The Dynamics of Opinion Formation: Panel Data Evidence from the Iowa Land Value Survey

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Abstract

Opinion surveys of agricultural professionals or producers are the dominant method used by land grant universities and USDA to gauge the pulse of changes in farmland values. In lieu of the futures market for corn or Zillow-style databases for residential housing prices, these opinion surveys help market participants establish values. However, there lacks a systematic evaluation of how respondents formulate their responses to these opinion surveys and especially how they adjust their responses over time. Using a panel data of 311 agricultural professionals from the Iowa Land Value Survey from 2005 to 2015, this paper examines how these surveyed experts update their estimates of agricultural land values year over year. In particular, we examine the degree to which respondents adjust their responses to differences between their prior stated opinions and prevailing farmland prices in the last period. Using others' median responses as a proxy for true market value and an error-correction model estimated using Bayesian methods; we provide the first micro-level empirical instigation in the formation of farmland value estimates collected through surveys of market experts. Our analysis suggests that it typically takes one or two periods for respondents to almost fully adjust to prior "errors" measured as differences between the respondent's prior estimate and the prior prevailing price. Our results also reveal that the pace of self-correction is faster for higher quality lands, relative to lower-quality land. This difference is likely the result of greater attention paid to well-broadcasted, "high stake" auction sales for high quality lands, as well as the greater heterogeneity in productivity associated with lower-quality land. The Bayesian estimation techniques we employ in our estimation also makes an important contribution to the literature of agricultural real estate analysis by offering an easier setting to conduct inference and hypothesis testing, which is especially important with nonstationary land values.

JEL Codes: Q15, Q13, Q14

Keywords: Farmland Value, Expert Opinion Survey, Error Correction Model, Bayesian, Panel Data

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1. Introduction

Farmland plays a central role in the financial health of the U.S. agricultural sector. Farm real estate makes up over 80% of the value of the sector's asset base and serves as the primary source of collateral for farm loans (U.S. Department of Agriculture 2018). Despite farmland's prominent role in the agricultural economy, it remains difficult to accurately measure the aggregate value of farm real estate. Farmland is characterized by very low turnover, with an average of less than one percent of the stock of U.S. farmland being traded every year (Sherrick and Barry 2003; Zhang and Beek 2016). In addition, there lacks a consolidated data source such as commodity futures market, Case-Shiller residential housing price index, or Zillow-style farmland sales information that allow market participants to quickly gauge the representative farmland value.[1] Two other issues make it even more challenging to solely rely on farmland sale prices to establish a representative value for farmland. First, farmland is often held by the same owners for a long time, which makes farmland sales even more infrequent. Previous research, for example, shows that half of the land in Iowa has been owned by the same owner for at least twenty years (Zhang et al. 2018). Second, the tracts of farmland being traded at any point in time are heterogeneous in quality, location, surround land use mix, and sale type (Borchers et al. 2014). Thus, market prices may not be entirely informative of the value of the stock of farmland.

In response, a number of institutions, such as Land Grant Universities, Federal Reserve Banks, professional societies, and USDA, conduct periodic surveys of producers or agricultural professionals to measure current and expected farmland market conditions (Kuethe and Ifft, 2013). While USDA survey samples agricultural producers, most other opinion surveys rely on

[1] Recently, several startup companies, such as Granular AcreValue, or FarmlandFinder, have tried to build showcase farmland sale prices. County assessors' offices increasingly utilize web interfaces such as Beacon and Vanguard that allow current and future landowners and home buyers to search and view characteristics of residential houses and land parcels. However, this information is still very fragmented, limited to only the most recent sales, and is not in standardized formats.

agricultural “experts” or professionals, including real estate agents, rural appraisers, agricultural lenders, farm managers, and county assessors (Zhang and Beek 2016). Previous research suggests that the various surveys are highly correlated with one another (Kuethe and Ifft, 2013) and are good predictors of future farmland transaction values (Zakrzewicz, et al., 2012; Stinn and Duffy, 2012). However, in spite of the wide use of such opinion surveys of land values and the attention they receive, little is known about the process by which the surveyed experts formulate their estimates. In particular, to the best of our knowledge, no study has investigated the degree to which their responses reflect past and current information, and whether and to what extent they adjust or self-correct their responses over time in these opinion surveys.

