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**Housing Market Shocks in Italy:
a GVAR Approach**

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Housing Market Shocks in Italy: a GVAR approach

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Abstract

In this paper, we use a Global Vector Autoregression (GVAR) model to assess the spatio-temporal mechanism of house price spillovers, also known as “ripple effect”, among 93 Italian provincial housing markets, over the period 2004 – 2016. In order to better capture the local housing market dynamics, we use data not only on house prices but also on transaction volumes. In particular, we focus on estimating, to what extent, exogenous shocks, interpreted as negative housing demand shocks, arising from 10 Italian regional capitals, impact on their house prices and sales and how these shocks spill over to neighbours housing markets. The negative housing market demand shock hitting the GVAR model is identified by using theory-driven sign restrictions. The spatio-temporal analysis carried through impulse response functions shows that there is evidence of a “ripple effect” mainly occurring through transaction volumes.

Keywords: Ripple effect, housing market prices and volumes, Global VAR, sign restrictions

JEL: C32, C33, R21, R50

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1 Introduction

This paper investigates the spatial and temporal diffusion of house prices and transaction volumes across 93 Italian provincial housing markets, over the period 2004 – 2016.

The transmission mechanism of house price spillovers across space and time is known in literature as “ripple effect”. Meen (1999) gives four different explanations of the “ripple effect” in the UK housing markets – migration, equity transfer, spatial arbitrage and exogenous shocks. In particular, migration or equity transfer (e.g. longer-term residents of one area accumulate significant wealth in their home equity, cash out that equity by selling their home and moving to a lower cost region where a similar quality house costs much less) could lead to the ripple effect by increasing demand and thereby prices. Moreover, investors could spatially arbitrage their funds to acquire properties in lower priced regions, where higher anticipated returns exist on housing investment. In this case, financial capital moves, rather than households, between regions to link house prices. Finally, ripple effect pattern can be ascribed to heterogeneous responses of each region to exogenous macro conditions.

Empirical evidence of house prices spillovers across regions has been provided for UK (see Holly *et al.*, 2011; Gray, 2012; Tsai, 2014; Montagnoli & Nagayasu, 2015, among the others), for US (Brady, 2011, 2014), for China (Gong *et al.*, 2016) or for Denmark (Hviid, 2017). Most of these studies control for long run convergence in house prices by taking into account error correcting dynamics to long-run equilibrium relationship between house prices. The long-run analysis is particularly suitable to explore the role played by observed fundamentals (income and interest rates) in shaping the house prices long-run dynamics. However, given the short time data span, our analysis does not control for long-run equilibrium and error correcting dynamics.

Our first contribution to the existing studies on ripple effect using only house prices is based on an extension of the information set to transaction volumes in order to better capture the local housing market dynamics and the associated spillovers effect across space and time.¹

Second, our analysis allows to assess heterogeneity in the spatial-temporal diffusion. While most of the studies on “ripple effect” focus on spillovers from a dominant unit, in this paper we analyze how a specific shock to the house prices and transaction volumes arising from 10 Italian regional capitals spills over to other urban areas (their neighbours).

Finally, we contribute to the literature on the house price-volume correlation,

¹To our knowledge, the only study taking into account transaction volumes in estimating the “ripple effect” is the study of Tsai (2014).

which is based on the evaluation of the dynamic effects of observable housing market fundamentals on the price-volume co-movements (see Andrew & Meen, 2003; Clayton *et al.*, 2010, among the others). In particular, we analyze the spatio-temporal diffusion of house prices and volumes driven by unobserved fundamentals. The latent variable is interpreted as a negative housing demand shock identified through sign restrictions on house prices and transaction volumes modelled through a Global VAR, GVAR. The structural form impulse response analysis is informative on how local adverse shocks to fundamentals (which could be interpreted as a combination of negative income shock and a rise to interest rates) impact on house price and volumes of the other areas (neighbours).

The GVAR model used for the empirical analysis, introduced by Pesaran *et al.* (2004), is a multi-country extension of the standard VAR model which allows to examine the temporal transmission of shocks within and between different geographical areas. The model allows to control for common factor effects, by using a spatial exogenous regressor, and therefore, it allows to evaluate “genuine” spatial spillover effects across different housing markets. The structural housing demand shock is identified through theory-driven sign restrictions following the approach recently proposed in the study of Eickmeier & Ng (2015), which focuses on the transmission of US credit supply shocks across a panel of 33 countries over the period 1983 – 2009.

In this paper, we use semi-annual observations on real house prices and transaction volumes for 93 Italian provinces, over the period 2004 – 2016. More specifically, we use a confidential and unique dataset provided by the Real Estate Market Observatory managed by the Italian Revenue Agency (“Agenzia delle Entrate - Osservatorio del Mercato Immobiliare”) for the house prices. This rich dataset contains information at semi-annual frequency on maximum and minimum house prices (nominal, in euro) categorized by types of real estate (housing, appurtenances, office, retail and industrial) and areas (i.e. central, suburbs, hinterlands), at municipal level, over the period from second semester 2002 to second semester 2016. As for the transaction volumes, we use quarterly observations for the number of normalized transaction (NNT), collected from the publicly available database of the Real Estate Market Observatory - Italian Revenue Agency (“Agenzia delle Entrate - Osservatorio del Mercato Immobiliare”), covering the 2004Q1 - 2016Q4 time span. To match the semi-annual data frequency of house prices, we aggregate the quarterly data on volumes, by taking the sum over two consecutive quarters. Our analysis provides some interesting findings. First, contrary to a large body of literature, this study does not find evidence of a “ripple effect” in house prices, with the notably exception of Rome. Second, we find evidence of a “ripple effect” in transaction volumes. In particular, the empirical results show that transaction

volumes largely spill over across regional capitals and neighbours in response to the negative housing demand shock.

This paper is structured as follows. Section 2 provides a literature review on “ripple effect” and the price-volume correlation. Section 3 describes the empirical methodology. Section 4 describes data and the empirical findings and Section 5 concludes.

2 Literature review

2.1 Spatio-temporal analysis of “ripple effect”

The “ripple effect” embodies two prominent features of house price dynamics. The first is spatial dependence, e.g. cross-sectional correlation, relating each cross-section unit to its neighbours. The second one (which is fully accounted for by recent empirical studies based on spatial autoregressive and spatial error component models) is the lagged transmission of price changes across neighbours, given that information takes time to travel, especially in a market for relatively illiquid assets. Recently, Holly *et al.* (2011) compute impulse response analysis based on a Vector Autoregression (VAR) model (which includes a common spatial regressor as exogenous variable) fitted to house prices in London and 11 UK regions. The authors find evidence of dynamic house price spillovers from London to neighbouring regions in the UK. Brady (2011), focusing on California counties, estimates spatial IRFs obtained from a single-equation spatial autoregressive panel model. The author, using the Jordà (2005) local projection method (involving direct forecasting techniques) to get the impulse response function, finds that a shock to an average county house price in California has a positive (lasting two and half years) effect on the average house price in a neighbouring region. Brady (2014) computes spatial IRFs for US states, obtained from the estimation of a single equation spatial autoregressive model for house prices, including state-specific covariates such as real income, interest rates and housing starts (and their lags). A central role in the single equation dynamic model used in both studies is played by the “spatial regressor” treated as exogenous variable. The spatial IRF analysis in Brady (2014) shows that a shock to housing prices at the state level has a persistent effect (reaching the steady state within four years) on the panel of US states. The study of Gong *et al.* (2016) lends support to the house price temporal diffusion effect in a large emerging market such as China. The authors focus on monthly house price indexes of 10 cities’ housing markets in the Pan-Pearl River Delta (Pan-PRD) area of China, covering the period from June 2005 to May 2015. The generalized impulse response functions (GIRF) obtained from traditional VAR (without spatial

regressors) confirm a propagation of the house price shocks occurring to a given city approximately in accordance with the distance decay pattern found in the study of Holly *et al.* (2011). Hviid (2017), using a Global Vector Error Correction Model (VECM), augmented with a common spatial regressor, fitted to Danish house price data, finds strong evidence of a “ripple effect” in the short run of the model, but less so in the long run. This finding is interpreted as the “ripple effect” playing an important role as push factor in the short run, while house prices are mainly determined by regional fundamental factors in the long run.

All the aforementioned studies control for long run convergence in house prices (at least within clubs) by taking into account error correcting dynamics to long-run equilibrium relationship between house prices.

The study of Meen (1999) highlights the important role played by structural differences in regional housing markets (including different local economic conditions), beyond migration and spatial arbitrage. Therefore, the author suggests to focus on spatial coefficient heterogeneity when studying the dynamics of UK regional house prices. The study of Meen (1999) has inspired a number of researchers to analyze heterogeneity in the “ripple effect” (e.g. spatial heterogeneity). Van Dijk *et al.* (2011) detect the existence of two clusters of regions (mainly in terms of the average house prices growth rate) in the Netherlands: regions within the cluster have the same house price dynamics. Moreover, Gray (2012), using exploratory spatial data analysis and house price data from local authority districts in England and Wales, finds evidence that house price spillover north of the East Midlands appears much more rapid than what would be consistent with a “ripple effect”. The empirical findings of the study suggest that there is some support for the analysis of the British housing market on a spatially segmented basis, even at a regional level. The study of Montagnoli & Nagayasu (2015) investigates the presence of house prices spillover among 12 UK regions over the period 1983Q1-2012Q3. The authors, using the approach proposed by Diebold & Yilmaz (2009) on VAR models fitted to either 12 regional house price inflation rate or to the corresponding house price inflation volatility, find evidence of a “ripple effect” from London house prices to the other UK regions, whose magnitude declines as the spatial distance from London increases.² Pijnenburg (2017), focusing on a balanced panel of 319 Metropolitan Statistical Areas (MSAs) of the US, observed over the period from 2004Q2 to 2009Q2, estimates a panel smooth transition regression model in order to capture the heterogeneity in spatial dependence across time and space as well as the heterogeneity in the effect of the fundamentals. The author finds evidence of heterogeneity spatial spillovers of house prices across space and time. In particular, heterogeneity in the effect of the fundamentals on house price dynamics is

²In a first stage of the analysis, Montagnoli & Nagayasu (2015) test the UK regional house prices convergence, finding evidence of four convergence clubs.

only found for population growth and building permits, but not for real per capita disposable income and the unemployment rate.

