



# The spatial diffusion of regional housing prices across U.S. states<sup>☆</sup>

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## ABSTRACT

In this paper I estimate the spatial diffusion of housing prices across U.S. states over a period from 1975 to 2011, showing how long and to what magnitude state-level housing prices are affected by a price shock emanating from surrounding states. I capture the spatial diffusion of regional housing prices with impulse response functions estimated directly from a single equation spatial autoregressive model. In addition, I compare and contrast spatial impulse response estimates over sub-periods. Results show that for the 1975 to 2011 period spatial diffusion of housing prices is statistically significant and persistent across states. This conclusion is robust to whether the model is estimated in levels or in first differences controlling for cointegration. Sub-period estimation, too, suggests the magnitude and persistence of spatial diffusion may be more pronounced after 1999 than before.

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## 1. Introduction

In this paper I measure the “spatial diffusion” of housing prices across the continental United States over a period from 1975 to 2011. Spatial diffusion is characterized by the persistence of spatial correlation over a forecast horizon, showing how long and to what magnitude a region's housing price will be affected by a shock emanating from surrounding states via the feedback between adjacent markets. Spatial correlation embodies various possible mechanisms including employment-migration patterns, arbitrage opportunities for home buyers and developers, or the type of geographic “yardstick” competition discussed by Besley and Case (1995) and others (see also Meen (1999)). The persistence of spatial correlation, too, may hold insight into understanding apparent “bubble” formation in some parts of the country or the lack thereof in other parts (just as the persistence of the time lag of housing prices is often cited as evidence of inefficiencies

in housing markets). I measure spatial diffusion with spatial impulse response functions, capturing the persistence of the spatial correlation between housing markets, holding constant conditions with each region. In doing so I document how spatial contiguity between housing markets serves as a transmission mechanism for a change in housing prices at the state level, and how the spatial diffusion differs before and after structural breaks in state-level housing prices over the 35 year period.

The economic and statistical significance of spatial correlation in regional housing markets is well-documented by various researchers.<sup>1</sup> The persistence of the spatial correlation—how long spatial contiguity appears to transmit price changes between regions—is of more recent interest. Holly et al. (2010, 2011), Kuethe and Pede (2011), and Beenstock and Felsenstein (2007) each model spatial correlation in a VAR-model. Doing so however, requires a number of restrictions on the system of equations since the spatial dimension strains the degrees of freedom necessary to estimate a fully-specified VAR model. As an alternative Brady (2011) estimates spatial IRFs which are generated from a single-equation spatial autoregressive panel model, where the response of a region's average housing price to a shock to housing prices in adjacent regions is estimated using direct forecasting techniques. The single-equation approach of Brady (2011) provides the flexibility

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<sup>1</sup> See Lesage (1999), Elhorst (2003), Anselin (1988, 2003), and Kapoor et al. (2007). A discussion of the literature follows in Section 2 and parts of Section 3.

for a researcher to control for within-region factors, specify the spatial factor (spatial correlation between regions), and measure the dynamics of the phenomenon with which the researcher is concerned.

Hence, in this paper I estimate spatial IRFs for U.S. states from a dynamic-panel spatial autoregressive model on housing market data from the 48 (plus the District of Columbia) contiguous states in the U.S. over a period from 1975 through 2011. The primary object of interest is the diffusion of a shock to housing prices across regions and how long that effect persists. The spatial model in question includes lags of the dependent variable, the “spatial regressor” common to spatial autoregressive models (which captures the spatial correlation between regions), state-fixed effects, as well as state-specific covariates including real income and housing starts (and their lags). The specification is estimated first in levels, which is consistent with many VAR-based studies of housing markets, and also transformed in first differences and including error correction terms, which is motivated by possible unit roots and cointegration among the regional housing price indices used in this paper. The estimation for the 1975 to 2011 time span establishes a baseline picture of the diffusion of a shock to housing prices across states over time. In addition, I make sub-period comparisons of the spatial impulse response functions. I estimate across sub-periods defined by structural break points identified in the housing price indices for the 49 regions in (approximately) 1988, 1998 and 2006.

The key result from this paper is the spatial IRFs which show a shock to housing prices at the state level has a statistically significant and persistent effect for up to 16 quarters for the panel of U.S. states. This suggests that a shock emanating from a neighboring state has a long-lasting effect on a state controlling for conditions within each state (this result is robust at sub-regional levels as well, specifically for the four U.S. Census regions). The result provides novel insight into regional housing markets. While spatial correlation is a well-documented feature of housing markets, previously little has been said on how persistent the feedback effect between states might be and how that might help explain the nature of housing price appreciation (or depreciation).

In addition, the results for the sub-period estimation reveal variation in the magnitude and persistence of the spatial diffusion over the sample period. Applying structural break techniques to each region's price index reveals common break points in the late-1980s, the very late 1990s, and the mid-2000s. Using the break points to delineate the sub-periods, the sub-period evidence suggests that the magnitude and persistence of spatial diffusion is stronger across the U.S. states after the late-1990s. In fact, for the model-in-levels spatial diffusion is weak to nonexistent before 1999, yet persistent and statistically significant in the 1999 to 2011 period.

The estimation and results of this study may be of interest to various researchers. First, the diffusion of housing prices across states may provide useful information for policy makers and academic economists. For example, a monetary economist might consider how the evidence from this paper bears on the transmission mechanism of monetary policy (monetary policy-related studies are discussed briefly in Section 3). Fratanoni and Schuh (2003) emphasize that factors within regions in the U.S. affect the efficacy of monetary policy. As noted in Brady (2011), the spatial forecasting approach of this paper provides an easy way to consider whether spatial correlation matters for the monetary transmission mechanism. The results of this paper, suggesting spatial diffusion matters at regional levels beyond just neighborhoods or counties, provide impetus for that possibility. More generally, one might consider how the spatial transmission of housing prices may or may not have mattered for the housing price “boom” in the first half of the 2000s and the subsequent bust. For example, typically the persistence of housing prices over time is cited as an example of the inefficiencies that drive bubble formation in housing markets (Case and Shiller (2003)). The persistence of a change in housing prices across space suggests an additional mechanism through which such potential inefficiencies manifest and why a housing price rise in California, say, will reliably precede a rise in Nevada.

Finally, the econometric application of this paper should be of interest to regional economists or any application with a regional focus. This paper extends the spatial IRF framework in a couple of useful ways. First this paper expands the application to consider richer specifications in the dynamic-panel framework. In addition to estimating the spatial IRFs in levels, as one might do in a simple VAR model, this paper also generates spatial IRFs from a single-equation specification controlling for non-stationary and cointegration. Second, this paper provides estimation over both long panels and over short panels using instrumental variables (Brady (2011) estimates over a long panel using data on California counties). The latter should be of interest since (anecdotally) the preponderance of panel applications involves data with few  $T$  but many  $N$ . Lastly, the single-equation, direct forecasting approach provides more parsimony in estimating impulse response functions over relatively short sub-periods, more than might be possible in a multi-equation setting.

The remainder of this discussion is ordered as follows. In the next section I provide a brief review of spatial econometric research including recent efforts to exploit the time dimension of spatial models. Thereafter, in Section 3 I provide an explanation of the spatial impulse response function estimation. In Sections 4 and 5, I present the estimation for the 49 regions over the 1975 to 2011 time period. In Section 6 I estimate for structural breaks in the 49 regional price indices and then estimate the spatial IRFs over sub-periods marked by the break estimates. In Section 7 I offer concluding comments.

## 2. Background on spatial research and the time dimension

The economic and statistical significance of spatial correlation in housing markets is well-established, with studies ranging from analysis of specific cities to across states or more broadly defined regions. Basu and Thibodeau (1998) find evidence of spatial autocorrelation in some Dallas, Texas neighborhoods in the 1990s, while Holly et al. (2010) find a spatial effect in state-level data (for other examples see Tirtiroglu (1992), Clapp and Tirtiroglu (1994), Case (1991) and Elhorst (1996)). The theoretical support for estimation of spatial models with panel or cross-section data is established in Anselin (1988, 2003), Lesage (1999), Elhorst (2003), Kelejian and Robinson (1993), Kelejian and Prucha (2002), Lee (2003), Fingleton (2008), and Kapoor et al. (2007).

Spatial correlation arises due to shared market features by contiguous neighborhoods or more general regions, where the spatial relationship inspires a “feedback” effect between regions. Spatial econometric models embody a number of possible transmission mechanisms that explain how economic activity spills across boundaries. For example, in the “yardstick competition” analysis of Besley and Case (1995) policy makers consider the actions of their counterparts in neighboring regions before deciding on tax policy. Or similarly, in the yardstick study of Bivand and Szymanski (1997) municipal garbage-service contracts are written with a comparing-eye toward similar contracts in adjacent locales. Company officials use the surrounding contracts as a gauge in their dealing with the local municipality.<sup>2</sup>

In housing markets, yardstick competition could explain the spatial correlation found in the numerous studies mentioned at the outset of this section. It is well-known that real estate agents use “comps”—houses of comparable features—as the basis for a listing price. And while those comparisons are likely to take place at the very local level, the spatial spillovers involving real estate could easily extend beyond neighborhoods at larger spatial dimensions. At larger spatial levels, housing market activity can be spread through social networks, professional networks, and the news. In the spirit of yardstick analysis, market participants are inspired to compete with their neighbors or co-workers to upgrade their home, to own a home, and otherwise seek property at

<sup>2</sup> Anselin (2001) provides a summary of other areas in regional studies, such as economic geography, where motivation for spatial correlation can be found.

the margin of the activity (where homes may still be affordable in the short term). Home developers, too, push their business to the margins of undeveloped or previously undesirable locations to accommodate the demand. Simply put, the feedback effect arises when price changes in one region affect the attitudes and behavior of market participants in surrounding regions (see Pollakowski and Ray (1997) for more discussion on the feedback effect).

Related to the idea of yardstick competition, Meen (1999) cites four general mechanisms that help explain the feedback effect: migration, equity transfer, spatial arbitrage, and spatial patterns (see also Kuethe and Pede (2011) for a discussion of these categories; and Basu and Thibodeau (1998) for additional discussion of these ideas). Migration captures the possibility that buyers migrate to cheaper areas on the periphery of high-price locations. Related to migration is equity transfer, households sell high in one region, then buy low in an adjacent region. Spatial arbitrage captures the dissemination of behavior emphasized by Pollakowski and Ray (1997), where market participants gradually push to surrounding areas. Lastly, the spatial patterns explanation means that regional housing markets evolve similarly, driven by some common mechanism (even if they are not spatially connected directly).

