Sant'Anna, A.C., and A.L. Katchova. "Determinants of Land Value Volatility in the U.S. Corn Belt." *Applied Economics* (2020). https://doi.org/10.1080/00036846.2020.1730760

Determinants of land value volatility in the U.S. Corn Belt

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Understanding land value volatility and its reaction to exogenous shocks helps land owners, investors, and lenders assess risk. Land value volatility, the variance of the unpredictable component of land value growth rates, is modelled for each of the Corn Belt states in the U.S. using EGARCH. A pooled VAR system is then estimated to capture the interactions between land value determinants and land value volatility. The variables of the pooled VAR are split into negative and positive vectors to allow for asymmetric impacts. Impulse response functions are mapped. All states exhibit land value volatility clustering. Inflation, cash rent and population growth rates granger cause land value volatility. Land value volatility responses to negative shocks are greater than those to positive shocks. Lenders and investors should expect greater swings in land values after negative shocks to land value growth rates, but not an overreaction of land values from shocks to cash rent growth rates. Positive shocks to changes in interest rates increases land value volatility, but unexpected shocks to population growth rates do not have statistically significant impact on land value volatility.

Keywords: asymmetric effects; land value volatility; interest rates; cash rents; vector auto-regression

Subject classification codes: Q14; C22; G12

1. Introduction

Land serves as an investment and a production tool. Farmland values are of importance to land owners, farmers, agricultural lenders and policy makers for their role in farm loans as a collateral and for their farm income generation (Nickerson et al. 2012; Cowley 2016). Therefore, land values lows and highs may indicate times of financial stress or strength in the farm sector (Cowley 2016). Understanding the factors that impact land value variance (i.e. land value volatility) and how it reacts to innovations (e.g. good or bad news) can help land owners and lenders prepare for changes in the land market. Previous studies have focused on land value volatility using the assumption of constant growth rates (Benirschka and Binkley 1994; Young, Binkley and Florax 2016) or as percentage variations in land values (Just and Miranowski 1993). We propose to use and analyse the variance of the unpredicted component of land values.

Volatility forecasting is a common element in investment risk management analysis (Hossain and Latif 2009). In financial markets, volatility is measured by the standard deviation of stock returns (Zheng 2015). Wheaton et al. (2001), though, argue that in the case of real estate markets, volatility should not be measured based on historical returns but based on the unpredictable component of housing prices. Since future housing prices can be predicted by historical price behavior, the uncertain portion in housing price variation is the unpredictable component of house price growth rates (Zheng 2015). This approach is applicable to land values, as they can be predicted based on historical land values (see Just and Miranowski 1993), linking uncertainty in land value behavior to the unpredictable portion. Analogous to the housing market (see Wheaton et al. 2001), we assume that uncertainty in the land value market has a predictable and an unpredictable component. We measure land value volatility as the variance of the unpredictable component of the land value growth rate. Although it may be common to analyze volatility, volatility clustering, and spillovers in financial and housing markets (Lee 2009), this is the first study to model land value volatility as the variance of the unexpected changes in land values. Our objective is to analyze land value volatility and its asymmetric responses to positive and negative shocks from land value determinants. We also test how land value volatility responds to good or bad news (i.e. we check for the presence of asymmetric effects). This article is composed of this introduction, followed by an analysis of current land value trends and past literature. Thereafter, the empirical method is discussed along with the data. This is followed by the results section and concluding remarks.

1.2 Overview of land value trends

The greater variation in land values in the Corn Belt in the U.S. has motivated us to study this region and to investigate how land value volatility is impacted by changes in land value determinants. Land values in the Corn Belt states experienced larger changes over time than average U.S. land values. There are two major peaks in land values during the period of 1953 to 2017, one before the farm crisis in the 1980s and the second one from 2011 onwards (Figure 1). The second peak in land values is 1.85 times larger than the first peak in real values. From 1987 to 2009, land values in the Corn Belt have been steadily increasing, with a sharp increase from 2009 onwards. Since mid-2015, though, farmland values have been decreasing and this is likely to continue (Sherrick, Schnitkey and Kuethe 2015).

[t]Figure 1 near here[/t]

Trends in farmland values can also be analyzed by studying land values to cash rent ratios (Figure 2). From 1960s to early 2000s, land values to cash rent ratios have ranged from 13.64 to 20. Following a decrease in interest rates since the late 1990s, land values to cash rent ratios have increased, reflecting the steady increases in land values. Johnson (2016) suggests that lower interest rates may be responsible for the increases seen in land values to cash rent ratios. Lower interest rates imply lower opportunity costs, making investors willing to pay a higher amount for each dollar in current earnings from farmland.

[t]Figure 2 near here[/t]

1.3 Previous research on land values

Volatility, studied extensively in finance, is normally applied to stocks, exchange rates and interest rates (Lee 2009). Nevertheless, applications to housing prices have become common (Lee 2009; Miller and Peng 2006; Hossain and Latif

2009). Housing, as an asset, holds similar traits to house owners, as land does to land owners. Namely it represents a large share of the total assets (land represents 80% of the total farm assets), and it has low liquidity and transaction costs. Positive shocks to the housing market may increase demand and consequently house price volatility. Housing supply, though, may not react as quickly to higher demand. The short-term inelastic supply may further affect housing price volatility (Zheng 2015). As the land market holds similar traits to the housing market, we expect land value volatility to display similarities to house price volatility (i.e. time varying volatility and clustering).

The fundamentals of farmland pricing are the discounted value of its economic rent (i.e. the return to farmland from the cultivation of the land including all variable factors of production) (Ricardo 1996; Moss and Katchova 2005). The relationship between land values and returns can be represented through the capitalization formula (i.e. Land Value = Returns/Discount Rate) (Brorsen, Doye and Neal 2015). The observed land value is, generally, the lowest value the seller is willing to accept and the highest value the buyer is willing to pay (Robison, Lins and VenKataraman 1985). Hence, the opportunity costs of the seller equals the returns from the land for the buyer (Featherstone and Baker 1987; Robison, Lins and VenKataraman 1985). By re-organizing the capitalization formula we find that Land Value/Returns = 1/Discount Rate. Without market distorting factors, such as inflation, the ratio of Land Value/Returns would be constant (Robison, Lins and VenKataraman 1985). However, we know that this is not the case (Figure 2). Thus, expansions to the capitalization model have been suggested over time. Studies have found that land values are also determined by macroeconomic factors (e.g. inflation), government payments, and population growth among other factors (Just and Miranowski 1993; Borchers, Ifft and Kuethe 2014; Devadoss and Viswanadham, 2007). Therefore, we assume that shocks to factors beyond returns to land and interest rates, such as population growth and inflation, will also effect land value volatility.