To our knowledge, the only study on the “ripple effect” taking into account transaction volumes is the one of Tsai (2014). The author, using monthly data on house prices and transaction volumes over the period 1995m2-2012m3, examines the presence of long-run convergence among 10 UK regional housing market. The use of panel-based unit root tests (developed by Im *et al.* (2003)) finds evidence of stationarity in the ratios of the regional to national house prices (as well as the one for transaction volumes). These findings are interpreted as evidence of convergence for both house prices and transaction volumes. Moreover, the analysis of Tsai (2014) shows that volumes converge to its equilibrium faster than the house prices.

2.2 House price-volume correlation

This paper also seeks to contribute to the literature on the relationship between prices and transaction volumes and the underlying housing market fundamentals. An early studies of Follain & Velz (1995) for the US and the one of Hort (2000) for Sweden suggest a negative relationship between house prices and sales volumes. In particular, Hort (2000) investigates to what extent a housing demand shock impacts on house prices and transaction volumes in the Swedish regional housing markets. Using data on house prices, transaction volumes and after-tax mortgage rate, the author employs VAR using monthly data (over the 1981 – 1993 time data span) or quarterly data (over the 1982 – 1996 sample period). The empirical findings (especially those based on monthly observations) reveal a strong negative reaction of sales, on impact, to a positive shock on nominal interest rate, while house prices start to decrease after 3 – 4 months.

Other more recent empirical studies point at a positive correlation between the two covariates. Andrew & Meen (2003), using data for UK house prices and transaction volumes over the period 1969 – 1996, estimate the adjustment mechanism of the two variables to their fundamentals. First, the authors construct a measure of long-run housing market disequilibrium (defined as the ratio of the desired owner-occupier housing stock to the actual stock), by using housing market fundamentals variables, such as income, housing stock, number of households and construction costs. In a second stage of the analysis, the authors estimate a conditional VAR model where house prices and turnover rate are regressed on deviations from equilibrium. Their findings show a positive correlation between house price and volume in the short-run period. Further, the authors find that volumes exhibit an adjustment faster than the house price in reaction to a shock to fundamentals. Empirical evidence of a positive price-volume correlation is also

provided by the study of Clayton *et al.* (2010). Using data for 114 MSA of the US observed over the 1990 – 2002 period, the authors estimate a panel VARX fitted to house prices and turnover rates. The exogenous variables are covariates related to labour market conditions and they are used as proxies of fundamentals. The authors show that the positive co-movement of the housing market aggregates is mainly driven by shocks to employment and household’s income. Moreover, the authors find that transaction volumes react more than house prices to exogenous shocks. De Wit *et al.* (2013) focus on the Dutch economy (the sample period considered is 1985 – 2007) and they use a Vector Error Correction model (VECM) fitted to proxies of house price (the real list price and the real transaction price), proxies of volume (the rate of entry and the rate of sale) and proxies of housing market fundamentals (unemployment and the real mortgage interest rate). The authors find evidence of an interest shock reducing both house prices and transaction volumes.

A number of studies provide some theoretical support to the evidence of a positive correlation between house prices and transaction volumes.³ The positive price-volume correlation might depend on the presence of financial constraints. For example, the study of Stein (1995) develops a model where a positive shock to the housing market fundamentals increases prices as well as producing more incentive in demanding house, with an increase in the entry of new houses for sales, hence in the transaction volumes. Other studies have stated that the empirical evidence on the positive relationship between house prices and sales can be explained with the use of a search model where the idiosyncratic preferences of potential buyers are modelled on the basis of a mismatch costs between buyers and sellers (see Berkovec & Goodman, 1996, among the others). Finally, the positive correlation between house prices and transaction volumes might be caused by the market liquidity. In particular, Krainer (2001) considers a model of individual choice under uncertainty and frictions, where buyer and seller’s decisions are jointly modelled. In equilibrium, both sellers and buyers maximize their expected values in a price-setting model. When the market price is high, “the opportunity cost of keeping an empty house” on the market increases, because the value of the house might decrease in the next period. In such a context, sellers slightly decrease their reservation price, matching the one that buyers are willing to pay, and the transaction volume increases.

While the aforementioned studies focus on observed fundamentals as drivers of price-volume co-movement, in this study we focus on unobserved fundamentals identified on housing demand shock.

³De Wit *et al.* (2013) provide an extended review of the main theoretical frameworks.

Recently, a number of studies have focused on the role played by unobservable fundamentals, that is a housing demand shock in driving the international transmission of house price across countries. Vansteenkiste & Hiebert (2011) analyze the house price spillover mechanism across 7 Euro area countries, over the 1971 – 2009 time span. The empirical model used is a Global VAR, GVAR, fitted to real house prices, real per capita income, and real long-term interest rate. Vansteenkiste & Hiebert (2011) find evidence of heterogeneity in the relatively small country house price responses to demand shocks. Cesa-Bianchi (2013) examines the international transmission of housing demand shocks using data on 33 Advanced Economies (AEs) and Emerging Market Economies (EMEs), for the period 1983 – 2009. The author uses a GVAR model to evaluate to what extent a housing demand shock in US impact on a set of macroeconomic and financial variables, including GDP and house price. In a second stage of the analysis, the authors estimates the GDP response to regional housing demand shocks (a synchronized increase in house prices in AEs). Although the main focus of the paper is on the response of the GDP across countries, Cesa-Bianchi (2013) finds that an increase in house prices also affects foreign housing markets.

3 Empirical methodology

3.1 Estimation procedure

For each of the 5 Italian macro-regions, that is Northwest, Northeast, Central, South and Insular Italy (see Table 1), we construct a bivariate GVAR model (with no time trend) for real house price ($\Delta H P$) and sales ($\Delta N T N$) changes, where the corresponding province-specific $VARX^*$ models present a lag of order one for both domestic and foreign variables, $VARX^*(1, 1)$:

$$y_{it} = a_{i0} + \Phi_{i1}y_{i,t-1} + \Lambda_{i0}y_{it}^* + \Lambda_{i1}y_{i,t-1}^* + u_{it} \quad (1)$$

for $i = 1, \dots, N$ and for $t = 1, \dots, T$, where y_{it} is a $k_i \times 1$ vector of domestic variables, y_{it}^* is a $k_i^* \times 1$ vector of foreign variables, a_{i0} is a $k_i \times 1$ vector of intercepts and $u_{it} \sim iid(0, \Sigma_{u_i})$ is a $k_i \times 1$ vector of reduced form residuals, while Φ_{i1} and $\Lambda_{i\ell}$, for $\ell = 0, 1$, are the coefficients matrices.

The foreign variables, $y_{it}^* = \sum_{j=1}^N w_{ij}y_{jt}$, are constructed using spatial weights ($w_{ij} \geq 0$) based on contiguity between provinces i and j , with $w_{ij} = 1/n_i$ if provinces i and j share a border and zero otherwise, where n_i is the number of neighbours of i . Note that $w_{ii} = 0$, by construction (see Appendix A).

Defining $z_{it} = (y_{it}, y_{it}^*)' = W_i y_t$ as the $(k_i + k_i^*) \times 1$ vector containing both domestic and foreign variables, where y_t is the $K \times 1$ stacked vector of all the endogenous

variables in the N provinces, with $K = \sum_{i=1}^N k_i$, and W_i is a $(k_i + k_i^*) \times K$ matrix containing the spatial weights, w_{ij} :

$$W_i = \begin{pmatrix} 0 & \dots & I_{k_i} & \dots & 0 \\ w_{i1}I_{k_i^*} & \dots & w_{ii}I_{k_i^*} & \dots & w_{iN}I_{k_i^*} \end{pmatrix} \quad (2)$$

the model in eq.(1) can be written as:

$$A_i W_i y_t = a_{i0} + B_{i1} W_i y_{t-1} + u_{it} \quad (3)$$

where $A_i = (I_{k_i}, -\lambda_{i0})$, $B_{i1} = (\Phi_{i1}, \lambda_{i1})$ are the $k_i \times (k_i + k_i^*)$ matrices of coefficients constructed from estimating the model in eq.(1).

Furthermore, the province-specific models are rearranged into the corresponding GVAR models:

$$G y_t = a_0 + H_1 y_{t-1} + u_t \quad (4)$$

where

$$G_{(K \times K)} = \begin{pmatrix} A_1 W_1 \\ A_2 W_2 \\ \vdots \\ A_N W_N \end{pmatrix}, \quad H_1_{(K \times K)} = \begin{pmatrix} B_{11} W_1 \\ B_{21} W_2 \\ \vdots \\ B_{N1} W_N \end{pmatrix}, \quad a_0_{(K \times 1)} = \begin{pmatrix} a_{10} \\ a_{20} \\ \vdots \\ a_{N0} \end{pmatrix}, \quad u_t_{(K \times 1)} = \begin{pmatrix} u_{1t} \\ u_{2t} \\ \vdots \\ u_{Nt} \end{pmatrix} \quad (5)$$

with $u_t \sim iid(0, \Sigma_u)$. If G is invertible, the model in eq.(4) can be written as:

$$y_t = b_0 + F_1 y_{t-1} + \epsilon_t \quad (6)$$

where $b_0 = G^{-1}a_0$, $F_1 = G^{-1}H_1$ and $\epsilon_t = G^{-1}u_t$.

3.2 Structural Identification

Generally, the identification of shocks in GVARs is based on the Generalized impulse response functions (GIRF) framework originally proposed by Koop *et al.* (1996). Although this approach is not sensitive to the ordering of the variables, it admits correlated errors, hence the economic interpretation of the resulting shocks might be difficult (see Pesaran *et al.*, 2004). More recently, a number of studies have extended structural identification schemes to GVARs, to identify a single shock or a subset of shocks through either a Cholesky factorization (see Dees *et al.*, 2007a; Cesa-Bianchi, 2013, among the others) or through sign restrictions (Chudik & Fidora, 2011).

In this paper, we follow the suggestions of Eickmeier & Ng (2015) relying on sign restrictions on the impulse responses obtained from a GVAR model. The generation

of candidate structural impulse response relies on the Householder transformation approach proposed by Rubio-Ramirez *et al.* (2010).

Before commenting on the strategy used to identify the structural shocks, it is important to note that the spillover analysis in GVARs, which captures the transmission mechanism of shocks across different cross-sectional units, relies on designating one unit (province in our analysis) as a “dominant unit”.⁴

The structural identification strategy we adopt in the analysis requires the orthogonalization of the shocks originating from the dominant unit (or units), while it admits for shocks which are correlated with those originating from the remaining units.