As the brief descriptions suggest, the phenomena categorized by Meen (1999) are overlapping. In a study of spatial correlation across the western United States, Kuethe and Pede (2011) note that spatial correlation is evident even across large spatial units such as California and adjacent Arizona, since equity transfer attracts residents of the former to the lower prices in the latter (which inspires migration). Spatial arbitrage then inspires developers to follow suit. The combination of forces described by Meen (1999) also suggests spatial correlation may be positive or negative—that is, migration and equity may not just lead to a positive spillover but result in a “drain” from one area to another.

With respect to the latter possibility, Holly et al. (2011) discuss that regions may be complements or substitutes with respect to migratory patterns. They note that in the United States people have moved from states in the Midwest to states in the Southwest leading to changes in relative prices between those regions. Of course the timing of forces underlying the spillovers is not clear. For example Holly et al. (2011) find that the spillover from London to Wales is positive in time  $t$  (consistent with the majority of spatial correlation studies), but lagged changes in the former have a negative effect on the latter. With respect to regions in the U.S., it is certainly likely any negative “drain,” such as movement of population between the Midwest and Southwest, would take decades.

What is clear from the spatial correlation literature is that spatial correlation does matter for understanding housing markets. Yet, less understood is the timing of the feedback effect between regions. That is, how long should we expect things like spatial arbitrage, equity transfer and the like, to matter for the transmission of price changes across space? Amidst the litany of papers cited above, studies that focus on the time-series dimension are relatively scant, despite the fact that incorporating dynamics into a spatial model is not new to the spatial literature. Anselin (2001), for example, describes a “time-space simultaneous” model, where housing prices are spatially correlated for multiple periods. Pace et al. (1998), too, capture something similar with their “STAR” model (I say more on these models in Section 3).

Recently, the work by Holly et al. (2011), Kuethe and Pede (2011), and Beenstock and Felsenstein (2007) have incorporated features of spatial correlation into a VAR-framework. Holly et al. (2011), in particular, generate “spatio-temporal impulse responses” of a shock to prices in London—the designated dominant region—to surrounding regions in the United Kingdom. The distinguishing feature of the estimation is one region is chosen as the “dominant” region, where its housing price is a function of its own time lag and the lag of the term capturing spatial correlation (which is defined below in Section 3, or readily discussed in the references mentioned throughout this section). The non-dominant regions are specified as a function of their own respective time lag, the

spatial regressor and the contemporaneous value of the dominant region's price. Shocks emanate from the dominant region out to surrounding regions, while shocks from the outer regions do not affect the dominant locale contemporaneously (see also Pesaran and Chudik (2010) for details on the “dominant-region” VAR framework). Each region's housing price is defined as an endogenous variable in the VAR model, with the “direction” of the diffusion restricted a priori.<sup>3</sup>

By comparing the impulse response of Wales to Scotland, for example, to the same shock in London housing prices, the authors quantify the significance of distance in the transmission of the shock across space (the closer to London, the quicker the price changes affect a region's housing price). One trade-off to gaining the dominant-region perspective is that assumptions must be asserted a priori on the structure of the system. The primary assumption, of course, is the researcher must choose the dominant region (which is not necessarily controversial in Holly et al.'s (2011) case given that they use data on regions in the United Kingdom).

In an alternative effort, Kuethe and Pede (2011) employ a “spatial” VAR model that builds spatial correlation into a multivariate VAR model (in contrast to Holly et al. (2011) where the only endogenous variable is housing prices, as noted above). They specify a three-variable model with housing prices, unemployment rates and per capita income for the eleven U.S. states that make up the West Region as defined by the U.S. Census Bureau (spanning 1988 to 2007). The spatial VAR model includes spatial lags of the temporal lags, meaning the lags of each endogenous variable are multiplied by a spatial weighting matrix. The spatial VAR in Kuethe and Pede (2011) is an application of Beenstock and Felsenstein (2007). The latter provide the theoretical details of the model and demonstrate its applicability with data on nine regions in Israel.

In the spatial VAR of Kuethe and Pede (2011) and Beenstock and Felsenstein (2007) the parameters on the contemporaneous values of the spatial regressors are assumed zero to make estimation of the model tractable (see Kuethe and Pede (2011) for an overview and Beenstock and Felsenstein (2007) for details). Also each of the three variables is estimated separately from the others. That is, the housing price VAR consists of eleven equations with the housing price of each region defining the endogenous variables in the system and interest rates and per capita income of each region entering as lagged predetermined variables on the right-hand side. Kuethe and Pede (2011) then use the separate “bloc” VARs to understand the effect of a shock to unemployment, for example, on California's housing prices (Kuethe and Pede (2011) emphasize the response of one region, California, to shocks emanating from surrounding states, which is evocative of Holly et al. (2011)).

The examples above are explicit attempts to incorporate the spatial weighting scheme found in spatial autoregressive models into a “typical” time series model. However, the preceding discussion is not meant to imply that other time series efforts have not considered regional factors at all in understanding housing prices. Pollakowski and Ray (1997) estimate a VAR model with the lags of price changes in adjacent regions included as regressors in the equation for a change in housing prices in a region (they do so with data on census regions and metropolitan statistical areas in the U.S.). They also estimate single-equation (time series) autoregressive models. However, in contrast to the spatial-oriented research discussed above, they eschew the modeling techniques of spatial econometrics (i.e., incorporating a spatial weighting scheme).

Other studies seek to assess the relevance of regional factors on the monetary transmission mechanism. Carlino and Defina (1998, 1999) show how a monetary policy shock affects different regions in the United States. They incorporate regional correlation in a manner similar

<sup>3</sup> Hence, the model is not a panel-VAR but a “typical” VAR with each region's housing price treated as a separate variable. Other regional covariates are not included though Holly et al. (2011) do discuss that possibility.

to Pollakowski and Ray (1997) with a shock to a factor (regional income) within a region only affecting surrounding regions with a delay. Similarly, Owyang and Wall (2009) use VAR analysis to examine how characteristics within regions matter for monetary policy and compare the effect of policy across a split-sample (pre and post-1983).

However, as noted by Fratantoni and Schuh (2003) a problem analyzing regional phenomena such as housing markets with a typical monetary VAR is that the model may not fully incorporate the regional dimension (that is, simultaneously control for factors within a number of regions and include national information as well). Instead, Fratantoni and Schuh (2003) incorporate housing data from regions of the U.S. into their monetary VAR model. They call the model a heterogeneous-agent VAR, or a “HAVAR.” The HAVAR includes the national mortgage rate, the Federal funds rate in addition to regional housing prices, housing starts and regional income. With their HAVAR model, the authors show that the dynamic responses of the variables in the system depend on the initial conditions in each region and how the shocks are transmitted across regions. The authors show that the magnitude and the duration of the responses to monetary policy calculated from the HAVAR model differ from the typical responses calculated for a VAR. Even in the HAVAR model, however, a number of restrictions must be imposed on the regional dimension in order to make estimation of the system possible.

Time series studies such as Owyang and Wall (2009), Fratantoni and Schuh (2003) and the others provide an impetus for taking account of regional heterogeneity in measuring the dynamics of housing markets. The challenge researchers face, as evidenced by the creative approaches of Fratantoni and Schuh (2003), Holly et al. (2011) and others, is estimating a fully-specified VAR model which also includes explicit controls for spatial correlation. As an alternative to the full-system approach, in Brady (2011) “spatial impulse response functions” are estimated directly from a single-equation spatial autoregressive model. In the next section I explain the single equation approach from Brady (2011).

### 3. Spatial impulse response functions

I estimate spatial impulse response functions from a single-equation, dynamic-panel spatial autoregressive model. A common form of the spatial autoregressive model can be written in stacked form as,

$$Y_t = \rho WY_t + \alpha Y_{t-1} + \beta X_t + \delta + u_t \quad (3.1)$$

where  $Y_t = (Y_{1t}, \dots, Y_{Nt})$  is a  $NT \times 1$  vector of the dependent variable,  $WY_t$  is the “spatial lag” term,  $Y_{t-1}$  is the time-lag of the dependent variable,  $X_t$  is an  $NT \times r$  matrix of  $r$  exogenous variables,  $\delta = (\delta_1, \dots, \delta_N)$  is the vector of fixed effects, and  $u_t = (u_{1t}, \dots, u_{Nt})$  is the error term. The “spatial lag” captures the direct effect of the spatial correlation in determining the dependent variable, and corrects for what may be an omitted variable (see Brady (2011), Elhorst (2003), and Lesage (1999) for discussion).<sup>4</sup>  $W$  is a  $N \times N$  matrix that defines the spatial relationship, and  $\rho$  is the parameter measuring the effect.  $W$  is defined by contiguity, where each adjacent region is weighted equally for simplicity (which is a standard practice in the literature, see references already cited for complete discussion).

The model expressed in Eq. (3.1) is a specific version of what could be a very general spatial autoregressive process. For example, Elhorst (2012) describes a more general version of Eq. (3.1) where the dependent variable is a function of temporal lags of the spatial lag (i.e.,  $WY_{t-1}$ ), plus a distributed lag process for the exogenous variables in

$X$ , and spatial lags of the exogenous variables (that is, each exogenous regressor weighted by the spatial matrix in the same manner as the dependent variable; see also Anselin (2001) for a description of the general spatial autoregressive model). Or one can be even more general as in Pace et al. (1998) “STAR” specification, which expresses the dependent variable as a function of multiple temporal lags of itself, multiple temporal lags of the spatial regressor (say,  $WY_{t-p}$ , where  $p$  is some lag length), multiple lags of the exogenous variables, plus spatial lags of the exogenous variables (and also allow for the spatial weighting matrix to have a temporal ordering—see their equation (4) and associated discussion; see also Liu (2013) for recent application of the STAR model). Ultimately, in the spirit of these more general specifications, I estimate with additional temporal lags of the regressors. I discuss those specifics along with the data in Section 4.

The estimator for the dynamic spatial model shown in Eq. (3.1) is consistent. I provide a quick review here and refer the reader to Brady (2011), Lee and Yu (2010) or Elhorst (2012) for more detail. For panel spatial models estimated with a short panel ( $T$  is fixed and  $N \rightarrow \infty$ ) the primary challenge is that the spatial lag will be correlated with the error term, rendering the fixed-effects estimator inconsistent. In this case, one can either estimate with maximum likelihood techniques or instrumental variables (for examples of the former, see Anselin (2001) and Kelejian and Prucha (1999)). Brady (2011) estimates the dynamic spatial model consistently with two-stage least squares (TSLS)—where in addition to the spatial lag, the lag of the dependent variable will also be correlated with the error term.<sup>5</sup>

Given the consistent estimation of the model expressed in Eq. (3.1), Brady (2011) then shows that one can apply Jordà's (2005) local linear projections to the dynamic spatial model. Jordà (2005) shows that impulse response functions can be estimated from a single equation by projecting the endogenous variables in a system onto their lags for each horizon,  $h$ . The benefit of doing so is that impulse response functions calculated from one-step-ahead forecasts by linear projection are less likely to suffer from misspecification than impulse response functions generated from a “traditional” VAR. Impulse response functions from VARs are calculated for long horizons, yet VARs are optimally designed for one-period ahead forecasting (as explained by Jordà (2005)). As a result the forecast error can be magnified as the horizon increases.

