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NORGES BANK RESEARCH

08 | 2014

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ISSN 1502-8143 (online)
ISBN 978-82-7553-810-7 (online)

Regional US house price formation: One model fits all?*

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May 27, 2014

Abstract

Does a "one model fits all" approach apply to the econometric modeling of regional house price determination? To answer this question, we utilize a panel of 100 US Metropolitan Statistical Areas over the period 1980q1–2010q2. For each area we estimate a separate cointegrated VAR model, focusing on differences in the effect of subprime lending and lagged house price appreciation. Our results demonstrate substantial differences in the importance of subprime lending for house price determination across regional housing markets. Specifically, we find a greater impact of subprime lending in areas with a high degree of physical and regulatory restrictions on land supply. Likewise, lagged house price appreciation – interpreted as capturing an adaptive expectation channel – is found to be more important in areas where the supply of dwellings is more constrained, in areas located in a state with non-recourse lending and in more populous areas. Our results also suggest that disequilibrium constellations are restored more slowly in areas located in a state with non-recourse lending.

Keywords: *Cointegration; Panel heterogeneity; Regional house price dynamics; Subprime lending.*

JEL classification: *C32; C51; C52; G01; R21; R31.*

*This Working Paper should not be reported as representing the views of Norges Bank. The views expressed are those of the authors and do not necessarily reflect those of Norges Bank. The paper was presented at the 13th OxMetrics User Conference in Aarhus, September 2013, the 36^{th} meeting of the Norwegian Economic Association, the 7^{th} RGS Doctoral Conference in Economics in Dortmund, March 2014, the 2014 Annual Conference of the Royal Economic Society in Manchester, April 2014, and at workshops and seminars in Norges Bank and Statistics Norway. We would like to thank the participants at these events for their comments and suggestions. The paper has been improved as a result of discussions with, and comments from, Farooq Akram, Steinar Holden, Håvard Hungnes, Søren Johansen, Andreas Kotsadam, Svein Olav Krakstad, Ragnar Nymoen, Asbjørn Rødseth, Bernt Stigum and Jean-Pierre Urbain. For great proof reading, we would like to thank Veronica Harrington. We would also like to thank the New York Library staff and Frederic Jean-Baptiste at Moody's Analytics for helping us collecting the data. Contact details: *André Kallåk Anundsen*: Norges Bank Research, Norges Bank, Bankplassen 2, P.O. Box 1179 Sentrum, NO-0107 Oslo, Norway. Email: Andre-Kallak.Anundsen@norges-bank.no.

1 Introduction

The evolution of US house prices differed markedly across geographical regions over the recent house price cycle. For example, coastal areas experienced much greater house price volatility relative to inland areas (Huang and Tang, 2012; Cohen et al., 2012; Sinai, 2012; Anundsen and Heebøll, 2013). Higher house price volatility was also related to a more severe worsening of employment conditions and a higher rise in foreclosures during the financial crisis period (Rogers and Winter, 2013). Against this background, the objective of this paper is to understand what the drivers of regional US house prices are. For that purpose, we analyze individual time series models for the 100 largest Metropolitan Statistical Areas (MSAs) in the US, paying particular attention to regional differences in the effect of lagged house prices, the speed of equilibrium adjustment and the role of subprime lending.

To analyze the heterogeneity across local US housing markets, we apply a modeling strategy built on three steps. First, we estimate an autoregressive distributed lag (ARDL) model on our sample of 100 MSAs over the period 1980q1–2010q2. The econometric analysis takes as a starting point a standard inverted demand equation, allowing for shifts in credit constraints – as approximated by developments in subprime lending. The model is estimated both the conventional dynamic fixed effects (DFE) approach, and the mean group (MG) and the pooled mean group (PMG) estimators suggested by Pesaran and Smith (1995) and Pesaran et al. (1999), respectively. Considering all approaches allows us to study similarities and differences in the results obtained, and – of particular relevance to the focus of this paper – to test the homogeneity assumption imposed in standard panel studies of house prices (Abraham and Hendershott, 1996; Gallin, 2006, 2008; Mikhed and Zemcik, 2009a,b).

Our results firmly reject the assumption of equal slope coefficients. This suggests that econometric models for regional house prices should allow for possible heterogeneity in the effect of changes in the drivers of house prices. Models based on the homogeneity assumption can obscure important differences in the effect on house prices of changes key economic variables across regional markets, cf. Muellbauer (2012).

After rejecting the homogeneity assumption in the first step of our estimation strategy, we estimate separate cointegrated VAR models using the Johansen (1988) method. While our approach is comparable to Ashworth and Parker (1997) who study heterogeneity for 11 regions in the UK, the scope and focus of this paper are different in several respects. Our attention is paid to the US housing market, where we investigate the role of subprime lending and lagged house price appreciation during the recent housing boom, by allowing them to affect house prices differently in each area. The results from our second step indicate several substantial differences in house price formation across Metropolitan Statistical Areas. These heterogeneities relate to both the long-run elasticities, the speeds of adjustment towards equilibrium, the effect of lagged house price appreciation, and the role of subprime lending.

Finally, we investigate what factors may explain these heterogeneities. In particular, we analyze the characteristics of the areas in which subprime lending is found to have a greater influence on house price developments. Further, we explore possible explanations of regional differences in the coefficients for lagged house price appreciation and the speed of equilibrium adjustments, which – using the terminology of Abraham and Hendershott

(1996) – may be interpreted as capturing a "bubble builder" and a "bubble burster" effect, respectively. For these purposes, we utilize both cross-sectional models and a logit model.

We find that subprime lending had a greater influence on house price developments in areas with more restrictions on land supply. This finding is consistent with recent cross-sectional studies by Glaeser et al. (2008), Huang and Tang (2012) and Anundsen and Heebøll (2013), who demonstrate that disparities in restrictions on land supply between areas are important in explaining inter-MSA differences in house price volatility over the course of a boom-bust cycle. While it is reassuring that this finding is retained when using a different methodological approach, the main advantage with the approach taken in this paper is that it also allow us to study heterogeneities in house price dynamics. In this regard, we find that the coefficients on lagged house price appreciation are significantly greater in areas with more restrictions on land supply. To the extent that these coefficients reflect differences in the importance of expectations, our results suggest a stronger price-to-price feedback loop in more supply restricted areas. We also find that lagged house price appreciation is significantly more important in areas with a higher population and in areas situated in a state with non-recourse lending. This might be related to a greater prevalence of herd behavior in large urban areas and the lower (perceived) risk associated with a housing purchase faced by home buyers in states where lending is non-recourse. Finally, the "bubble burster" (the adjustment parameter) is found to be stronger in areas where lending is recourse.

Mian and Sufi (2010) have shown that the areas which experienced the greatest run-ups in household leverage are the same areas that saw the greatest fall in consumption and the greatest hike in unemployment rates during the financial crisis period. At the same time, Mian and Sufi (2009) and Pavlov and Wachter (2011) have shown that areas with more subprime lending also witnessed a greater build-up of house prices, while Goetzmann et al. (2012) have shown a positive impact of house price appreciation on approval rates. Our study suggests that areas that have many restrictions on land supply were more influenced by subprime lending and an adaptive expectation channel. Thus, supply restrictions are found to amplify the effects of price-to-price feedback loops. Combined with slow adjustments in states with non-recourse lending, these results contributes to explain why areas located in non-recourse states with many restrictions on land supply, such as California, witnessed the greatest volatility over the boom bust cycle, and also why the housing bust has been relatively long-lasting in these areas.

There exists a voluminous time series literature on the determinants of national US house prices (see e.g. Meen (2002); Duca et al. (2011a,b); Anundsen (2013), as well as the references therein). These studies are important both in order to assess the vulnerability of the housing market to different types of national economic shocks, and to get an understanding of potential spill-over effects from the housing market to the real economy, see e.g. Aron et al. (2012). Aggregate models, however, remain limited to the extent that they do not shed light on the variations that exist at a disaggregate level. In addition, aggregate models make it difficult to distinguish between alternative mechanisms, because a number of different economic forces are at work at the same time in different regional markets. The results established in this paper are interesting in this respect, as they suggest that there exists large heterogeneities at the disaggregate level that may be relevant for the monitoring of local housing markets, and for both policy analysis and forecasting purposes.

The rest of the paper proceeds as follows. As a theoretical background, the life-cycle model of housing is discussed in the next section. In Section 3, we present the data and the three steps that constitute our modeling approach. In Section 4, we test the validity of the assumption of coefficient homogeneity, while the results from estimating the separate cointegrated VAR models are summarized in Section 5. The results from the individual models demonstrate very wide geographical variations in house price determination, and possible explanations of the observed regional heterogeneity are analyzed in Section 6. The final section concludes the paper.

2 Theoretical background

Our theoretical starting point is the life-cycle model of housing, as described in e.g. Buckley and Ermisch (1983), Meen (2001) and Muellbauer and Murphy (1997). The theory is based on a utility maximizing framework, resulting in a long-run equilibrium relationship between real house prices, real income, the real user cost of housing and the housing stock. Extensions of the model include an explicit role for credit constraints, see e.g. Dougherty and Van Order (1982), Meen (1990) and Meen and Andrew (1998). If we consider a particular regional housing market j, the life-cycle model with credit constraints postulates the following equilibrium relationship:

$$\frac{U_{H,j}}{U_{C,j}} = PH_j \left[(1-\tau_j^y)(i_j+\tau_j^p) - \pi_j + \delta_j - \frac{\dot{PH_j}}{PH_j} + \frac{\lambda_j}{U_{C,j}} \right] \tag{1}$$

where PH_j measures real house prices in area j, τ_j^y is the tax rate at which interest expenses are deducted, while i_j and τ_j^p are the nominal interest rate and the property tax rate, respectively. The term π_j is the general CPI inflation rate, δ_j is the depreciation rate on housing capital, and λ_j is the shadow price of a mortgage credit constraint. The optimality condition given by (1) states that the representative consumer's marginal willingness to pay for housing goods in terms of other consumption goods should on the margin be equal to the cost of owning one more unit of the property (in terms of forgone consumption of other goods), where the user cost also takes into account credit constraints.

Imposing a no-arbitrage condition between the rental market and the owner-occupied market, we further have:

$$\frac{PH_j}{Q_j} = \frac{1}{UC_j + CC_j} \tag{2}$$

where Q_j is the real imputed rent in housing market j, $UC_j = (1-\tau_j^y)(i_j+\tau_j^p) - \pi_j + \delta_j - \frac{\dot{PH_j}}{PH_j}$ denotes the real user cost of housing, whereas $CC_j = \frac{\lambda_j}{U_{C,j}}$ is a measure of credit constraints. The real imputed rent is unobservable, but two approximations are common in the literature: either to substitute Q_j with an observed rent, or to assume that it is a function of income and the stock of dwellings. In this paper, we confine our analysis to the second approximation, which gives:

$$PH_j = \frac{f_j\left(Y_j, H_j\right)}{UC_j + CC_j} \tag{3}$$

A log approximation yields:

$$ph_j = \beta_{h,j} h_j + \beta_{y,j} y_j + \beta_{UC,j} UC_j + \beta_{CC,j} CC_j \tag{4}$$

where lower case letters indicate that the variables are measured on a log scale. In both Poterba (1984) and Meen (2002), (4) is interpreted as an inverted housing stock demand equation.

In the empirical analysis, we shall make two assumptions: first, we shall assume that expected house price appreciation is captured by the short-run dynamics of the econometric models, i.e. modeled by the lagged house price appreciation terms. A similar assumption has been made in Abraham and Hendershott (1996), Gallin (2008), Anundsen and Jansen (2013) and Anundsen (2013). This assumption is also consistent with the view that lagged house price appreciation does not have permanent effects, but rather that it picks up a momentum, or a "bubble builder" effect, to use the terminology of Abraham and Hendershott (1996). The assumption that house price expectations are formed adaptively rather than rationally calls for some justification given the strong position that rational expectations have in modern macroeconomics. Perhaps surprisingly, there is strong evidence in the literature that house price expectations are formed in an adaptive manner, see e.g. Jurgilas and Lansing (2013) and the references therein. In particular, survey evidence from the US for the years 2006 and 2007 (Shiller (2008)) suggests that individuals in areas with increasing house prices expected further increases, while the opposite was the case in areas with recent declines in home prices. Conducting a similar survey in the midst of the national housing bust (in the year 2008), Case and Shiller (2012) find that individuals living in previously booming areas now expected a decline in house prices.

The second assumption we shall make is that the real direct user cost ($\tilde{UC}_j = (1 - \tau_j^y)(i_j + \tau_j^p) + \delta_j - \pi_j$) is equal across regional markets, and that it can be approximated by the evolution of the real national interest rate, i.e. $\tilde{UC}_j = R \; \forall \; j$, where R denotes the real interest rate.[1]

The credit constraint variable is unobservable, but Anundsen (2013) has shown that the expansion of subprime borrowing became an important driver of national US house prices in the previous decade.[2] Consistent with this, we assume that $CC_j = CC \; \forall \; j$, where CC is proxied by the share of new loan originations that are given to the subprime segment ($CC = SP$). We acknowledge that there are differences in tax policies and credit constraints also at the regional level. Hence, another way to interpret these assumptions is that we analyze regional responses to the developments in national interest rates and credit conditions.

[1] We have also experimented with an alternative approach, where we assume equal nominal interest rates, but where we allow for separate MSA inflation effects. The qualitative results are similar to those reported below, but we save valuable degrees of freedom by not pursuing that approach. In addition, we have data for the CPI at the MSA level only from 1980q1, meaning that we lose an additional 4 observations when constructing the annual MSA inflation rate. For that reason, we have decided to retain the assumption that the user cost may be approximated by the real national interest rate.

[2] An alternative approach to modeling credit constraints has been advocated in a series of papers by John Muellbauer and co-authors who extract a latent credit conditions index (see e.g. Fernandez-Corugedo and Muellbauer (2006), Aron et al. (2012), and Muellbauer and Williams (2011)). In Duca et al. (2011a,b), a measure of the LTV ratio for first-time home buyers is used to measure credit constraints in the US.

Conditional on these assumptions, the inverted demand equation takes the following form:

$$ph_j = \beta_{h,j} h_j + \beta_{y,j} y_j + \beta_{R,j} R + \beta_{SP,j} SP \tag{5}$$

There is an important difference between the local economic variables and the national variables in that the latter are approximately exogenous with respect to developments in a given regional market – especially when each market is small relative to the size of the national economy. From a theoretical point of view, one would expect – for all j – that $\beta_{h,j} < 0$, $\beta_{y,j} > 0, \beta_{SP,j} \geq 0$. The sign of $\beta_{R,j}$ is in principle expected to be negative – though empirically, the sign has been found to be ambiguous. This may partly be explained by the fact that a large share of the interest rate effect is captured by changes in disposable income.