Following Eickmeier & Ng (2015), the first step consists of computing the Cholesky decomposition of the N residuals covariance matrices, $\Sigma_{u_i} = E(u_{it}u'_{it})$, for $i = 1, \dots, N$, obtained from the estimation of the individual reduced form province-specific VARX* models and, then, we combine the resulting Cholesky decomposition matrices, P_i into a $K \times K$ block diagonal matrix, P :

$$P = \begin{pmatrix} P_1 & 0 & \dots & \dots & 0 \\ 0 & \ddots & & & \vdots \\ \vdots & & P_i & & \vdots \\ \vdots & & & \ddots & 0 \\ 0 & \dots & \dots & 0 & P_N \end{pmatrix} \quad (7)$$

The P matrix in eq.(7) is then used for the purpose of orthogonalizing the residuals of GVAR, u_t , defined in eq.(4), as $v_t = (v_{1t} \dots v_{it} \dots v_{Nt})' = P^{-1}G\epsilon_t$, where v_t has dimension $K \times 1$. Note that the relationship between u_t and ϵ_t is defined as $G^{-1}u_t = \epsilon_t$. Therefore, the h -step ahead impulse responses matrices (which have dimension $K \times K$) associated with the orthogonalized residuals, v_t , are given by $\Psi^h = F_1^h G^{-1}P$. The (i, j) -th element denotes the h -step ahead response of the i -th endogenous variable to a shock occurring in the j -th endogenous variable.

Let us define m dominant (main) units, with $m \in N$. Following Eickmeier & Ng (2015), for the m -th dominant unit, we randomly draw $k_m \times k_m$ independent standard gaussian matrices, \tilde{X}_m , where k_m denotes the number of endogenous variables for the m -th unit. Since in our analysis the number of endogenous variables is equal to two, for each province, we let k_m equal to two for the rest of the section.

Further, we compute the QR decomposition of \tilde{X}_m , that is $\tilde{X}_m = \tilde{Q}_m \tilde{R}_m$ (see Rubio-Ramirez *et al.*, 2010).⁵ For each replication, we multiply the $2 \times K$ orthog-

⁴Generally, the dominant cross-section unit is labelled as unit 0 (see Pesaran *et al.*, 2004; Chudik & Pesaran, 2016, for example). However, the GVAR model we consider for each macro-region includes more than one dominant unit in the analysis.

⁵To ensure that the QR decomposition of the independent standard gaussian matrix is unique,

onalized residuals of the dominant unit, v_{mt} , by the 2×2 orthogonal matrix, \tilde{Q}_m , to obtain the structural shock for the m -th dominant unit, $\eta_{mt} = (\tilde{Q}_m v_{mt})'$.

Since we impose sign restrictions on the impulse response only on impact, we remove the superscript h from the notation, for the rest of this subsection.

The corresponding impulse responses ($h = 0$) are computed as $\Theta_m = (\Psi_m \tilde{Q}'_m)'$, where Ψ_m is the 2×2 block matrix, for the selected m -th unit, in the impulse response matrix, Ψ (which has dimension $K \times K$). We discard the rotation matrices whose multiplications by the impulse responses, Ψ_m , do not satisfy the sign restrictions. In particular, we check the sign restrictions by focusing on the 2×2 matrix, Θ_m , for the m -th “dominant” unit. We repeat the algorithm until we save 1000 valid rotation matrices, \tilde{Q}_m .

For each of the 5 macro-regional GVAR models, we select one or more “dominant” units which correspond to the main regional capitals (or provinces) under investigation. Therefore, we apply the above described algorithm for the selected “dominant” unit. Following Eickmeier & Ng (2015), we also report the acceptance rates of the rotation matrices which satisfy the sign restrictions (see Table 2).⁶ To better explain how the above described algorithm works, in Table 2 we also report some information on the dimension of matrices for each macro-regional GVAR model.

Our focus is, first, on the identification of a negative innovation to housing demand in a specific regional capital (which is related to a combination of negative shock to income and a positive shock to interest rates), and also on the propagation of this shock to house prices and transaction volumes across neighbouring Italian provinces. For this purpose, we impose, on impact, a negative response both for house prices and transaction volumes (see Table 3).

The identification of only one structural shock in a system with two endogenous variables (house prices and sales) implies the estimation of a “partially identified” VAR (or $VARX^*$) model (see Kilian & Lütkepohl, 2017). To overcome the partial identification issue in a GVAR framework, we follow the suggestion reported by the study of Eickmeier & Ng (2015) which concentrates only on the identification of US credit supply shock.

Let us consider a generic m dominant unit. For each draw, we focus on the 2×2 block matrix $\Theta_m = (\Psi_m \tilde{Q}'_m)'$ at zero horizon and check if the response of the variables agrees with the sign restrictions in Table 3 as:

$$\Theta_m = \begin{bmatrix} \leq & \leq \\ n.a & n.a \end{bmatrix} \quad (8)$$

the diagonal of the upper triangular matrix, \tilde{R}_m , is normalized to be positive (see also Arias *et al.*, 2014).

⁶The analysis of this paper is conducted in R. Our codes are, to a large extent, an adaptation of Eickmeier & Ng (2015)’s MATLAB codes and Galesi & Smith (2014)’s GVAR toolbox.

It is important to note that the structural shock is reported in a row by construction. However, it is possible that a generic draw leads to the following situation:

$$\Theta_m = \begin{bmatrix} \leq & \leq \\ \leq & \leq \end{bmatrix} \quad (9)$$

where both of the two shocks are orthogonal, but their economic interpretation become difficult. Since we focus on identifying one structural shocks (e.g. a negative housing demand shock), Eickmeier & Ng (2015) suggest to check the sign of the responses also in the second row and keep the draw if the signs in the second row are complement of the ones in the first row (see also Kilian & Lütkepohl, 2017):

$$\Theta_m = \begin{bmatrix} \leq & \leq \\ \leq & \geq \end{bmatrix} \text{ or } \begin{bmatrix} \leq & \leq \\ \geq & \leq \end{bmatrix} \quad (10)$$

Hence, we discard the draw in which the responses of the variables to the structural shocks report the same signs, as in eq.(9), otherwise we keep the draw. As mentioned before, we repeat the algorithm until we save 1000 valid rotation matrices, for each m -th dominant unit.

3.2.1 Median Target (MT) approach

In the last few years, the use of theory-driven sign restrictions has become a valid alternative tool for the identification of the structural shocks in VAR models. However, there are drawbacks associated with the use of sign restrictions. As argued by Fry & Pagan (2007), there is no guarantee that the impulse responses, which satisfy the imposed sign restrictions, come from the same model. Therefore, reporting the uncertainty of the identified impulse responses through the use of their quantiles might lead to wrong conclusions.

In line with Eickmeier & Ng (2015), once obtaining the set of impulse responses satisfying the sign restrictions, we apply the Median Target (MT) approach originally proposed by Fry & Pagan (2007), which is based on selecting the impulse responses which are the closest to the median values of those generated by all the admissible models.

According to the MT approach proposed by Fry & Pagan (2007), for each saved draw, that is $\tilde{Q}_m^{(r)}$, with $r = 1, \dots, 1000$, we first standardize the associated identified h -step ahead impulse responses of the “dominant” unit by subtracting their median and dividing by their standard deviation. Further, since we only focus on the response on impact, we vectorize the 2×2 block matrix of impulse responses at $h = 0$, that is $\Theta_m^{(r)'} = (\Psi_m^{(r)} \tilde{Q}_m^{(r)'})$, in a 4×1 vector, $\theta_m^{(r)}$.

Finally, once selecting the r -th draw that minimizes $\theta_m^{(r)'} \theta_m^{(r)}$, say \tilde{Q}_m^* , we select from the $(K \times K)$ h -step ahead impulse responses matrix, Ψ^h , a $2 \times K$ matrix, ψ_m^h ,

for the m -th “dominant” unit and we multiply this matrix by \tilde{Q}_m^* , as $(\psi_m^{h'} \tilde{Q}_m^*)'$, for $h = 0, \dots, H$, to produce the new set of impulse responses, which contains the responses of the K endogenous variables in the system to a shock occurring in the m -th “dominant unit”.

Following Eickmeier & Ng (2015), \tilde{Q}_m^* is also used to produce bootstrap for the GVAR model.

3.2.2 Bootstrapping the GVAR model

In particular, we use the sieve bootstrap procedure originally proposed by Bühlmann (1997) for Autoregressive (AR) processes and, more recently, employed by Dees *et al.* (2007a), Dees *et al.* (2007b) and Eickmeier & Ng (2015).

Following the approach reported in the study of Dees *et al.* (2007b), given the K -dimensional vector of residuals, $\hat{\epsilon}_t = (\hat{\epsilon}_{1t}, \hat{\epsilon}_{2t}, \dots, \hat{\epsilon}_{Nt})'$, with $K = \sum_{i=1}^N k_i$, obtained from eq.(6), we randomly draw B series with replacement from the residuals, that is $\epsilon_t^{(b)} = (\epsilon_{1t}^{(b)}, \epsilon_{2t}^{(b)}, \dots, \epsilon_{Nt}^{(b)})'$.⁷

To obtain the bootstrapped residuals $\epsilon_t^{(b)}$, we first pre-whiten the residuals $\hat{\epsilon}_t$ as $\hat{\eta}_t = \hat{A}^{-1} \hat{\epsilon}_t$, where \hat{A}^{-1} is the generalized inverse obtained through a spectral decomposition of $\hat{\Sigma}_\epsilon$. In fact, the covariance matrix of the residuals $\hat{\epsilon}_t$ can be decomposed through a spectral decomposition, that is $\hat{\Sigma}_\epsilon = \hat{V} \hat{\lambda} \hat{V}'$, where \hat{V} is an orthogonal matrix containing the eigenvectors, while $\hat{\lambda}$ is a diagonal matrix reporting the eigenvalues. The generalized matrix, \hat{A} , is then computed as $\hat{A} = \hat{V} \hat{\lambda}^{1/2}$. The resampling with replacement is conducted on the pre-whiten residuals, $\hat{\eta}_t$.⁸ For each b -th replication, with $b = 1, \dots, B$, we compute the bootstrapped residuals of the GVAR model as $\epsilon_t^{(b)} = \hat{A} \hat{\eta}_t^{(b)}$ and use them, together with the point estimate retrieved from eq.(6), to generate new artificial series, $y_t^{(b)}$:

$$y_t^{(b)} = \hat{b}_0 + \hat{F}_1 y_{t-1}^{(b)} + \epsilon_t^{(b)} \quad (11)$$

where $y_0^{(b)} = y_0$ are the actual initial observations. For each replication b , the artificial series are then used to retrieve new provincial-specific $VARX^*(1, 1)$ estimates from:

$$y_{it}^{(b)} = \hat{a}_{i0}^{(b)} + \hat{\Phi}_{i1}^{(b)} y_{it-1}^{(b)} + \hat{\lambda}_{i0}^{(b)} y_{it}^{*(b)} + \hat{\lambda}_{i1}^{(b)} y_{it-1}^{*(b)} + \hat{u}_{it}^{(b)} \quad (12)$$

⁷We use the notation $\hat{\epsilon}_t$ to distinguish them from the bootstrapped residuals, $\epsilon_t^{(b)}$. However, it is important to note that $\hat{\epsilon}_t$ are not directly estimated, since the estimation is conducted for the provincial-specific $VARX^*(1, 1)$ models. In explaining the bootstrap procedure, we follow the same notation reported in Dees *et al.* (2007b) and use the superscript “ $(\hat{\cdot})$ ” to distinguish the quantities obtained through point estimation from the ones obtained by bootstrapping the GVAR.

