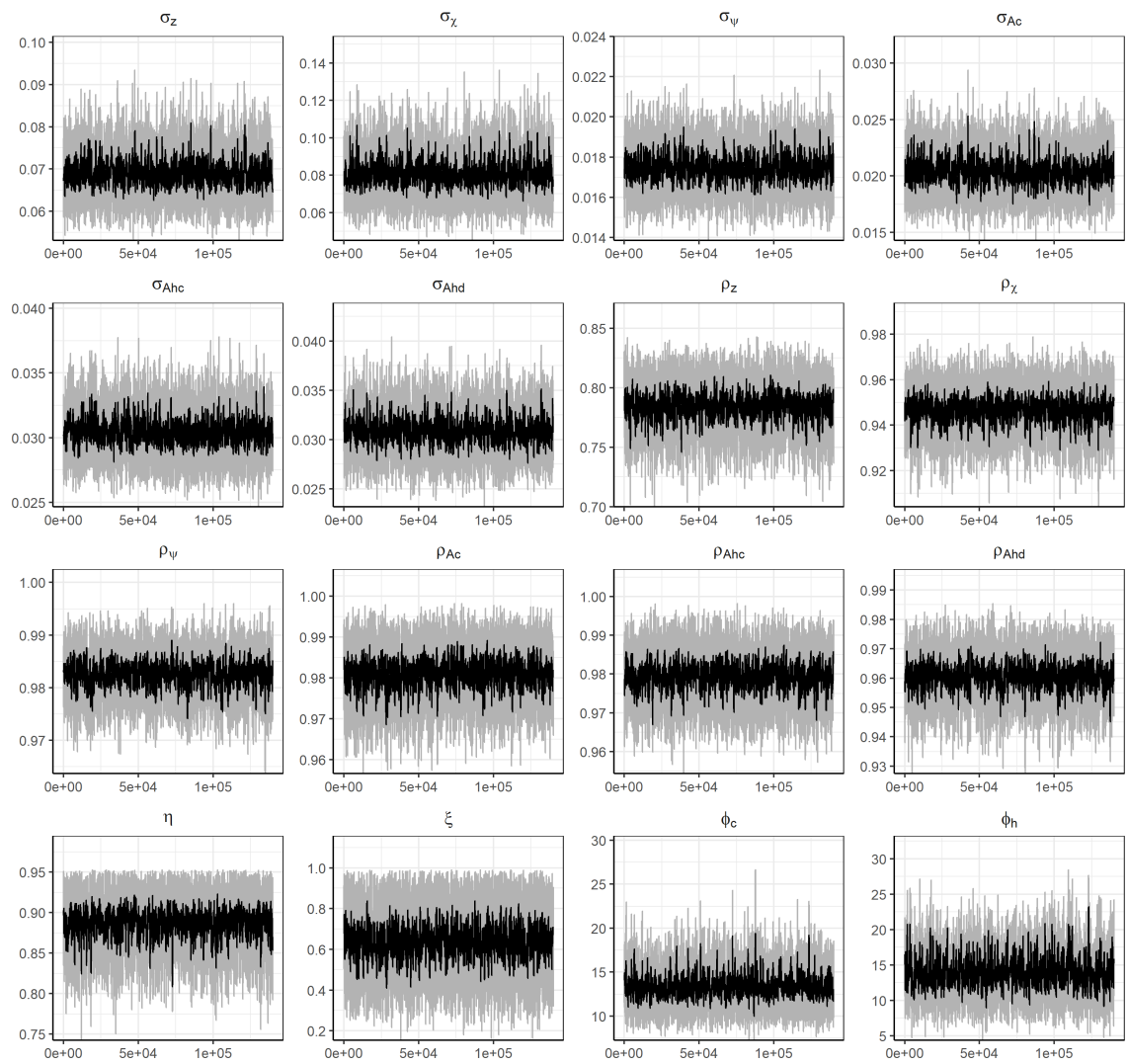


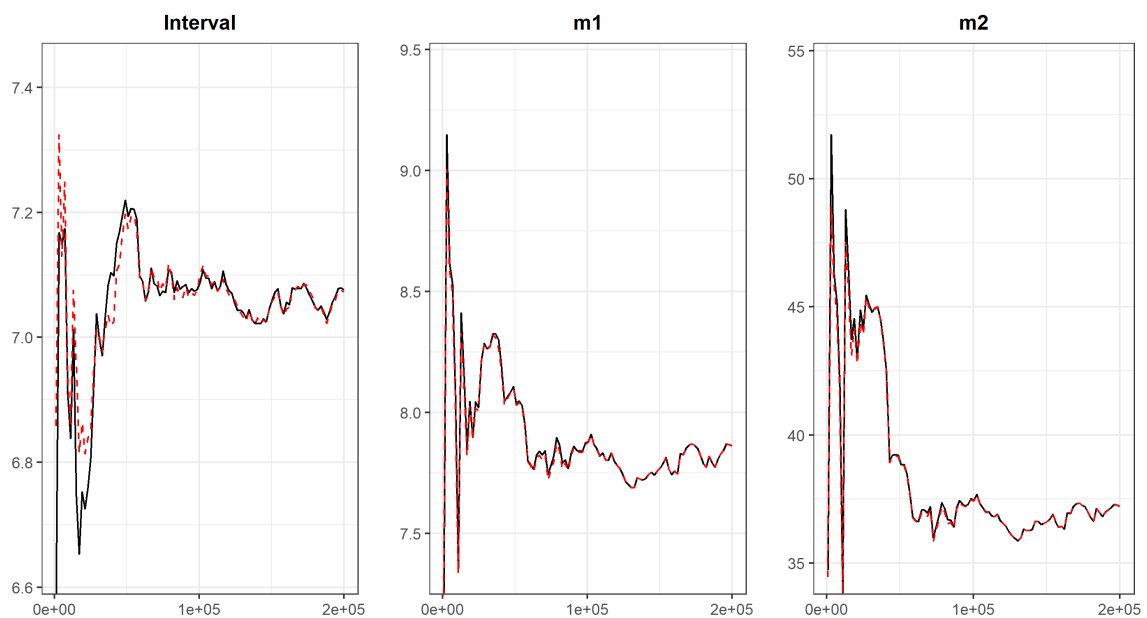
Fig. A.8 Structural Shock Traceplot - Chain 2



A.5.5 Brooks and Gelman (1998) Diagnostics

Brooks and Gelman (1998) convergence diagnostics is based on comparing pooled and within chain variability of MC draws using the 80% interval/quantile range. The convergence diagnostics displays the 80% interval range of draws from the pooled and within chain means as well as the 80% interval range of the second and third central moments (squared and cubed absolute deviations).