A minimum requirement for the theory model to constitute a relevant representation of the data is that the following set of parameter restrictions is satisfied: $\beta_{h,j} < 0$, $\beta_{y,j} > 0, \beta_{SP,j} \geq 0$. Furthermore, since the theory describes a long-run equilibrium relationship, and since the above variables are usually found to be non-stationary and integrated of the first order, an additional requirement for the theory to be relevant is that there is evidence of cointegration, i.e. that $ph_j - \beta_{h,j} h_j - \beta_{y,j} y_j - \beta_{R,j} R - \beta_{SP,j} SP \sim I(0)$.

While it is obvious that the dynamic shocks hitting the regional markets differ across time and space, there might also be differences in the way in which these shocks are absorbed. Specifically, there might be spatial coefficient heterogeneity, where all the coefficients in (5) are regional-specific.

3 Data and econometric approach

3.1 Data

Our data set includes the 100 largest Metropolitan Statistical Areas (MSAs) in the United States, covering about 60 percent of the entire US population and all but four of the 50 US states.[3] Following the Census Bureau, the US may be split into four distinct regions: West, South, Midwest and Northeast, confer Figure 1. With reference to those regions, our data set includes 25 areas in the West and the Midwest regions, while we have 20 MSAs situated in the Northeast and 30 in the South. In addition to having a rich cross-sectional dimension, we also have a fairly long time series dimension for each of these areas. The sample runs through the period from 1980q1 to 2010q2 ($T = 122$) for 82 of the areas, while the shortest samples (Fargo (ND-MN) and Sioux Falls (SD)) contain 95 observations. The estimation starting point will therefore be somewhat later for these areas. Thus, the sample covers both the recent housing cycle and the previous boom-bust cycle in the period 1982–1996 for a majority of the areas considered.[4]

The house price data have been gathered from the Federal Housing Finance Agency (FHFA), while households' disposable income, the housing stock and the CPI index – used for the nominal-to-real transformations – have been supplied by Moody's Analytics. Our measure of the real interest rate is the real 3-month T-bill. The credit constraint variable,

[3] Note that some of the MSAs belong to multiple states.

[4] Here, we rely on the boom-bust cycle classification provided by Glaeser et al. (2008).

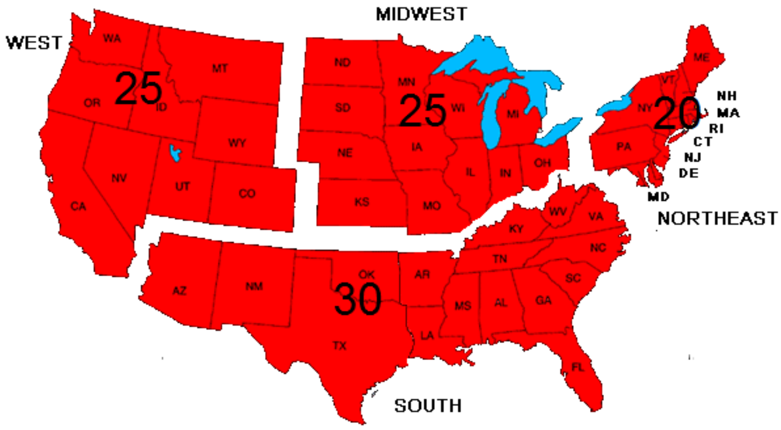

Figure 1: Main geographical regions in the US

CC in (4), is a latent variable, but it is reasonable to assume that while this variable was fairly stable (and stationary) over the period from 1980 until the late 1990s, it shifted dramatically with the subprime explosion in the ensuing period.[5] As already mentioned, we use as our operational measure of credit constraints the number of subprime loans as a share of total loans serviced by the participants in the mortgage delinquency survey.

The interest rate is approximately equal at the regional level due to a common monetary policy, but the credit constraints may be quite different, depending on our conceptual understanding of credit constraints. In this paper, we think of credit constraints as shifts in national regulations, to which different areas may have responded differently. Thus, we believe that the national subprime measure can capture a common country-wide – or secular – trend in lending practices.

All monetary variables are measured in real terms, and all variables except the subprime share and the interest rate are measured on a logarithmic scale, where we throughout the paper let lower case letters indicate that a variable is measured on a logarithmic scale. Table A.1 in Appendix A provides more details on the data definitions and sources of the variables used in the empirical analysis.

To control for the interest rate uncertainty caused by the monetary targeting period between 1979q4 and 1982q3, we include a dummy, MT, which is equal to one between 1980q1 and 1982q3. Duca et al. (2011a,b) and Anundsen (2013) used a similar dummy variable in studying the determinants of national US house prices.

Figure 2 displays the evolution of real house prices (Panel a) and households' disposable income (Panel b) for four of the areas included in our information set, as well as the housing stock (Panel c) and the subprime variable and the interest rate series (Panel d).[6] The areas were chosen to illustrate four different types of housing markets, located in different regions of the US. As shown, real house prices in particular have moved quite

[5]This is also consistent with Figure 1 in Duca et al. (2011a), which shows that the LTV ratio for first-time home buyers – an alternative measure of credit constraints – was fairly stable (and stationary) until the surge in subprime lending over the previous decade.

[6]Due to the lack of data for previous periods, we have set this series to zero prior to 1998q1. That said, since subprime lending is a relatively new phenomenon and since the credit constraints are likely to have been fairly stable prior to this, such an approximation should not have an important impact on the key results of this paper.

differently in the four different areas, with a much more pronounced run-up (and subsequent bust) in San Francisco and Boston than in Houston and Wichita over the previous decade.

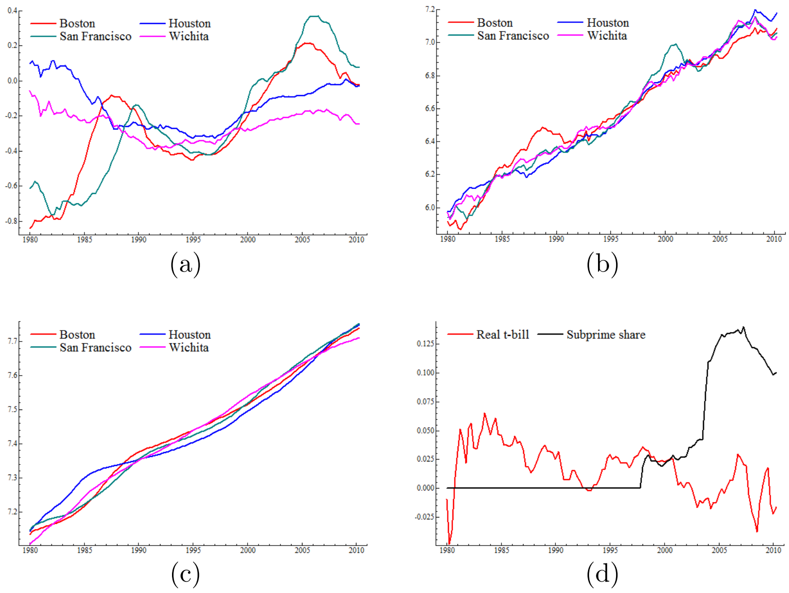

Figure 2: a) Log of real house prices, 1980q1-2010q2. Panel b) Log of real households' disposable income (re-scaled to have equal means), 1980q1-2010q3. Panel c) Log of the housing stock (re-scaled to have equal means), 1980q1–2010q2. Panel d) Real 3-month T-bill (red) and subprime share (black), 1980q1–2010q2. (*Sources:* Confer A.1 in Appendix A)

All variables are regarded as I(1), for the purpose of modeling, which is also supported by the individual augmented Dickey-Fuller tests (Dickey and Fuller (1979) and Dickey and Fuller (1981)). The average order of integration of real house prices and real disposable income is found to be one, while in several cases the housing stock is found to be trend stationary, which seems implausible.[7] Though in some areas, the tests indicate that house prices and the housing stock may be I(2), we conduct our analysis under the modeling assumption that all variables are at most integrated of order one.

3.2 Testing for slope homogeneity

Several papers have considered a panel model of US MSAs to explore house price dynamics, see e.g. Abraham and Hendershott (1996); Gallin (2006, 2008); Mikhed and Zemcik (2009a,b). While the panel approach has some advantages, a drawback is that usually only the intercept is allowed to vary along the cross-sectional dimension. As has been highlighted by e.g. Pesaran and Smith (1995); Im et al. (2003); Pesaran et al. (1999); Phillips and Moon (2000), the pooling assumption of equal slope coefficients may often be disputed as well. The validity of the pooling assumption is often difficult to test due to

[7]Even if the housing stock was stationary, this would not cause any problems with inference, but it would not "help" for cointegration.

limited access to data at a higher frequency than the annual level, but in cases where both the cross-sectional and time series dimensions are large, this seems to be a particularly relevant issue to explore.

As a first test of the validity of this assumption, we estimate an inverted demand equation by considering the following $ARDL(p, q)$ representation of the underlying theoretical model (confer (5)):

$$\begin{aligned}\Delta ph_{j,t} = \mu_j + \alpha_{ph,j}\left(ph_{j,t-1} - \boldsymbol{\beta}_j' \boldsymbol{w}_{j,t-1}\right) + \sum_{s=1}^{p-1} \gamma_{\Delta ph,j,s} \Delta ph_{j,t-s} \\ + \sum_{s=0}^{q-1} \boldsymbol{\gamma}_{\Delta \tilde{\boldsymbol{w}},j,s}' \Delta \tilde{\boldsymbol{w}}_{j,t-s} + \boldsymbol{\Phi}_j \boldsymbol{D}_t + \epsilon_{j,t}\end{aligned} \tag{6}$$

where the vector $\boldsymbol{w}_{j,t}$ contains the income measure, the housing stock, the interest rate, as well as the subprime variable. The tilde above $\boldsymbol{w}_{j,t}$ in the short-run dynamics indicates that we abstract from the supply side by assuming it to be rigid in the short run. The vector $\boldsymbol{D}_t$ contains centered seasonal dummies for the first three quarters along with the MT dummy variable. When estimating (6), we let $p = q = 5$.

The key parameters of interest in this paper are the long-run (cointegrating) coefficients that are collected in the $\boldsymbol{\beta}_j$ vectors, as well as the adjustment parameter $\alpha_{ph,j}$. We also pay attention to the coefficients (or the sum thereof) of lagged house price inflation, i.e. the sum of the $\gamma_{\Delta ph,j,s}$ coefficients. Following the discussion in Section 2, these coefficients are assumed to measure an expectational effect.

The standard point of departure in the panel literature is to estimate (6) by the use of a dynamic fixed effects estimator (DFE). Obviously, this may have some advantages in that – conditional on the pooling assumption being valid – it increases the precision of the estimates of the parameters of interest, and it may also be the only admissible technique when the time dimension for each cross-sectional unit is limited. However, the potential drawback of this method is obvious: it only allows the intercept to be region-specific, while imposing the rather strict assumptions that $\alpha_{ph,j} = \alpha_{ph}, \boldsymbol{\beta}_j = \boldsymbol{\beta}, \gamma_{\Delta ph,j,s} = \gamma_{\Delta ph,s}, \boldsymbol{\gamma}_{\Delta \tilde{\boldsymbol{w}},j,s}' = \boldsymbol{\gamma}_{\Delta \tilde{\boldsymbol{w}},s}' \; \forall \; j, s$.

In addition to considering the DFE, we consider two alternative estimators as well. First, we estimate (6) separately for all areas in our sample, i.e. allowing all the coefficients to vary freely along the cross-sectional dimension. These estimates may be averaged using the mean group (MG) estimator of Pesaran and Smith (1995) for the parameters of interest, so that we can compare them to those obtained from the dynamic fixed effects model. Second, we consider an intermediate case by using the pooled mean group estimator suggested by Pesaran et al. (1999). In that case, the long-run coefficients are restricted to being equal along the cross-sectional dimension ($\boldsymbol{\beta}_j = \boldsymbol{\beta} \; \forall \; j$), while the other coefficients are allowed to be region-specific. Again, the estimates may be compared to those obtained using the MG and DFE estimators, respectively. This approach allows us to calculate the likelihood of the restricted models (either the DFE or the PMG model) and test the relevance of the imposed homogeneity restrictions against the unrestricted model where all parameters are allowed to vary freely by using a likelihood ratio test.

3.3 Region-specific cointegrated VAR models

Having tested for systematic differences in the parameters of interest, we develop MSA-specific econometric models to shed more light on regional differences in US house price determination. Independent of whether there are signs of slope heterogeneity or not, there are several reasons to consider MSA-specific models. First, subprime lending may have been relevant for house price formation in some areas, but not in others, which can be formally explored by considering separate regional models. Second, the areas considered in this paper are different in several respects and might be hit by MSA specific shocks, or be subject to structural breaks that are simply not possible to capture by any economic variable – or there might be problems with measurement errors and data contamination. To deal with these potential challenges, we make use of the *impulse indicator saturation* (IIS) algorithm which is an integrated part of the *Autometrics* routine implemented within PcGive (see Doornik (2009) and Hendry and Doornik (2009)).

The IIS algorithm includes an impulse dummy for each observation in the information set and the model is estimated in blocks to determine which indicators are significant (see Hendry et al. (2008) and Johansen and Nielsen (2009)). On average, only αT indicators will be retained by chance, where α denotes a pre-specified significance level and T is the number of time series observations. This is indeed a low cost to pay for robustifying a model to intermittent structural breaks and past data contamination that can cause an otherwise sensible econometric model to break down. Castle et al. (2012) show that the IIS algorithm is successful in detecting multiple breaks in the data.