⁸To reduce the complexity of the algorithm, Dees *et al.* (2007b) suggest to resample on a stacked version of the pre-whiten residuals $\hat{\eta}_t$.

with $i = 1, \dots, N$. From estimation of the new provincial-specific $VARX^*(1, 1)$ models in eq.(12), we construct the corresponding GVAR model and compute the bootstrapped impulse responses.

In line with Eickmeier & Ng (2015), these impulse responses, identified once again through sign restrictions, are computed following the algorithm described above (see Section 3.2). However, differently from the point estimate, to check whether the impulse response of the m -th “dominant unit” respects the signs, we use the selected rotation matrix, $\tilde{Q}_m^{*'}$, to compute $\Theta_m^{(b)} = (\Psi_m^{(b)} \tilde{Q}_m^{*'})'$.

Finally, the $100(1 - \alpha)\%$ confidence interval is constructed as $\alpha/2$ and $(1 - \alpha)/2$ quantiles of the whole set of impulse responses to the identified structural shock, for each i -th province and h -th step ahead, on the basis of 200 bootstrap replications.

It is important to note that in a GVAR model correlation between residuals arises within-country (e.g. between the innovations associated with variables of a province-specific model) and across-countries (e.g. between the innovations to the same endogenous variable corresponding to different units, provinces). The identification through sign restrictions allows to address the issue of within-country residuals correlation. The issue of across-countries residuals correlation is addressed by conditioning the domestic endogenous variables, y_{it} , on the “foreign” variables, y_{it}^* . In order to check the cross-country correlation, we compute the average pairwise cross-country correlations among the endogenous variables and the individual $VARX^*(1, 1)$ residuals (see Cesa-Bianchi, 2013; Eickmeier & Ng, 2015). Similar to the empirical findings of Cesa-Bianchi (2013) and of Eickmeier & Ng (2015), we obtain that the largest pairwise cross-country correlation between residuals (in absolute value) is 0.24, while the corresponding mean is 0.04 (see Table 4).

4 Empirical analysis

4.1 Data

We use semi-annual observations on real house prices and transaction volumes for 93 Italian provinces, over the sample period 2004 – 2016.

More specifically, we use a confidential and unique dataset provided by the Real Estate Market Observatory managed by the Italian Revenue Agency (“Agenzia delle Entrate - Osservatorio del Mercato Immobiliare”) for house prices. This rich dataset contains information at semi-annual frequency on maximum and minimum values of house prices (nominal, in euro) categorized by types of real estate (housing, appurtenances, office, retail and industrial) and areas (i.e. central, suburbs,

hinterlands), at municipal level, over the sample period running from the second semester 2002 to the second semester 2016. To construct the provincial house prices series for the residential property, we take the average value between the minimum and maximum house prices (for housing category) of the corresponding regional capital. Given the presence of missing data, we discard the series for the provinces of L’Aquila and Macerata.⁹ We compute the real house prices by applying the Italian Consumer price index (CPI), downloaded from the statistical database of the Italian National Institute of Statistics (ISTAT), on the provincial house prices series.

As for the transaction volumes, we use time series (available at quarterly frequency) for the number of normalized transactions (NNT)¹⁰, collected from the publicly available database of the Real Estate Market Observatory - Italian Revenue Agency (“Agenzia delle Entrate - Osservatorio del Mercato Immobiliare”), covering the 2004Q1 – 2016Q4 time span. It is important to observe that, in order to match the semi-annual data frequency of house prices, we aggregate the quarterly data on volumes, by taking the sum over two consecutive quarters. Given the lack of volumes data for 11 provinces, the final number of provinces considered is equal to 93 (see Table 1).¹¹

Given the lack of data for most of provinces which belong to Sardinia, we exclude this region from the analysis.

Since the time series for prices and volumes are not stationary, we apply the first order difference operator to the log transformation of the real house prices and of the number of transactions.¹²

4.2 Results

Figures 1 and 2 show the structural impulse responses of house prices and transaction volumes (in levels) to a negative housing demand shock to 10 Italian regional

⁹The house prices series for L’Aquila reveal a relevant number of missing entries. Particularly, data for the period July 2009 - June 2012 are not provided. This lack of observations might be due to the heavy earthquakes which devastated part of the Central Italy, including L’Aquila and its neighbourhood zones, on April 2009. We also discard the house prices series for Macerata, where the last observation is missing.

¹⁰The NNT is the number of “standardized” units sold, taking into account the share of property transferred.

¹¹The missing time series series refer to the following provinces: Bolzano/Bozen, Trento, Gorizia and Trieste (Northeast), where the cadastre and/or the land registry are managed by local administrations, and Monza e della Brianza (Northwest), Fermo (Centre), Barletta-Andria-Trani (South), Carbonia-Iglesias, Medio-Campidano, Ogliastra and Olbia-Tempio (Islands).

¹²Results based on the autocorrelation functions (ACF) plots are available upon request.

capitals.¹³

Given the use of first order difference of the log transformation of the real house prices and of the transaction volumes, the impulse responses for the series in levels are computed as cumulative sum of ones obtained for the first order difference.

In line with Eickmeier & Ng (2015), all the figures show the bootstrap median estimates (black line) and the 90 percent confidence intervals (shadow area) obtained through the Median Target (MT) approach. Each figure displays two Charts. Chart *a* is the plot of the impulse response of the m -th main regional capital house prices and sales to a negative housing demand shock occurring to the m -th main regional capital. Chart *b* is the plot of the impulse response of the house prices and sales of the m -th main regional capital's neighbours to a negative housing demand shock arising from the m -th main regional capital.

For the sake of simplicity, we define the response of the m -th main regional capital's aggregate to the exogenous shock arising from the m -th main regional capital as "Domestic response", while the response of the neighbours' house prices and volumes to the exogenous shock occurring to the m -th main regional capital is labelled as "Spillover effect".

In Chart *b*, the spatial dimension is captured by considering the provinces which share a common border with the main province (say, its neighbours). Since a regional capital is likely to share common borders with more than one province (see Table 5), we aggregate the impulse responses of individual neighbours using their Value added reported on 2014 as weights (see Eickmeier & Ng, 2015; Vansteenkiste & Hiebert, 2011).¹⁴

The orthogonalized impulse response are to a one standard deviation negative shock to housing demand and they are computed over a 10 semesters (e.g. 5 years) forecast horizon.

All the impulse responses of house prices in regional capitals ("domestic response") are negative and statistically significant (see Figure 1, Chart *a*). Inspection of Figure 1 (Chart *a*) shows that the largest "domestic response" of the house prices level, on impact, is recorded for Milano (2.98 percent) and the lowest is for Torino (0.81 percent). Figure 1 (Chart *a*) shows that the "domestic" negative response persists and it converges to a new equilibrium value, at most, over a five-year horizon. This finding is confirmed by Table 6 (panel *a*) showing the *Within domestic ratio*, that is the "domestic response" for each forecast horizon relative to the one occurring'

¹³Given the focus on house prices and transaction volumes of regional capitals in each province, "regional capital" and "province" are used, in this section, as synonymous.

¹⁴To weight impulse responses of individual units, Eickmeier & Ng (2015) use the PPP-adjusted GDP averaged over 2006 – 2008, while Vansteenkiste & Hiebert (2011) use 2007 real GDP to aggregate the impulse responses of a group of Euro area countries.

In our analysis, we use provincial Value added downloaded from the Statistical Database of the Italian National Institute of Statistic (ISTAT). The latest available observations refer to 2014.

at time 0. Table 6 (panel a) shows that the index slightly increases reaching the highest value in the last semesters, in almost all main regional capitals.

This results are also confirmed by inspecting Figure 3, which shows the “domestic response” of house prices changes (Chart *a*) and the corresponding “spillover effect” (Chart *b*) to a negative housing demand shock to 10 Italian regional capitals. As shown in Figure 3 (Chart *a*), changes in house prices in response to a negative housing demand shock to main regional capitals become smaller as the forecast horizons increase.

The analysis of the “ripple effect” is carried out by, first, inspecting “spillover effect” on impact. In order to interpret the empirical evidence shown in Chart *a* and Chart *b*, we compute the *Spillover index* which is measured, on impact, by the ratio of the median response (at horizon 0) of the neighbours (the “spillover effect”) to the median response (at horizon 0) of the main regional capitals (the “domestic response”). Table 7 (panel a) shows that, on impact, the largest transmission of the shock to neighbours is recorded in the main cities of Mezzogiorno, such as Palermo (37.95 percent), Bari (27.74 percent) and Napoli (27.56 percent).¹⁵ The lowest values of the transmission mechanism on impact are recorded in Bologna (−1.40 percent) and Milano (3.84 percent). The relative small values of the impact *Spillover index* in Torino, Genova, Venezia and Firenze are 12.91, 13.29, 14.95 and 11.24 percent, respectively.