Fig. A.9 Multivariate Diagnostics



Univariate Diagnostics

Fig. A.10 Univariate Diagnostic - Interval

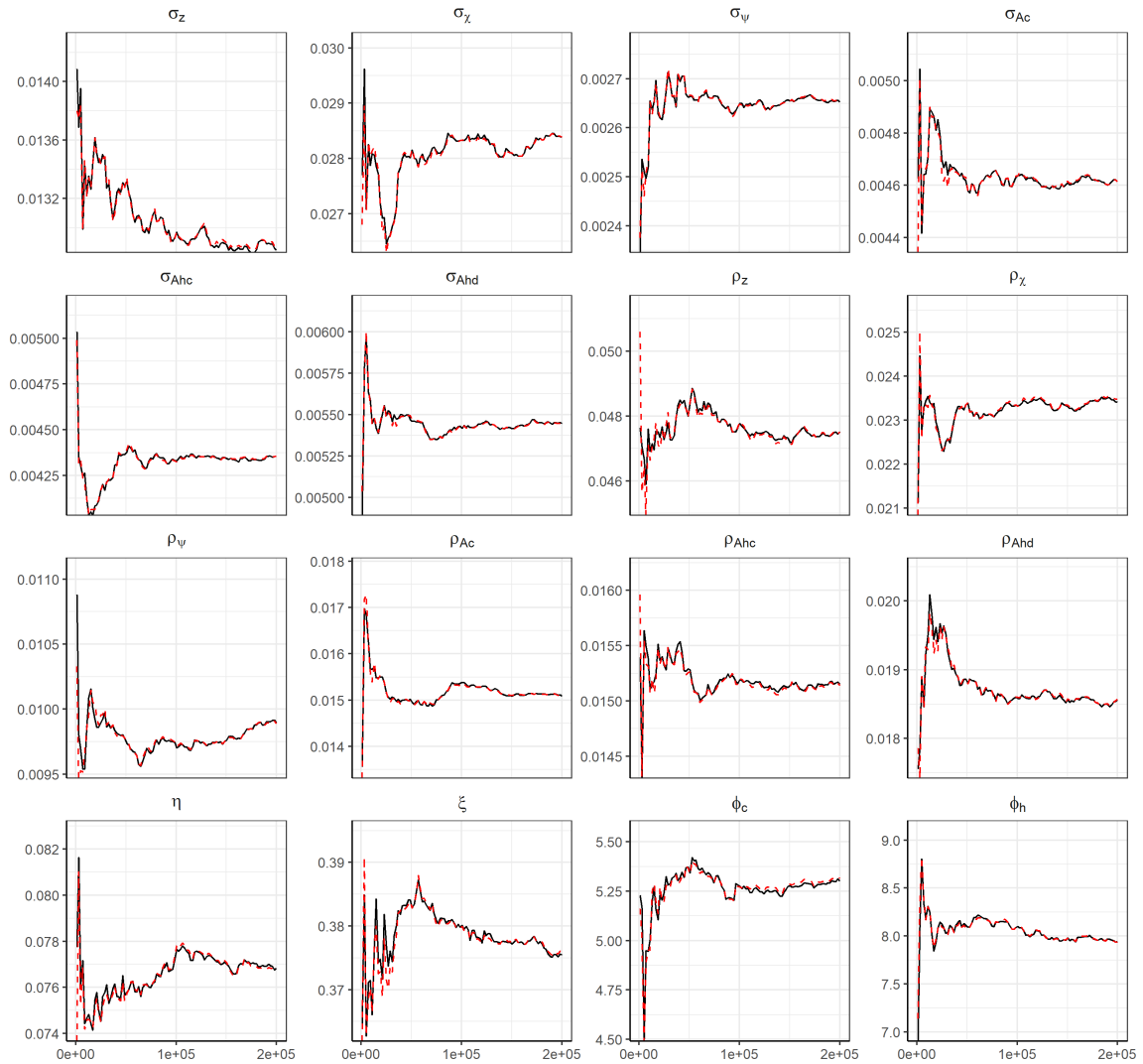


Fig. A.11 Univariate Diagnostic - m1

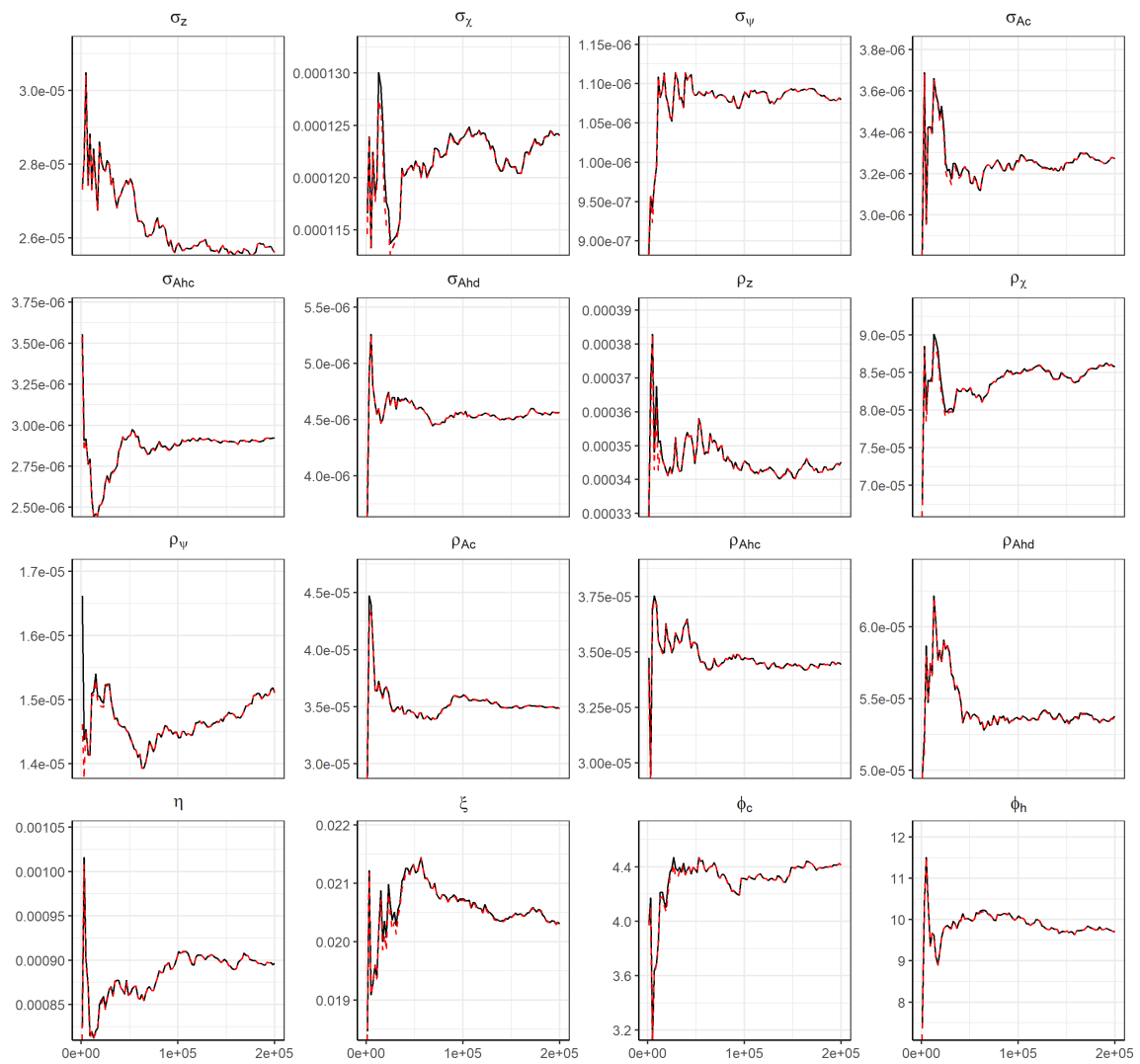
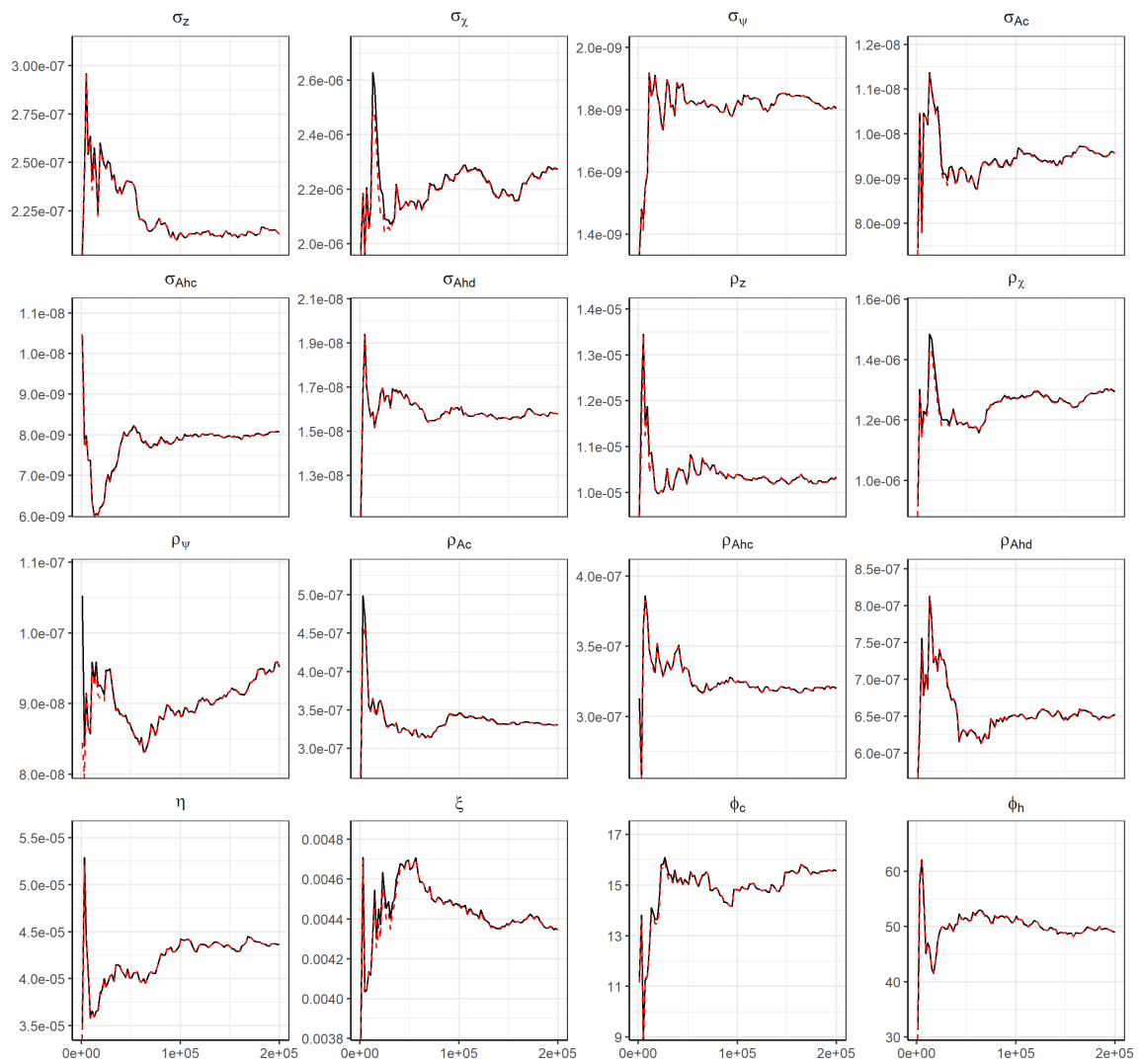


