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Housing is local: Applying a dynamic unobserved factor model for the Dutch housing market

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HIGHLIGHTS

- This article investigates regional Dutch house price fluctuations.
- The paper employs a Bayesian multi-factor extension of Otrok and Whiteman (1998).
- Local factors play the most important role explaining house price fluctuations.

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ABSTRACT

We employ the multi-factor extension of the Otrok and Whiteman (1998) single, dynamic unobserved factor model in order to investigate regional Dutch house price fluctuations for the years 1995–2012. This paper is mainly concerned with two questions: First, is the Dutch housing market localized? Second, to which factors can we trace back this localization? We find that the Dutch housing market is highly localized. Although there is an important common housing cycle explaining house price comovement across all regions, idiosyncratic factors play the most important role. Although notably, group specific factors, separating Randstad of non-Randstad regions, are only of minor importance. Nevertheless, they can explain region-specific housing supply shocks. This latter finding can be partly traced back towards an agglomeration effect for Randstad regions.

1. Introduction

Is the so-called Randstad area.[1] – which is the economic and cultural heart of The Netherlands – different from non-Randstad regions in terms of its housing market? We use regional Dutch housing market data for 40 *corop* regions[2] for the time span 1995–2012[3] on a quarterly level and estimate a multi-factor extension of the Otrok and Whiteman (1998) single, dynamic unobserved factor model to find answers to the questions raised. Our aim is to identify common as well as region-specific factors explaining Dutch house price fluctuations. Our work is motivated by compelling empirical evidence that housing markets are local (among others, see Flor and Klarl (2017) or Ghent and Owyang (2010)) but national factors may also play a role (Del Negro and Otrok, 2007). We focus on the Dutch housing market because for several reasons it is special compared to the rest of Western-Europe countries.[4] In particular, and unlike most other neighboring Western-European countries, national annual real house price change was negative from 2008 until 2014. Hence, local characteristics may drive the Dutch housing market. Taking the arguments together, we conjecture that the Dutch house price comovement is explained by a common as well

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1 Randstad is a megalopolis in the central-western part of The Netherlands comprising the four largest Dutch cities, Amsterdam, Rotterdam, The Hague and Utrecht.

2 A *corop* region is a regional area within The Netherlands. The abbreviation stands for ***Co****ördinatiecommissie* ***R****egionaal* ***O****nderzoeks****p****rogramma*. Randstad regions are printed in bold letters in Table 1. We use the definition of corop regions valid from 1st January 2017.

3 Unfortunately, disaggregated data for corop regions are only available for the years 1995–2012.

4 For instance, the national Dutch housing market has a large social housing sector and has one of the lowest supply elasticities in the world (Sanchez and Johansson, 2011). See Boelhouwer (2017) for a detailed overview.

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as by group-specific factors which distinguish Randstad from non-Randstad housing markets and by a region-specific, idiosyncratic component.

The overall finding is that the Dutch housing market is highly localized but house price dynamics slightly differ between Randstad and non-Randstad areas. This is due to the fact that (i) the common factor comoves with financial factors and can further be associated with the Dutch business cycle, this factor, however, can only explain 27% of regional Dutch house price fluctuations. (ii) Although group specific factors are not quantitatively important they nevertheless can be used to explain region-specific housing supply shocks. (iii) In turn, idiosyncratic factors play the most important role. They account for more than 65% percent of the housing price variation of more than 50% of the Randstad as well as for non-Randstad regions.

The paper is structured as follows: The next section introduces the dynamic factor model followed by motivating the Bayesian estimation procedure and deriving the variance decomposition in Section 3. Next, Section 4 present the results. Section 5 concludes.

2. Dynamic factor model for the Dutch housing market

We employ the multi-factor extension of the Otrok and Whiteman (1998) single, dynamic unobserved factor model which is nowadays routinely used for analyzing business cycle comovement (see Jackson et al. (2016)). We postulate that house price dynamics can be explained by three factors. First, a common factor f^n which encompasses the house price dynamics across all Dutch *corop* regions and, second, the factors f^r (with r = Randstad or non-Randstad region) which drive the dynamics of either Randstad or non-Randstad regions conditional on comovement already captured by the common factor. Hence, having a balanced panel of $i = 1, \dots, N$ *corop* regions, each observed for $t = 1, \dots, T$ time periods, the dynamic factor model for the real house price $h_{i,t}$ of a region i at date t can be written as:

$$h_{i,t} = \beta_{c,i} f_t^c + \beta_{r,i} f_{i,t}^r + \epsilon_{i,t}, \tag{1}$$

for $i = 1, \dots, N$; $t = 1, \dots, T$. $\beta_{k,i}$ for $k = c, r$ is the factor loading that captures the sensitivity of the house price evolution of a region i due to changes of factor k. It is important to note that for a *corop* region, the factor loading associated to a region not belonging to this specific group is constrained to zero, and vice versa for the other regions. The region-specific, idiosyncratic error $\epsilon_{i,t}$ follows an $AR(p_i)$ process:

$$\epsilon_{i,t} = \phi_{i,1}\epsilon_{i,t-1} + \phi_{i,2}\epsilon_{i,t-2} + \cdots + \phi_{i,p_i}\epsilon_{i,t-p_i} + \zeta_{i,t}, \tag{2}$$

with $E\zeta_{i,s}\zeta_{j,t-s} = \sigma_i^2$ for $i = j$ and 0 for $s = 0$, otherwise. Likewise, the evolution of the factors is governed by an autoregression of order q_k:

$$f_{k,t} = \epsilon_{f_{k,t}} \tag{3}$$

$$\epsilon_{f_{k,t}} = \phi_{f_{k,1}}\epsilon_{f_{k,t-1}} + \phi_{f_{k,2}}\epsilon_{f_{k,t-2}} + \cdots + \phi_{f_{k,q_k}}\epsilon_{f_{k,t-q_k}} + \iota_{f_{k,t}}, \tag{4}$$

with $E\iota_{f_{k,t}}\iota_{f_{k,t-s}} = \sigma_{f_k}^2$ and $E\zeta_{i,t-s}\iota_{f_{k,t}} = 0 \forall\ k, i, s$. Note further that $\iota_{f_{k,t}} \sim i.i.d.\ \mathcal{N}(0, \sigma_{f_k}^2)$ and $\zeta_{i,t} \sim i.i.d.\ \mathcal{N}(0, \sigma_i^2)$ for $i = 1, \dots, N$; $k = 1, \dots, K$. Thus, all comovement in the data is entirely mediated by the above introduced factors, which in turn exhibit an autoregressive representation.

3. Bayesian estimation of the dynamic factor model and variance decomposition

3.1. Estimation procedure

We employ the Bayesian approach developed by Otrok and Whiteman (1998) to estimate the model (1)–(4).[5] As Kose et al. (2003) provide a detailed discussion of the multi-factor model, this section contains a brief description of the Bayesian estimation of the dynamic factor model. Estimating the dynamic factor model allows us to characterize the joint posterior of the model's parameters as well as the latent factors (see Crucini et al. (2011)). Based on a Markov Chain Monte Carlo (MCMC) algorithm, we have to simulate from the joint posterior of the latent factors as well as from the parameters since analytic forms for the joint posterior of the factors and parameters are not available. Essentially, the main part of Otrok and Whiteman (1998)'s approach is based on a Gibbs sampler that sequentially draws parameters conditional on the factors, followed by a conditional draw of the factors on the parameters. Moreover, conditioned on the factors, the innovations of the idiosyncratic terms are uncorrelated. Hence, our model contains N independent linear regression equations. Employing Chib and Greenberg's (1996) procedure, conditional on the factors, we separately draw parameter values for each equation.[6]

3.2. Prior specification

We closely follow Jackson et al. (2016) or Kose et al. (2008) and set the (conjugate) priors as follows. The prior mean for the factor loading vector $\boldsymbol{\beta}$ is Gaussian with mean zero and precision[7] equal to 0.01. The length of both, the idiosyncratic as well as the autoregressive polynomial is set to 3. The prior mean of each of the autoregressive factor-related or idiosyncratic coefficients is Gaussian with mean zero and precision 0.25 for all lags. Finally, the prior innovation variances in the observation equations are InvGam $\sim$ (4, 0.0625). We normalize the factor innovations to obtain a unit variance. Hence, these are quite diffuse priors. We have experimented also with different (and tighter) priors and lags. We find that our results are robust according to these changes.

3.3. Variance decomposition

In order to measure the relative importance of the national factor as well as regional and idiosyncratic factors to house price variations for Dutch regions, we also estimate the relative share of a region's house price variance due to each factor. With orthogonal factors, we can easily employ the variance operator on Eq. (1) to obtain the following expression:

$$var(h_{i,t}) = (\beta_{c,i})^2 var(f_i^c) + (\beta_{r,i})^2 var(f_i^r) + var(\epsilon_{i,t}). \tag{5}$$

Hence, the fraction of a region-specific house price volatility due to common (c), regional (r) or idiosyncratic (I) factors can be

[5] As we are not only interested in the common factor, we favor the Bayesian approach developed by Otrok and Whiteman (1998) against the simple computation of principal components (PC): Bayesian methods deliver more accurate results when model complexity increases and in contrast to the PC method, Bayesian methods automatically capture factor uncertainty. See Jackson et al. (2016) for a comparison of the PC procedure with the method suggested by Otrok and Whiteman (1998).

[6] Saying this, it is important to note that the Markov chain converges under some regularity conditions, which are satisfied here. For details, see Otrok and Whiteman (1998).

[7] The precision is the inverse of the prior's variance.