To explore the intra-MSA differences, we take the following VARX(p_j, q_j) model as a starting point for each of the $N = 100$ areas in the sample:

$$\boldsymbol{y}_{j,t} = \boldsymbol{\mu}_j + \sum_{s=1}^{p_j} \boldsymbol{A}_{j,s}\boldsymbol{y}_{j,t-s} + \sum_{s=0}^{q_j} \boldsymbol{B}_{j,s}\boldsymbol{x}_{j,t-s} + \boldsymbol{\Phi}_j\boldsymbol{D}_{j,t} + \boldsymbol{\varepsilon}_{j,t} \quad t = t_j, \ldots, T \tag{7}$$

where t_j indicates that for some areas we do not have data available from 1980q1. The vector $\boldsymbol{y}_{j,t}$ comprises real house prices and real disposable income, $\boldsymbol{x}_{j,t}$ contains the housing stock, as well as the national interest rate and the subprime measure. All deterministic terms (linear trend, centered seasonal dummies and the MT dummy), except the constant, are collected in the vector $\boldsymbol{D}_{j,t}$. The disturbances are assumed to follow a multivariate normal distribution with expectation $\mathbf{0}_{2\times 1}$ and covariance matrix $\boldsymbol{\Sigma}_j$, i.e. $\boldsymbol{\varepsilon}_{j,t} \sim N(\mathbf{0}_{2\times 1}, \boldsymbol{\Sigma}_j)$.[8]

For all areas, we start with a lag length of 5 in all variables, i.e. $p_j = q_j = 5$. Then, we employ the IIS algorithm to test whether there is evidence of un-modeled structural breaks. When applying the IIS algorithm, the significance level is set to 1%, which means that (with 122 observations in most cases) approximately one irrelevant dummy is – on average – retained by chance. Thus, with this significance level, the expected cost in terms of retaining irrelevant dummies is relatively low. Conditional on the dummies found by IIS, we adopt the following two-stage procedure to reduce the dimension of the VARX model: first, we test whether the subprime measure can be excluded altogether. Then, we investigate whether the lag length of the endogenous and the exogenous variables may

[8] It should be noted that we abstract from any cross-sectional dependence in this paper. While this is a limitation, we have purposefully left that for future work due to the complexity of the current modeling exercise.

be reduced. Our decision criterium is in both cases the Akaike Information Criterium (AIC).

Given the optimal lag truncation of the endogenous and the assumed to be weakly exogenous variables – p_j^* and q_j^* – we consider (7) on vector equilibrium correction (VECM) form. Following the suggestion of Harbo et al. (1998) for partial systems, we restrict a deterministic trend to enter the cointegration space when testing for cointegration. Letting $\tilde{\boldsymbol{y}}_{j,t} = \left(\boldsymbol{y}'_{j,t}, \boldsymbol{x}'_{j,t}, t_j\right)'$, the VECM representation of the VAR model takes the following form:

$$\Delta \boldsymbol{y}_{j,t} = \boldsymbol{\mu}_j + \boldsymbol{\Pi}_j \tilde{\boldsymbol{y}}_{j,t-1} + \sum_{s=1}^{p_j^*-1} \boldsymbol{\Gamma}_{j,s} \Delta \boldsymbol{y}_{j,t-s} + \sum_{s=0}^{q_j^*-1} \boldsymbol{\Psi}_{j,s} \Delta \tilde{\boldsymbol{x}}_{j,t-s} + \tilde{\boldsymbol{\Phi}}_j \tilde{\boldsymbol{D}}_{j,t} + \boldsymbol{\varepsilon}_{j,t} \tag{8}$$

where $\tilde{\boldsymbol{D}}_{j,t}$ contains a constant, centered seasonal dummies as well as the dummies retained after using the IIS routine. The deterministic trend is included in $\tilde{\boldsymbol{y}}_{j,t-1}$. Note that the vector $\tilde{\boldsymbol{x}}_{j,t}$ contains subprime lending and the interest rate only. This ensures a theory-consistent specification, where the housing stock is assumed to be fixed in the short run (confer the discussion in Section 2). All coefficient matrices are redefined conformably.

To determine the rank of the matrix $\boldsymbol{\Pi}_j$, we use the trace test of Johansen (1988). The rank of $\boldsymbol{\Pi}_j$ corresponds to the number of independent linear combinations between the variables in $\tilde{\boldsymbol{y}}_{j,t}$ that are stationary, i.e. the number of cointegrating relationships. When $\boldsymbol{\Pi}_j$ has reduced rank, we can write $\boldsymbol{\Pi}_j = \boldsymbol{\alpha}_j \boldsymbol{\beta}'_j$, where $\boldsymbol{\beta}_j$ is a $(l_j + m_j + 1) \times r_j$ matrix and $\boldsymbol{\alpha}_j$ is a $l_j \times r_j$ matrix corresponding to the long-run coefficients and loading factors (adjustment coefficients), respectively. The rank of $\boldsymbol{\Pi}_j$ is denoted by r_j, while l_j refers to the number of endogenous variables and $m_j + 1$ is the number of exogenous variables (including the deterministic trend, which is restricted to lie in the cointegration space). In all areas, l_j is equal to 2 (real house prices and real disposable income), whereas m_j is either 2 or 3, depending on whether subprime lending can be excluded from the econometric model or not in the first stage of the estimation routine.

When including weakly exogenous variables in the space spanned by $\boldsymbol{\alpha}_j$, the distribution of the trace statistic will change. It is therefore important to use critical values that take account of this (see the discussion in Harbo et al. (1998)).[9] Conditional on reduced rank, we test whether there is evidence of co-trending (that the trend may be excluded from the cointegration space) and whether the income variable may be considered weakly exogenous with respect to the long-run cointegrating relationship. Finally, we test whether the subprime measure can be excluded from the cointegrating vector, i.e. whether subprime lending has long-run, or temporary, short-run effects only.[10]

3.4 A framework for exploring regional heterogeneity

Based on the results obtained when we estimate the individual VECMs, several interesting questions may be asked. Here First, regarding the subprime variable, we might find that

[9]For that purpose, we use the critical values that are reported in Doornik (2003), which updates the critical values of Harbo et al. (1998). We use critical values consistent with a 5% significance level.

[10]All steps in our estimation strategy have been automatized by writing an Ox-code that conducts the above described econometric analysis for each MSA in the data set. The code will be made available on http://www.andre-anundsen.com/ for ease of replicability.

this variable enters the econometric model for some areas only. To investigate what factors may explain any such differences, we consider a simple binary model of the following form:

$$Subprime_j = \rho_{\text{Subprime}} + \boldsymbol{\eta}'_{\text{Subprime}} \boldsymbol{z}_j + u_{Subprime,j} \tag{9}$$

where $Subprime_j$ is a variable that takes the value one if the subprime measure cannot be excluded from the econometric model of area j and a value of zero otherwise. The vector $\boldsymbol{z}_j$ contains cross-sectional variables that are relatively constant over time; the Wharton residential land use regulation index (WRLURI) developed by Gyourko et al. (2008), an index on physical land use restrictions (see Saiz (2010)), whether the MSA belongs to a recourse or non-recourse state, log of population, log population density and poverty rates (as a measure of income distribution).[11] In addition, we include dummies to control for the census region in which the MSA is situated, i.e. West, South, Northeast or Midwest.[12] We estimate (9) using a logit specification, while the Autometrics algorithm is used as a general-to-specific device to see which of the variables in $\boldsymbol{z}_j$ – if any – can explain cross-sectional differences in the importance of subprime lending for US house price determination.

Second, we collect all the estimates of $\boldsymbol{\beta}_j$ and $\alpha_{ph,j}$ (the speed of adjustment parameter) for the regions where there is evidence of cointegration, and where the signs of the coefficients are in accordance with the conjectures of the theoretical model (as explained in Section 2). Let $\beta_{k,j}$ denote the k^{th} element in the vector $\boldsymbol{\beta}_j$. We then explore what factors may explain the regional coefficient heterogeneity and differences in the speeds of adjustment towards equilibrium ("the bubble burster") by considering a set of models of the following form:

$$\beta_{k,j} = \rho_{\beta_k} + \boldsymbol{\eta}'_{\beta_k} \boldsymbol{z}_j + u_{\beta_k,j} \;\; \forall \;\; k = \{y, h, R\} \tag{10}$$

$$\alpha_{ph,j} = \rho_{\alpha_{ph}} + \boldsymbol{\eta}'_{\alpha_{ph}} \boldsymbol{z}_j + u_{\alpha_{ph},j} \tag{11}$$

These models are estimated by OLS and they are reduced in conjunction with the procedure described above.

Finally, to explore any differences in the importance of extrapolative expectations, we make use of the time series estimates obtained when estimating the individual VEC models. More precisely, we use the estimated equilibrium correction terms and consider conditional equilibrium correction models of the following kind:

$$\begin{aligned} \Delta ph_{j,t} = {} & \mu_j + I_j \alpha_{ph,j} e\hat{c}m_{j,t-1} + \sum_{s=1}^{p_j^*-1} \gamma_{\Delta ph,j,s} \Delta ph_{j,t-s} \\ & + \sum_{s=0}^{q_j^*-1} \boldsymbol{\gamma}'_{\Delta \tilde{\boldsymbol{w}},j,s} \Delta \tilde{\boldsymbol{w}}_{j,t-s} + \boldsymbol{\Phi}_j \boldsymbol{D}_t + \epsilon_{i,j} \end{aligned} \tag{12}$$

where $e\hat{c}m_j = ph_j - \hat{\beta}_{y,j} y_j - \hat{\beta}_{h,j} h_j - \hat{\beta}_{R,j} R - \hat{\beta}_{SP,j} SP$, while I_j is an indicator function taking the value one if the system-based approach supports cointegration in area j, and

[11] Admittedly, the latter three are not constant over time, but we follow Anundsen and Heebøll (2013) and use the 1996 measures. As we only have data for poverty rates from 1997, the poverty rates are measured as of 1997.

[12] Since a constant is also included in the model, we naturally only include three of these dummies.

zero otherwise. In the case where there is evidence of cointegration, $e\hat{c}m_j$ is constructed based on the estimates of the β_k parameters obtained from the system-based approach. We then use the Autometrics algorithm with a significance level of 5% to reduce the dimensionality of the model.[13] Having reduced the dimensionality of (12), we take the sum of the coefficients on the retained lagged house price appreciation terms – call this variable $exp._j$ – and estimate the following model:

$$exp._j = \rho_{exp.} + \boldsymbol{\eta}'_{exp.}\boldsymbol{z}_j + u_{exp.,j} \tag{13}$$

Again, we use the Autometrics algorithm to explore which of the variables in $\boldsymbol{z}_j$ may explain differences in the importance of lagged house price appreciation. Another way to view this is as a test of whether any of the variables contained in $\boldsymbol{z}_j$ may explain regional differences in the importance of the "bubble builder" term.

4 Are there signs of heterogeneity in slope coefficients?

When estimating the ARDL models in (6), we distinguish between the four major regions mentioned above: Northeast, West, South and Midwest. This is obviously less stringent than pooling all the regions together, which means that we give the pooled models (DFE and PMG) the best possible chance of not being rejected. Centered seasonal dummies and the MT dummy are included in all cases, and we allow for a total of four lags in the first differences of all variables, i.e. five lags in the levels. The results are summarized in Table 1.

There are several noteworthy results in Table 1: in a majority of the cases, all three estimators give theoretically reasonable signed and significant estimates of the different elasticities in all regions. That said, in several cases the estimates produced by the alternative estimators are wildly different, and in some cases the results seem impossible to rationalize. This suggests that the choice of estimation method matters a great deal for the estimates of the population means. Notably, all estimators suggest a negative effect of subprime lending in the Midwest region, and – judged by the significance of the loadings – there is rather weak evidence of cointegration in that region as well. It is also noticeable that the average adjustment parameter is substantially lower in all regions when applying the pooled techniques relative to the unrestricted case. In summary, it is clear that the estimation results are highly dependent on the choice of a pooled versus an unrestricted approach, which suggests that we should have a good reason to prefer one approach to another – a point we shall now turn to.

In order to formally test whether there is any information loss from imposing long-run coefficient homogeneity across the MSAs within a given region, we make use of a likelihood-ratio test. The restricted likelihood is obtained from the model where we use the PMG estimator, i.e. even though the long-run coefficients are restricted to be the same across the MSAs, we allow for heterogeneity in the short-run coefficients and

[13]Note that we do not use the IIS algorithm in this case, as the dummies that were picked up when using the IIS routine on the unrestricted VAR models are included in the vector $\boldsymbol{D}_t$. Thus, in this case, Autometrics is used only as a tool for an automated general-to-specific search.

Table 1: Long-run estimates from alternative panel estimators, ordered by census region

Coefficient of interest	*West*		*Northeast*		*South*		*Midwest*	
β_y:	Coeff.	t-val	Coeff.	t-val	Coeff.	t-val	Coeff.	t-val
MG	0.325	0.10	2.713	7.32	1.483	2.46	7.481	2.31
PMG	1.465	11.37	1.227	8.17	1.706	12.26	14.715	3.14
DFE	1.557	7.47	0.959	4.31	0.846	5.09	3.092	1.80
β_h:								
MG	0.875	0.16	-6.697	6.34	-2.798	2.40	-9.814	1.36
PMG	-2.134	10.66	-2.313	7.10	-2.770	12.23	18.847	1.92
DFE	-2.059	8.40	-1.759	3.67	-1.257	4.79	-2.672	1.03
β_r:								
MG	-0.587	0.47	-1.928	4.62	-1.121	1.61	10.118	0.86
PMG	-2.196	4.22	0.150	0.35	-1.035	3.00	3.139	0.90
DFE	-1.654	1.67	1.849	2.17	-0.072	0.07	-5.062	1.52
β_{sp}:								
MG	-2.706	0.73	1.858	3.63	1.699	2.44	-9.452	1.60
PMG	1.766	8.76	1.709	12.00	2.433	19.72	-8.504	2.40
DFE	1.187	4.66	1.605	4.66	0.826	2.43	-13.254	1.91
α:								
MG	-0.077	6.20	-0.088	5.25	-0.087	7.89	-0.054	3.23
PMG	-0.059	9.69	-0.057	3.15	-0.039	4.21	-0.001	0.73
DFE	-0.060	11.14	-0.039	11.85	-0.030	8.69	0.011	2.27
Likelihood								
MG	7860.881		6608.622		10305.636		8384.152	
PMG	7768.225		6518.827		10161.360		8164.265	
H_0: Equal coefficients ($\boldsymbol{\beta}_j = \boldsymbol{\beta}\ \forall\ j$)	0.0000		0.0000		0.0000		0.0000	
Number of MSAs (N^r)	2906		2259		3502		2821	
Number obs. ($\sum_{i=1}^{N^r} T_i^r$)	25		20		30		25	
Average obs. per MSA $\frac{\sum_{i=1}^{N^r} T_i^r}{N^r}$	116.24		112.95		116.73		112.84	

Notes: This table reports the Mean Group (MG), Pooled Mean Group (PMG) and Dynamic Fixed Effects (DFE) estimates for the long-run coefficients and the adjustment parameter of the model (6). Absolute t-values are reported next to the point estimates, and the test reported in the lower part of the table explores whether there is any information loss from constraining the long-run coefficients to be equal across areas ($\boldsymbol{\beta}_j = \boldsymbol{\beta}\ \forall\ j$). The table sorts the MSA by the four census regions, and N^r is the number of areas in region $r = \{\text{West, Northeast, South, Midwest}\}$, while T_i^r is the number of time series observations for area i in region r. All estimations are carried out using the Stata routine *xtpmg* developed by Blackburne and Frank (2007).

the adjustment parameter. Thus, we give the pooled model the best possible chance of surviving relative to the completely unrestricted model, where all parameters are allowed to be MSA-specific.[14] The likelihood-ratio statistic in area r is χ^2 distributed with $(N^r - 1) \times 4$ degrees of freedom under the null.[15] It is clear that the hypothesis of homogenous long-run coefficients for the MSAs located within a given geographical region is firmly rejected in all cases, with p-values from the likelihood-ratio test of 0.0000.