Moreover, in line with previous empirical studies on “ripple effect”, we need to compare the plots of Chart *a* and Chart *b* by computing a *Spillover index* for horizons beyond time 0. For this purpose, we choose to focus on a time span involving at most five years ahead (ten semesters). Both the numerator and the denominator of the *Spillover index* for the different forecast horizons are responses to a 1 standard deviation negative housing demand shock to the regional capital occurring at time 0. We focus, first, on discussing results for the house prices spillovers. From Table 7 (panel a), it can be observed that the *Spillover index* decreases (over a time span involving forecast horizons beyond time 0 up to the next five years) in three Northern cities, such as Torino (from 7.92 to 5.23 percent), Milano (from 8.21 to 5.85 percent) and Venezia (from 12.04 to 7.82 percent), and in two Mezzogiorno cities, such as Napoli (from 34.84 to 27.79 percent) and Palermo (the average *Spillover index*, across forecast horizons beyond time 0 is equal to 11.84 percent, lower than the initial impact equal to 37.95 percent). All the remaining cities exhibit an heterogeneous increase in the *Spillover index*. More specifically, a moderate increase can be observed in the Northern cities: Genova, from 13.61 to 14.64 percent, and Bologna, from 14.77 to 18.88 percent. The cities in Central Italy and Bari exhibit the largest increase (Firenze, from 21.95 to 29.18 percent,

¹⁵ISTAT defines Mezzogiorno as the macro-area which includes the six Southern regions and the Islands of Sardinia and Sicily

Roma, from 47.84 to 61.27 percent, and Bari, from 41.02 to 47.22 percent). The convergence of the *Spillover index* to an equilibrium value is fastest in Northern cities, such as Genova, Milano and Bologna, where the index reaches an equilibrium value over one-year horizon, while it takes longer, say 2–3 years, in the two Central regions, Firenze and Roma, where the *Spillover index* reaches equilibrium values equal to around 28 and 61 percent, respectively, and in two Mezzogiorno cities, such as Napoli and Palermo, in which the *Spillover index* reaches values equal to around 28 and 13 percent, respectively.

We now turn the focus on the responses of transaction volumes to negative housing demand shock. From Figure 2, it can be observed that, on impact, both the “domestic response” and the “spillover effect” are larger than the ones recorded in house prices. Similarly to the results obtained for house prices level, all the “domestic responses” are negative and statistically significant, with the exception of Torino and Palermo where the median impulse response becomes not statistically significant for long forecast horizons (see Figure 2, Chart a). The largest impact “domestic response” of the transaction volumes level is recorded in Bari (7.14 percent), while the lowest is associated once more in Torino (2.95 percent). Differently from the results obtained for house prices, the “domestic response” of transaction volumes level reaches its maximum value over one-year horizon, in almost all main cities. As shown in Table 6 (panel b), the *Within domestic ratio* reaches its peak throughout two semesters in almost all cities (with the exception of Milano and Bologna) showing values of the ratio larger than the ones recorded at a five-years horizon.

Figure 4 shows the impulse response of main regional capital’s transaction volumes changes (Chart a) and neighbours’ transaction volume changes (Chart b) to a negative housing demand shock to 10 Italian regional capitals. If we focus on the “domestic response”, it can be seen from Figure 4 (Chart a) that the transaction volumes changes strongly react to the exogenous shock over the first semester before reaching their base value.

To investigate the presence of a “ripple effect” in the Italian main provinces, we also focus on the *Spillover index* constructed for transaction volumes (see Table 7, panel b). At horizon 0, the largest transmission of the housing demand shock to neighbours transaction volumes level is observed for Milano (76.59 percent) and, to less extent, in Bari (54.91 percent), while the *Spillover index* is similar for the other main cities, with values ranging from 26.96 percent (Roma) to 44.18 percent (Bologna). Moreover, we focus on the transitional path of the volumes “spillover effect” from time 0 to a five-year forecast horizon, by comparing the *Spillover index* corresponding to a forecast horizon beyond time 0 with the one associated with a five-years horizon. It can be seen from Table 7 (panel b) that the *Spillover index*

strongly increases in Bari (from 44.63 to 73.96 percent) and in Roma (from 10.72 to 36.14 percent). Since confidence intervals for Bari get dramatically wider as the forecast horizons increase (see Figure 2), we focus only on Bari spillover effect over a short-run forecast horizon. More specifically the empirical results for Bari suggest an average *Spillover index* beyond time 0 up to e.g. 2 years equal to 58 percent, that is a value bigger than the one for the impact effect. The other main city in Mezzogiorno, Napoli, shows an increase in the *Spillover index*, since there is a moderate increase by 5 percent. A rise of the *Spillover index* across forecast horizon beyond time 0 is also recorded by the Northern cities, including: Bologna (from 77.36 to 89.45 percent), Torino (from 60.23 to 70.07 percent) and, to less extent, Genova (from 59.73 to 63.41 percent). However, all the three Northern cities report values of the index at a five-years horizon decisively larger than the ones reported at time 0 (44.18, 29.96 and 39.71 percent, respectively). All the remaining main cities exhibit a decrease of the *Spillover index*: Venezia (from 65.94 to 51.29), Firenze (from 65.75 to 56.94), Milano (from 106.72 to 99.58 percent) and, to less extent, Palermo (from 59.03 to 55.96 percent). However, the average *Spillover index*, across forecast horizon beyond time 0, in each of these four cities is larger than the index measured at time 0 (the average values are equal to 51.74, 55.34, 99.39 and 53.44 percent, respectively).

The convergence of the volumes *Spillover index* to its equilibrium value is slower than the one observed for the house prices. The fastest convergence (over two years) is recorded in two Northern cities, such as Genova and Bologna, and only in one city of the Mezzogiorno, Napoli. All the remaining cities show a slower convergence process, taking the whole five-years horizon.

To summarize, the structural impulse response (IRF) analysis together with the associated *Spillover index* provides some interesting findings. First, contrary to a large body of literature, this study does not find evidence of a “ripple effect” in house prices. There is evidence of neighbours small response to a negative housing demand shock to the main regional capital, especially in the North of Italy. The only exception is Roma, where the *Spillover index* increases over the whole forecast period, showing a “spillover effect” at five-years horizon three times bigger than the one reported on impact.

We find that transaction volumes largely spill over across regional capitals and neighbours in response to the negative housing demand shock. In all the 10 main regional capitals, the *Spillover index* at five-years horizon is larger than its value on impact. Our findings are consistent with the study of Tsai (2014), which focuses on UK housing market. In particular, the empirical evidence in this paper supports the presence of a “ripple effect” in transaction volume. Our findings are consistent with a number of studies which focus on the impact of unobserved

shocks to fundamentals on price-volume correlation. While the literature concentrates on reduced form shocks to fundamentals, we focus on the response to an unobserved structural form shock to fundamentals, interpreted as negative housing demand shock. Focusing on the “domestic response”, our findings show a stronger reaction, on impact, of transaction volumes than house prices. This results support those of Hort (2000) and Clayton *et al.* (2010), which find a reaction of the number of sales and the turnover rates (respectively) to reduced form shocks to fundamentals, on impact, larger than the response of house prices. The two housing market aggregates show a different behaviour beyond time 0. In line with the study of Andrew & Meen (2003), which focuses on the response of house prices and transaction volumes (changes) to an interest rate shock in UK housing market, we find that house prices slightly decrease over the whole forecast period, while transaction volumes strongly react over few semesters, say 2 – 3 semesters, before reaching their base value, in almost all the 10 main regional capitals. Finally, we find evidence of an heterogeneity in the ripple effect given a different propagation of the negative housing demand shock arising in each dominant unit to the price and the volumes of neighbours.

5 Conclusions

In this paper, we have contributed to the literature on the spatio-temporal diffusion house prices, which is known as “ripple effect”. First, we have focused not only on house prices but also on transaction volumes. The bi-annual dataset is for 93 Italian provinces, over the period 2004 – 2016. Second, we have explored heterogeneity in the “ripple effect” by considering different dominant units. Third, we have also contributed to the literature on price-volume co-movement associated to reduced form shocks to the fundamentals, by focusing on a structural form innovation identified as negative housing demand shock. The use of a structural shock allows to circumvent the issue related to the lack of provincial data for fundamental drivers of house prices such as interest rates on loan and income.

The spillover analysis has been carried out by using a GVAR model based on a spatial exogenous regressor obtained from the construction of a spatial weight matrix (spatial econometric approach). The structural housing demand shocks in each of the 10 Italian main regional capitals have been identified by using theory-driven sign restrictions.

The structural impulse response functions obtained from the estimated GVAR allow to address the three aforementioned issues.

As for the analysis on “ripple effect”, we do not find evidence of a strong propagation mechanism of the housing demand shocks on neighbours house prices.

Oppositely, in line with the study of Tsai (2014) which finds evidence of a “ripple effect” in transaction volumes for UK, we find a significant transmission mechanism of the exogenous shock to neighbours through sales, in almost all the 10 provinces under investigation.

Second, there is evidence of heterogeneity in the ripple effect given the different responses to a shock to each dominant unit.

Finally, we also focus on the relationship between house prices and transaction volumes in response to a housing demand shock. This results support those of Hort (2000) and Clayton *et al.* (2010), which find a reaction of the number of sales and the turnover rates (respectively) to reduced form shocks to fundamentals, on impact, larger than the response of house prices. The two housing market aggregates show a different behaviour beyond time 0. In line with the study of Andrew & Meen (2003), which focuses on the response of house prices and transaction volumes (changes) to an interest rate shock in UK housing market, we find that house prices slightly decrease over the whole forecast period, while transaction volumes strongly react over few semesters, say 2 – 3 semesters, before reaching their base value, in almost all the 10 main regional capitals.

The evidence of heterogeneity in the ripple effect implies the existence of segmented housing markets regardless of the geographical location and it might suggest housing market policy intervention tailored to the local condition of a given housing market.

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Appendices

Appendix A

Weighting strategy

The estimation of the province-specific $VARX^*(1,1)$ models involves the construction of the N weights matrices, W_i , with $i = 1, \dots, N$, in order to get spatial regressors by averaging out the foreign variables, $y_{it}^* = \sum_{j=1}^N w_{ij} y_{jt}$.

Generally, the weighting strategy is modelled by using shares of cross-country trade flows (Pesaran *et al.*, 2004; Dees *et al.*, 2007a; Cesa-Bianchi, 2013, among the others), cross-country bank lending exposures (Galesi & Sgherri, 2009, among the others), a combination of weights based on both trade and financial flows (Eickmeier & Ng, 2015) or spatial-based weights (Vansteenkiste, 2007; Vansteenkiste & Hiebert, 2011).