Farmland markets have undergone boom and bust cycles over time (Henderson, Gloy and Boehlje 2011) and are prone to bubbles (Featherstone and Baker 1987). Land values overreact to shocks to asset values, rents and real interest rates (Featherstone and Baker 1987). Land further from the market are sensitive to boom and bust periods (Benirschka and Binkley 1994). Similarly, land in regions heavily dependent on government payments is more sensitive to variations in inflation, returns on assets and capital costs (Moss 1997). Government payments, though, only minimally explain variations in land value minimally, while inflation and returns on alternative capital largely explain land price swings (Just and Miranowski 1993). We use past research to determine the fundamental and other variables that influence land values used in this study. Given the many factors that determine land values and swings in land prices, we investigate the role of these factors on land value volatility. Whether and how much land value volatility reacts to unexpected shocks to land value determinants provides valuable insight to investors, agricultural lenders and landowners.

2. Methodology and Empirical Analysis

We assume that agents in the land market can predict future land value growth rates based on rational expectations, with knowledge of available information and the optimal strategies of other agents (Hossain and Latif 2009). The general technique used for modeling rational expectations is the ARMA model (Hossain and Latif 2009; Miller and Peng 2006). That is, the expected land value growth rate is a function of past information and shocks. Therefore, the observed growth rate of land value in state *i* in year *t*, ($lv_{i,t}$), is equal to the sum of expected land value growth rate conditional on the information set available (I_{i-1}) and an unpredicted shock ($\varepsilon_{i,t}$) (Miller and Peng 2006):

$$lv_{i,t} = E\left[lv_{i,t} \middle| I_{i-1}\right] + \varepsilon_{i,t} \qquad (1)$$

where the land value growth rate is $lv_{i,t} = \log\left(\frac{L_{i,t}}{L_{i,t-1}}\right)$, and $L_{i,t}$is the land value in state *i* in year *t*.

We estimate the expected future land value growth rate for each Corn Belt state using an ARMA(p,q) model. The p and q order of lags for the ARMA model is established by analyzing the AIC of various model specifications (see Appendix). A dummy for the farm crisis period and a time dummy for the recent increase in land values (i.e. from 2005-2014) are added to the ARMA models. The residuals from the estimated ARMA model are equivalent to the unpredicted portion of the realized land value growth rates ($lv_{\mathrm{i,t}}$). From equation (1), the realized land value growth rate is a function of the expected land value growth rate ($\mathrm{E}\left[lv_{\mathrm{i,t}} \middle| \mathrm{I}_{\mathrm{i-1}}\right]$) and of unpredictable shocks or innovations ($\varepsilon_{\mathrm{i,t}}$).

We test each of the Corn Belt states' land value growth rates for the presence of volatility clusters (i.e. if years of higher volatility are followed by high volatility and low volatility periods are followed by low volatility periods) (Hossain and Latif 2009; Enders 2015). Volatility cluster is checked by testing whether the residuals follow an ARCH(q) process using the Lagrange Multiplier test (ARCH-LM)[1] (Engle and Ng 1993; Lee 2009):

$$\varepsilon_{i,t}^2 = \varphi_{i,0} + \varphi_{i,1}\varepsilon_{i,t-1}^2 + \varphi_{i,2}\varepsilon_{i,t-2}^2 + \cdots + \varphi_{i,p}\varepsilon_{i,t-q}^2 \qquad (2)$$

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[1] The ARCH-LM test was conducted using the MTS package in R (Tsay 2016).

where $\varepsilon_{i,t}^2$ is the squared residuals for the land value growth rates of state i and q is the order of the ARCH process. The ARCH-LM test can then be estimated for each state using the sample size T, which in our case is 107 observations per state, and the R^2 from equation (2):

$$LM_i = T_i * R_i^2 \tag{3}$$

2.1 Volatility Estimation

The presence of cluster volatility provides evidence that estimating volatility with an ARCH/GARCH model is appropriate. We opt to model volatility with an exponential-generalized autoregressive conditional heteroscedasticity model (EGARCH). The EGARCH, an extension of the GARCH model, controls for volatility clustering as well as asymmetric effects in volatility (Lee 2009). It also allows for asymmetric effects and nonnegative constraints (Enders 2015). Asymmetric effects occur when there is a tendency for volatility to react more to negative "news" (e.g. a decline in returns) than to positive "news" (e.g. a rise in returns) (Enders 2015). The conditional mean and variance equations used in the EGARCH(1,1) estimation are (McAleer and Hafner 2014; Lamoureux and Lastrapes 1990):

Conditional mean equation

$$lv_{i,t} = E\left[lv_{i,t} \middle| I_{i-1}\right] + \varepsilon_{i,t}, (\varepsilon_{i,t}|\varepsilon_{i,t-1}, \varepsilon_{i,t-2}, \dots) \sim N(0, h_{i,t}) \tag{4}$$

where $lv_{i,t}$ is the land value growth rate and $\varepsilon_{i,t}$ the residuals for state i at time t. $\varepsilon_{i,t}$ follows a normal distribution with mean 0 and a conditional variance $h_{i,t}$. Equation (4) is equivalent to the ARMA in equation (1). In the EGARCH model, variance is conditional on past shocks and past information. Hence, the variance is not constant (i.e.

unconditional[2]) throughout the years[3]. The conditional variance equation proposed by Nelson (1991) is (McAleer and Hafner 2014):

Conditional variance equation

$$ln\left(h_{i,t}\right) = \omega_{i,0} + \alpha_i|\eta_{t-1}| + \gamma_i\eta_{t-1} + \beta_i\, ln\left(h_{i,t-1}\right), |\beta| < 1 \qquad (5)$$

where $h_{i,t}$ is the conditional variance for the land value growth rate in state *i*. $h_{i,t}$ varies over time. The stability condition is given by $|\beta| < 1$. $\omega_{i,0}$ is the constant, and $\varepsilon_{i,t-1}$ is the lag of the residual from the mean equation. If $\gamma_i \neq 0$ then we know that for state *i*, asymmetry exists (McAleer and Hafner 2014). Asymmetry effects means that land value volatility reacts differently to good and bad news (e.g. a decrease in returns). For a better interpretation of shock sizes and persistence, the EGARCH uses standardized shocks η_{t-1}, which are calculated as $\eta_{t-1} = \frac{\varepsilon_{i,t-1}}{h_{i,t-1}^{0.5}}$ (Enders 2015; Nelson 1991; McAleer and Hafner 2014)[4]. The EGARCH specification that is used to model land value volatility is chosen by analyzing the AIC of different EGARCH models (see Appendix). Land value volatility (*vly*) predicted from the EGARCH model (i.e. $\hat{h}_{i,t}$) is then used in a pooled vector autoregression (VAR).