The results in this section suggest that there is important regional heterogeneity in the long-run determination of US house prices which is not detected by resorting to a pooled model. For that reason, we shall in the next section develop separate econometric models for all the MSAs in our sample in order to study this coefficient heterogeneity in more detail. Furthermore, implicit in the analysis so far has been the assumption that subprime lending affects house prices in all areas. That does not need to be the case – an issue that we shall explicitly address when building the MSA-specific econometric models in the next section.

5 MSA-specific models for house prices

In this section, we present the results obtained when we utilize the econometric approach outlined in Section 3.3 for each of the areas in our sample. This approach enables us to allow for both region-specific shocks (using IIS), a varying role of subprime lending, and heterogeneity in the parameters of interest. At the first stage of the estimation routine, where we use the IIS algorithm, around 10 dummies are picked up on average (confer the final row in the second column of Table 2).

It is clear from an inspection of the third and fourth columns of Table 2 that the selected lag length is – on average – approximately the same across the major geographical regions, and that (considering all areas) an average of approximately 4 lags are selected for both the endogenous and the weakly exogenous variables.

It is interesting to note the geographical dispersion in the importance of subprime lending (see the final column of Table 2). Based on AIC, we find that the subprime measure can be excluded from 35-40 percent of the econometric models for the areas belonging to the West and the Northeast regions, while the same number is around 65 percent for the areas in the Midwest and South regions. Already at this stage, we get an indication that the role of subprime lending in driving local house prices in the recent boom was more pronounced for the MSAs situated in some regions – notably the West and the Northeast regions – than in the other regions. A formal exploration of what characterizes the areas where subprime lending was most important is reserved for the next section.

Conditional on the number of dummies that were selected by the IIS routine, the lag lengths of the endogenous and the exogenous variables, and whether subprime lending was found to be part of the econometric model, we estimated all models and tested for

[14] Clearly, a more stringent test would be to evaluate the estimates from the dynamic fixed effects approach compared to those based on the freely estimated models.

[15] There are a total of 4 parameters in the long-run cointegrating relationship, and in region r there are a total of N^r areas, meaning that $(N^r - 1) \times 4$ restrictions are imposed under the null that all areas in region r have the same cointegrating coefficients.

Table 2: Averages of some key model features, ordered by census region

Area	Dummies (avg.)	p^* (avg.)	q^* (avg.)	*Subprime* (%)
West	10.92	4.56	3.80	60.00
East	7.45	4.20	3.40	65.00
South	9.43	4.37	3.80	33.33
Midwest	10.28	4.24	3.40	36.00
All	9.62	4.35	3.62	47.00

Notes: Columns 2–4 report the average number of dummies, Dummies (avg.), included in the econometric models within each of the four major regions, as well as the average number of lags retained for the endogenous, p^* (avg.) and the exogenous, q^* (avg.), variables. The final column displays the percentage number of areas where the subprime measure is found to enter the model, *Subprime* (%). The final row in each column report the same figures for all the MSAs covered by the sample (all areas).

cointegration using the trace test of Johansen (1988).[16] The first two columns of Table 3 summarize the percentage number of areas where there was no evidence of autocorrelation nor any sign of departures from normality or homoskedastic residuals. The average rank – according to the trace test – is reported in the final column. Again, the first four rows of the table displays the results for the four census regions, while the final row does so based on all MSAs.

Table 3: Diagnostics and average rank across census regions

Area	No autocorrelation (%)	Normality (%)	Homoskedasticity (%)	*Rank*($\mathbf{\Pi}_j$) (avg.)
West	92.00	88.00	92.00	1.36
East	100.00	100.00	80.00	1.15
South	93.33	100.00	83.33	1.10
Midwest	96.00	96.00	96.00	1.20
All	95.00	96.00	88.00	1.20

Notes: Columns 2–4 report the percentage number of areas within each of the four census regions where there is no evidence of autocorrelation, no signs of departures from normality and no signs of heteroskedasticity. The final column reports the average rank. While the first four rows diplays the results for each of the census regions, the final row reports the same figures for all the areas.

In most of the cases, there are no signs of residual autocorrelation (95 percent in total), nor any signs of departures from normality (96 percent in total), or heteroskedasticity (88 percent in total). Furthermore, we find that the average rank among all the areas in the sample is around one, which is in accordance with the conjectures of the theoretical model we discussed in Section 2. Though the trace test indicates that the rank might be zero (or two) in some areas, we shall continue the analysis under the modeling assumption of a rank of one in all areas, which is consistent with the discussion in Section 2, and which is also found to be the average rank when considering all areas. In addition, as stressed in e.g. Juselius (2006), it is relevant to see the trace test in combination with – among other things – the economic interpretability of the estimated cointegrating vectors, and in

[16]A significance level of 5% was chosen for the trace test, and we have considered the finite sample adjusted version of the test statistic. Since we condition on the subprime measure, the housing stock and the real interest rate in the models, we have used critical values that adjust for this (confer the discussion in Section 3 and Table 13 in Doornik (2003)).

particular the significance of the equilibrium correction terms.[17] In our case, this amounts to evaluating the empirical findings against the theoretical conjectures outlined in Section 2, i.e. to investigate whether the life-cycle model constitutes a valid representation of the data. Tables D.2, D.4, D.6 and D.8 in Appendix C display detailed specification results and diagnostics for each area included in our information set.

When exploring the structure of the cointegrating relationship for each of the areas, we normalize on the house price variable. Further, we impose the two additional and testable restrictions that the trend can be excluded from the cointegrating space (co-trending) and that income is weakly exogenous. The validity of these overidentifying restrictions is tested by use of a likelihood ratio test (p-values from the test are reported in Column 11 of Table D.2, D.4, D.6 and D.8). It is clear that the test for overidentifying restrictions is rejected in several cases. While the fraction of areas where these restrictions are rejected is 29 percent in the West region, the corresponding figure is as high as 71 percent in the Midwest. Mostly, this is due to rejection of co-trending, i.e. leaving out the trend from the the VAR model from the outset the restriction is not rejected.[18] When omitting the trend all together, we reject weak exogeneity of income only in 5 percent of the areas in the West, while the same number is 47 percent in the Midwest. For all areas, weak exogeneity is rejected in about 29 percent of the cases.[19]

For the areas where we found that the subprime measure is part of the econometric model, we decided to keep it in the cointegrating space only if the p-value from the likelihood ratio test that tests whether the coefficient is zero is less than 0.2 and as long as it has a positive effect.[20] The results are summarized in Column 4 in the same tables, where a 1 indicates that subprime lending is part of the cointegrating vector, and a 0 means that it is not.

In the following, we investigate the average results within each of the four regions in a little more detail to better understand the heterogeneity across regional markets. We have summarized the results in Table 4. It is clear that the mean and median estimates of the long-run elasticities and the adjustment parameter are quite close for all coefficients in the West, Northeast and the South region, while they are somewhat more different in the Midwest region, though not substantially.

Looking first at the estimated income elasticity, we see that even though the average estimates differ somewhat across the regions, there are no radical differences. We also note that the income coefficient is positive, highly significant and of a reasonable magnitude. Also, the average subprime coefficient is rather similar across the regions, and it has a

[17] As a rule of thumb, Juselius (2006) suggests that if the rank is found to be r, there is not much to gain from including the $(r+1)^{th}$ in the econometric model if the t-value of the adjustment coefficients for the $(r+1)^{th}$ cointegrating vector is less than 2.6. Consequently, if either (or both) the trace test suggests a non-zero rank and the t-value of the adjustment coefficient exceeds 2.6, we shall continue our analysis under the modeling assumption that there exists a cointegrating relationship.

[18] Another option would be to allow the trend to enter the cointegrating vectors, but due to the high correlation with the housing stock variable, this causes problems with estimating the other parameters in the model precisely.

[19] The problems with the test for overidentifying restrictions may partly be due to the housing stock measure used in this paper, but a more "correct" measure for the housing stock is hard to obtain at the MSA level.

[20] The sign restriction became binding only for 5 areas, of which 3 are located in the Midwest region. The latter explains the finding of a negative interest rate effect in the Midwest region as a whole in the case where we considered the different panel estimators (confer Table 1).

large positive impact on house prices. Nevertheless, there are major differences in these elasticities across the MSAs within each region, as is evident from the results summarized in the tables in Appendix C. This is in contrast to Ashworth and Parker (1997), who find little coefficient heterogeneity for the different regions in the UK, though they do find that the regional estimates are significantly different from the national estimates. The reason why they find relatively little variation across the regions may be because they consider a higher aggregation level, which hides part of the heterogeneity.

In all cases, the housing stock elasticity has the expected negative sign, but there are still notable differences in this coefficient across the regions. In particular, it is substantially higher in the Midwest and the Northeast regions relative to the West and the South region. Also the interest rate effect seems to differ quite substantially across the regions. Notably, the average interest rate effect is insignificantly different from zero in both the South and the Midwest regions.

Judged by the signs of the estimated coefficients (confer the discussion in Section 2), we find theory-consistent cointegrating relationships in 84 percent of the cases in the West region and 85 percent in the Northeast region, while the corresponding figures for the South and the Midwest regions are around 70 percent. In most cases, both the income variable and the housing stock are significant and have reasonable numerical sizes compared with the international literature, see Girouard et al. (2006) for a useful summary. The interest rate is found to have a negative sign in a majority of the cases where a theory-consistent cointegrating relationship is found, but in several cases the estimate is insignificantly different from zero – and in some cases it is even found to be positive.

It is noteworthy that the MG estimates reported in Table 4 deviate quite substantially from the MG estimates obtained when estimating separate ARDL models for all areas (confer Table 1). There are several reasons for this. First, we have now excluded the areas where no interpretable cointegrating relationships were found. Further, compared with that approach, we no longer "force" the subprime variable to have an effect on house prices in all MSAs. This illustrates the importance of a detailed MSA-specific econometric analysis, even if the parameters of interest are the mean estimates.

In the next section, we return to a more systematic and detailed analysis of the observed coefficient heterogeneity and the regional differences in the importance of subprime lending for house price dynamics.

Table 4: Summary of cointegration results

	β_y			β_h			β_R			β_{SP}			α_{ph}		
Area	Mean	Median	Standard error	Mean	Median	Standard error	Mean	Median	Standard error	Mean	Median	Standard error	Mean	Median	Standard error
West	2.338	2.044	0.420	-3.297	-2.918	0.692	-2.536	-2.734	0.586	3.115	2.943	0.179	-0.057	-0.046	0.006
East	2.939	2.853	0.502	-7.422	-6.193	1.428	-2.438	-2.013	0.558	3.078	2.023	0.973	-0.071	-0.056	0.009
South	2.113	1.768	0.395	-3.757	-3.447	0.758	-0.666	-0.958	0.594	3.688	3.953	0.323	-0.070	-0.054	0.011
Mid-West	3.403	2.593	0.654	-6.567	-5.385	1.428	-1.288	-2.134	0.905	2.414	2.414	0.282	-0.054	-0.052	0.006

Notes: The table reports the average long-run estimates of the coefficients on income (β_y), the housing stock (β_h), the interest rate (β_R) and the subprime variable (β_{SP}), grouped by census region. For the first three, the averages are based on the coefficients for the areas where a meaningful cointegrating relationship was found. The average subprime coefficient is based on the areas in which we found a long-run effect of subprime lending. The table also reports the median and the standard error for each of these coefficients, and for each of the regions. Note, the MG estimates are based on the results from estimating the individual cointegrated VAR models, and not the ARDL approach. The MG estimator of the β_k's in region r is calculated in the following way $\beta_k^{MG,r} = \frac{\sum_{i=1}^{M^r} \beta_{i,k}}{M^r}$ $k = \{y, h, r, sp\}$ and $r = \{West, Northeast, South, Midwest\}$, with M^r denoting the number of areas with a meaningful cointegrating relationship in region r. The same calculation applies to the adjustment parameter. Note that since the subprime variable only enters the model of one area in the Midwest, the standard error of that coefficient in that region is the standard error of that coefficient in that area. Detailed results for each area can be found in D.1, D.3, D.5 and D.7 in Appendix C.

6 What explains the heterogeneity?

6.1 On the role of subprime lending

Having estimated interpretable long-run effects of the economic variables for a total of 76 of the 100 areas included in our sample, we now turn to the question of what may explain the observed heterogeneity. We start by exploring the characteristics of the areas in which the subprime measure is found to matter. For this purpose, we follow the approach outlined in Section 3.4 and estimate (9) using a logit specification. The dependent variable is an indicator variable which takes the value one if the subprime measure is part of the econometric model and zero otherwise. We estimate the model on the full 100 MSA sample, as well as the subsample where only the MSAs where meaningful cointegrating relationships are found are included in the information set.[21] The results are summarized in Table 5.[22]

The results in Table 5 suggest that the probability of the subprime variable entering the model is higher in areas where there are more restrictions on land supply – either geographically or man-made. This suggests that the subprime explosion of the previous decade had a greater influence on house prices in more supply-restricted areas than areas without such restrictions. This result corroborates the findings of Huang and Tang (2012) and Anundsen and Heebøll (2013), who find that differences in cumulative house price growth over over the 2000–2006 boom period were related to a combination of tight restrictions on land supply and exposure to the subprime segment.

6.2 Long-run coefficient heterogeneity

We now ask if we can find a similar link between the cointegrating coefficients and the time-invariant explanatory variables (see (10)). For this purpose, we estimate equation (10) for β_y, β_h and β_R by OLS. The results are summarized in Table 6.

We do not find any relationship between the explanatory variables and most of the long-run elasticities. That said, the results suggest a larger negative effect of the interest rate in areas with higher poverty rates. It is reassuring that the supply restriction indexes do not affect the long-run elasticities of the inverted demand equation, as they should affect the supply of – and not the demand for – housing given that they alter supply elasticity.

These results may suggest that the differences we find in the cointegrating coefficients are due to the lack of observations in the time series domain, or it could mean that other time-invariant cross-sectional differences that we do not control for can explain the differences. In both interpretations, the varying role of subprime lending suggests that one should be cautious about fitting the same model to all areas.