The aim of our article is to examine the process by which the surveyed agricultural professionals (“experts” hereafter) update their estimates of agricultural land values year over year. In particular, we examine the degree to which respondents adjust their responses to differences between their prior stated opinions and prevailing farmland prices in the last period, as well as the degree to which respondent opinions are shaped by contemporaneous changes in current market signals. We hypothesize that survey respondents self-correct to prior errors between their stated opinion and the prevailing price or “true” market value. For example, if a respondent provided a land value estimate for a particular county that was substantially higher than the true market value, we expect that she may adjust her market beliefs downward in the subsequent survey to be closer to the current prevailing price. However, consistent with the rational expectations hypothesis, we also expect the respondent to update her beliefs based on other relevant, contemporaneous farmland price signals.

We conduct our investigation by analyzing the responses of experts to the annual Iowa State University land value survey from November 2005 to November 2015. We construct panel data of 311 agricultural professionals that participated in at least seven of the eleven surveys. Every November respondents provide land value estimates for high-, medium-, and low-quality farmland for their primary county. The process by which respondents update their price opinions from year to year are captured by an error-correction model (ECM). Previous research has shown that aggregate farmland prices tend to be nonstationary, and as a result, our ECM model is estimated using Bayesian regression methods, which allow us to conduct credible causal inference under nonstationarity without assuming parametric distributions. Importantly, there lacks a universal, readily available measure of "true" land value or prevailing price. For each respondent we use the median land value estimates by other professionals for the same land quality class and same year at the county or district level as a proxy for the prevailing price. We also examined other proxies for robustness checks that include average cropland sales prices, as well as published land value estimates from ISU and other opinion surveys.

Our analysis suggests that agricultural professionals' responses conform to an error correction model that reflects corrections to prior "errors" in one or two periods. The long-run elasticity of experts' estimate with respect to the prevailing price ranges between 0.8 and 1. Thus, the estimates suggest that it typically takes one or two periods for respondents to almost fully adjust to differences between the respondent's prior estimate and the prior prevailing price (prior "errors"). This finding is consistent with prior research on learning from peers and experts and the "wisdom of the crowd" (Prelec et al. 2017). This is also consistent with the "appraisal smoothing," behavior exhibited by the residential and commercial real estate appraisers do not fully rely on current market information, but also exhibit anchoring behavior by relying, at least in part, on prior information (Clayton et al. 2001). In addition, our results suggest that the pace of self-correction is faster for higher quality lands, relative to lower-quality land. This difference is likely the result of greater attention paid to well-broadcasted, “high stake” auction sales for high quality lands, as well as the greater heterogeneity in productivity associated with lower-quality land. Our results are robust to the definition of prior “prevailing price,” yet the pace of self-correction is faster when prevailing prices are measured at the regional, crop reporting district (CRD) level, as opposed to the county level. Although this result may be a statistical artifact driven by the noisier county-level prevailing prices, this finding may also be the result of more salient and informative signal provided by CRD prevailing prices. Finally, our results suggest respondents opinions adjust instantaneously to changes in contemporaneous farmland price signals. Specifically, our expanded ECM includes the contemporaneous price signals as captured by the orthogonal components of cash rent and interest rates. These auxiliary price signals are more important for understanding lower-quality land value estimates when the land signals alone were less salient, and when noisier county-level land value measures were used to capture the prevailing price.