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[2] The unconditional variance can be treated as a constant and is estimated as the long-run forecast of the variance (Asteriou and Hall 2016).

[3] The assumption of homoscedasticity or constant variance was rejected through the ARCH-LM tests.

[4] The fact that the standardized shocks (η_{t-1}) are a function of variables (i.e. $h_{i,t-1}^{0.5}$and $\varepsilon_{i,t-1}$) that are dependent on the parameters in the mean and variance equations makes the quasi-maximum likelihood estimation and the invertibility of the EGARCH challenging (McAleer and Hafner 2014). McAleer and Hafner (2014) use a random coefficient complex nonlinear moving average process to estimate the conditional variance as $h_{i,t} = E(\varepsilon_t^2|I_{t-1})$.

2.2 Reduced Form Vector-Autoregression Model

The vector autoregressive (VAR) model, introduced by Sims (1980), is commonly used for analyzing dynamic systems due to its ease in estimation and its similarity to multivariate multiple linear regressions (Featherstone and Baker 1987; Tsay 2013). By allowing the lags of every variable in the system to impact other variables, the VAR minimizes spurious relationships due to restrictions made a priori of the dynamic interactions (Featherstone and Baker 1987; Sims 1980). In this study, we propose a slight modification to the usual vector autoregression (VAR) system found in the literature. Following Miller and Peng (2006) we estimate a pooled VAR model composed of land value volatility ($vly_{i,t}$) along with other variables:

Pooled VAR

$$\begin{pmatrix} Y_{i,t} \\ cpi_{i,t} \\ vly_{i,t} \end{pmatrix} = \begin{pmatrix} D_i \\ d_i \end{pmatrix} + \begin{pmatrix} D_t \\ d_t \end{pmatrix} + \begin{pmatrix} AY^{+}_{i,t-1} \\ \alpha Y^{+}_{i,t-1} \\ aY^{+}_{i,t-1} \end{pmatrix} + \begin{pmatrix} BY^{-}_{i,t-1} \\ \beta Y^{-}_{i,t-1} \\ bY^{-}_{i,t-1} \end{pmatrix} + \begin{pmatrix} Rcpi_{i,t-1} \\ \rho cpi_{i,t-1} \\ rcpi_{i,t-1} \end{pmatrix} + \begin{pmatrix} Gvly_{i,t-1} \\ \gamma vly_{i,t-1} \\ gvly_{i,t-1} \end{pmatrix} + \begin{pmatrix} U_{i,t} \\ e_{i,t} \\ u_{i,t} \end{pmatrix} \tag{6}$$

where $vly_{i,t}$ is the conditional variances predicted from the EGARCH model (see equation (5)), $Y_{i,t}$ is a vector of a change in risk-free interests (*cmt*), growth rates of cash rent (*cr*), land values (*lv*)[5] and population (*pop*). D_i is a vector of state dummies and D_t is a vector of time dummies of 10 year intervals[6]. Time and states dummies are added to control for time-invariant state attributes, as well as, macro factors affecting

[5] *lv* are the land value growth rates used in the ARMA models. Recall that the residuals from the ARMA models are then used to model land value volatility.

[6] The last dummy accounts for 7 years instead of 10 due to the length of the time series.

the states (Miller and Peng 2006). The variables (*pop, cmt, lv* and *cr*) on the right hand side were split into positive and negative values (i.e. $Y_{i,t}^{+}$ and $Y_{i,t}^{-}$). For example, $Y_{i,t}^{+}$ contains only positive values of (*pop, cmt, lv* and *cr*) and zero for negative values. Analogously, $Y_{i,t}^{-}$ contains only negative values of (*pop, cmt, lv* and *cr*) and zero for positive values. In the case of *cpi* and *vly* no negative values were observed so they are not split[7]. The separation of positive and negative values was conducted in order to capture the asymmetric effects of the variables on land value volatility (Miller and Peng 2006). A, B, R, G are vectors of coefficients, while $\alpha, \beta, \gamma, \rho, a, b, r, g$ are scalars of coefficients. $U_{i,t}$ is a vector and $e_{i,t}, u_{i,t}$ are scalars of error terms orthogonal to the space spanned by the right hand side variables (Miller and Peng 2006).

Due to the size of our sample, estimating a VAR system for each of the states is not recommended, hence, we pool the VAR system (Miller and Peng 2006). Pooling allows us to control for fixed effects and for the lagged effects pertinent to each state (Miller and Peng 2006). We use state level data instead of national level since we believe that using disaggregated data is more appropriate to analyze land value volatility in the Corn Belt. Following Miller and Peng (2006), we estimate the pooled VAR row by row using feasible GLS. First, the VAR system is estimated using OLS with fixed effects. Residuals from the OLS are then used to construct the weighted matrix to control for heteroscedasticity and serial correlation in the error terms (see Wooldridge 2009). Next, the weighted OLS is estimated. An optimal lag length of the VAR is

[7] There was only one negative value for CPI in 2009 of -0.0015, which was excluded as an outlier.