[21] The reason why we also consider the full sample is that even though we do not find evidence of a meaningful cointegrating relationship, there is no reason to rule out subprime lending as a possible driver of house prices. An econometric model other than the cointegrated VAR model may be more appropriate to model house prices in that case, but the role of subprime lending may be equally important.

[22] Note that we lack data for the two restriction indexes in Honolulu, which is the reason why the number of observations are 99 and 75 and not 100 and 76 in the two cases.

Table 5: What factors determine the importance of subprime lending?

Variable	Coefficient	t-value	Coefficient	t-value
Constant	-2.264	-2.743	-2.702	-3.510
WRLURI	3.236	2.375	3.644	2.794
UNAVAL	2.398	2.076	2.753	2.642
LPop.Den	*	*	*	*
LPop.	*	*	*	*
Poverty	*	*	*	*
Recourse	*	*	*	*
South	*	*	*	*
Midwest	*	*	*	*
East	*	*	*	*
N	99		75	

Notes: This table reports results when we estimate (9) using a logit specification and use Autometrics with a significance level of 5% to explore what variables are relevant. The dependent variable is an indicator variable taking the value one if subprime lending is part of the econometric model and zero otherwise. The reported t-values are measured in absolute terms and an asterisk is reported if the variable was not retained by Autometrics. Variable definitions for the explanatory variables are given in Table A.1 in Appendix A.

Table 6: Coefficient heterogeneity

	β_y		β_h		β_R	
Variable	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Constant	2.652	10.660	-4.429	-7.066	0.607	0.667
WRLURI	*	*	*	*	*	*
UNAVAL	*	*	*	*	*	*
LPop.Den	*	*	*	*	*	*
LPop.	*	*	*	*	*	*
Poverty	*	*	*	*	-15.042	-2.682
Recourse	*	*	*	*	*	*
South	*	*	*	*	*	*
Midwest	*	*	*	*	*	*
East	*	*	-2.993	-2.274	*	*
N	75		75		75	

Notes: This table reports the results we obtain when we estimate (10) by OLS and use Autometrics with a significance level of 5% to explore what variables are relevant. The dependent variable(s) are the long-run elasticities. The reported t-values are measured in absolute terms and an asterisk is reported if the variable was not retained by Autometrics. Variable definitions for the explanatory variables are given in Table A.1 in Appendix A.

6.3 Regional differences in the bubble builder and the bubble burster

Lastly, we briefly explore what factors may explain the cross-sectional differences in the bubble builder and in the bubble burster terms. We estimate (11) and (13) by OLS, and the results are displayed in Table 7.

Again, strikingly, we find a greater influence of the expectation channel in areas where

Table 7: The bubble builder and the bubble burster

	α_{ph}		$exp.$	
Variable	Coefficient	t-value	Coefficient	t-value
Constant	-0.047	-6.529	-1.650	-3.320
WRLURI	*	*	0.655	4.206
UNAVAL	*	*	0.652	4.719
LPop.Den	*	*	*	*
LPop.	*	*	0.119	3.398
Poverty	*	*	*	*
Recourse	-0.025	-2.813	-0.144	-2.185
South	*	*	*	*
Midwest	*	*	*	*
East	*	*	*	*
N	75		75	

Notes: This table reports the results we obtain when we estimate (11) and (13) by OLS and use Autometrics with a significance level of 5% to explore what variables are relevant. The dependent variable(s) are the adjustment parameter and the measure of extrapolative expectations measure. The reported t-values are measured in absolute terms and an asterisk is reported if the variable was not retained by Autometrics. Variable definitions for the explanatory variables are given in Table A.1 in Appendix A.

the supply of housing is restricted. Theoretically, this seems plausible, since the price-to-price feedback loop would be expected to be greater the more restricted the housing supply is. The results also suggest that there is a stronger expectational effect in areas with a higher population, which may be linked to the theory of herd behavior. We also find that the expectational component is more important in areas belonging to a state with non-recourse lending, possibly a result of more speculative behavior among home buyers when there is less at stake for them. Finally, regarding the equilibrium correction term, we find a slower adjustment to equilibrium in areas where lending is non-recourse than in areas where it is is not.

One objection to the results regarding the bubble builder term is that we might get different results if we decide to put the ecm-term at another lag, since this will alter the short-run coefficients while the adjustment parameter is invariant to this. As a result, the lagged house price appreciation terms retained when we use Autometrics on (12) may change as well, which again may influence the results we get when we estimate (13). For that reason, we did a robustness exercise to investigate the sensitivity of our results. More specifically, if the optimal lag length of the endogenous variables in area j was chosen to be p_j^* in the VAR analysis, we initially put the ecm-term at lag $p_j^* - 1$ and tested the significance of $\Delta ph_{t-(p_j^*-1)}$. If significant, the ecm-term was kept at lag $p_j^* - 1$. Otherwise, we used a similar procedure to decide whether the ecm-term should be put at lag $p_j^* - 2$. The lag of the ecm-term in area j was chosen as the maximum of one and the lag length chosen from the above described procedure. The results from that procedure are similar to those reported in the above table.[23]

[23]Detailed results are available upon request.

7 Conclusion

This paper has studied regional differences and similarities in US house price formation. As shown, the assumption of heterogenous long-run coefficients across areas was strongly rejected by poolability tests. For that reason, we developed econometric models for 100 US Metropolitan Statistical Areas (MSAs) to explore the regional heterogeneity in a little more detail. In particular, our results suggest a varying role of subprime lending across MSAs, with subprime lending affecting house price formation to a larger extent in the MSAs in the West and Northeast regions compared to the South and Midwest regions.

Exploring in more detail what may explain these geographical differences in the importance of subprime lending, we find that subprime lending was more important in areas that have more restrictions on land supply – in both physical and regulatory terms. We also find geographical variations in the long-run response to a change in income, housing supply and the interest rate, as well as the speed in which disequilibrium constellations are restored. We find that the adjustment towards equilibrium is faster in areas where lending is recourse. Finally, we find a greater effect of lagged house price appreciation – interpreted as capturing an adaptive expectations channel – in areas where the supply of housing is restricted, in areas that are more populous and in areas with non-recourse lending.

Our results have several implications, both for the econometric modeling of regional housing markets, and for the understanding of regional variations in long-run house price determination. First, our results suggest that a homogenous panel data analysis is too restrictive and that it will hide the large local differences that exist at the regional level – particularly concerning the effect of the recent subprime explosion. Thus, a model for regional house price determination should allow for at least some heterogeneity in slope coefficients. Second, our results suggest that a forecasting model – or a model used for assessing financial vulnerability at a disaggregate level – should account for the large regional differences by e.g. estimating separate time series models for the areas under consideration.

There are several ways in which the results in this paper may be extended in future research projects. First of all, the regional models established in this paper may be incorporated into a global VAR model to analyze how shocks are propagated and amplified across space. Second, in building forecasting models for regional house prices, it seems particularly relevant to take account of the major heterogeneity documented in this paper. It would also be highly relevant to explore the effect of using region-specific measures of changes in credit conditions as well as accounting for differences in tax policies across the areas.

References

Abraham, J. M. and P. H. Hendershott (1996). Bubbles in metropolitan housing markets. *Journal of Housing Research 7*(2), 191–207.

Anundsen, A. K. (2013). Econometric regime shifts and the US subprime bubble. *Journal of Applied Econometrics*. Forthcoming.

Anundsen, A. K. and C. Heebøll (2013). Supply restrictions, subprime lending and regional US housing prices. Memorandum 4, Department of Economics, University of Oslo.

Anundsen, A. K. and E. S. Jansen (2013). Self-reinforcing effects between housing prices and credit. *Journal of Housing Economics 22*(3), 192–212.

Aron, J., J. V. Duca, J. Muellbauer, K. Murata, and A. Murphy (2012). Credit, housing collateral and consumption: Evidence from the UK, Japan and the US. *Review of Income and Wealth 58*(3), 397–423.

Ashworth, J. and S. C. Parker (1997). Modelling regional house prices in the UK. *Scottish Journal of Political Economy 44*(3), 225–246.

Blackburne, E. F. and M. W. Frank (2007). Estimation of nonstationary heterogeneous panels. *Stata Journal 7*(2), 197–208.

Buckley, R. and J. Ermisch (1983). Theory and empiricism in the econometric modelling of house prices. *Urban Studies 20*(1), 83–90.

Case, K. E. and R. J. Shiller (2012). What have they been thinking? Home buyer behavior in hot and cold markets. Working Paper 18400, National Bureau of Economic Research.

Castle, J. L., J. A. Doornik, and D. F. Hendry (2012). Model selection when there are multiple breaks. *Journal of Econometrics 169*(2), 239–246.

Cohen, J. P., C. C. Coughlin, and D. A. Lopez (2012). The boom and bust of US housing prices from various geographic perspectives. *Federal Reserve Bank of St. Louis Review 94*(5), 341–67.

Dickey, D. A. and W. A. Fuller (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association 74*(366), 427–431.

Dickey, D. A. and W. A. Fuller (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica 49*(4), 1057–1072.

Doornik, J. (2009). Autometrics. In J. L. Castle and N. Shephard (Eds.), *The Methodology and Practice of Econometrics*, pp. 88–121. Oxford University Press.

Doornik, J. A. (2003). Asymptotic tables for cointegration tests based on the gamma-distribution approximation. Unpublished note, Nuffield College, Oxford.

Dougherty, A. and R. Van Order (1982). Inflation, housing costs, and the consumer price index. *American Economic Review 72*(1), 154–164.

Duca, J., J. Muellbauer, and A. Murphy (2011a). House prices and credit constraints: Making sense of the US experience. *Economic Journal 121*, 533–551.

Duca, J., J. Muellbauer, and A. Murphy (2011b). Shifting credit standards and the boom and bust in US home prices. Technical Report 1104, Federal Reserve Bank of Dallas.

Fernandez-Corugedo, E. and J. Muellbauer (2006). Consumer credit conditions in the United Kingdom. Bank of England working papers 314, Bank of England.

Gallin, J. (2006). The long-run relationship between house prices and income: Evidence from local housing markets. *Real Estate Economics 34*(3), 417–438.

Gallin, J. (2008). The long-run relationship between house prices and rents. *Real Estate Economics 36*(4), 635–658.

Girouard, N., M. Kennedy, P. van den Noord, and C. Andre (2006). Recent house price developments: The role of fundamentals. OECD Economics Department Working Papers 475.

Glaeser, E., J. Gyourko, and A. Saiz (2008). Housing supply and housing bubbles. *Journal of Urban Economics 64*(2), 198–217.

Goetzmann, W., L. Peng, and J. Yen (2012). The subprime crisis and house price appreciation. *Journal of Real Estate Finance and Economics 44*(1), 33–66.

Gyourko, J., A. Saiz, and A. Summers (2008). A new measure of the local regulatory environment for housing markets. *Urban Studies 45*(3), 693–729.

Harbo, I., S. Johansen, B. Nielsen, and A. Rahbek (1998). Asymptotic inference on cointegrating rank in partial systems. *Journal of Business and Economic Statistics 16*, 388 – 399.

Hendry, D. F. and J. Doornik (2009). *Empirical Econometric Modelling using PcGive: Volume I.* Timberlake Consultant Press, London.

Hendry, D. F., S. Johansen, and C. Santos (2008). Automatic selection of indicators in a fully saturated regression. *Computational Statistics 33*, 317–335.

Huang, H. and Y. Tang (2012). Residential land use regulation and the US housing price cycle between 2000 and 2009. *Journal of Urban Economics 71*(1), 93–99.

Im, K. S., M. H. Pesaran, and Y. Shin (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics 115*(1), 53–74.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control 12*, 231–254.

Johansen, S. and B. Nielsen (2009). An analysis of the indicator saturation estimator as a robust regression estimator. In J. L. Castle and N. Shepard (Eds.), *The Methodology and Practice of Econometrics*, pp. 1–36. Oxford University Press.

Jurgilas, M. and K. J. Lansing (2013). Housing bubbles and expected returns to home ownership: Lessons and policy implications. In M. Balling and J. Berg (Eds.), *Property Prices and Real Estate Financing in a Turbulent World*. Societe Universitaire Europeenne de Recherches Financieres (SUERF).

Juselius, K. (2006). *The Cointegrated VAR Model: Methodology and Applications*. Oxford University Press.

Meen, G. (1990). The removal of mortgage market constraints and the implications for econometric modelling of UK house prices. *Oxford Bulletin of Economics and Statistics 52*(1), 1–23.

Meen, G. (2001). *Modelling Spatial Housing Markets: Theory, Analysis and Policy.* Kluwer Academic Publishers, Boston.

Meen, G. (2002). The time-series behavior of house prices: A transatlantic divide? *Journal of Housing Economics 11*(1), 1–23.

Meen, G. and M. Andrew (1998). On the aggregate housing market implications of labour market change. *Scottish Journal of Political Economy 45*(4), 393–419.

Mian, A. and A. Sufi (2009). The consequences of mortgage credit expansion: Evidence from the U.S. mortgage default crisis. *Quarterly Journal of Economics 124*(4), 1449–1496.

Mian, A. and A. Sufi (2010). Household leverage and the recession of 2007–09. *IMF Economic Review 58*(1), 74–117.

Mikhed, V. and P. Zemcik (2009a). Do house prices reflect fundamentals? Aggregate and panel data evidence. *Journal of Housing Economics 18*(2), 140–149.

Mikhed, V. and P. Zemcik (2009b). Testing for bubbles in housing markets: A panel data approach. *Journal of Real Estate Finance and Economics 38*, 366–386.

Muellbauer, J. (2012). When is a housing market overheated enough to threaten stability? In A. Heath, F. Packer, and C. Windsor (Eds.), *Property Markets and Financial Stability*, RBA Annual Conference Volume. Reserve Bank of Australia.

Muellbauer, J. and A. Murphy (1997). Booms and busts in the UK housing market. *Economic Journal 107*(445), 1701–1727.

Muellbauer, J. and D. M. Williams (2011). Credit conditions and the real economy: The elephant in the room. CEPR Discussion Papers 8386, C.E.P.R. Discussion Papers.

Pavlov, A. and S. Wachter (2011). Subprime lending and real estate prices. *Real Estate Economics 39*(1), 1–17.

Pesaran, M. H., Y. Shin, and R. P. Smith (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association 94*(446), 621–634.

Pesaran, M. H. and R. Smith (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics 68*(1), 79–113.

Phillips, P. C. B. and H. R. Moon (2000). Nonstationary panel data analysis: An overview of some recent developments. *Econometric Reviews 19*(3), 263–286.

Poterba, J. M. (1984). Tax subsidies to owner-occupied housing: An asset-market approach. *Quarterly Journal of Economics 99*(4), 729–752.