This study makes a number of important contributions to the literature. First, to the best of our knowledge, we provide the first micro-level empirical instigation in the formation of farmland value estimates collected through surveys of market experts. The analysis demonstrates that respondents conform to an error correction model in which they quickly self-correct “prior errors” and instantaneously adjust to changes in market price signals. Given the widespread use of similar survey instruments in agricultural economic research and extension, the finding is expected to be of interest to landowners, farmers, extension educators, and researchers. Second, our Bayesian estimation yields the full posterior distribution of key model parameters in the presence of nonstationarity. The approach avoids key estimation issues that often plague parametric time-series analysis of farmland values, including nonstationarity, serial correlation, misspecification, and cointegration.

2. Model

Farmland value surveys elicit respondents' opinion of the current value of farm real estate of a given quality within a certain market boundary (such as a county). Each respondent i reports her individual subjective value for the current time period t, donated $Y_{i,t}$, for the prevailing price of farmland X_t. If market boundaries are defined such that farmland is homogenous in quality and all other attributes, free and complete information would yield:

$$(1) \qquad Y_{i,t} = X_t, \quad \forall\ i, t.$$

The process by which respondent updates their subjective valuations between the current and previous periods can be obtained by taking the natural logarithms of both sides of (1) and adding and subtracting lagged terms. Rearranging, the expression can be written in an error-correction form as:

$$(2) \qquad \Delta y_{i,t} = -\,(y_{i,t-1} - x_{t-1}) + \Delta x_t, \quad \forall\ i, t,$$

where $y_{i,t} \equiv ln(Y_{i,t})$, $\Delta y_{i,t} \equiv y_{i,t} - y_{i,t-1}$, $x_t \equiv ln(X_t)$, and $\Delta x_t \equiv x_t - x_{t-1}$. According to (2), for an individual's subjective valuation in year t to be identical to the corresponding prevailing price, the change in the individual's subject valuation from the previous year (i.e., $\Delta y_{i,t}$) must consist of two parts. The first component, $-\,(y_{i,t-1} - x_{t-1})$, is an "error correction" term that fully corrects any difference between the respondent's prior subjective valuation and the prior prevailing price. The second component, Δx_t, is the full innovation in the prevailing price, which reflects changes in the prevailing price driven by market fundamentals. Thus, a respondent's individual subjective valuation will be identical to the prevailing price in year *t* if the respondent (a) fully corrects for the previous year's difference between her subjective valuation and the prevailing price and (b) fully incorporates the innovation in the prevailing price. The ECM shown in equation (2) forms the basis for our analysis. A respondent's error correction behavior may be driving by self-pride, professional ethic, peer pressure, or "herd behavior" in which the respondent leverages the collective decisions or information exhibited by other experts in the previous period (Banerjee 1992).

For estimation and hypothesis testing purposes, ECM (2) is generalized by incorporating coefficients multiplying the explanatory variables, and adding an intercept (α) and a zero-mean residual term ($e_{i,t}$) to its right-hand side, so as to yield the regression

$$(3) \qquad \Delta y_{i,t} = \alpha + \beta_y\, y_{i,t-1} + \beta_x\, x_{t-1} + \gamma\, \Delta x_t + e_{i,t}. \ \ \forall\ i, t$$

If the coefficients satisfy the conditions $\{\alpha = 0, -\beta_y = \beta_x = \gamma = 1\}$, the regression shown in (3) above collapses into the regression form for equation (2), which implies that the data are consistent with the ideal scenario shown in equation (2) where the experts' estimates fully reflect true land values. More generally, according to the regression shown in (3), the innovation in the i^{th} expert's estimate incorporates a fixed amount of α, which is identical for all experts, and $100\,\gamma$ percent of the innovation in the true value Δx_t. In addition, noting that $(\beta_y\, y_{i,t-1} + \beta_x\, x_{t-1}) = [\beta_y\, (y_{i,t-1} - x_{t-1}) + (\beta_y - \beta_x)\, x_{t-1}]$, the regression indicates that the innovation in the expert's response “corrects” $100\ \beta_y$ percent of the lagged error ($y_{i,t-1} - x_{t-1}$) in a single period, and includes ($\beta_y - \beta_x$) of the lagged true value x_{t-1} from the previous period.