From Jordà (2005) consider a  $n \times 1$  vector of a time series  $y_t$  written as,

$$y_{t+h} = A_1^h y_t + A_2^h y_{t-1} + \dots + \varepsilon_{t+h} + B_1 \varepsilon_{t+h-1} + \dots + B_{h-1} \varepsilon_{t+1}, \quad (3.2)$$

which is an expression derived from the Wold decomposition of the series.<sup>6</sup> The infinite expression can be written for any practical lag length  $k$ , e.g.,

$$y_{t+h} = A_1^h y_t + A_2^h y_{t-1} + \dots + A_k^h y_{t-k+1} + v_{k,t+h} \quad (3.3)$$

where the error term,  $v$ , is a function of the moving average terms and the infinite lags greater than  $k$ . When deriving impulse response functions in a VAR model the coefficient estimates are derived indirectly from the parameters on the moving average terms. In contrast, in Jordà's (2005) local projection method the term  $A_1^h$  is estimated directly from Eq. (3.2) and provides a consistent estimate of impulse response function coefficients. Even if the VAR does properly capture the data

<sup>4</sup> In the spatial econometric literature “spatial correlation” is often referred to as “spatial autocorrelation.” I follow Brady (2011) in referring to the correlation between regions simply as spatial correlation. Brady (2011) does so to avoid confusion between the spatial dimension and the time dimension, both of which are of interest in the computation of spatial impulse response functions.

<sup>5</sup> See Brady (2011) and references therein for cases when generalized methods of moments can be applied to the spatial autoregressive model.

<sup>6</sup> Parts of the summary of the method in this section are based on Brady (2011). See Jordà and Kozicki (2011) and Jordà (2009), in addition to Jordà (2005) for detailed explanation of the local projection method. For exposition on VAR estimation see Hoover and Jordà (2001). The interested reader can also see the working paper version (on the author's website) of this study for an example of how impulse response functions are estimated from a VAR.

generating process, the loss of efficiency from estimating with Jordà's (2005) local projections is not substantial. Moreover, Jordà (2005) demonstrates that the local projections can be jointly estimated (from a system of equations), and, as such, one can impose short run or long run restrictions on the system just as one would do to estimate a structural VAR. Or, the impulse response coefficient estimates can be estimated from a single-equation.

A few recent papers have applied Jordà's (2005) methodology to system estimation. Haug and Smith (2012) apply the local projection technique to time series data on New Zealand, while Brady and Stimel (2011) calculate local projection-based IRFs for a time series study on the wealth effect for the United States (see also an application to marriage and divorce by Schaller (2013)). Less common are single-equation applications; the only two examples known to this author are Brady (2011) and Auerbach and Gorodnichenko (2012). The latter estimate the effects of fiscal policy in a panel of OECD countries, eschewing panel-VAR estimation to focus just on the effect of fiscal policy on gross domestic product (GDP) from a single-equation. Auerbach and Gorodnichenko (2012) also provide a useful explanation of the Jordà (2005) projection method, while Haug and Smith (2012) provide a succinct discussion on the benefits of direct forecasting versus VAR-based methods. Brady (2011), as already noted, not only applies the local projections to a single-equation panel model, but also extends the application to the spatial context.

Hence, in the next section, the spatial impulse response functions are estimated from a single equation such as Eq. (3.1). If  $x_{it}$  is an exogenous regressor in  $X_t$  (as in Eq. (3.1)), then the impulse response of  $Y_{t+h}$  to  $x_{it}$  is calculated from the coefficient estimate on  $x_{it}$  from  $h$  regressions (this explanation is paraphrased from Brady (2011), page 219; see also Haug and Smith (2012)). Then, the standard errors for each coefficient estimate at each horizon,  $h$ , provide the standard error bands typically reported for impulse response functions (and since estimation is done with standard least squares techniques, the standard errors can be adjusted to account for heteroscedasticity and autocorrelation). And as noted above, Brady (2011) shows that for the single-equation spatial model, one can estimate structural spatial impulse response functions through the use of instrumental variables with spatial lags of the independent regressors. This practice is employed in the sections below.

#### 4. Spatial impulse response functions for U.S. states

I estimate spatial impulse response functions with housing market data from the 48 contiguous states plus the District of Columbia over a period from 1975 through 2011. The dependent variable is the quarterly value for the Federal Housing Finance Agency (FHFA) home price index for single-family homes for each state.<sup>7</sup> The state-specific regressors are the following: state  $i$ 's unemployment rate, state  $i$ 's population, state  $i$ 's level of real personal income, the number of housing starts in state  $i$ , the effective interest rate on conventional mortgages for state  $i$ , and a regional consumer price index.<sup>8</sup> The primary source for the regional data is from Haver Analytics with other data available from public sources. Data are at the quarterly frequency. The final results are estimated from a slightly more general version of Eq. (3.1), with two lags of the dependent variable and the exogenous covariates (adding a third or fourth lag did not make a substantive difference). Consistent

with typical spatial autoregressive models the spatial regressor is defined by the time  $t$  value of the dependent variable ( $WY_t$  in Eq. (3.1)). Table 1 provides a summary of the variables and the respective sources.<sup>9</sup>

The single-equation model estimated in this paper can be thought of as one equation plucked from a VAR system with housing prices ordered last. In full-system estimation, the ordering would be implemented and justified by the researcher in order to identify structural impulse response coefficients. With housing prices ordered last this implies that housing prices respond contemporaneously to each variable in the system. Conversely, the variable ordered first responds only to itself contemporaneously, the variable ordered second responds to itself and only the first variable in time  $t$ , and so on. Such a recursive ordering is typically applied with the Cholesky decomposition and the structural impulse response coefficients are recovered from the associated transformation of the system's estimated variance-covariance matrix. As noted in Section 3, with local projections, however, the coefficients are estimated directly with some assumptions made on the contemporaneous relationships (for an example, see Auerbach and Gorodnichenko (2012)). Here, the response of housing prices at  $t+h$  to a shock in  $t$  is estimated directly at each  $h$  using least squares techniques (OLS or instrumental variables).

For the baseline estimation I invoke simple assumptions on the contemporaneous parameters to identify the structural impulse response coefficients. In the estimation of monetary VARs, for example, it is typical to specify that a real variable is ordered ahead of a nominal variable in the sense that the nominal variable responds more quickly to current information while a real variable responds with a lag (meaning the real variable is ordered first). In that tradition, I assume that housing prices are affected in the quarter by changes in the real variables as well as the other nominal variables in the system, but not the other way around (so among the nominal variables, home prices are "ordered" after the interest rate and the CPI). In other words the covariates (except for the spatial regressor and the lag of the dependent variable) are predetermined with respect to housing prices in time  $t$ .<sup>10</sup> Since spatial correlation is expressed as a contemporaneous effect, in due course I deal with the endogeneity of the spatial regressor with instrumental variables (I discuss this further in Section 6).

For the baseline analysis, I estimate with the variables in levels. Housing prices, real income, housing starts, and population are in log form, while the unemployment rate and the interest rate are in percent. Specifying the relationships between macroeconomic variables in levels is a common practice in the VAR literature (for examples see Hoover and Jordà (2001) and Stock and Watson (2001)). Ashley and Verbrugge (2009) show that even in the presence of non-stationarity and cointegration, estimating a VAR in levels provides impulse response functions that are robust to those specification issues. Moreover, Lin and Tsay (1996) provide evidence that direct forecasts from specifications with variables-in-levels perform better than responses generated from a vector error correction model despite the possibility of misspecification in the former (see Hauenberger (2010) and Haug and Smith (2012) for discussions on this point).

Aside from the theoretical work just cited, it is not unanimous in housing research if regional housing prices are stationary or are

<sup>7</sup> The FHFA series was formerly the "OFHEO" price index produced by the Office of Federal Housing Enterprise Oversight. The latter was absorbed by the Federal Housing Finance Agency in 2008.

<sup>8</sup> The regional indices for the West, Midwest, Northeast, and South were applied to the appropriate states. CPI indices for each state are not available. State level income was deflated with the Bureau of Labor Statistics' (BLS) regional consumer price indexes (CPI). The effective interest rate is defined by the Federal Housing Financing Board as the contract rate plus fees and charges amortized over a 10-year period.

<sup>9</sup> The choice of variables is motivated by previous spatial research on housing including Brady (2011), references cited therein, and others cited in Sections 2 and 3. The spatial weighting matrix is the most common version found in the literature, with adjacent neighbors to a region marked by a "1", then each row normalized to equal one.

<sup>10</sup> I follow the justification found in Brady (2011) which cites a number of examples from housing-related studies to motivate the timing assumptions between housing prices and housing-related covariates. However, the estimation in this paper can be easily extended to use instrumental variables for other potentially endogenous covariates, which is what is done later for the spatial regressor and the lag of the dependent variable, for example. Note also that Jordà's (2005) local projections easily accommodate an instrumental variables approach even when the impulse response functions are estimated jointly from a system of equations. That is, one could employ instrumental variables instead of recursive identification (I thank Óscar Jordà for making this point to me via email correspondence).

**Table 1**  
Data description and sources.

| Regional variables       | Span              | Source                                                                                         | Notes                                                                                                                                                                                                     |
|--------------------------|-------------------|------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| FHFA Housing Price Index | 1975Q1 to 2011Q3  | Federal Housing Finance Agency via Haver Analytics (HPI)                                       | The FHFA index was formerly known as the “OFHEO” index.                                                                                                                                                   |
| Housing starts           | 1970M1 to 2011M10 | Bank of Tokyo-Mitsubishi UFJ via Haver Analytics (HST)                                         | Last month of quarter represents quarterly value.                                                                                                                                                         |
| Effective interest rate  | 1978 to 2010      | Federal Housing Finance Agency via Haver Analytics (FCMEA)                                     | Interpolated with cubic spline. Last quarter of 2010 used for 2011 values. Last quarter of 1978 used for prior dates. Defined as the contract rate plus fees and charges amortized over a 10-year period. |
| Total personal income    | 1948Q1 to 2012Q1  | Regional Economic Information System, Bureau of Economic Analysis, U.S. Department of Commerce |                                                                                                                                                                                                           |
| Unemployment rate        | 1976M1 to 2011M7  | U.S. Department of Labor: Bureau of Labor Statistics                                           | Last month of quarter represents quarterly value.                                                                                                                                                         |
| State population         | 1959 to 2009      | U.S. Census Bureau                                                                             | Interpolated using cubic spline from 1950 through 2009. Last quarterly value for 2009 was used for 2010 and 2011 values.                                                                                  |
| Consumer price index     | 1967 to 2012M7    | Bureau of Labor Statistics                                                                     | For U.S. Census regions West, Midwest, South and Northeast. See notes to Table 1.                                                                                                                         |

Notes: The consumer price index is not available at the state level. At the monthly frequency the CPI data are available by designated BLS regions or for major population centers. The acronyms in parentheses (under “Source”) denote Haver’s code for the series. The “Span” column shows the available period for each series as of August 2012.

cointegrated with income or one region’s price index is cointegrated with adjacent regions’ indices. For example, in their VAR study of state-level housing prices in the western U.S., [Kuethe and Pede \(2011\)](#) find that state-level data on housing prices and income appear to be stationary (over 1987 to 2007). As such they estimate their VAR in levels. Similarly, [Gallin \(2006\)](#) suggests error correction models may not be the right choice in estimating models of housing prices. He finds evidence against the presence of unit roots and cointegration in national and city-level data for housing prices and income. In contrast, [Baffoe-Bonnie \(1998\)](#) finds unit roots in the variables in his housing-related-VAR model though he also finds against cointegration (hence he estimate his VAR in first difference). In further contrast, [Holly et al. \(2010\)](#) do find evidence of cointegration between regional housing prices and regional incomes (in annual data for U.S. states from 1975 to 2003).