Rogers, W. H. and W. Winter (2013). The relationship between the housing and labor market crises and doubling-up: An MSA-level analysis, 2005-2010. Discussion Paper 7263, IZA.

Saiz, A. (2010). The geographic determinants of housing supply. *Quarterly Journal of Economics 125*(3), 1253–1296.

Shiller, R. J. (2008). Understanding recent trends in house prices and homeownership. Housing, housing finance and monetary policy, *Jackson Hole Conference series*, Federal Reserve Bank of Kansas.

Sinai, T. (2012). House price moments in boom-bust cycles. In *Housing and the Financial Crisis*, NBER Chapters, pp. 19–68. National Bureau of Economic Research, Inc.

Appendix A: Data definitions

Table A.1: Raw data definitions and sources

Name	Description	Source
Data for cointegration analysis		
$Y_{j,t}$	Personal Disposable Income, (mill. \$)	Moody's
$PH_{j,t}$	House price index	FHFA
$CPI_{j,t}$	Consumer price index, Total - All Urban Consumers, (Index $1982-84=100$)	Moody's
$H_{j,t}$	Housing Stock (thou.)	Moody's
SP_t	Number of subprime loans as a share of total loans	MDS
R_t	Real 3-month T-bill	FRED
$Y_{j,t}$ and $PH_{j,t}$ are deflated by $CPI_{j,t}$ to construct the real variables		
Data for analysis of regional heterogeneity		
$WRLURI_j$	The Wharton residential land use regulation index	Gyourko et al. (2008)
$UNAVAL_j$	The index on physical land use restrictions	Saiz (2010)
$Poverty_j$	Poverty rates	Moody's
$Pop.Den._j$	Population density	Moody's
$Recourse_j$	Dummy variable equal to 1 if MSA belongs to recourse state	
$South_j$	Dummy variable equal to 1 if MSA belongs to South region	
$West_j$	Dummy variable equal to 1 if MSA belongs to West region	
$East_j$	Dummy variable equal to 1 if MSA belongs to East region	
MT_t	Dummy variable equal to 1 between 1980q1 and 1982q3	

Notes: The table reports the definitions and sources of the variables used in the econometric analyses. The abbreviations are as follows: HMDA=Home Mortgage Disclosure Act, FHFA=Federal Housing Finance Agency, FRED=Federal Reserve Economic Data, MDS=Mortgage Delinquency Survey.

Appendix B: Information on MSAs in the sample

Table B.1: General information on the MSA covered by our sample

Nr.	MSA name and state	Code	UNAVAL	WRLURI	Jan.temp.(°F)	Dist.ocean (th.m.)
1	Akron, OH	10420	0.06	0.07	26	4.4
2	Albany-Schenectady-Troy, NY	10580	0.23	-0.09	22.2	1.1
3	Albuquerque, NM	10740	0.12	0.37	35.7	6.8
4	Ann Arbor, MI	11460	0.10	0.31	25	7.2
5	Atlanta-Sandy Springs-Marietta, GA	12060	0.04	0.03	42.7	2.6
6	Austin-Round Rock-San Marcos, TX	12420	0.04	-0.28	50.2	1.3
7	Baltimore-Towson, MD	12580	0.22	1.60	32.3	0.0
8	Birmingham-Hoover, AL	13820	0.14	-0.23	42.6	2.1
9	Boise City-Nampa, ID	14260	0.36	-0.46	30.2	6.0
10	Boston-Quincy, MA	14484	0.34	1.70	29.3	0.0
11	Boulder, CO	14500	0.43	3.12	35	11.4
12	Bridgeport-Stamford-Norwalk, CT	14860	0.45	0.19	29.9	0.0
13	Buffalo-Niagara Falls, NY	15380	0.19	-0.23	24.5	3.8
14	Camden, NJ	15804	0.10	1.13	33	0.0
15	Charlotte-Gastonia-Rock Hill, NC-SC	16740	0.05	-0.53	41.7	1.5
16	Chicago-Joliet-Naperville, IL-IN-WI	16974	0.40	0.02	22	10.4
17	Cincinnati-Middletown, OH-KY-IN	17140	0.10	-0.58	31	6.3
18	Cleveland-Elyria-Mentor, OH	17460	0.40	-0.16	25.7	4.6
19	Colorado Springs, CO	17820	0.22	0.87	31	10.8
20	Columbus, OH	17980	0.02	0.26	28.3	1.8
21	Dallas-Plano-Irving, TX	19124	0.09	-0.23	44.1	2.8
22	Dayton, OH	19380	0.01	-0.50	29	6.4
23	Denver-Aurora-Broomfield, CO	19740	0.17	0.84	29.2	10.4
24	Des Moines-West Des Moines, IA	19780	0.06	-0.84	20.4	11.2
25	Detroit-Livonia-Dearborn, MI	19804	0.25	0.05	24.5	6.8
26	Edison-New Brunswick, NJ	20764	0.40	0.65	31	0.0
27	Eugene-Springfield, OR	21660	0.63	0.34	41	0.0
28	Fargo, ND-MN	22020	0.03	-1.27	6.8	10.3
29	Fort Lauderdale-Pompano Beach-Deerfield Beach, FL	22744	0.76	0.72	45	0.0
30	Fort Wayne, IN	23060	0.03	-1.22	45	7.8
31	Fort Worth-Arlington, TX	23104	0.05	-0.27	45	3.2
32	Gary, IN	23844	0.32	-0.69	46	9.9
33	Grand Rapids-Wyoming, MI	24340	0.09	-0.15	26.1	8.5
34	Greensboro-High Point, NC	24660	0.03	-0.29	43	1.9
35	Greenville-Mauldin-Easley, SC	24860	0.13	-0.94	43	2.0
36	Harrisburg-Carlisle, PA	25420	0.24	0.54	31	0.8
37	Hartford-West Hartford-East Hartford, CT	25540	0.23	0.49	25.7	0.0
38	Honolulu, HI	26180		2.30	73	0.0
39	Houston-Sugar Land-Baytown, TX	26420	0.08	-0.40	51.8	0.0
40	Indianapolis-Carmel, IN	26900	0.01	-0.74	26.5	8.3
41	Jacksonville, FL	27260	0.47	-0.02	53.1	0.0
42	Kansas City, MO-KS	28140	0.06	-0.79	26.9	8.0
43	Lansing-East Lansing, MI	29620	0.07	0.19	24	7.9
44	Las Vegas-Paradise, NV	29820	0.32	-0.69	47	3.1
45	Little Rock-North Little Rock-Conway, AR	30780	0.14	-0.85	40.1	4.2
46	Los Angeles-Long Beach-Glendale, CA	31084	0.52	0.49	57.1	0.0
47	Louisville-Jefferson County, KY-IN	31140	0.13	-0.47	33	6.9
48	Madison, WI	31540	0.11	0.40	17.3	10.9
49	Manchester-Nashua, NH	31700	0.34	1.70	38	0.4
50	Memphis, TN-MS-AR	32820	0.12	1.18	39.9	4.0
51	Miami-Miami Beach-Kendall, FL	33124	0.77	0.94	68.1	0.0
52	Milwaukee-Waukesha-West Allis, WI	33340	0.42	0.46	20.7	10.1
53	Minneapolis-St. Paul-Bloomington, MN-WI	33460	0.19	0.38	13.1	11.2
54	Nashville-Davidson–Murfreesboro–Franklin, TN	34980	0.13	-0.41	36.8	4.9
55	Nassau-Suffolk, NY	35004	0.40	0.65	24	0.0
56	New Haven-Milford, CT	35300	0.45	0.19	30	0.0
57	New Orleans-Metairie-Kenner, LA	35380	0.75	-1.24	52.6	0.0
58	New York-White Plains-Wayne, NY-NJ	35644	0.40	0.65	32.1	0.0
59	Newark-Union, NJ-PA	35084	0.31	0.68	31.3	0.0
60	Oakland-Fremont-Hayward, CA	36084	0.62	0.62	51	0.0
61	Ocean City, NJ	36140	0.65	0.69	33	0.0
62	Oklahoma City, OK	36420	0.02	-0.37	36.7	5.5
63	Omaha-Council Bluffs, NE-IA	36540	0.03	-0.56	21.7	11.0

Continued on next page

Table B.1 – General information on the MSA covered by our sample (*Continued from previous page*)

Nr.	MSA name and state	Code	UNAVAL	WRLURI	Jan.temp.(°F)	Dist.ocean (th.m.)
64	Orlando-Kissimmee-Sanford, FL	36740	0.36	0.32	60	0.1
65	Oxnard-Thousand Oaks-Ventura, CA	37100	0.80	1.21	55	0.0
66	Peoria, IL	37900	0.05	-0.38	25	9.7
67	Philadelphia, PA	37964	0.10	1.13	32.3	0.0
68	Phoenix-Mesa-Glendale, AZ	38060	0.14	0.61	54.2	1.1
69	Pittsburgh, PA	38300	0.30	0.10	27.5	2.4
70	Portland-South Portland-Biddeford, ME	38860	0.49	0.74	21.7	0.0
71	Portland-Vancouver-Hillsboro, OR-WA	38900	0.38	0.27	21.7	0.0
72	Providence-New Bedford-Fall River, RI-MA	39300	0.14	1.89	28.7	0.0
73	Provo-Orem, UT	39340	0.60	0.21	31	7.1
74	Raleigh-Cary, NC	39580	0.08	0.64	39.7	0.9
75	Richmond, VA	40060	0.09	-0.38	36.4	0.0
76	Riverside-San Bernardino-Ontario, CA	40140	0.38	0.53	54	0.1
77	Rochester, NY	40340	0.30	-0.06	25	12.4
78	Sacramento–Arden-Arcade–Roseville, CA	40900	0.14	0.20	46.3	0.0
79	Salt Lake City, UT	41620	0.72	-0.03	29.2	7.4
80	San Antonio-New Braunfels, TX	41700	0.03	-0.21	50.3	1.1
81	San Diego-Carlsbad-San Marcos, CA	41740	0.63	0.46	57.8	0.0
82	San Francisco-San Mateo-Redwood City, CA	41884	0.73	0.72	49.4	0.0
83	San Jose-Sunnyvale-Santa Clara, CA	41940	0.64	0.21	50	0.0
84	Santa Ana-Anaheim-Irvine, CA	42044	0.52	0.49	59	0.0
85	Seattle-Bellevue-Everett, WA	42644	0.44	0.92	40.9	0.0
86	Sioux Falls, SD	43620	0.03	-0.96	14	13.4
87	Spokane, WA	44060	0.27	0.69	27.3	4.4
88	Springfield, MA	44100	0.27	0.72	25.1	8.9
89	St Louis, MO-IL	41180	0.11	-0.73	29.6	7.4
90	Syracuse, NY	45060	0.18	-0.59	24	1.7
91	Tacoma, WA	45104	0.37	1.34	43	0.0
92	Tampa-St. Petersburg-Clearwater, FL	45300	0.42	-0.22	61.3	0.0
93	Toledo, OH	45780	0.19	-0.57	23.9	6.2
94	Trenton-Ewing, NJ	45940	0.12	1.75	31	0.3
95	Tucson, AZ	46060	0.23	1.52	51.7	0.6
96	Virginia Beach-Norfolk-Newport News, VA-NC	47260	0.60	0.12	40.1	0.0
97	Washington-Arlington-Alexandria, DC-VA-MD-WV	47894	0.14	0.31	34.9	0.0
98	West Palm Beach-Boca Raton-Boynton Beach, FL	48424	0.64	0.31	66	0.0
99	Wichita, KS	48620	0.02	-1.19	30.2	7.5
100	Wilmington, DE-MD-NJ	48864	0.15	0.47	31.5	0.0

Note: This table reports general information on the MSAs included in our data set. The MSA code is the 2004 FIPS code of the US Census Bureau. The classification of regions is based on the definitions of the Bureau of Labor Statistics.

Appendix D: Supplementary results

Table D.1: Cointegration results for West region

Name and state	MSA	β_y	$se(\beta_y)$	β_h	$se(\beta_h)$	β_R	$se(\beta_R)$	β_{SP}	$se(\beta_{SP})$	α_{ph}	$se(\alpha_{ph})$	Likelihood
ALBUQUERQUE NM	10740	2.337	0.455	-3.703	0.733	-0.706	0.815	3.173	0.326	-0.102	0.015	810.888
BOISE CITY ID	14260	3.195	0.849	-4.839	1.399	1.862	1.294	4.409	1.100	-0.104	0.018	694.391
BOULDER CO	14500	1.067	0.566	-0.474	1.091	-1.484	2.039	*	*	-0.053	0.013	730.559
COLORADO SPRINGS CO	17820	2.508	0.539	-3.613	0.984	-4.407	1.635	*	*	-0.063	0.012	776.615
DENVER CO	19740	6.951	2.433	-12.797	4.617	-5.743	4.356	*	*	-0.018	0.005	785.051
EUGENE OR	21660	2.044	0.569	-3.113	1.443	-4.549	1.592	2.740	1.077	-0.046	0.008	791.810
HONOLULU HI	26180	2.415	0.926	-2.918	1.339	-5.062	3.192	*	*	-0.056	0.015	747.334
LAS VEGAS NV	29820	0.095	0.563	-0.231	0.740	-1.396	1.321	2.943	0.649	-0.099	0.015	767.965
LOS ANGELES CA	31084	2.529	0.654	-5.156	1.953	-7.639	2.914	*	*	-0.040	0.008	763.807
OAKLAND CA	36084	0.903	1.237	-0.515	2.314	2.026	3.414	*	*	-0.030	0.006	773.917
OXNARD CA	37100	1.902	1.781	-3.041	2.994	-5.409	3.526	*	*	-0.027	0.005	772.899
PHOENIX AR	38060	1.754	0.418	-2.872	0.614	-2.328	1.348	3.577	0.556	-0.117	0.018	757.189
PORTLAND WA OR	38900	*	*	*	*	*	*	*	*	*	*	818.844
PROVO UT	39340	1.048	0.590	-0.625	0.874	0.663	1.174	*	*	-0.086	0.018	677.942
RIVERSIDE CA	40140	8.369	2.547	-10.295	3.103	-1.964	6.181	*	*	-0.024	0.005	772.813
SACRAMENTO CA	40900	1.727	1.177	-1.967	1.822	1.964	3.414	*	*	-0.036	0.007	786.398
SALT LAKE CITY UT	41620	0.839	0.465	-0.309	0.947	-1.725	1.990	*	*	-0.055	0.012	750.092
SAN DIEGO CA	41740	1.588	0.462	-1.694	0.865	-2.938	2.517	*	*	-0.046	0.008	785.910
SAN FRANCISCO CA	41884	1.158	1.018	-0.411	5.363	-3.722	3.533	*	*	-0.040	0.011	720.100
SAN JOSE CA	41940	*	*	*	*	*	*	*	*	*	*	725.835
SANTA ANA CA	42044	2.311	0.947	-4.113	1.430	-5.116	2.146	2.569	0.604	-0.042	0.007	842.696
SEATTLE WA	42644	*	*	*	*	*	*	*	*	*	*	809.667
SPOKANE WA	44060	2.086	1.193	-3.828	2.409	-2.734	1.590	2.396	0.790	-0.083	0.018	732.189
TACOMA WA	45104	*	*	*	*	*	*	*	*	*	*	749.397
TUCSON AZ	46060	2.280	1.008	-2.727	1.709	-2.844	3.291	*	*	-0.036	0.014	781.911

Notes: This table reports the cointegration results for the MSAs in our sample that are situated in the West region of the US. The first column lists the name of the MSA, as well as the state it belongs to. The next six columns show the estimated long-run elasticities (and standard errors thereof) of income, the housing stock and the interest rate (semi-elasticity). The final four columns display the long-run effect of subprime lending and the speed of adjustment parameter, along with the estimated standard errors. An asterisk means that the theoretical conjectures of the life-cycle model were rejected, or – in the case of subprime lending – that the variable does not enter the cointegrating vector. Absolute standard errors are reported. The final row shows the same numbers based on the mean group estimator. An asterisk is reported for the areas where interpretable cointegrating relationships were impossible to rationalize.