Fig. A.12 Univariate Diagnostic - m2



A.5.6 Recursive Mean

Fig. A.13 Recursive Mean - Chain 1

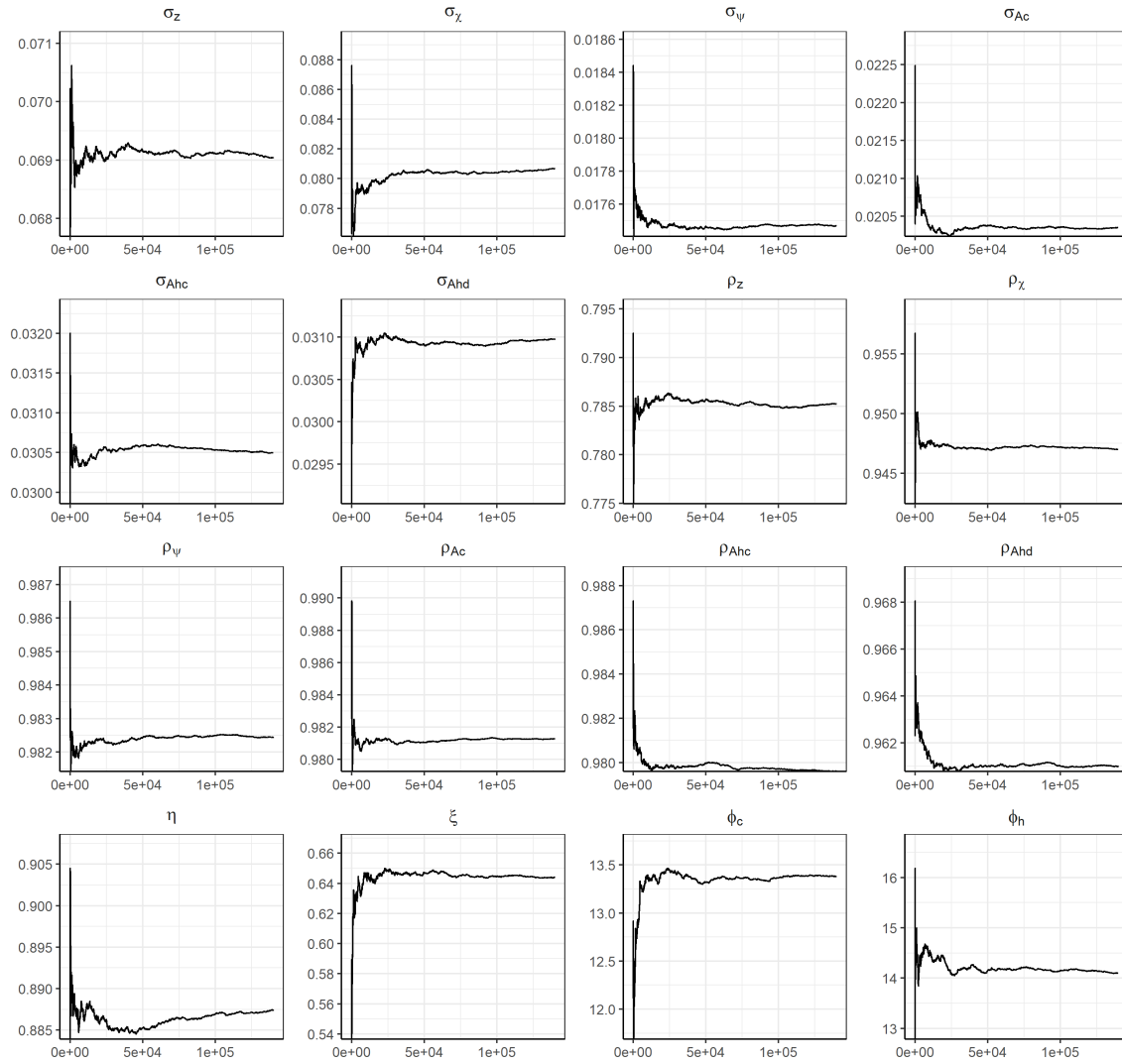
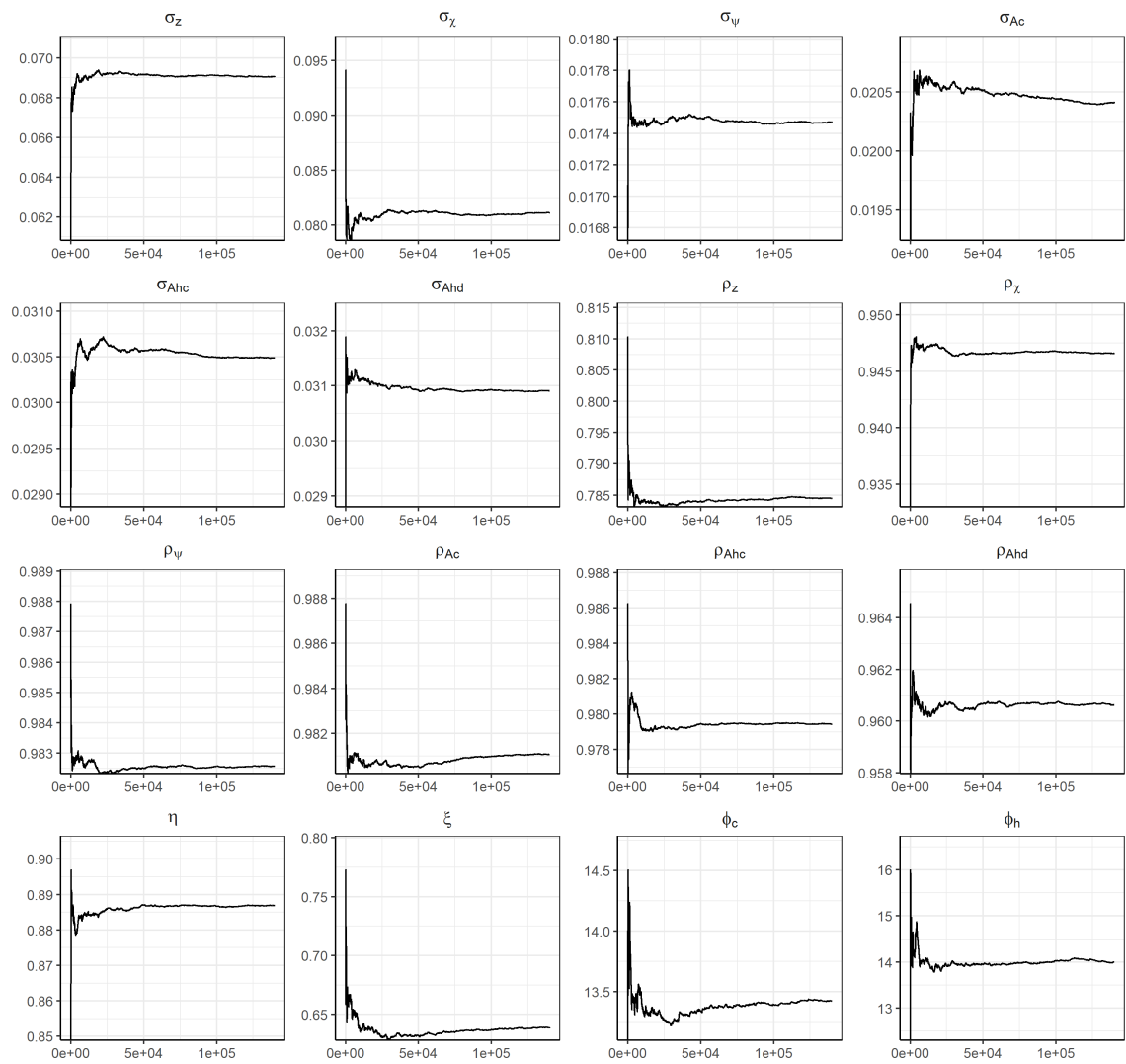


Fig. A.14 Recursive Mean - Chain 2



Appendix B

Speculative Bubbles in Segmented Markets: Evidence from Chinese Cross-Listed Stocks

The Appendix describes the econometric methods employed to test for speculative bubbles, and provides technical details for their estimation. Specifically, it outlines the GSADF test of Phillips et al. (2015a,b), the proposed extension to a panel setting of Pavlidis et al. (2016), and the IVX method of Phillips and Magdalinos (2009) and Kostakis et al. (2015). The last section of the Appendix presents estimation results for the dynamic panel probit that includes changes in forward exchange rates.