chosen based on three selection criteria proposed by Andrews and Lu (2001)[8]. We then test for granger causality between the variables using a test specific to panel data designed by Dumitrescu and Hurlin (2012). The test allows us to verify the suitability of the VAR system. Lastly, we plot unit impulse response functions (IRFs) to analyze the land value volatility response to exogenous shocks in the other variables (following Hamilton 1994; Lütkepohl 2005). To estimate the IRFs we transform the VAR into a moving average, MA(∞) process (Hamilton 1994):

$$y_t = \boldsymbol{\mu} + \Psi_0 \boldsymbol{\epsilon}_t + \Psi_1 \boldsymbol{\epsilon}_{t-1} + \Psi_2 \boldsymbol{\epsilon}_{t-2} + \cdots \qquad (7)$$

where $\boldsymbol{\mu}$ is a vector of intercepts, assumed to be zero, and $\boldsymbol{\epsilon}$ is a vector of exogenous shocks or innovations. $\Psi_{\boldsymbol{s}}$ is a matrix that can be interpreted as (Hamilton 1994, p. 318):

$$\frac{\partial y_{t+s}}{\partial \epsilon_t'} = \Psi_s \qquad (8)$$

The element in the i^{th} row and j^{th} column of the matrix Ψ_s identifies the response from a one unit increase in the j^{th} variable's innovation at the time $t(\boldsymbol{\epsilon}_{jt})$ for the value of variable i at $t+s$ ($y_{i,t+s}$) (Hamilton 1994, p. 318). All other innovations are held constant[9] (Hamilton 1994, p. 318). In simple terms, the impulse response gives the

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8 The selection criteria were performed using the pvarsoc program by Abrigo and Love 2016. The pooled vector autoregression model (VAR) with one lag was preferred, as it was the case where all criteria displayed the lowest values (Abrigo and Love 2016).

9 We preferred to analyze the response to a unit shocks because the standard deviations of the variables were very small and we need to be able to analyze the effects from the shocks isolated. We acknowledge that this assumes that shocks from other variables remain constant and that we may be underestimating the impact on land value volatility. Nevertheless, we found similar movements from shocks using the orthogonalized impulse-response functions, which makes our results and conclusions more robust.

difference between forecasts of y with a one-time shock (y_t') and forecasts of y without the shock (y_t^0) (e.g. the impulse response for one period is $IRF_0 = y_t' - y_t^0$). It provides the marginal effects from a one-time shock.

2.3 Choice of variables

The proposed pooled VAR model is composed of land value volatility, land values and four other variables that are important in determining land values. The variables we use can be divided between fundamental and other variables that influence land values and land value volatility. The fundamental variables are those related to asset pricing theory and land value formation (Featherstone and Baker 1987; Robison, Lins and VenKataraman 1985). The other variables comprise external factors that influence land values such as inflation and demand for land for conversion to non-agricultural purposes.

2.3.1 Fundamental variables

In the literature on land value determination there is a consensus that land value is a function of returns to the land and interest rates. The fundamental variables (returns and interest rates) determine the long-run equilibrium of land values (Featherstone and Baker 1987). Robison et al. (1985) argue that the rent received for the land (e.g. cash rent) can be a measure of returns from the land, and is readily available for investors seeking to buy land. Therefore, we use cash rents as a proxy for returns to the land. We use the 10-year treasury constant maturity rate as the interest rate. This interest rate is commonly used as a proxy for a risk-free interest rate for long-term investments (e.g. land acquisition), and is helpful in determining the capital’s opportunity cost (Gloy et al. 2011).

2.3.2 Other variables that impact land values and its volatility

Apart from the fundamental variables, there are factors present in the economy that impact land value and land value volatility. In this study, we limit these factors to inflation and urbanization pressures. Robinson, Lins and VenKataraman (1985) argue that inflation can affect fundamental variables and land values. We control for inflation by using the consumer price index with 2017 as the base year. Competition for land causes an increase in its value (Kuethe, Ifft and Morehart 2011). As the population increases, there is a rise in demand for land for conversion into non-agricultural purposes. We use population growth rate as a proxy for urbanization pressure.

3. Data

Data on land values for the Corn Belt states (Iowa, Illinois, Ohio, Indiana and Missouri) come from the National Agricultural Statistics Service of the United States Department of Agriculture. We use land value instead of actual farmland prices registered in transaction costs in order to reflect the value of all land, not only land that was sold (Raup 2003). Land value volatility estimates are produced using yearly data from 1912 to 2017. These are predicted from the EGARCH model (see equation 5)[10]. A larger sample is used since the GARCH modelling requires a larger dataset. Variables for the pooled VAR are available from 1960 to 2017. The shorter time-series considered in the pooled VAR is due to the time periods that data on cash rents are available.

Cash rents from 1960 to 2017 are from the USDA National Agricultural Statistics Service[11]. Annual population data come from the United States Census

[10] Results from the EGARCH regressions can be found in the appendix.

[11] Recent data on cash rents is downloaded from NASS QuickStats. Data from 1960 to 1994 is accessible at (USDA, Economic Research Service, NRE Division n.d.).

Bureau, and are only available from 1990 to 2016. Population between 1981 and 1989 and between 1971 and 1979 are estimated using the weighted average of the shares of the state population over the total U.S. population from beginning and ending years[12]. The 10-year treasury constant maturity rate is obtained from the Federal Reserve Bank of St. Louis with an annual frequency[13]. Information on annual consumer price index comes from the U.S. Bureau of Labor Statistics[14]. All variables, except volatility and the treasury rates, were transformed into growth rates[15]. The 10-year treasury constant maturity rate is calculated as the percentage change (i.e. the rate in the current year subtracted by the rate in the last year). Variables are transformed as to avoid the case where some variables are pre-whitened[16] and others not (Conway et al. 1984). The mean and standard deviation of the variables prior to the transformation are presented in Table 1.

[t]Table 1 near here[/t]

4. Results

In order to run the vector autoregression system we must first test for stationarity in the

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[12] For example, if in 1980, Iowa had a population share of 1.3% of the total population in the U.S. and in 1970 that share was 1.4% then: Estimated population in 1981 = U.S. population in 1981 *(1.3%*0.1) + (1.4%*0.9). Estimated population in 1989 = U.S. population in 1989 *(1.3%*0.9) + (1.4%*0.1). Data is available at https://www.census.gov/programs-surveys/popest/data/data-sets.html.

[13] The Federal Reserve Bank dataset is available at https://fred.stlouisfed.org.

[14] Information on the consumer price index is available at https://www.bls.gov/cpi/home.htm.

[15] Each variable (i.e. land values, cash rent, consumer price index and population density) is transformed into logged first differences ($l_{i,t} = log(L_{i,t}/ L_{i,t-1})$), interest rates are as percentage changes (Hossain and Latif 2009).