Since our aim is to highlight a spatial dimension of the propagation mechanism of housing market shocks in the Italian provinces, we use time-fixed geographic weights.¹⁶

In order to construct the $(k_i + k_i^*) \times K$ province-specific link matrix, W_i , our methodology relies on constructing spatial weights based on contiguity between province i and province j (see Holly *et al.*, 2011).¹⁷ Given N geographical units, the spatial matrix, labelled as S , is a $N \times N$ binary matrix with generic entries $w_{ij} \geq 0$, where $w_{ij} = 1$ if provinces i and j share a border and zero otherwise:

$$S = \begin{pmatrix} 0 & w_{12} & \dots & w_{1N} \\ w_{21} & 0 & \dots & w_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1} & \dots & \dots & 0 \end{pmatrix} \quad (\text{A.1})$$

with $w_{ij} = w_{ji}$. Note that the main diagonal elements in S are zero, $w_{ii} = 0$, by construction. Furthermore, we standardize S by row sum (\bar{S}), with generic entries $\bar{w}_{ij} = 1/n_i$, where n_i is the number of neighbours of the i -th province (see

¹⁶Most of the data used in Spatial econometrics are on irregular areas, such as regions or provinces. Generally, information on irregular areas take the form of *shape files*, which include, for example, the spatial coordinates and the attributes associated to each spatial unit. In our analysis, we use the *shape file* downloaded from the Italian National Institute of Statistic (ISTAT), containing spatial information for the Italian provinces. The construction of the spatial weights matrix is implemented by using the **spdep** and **maptools** packages in R.

¹⁷The spatial weights can be also constructed on the basis of geographic distance (see Vansteenkiste, 2007; Vansteenkiste & Hiebert, 2011, among the others) or socio-economic distance (see Conley & Topa, 2002, for example).

also Holly *et al.*, 2011). Those spatial weights are then rearranged into the link matrices, W_i (see eq.(2)).

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Table 1: Italian provinces grouped at NUTS1 (macro-regional) and NUTS2 (regional) levels.

Macro-regions	Regions	Provinces
North-West	Aosta Valley	Aosta
	Liguria	Genoa, Imperia, La Spezia and Savona
	Lombardy	Bergamo, Brescia, Como, Cremona, Lecco, Lodi, Mantova, Milano, Pavia, Sondrio and Varese
	Piedmont	Alessandria, Asti, Biella, Cuneo, Novara, Torino Verbania and Vercelli
North-East	Emilia-Romagna	Bologna, Ferrara, Forl�-Cesena, Modena, Parma, Piacenza, Ravenna, Reggio Emilia and Rimini
	Friuli Venezia-Giulia	Pordenone and Udine
	Veneto	Belluno, Padova, Rovigo, Treviso, Venezia, Verona and Vicenza
Centre	Lazio	Frosinone, Latina, Rieti, Roma and Viterbo
	Marche	Ascoli Piceno, Ancona and Pesaro (and Urbino)
	Tuscany	Arezzo, Firenze, Grosseto, Livorno, Lucca, Massa (and Carrara), Pisa, Pistoia, Prato and Siena
	Umbria	Perugia and Terni
South	Abruzzo	Chieti, Pescara and Teramo
	Apulia	Bari, Brindisi, Foggia, Lecce and Taranto
	Basilicata	Matera and Potenza
	Calabria	Cosenza, Catanzaro, Crotona, Reggio Calabria and Vibo Valentia
	Campania	Avellino, Benevento, Caserta, Napoli and Salerno
	Molise	Campobasso and Isernia
Islands (or Insular)	Sicily	Agrigento, Caltanissetta, Catania, Enna, Messina, Palermo, Ragusa, Siracusa and Trapani

Notes. Since the presence of missing values, we exclude provinces in Trentino Alto-Adige (a region of the North-East of Italy) and Sardinia (a region of Insular Italy) from the analysis (see Section 4.1).

Table 2: GVAR models, acceptance rate and matrix dimension.

GVAR	Regional capital	Acceptance rate	Matrix dimension
Northwest	Torino	1036/1000	$k = 2, N = 24, K = 48$
	Genova	1086/1000	
	Milano	1317/1000	
Northeast	Venezia	1262/1000	$k = 2, N = 18, K = 36$
	Bologna	1162/1000	
Centre	Firenze	1174/1000	$k = 2, N = 20, K = 40$
	Roma	1313/1000	
South	Napoli	1116/1000	$k = 2, N = 22, K = 44$
	Bari	1012/1000	
Islands	Palermo	1396/1000	$k = 2, N = 9, K = 18$

Notes. The acceptance rate indicates the number of rotation matrices drawn, \tilde{Q}_m , necessary to obtain the 1000 valid point estimates of impulse responses. The Table also provides some information helpful to understand the dimension of matrices described in Section 3. k is the number of endogenous variables for each of the 93 Italian provinces, N is the number of provinces for each macro-regional GVAR and $K = \sum_{i=1}^N k_i$.

Table 3: Sign restrictions on impact

	Volumes	Prices
Housing market shock	-	-

Notes. The sign restrictions refer to a negative shock. The restrictions are imposed as \leq .

Table 4: Average pairwise cross-section correlations.

	Northwest				Provinces	Northeast			
	Sales		HP			Sales		HP	
	Δy_{it}	Res	Δy_{it}	Res		Δy_{it}	Res	Δy_{it}	Res
ALESSANDRIA	0.302	0.021	0.141	0.075	BELLUNO	0.256	-0.025	0.286	0.067
AOSTA	0.123	0.000	-0.003	0.005	BOLOGNA	0.484	0.018	0.088	0.026
ASTI	0.406	0.041	0.019	0.000	FERRARA	0.519	-0.008	0.241	0.110
BERGAMO	0.352	0.074	0.066	-0.042	FORLÍ-CESENA	0.238	-0.081	0.300	0.007
BIELLA	0.382	0.045	0.045	0.075	MODENA	0.382	-0.039	0.269	0.083
BRESCIA	0.313	0.057	0.060	0.037	PADOVA	0.311	0.002	0.312	0.061
COMO	0.382	0.099	-0.099	-0.112	PARMA	0.413	-0.061	0.341	0.045
CREMONA	0.157	-0.017	0.017	-0.013	PIACENZA	0.385	-0.020	0.349	0.078
CUNEO	0.197	-0.047	0.070	0.073	PORDENONE	0.425	0.004	0.110	-0.072
GENOVA	0.475	0.063	0.181	-0.025	RAVENNA	0.494	0.016	0.111	-0.010
IMPERIA	0.227	0.020	0.115	0.030	REGGIO EMILIA	0.511	0.006	0.230	0.038
LA SPEZIA	0.297	0.022	0.223	0.043	RIMINI	0.418	0.077	0.389	0.082
LECCO	0.259	-0.038	0.208	0.113	ROVIGO	0.312	-0.044	0.105	0.013
LODI	0.141	0.053	0.054	0.038	TREVISO	0.389	-0.029	0.321	0.078
MANTOVA	0.278	0.040	0.176	0.073	UDINE	0.317	-0.011	0.307	0.103
MILANO	0.433	0.044	0.093	0.050	VENEZIA	0.403	-0.006	0.325	0.069
NOVARA	0.406	0.026	0.107	0.017	VERONA	0.434	0.027	0.373	0.058
PAVIA	0.271	-0.016	0.092	-0.015	VICENZA	0.390	-0.020	-0.013	-0.007
SAVONA	0.251	-0.044	0.172	-0.001					
SONDRIO	0.163	-0.037	0.136	0.010					
TORINO	0.487	0.035	0.133	-0.025					
VARESE	0.224	-0.055	-0.098	-0.025					
VERBANIA	0.280	0.073	0.136	0.010					
VERCELLI	0.262	-0.042	0.197	-0.007					
	Centre				Provinces	South			
	Sales		HP			Sales		HP	
	Δy_{it}	Res	Δy_{it}	Res		Δy_{it}	Res	Δy_{it}	Res
ANCONA	0.415	0.046	0.445	0.004	AVELLINO	0.219	0.018	0.107	0.042
AREZZO	0.424	0.061	0.393	0.049	BARI	0.230	-0.006	0.326	-0.008
ASCOLI PICENO	0.204	0.045	0.358	-0.014	BENEVENTO	0.071	-0.086	0.192	-0.022
FIRENZE	0.356	0.019	0.413	0.031	BRINDISI	0.306	0.026	0.282	-0.038
FROSINONE	0.064	0.024	0.387	0.052	CAMPOBASSO	0.209	0.009	0.278	0.001
GROSSETO	0.238	0.055	0.113	-0.080	CASERTA	0.159	0.087	0.336	0.057
LATINA	0.346	0.085	0.374	-0.015	CATANZARO	0.273	0.082	0.294	-0.022
LIVORNO	0.450	0.081	0.498	0.042	CHIETI	0.032	-0.008	0.279	0.051
LUCCA	0.391	0.015	0.459	-0.013	COSENZA	0.238	0.087	0.104	0.104
MASSA	0.225	0.044	0.211	-0.039	CROTONE	0.124	-0.002	0.201	-0.005
PERUGIA	0.342	-0.068	0.505	-0.008	FOGGIA	0.169	-0.049	0.393	0.164
PESARO	0.285	-0.072	0.365	-0.017	ISERNIA	-0.033	0.004	0.280	0.041
PISA	0.316	-0.006	0.462	-0.013	LECCE	0.262	-0.004	0.331	0.096
PISTOIA	0.212	-0.032	0.377	0.001	MATERA	0.102	-0.054	0.220	0.030
PRATO	0.248	0.097	0.351	0.043	NAPOLI	0.166	0.004	0.432	0.104
RIETI	0.339	0.002	0.418	0.053	PESCARA	0.163	0.021	0.334	0.060
ROMA	0.440	0.081	0.344	-0.005	POTENZA	0.054	0.003	0.118	-0.030
SIENA	0.166	-0.076	0.253	0.009	REGGIO CALABRIA	-0.025	-0.064	0.245	0.048
TERNI	0.279	0.085	0.080	-0.073	SALERNO	0.095	0.045	0.299	0.016
VITERBO	0.115	-0.067	0.372	0.050	TARANTO	0.234	-0.046	0.410	0.003
					TERAMO	0.065	-0.018	0.162	0.101
					VIBO VALENTIA	0.078	0.027	0.141	0.023
	Islands								
	Sales		HP						
	Δy_{it}	Res	Δy_{it}	Res					
AGRIGENTO	0.207	-0.063	-0.095	-0.138					
CALTANISSETTA	0.201	-0.072	0.297	-0.054					
CATANIA	0.506	0.069	0.352	-0.047					
ENNA	-0.021	-0.197	0.200	-0.039					
MESSINA	0.363	0.122	0.119	0.094					
PALERMO	0.500	-0.020	0.339	-0.242					
RAGUSA	0.276	0.024	0.273	0.081					
SIRACUSA	0.259	-0.069	0.214	-0.014					
TRAPANI	0.365	0.008	0.145	0.029					

Notes. Δy_{it} is the variable in log-differences while Res corresponds to residuals of the country-specific VARX*(1, 1).