B.1 Recursive Unit Root Tests

The GSADF Test Consider the following augmented Dickey-Fuller regression equation

$$\Delta y_t = a_{r_1, r_2} + \gamma_{r_1, r_2} y_{t-1} + \sum_{j=1}^k \psi_{r_1, r_2}^j \Delta y_{t-j} + \epsilon_t, \quad (\text{B1.1})$$

where y_t denotes a time series process, $\epsilon_t \stackrel{iid}{\sim} N(0, \sigma_{r_1, r_2}^2)$, and r_1 and r_2 denote fractions of the total sample size that specify the starting and ending points of a subsample

period. We are interested in testing the null hypothesis of a unit root, $H_0 : \gamma_{r_1, r_2} = 0$, against the alternative of explosive behaviour in y_t , $H_1 : \gamma_{r_1, r_2} > 0$. Let

$$\text{ADF}_{r_1}^{r_2} = \hat{\gamma}_{r_1, r_2} / \text{s.e.}(\hat{\gamma}_{r_1, r_2})$$

denote the test statistic corresponding to this null hypothesis. Phillips et al. (2015a) propose a recursive-rolling testing procedure which consists of estimating the ADF regression (B1.1) on a large number of subsamples of the available data. The authors show that, under the null, the supremum of the resulting ADF statistics

$$\text{GSADF}(r_0) = \sup_{r_2 \in [r_0, 1], r_1 \in [0, r_2 - r_0]} \text{ADF}_{r_1}^{r_2}$$

has the following limit distribution

$$\sup_{r_2 \in [r_0, 1], r_1 \in [0, r_2 - r_0]} \left\{ \frac{\frac{1}{2} [W(r_2)^2 - W(r_1)^2 - r_w] - \int_{r_1}^{r_2} W(r) dr [W(r_2) - W(r_1)]}{r_w^{1/2} \{r_w \int_{r_1}^{r_2} W(r)^2 dr - [\int_{r_1}^{r_2} W(r) dr]^2\}^{1/2}} \right\}.$$

where r_0 denotes the minimum window size, $r_w = r_2 - r_1$, and W is the standard brownian motion.

If the GSADF test rejects the null hypothesis of a unit root then, in a second stage, the exact period(s) during which the series under examination displayed explosive dynamics can be identified. The dating strategy of Phillips et al. (2015a,b) is based on the BSADF statistic given by

$$\text{BSADF}_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} \text{ADF}_{r_1}^{r_2}. \quad (\text{B1.2})$$

The origination date of the bubble corresponds to the first observation that the BSADF statistic exceeds its critical value

$$\hat{r}_e = \inf_{r_2 \in [r_0, 1]} \{r_2 : \text{BSADF}_{r_2}(r_0) > scu_{r_2}^{\beta_T}\},$$

and the termination date to the first observation after which the BSADF falls below its critical value

$$\hat{r}_f = \inf_{r_2 \in [r_0, 1]} \{r_2 : \text{BSADF}_{r_2}(r_0) < scu_{r_2}^{\beta_T}\},$$

where $scu_{r_2}^{\beta_T}$ is the $1 - \beta_T$ critical value of the supremum ADF test based on $[r_2 T]$ observations, and β_T is the chosen significance level.

The computation of the BSADF and GSADF test statistics requires the selection of the minimum window size r_0 and the lag length k . Following Phillips et al. (2015a), we use the rule-of-thumb $r_0 = 0.01 + 1.8/\sqrt{T}$, and select a short lag length, $k = 1$. The implementation of the unit root tests also necessitates the limit distributions of the BSADF and GSADF test statistics, which are non-standard. To obtain finite-sample critical values, we simulate 2000 random walk processes with $N(0, 1)$ errors.

The Panel GSADF Test Inspired by the work of Im et al. (2003), Pavlidis et al. (2016) propose an extension of the GSADF test procedure to heterogeneous panels. Consider the multivariate version of the ADF regression equation

$$\Delta y_{i,t} = a_{i,r_1,r_2} + \gamma_{i,r_1,r_2} y_{i,t-1} + \sum_{j=1}^k \psi_{i,r_1,r_2}^j \Delta y_{i,t-j} + \epsilon_{i,t}, \quad (\text{B1.3})$$

where $i = 1, \dots, N$, denotes the cross-listed company index. The null hypothesis of the panel test is that all N cross-listed companies have a unit root, $H_0 : \gamma_{i,r_1,r_2} = 0$, against the alternative of explosive behaviour in a subset of units, $H_1 : \gamma_{i,r_1,r_2} > 0$ for some i . This alternative allows for γ_{i,r_1,r_2} to differ across units and, therefore, is more general than approaches based on the homogeneous alternative hypothesis.

The panel procedure of Pavlidis et al. (2016) is based on the average of the individual BSADF statistics at each time period

$$\text{panel BSADF}_{r_2}(r_0) = \frac{1}{N} \sum_{i=1}^N \text{BSADF}_{i,r_2}(r_0), \quad (\text{B1.4})$$

which provides a measure of *overall* exuberance in the sample. Given (B1.4), the definition of the panel GSADF is simply

$$\text{panel GSADF}(r_0) = \sup_{r_2 \in [r_0, 1]} \text{panel BSADF}_{r_2}(r_0). \quad (\text{B1.5})$$

The results of Maddala and Wu (1999) and Chang (2004) show that the distribution of panel unit root tests based on mean statistics is not invariant to cross-sectional dependence of the error terms ϵ_i . To deal with this complication, Pavlidis et al. (2016) employ a sieve bootstrap procedure to draw statistical inference. The procedure consists of the following steps:

1. For each panel unit i , impose the null hypothesis and fit the restricted ADF regression,

$$\Delta y_{i,t} = a_{i,r_1,r_2} + \sum_{j=1}^k \psi_{i,r_1,r_2}^j \Delta y_{i,t-j} + \epsilon_{i,t},$$

to obtain \hat{a}_{i,r_1,r_2} , $\hat{\psi}_{i,r_1,r_2}^j$ for $j = 1, \dots, k$, and $\hat{\epsilon}_i$.

2. To preserve the dependence structure of the error term, generate bootstrap residuals, $\epsilon_{i,t}^b$, by sampling with replacement columns from the residual matrix $\hat{\epsilon}$.
3. Recursively simulate artificial samples for first differences,

$$\Delta y_{i,t}^b = a_{i,r_1,r_2} + \sum_{j=1}^k \psi_{i,r_1,r_2}^j \Delta y_{i,t-j}^b + \epsilon_{i,t}^b,$$

and for levels,

$$\Delta y_{i,t}^b = \sum_{p=1}^t \Delta y_{i,p}^b.$$

4. Compute the sequence of panel BSADF statistics and the panel GSADF statistic for the simulated series.
5. Repeat steps 2 to 4 one thousand times to obtain the empirical distribution of the test statistics under the null.

Similarly to the univariate testing procedure, dating episodes of overall exuberance consists of comparing the panel BSADF with the sequence of critical values obtained from the bootstrap procedure. The origination date is set equal to the first observation that the panel BSADF statistic exceeds the $1 - \beta_T$ critical value, and the termination date is set equal to the first observation that the Panel BSADF falls below the $1 - \beta_T$ critical value.