Table D.2: Specification results for West region

Name and state	MSA	Subprime?	Subprime LR?	p^*	q^*	*Dum.*	*Auto.*	*Norm.*	*Hetero.*	$Rank(\mathbf{\Pi}_i)$	p(Theory ok)
ALBUQUERQUE NM	10740	1	1	5	5	10	0.3275	0.7514	0.6980	2	0.1288
BOISE CITY ID	14260	1	1	5	3	7	0.0363	0.3619	0.0244	2	0.0981
BOULDER CO	14500	0	0	5	5	8	0.2425	0.5809	0.7965	0	0.1418
COLORADO SPRINGS CO	17820	0	0	3	3	17	0.4829	0.3650	0.0253	1	0.0003
DENVER CO	19740	0	0	5	4	6	0.0322	0.3021	0.7997	0	0.8039
EUGENE OR	21660	1	1	5	3	17	0.6008	0.0314	0.8041	2	0.1213
HONOLULU HI	26180	1	0	5	4	13	0.5553	0.8236	0.2611	1	0.0000
LAS VEGAS NV	29820	1	1	4	3	18	0.1763	0.0009	0.6919	2	0.6498
LOS ANGELES CA	31084	1	0	5	5	5	0.2057	0.0225	0.9823	2	0.0009
OAKLAND CA	36084	0	0	3	3	11	0.2731	0.1556	0.0004	2	0.0008
OXNARD CA	37100	0	0	4	3	11	0.4908	0.6822	0.5763	1	0.9110
PHOENIX AR	38060	1	1	5	4	10	0.1000	0.3693	0.0262	2	0.0162
PORTLAND WA OR	38900	0	0	5	2	11	0.0037	0.7298	0.2776	0	*
PROVO UT	39340	0	0	5	3	10	0.0580	0.8871	0.2654	2	0.2314
RIVERSIDE CA	40140	1	0	5	5	10	0.0446	0.0034	0.5392	1	0.0228
SACRAMENTO CA	40900	1	0	5	3	10	0.2297	0.2911	0.8185	2	0.0381
SALT LAKE CITY UT	41620	0	0	5	5	8	0.3792	0.3858	0.2712	0	0.3391
SAN DIEGO CA	41740	1	0	4	3	13	0.0075	0.1110	0.0071	2	0.0050
SAN FRANCISCO CA	41884	0	0	4	3	4	0.4703	0.6821	0.1753	1	0.0000
SAN JOSE CA	41940	1	0	4	3	8	0.0403	0.5787	0.2898	2	*
SANTA ANA CA	42044	1	1	5	5	15	0.0773	0.0010	0.9995	2	0.2423
SEATTLE WA	42644	1	0	5	5	14	0.9675	0.0520	0.4461	2	*
SPOKANE WA	44060	1	1	5	5	10	0.0206	0.3153	0.3589	1	0.0851
TACOMA WA	45104	1	0	4	4	10	0.8350	0.1029	0.3057	2	*
TUCSON AZ	46060	0	0	4	4	17	0.0832	0.2423	0.4032	0	0.1001

Notes: This table reports supplementary results for the MSAs in our sample that are situated in the West region of the US. The first two columns signify whether the subprime measure is part of the econometric model and the cointegrating vector, respectively. A value of one indicates that they are. The next three columns report the selected lag length for the endogenous (p_i^*) and the exogenous variables (q_i^*), as well as the number of dummies that were selected by the IIS algorithm. The next two columns report the p-value from tests for no autocorrelation and normality. The next column reports the estimated rank of the $\mathbf{\Pi}_i$ matrix in (8) as suggested by the trace test, i.e. the number of cointegrating relationships we find support for. The final two columns report the p-value for the test of whether the trend can be excluded and whether weak exogeneity is supported, and, conditional on subprime lending being in the model, whether it can be excluded from the cointegrating space. An asterisk is reported for the areas where interpretable cointegrating relationships were impossible to rationalize.

Table D.3: Cointegration results for East region

Name and state	MSA	β_y	$se\,(\beta_y)$	β_h	$se\,(\beta_h)$	β_R	$se\,(\beta_R)$	β_{SP}	$se\,(\beta_{SP})$	α_{ph}	$se\,(\alpha_{ph})$	Likelihood
ALBANY NY	10580	3.339	1.440	-8.403	2.736	-3.606	2.189	2.023	1.035	-0.056	0.012	662.017
BOSTON MA	14484	4.316	0.535	-15.226	2.003	-3.454	1.299	3.073	0.484	-0.077	0.011	758.931
BRIDGEPORT CT	14860	2.592	0.680	-8.373	2.629	-1.145	3.551	*	*	-0.043	0.008	738.297
BUFFALO NY	15380	0.888	0.581	-4.698	2.045	-4.372	1.838	*	*	-0.065	0.014	715.925
CAMBDEN NJ	15804	1.336	0.915	-3.281	1.595	-5.165	2.046	1.883	0.848	-0.062	0.013	772.600
EDISON NJ	20764	0.915	1.888	-1.121	3.571	1.394	5.061	*	*	-0.030	0.007	779.418
HARRISBURG PA	25420	1.095	0.323	-2.039	0.700	-0.738	0.565	1.702	0.204	-0.182	0.036	798.676
HARTFORD CT	25540	2.853	0.750	-5.354	1.464	-0.808	2.594	*	*	-0.055	0.014	691.805
MANCHESTER NH	31700	3.080	0.582	-5.165	1.130	-5.846	2.791	*	*	-0.047	0.012	640.066
NASSAU NY	35004	*	*	*	*	*	*	*	*	*	*	753.920
NEWARK PA NJ	35084	*	*	*	*	*	*	*	*	*	*	765.698
NEW HAVEN CT	35300	3.338	1.166	-6.193	2.422	0.712	3.760	*	*	-0.044	0.012	682.858
NEW YORK NJ NY	35644	*	*	*	*	*	*	*	*	*	*	750.559
OCEAN CITY NJ	36140	9.607	1.843	-24.843	5.228	-0.660	3.768	10.696	2.421	-0.052	0.009	549.963
PHILADELPHIA PA	37964	3.121	1.433	-12.429	5.303	-6.664	2.499	3.010	0.955	-0.042	0.011	788.185
PITTSBURG PA	38300	0.662	0.369	-0.385	1.874	-1.100	0.646	*	*	-0.120	0.040	839.430
PORTLAND ME	38860	2.510	0.381	-4.684	0.686	-3.576	0.918	2.234	0.410	-0.124	0.025	638.346
PROVIDENCE MA RI	39300	4.304	1.000	-8.713	2.227	-3.458	1.964	1.168	0.730	-0.067	0.013	785.777
SYRACUSE NY	45060	2.753	0.378	-7.097	0.901	-2.013	1.094	*	*	-0.101	0.019	664.597
TRENTON NJ	45940	3.259	1.732	-8.169	4.133	-0.951	3.768	1.910	1.180	-0.049	0.013	646.866

Notes: This table reports the cointegration results for the MSAs in our sample that are situated in the East region of the US. The first column lists the name of the MSA, as well as the state it belongs to. The next six columns show the estimated long-run elasticities (and standard errors thereof) of income, the housing stock and the interest rate (semi-elasticity). The final four columns display the long-run effect of subprime lending and the speed of adjustment parameter, along with the estimated standard errors. An asterisk means that the theoretical conjectures of the life-cycle model were rejected, or – in the case of subprime lending – that the variable does not enter the cointegrating vector. Absolute standard errors are reported. The final row shows the same numbers based on the MG estimator. An asterisk is reported for the areas where interpretable cointegrating relationships were impossible to rationalize.

Table D.4: Specification results for East region

Name and state	MSA	Subprime?	Subprime LR?	p^*	q^*	*Dum.*	*Auto.*	*Norm.*	*Hetero.*	$Rank(\mathbf{\Pi}_i)$	p(Theory ok)
ALBANY NY	10580	1	1	3	3	8	0.0428	0.5754	0.7658	1	0.7579
BOSTON MA	14484	1	1	3	3	8	0.7367	0.5939	0.7915	2	0.0000
BRIDGEPORT CT	14860	1	0	4	3	9	0.8070	0.6055	0.8435	1	0.9322
BUFFALO NY	15380	0	0	3	3	11	0.2979	0.8196	0.0883	1	0.0000
CAMBDEN NJ	15804	1	1	5	5	7	0.0721	0.3691	0.4491	1	0.0003
EDISON NJ	20764	1	0	5	5	8	0.3222	0.8181	0.8781	1	0.0197
HARRISBURG PA	25420	1	1	4	3	9	0.0377	0.7162	0.9855	1	0.0478
HARTFORD CT	25540	0	0	5	3	4	0.1903	0.2289	0.9481	1	0.0471
MANCHESTER NH	31700	0	0	4	3	4	0.2796	0.4072	0.0025	1	0.0224
NASSAU NY	35004	0	0	4	2	12	0.2719	0.4301	0.0448	1	*
NEWARK PA NJ	35084	1	0	4	3	9	0.0261	0.0523	0.3423	1	*
NEW HAVEN CT	35300	1	0	5	3	8	0.3603	0.4823	0.0007	1	0.0000
NEW YORK NJ NY	35644	0	0	5	5	8	0.1208	0.1541	0.2572	1	*
OCEAN CITY NJ	36140	1	1	5	2	3	0.1073	0.3743	0.1737	2	0.0004
PHILADELPHIA PA	37964	1	1	4	4	6	0.2939	0.6290	0.5050	1	0.0000
PITTSBURG PA	38300	0	0	4	4	12	0.2769	0.3045	0.6728	0	0.0000
PORTLAND ME	38860	1	1	4	2	3	0.0155	0.1510	0.0044	2	0.7919
PROVIDENCE MA RI	39300	1	1	5	5	11	0.0224	0.6806	0.0933	2	0.0072
SYRACUSE NY	45060	0	0	3	2	8	0.9229	0.6365	0.0036	2	0.0041
TRENTON NJ	45940	1	1	5	5	1	0.1037	0.0186	0.5301	0	0.0169

Notes: This table reports supplementary results for the MSAs in our sample that are situated in the East region of the US. The first two columns signify whether the subprime measure is part of the econometric model and the cointegrating vector, respectively. A value of one indicates that they are. The next three columns report the selected lag length for the endogenous (p_i^*) and the exogenous variables (q_i^*), as well as the number of dummies that were selected by the IIS algorithm. The next column reports the estimated rank of the $\mathbf{\Pi}_i$ matrix in (8) as suggested by the trace test, i.e. the number of cointegrating relationships we find support for. The final two columns report the p-value for the test of whether the trend can be excluded and whether weak exogeneity is supported, and, conditional on subprime lending being in the model, whether it can be excluded from the cointegrating space. An asterisk is reported for the areas where interpretable cointegrating relationships were impossible to rationalize.

Table D.5: Cointegration results for South region

Name and state	MSA	β_y	$se(\beta_y)$	β_h	$se(\beta_h)$	β_R	$se(\beta_R)$	β_{SP}	$se(\beta_{SP})$	α_{ph}	$se(\alpha_{ph})$	Likelihood
ATLANTA GA	12060	*	*	*	*	*	*	*	*	*	*	839.828
AUSTIN TX	12420	*	*	*	*	*	*	*	*	*	*	737.548
BALTIMORE MD	12580	2.439	0.646	-4.470	1.246	-1.840	1.259	1.615	0.373	-0.087	0.016	779.066
BIRMINGHAM AL	13820	0.697	1.277	-0.353	3.050	1.136	2.198	*	*	-0.043	0.027	793.624
CHARLOTTE SC NC	16740	3.224	1.943	-4.312	3.150	7.144	5.646	*	*	-0.012	0.006	831.284
CINCINNATI IN KY OH	17140	2.616	1.056	-4.731	2.244	0.110	1.480	*	*	-0.034	0.013	846.730
COLUMBUS OH	17980	*	*	*	*	*	*	*	*	*	*	843.014
DALLAS TX	19124	4.603	1.858	-8.392	3.752	1.807	5.886	*	*	-0.015	0.004	787.415
FORT LAUDERDALE FL	22744	0.118	0.805	-0.562	1.196	-1.071	0.997	3.953	0.375	-0.120	0.021	795.592
FORT WORTH TX	23104	*	*	*	*	*	*	*	*	*	*	771.688
GREENSBORO NC	24660	*	*	*	*	*	*	*	*	*	*	786.506
GREENVILLE SC	24860	*	*	*	*	*	*	*	*	*	*	812.239
HOUSTON TX	26420	1.768	0.573	-2.673	1.393	1.362	2.538	*	*	-0.033	0.006	739.343
JACKSONVILLE FL	27260	1.226	0.643	-2.458	1.107	-1.780	1.430	4.778	0.699	-0.088	0.022	780.496
LITTLE ROCK AR	30780	8.349	3.841	-16.111	7.805	1.159	3.369	*	*	-0.035	0.011	752.816
LOUISVILLE IN KY	31140	1.784	2.460	-3.447	5.119	-2.236	4.163	*	*	-0.016	0.007	818.177
MEMPHIS AR MS TN	32820	0.322	1.259	-0.219	2.793	0.035	1.927	*	*	-0.048	0.021	807.151
MIAMI FL	33124	1.011	0.729	-1.540	1.251	-1.153	1.285	4.631	0.499	-0.118	0.022	769.717
NASHVILLE TN	34980	*	*	*	*	*	*	*	*	*	*	809.226
NEW ORLEANS LA	35380	2.170	0.468	-3.996	2.248	0.861	2.436	*	*	-0.045	0.010	779.105
OKLAHOMA CITY OK	36420	2.260	0.158	-5.157	0.419	-0.958	0.747	*	*	-0.125	0.021	765.271
ORLANDO FL	36740	0.875	0.619	-1.629	0.928	-1.941	1.355	4.679	0.886	-0.077	0.019	768.634
RALEIGH NC	39580	*	*	*	*	*	*	*	*	*	*	813.020
RICHMOND VA	40060	1.456	0.015	-2.248	0.349	-0.534	0.443	2.396	0.153	-0.209	0.037	820.246
SAN ANTONIO TX	41700	0.991	1.412	-0.913	2.583	-6.454	4.264	*	*	-0.025	0.005	745.589
TAMPA FL	45300	1.404	0.581	-3.498	1.239	-3.899	1.280	4.115	0.540	-0.082	0.013	753.021
VIRGINIA BEACH NC VA	47260	1.045	0.707	-2.150	1.034	-1.312	1.091	3.326	0.688	-0.098	0.021	731.812
WASHINGTON WV MD VA	47894	2.353	0.668	-4.606	1.245	-4.527	1.233	3.694	0.426	-0.101	0.017	786.687
WEST PALM BEACH FL	48424	*	*	*	*	*	*	*	*	*	*	760.712
WILMINGTON NJ MD DE	48864	3.659	0.780	-5.435	1.309	0.111	2.002	*	*	-0.054	0.013	783.267