For a visual perspective, [Fig. 1](#) displays the individual time series for each of the 49 regions’ housing price index since 1975 (grouped together in four panels by the four Census regions, West, Midwest, Northeast, and South, respectively). Across the 49 regions there is not a uniform pattern save an upward trend (on average). Some state price indices appear to follow a moderate trend for the better part of the sample period (such as Texas in panel D), while others’ indices are punctuated by more dramatic appreciation at various points over the time span, interspersed with stagnation or even a decline in the index (see most of the states in the Northeast in panel C). From this glance it appears some regions’ indices may be stationary about a trend, while others’ indices appear non-stationary. Some states’ indices appear to follow similar patterns over time, while others appear to exhibit little cointegration with other states. Given the ambiguity and the mixed results across the literature, to be thorough, in [Section 5](#) I estimate the spatial autoregressive model specified in first differences and including error correction terms. I compare those results to the results from the model estimated in levels (later, too, I discuss unit root and cointegration tests on the 49 price indices).

Finally, for the baseline estimation over 1975 to 2011, given the long panel, I follow [Brady \(2011\)](#) and controls for the fixed effects,  $\delta = (\delta_1, \dots, \delta_N)$ , with dummy variables.<sup>11</sup> While the consistency of the fixed-effects estimator (or the least squares dummy variable) in a long panel does not necessarily necessitate the use of instrumental

variables (for the lagged dependent variable), later in [Section 6](#) when I estimate over sub-periods I employ IV estimation.<sup>12</sup>

#### 4.1. Results for the baseline sample: 1975 to 2011

[Fig. 2](#) displays the spatial impulse response functions of housing prices to each regressor in the system. The dotted lines show the plus and minus two-standard error bands. On balance, the response of regional housing prices to the various covariates are first, comparable to what one finds in VAR-based studies of housing markets, and second, evocative of what the few studies focusing on spatial diffusion have found ([Holly et al. \(2011\)](#) and [Brady \(2011\)](#) in particular). With respect to the regressors, for example, the responses of the housing price index to both real income and the unemployment are as one might expect. In response to the former, housing prices increase following the shock to income. The increase in the housing price index reaches a maximum of about one and half percent after the income shock. The positive response to income result is analogous to the positive responses that [Iacoviello \(2005\)](#) found for housing prices after a shock to industrial production at the national level (analogous in so far as state-level income represents state-level production). Moreover, [Brady \(2011\)](#) finds a similar positive response to industrial production (where county-level housing prices respond to the national measure of production). In response to the unemployment rate shock (one percent increase), the decline in housing prices reaches a trough of almost four percent.

The response of housing prices to a shock to housing starts is also positive and remains so (and statistically significant) for the entire displayed horizon. The magnitude, however, is relatively small, reaching a magnitude of less than a tenth of a percent. The positive response is in contrast to the lack of an effect that county-level construction has on housing prices found by [Brady \(2011\)](#) for different sub-samples comprised of California counties. In contrast, in [Fratantoni and Schuh \(2003\)](#) initial benchmark monetary-VAR, their housing price index shows an initial positive response to real per-capita housing investment (and does so also in their HAVAR model for up to four quarters after the shock).

The housing price index does not respond much to the consumer price index shock (though there is statistically significant decline in the middle of the horizon). The general lack of a response to inflation is consistent with what [Baffoe-Bonnie \(1998\)](#) found using pre-1991

<sup>11</sup> As a referee noted the regional model estimated in this paper leaves out national factors, which may affect the magnitude of spatial diffusion between regions (and the omission of which may introduce bias). As a robustness check, I included both real GDP for the United States and the Federal Funds rate as controls. Ultimately the qualitative inference in this paper did not change. The results are available in the online appendix. I discuss the possible implications of national variables for the estimation more in the conclusion.

<sup>12</sup> If  $T$  is relatively small, or if  $N$  and  $T$  converge at different rates asymptotically, then the bias may remain. [Ruth and Owen \(1999\)](#) show, for example, that with  $T = 30$  the bias is still large.

### A) FHFA Housing Price Index 1975 to 2011, West Region

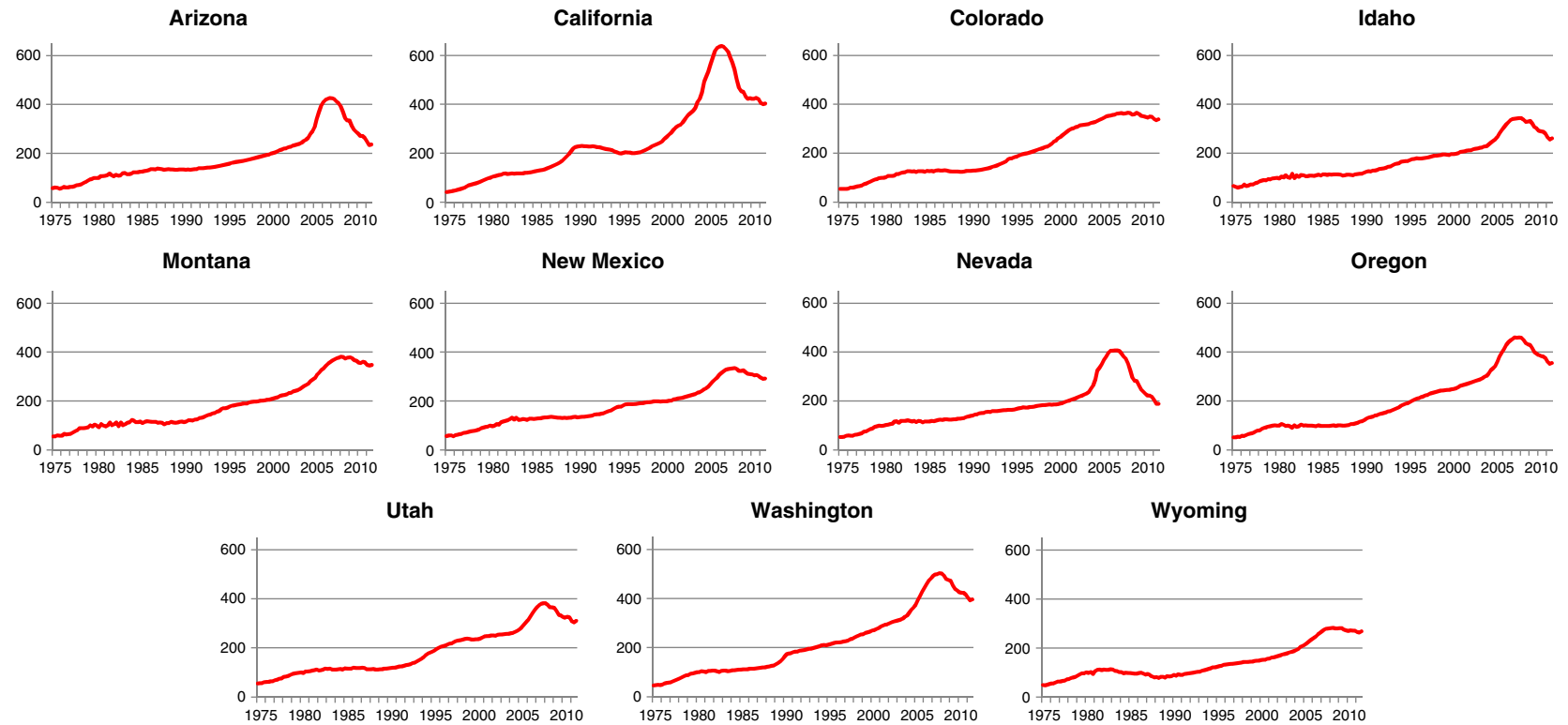


**Fig. 1.** Panel A: FHFA Housing Price Index 1975 to 2011, West Region. Notes: Figures display the FHFA (Federal Housing Finance Agency) Housing Price Index from the first quarter of 1975 through the third quarter of 2011 for the 48 contiguous states plus the District of Columbia. The panels of Fig. 1 are broken up by U.S. Census regions West, Midwest, Northeast, and the South. Index units are displayed on the vertical axis. 1980 Quarter 1 = 100. Panel B: FHFA Housing Price Index 1975 to 2011, Midwest Region. Notes: See comments under first panel for Fig. 1. Panel C: FHFA Housing Price Index 1975 to 2011, Northeast Region. Notes: See comments under first panel for Fig. 1. Panel D: FHFA Housing Price Index 1975 to 2011, South Region. Notes: See comments under first panel for Fig. 1.