[16] Pre-whitening is the transformation of a time series variable to make it have the statistical properties of white noise.

variables and in the VAR model. Additionally, we discuss the results from the ARCH tests for land value volatility clustering and asymmetric effects from the EGARCH models, before discussing the results from the VAR model, granger causality tests and impulse response graphs.

4.1 Stationarity

To verify whether or not the VAR is stationary, a panel unit root test is run using the Harris-Tzavalis unit-root test. Similarly, we test the stationarity of the land value series used in the GARCH modelling using the Augmented Dickey Fuller test and the Phillips-Perron unit test. The presence of a unit root is rejected in every case (Table 2).

[t]Table 2 near here[/t]

4.2 ARCH effects

ARCH LM tests confirm the existence of volatility clustering in all Corn Belt states (Table 3). P-values for the ARCH LM tests indicate that the hypothesis of homoscedasticity can be rejected at a 5% level of statistical significance. Given the presence of volatility clustering, modelling volatility with EGARCH is appropriate, whereas modelling volatility as a constant variance (i.e. as an unconditional variance) can lead to underestimating actual risk (Lee 2009).

[t]Table 3 near here[/t]

4.3 Asymmetric effects

After testing for the presence of ARCH effects, ARMA models are estimated for each state. The residuals from the ARMA models are then used to model volatility using EGARCH. The optimal model is chosen by estimating different EGARCH specifications and choosing the one with the lowest Akaike information criterion (AIC) (see Appendix)[17]. Results from the EGARCH regression are also in the appendix.

Once the models for each state are specified we analyze the asymmetric effect from volatility in each series. Recall that asymmetric effects exist if $\gamma_i \neq 0$ in the EGARCH model (Equation 5). Asymmetric effects are found for land value volatility in all states (Table 4). This means that large swings in land value are followed by large swings in land value while low land value volatility is followed by low land value volatility. The asymmetric coefficients are positive, meaning that bad news have larger impacts on volatility than good news. The presence of asymmetric effects highlights the importance of using an EGARCH instead of a GARCH model for land values series (Lee 2009).

[t]Table 4 near here[/t]

4.4 Pooled VAR

Results from the pooled VAR system composed of the variables: land value volatility (vly), cash rent growth rates (*cr*), land value growth rates (*lv*), population growth rates (*pop*), and change in interest rates (*cmt*) are presented in Table 5. The R^2 of 0.50 for the volatility equation (6th column) indicates a reasonably good fit of the equation. The lagged land value volatility, negative change in interest rates, negative and positive growth rates in land values, and positive growth rates in population are statistically significant determinants of land value volatility. The coefficients of the pooled VAR system are complex to interpret independently (Featherstone and Baker 1987). In order to understand further the impacts of the variables in the VAR model on land value

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[17] Differently from GARCH models, there is no consensus that the EGARCH (1,1) provides the best and most convenient fit (Lee 2009).

volatility, we test for granger causality between the variables.

[t]Table 5 near here[/t]

4.5 Panel granger causality

In the case of vector autoregressive models, individual hypothesis t-tests on the coefficients may not be useful (Featherstone and Baker 1987). The reason is that the amount of lagged variables in the regressions make the presence of correlations among exogenous variables likely (Featherstone and Baker 1987). As an alternative, granger causality tests are performed. Dumitrescu and Hurlin (2012) provide a test for granger causality for panel data models that performs well with small samples. This test is an adaptation of the granger causality test (Granger 1969) with a null hypothesis that there are no causal relationships in any of the cross-section variables.

Results show that land value volatility is significantly impacted by land value, cash rent, inflation and population growth rates (Table 6). This is similar to other authors' (Featherstone and Baker 1987; Just and Miranowski 1993; Moss 1997) findings that returns to land, interest rates and inflation have statistically significant effects on land values. In our case, though, changes in interest rates impact land value volatility through land value growth rates. Past land value volatility affects future volatility, which may suggest a potential for bubbles in the land value market. Land value growth rates granger causes cash rent growth rates, but not the other way around. This result is in line with Schnitkey (2016) reasoning that economic theory points to a unidirectional causality from land values to cash rent. In some cases, only negative (positive) growth rates granger cause another variable (e.g. population growth rate affecting land value volatility), highlighting the importance of splitting the variables in the pooled VAR.

[t]Table 6 near here[/t]

4.6 Impulse response functions

In order to interpret the economic significance of the granger causality relations, impulse response functions were constructed. These map the responses of land value volatility, to a one-time shock to one of the error terms, over the years (equations 7 and 8). Given that some of the variables were split into negative and positive, the multiplication of the positive vector ($Y_{i,t-1}^{+}$) by 1% is considered a positive shock. Likewise, the multiplication of the negative vector ($Y_{i,t-1}^{-}$) by -1% is a negative shock. We investigate the dynamic responses of land value volatility to positive and negative shocks to population, cash rents and land value growth rates, as well as changes in interest rates (Figure 3). These shocks are considered transitory with zero representing a return to the equilibrium level. For the variables consumer price index and land value volatility only positive shocks are analyzed since negative shocks would be simply mirror images.

[t]Figure 3 near here[/t]

The unpredicted component of land value growth rates (i.e. land value volatility) seems to respond similarly to shocks in the growth rates of the determinants of land value, the same way land value responds to changes in its determinants. In some cases, though, the responses are not statistically significant. Our results do not show statistically significant impacts of shocks to population grown rates on land value volatility, although Kuethe, Ifft and Morehart (2011) found linkages between increases in land values and population growth. Land value volatility responses to shocks to cash rent growth rates are also statistically insignificant, even though Featherstone and Baker (1987) find an overreaction of land prices to rent.

The responses of land value volatility to positive and negative exogenous shocks are asymmetric. Negative shocks appear to have larger effects on land value volatility than positive ones. For instance, negative shocks to land value growth rates have greater impacts on land value volatility than positive shocks. In the first year, a negative shock causes an increase of 0.50% in land value volatility while a positive shock causes an increase on 0.10%. The reaction in land value volatility from shocks to land value growth rates is relatable to Featherstone and Baker (1987). They find that increases in land prices cause further increases in land prices. The response of land value volatility to shocks aligned with the presence of asymmetric effects of land value volatility (see section 4.3) may indicate a market prone to bubbles.