Table 5: GVAR models, regional capitals and neighbours.

GVARs	Regional capitals	Neighbours
Northwest	Torino	Alessandria, Aosta, Asti, Biella, Cuneo and Vercelli
	Genova	Alessandria, La Spezia and Savona
	Milano	Bergamo, Cremona, Lodi, Novara, Pavia and Varese
Northeast	Venezia	Padova, Pordenone, Rovigo, Treviso and Udine
	Bologna	Ferrara, Modena and Ravenna
Centre	Firenze	Arezzo, Lucca, Pisa, Pistoia, Prato and Siena
	Roma	Frosinone, Latina, Rieti and Viterbo
South	Napoli	Avellino, Benevento, Caserta and Salerno
	Bari	Brindisi, Matera, Potenza and Taranto
Islands	Palermo	Agrigento, Caltanissetta, Enna, Messina and Trapani

Notes. For each regional capital, the corresponding neighbours are identified through a contiguity-based method. According to this criteria, it is possible to define as neighbours those provinces (regional capitals) which share a common border.

Table 6: Within domestic ratio.

Panel a: Within domestic ratio for real house prices level.

horizon (h)	Torino	Genova	Milano	Venezia	Bologna	Firenze	Roma	Napoli	Bari	Palermo
h=0 / h=0	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
h=1 / h=0	2.071	1.154	0.792	0.814	1.192	1.102	0.824	0.717	1.180	1.427
h=2 / h=0	2.355	1.273	0.877	0.856	1.509	1.310	0.985	0.867	1.410	1.680
h=3 / h=0	2.762	1.309	0.865	0.820	1.580	1.344	0.947	0.839	1.471	1.877
h=4 / h=0	2.802	1.330	0.884	0.865	1.664	1.447	1.054	0.838	1.643	2.024
h=5 / h=0	2.899	1.326	0.882	0.815	1.656	1.441	1.007	0.834	1.586	2.110
h=6 / h=0	2.868	1.329	0.910	0.863	1.685	1.479	1.082	0.860	1.728	2.193
h=7 / h=0	2.866	1.326	0.883	0.819	1.692	1.505	1.038	0.835	1.643	2.239
h=8 / h=0	2.850	1.328	0.911	0.861	1.701	1.548	1.090	0.849	1.761	2.274
h=9 / h=0	2.870	1.324	0.880	0.829	1.723	1.531	1.059	0.828	1.653	2.300
h=10 / h=0	2.885	1.328	0.904	0.854	1.714	1.534	1.095	0.837	1.829	2.321

Panel b: Within domestic ratio for transaction volumes level.

horizon (h)	Torino	Genova	Milano	Venezia	Bologna	Firenze	Roma	Napoli	Bari	Palermo
h=0 / h=0	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
h=1 / h=0	0.507	1.144	0.646	0.492	0.898	0.525	0.718	0.861	0.561	0.671
h=2 / h=0	0.636	1.173	0.889	0.824	1.028	0.850	0.881	0.786	0.816	0.675
h=3 / h=0	0.417	1.151	0.793	0.637	1.039	0.647	0.751	0.823	0.600	0.619
h=4 / h=0	0.469	1.154	0.898	0.749	1.057	0.810	0.826	0.821	0.809	0.666
h=5 / h=0	0.403	1.142	0.849	0.676	1.050	0.690	0.767	0.796	0.636	0.618
h=6 / h=0	0.433	1.149	0.900	0.732	1.059	0.778	0.800	0.821	0.780	0.660
h=7 / h=0	0.375	1.151	0.865	0.688	1.036	0.719	0.773	0.798	0.661	0.603
h=8 / h=0	0.427	1.156	0.927	0.723	1.059	0.751	0.800	0.824	0.778	0.663
h=9 / h=0	0.368	1.153	0.861	0.693	1.048	0.723	0.778	0.790	0.654	0.622
h=10 / h=0	0.423	1.156	0.925	0.719	1.056	0.743	0.790	0.823	0.786	0.667

Notes. The *Within domestic ratio* is computed as the ratio between the median impulse response of main regional capitals house prices (transaction volumes) to domestic shock at each h -step ahead and the median impulse response of main regional capitals house prices (transaction volumes) to domestic shock at time 0.

Table 7: Spillover index (in percentage).

Panel a: Spillover index for real house prices level.

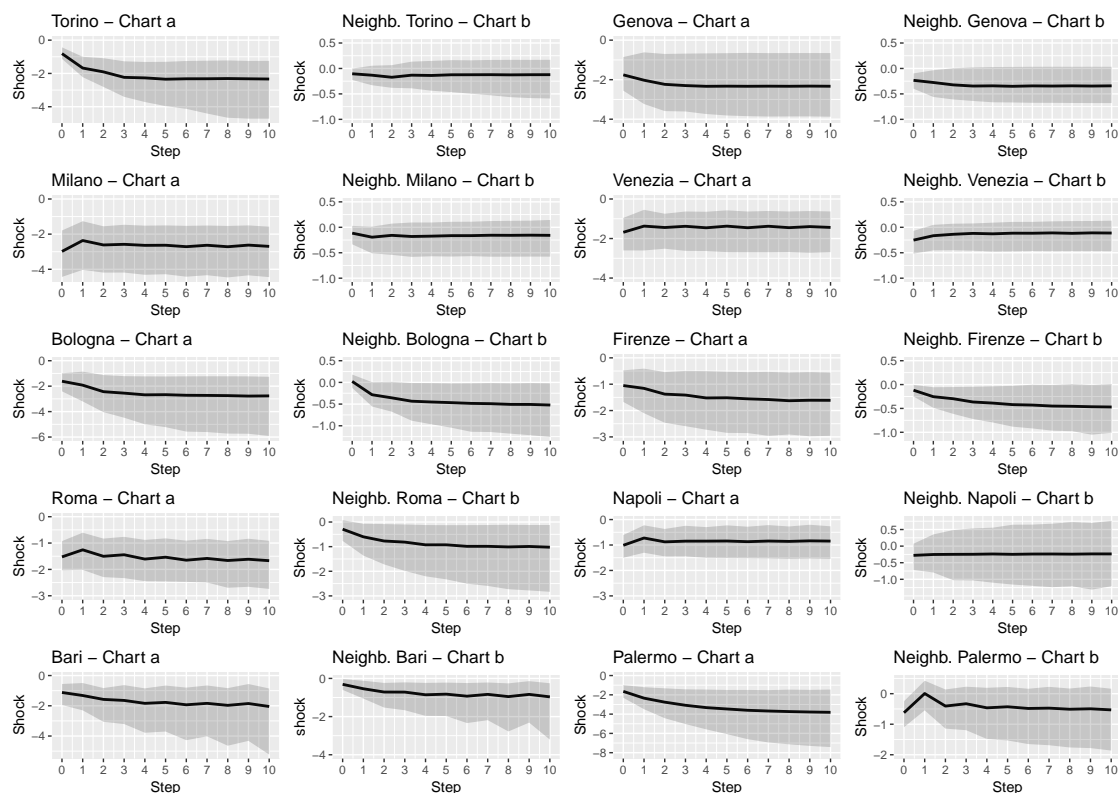
horizon (h)	Torino	Genova	Milano	Venezia	Bologna	Firenze	Roma	Napoli	Bari	Palermo
h=0	12.912	13.287	3.844	14.947	-1.404	11.243	19.102	27.561	27.743	37.946
h=1	7.923	13.606	8.207	12.036	14.772	21.952	47.836	34.843	41.024	-0.232
h=2	9.081	14.431	6.043	9.516	14.647	21.534	51.292	28.281	45.220	14.716
h=3	5.906	15.034	6.992	8.647	17.020	25.854	56.491	28.974	43.553	10.692
h=4	6.088	14.632	6.587	8.784	16.834	25.501	57.632	27.989	46.635	13.943
h=5	5.304	15.073	6.231	8.407	17.485	27.752	60.270	29.355	46.471	12.372
h=6	5.325	14.687	6.029	8.020	17.812	27.639	59.856	27.484	48.119	13.442
h=7	5.268	14.840	5.923	7.975	17.993	28.469	62.325	28.156	45.435	12.863
h=8	5.461	14.642	5.805	8.166	18.485	27.997	60.858	28.269	48.388	13.635
h=9	5.299	14.865	5.891	7.845	18.293	28.888	61.476	28.082	45.201	13.088
h=10	5.230	14.644	5.853	7.822	18.880	29.177	61.270	27.794	47.217	13.908

Panel b: Spillover index for transaction volumes level.

horizon (h)	Torino	Genova	Milano	Venezia	Bologna	Firenze	Roma	Napoli	Bari	Palermo
h=0	29.963	39.705	76.593	31.330	44.182	40.196	26.957	31.371	54.905	30.716
h=1	60.225	59.733	106.715	65.939	77.363	65.745	10.722	39.653	44.632	59.034
h=2	55.864	61.421	86.677	40.909	77.186	51.363	37.569	46.568	66.294	42.703
h=3	63.437	64.711	103.948	54.267	82.224	56.969	17.791	42.296	50.230	50.775
h=4	66.546	62.680	93.177	46.545	85.863	49.755	35.701	44.759	71.574	49.845
h=5	66.461	63.442	100.071	51.377	86.488	56.169	22.549	45.609	49.019	51.273
h=6	67.431	63.148	98.572	49.533	88.583	51.656	36.190	45.660	73.410	53.091
h=7	66.940	62.332	102.543	52.390	88.105	55.118	25.151	44.649	50.206	58.812
h=8	70.035	63.215	99.423	51.620	89.110	54.765	36.084	45.445	74.749	55.575
h=9	68.560	62.874	103.223	53.574	88.155	54.980	26.543	44.950	51.534	57.363
h=10	70.065	63.408	99.578	51.288	89.451	56.943	36.135	45.022	73.955	55.955