## B) FHFA Housing Price Index 1975 to 2011, Midwest Region

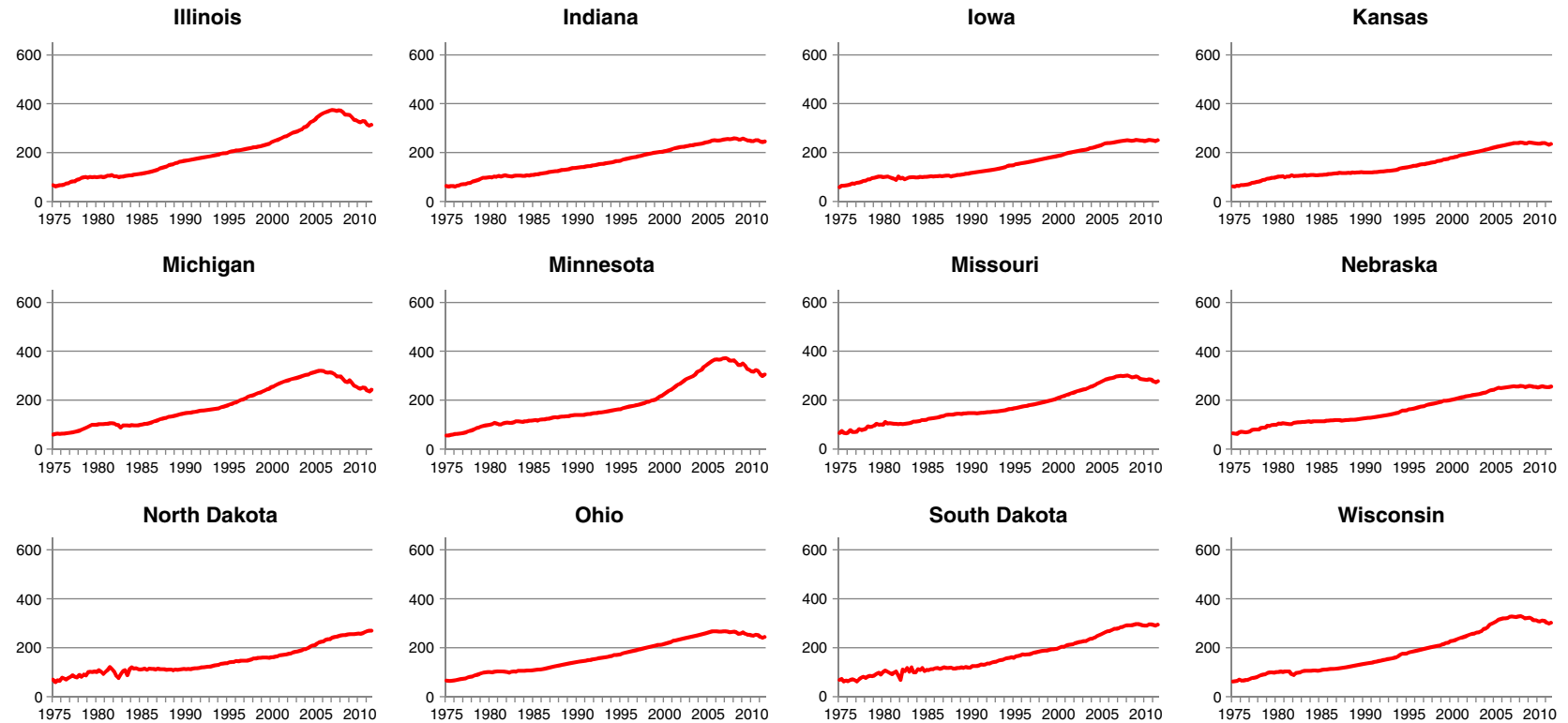


Fig. 1 (continued).

### C) FHFA Housing Price Index 1975 to 2011, Northeast Region

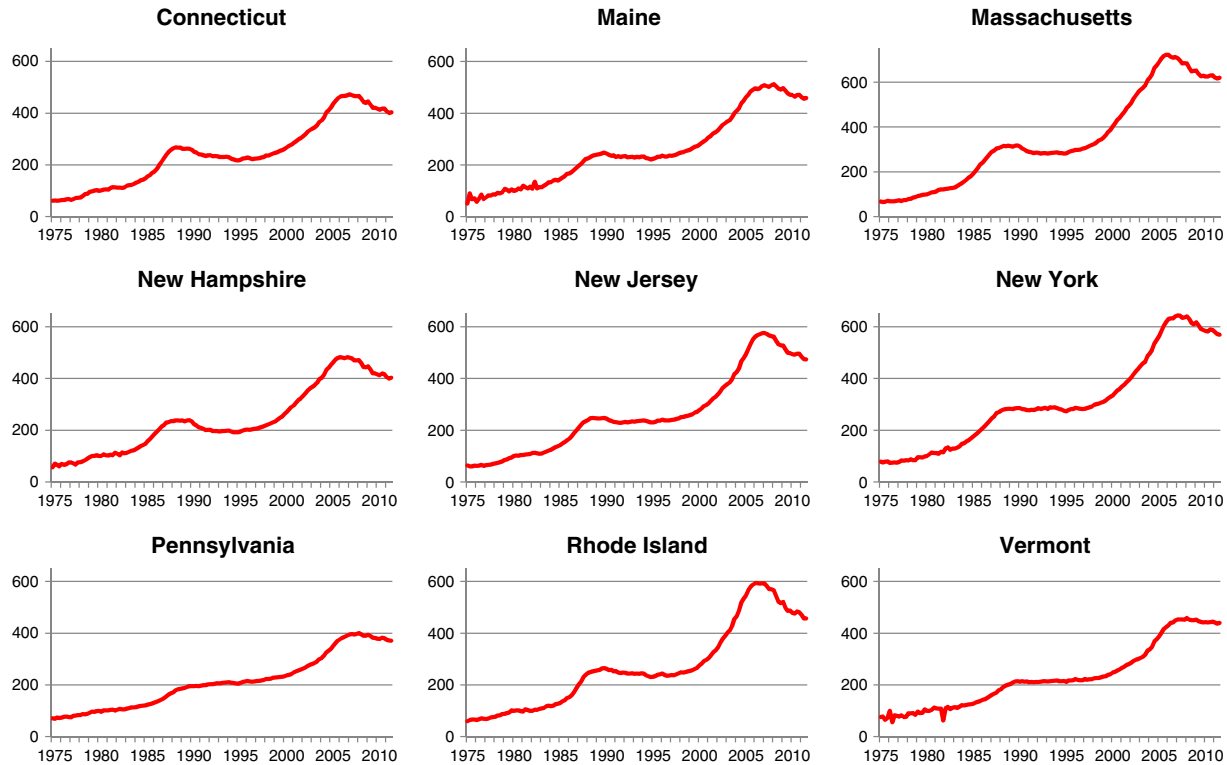


Fig. 1 (continued).

data for U.S. Census (and BLS) regions. In contrast, housing prices show a positive and sustained response to a shock to population (the response being statistically significant for up to 16 quarters). The response reaches a magnitude of about three percent.

In response to the effective interest rate the housing price index declines over the horizon. The magnitude suggests that the index declines by up to twenty percent. The decline in housing prices after an interest rate shock is consistent with Vargas-Silva (2008) and Brady (2011), though the magnitude shown in Fig. 2 is curiously large. One possible explanation for the magnitude is that the variable is measuring the effective rate as opposed to a simple interest rate (in contrast, the results (not reported) controlling for the federal funds alluded to earlier show the magnitude of the response to the short term interest rate is consistent with magnitudes found in the housing-monetary policy literature). It should be noted that some VAR-based studies find a positive response of housing to either a short term interest rate or to the mortgage interest rate (see McCarthy and Peach (2002) or Fratantoni and Schuh (2003) aggregate benchmark VAR for examples). Baffoe-Bonnie (1998) finds a positive relationship for national data, though identifies a negative response of housing prices to an interest rate looking separately at BLS regions. Similarly, Fratantoni and Schuh (2003) find that once they incorporate regional data into a VAR, the home price index declines immediately to the interest rate shock.

Fig. 2 displays the response of the housing price index to the spatial regressor. The response is positive, statistically significant, and persistent over the 16 quarter forecast horizon. The response reaches a magnitude of just over a tenth of a percent. This result matches numerous econometric studies that find a statistically significant spatial effect. The result also matches general findings from the studies that focus on the dynamics of the spatial effect, such as Holly et al. (2011). And this result matches Brady (2011), in particular, in finding a persistent effect over time from estimating spatial IRFs. A notable difference between the

results found here for U.S. states versus Brady (2011) is that the latter estimates a spatial factor at the county level of over a half of a percent (a magnitude which persists over the forecast horizon). The lower estimate here is not surprising, however, given the notable expanse of the borders between U.S. states relative to the California counties examined in Brady (2011).

Lastly, many of the papers cited thus far focus their spatial analysis on various sub-regions of the United States (such as Baffoe-Bonnie (1998) and Kuethe and Pede (2011)). Hence, for robustness I compared the results of the 49 regions to estimation on the four Census Bureau regions in the United States (the West, Midwest, South and Northeast—the states within each sub-region are delineated in Fig. 1). Clearly, an obvious feature of the geography of the United States is the disparate sizes of the 48 contiguous states. Factors such as the length of the borders between states, the population density of each, or perhaps the proximity of major population centers within a particular region are likely to matter for magnitude and persistence of spatial diffusion.<sup>13</sup> Once might expect spatial diffusion to be more pronounced, for example, in the northeast part of the United States than in the southwest region.

For brevity I do not report the figures from the sub-region estimation, but briefly comment on the general findings here.<sup>14</sup> Overall, spatial diffusion is evident in each sub-region though with variation coming primarily in the persistence of the effect. In particular, the spatial effect is similar in the first few periods after a shock regardless of

<sup>13</sup> These aspects of geography can be incorporated into the spatial weighting matrix, see Lesage (1999) for discussion. Such variations of the spatial weighting matrix, while not the focus of this paper, can easily be considered in extensions of this research.

<sup>14</sup> The interested reader can find figures for the sub-region estimation, along with detailed explanation of each, in the working paper version of this paper available on the author's website.