Just and Miranowski (1993) argue that variations in inflation and interest rates cause overreaction of land prices. Similarly, we find statistically significant responses of land value volatility to shocks to inflation and interest rates but not to shocks to rents. Responses of land value volatility to shocks to cash rent growth rates, though, are small and statistically insignificant. Shocks of 1% to inflation growth rates, though, increase land value volatility up to 0.70% and last over 8 years. A positive shock to changes in interest rates of 1% increases land value volatility by 0.60% in the second year. This result is best explained by the fact that investment in monetary assets are preferred when interest rates are high (Devadoss and Manchu 2007).

5. Conclusions

Our study follows theory applied to the housing market by modelling land value volatility as the variance of the unexpected changes in land values. Residuals from rational expectation models on land values for each of the Corn Belt states are used to model a land value volatility series for each state using exponential GARCH models. A pooled VAR system is then estimated to model time change volatility of land values and the interactions between land value determinants and land value volatility. Asymmetric impacts are allowed by splitting the determinants of land value into negative and positive vectors. Finally, coefficients of the pooled VAR are used to estimate impulse response functions. We report on the asymmetric effects of land value volatility and perform granger causality tests.

We confirm the presence of land value volatility clustering in all Corn Belt states. This means that land value volatility is consistent with other real estate markets such as the housing market and should not be modelled as an unconditional variance (i.e. a constant variance). The presence of asymmetric effects in Corn Belt states' land values indicates a stronger reaction of land value volatility to bad news than to good news. This fact, associated with the response of land value volatility to shocks in land value growth rates, suggests a market prone to bubbles.

Our findings also show that land value volatility is granger caused by inflation, cash rent, land value and population growth rates. Impulse response functions show that the responses of land value volatility to innovations resemble the reactions of land values to changes in its determinants, found in previous studies. That is, the unpredicted component of land value growth rates (i.e. volatility) reacts similarly to shocks to the growth rates of land value determinants as land values react to changes in its determinants. Land value volatility responses to positive and negative shocks, though, are asymmetric with responses to negative shocks being larger than those to positive shocks.

The results aid lenders and land owners in their risk assessment. Findings indicate that these agents should expect greater swings in land values after negative shocks to land value growth rates. Though this response will be smaller than the shock itself. Unexpected positive shocks to changes in interest rates cause increases in land value volatility in the second year, as monetary assets are preferred over farmland. Investors should not expect an overreaction of land values due to unexpected shocks to cash rents, as these responses are statistically insignificant. Future research could expand this analysis to incorporate the transmission of commodity price volatility to land value and cash rent volatilities in order to investigate how these may further affect the farm income.

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Table 1. Mean and standard deviation of the variables.

Corn Belt States	Land Value Volatility (%)		Interest Rate (%)		Cash Rent ($)		Land Value ($)		Population Density (%)		Consumer Price Index	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Iowa	0.08	0.03	6.2	2.9	102.94	64.75	2089.98	2211.98	0.082	0.003	31.3	30.5
Ohio	0.06	0.04	6.2	2.9	66.59	36.97	1950.57	1581.48	0.919	1.232	31.3	30.5
Illinois	0.07	0.03	6.2	2.9	101.82	58.02	2281.57	2036.90	0.332	0.021	31.3	30.5
Indiana	0.06	0.03	6.2	2.9	88.18	48.90	2113.55	1924.10	0.250	0.023	31.3	30.5
Missouri	0.07	0.07	6.2	2.9	52.69	32.16	1087.26	920.93	0.121	0.010	31.3	30.5

Land value volatility is defined as the variance of the unpredictable component of the appreciation rate for land values.

Table 2. Panel unit root tests of Corn Belt land value series and of the VAR variables.

Variable	Augmented Dickey-Fuller	Phillips-Perron	Harris-Tzavalis
	GARCH modelling variables		
Land values per State			
Illinois	-3.536 **	-48.481 ***	
Iowa	-3.997 **	-45.043 ***	
Ohio	-3.408 *	-57.52 ***	
Missouri	-3.484 **	-53.52 ***	
Indiana	-3.861 **	-43 ***	
	VAR variables		
Land Value Volatility			0.483 ***
Consumer Price Index			0.813 ***
Constant Maturity Rate			-0.038 ***
Population Density			-0.075 ***
Land Values			0.597 ***
Cash Rents			0.388 ***

Note: Statistical significance level: ***1%, **5% and *10%

Table 3. ARCH LM Tests for the Residuals from an ARCH model.

State	ARCH-LM test	p-values
Indiana	47.46	0.000 ***
Illinois	74.16	0.000 ***
Ohio	79.48	0.000 ***
Missouri	48.69	0.000 ***
Iowa	40.13	0.003 ***

Notes: LM tests presented are with 4 lags. Comparable results were also obtained with 8 lags.
***indicates 5% level of statistical significance.

Table 4. Asymmetric effects from the univariate EGARCH volatility models.

State	Model		Asymmetric Coefficient (γ_i)	
Indiana	EGARCH(1,1)	lag1	0.88	***
Iowa	EGARCH(1,2)	lag1	0.69	***
Illinois	EGARCH(3,2)	lag1	0.70	***
		lag2	-0.07	
		lag3	0.67	**
Ohio	EGARCH(1,1)	lag1	0.90	***
Missouri	EGARCH(2,1)	lag1	1.55	***
		lag2	-0.20	

Notes: *indicates 10%, ** indicates 5% and ***indicates 1% level statistical significance.

Table 5. Results from the pooled vector auto-regression model.

Coefficients	POP	CMT	CR	LV	CPI	VLY
$pop-_{t-1}$	-0.253 *	5.140 **	-0.231	0.568 *	0.056 ***	-0.071
$cmt-_{t-1}$	0.002	-0.826 ***	0.011 *	0.022 ***	0.0003	0.008 **
$cr-_{t-1}$	0.009	-5.397 *	-0.168	-0.218	-0.013	0.032
$lv-_{t-1}$	0.012	12.059 ***	0.427 ***	0.150	0.025 **	-0.480 ***
cpi_{t-1}	-0.042	26.271 ***	0.336	-0.861 *	0.526 ***	0.312
$pop+_{t-1}$	-0.002	-8.314 ***	-0.257	-0.347 **	-0.115 ***	-0.235 **
$cmt+_{t-1}$	-0.003	-0.016	-0.014 **	-0.016 **	-0.0001	-0.002
$cr+_{t-1}$	-0.016	-0.940	-0.080	0.002	-0.017 **	0.017
$lv+_{t-1}$	-0.029	1.862 *	0.327 ***	0.495 ***	0.009	0.115 ***
vly_{t-1}	0.007	0.476	0.009	0.130	0.014 *	0.271 ***
R-Squared	0.079	0.337	0.418	0.548	0.802	0.502
Observations:				56 years and 280 observations		

Notes: The coefficients of the time and state dummies were supressed.
Codes: *** indicates 1%, ** 5% and * 10% level of statistical significance.
POP: Population density growth rate; CMT: Interest rate growth rate; CR: cash rents growth

Table 6. Results from the Dumitrescu and Hurlin Granger causality test.