Notes: This table reports the cointegration results for the MSAs in our sample that are situated in the South region of the US. The first column lists the name of the MSA, as well as the state it belongs to. The next six columns show the estimated long-run elasticities (and standard errors thereof) of income, the housing stock and the interest rate (semi-elasticity). The final four columns display the long-run effect of subprime lending and the speed of adjustment parameter, along with the estimated standard errors. An asterisk means that the theoretical conjectures of the life-cycle model were rejected, or – in the case of subprime lending – that the variable does not enter the cointegrating vector. Absolute standard errors are reported. The final row shows the same numbers based on the mean group estimator. An asterisk is reported for the areas where interpretable cointegrating relationships were impossible to rationalize.

Table D.6: Specification results for South region

Name and state	MSA	Subprime?	Subprime LR?	p^*	q^*	*Dum.*	*Auto.*	*Norm.*	*Hetero.*	$Rank(\mathbf{\Pi}_i)$	p(Theory ok)
ATLANTA GA	12060	0	0	5	5	11	0.1163	0.3975	0.2174	2	*
AUSTIN TX	12420	0	0	4	4	5	0.9623	0.2427	0.8025	0	*
BALTIMORE MD	12580	1	1	5	5	4	0.5481	0.6481	0.1732	2	0.0553
BIRMINGHAM AL	13820	0	0	3	3	10	0.0168	0.5777	0.1927	0	0.0001
CHARLOTTE SC NC	16740	0	0	4	3	16	0.0343	0.0213	0.0000	0	0.0000
CINCINNATI IN KY OH	17140	0	0	5	3	6	0.0255	0.5111	0.4425	1	0.0000
COLUMBUS OH	17980	0	0	5	5	9	0.0838	0.6251	0.0019	1	*
DALLAS TX	19124	0	0	3	3	9	0.3933	0.9867	0.0120	1	0.0000
FORT LAUDERDALE FL	22744	1	1	5	5	15	0.0518	0.3582	0.8535	2	0.0000
FORT WORTH TX	23104	0	0	4	4	8	0.0040	0.7741	0.0926	1	*
GREENSBORO NC	24660	0	0	4	3	12	0.6555	0.0180	0.0000	0	*
GREENVILLE SC	24860	0	0	5	5	11	0.5551	0.7587	0.6716	1	*
HOUSTON TX	26420	0	0	2	2	7	0.1949	0.7980	0.0020	2	0.0053
JACKSONVILLE FL	27260	1	1	5	3	11	0.0028	0.3106	0.3471	2	0.0000
LITTLE ROCK AR	30780	0	0	4	4	8	0.0882	0.0766	0.1853	1	0.0000
LOUISVILLE IN KY	31140	0	0	4	3	9	0.3597	0.5809	0.1879	0	0.0208
MEMPHIS AR MS TN	32820	0	0	4	3	17	0.5974	0.0199	0.0320	0	0.0002
MIAMI FL	33124	1	1	5	5	9	0.2534	0.0233	0.9809	1	0.0933
NASHVILLE TN	34980	0	0	5	3	9	0.6702	0.2637	0.0768	0	*
NEW ORLEANS LA	35380	0	0	3	3	19	0.3701	0.6168	0.5280	1	0.0000
OKLAHOMA CITY OK	36420	0	0	4	4	8	0.1241	0.9864	0.0040	2	0.1699
ORLANDO FL	36740	1	1	4	3	11	0.2404	0.5092	0.5804	0	0.4090
RALEIGH NC	39580	0	0	4	3	7	0.3924	0.8162	0.0356	0	*
RICHMOND VA	40060	1	1	5	5	9	0.3500	0.4370	0.5360	2	0.0000
SAN ANTONIO TX	41700	0	0	5	3	11	0.8782	0.7941	0.5786	2	0.0762
TAMPA FL	45300	1	1	5	2	10	0.1571	0.1421	0.2858	2	0.0021
VIRGINIA BEACH NC VA	47260	1	1	5	5	3	0.7252	0.7721	0.9514	1	0.0000
WASHINGTON WV MD VA	47894	1	1	5	5	5	0.3044	0.3042	0.8783	2	0.0027
WEST PALM BEACH FL	48424	1	0	5	5	6	0.2119	0.0102	0.8637	2	*
WILMINGTON NJ MD DE	48864	0	0	5	5	8	0.2948	0.6978	0.9140	2	0.0113

Notes: This table reports supplementary results for the MSAs in our sample that are situated in the South region of the US. The first two columns signify whether the subprime measure is part of the econometric model and the cointegrating vector, respectively. A value of one indicates that they are. The next three columns report the selected lag length for the endogenous (p_i^*) and the exogenous variables (q_i^*), as well as the number of dummies that were selected by the IIS algorithm. The next two columns report the p-value from tests for no autocorrelation and normality. The next column reports the estimated rank of the $\mathbf{\Pi}_i$ matrix in (8) as suggested by the trace test, i.e. the number of cointegrating relationships we find support for. The final two columns report the p-value for the test of whether the trend can be excluded and whether weak exogeneity is supported, and, conditional on subprime lending being in the model, whether it can be excluded from the cointegrating space. An asterisk is reported for the areas where interpretable cointegrating relationships were impossible to rationalize.

Table D.7: Cointegration results for Midwest region

Name and state	MSA	β_y	$se\,(\beta_y)$	β_h	$se\,(\beta_h)$	β_R	$se\,(\beta_R)$	β_{SP}	$se\,(\beta_{SP})$	α_{ph}	$se\,(\alpha_{ph})$	Likelihood
AKRON OH	10420	*	*	*	*	*	*	*	*	*	*	834.246
ANN ARBOR MI	11460	1.747	0.440	-0.837	0.648	1.233	0.894	*	*	-0.102	0.017	707.963
CHICAGO WI IN IL	16974	0.888	0.692	-0.195	1.745	-2.429	1.120	*	*	-0.061	0.014	817.781
CLEVELAND OH	17460	*	*	*	*	*	*	*	*	*	*	810.905
DAYTON OH	19380	4.612	0.503	-9.921	1.224	-1.267	1.002	*	*	-0.066	0.008	845.564
DES MOINES IA	19780	2.172	0.512	-3.611	1.056	-0.045	0.769	*	*	-0.100	0.021	761.209
DETROIT MI	19804	3.097	0.983	-12.097	3.529	7.093	2.290	*	*	-0.038	0.007	806.081
FARGO MN ND	22020	2.593	1.491	-4.476	2.607	-7.033	3.165	*	*	-0.038	0.013	531.670
FORT WAYNE IN	23060	*	*	*	*	*	*	*	*	*	*	803.644
GARY IN	23844	3.019	0.701	-6.396	1.712	-2.270	1.173	*	*	-0.062	0.013	779.594
GRAND RAPIDS MI	24340	4.935	1.400	-8.723	2.743	5.336	2.224	*	*	-0.045	0.010	769.659
INDIANAPOLIS IN	26900	1.691	1.031	-2.621	1.895	1.963	2.005	*	*	-0.031	0.015	810.370
KANSAS CITY KS MO	28140	12.099	3.196	-24.191	6.689	-3.114	4.626	*	*	-0.011	0.003	870.207
LANSING MI	29620	*	*	*	*	*	*	*	*	*	*	808.954
MADISON WI	31540	2.085	1.187	-2.751	2.090	-5.641	2.398	*	*	-0.044	0.011	734.647
MILWAUKEE WI	33340	1.114	0.409	-0.347	0.934	-0.741	0.915	*	*	-0.076	0.014	852.999
MINNEAPOLIS WI MN	33460	6.549	1.300	-10.658	2.497	-5.995	3.169	*	*	-0.024	0.004	824.286
OMAHA IA NE	36540	2.811	0.626	-5.958	1.574	-2.134	1.310	*	*	-0.052	0.010	799.937
PEORIA IL	37900	*	*	*	*	*	*	*	*	*	*	802.263
ROCHESTER NY	40340	*	*	*	*	*	*	*	*	*	*	629.847
ST LOUIS IL MO	41180	2.047	0.475	-5.385	1.335	-0.304	0.729	2.414	0.282	-0.076	0.013	891.124
SIOUX FALLS SD	43620	1.916	0.670	-3.293	1.244	-2.692	1.495	*	*	-0.068	0.016	546.764
SPRINGFIELD MA	44100	*	*	*	*	*	*	*	*	*	*	675.713
TOLEDO OH	45780	*	*	*	*	*	*	*	*	*	*	781.336
WICHITA KS	48620	4.483	2.102	-10.175	5.002	-3.855	3.823	*	*	-0.022	0.011	776.478

Notes: This table reports the cointegration results for the MSAs in our sample that are situated in the Midwest region of the US. The first column lists the name of the MSA, as well as the state it belongs to. The next six columns show the estimated long-run elasticities (and standard errors thereof) of income, the housing stock and the interest rate (semi-elasticity). The final four columns display the long-run effect of subprime lending and the speed of adjustment parameter, along with the estimated standard errors. An asterisk means that the theoretical conjectures of the life-cycle model were rejected, or – in the case of subprime lending – that the variable does not enter the cointegrating vector. Absolute standard errors are reported. The final row shows the same numbers for the mean group estimator. An asterisk is reported for the areas where interpretable cointegrating relationships were impossible to rationalize.

Table D.8: Specification results for Midwest region

Name and state	MSA	Subprime?	Subprime LR?	p^*	q^*	*Dum.*	*Auto.*	*Norm.*	*Hetero.*	$Rank(\mathbf{\Pi}_i)$	p(Theory ok)
AKRON OH	10420	1	0	5	5	11	0.0013	0.8577	0.5924	2	*
ANN ARBOR MI	11460	0	0	5	4	9	0.2776	0.1411	0.8795	1	0.0032
CHICAGO WI IN IL	16974	0	0	5	3	10	0.0328	0.4220	0.4355	2	0.0000
CLEVELAND OH	17460	0	0	4	3	9	0.7941	0.1960	0.0772	2	*
DAYTON OH	19380	0	0	3	3	13	0.5957	0.0061	0.1293	1	0.0000
DES MOINES IA	19780	0	0	5	2	9	0.2693	0.4190	0.9887	1	0.0474
DETROIT MI	19804	1	0	5	5	15	0.7483	0.0332	0.2503	2	0.0072
FARGO MN ND	22020	0	0	5	2	6	0.4045	0.0373	0.9712	1	0.0000
FORT WAYNE IN	23060	0	0	3	3	16	0.2422	0.1263	0.7522	2	*
GARY IN	23844	0	0	3	3	11	0.4665	0.5034	0.1772	1	0.0032
GRAND RAPIDS MI	24340	1	0	5	5	8	0.6418	0.4265	0.2162	2	0.0229
INDIANAPOLIS IN	26900	0	0	4	3	7	0.3667	0.3437	0.7229	0	0.0000
KANSAS CITY KS MO	28140	0	0	4	3	10	0.4711	0.4133	0.9934	1	0.0000
LANSING MI	29620	1	0	5	5	15	0.0382	0.3741	0.1451	1	*
MADISON WI	31540	1	0	4	4	6	0.8418	0.0636	0.4093	0	0.0103
MILWAUKEE WI	33340	1	0	5	3	13	0.6875	0.9709	0.9769	1	0.0495
MINNEAPOLIS WI MN	33460	1	0	4	3	15	0.5785	0.0628	0.9739	1	0.0014
OMAHA IA NE	36540	0	0	3	3	11	0.2523	0.7524	0.9590	2	0.0004
PEORIA IL	37900	1	0	3	3	18	0.5389	0.7484	0.5279	1	*
ROCHESTER NY	40340	0	0	5	2	8	0.0709	0.5428	0.2329	0	*
ST LOUIS IL MO	41180	1	1	5	5	11	0.1291	0.2900	0.2093	2	0.0000
SIOUX FALLS SD	43620	0	0	2	2	6	0.3841	0.7061	0.2741	2	0.5024
SPRINGFIELD MA	44100	0	0	5	5	3	0.1916	0.3965	0.6990	0	*
TOLEDO OH	45780	0	0	5	4	8	0.0615	0.1304	0.0037	2	*
WICHITA KS	48620	0	0	4	2	9	0.0678	0.2419	0.7454	0	0.0007

Notes: This table reports supplementary results for the MSAs in our sample that are situated in the Midwest region of the US. The first two columns signify whether the subprime measure is part of the econometric model and the cointegrating vector, respectively. A value of one indicates that they are. The next three columns report the selected lag length for the endogenous (p_i^*) and the exogenous variables (q_i^*), as well as the number of dummies that were selected by the IIS algorithm. The next two columns report the p-value from tests for no autocorrelation and normality. The next column reports the estimated rank of the $\mathbf{\Pi}_i$ matrix in (8) as suggested by the trace test, i.e. the number of cointegrating relationships we find support for. The final two columns report the p-value for the test of whether the trend can be excluded and whether weak exogeneity is supported, and, conditional on subprime lending being in the model, whether it can be excluded from the cointegrating space. An asterisk is reported for the areas where interpretable cointegrating relationships were impossible to rationalize.