## D) FHFA Housing Price Index 1975 to 2011, South Region

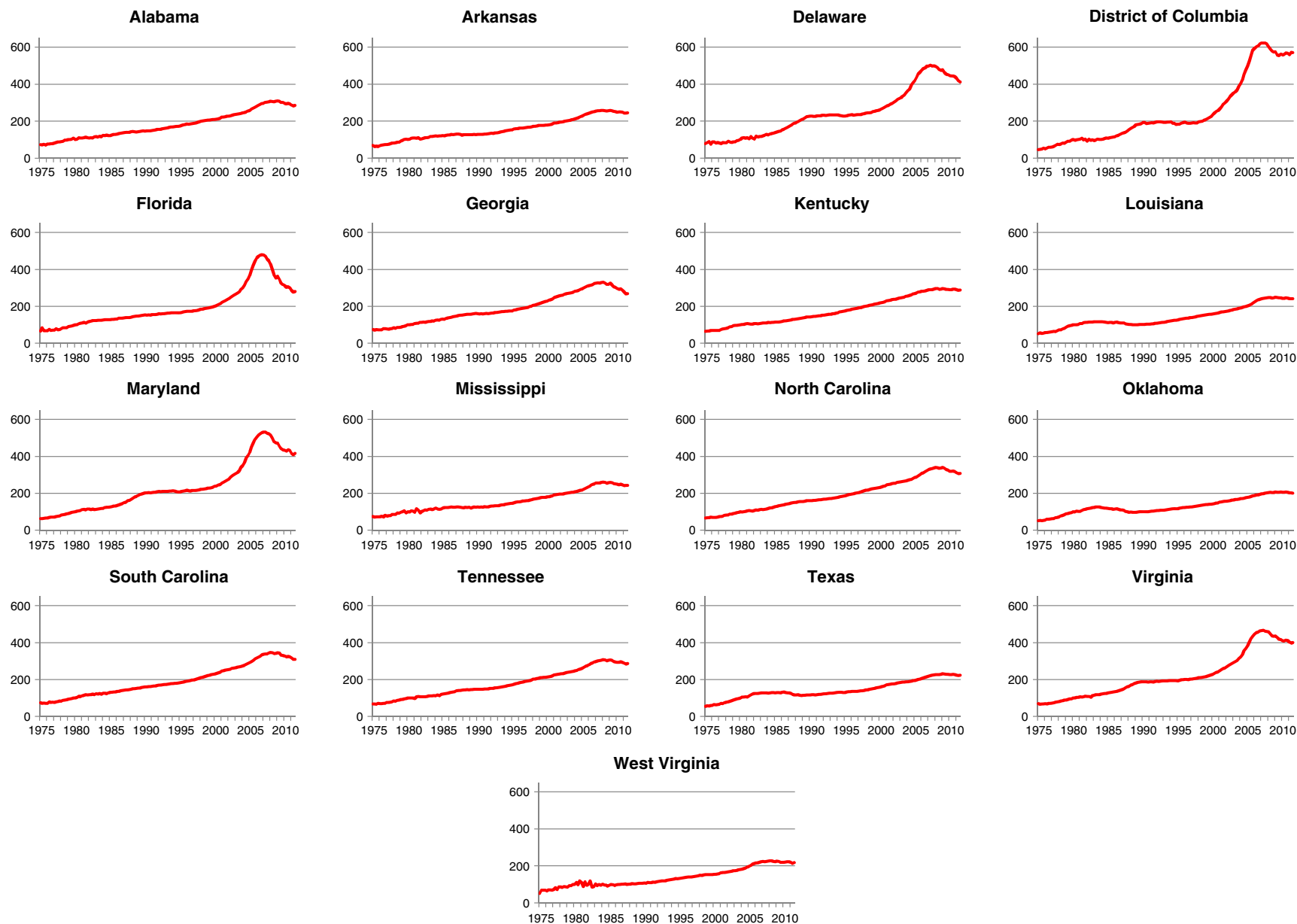


Fig. 1 (continued).

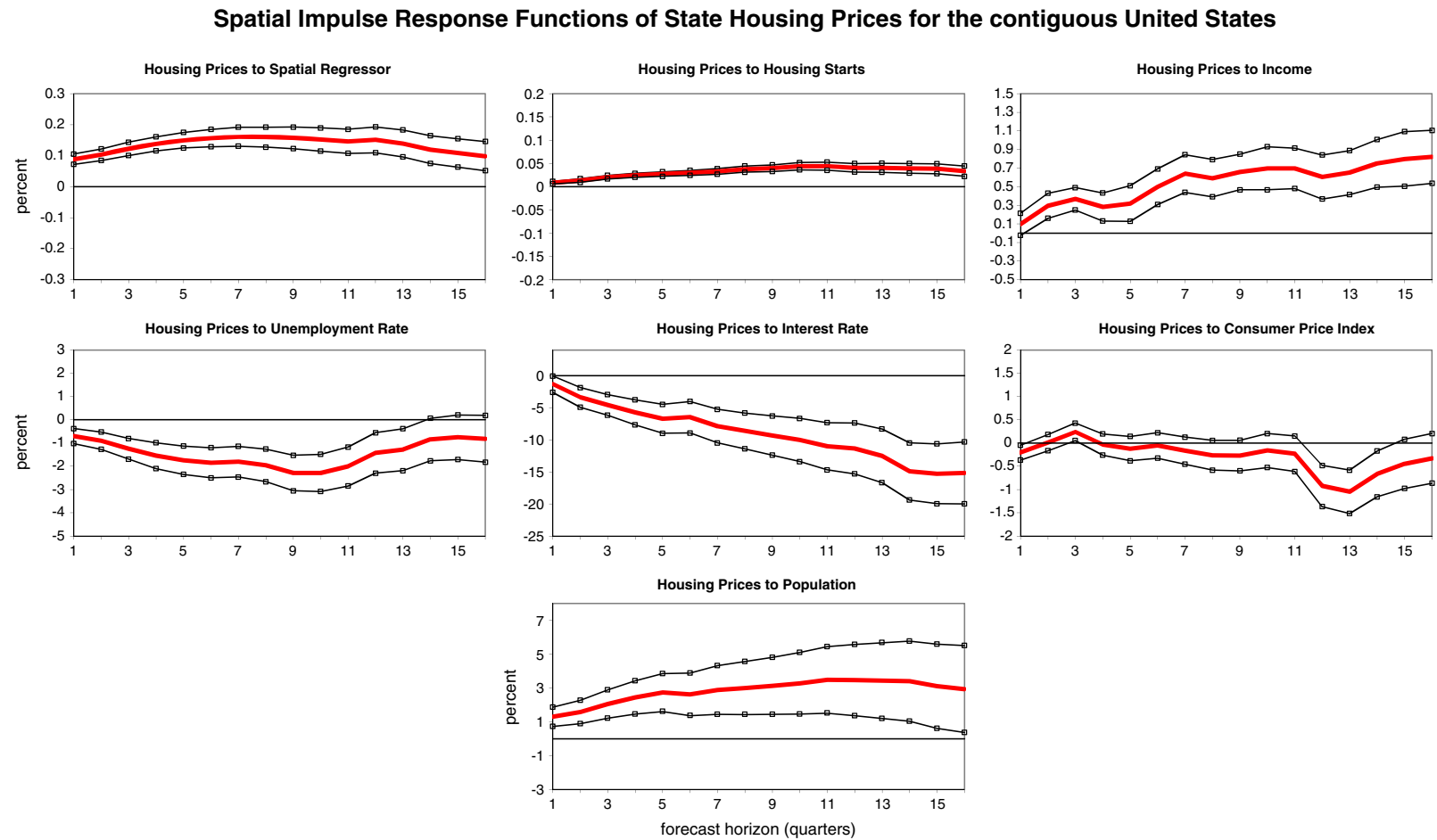


**Fig. 2.** Spatial impulse response functions of state housing prices for the contiguous United States. Notes: The figures show the response of the HPI housing price index to various regressors for the 48 contiguous United States (plus Washington D.C.), for a sample spanning 1975 to the third quarter of 2011, estimated from the dynamic panel-spatial model, controlling for state-fixed effects. See text for details. Please note the minimum and maximums on the vertical axis may be different for each variable.

the general region. Western states on average are larger with longer borders than those in the Northeast, yet the spatial diffusion as captured with the impulse response function does not appear that different for about four to five quarters after the shock save a smaller magnitude. However, after about a year there are differences in the persistence of the effect.

### 5. First differences and error correction

In this section I consider alternative specifications. First I estimate the model with the variables transformed in first differences, and then, I estimate again in first differences but also including controls for potential cointegration between housing prices and income and cointegration between housing prices across regions. Non-stationarity may explain why a response fails to converge in a “reasonable” period of time following the shock (such as in the case of the response of housing prices to income in Fig. 2).<sup>15</sup> To check the properties of the 49 regional price indices I performed unit root and cointegration tests on each. Ultimately the tests are not unanimous with respect to stationarity or cointegration (consistent with the lack of agreement in the literature and as suggested by Fig. 1).<sup>16</sup> Hence, I compare the results from the model-in-levels to the estimates in this section.

The spatial autoregressive model is now written generally as (still expressed in stacked form),

$$\Delta Y_t = \rho W \Delta Y_t + \alpha \Delta Y_{t-1} + \beta \Delta X_t + \varphi_1 (Y_{t-2} - WY_{t-2}) + \varphi_2 (Y_{t-2} - PY_{t-2}) + \varepsilon_t \quad (5.1)$$

where the dependent variable and each regressor are transformed as first differences.<sup>17</sup> The terms,  $(Y_{t-2} - WY_{t-2})$  and  $(Y_{t-2} - PY_{t-2})$ , control for the possible long term relationship between a region's housing price and the weighted average of its neighbors' housing prices, and between housing prices in region  $i$  and personal income in region  $i$ , respectively. I follow Holly et al. (2011) in specifying the error correction terms in this way with one exception. I use the  $t - 2$  lags to define the correction terms instead of the  $t - 1$  values. Ultimately the results for the long panel estimation are nearly identical with either choice, but using the earlier lag is advantageous in the sub-period estimation later in Section 6.

I estimate Eq. (5.1) in two forms, with the parameters on the two error correction terms restricted to equal zero ( $\phi_1 = \phi_2 = 0$ ) and then with the parameters left unrestricted (the former case is equivalent to each variable having a unit root but with no co-integration between the variables). The results turn out to be very similar whether the error correction terms are included or not; hence, I just report the set of results for the unrestricted version with the error correction terms included. I refer to this simply as the first difference-error correction model. Lastly, note that for the first difference-error correction specification the sample begins with the first quarter of 1979 (the “interpolation” done for the effective interest rate before 1979 resulted in zeros after first differencing).

Fig. 3 displays the results for the full sample with the impulse response functions estimated from Eq. (5.1). With respect to the spatial

regressor, spatial correlation is positive, statistically significant and persistent. Here, with the variables in first differences, the persistence of the effect of the spatial regressor on regional housing prices lasts about ten quarters after the shock (in contrast to the baseline case in Fig. 2). The magnitude of the effect is larger in the first difference-error correction model than in the case with the model estimated in levels. With respect to the rest of the independent variables, the impulse response functions between Figs. 3 and 2 are comparable, except in the former the responses are generally smaller in magnitude and the statistical significance is ephemeral relative to those shown in Fig. 2. This general finding is not surprising given that the variables are specified in first differences (smaller magnitudes with first differences (or growth rates) are not uncommon in the VAR literature).

Ultimately, the results from the first difference-error correction estimation show that the spatial diffusion of a shock to housing prices is relatively robust to typical time series issues—that is, there is evidence that spatial diffusion is statistically significant and persistent. The key difference is the spatial diffusion does not last as long as in the models-in-levels case.

### 6. Application: Spatial diffusion across sub-periods

In this section I estimate structural break points in regional housing prices over the 1975 to 2011 sample, and then use those dates to compare and contrast spatial diffusion across sub-periods. The *raison d'être* of this application is to consider how spatial diffusion changes before and after structural breaks in the data. Ultimately I focus on a comparison of spatial impulse response functions before and after a break period in the first quarter of 1999. The break date in 1999 is motivated by structural break tests on the 49 regional housing price series. The break tests and results are explained in the next section. Thereafter I discuss the sub-period spatial IRFs.