Hypothesis	$\bar{Z}$	$\tilde{Z}$	Hypothesis	$\bar{Z}$	$\tilde{Z}$
vly_{t-1} -> vly	46.6 ***	43.4 ***	pop^- -> cr	6.3 ***	5.8 ***
cmt^- -> vly	1.2	1.0	pop^+ -> cr	-0.8	-0.8
cmt^+ -> vly	-0.5	-0.5	cmt^- -> cr	5.8 ***	5.3 ***
cpi -> vly	5.4 ***	5.0 ***	cmt^+ -> cr	-0.5	-0.6
lv^- -> vly	10.9 ***	10.1 ***	cpi -> lv	-0.9	-0.9
lv^+ -> vly	7.5 ***	6.9 ***	cr^- -> lv	0.4	0.4
cr^- -> vly	2.7 ***	2.5 **	cr^+ -> lv	-0.6	-0.6
cr^+ -> vly	2.4 **	2.2 **	pop^- -> lv	-0.7	-0.7
pop^- -> vly	2.6 ***	2.4 **	pop^+ -> lv	-1.3	-1.3
pop^+ -> vly	0.5	0.4	cmt^- -> lv	-1.0	-1.0
vly -> cmt	1.3	1.2	cmt^+ -> lv	8.7 ***	8.0 ***
vly -> cpi	0.9	0.8	lv^- -> cpi	-0.7	-0.7
vly -> lv	0.8	0.7	lv^+ -> cpi	2.1 **	1.9 *
vly -> cr	0.1	0.1	cr^- -> cpi	-1.3	-1.3
vly -> pop	-0.6	-0.6	cr^+ -> cpi	-0.5	-0.5
cpi -> cmt	5.5 ***	5.1 ***	pop^- -> cpi	-1.2	-1.2
cr^- -> cmt	-0.9	-0.9	pop^+ -> cpi	-0.5	-0.5
cr^+ -> cmt	-0.9	-0.9	cmt^- -> cpi	-1.3	-1.3
lv^- -> cmt	6.9 ***	6.3 ***	cmt^+ -> cpi	-1.2	-1.2
lv^+ -> cmt	0.9	0.8	lv^- -> pop	-1.4	-1.3
pop^- -> cmt	-1.5	-1.4	lv^+ -> pop	1.3	1.2
pop^+ -> cmt	-1.1	-1.1	cr^- -> pop	-1.4	-1.4
cpi -> cr	2.1	0.1	cr^+ -> pop	-0.4	-0.4
lv^- -> cr	8.1 ***	7.5 ***	cpi -> pop	-0.6	-0.6
lv^+ -> cr	7.2 ***	6.7 ***	cmt^- -> pop	-1.3	-1.3
			cmt^+ -> pop	-0.7	-0.7

Notes: *indicates 10% **5% and ***indicates 1% level of statistical significance.

$\bar{Z} = \sqrt{\frac{N}{2K}} \cdot (\bar{W} - K) \xrightarrow[T,N\to\infty]{d} (0,1)$ and $\tilde{Z} = \sqrt{\frac{N}{2K} \cdot \frac{T-3K-5}{T-2K-3}} \cdot \left[\frac{T-3K-3}{T-3K-1} \cdot \bar{W} - K\right] \xrightarrow[N\to\infty]{d} N(0,1)$ where, N is the sample size, K is the lag order, $\bar{W}$ the average number of the N individual Wald statistics (Lopez and Weber 2017).

Figure 1. Land values in the Corn Belt in 2017 prices.

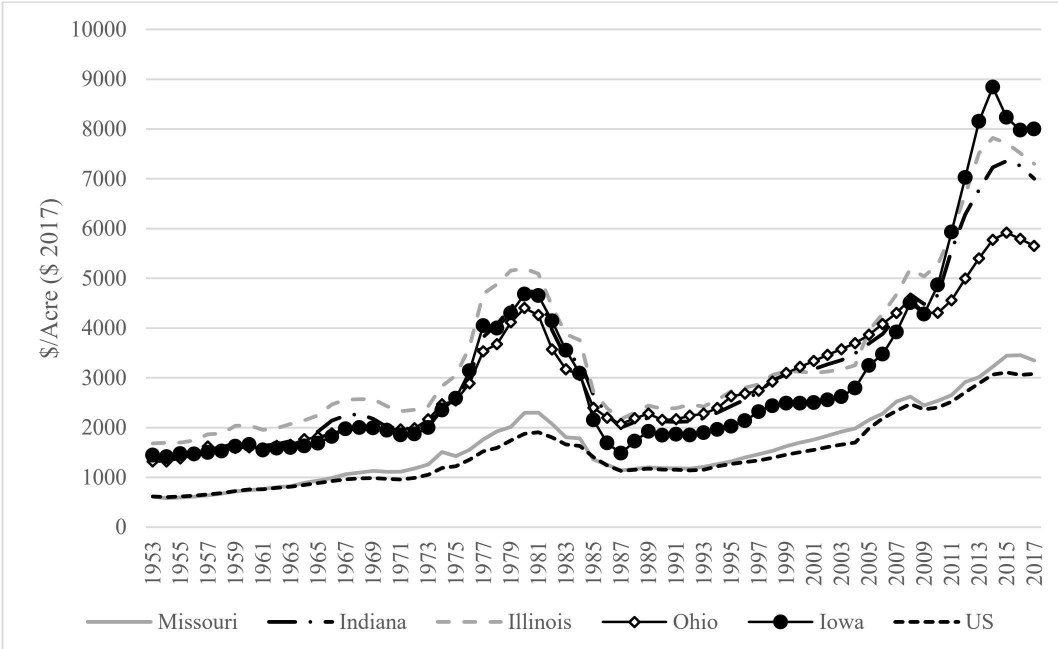


Figure 2. Land value to cash rent ratio and the 10-Year Constant Maturity Treasury Rate.