B.2 The IVX Testing Procedure

Consider the following bivariate system

$$y_{t+1} = \alpha x_t + u_{1,t+1}, \quad (\text{B2.1})$$

$$x_{t+1} = \rho x_t + u_{2,t+1}, \quad (\text{B2.2})$$

where the errors $(u_{1,t+1}, u_{2,t+1})'$ follow a martingale difference sequence, and $\rho = 1 + c/T^\gamma$ for some $\gamma \geq 0$. In this setting, the AR coefficient for the regressor is allowed to take a wide range of values. Depending on the value of c and γ , the regressor can be an i) integrated ($c = 0$ or $\gamma > 1$), ii) local-to-unity ($c \neq 0$ and $\gamma = 1$), iii) near stationary ($c < 0$ and $\gamma \in (0, 1)$), iv) locally explosive ($c > 0$ and $\gamma = 1$), or v) mildly explosive ($c > 0$ and $\gamma \in (0, 1)$) process. The IVX procedure is based on the creation of an instrument z_t which, although relies on the regressor, always falls in the near stationary category iii. In particular, given an artificial autoregressive scalar,

$$\rho_z = 1 + c_z/T^\zeta, \quad \zeta \in (0, 1), \quad c_z < 0, \quad (\text{B2.3})$$

the IVX instrument is initialized at zero and sequentially computed for the remaining periods according to

$$z_t = \rho_z z_{t-1} + \Delta x_t. \quad (\text{B2.4})$$

It can be shown that the estimator

$$\hat{\alpha}_{\text{IVX}} = \frac{\sum z_t y_{t+1}}{\sum z_t x_t}, \quad (\text{B2.5})$$

has the following limit theory

$$T^{\frac{1+\zeta}{2}}(\hat{\alpha}_{\text{IVX}} - \alpha) \implies \psi',$$

where ψ' is a mixed normal variable, and the IVX test statistic

$$\text{IVX} = \frac{\hat{\alpha}_{\text{IVX}} - \alpha}{\hat{\sigma}_{\text{IVX}}},$$

is standard normal (Kostakis et al., 2015; Phillips and Lee, 2013; Phillips and Magdalinos, 2009). Simulation results in Kostakis et al. (2015) and Pavlidis et al. (2017) indicate that the IVX test has good size and power properties in finite samples.

B.3 Dynamic Panel Probit Results for Forward Exchange Rates

Table B.1 Estimation results for the Dynamic Panel Probit model (Forward Rates)

	DPP1		DPP2	
	Coefficient Estimate	Marginal Effects	Coefficient Estimate	Marginal Effects
lagged exuberance	2.625*** (0.134)	0.466*** (0.051)	2.624*** (0.134)	0.464*** (0.052)
market	1.484*** (0.422)	0.017*** (0.004)	1.434*** (0.433)	0.016*** (0.004)
analyst coverage	-0.025*** (0.010)	-2.9e - 04*** (1.1e - 04)	-0.024** (0.010)	-0.000** (0.000)
short interest	-0.132 (0.103)	-0.001 (0.001)	-0.135 (0.104)	-0.001 (0.001)
margin	0.009*** (0.002)	1.0e - 04*** (2.3e - 05)	0.009*** (0.002)	0.000*** (0.000)
risk			-3.6e - 08 (7.1e - 07)	-0.000 (0.000)
volume			0.003 (0.005)	0.000 (0.000)
spread			-0.565 (1.327)	-0.006 (0.015)
forward			-0.553 (10.004)	-0.006 (0.111)
Constant	-2.861*** (0.136)		-2.868*** (0.140)	
McFadden R^2	0.447		0.447	
LR Statistic (p -value)			0.561(0.967)	

Notes: The table presents coefficient estimates, marginal effects, standard errors, and McFadden R^2 s for a restricted (DPP1) and an unrestricted (DPP2) model specification. It also reports the likelihood ratio (LR) statistic and the corresponding p -value for the restriction that the coefficients on risk, liquidity, spread, and forward are equal to zero. *, ** and *** denote statistical significance at the ten, five, and one percent levels, respectively.

Appendix C

Sentimental Housing Markets

C.1 Data and Sources

Fatalities: Number of fatalities. Source: Follman et al. (2015) & Wikipedia (2020)

Confidence Index of Consumer Expectations. Source: Survey of Consumers, University of Michigan URL: <https://data.sca.isr.umich.edu/>

The Index of Consumer Expectations (ICE) is derived from the following three questions:

- *PEXP*: Now looking ahead—do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?
- *BUS12*: Now turning to business conditions in the country as a whole—do you think that during the next twelve months we'll have good times financially, or bad times, or what?
- *BUS5*: Looking ahead, which would you say is more likely—that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?

$$ICE = \frac{PEXP + BUS5 + BUS12}{4.1134} + 2.0$$

There was no constant added until 1972:4 (except for 1972:1), from 1972:4 until 1981:11 the constant was 2.7, and from 1981:12 to present the constant is 2.0.

Industrial Production: Industrial Production Index (INDPRO), Index 2012=100, Seasonally Adjusted.

Unemployment: Unemployment Rate (UNRATE) Percent, Seasonally Adjusted.

House Prices: US Real Home Prices URL: <http://www.econ.yale.edu/shiller/data.htm>

Houses Sold: New One Family Houses Sold: United States (HSN1F), SA Annual Rate, Thousands, Seasonally Adjusted Annual Rate.

Housing Starts Housing Starts: Total: New Privately Owned Housing Units Started (HOUST), Thousands of Units, Seasonally Adjusted Annual Rate.

Federal Funds Effective Federal Funds Rate (FEDFUNDS) Percent, Not Seasonally Adjusted.

Shadow Rate Policy rate adjust for the zero lower bound from Wu and Xia (2016). Retrieved from <https://sites.google.com/view/jingcynthiawu/shadow-rates>

GS10 10-Year Treasury Constant Maturity Rate (GS10), Percent, Not Seasonally Adjusted. Accessed through FRED.

GS5 5-Year Treasury Constant Maturity Rate (GS5), Percent, Not Seasonally Adjusted. Retrieved from FRED.

Affordability Index: Housing Prices divided by the Real Disposable Personal Income (DSPIC96), SA Annual Rate.

Mortgage spread: 30-Year Fixed Rate Mortgage Average in the United States (MORTGAGE30US), percent, Not Seasonally Adjusted minus the average from GS5 and GS10 Walentin (2014).

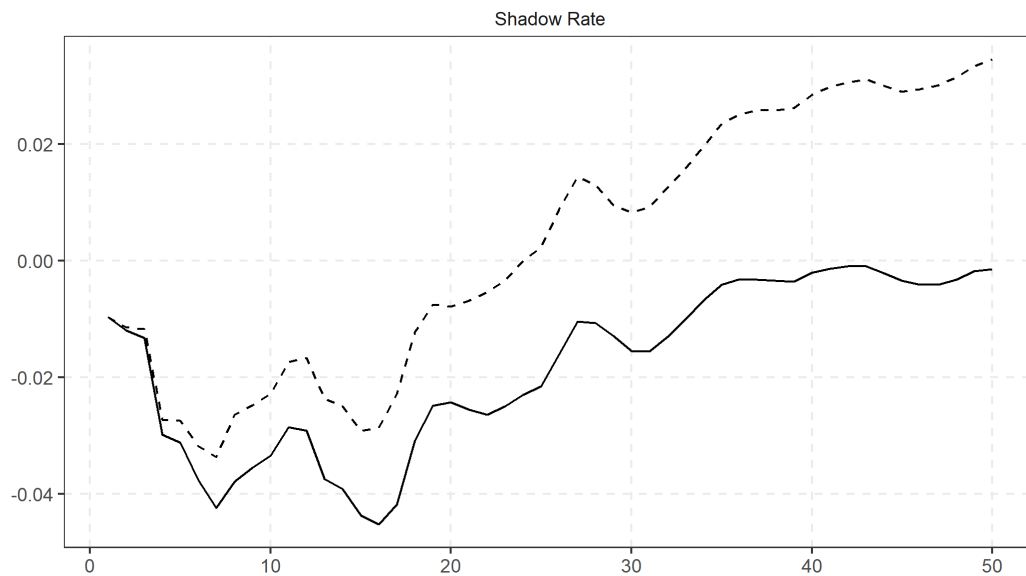
Real Consumption: Personal Consumption Expenditures (PCE), Billions of Dollars, Seasonally Adjusted Annual Rate divided by Personal Consumption Expenditures: Chain-type Price Index (PCEPI).