#### 6.1. Structural breaks in state-level housing prices

I apply the methods of Bai and Perron (1998, 2003) to estimate multiple break dates for each region's housing price index, over 1975 to 2011, without prior knowledge of when those breaks occur. Bai and Perron (1998, 2003) provide a least-squares based algorithm for estimating the break dates, significance tests, and suggestions for how to interpret the various tests. In this application I test six different specifications for each region since, as discussed earlier in Section 4, there is no unanimous agreement in the literature whether regional housing prices indices are stationary, stationary about a trend, cointegrated with each other and so forth. Hence, to be flexible I estimate with each housing price index in levels modeled as an AR1 without a trend, and then including a trend; and with each housing price index in growth rates modeled as AR(0) and AR(1) without a trend and with a trend, respectively. In addition, for further robustness, I apply the break tests for each of the six variants over a shorter time period, 1987 to 2011.<sup>18</sup>

In reporting the break date estimates, I focus on reporting the dates selected using Bai and Perron (2003) sequential procedure though the ultimate choice of sample division is based on an “average” view of the picture that emerges for the 49 regions (as will be explained). While Bai and Perron (1998, 2003) provide a battery of tests (including the sequential procedure) one can use to identify statistically significant structural break points, in practice many of the varying tests will choose the same (or close to it) break dates, offering corroborative evidence for the researcher. Hence, I simply report dates from one of the possible

<sup>15</sup> What is “reasonable” when examining impulse response functions is ultimately a matter of judgment. The VAR literature is replete with impulse responses that fail to converge which helps motivate, of course, the need to check for non-stationarity.

<sup>16</sup> Results from both the Augmented Dickey–Fuller (ADF) and Phillips and Perron (PP) unit root tests suggest that a unit root is present for the series in levels. However, depending on the test it is not unanimous. For example, based on the ADF test including an intercept and trend, for 25 of the regions one rejects the null hypothesis (at the ten percent level) that a unit root exists. I also applied the Engle–Granger cointegration test to the price indices. The null of “no cointegration” was easily rejected in the simple case where each state's index is modeled as a linear combination of the remaining states' indices. Tables displaying the test results are available on the author's website.

<sup>17</sup> This general first differences-error correction model is motivated by the approach of Holly et al. (2011). Though here I consider a general application of their approach where no dominant region is identified.

<sup>18</sup> The growth rate for each quarter is annualized. For many of the states the annualized growth rate is relatively volatile before 1987 than after. To check whether that pre-87 volatility was having undue influence on the break results, I estimated over the short 1987 to 2011 sample in addition to the full sample. The results for the shorter period are reported in the appendix. Ultimately the shorter-sample-break results offered support to the choice of where to demarcate the sub-periods for the analysis in this section.



**Fig. 3.** Spatial impulse response functions of state housing prices: First difference-error correction specification. Notes: See notes to Fig. 2. spatial IRFs estimated from spatial autoregressive panel model with the variables transformed in first differences and with error correction terms. The sample period for this estimation begins with the first quarter of 1979. See text for details.

tests. Moreover, given the procedure was applied 588 times (49 state-level prices indices times six versions of the specification for two sample periods), I eschew including the complete set of statistics underlying the break date estimates and just report the selected break dates themselves. However, as a representative of the reported statistics underlying the break estimates, the online appendix contains detailed output from the Bai and Perron (1998, 2003) tests for one of the model versions.<sup>19</sup>

In the interest of further brevity, I refer the reader to Bai and Perron (1998, 2003) for technical details on the methodology. I do note, here, however that I set a maximum number of breaks equal to five for the full sample, and to three for the 1987 to 2011 period (some upward bound must be imposed by the researcher).

The results of the 588 applications of the break tests suggest there are a number of estimated breaks for each model, though the number of breaks varies depending on the model. To generalize the results, there appear to be about four common break “clusters” for the 49 regions: in the early 1980s (between 1980 and 1983), in the late 1980s (1988 or 1989), in the very late 1990s (approximately 1999), and that around 2005 to 2006. For example, for the AR(0) model in growth rates, 28 of the 49 regions have estimated break dates over those two years. Fig. 4 offers a visual perspective of the clustering for the AR(0) models in growth rates (without and with trend).<sup>20</sup>

Obviously with 49 regions and the different model choices, there is no exact agreement on the estimated break dates or one could argue for different “clustering” (for example, 1994 to 1995 appears to be a common break date for a number of states). Moreover, the estimated break dates displayed in Fig. 4 should be taken with some caution as Perron (2006) suggests the sequential test can be unreliable.<sup>21</sup> Also, given break testing naturally relies on breaking up a sample period into shorter segments, there are statistical power considerations as well. Finally, structural break tests assume the series under examination is stationary, so it is likely the most reliable estimates, all else equal, are those reported for the models estimated in growth rates. Hence, with those cautionary notes in mind, I use these results as a guide to delineate between sub-periods for the spatial impulse response analysis to follow.<sup>22</sup>

It should be noted that the break points found for the housing price indices are evocative of related research. For example the break dates found for a number of states in the mid-to-late-1980s are generally consistent with what studies on the “Great Moderation” have found. Typical of that literature a break point is identified at some point between 1984 and 1986 (using data ending in the early 2000s; see Owyang et al. (2008) for a state-level analysis, and Benati and Surico (2009) for another example). With respect to housing wealth, Brady and Stimel (2011) estimate break points in 1985 and 1998 from a VAR comprised of aggregate data for the U.S. on housing wealth and related variables (income, and so forth). The Brady and Stimel (2011) study adds some corroboration to the late-1990s dates displayed in Fig. 4.

## 6.2. Spatial IRFs over sub-periods

Given the break results, I compare and contrast sub-period spatial IRFs in two ways. First, I estimate spatial IRFs over relatively short time periods marked by the four break points discussed above—1981 through 1987 ( $T = 28$ ); 1988 through 1998 ( $T = 44$ ); 1999 through 2005 ( $T = 28$ ); and 2006 through the third quarter of 2011 ( $T = 23$ ). Second I compare two (relatively) longer sub-periods, demarcated by the first quarter of 1999—1981 through 1998 vice 1999 through the end of the sample ( $T = 72$  and 51, respectively). Ultimately, in this section I focus on the longer pre-and-post-1999 sample comparisons. I do so since the results for the four sub-periods offered an ambiguous picture of the evolution of spatial diffusion over time.<sup>23</sup>

Of course ambiguity may be of economic and statistical interest unto itself, but given the time dimension is less than 30 quarters in three of the four sub-samples, the lack of a coherent picture may simply be due to the short time span in each. While the time dimensions of the pre-and-post-1999 periods may also leave one wanting, especially relative to the long panel estimation from the full sample ( $T = 145$ ), the analysis of this section is offered both as an exploration of the change in spatial diffusion over time, and as a demonstration of the type of analysis spatial IRFs may yield for any spatio-economic topic of interest (given the researcher should have sufficient time dimension in his or her particular application).

With the shorter time dimensions of the pre-and-post-1999 periods, the dynamic panel obviously becomes “shorter.” As such, the opportunity for bias comes in two particular forms. First, the spatial regressor is correlated with the error term (though of course the bias will dissipate at  $T$  increases as noted in Brady (2011), Elhorst (2003) and Anselin (2001)). Second, the fixed-effects estimator is biased since the lag of the dependent variable is correlated with the error term. Hence, I use instrumental variables to mitigate the potential biases. Consistent with the spatial literature, one can instrument with either lags of the spatial regressor or the spatial versions of the independent variables in the model. The latter are constructed from the spatial weighting matrix applied to each regressor (or lagged values of each). Also, one can use the common strategy in the dynamic panel literature and use additional lags of the dependent variable to instrument for the  $t - 1$  value of the dependent variable. For the estimation reported in this section, the instrument set includes the spatial version of each independent variable, the  $t - 2$  lag of the spatial regressor, and the third and fourth lags of the dependent variable.<sup>24</sup>

Fig. 5 displays the results for the 1981 to 1998 period and the 1999 to 2011 period. Consistent with earlier sections, results are displayed for both the model-in-levels and for the first difference-error correction model (using instrumental variables in each case). I focus on the response of regional housing price to the spatial regressor. For the results from the model-in-levels (top row) there is a clear difference in spatial diffusion before and after the first quarter of 1999. The effect is minimal in the first part of the sample yet positive and persistent in the second half of sample (evocative of the spatial IRF for the entire sample period shown in Fig. 2).<sup>25</sup> However, in the first-difference version of the estimation the effect appears similar across the two periods. While the statistical significance of the spatial diffusion is more noteworthy after

<sup>19</sup> As an example of the various statistical output from Bai and Perron (1998, 2003) methods, the online appendix provides detailed output for each region for one of the model versions (for the price index in levels modeled as an AR(1) without trend for the 1987 to 2011 sample). The detailed results for the 11 other model versions are available upon request, or are easily replicable (the Gauss code is publicly available on Phillip Perron's website).

<sup>20</sup> Tables displaying the break estimates for all 49 regions across all six specifications are available in the online appendix.

<sup>21</sup> Though ultimately the other procedures in the Bai and Perron (1998, 2003) toolkit choose similar dates—see again the appendix. The points of caution in this paragraph are paraphrased from discussion in Brady and Stimel (2011).

<sup>22</sup> Admittedly the break date search employed here is indirect in the sense that I use the break dates from tests on the single series to then set the sub-samples in the single-equation, dynamic-panel estimation. The application of break tests to the spatial models is beyond the scope of this paper; Mur et al. (2008) is an example of such an application.

<sup>23</sup> For the relatively short four sub-periods spatial diffusion is positive in many of the sub-periods, though the duration of statistical significance and even the estimated sign at various points over the horizon is variable, and depends on the modeling choice. The figures for the four sub-periods, for both the model-in-levels and the first-difference-error-correction model, can be viewed in the appendix.

<sup>24</sup> The F-statistics from the first stage estimation (not reported) for both the spatial regressor and the lag of the dependent variable suggest the instrument set is a strong predictor of each.

<sup>25</sup> Recall in contrast to the results reported in this section, the results shown in Figs. 2 and 3 are generated from the model-in-levels or the first-difference-error-correction model without instrumental variables. For comparison, figures for the pre-1999 and post-1999 periods estimated with OLS are available in the appendix.