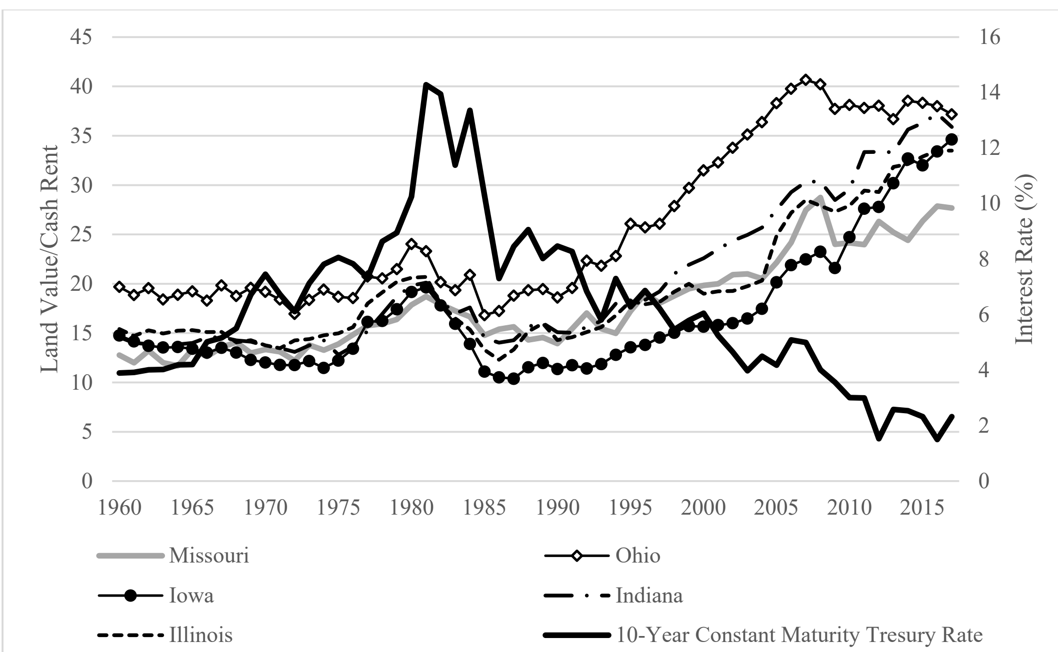
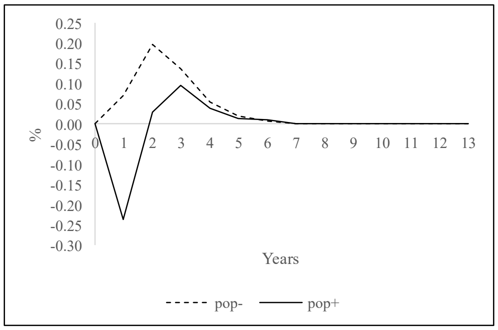
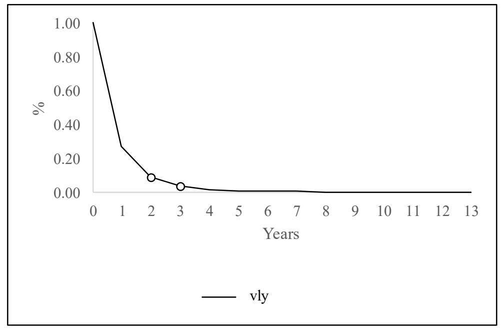


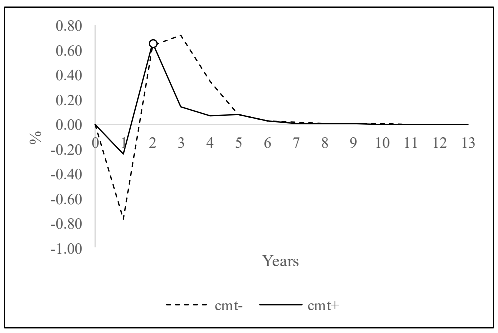
Figure 3. Impulse response functions: The response of land value volatility to exogenous shocks.



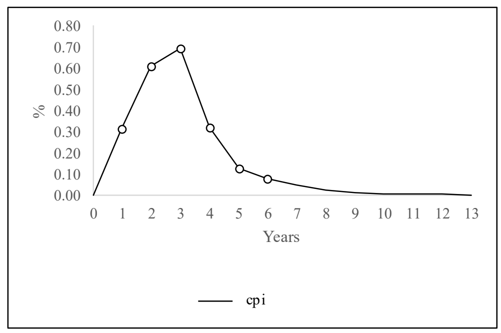
Response of land value volatility to a 1% exogenous shock to population growth rate



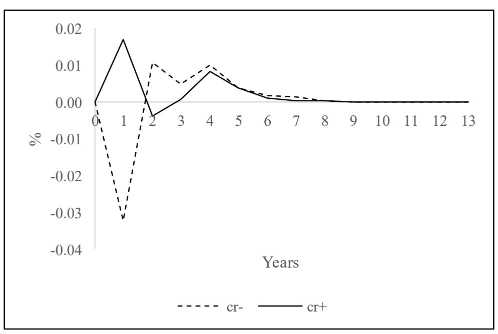
Response of land value volatility to a 1% exogenous shock to land value volatitlity



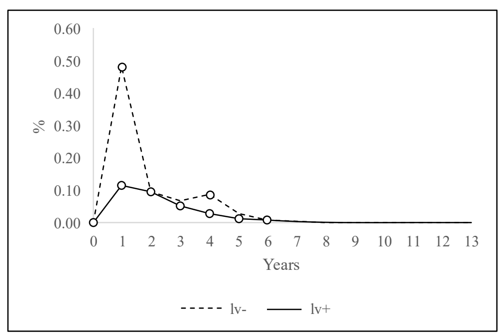
Response of land value volatility to a 1% exogenous shock to Interest rate growth



Response of land value volatility to a 1% exogenous shock to consumer price index growth rate



Response of land value volatility to a 1% exogenous shock to cash rents growth rate



Response of land value volatility to a 1% exogenous shock to land values growth rate

Note: The white circles indicate a coefficient with 10% level of statistical significance. The confidence bands were estimated by running 1500 bootstraps of the estimates and recording the 0.05 and 0.95 quantiles of the bootstrap distribution.