Comprised of Major Types of Product:

- Personal Consumption Expenditures: Durable Goods (PCEDG)
- Personal Consumption Expenditures: Nondurable Goods (PCEND)
- Personal Consumption Expenditures: Services (PCES)

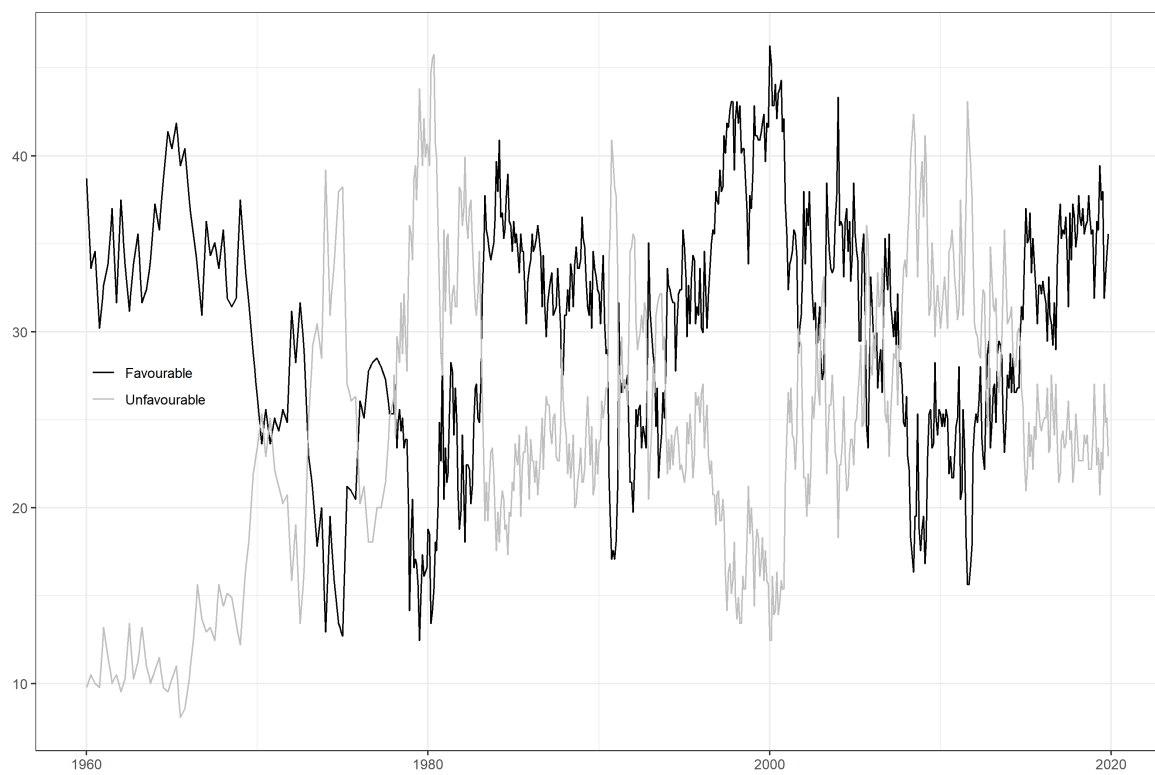
C.2 Robustness

Fig. C.1 Shadow Rates



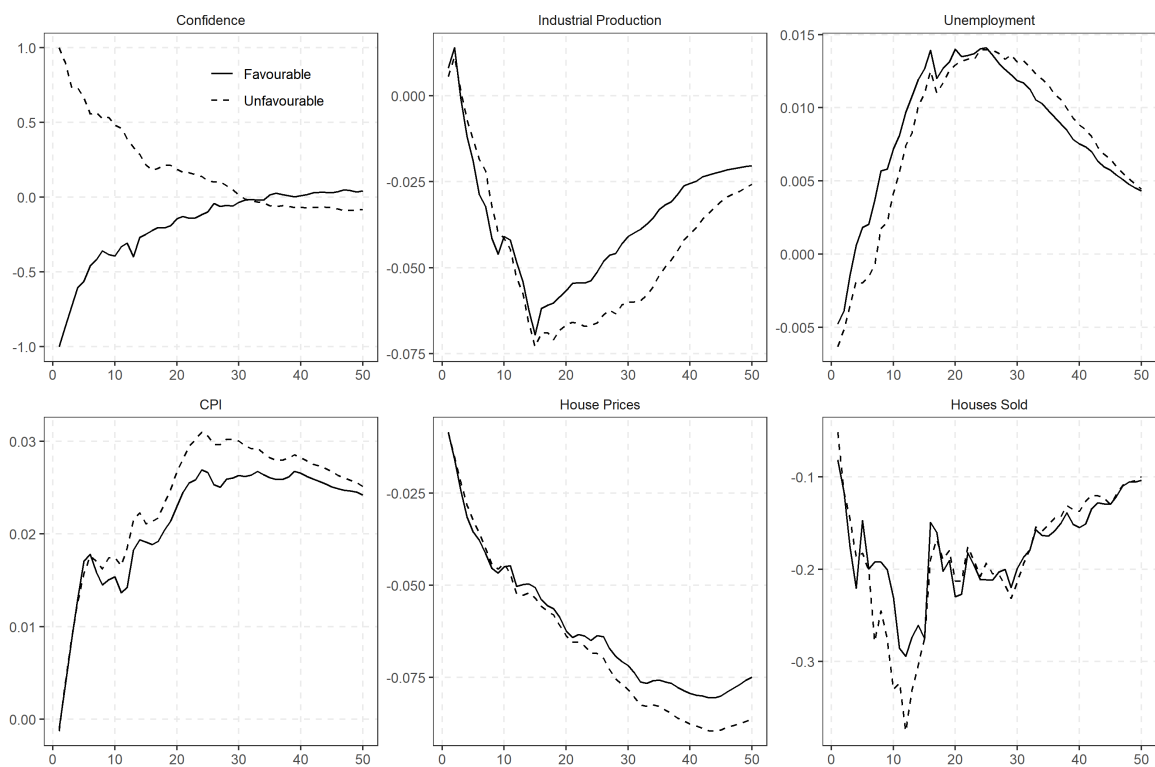
Note: Impulse response to a negative sentiment shock from proxy SVAR model. Identification is achieved by using mass fatalities as an instrumental variable to Confidence. Solid lines represent the estimated responses from the unrestricted mode, while dashed lines represent the estimated response from the restricted model.

Fig. C.2 Favourable and Unfavourable ICE



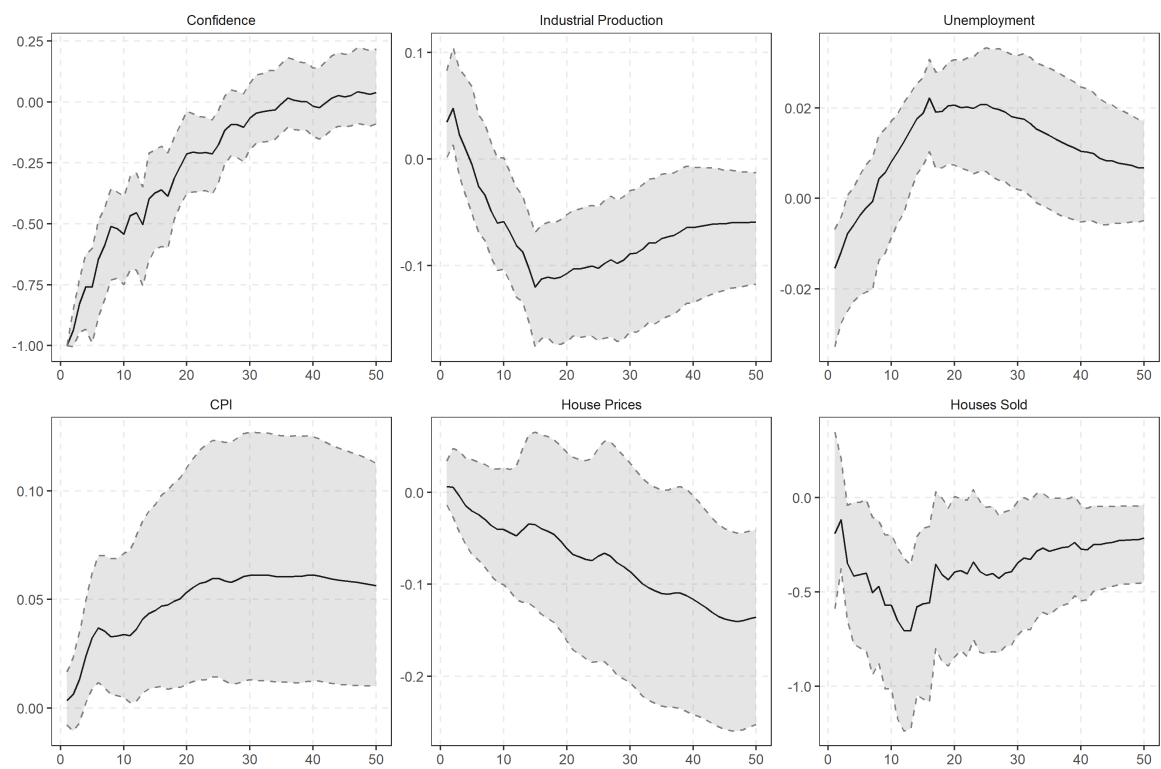
Note: The graph presents the favourable ICE (black) and the unfavourable ICE (grey).