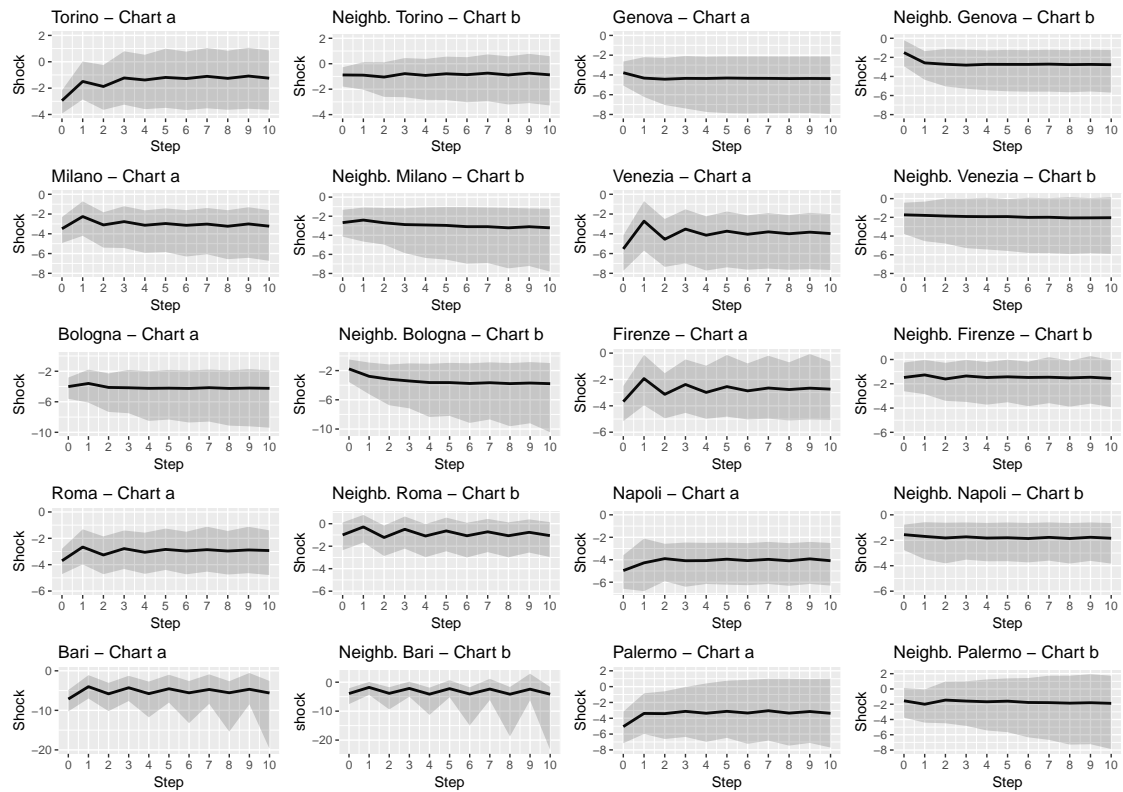
Notes. The *spillover index* is computed as the ratio between the median impulse response of main regional capitals house prices (transaction volumes) to domestic shock and the median response of neighbours house prices (transaction volumes) to shock arising from main regional capitals housing market, at h -step ahead.

Figure 1: Responses of the real house prices level in main regional capitals and neighbours to a negative housing demand shock occurring in main regional capitals.



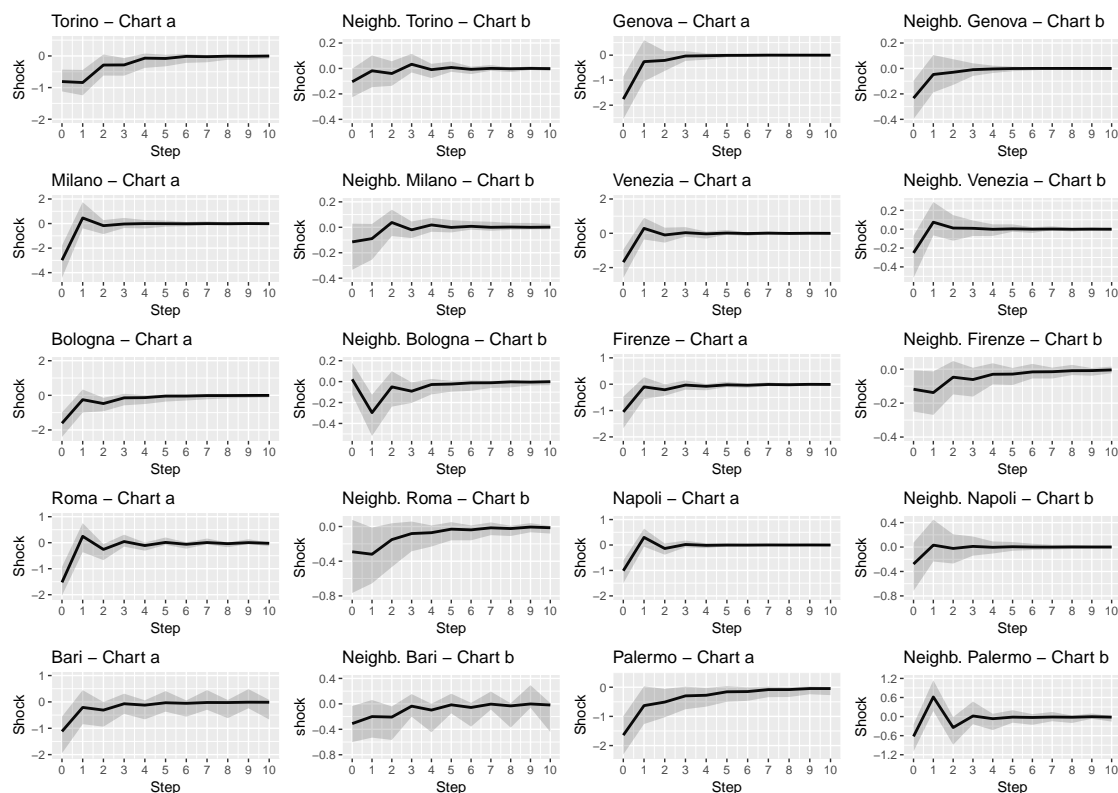
Notes. Impulse responses of real house prices level to a one standard deviation shock (in percentage) occurring in the Italian main regional capitals. The Bootstrap median estimates (black line) and the 90 percent confidence intervals (shadow area) are reported. Chart a shows the median response of main regional capitals' real house prices to domestic shock. Chart b presents the median response of neighbours house prices to shocks arising from the corresponding main regional capital housing market.

Figure 2: Responses of the transaction volumes level in main regional capitals and neighbours to a negative housing demand shock occurring in main regional capitals.



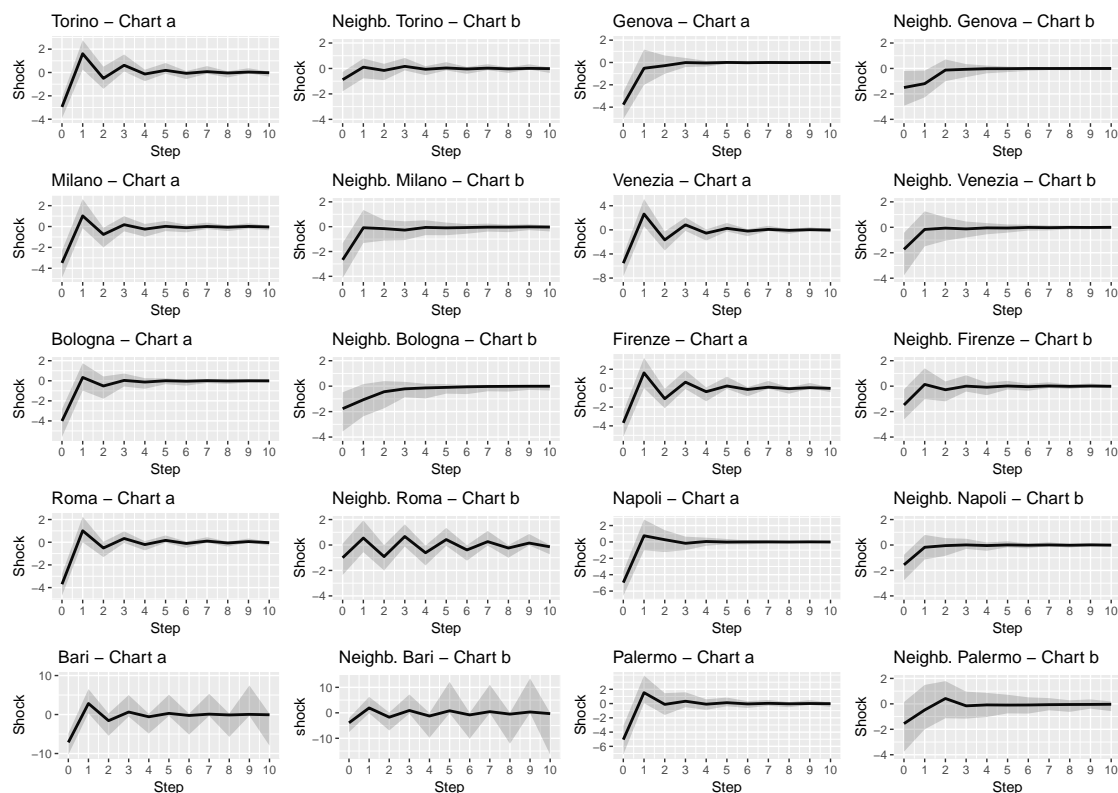
Notes. Impulse responses of transaction volumes level to a one standard deviation shock (in percentage) occurring in the Italian main regional capitals. The Bootstrap median estimates (black line) and the 90 percent confidence intervals (shadow area) are reported. Chart a shows the median response of main regional capitals' transaction volumes to domestic shock. Chart b presents the median response of neighbours transaction volumes to shocks arising from the corresponding main regional capital housing market.

Figure 3: Responses of the house price changes in main regional capitals and neighbours to a housing demand shock occurring in main regional capitals.



Notes. Impulse responses of real house prices changes to a one standard deviation shock (in percentage) occurring in the Italian main regional capitals. The Bootstrap median estimates (black line) and the 90 percent confidence intervals (shadow area) are reported. Chart a shows the median response of main regional capitals' real house prices changes to domestic shock. Chart b presents the median response of neighbours house prices changes to shocks arising from the corresponding main regional capital housing market.

Figure 4: Responses of the transaction volumes changes in main regional capitals and neighbours to a housing demand shock occurring in main regional capitals.



Notes. Impulse responses of transaction volumes changes to a one standard deviation shock (in percentage) occurring in the Italian main regional capitals. The Bootstrap median estimates (black line) and the 90 percent confidence intervals (shadow area) are reported. Chart a shows the median response of main regional capitals' transaction volumes changes to domestic shock. Chart b presents the median response of neighbours transaction volumes changes to shocks arising from the corresponding main regional capital housing market.



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