### Clusters of Break Dates estimated for 49 regional price indices, 1975 to 2011

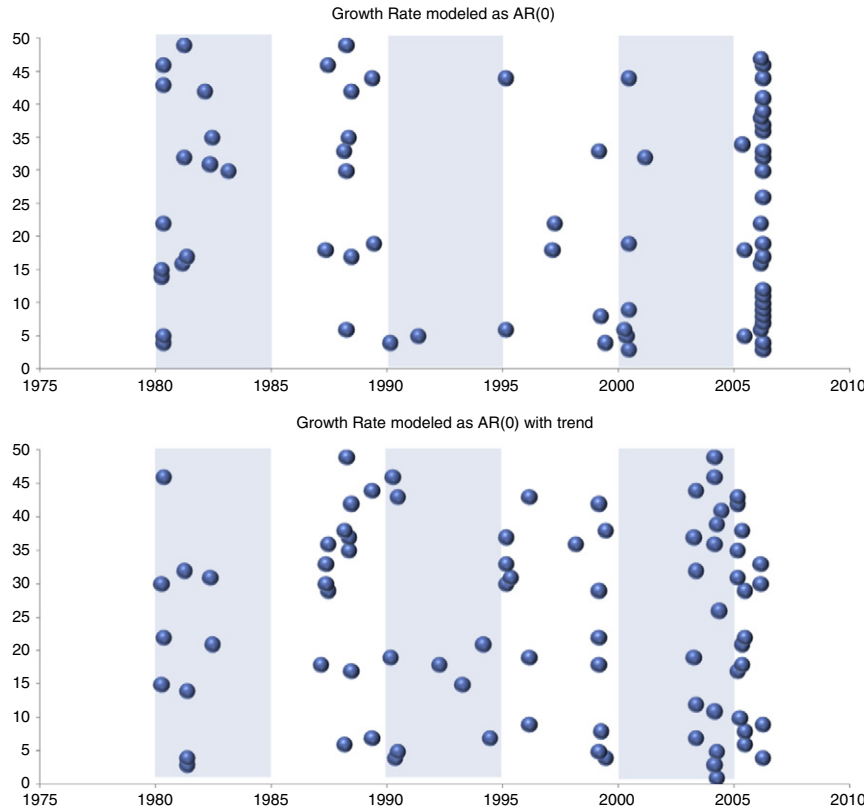


**Fig. 4.** Clusters of break dates estimated for 49 regional price indices, 1975 to 2011. Notes: Scatter plot represents break dates estimated for each regional home price index (dates estimated with the Bai and Perron (1998, 2003) methodology). Here the growth rate of each region's home price index is modeled as an AR(0) with and without trend, respectively (see the discussion in the text for more details). The vertical axis represents the 49 regions; a higher number corresponds to a state low in the alphabet and so on (so Wyoming is at the top of the axis). Tables displaying the exact break date estimate for each state are available in the online appendix. The shaded regions demarcate five year intervals simply for esthetic purposes.

1999, the duration of the effect is limited to about five quarters (in contrast to the more persistent effect shown in Fig. 3).

Overall, the two-period comparison marked by the first quarter of 1999 offers a suggestive “before-and-after” picture of spatial diffusion. The suggestion is that the persistence and magnitude of spatial diffusion is a recent phenomenon. Of course, the results across the two model versions are not without ambiguity. Nevertheless, the sub-period comparison demonstrated in this section perhaps provides motivation for additional spatial or regional research, and offers a simple template for any such effort to follow. With sufficient panel length (enough  $T$  in the panel data set, that is), the spatial or regional econometrician may find a similar before and after picture using different regional data sets. If spatial diffusion is a recent phenomenon, then understanding the mechanism behind the effect's emergence may be an interesting question to be addressed with data on “finer” regions (such as the county or city level).

## 7. Conclusion

The results of this paper for the contiguous U.S. provide a novel perspective on the characteristics of regional housing prices at the state level. The estimation provides results that are consistent with time series studies on the relative factors that explain housing prices, yet the single-equation spatial model provides the explicit spatial component often lacking from time series studies on state-level housing data. In particular, this paper documents the effect of spatial contiguity on a particular state's housing price index, holding constant whatever may be

occurring within the state. This paper shows that spatial diffusion is statistically significant for approximately three to four years following a housing price increase across regions.

Moreover, the spatial impulse response functions in this paper are easy to calculate since the method avoids the dimensionality issue of incorporating spatial correlation into a multi-equation model (such as a VAR). In the single-equation setting of the method described here, one can control for various covariates, incorporate directly a spatial weighting matrix, control for non-stationarity, and easily apply instrumental variables techniques to deal with issues of endogeneity. And one can then easily estimate impulse response functions from direct forecasting techniques. There are a few extensions of this paper that one might consider.

Much of the spatial literature cited at the beginning of Section 2 focuses on “smaller” regions such as counties, or neighborhoods within major cities (for example, the study by Basu and Thibodeau (1998)). Given this paper documents the extent of spatial diffusion at the state level, it is likely that the persistence of spatial diffusion is also pronounced at those more local levels. As suggested at the end of the previous section, applying the methods of this paper to such an inquiry would be a natural extension. Alternatively, one can consider the effect of common factors that may affect spatial diffusion. As suggested by Chung (2013) and Marquez et al. (2014) common factors may mitigate what at first appear to be significant spatial spillovers; national factors, for example, may dominate at larger regional definitions.<sup>26</sup> While the

<sup>26</sup> I am grateful to a referee for emphasizing this particular point.

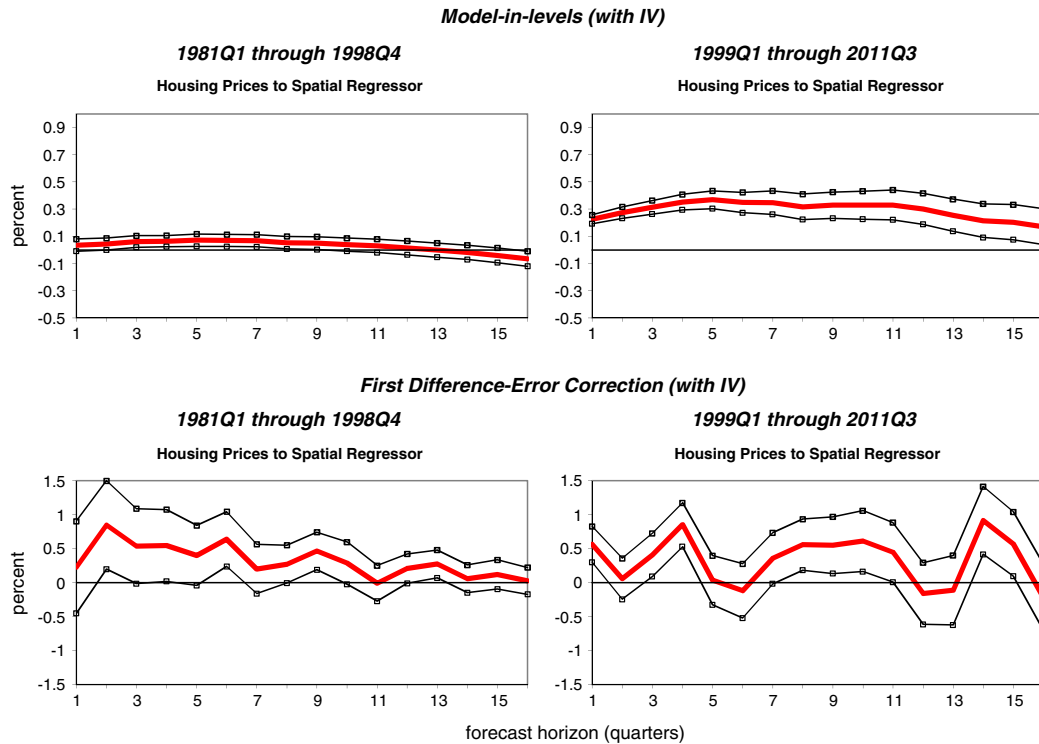


**Fig. 5.** Spatial impulse response functions of state housing prices to the spatial regressor, all 49 regions before and after 1999. Notes: The figures show the response of the FHFA Housing Price Index to the spatial regressor for the contiguous U.S. See Fig. 2 for additional details. See text for an explanation of the sample division.

main results in this paper are robust to controlling for national factors (as mentioned in Section 4), the interaction between spatial diffusion and common factors may be a fruitful line of inquiry. For example one immediate extension of this paper is to understand how spatial diffusion across U. S. states interacts with a monetary policy shock. A similar study might easily be applied to the nations in the European Union (or to measure the extent of spatial diffusion controlling for common factors).

Of course, if spatial diffusion is not of direct interest, but a nuisance to be controlled for in time series estimation, the single-equation approach provides an easy method for accounting for what might otherwise be an omitted variable. For example, one could use the estimation in the manner of this paper to update and expand upon the housing-monetary policy study of McCarthy and Peach (2002), which focuses on the effects of Federal Reserve policy on national housing aggregates (Owyang et al. (2008), Owyang and Wall (2009), Carlino and Defina (1998, 1999), and Baffoe-Bonnie are other relevant regional–national-monetary studies). Similarly one could apply the methods in this paper to other aspects of regional conditions related to business cycle and policy analysis, such as in the manner of the Fratantoni and Schuh's (2003) study mentioned in Section 3, or similar to Park and Hewings (2012), a study which focuses on within-region industry mix to understand regional business cycles.

The basic framework used in this paper could also be employed to focus on “core and periphery” spatial diffusion, in the spirit of Holly et al.'s (2011) study on shocks emanating from London to surrounding areas in England. Of course, with the large state-level panel data set used in this paper, it is difficult to assume that any one city in the vast expanse of the United States is “the” core. However, one could focus on a specific subset of the U.S. (such as the census regions discussed earlier), or, of course, use data at the metro or county level. At such “higher” frequency spatial levels, one could compare the magnitudes and persistence of spatial diffusion from major U.S. cities to surrounding areas, and compare these results to the spillovers that Holly et al. (2011) found for the United Kingdom.

Finally, the persistence of the spatial diffusion may provide insight into the nature of “bubble behavior” in housing markets. Typically the persistence of housing prices over time is cited as an example of the inefficiencies that drive bubble formation in housing markets (see Case and Shiller (2003) for an overview). Similarly “non-fundamental” behavior may be propagated by regional contiguity and be evident in the persistence of the spatial lag. The point is articulated succinctly by Pollakowski and Ray (1997). If housing markets are efficient, neither time lags nor activity in adjacent regions should forecast a region's housing price movement.

Hence, similar to the notion that the temporal lag of housing prices signals inefficiencies, the persistence of the spatial lag suggests a transmission mechanism for bubbles to occur. And obviously in the spatial context, herd behavior is likely to be more intense the more regional markets are connected (perhaps via the “yardstick” mechanism discussed in Section 2). As such, the discussion surrounding the issue of time persistence offers a testable relationship between spatial diffusion and housing price bubbles. A group of regions (neighborhoods, counties, states, etc.) characterized by statistically significant spatial correlation may exhibit larger rates of price appreciation than in those regions characterized by a weaker spatial connection. A researcher with access to data on county or city-level housing prices with sufficient time dimension may be able to provide insight on such a possible spatial-bubble connection.

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