Fig. C.3 Favourable and Unfavourable ICE Identified with IV



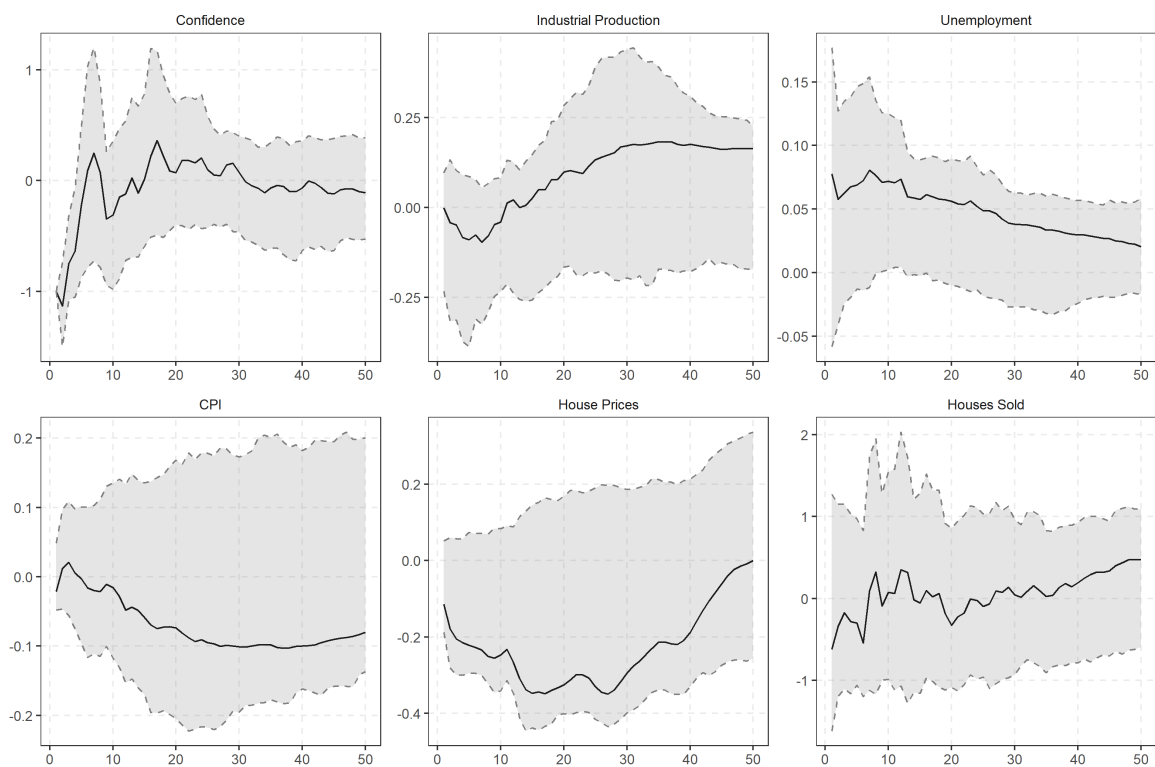
Note: Impulse response to a negative sentiment shock from proxy SVAR model. Identification is achieved by using mass fatalities3 as an instrumental variable to both indices of Confidence. Solid lines represent the estimated responses from the favourable ICE, while dashed lines represent the estimated responses from the unfavourable ICE.

Fig. C.4 Specification with Fatalities3



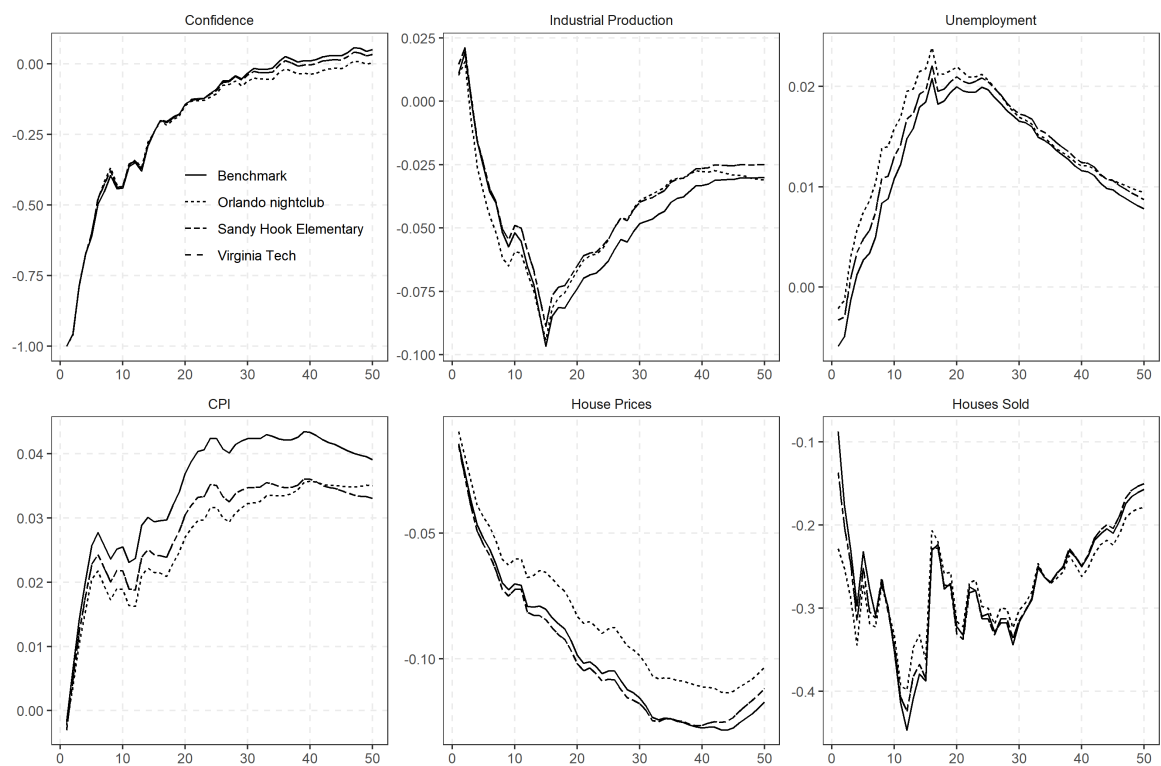
Note: Impulse response to a negative sentiment shock from proxy SVAR model. Identification is achieved by using mass fatalities3 as an instrumental variable to Confidence. Solid lines represent the estimated responses and shaded areas represent the 68% probability bands generated with the AR confidence bands.

Fig. C.5 Random Reshuffling



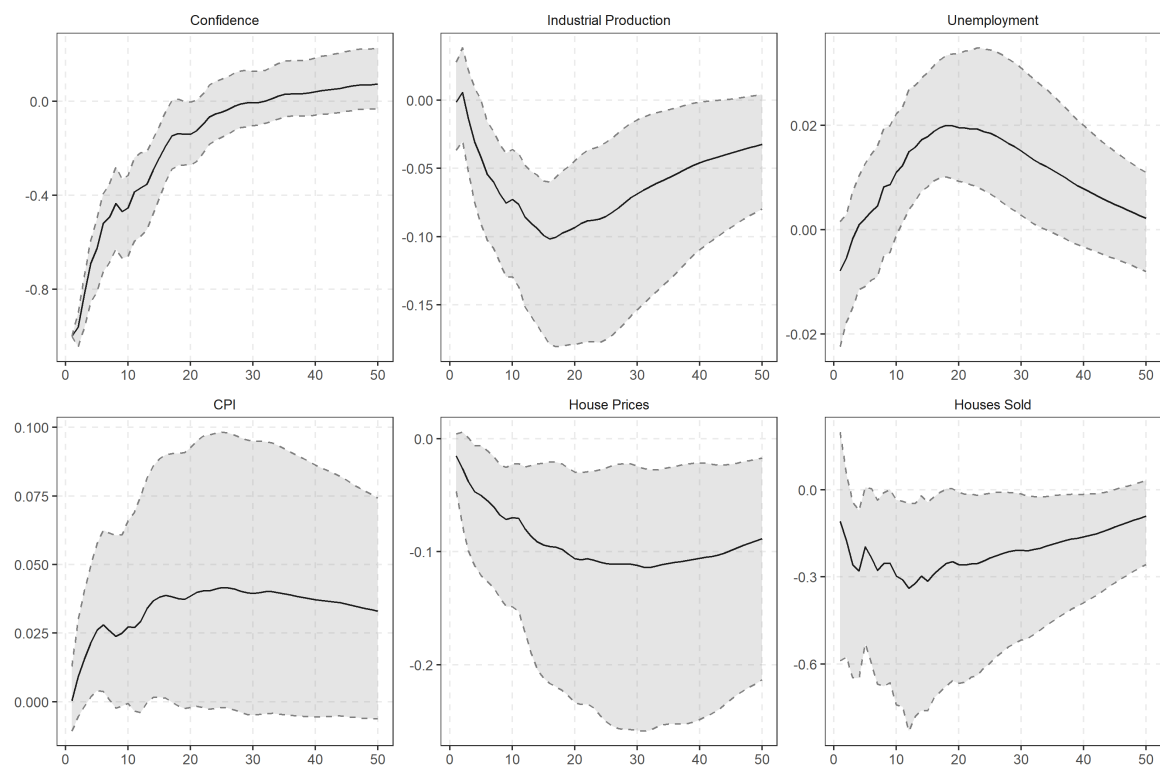
Note: Impulse response to a negative sentiment shock from proxy SVAR model. Identification is achieved by using mass fatalities as an instrumental variable to Confidence. Solid lines represent the estimated responses and shaded areas represent the 68% probability bands obtained from wild-bootstrap with 500 repetitions.

Fig. C.6 Exclude top 3 shootings



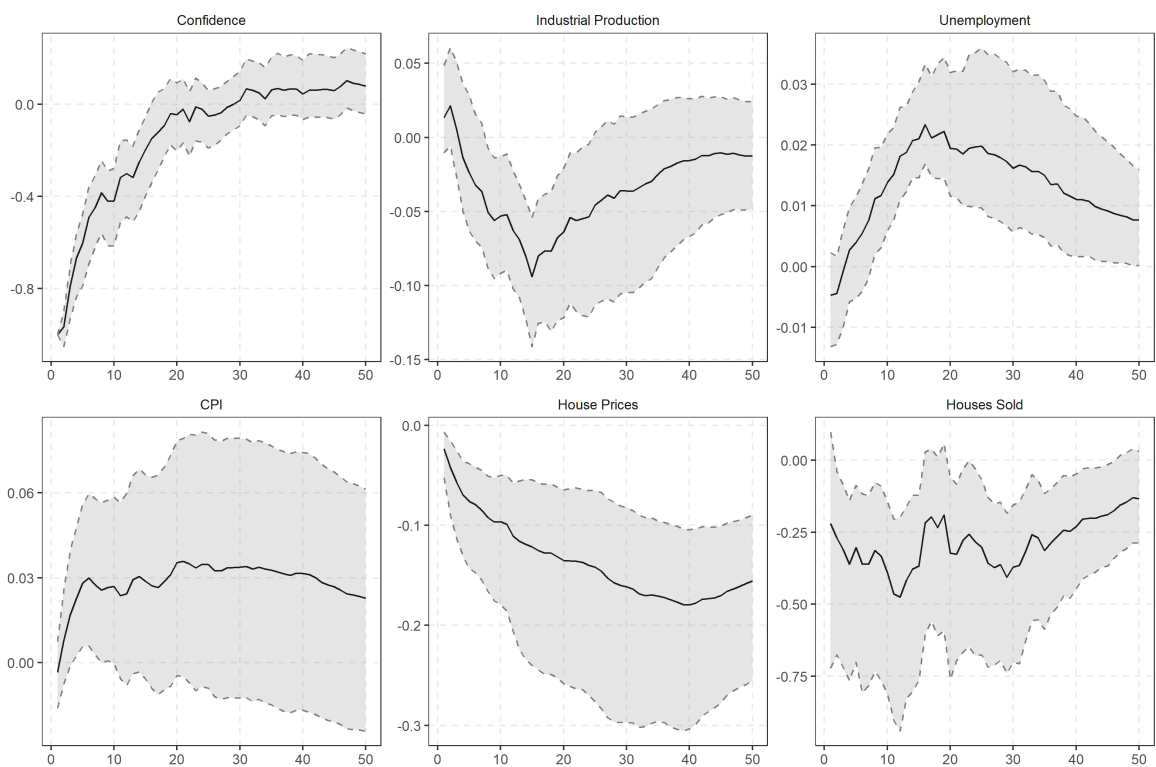
Note: Impulse response to a negative sentiment shock from proxy SVAR model. Identification is achieved by using mass fatalities as an instrumental variable to Confidence. The lines represent the estimated responses.

Fig. C.7 Specification with Lag = 12

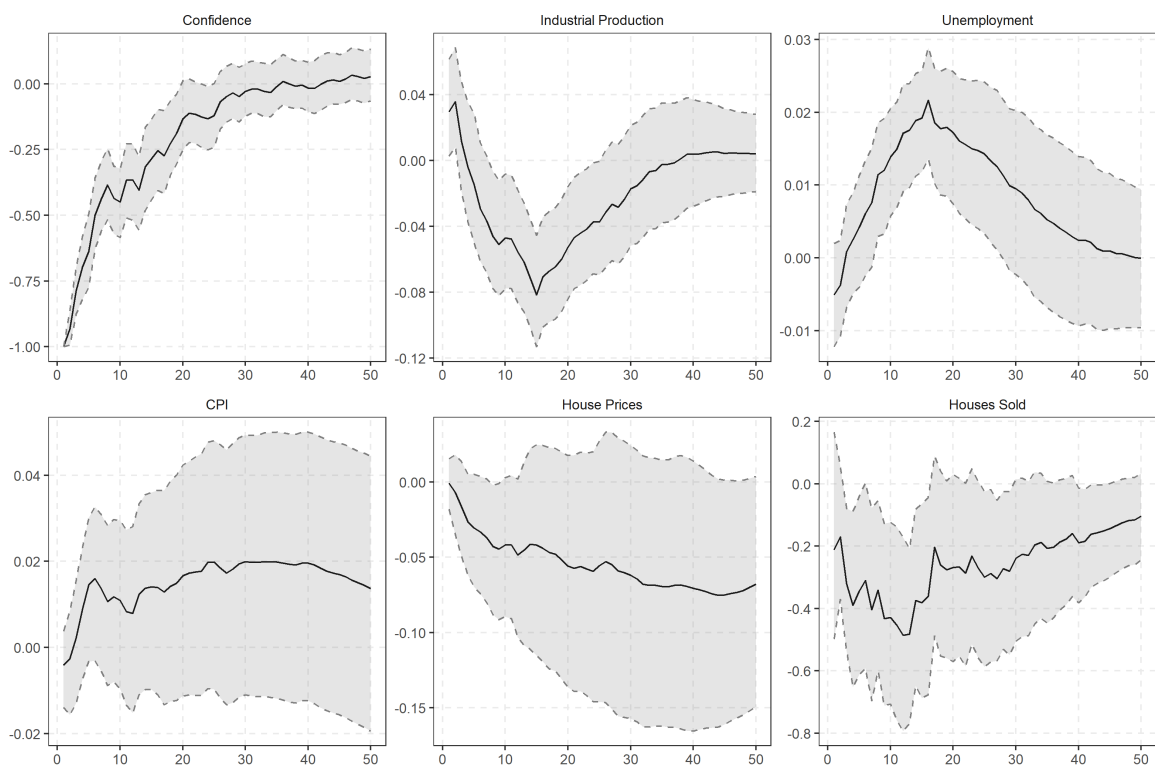


Note: Impulse response to a negative sentiment shock from proxy SVAR model. Identification is achieved by using mass fatalities as an instrumental variable to Confidence. Solid lines represent the estimated responses and shaded areas represent the 68% probability bands generated with the AR confidence bands.

Fig. C.8 Specification with Lag = 24



Note: Impulse response to a negative sentiment shock from proxy SVAR model. Identification is achieved by using mass fatalities as an instrumental variable to Confidence. Solid lines represent the estimated responses and shaded areas represent the 68% probability bands generated with the AR confidence bands.

Fig. C.9 Benchmark Specification with 4th order Polynomial

Note: Impulse response to a negative sentiment shock from proxy SVAR model. Identification is achieved by using mass fatalities as an instrumental variable to Confidence. Solid lines represent the estimated responses and shaded areas represent the 68% probability bands generated with the AR confidence bands.