In practice, farmland is heterogeneous in land quality, land use types, and extent of urban influence. Farmland available for sale is fairly limited especially for arm’s length transactions, farmland markets tend to be localized, and there is no widely accepted objective measure of the value for a representative tract of farmland similar to crop futures prices. Hence, a useful generalization of model (1) consists of allowing experts to hold subjective opinions regarding the type of land for which they must provide land value estimates. This generalization can be achieved by letting $Y_{i,t} = A_i\ X_t$ when A_i does not equal one, so that one expert may consistently under- or over-report the true value compared to another expert. This could arise from their different notions regarding which tract is representative of farmland for their region, or different beliefs or knowledge systems about movements in farmland and related markets. To incorporate this feature, regression (3) is generalized as the experts’ fixed-effects (FE) regression (4):

$$(4) \qquad \Delta y_{i,t} = \alpha_i + \beta_y\, y_{i,t-1} + \beta_x\, x_{t-1} + \gamma\, \Delta x_t + e_{i,t},$$

where $\alpha_i = -\beta_y\ ln(A_i)$ represents the extent to which the i^{th} expert’s response consistently under- or over-estimates the true land value.

Of particular relevance for the farmland market, land quality represents an important source of heterogeneity that makes the true land market signals for high quality land more salient compared to that for lower quality land for several reasons. First, experts tend to have a better grasp of what high-quality land means in terms of land productivity ranges as opposed to lower quality land. For example, Zhang and Duffy (2017) show that the standard deviation of the reported Corn Suitability Rating 2 for low-quality land in Iowa is much larger than that for high-quality land. Second, high-quality farmland is typically cropland, while low-quality farmland sometimes includes recreational grounds, pasture, and timberland. Third, auctioneers in practice often advocate higher quality land in land auctions, which also tends to receive more local news coverage as well as more frequent discussion among producers, landowners, and agricultural professionals. As a result, it is natural to assume that experts have better knowledge of true market value for high-quality land than that for low-quality land. Econometrically, this would suggest that the prevailing price for low-quality land x_t^L contains more noise, and the corresponding error terms e_{it}^L would have a larger variance. As a result, the corresponding coefficients for low-quality land following equation (4) would be more significantly different from the ideal conditions $\{\alpha_i = 0, -\beta_y = \beta_x = \gamma = 1\}$. More specifically, the magnitude of the underestimation or overestimation by experts for low-quality land will be more noticeable due to noisy land market signals than that for high-quality land, which means $|\alpha_{it}^L| > |\alpha_{it}^H| \geq 0$. In addition, the magnitude for β_y, β_x, and γ would be smaller for low-quality land as well due to the larger error terms.

2.1. Experts' Estimates in the Long Run, and Their Short-Term Dynamics

Ideally, regression (4) should satisfy the conditions $\{-\beta_x = \beta_x = \gamma = 1\}$, so that the innovation on the expert's response fully corrects a previous error in a single period, and fully incorporates the innovation in the true value. In reality, however, an expert may take a longer time to revise a previous estimate, in which case lagged innovations in the expert's estimate or in the true value may explain current innovation. To allow for this possibility, regression (4) is expanded as follows:

(5) $$\Delta y_{i,t} = \alpha_i + \beta_y\, y_{i,t-1} + \beta_x\, x_{t-1} + \gamma\,\Delta x_t + \Sigma_{n_y=1}^{N_y}\delta_{y,n_y}\Delta y_{i,t-n_y} + \Sigma_{n_x=1}^{N_x}\delta_{x,n_x}\Delta x_{t-n_x} + e_{i,t}.$$

A nice feature of the ECM is that it is straightforward to infer from it the “long-run” or “equilibrium” relationship between the experts’ estimates and the set of explanatory variables (i.e., the relationship when neither variable has a tendency to change). To illustrate this point, consider ECM (5). By setting all of its first-difference terms and the residuals equal to zero, dropping the time subscripts, and rearranging, we obtain equilibrium relationship (6) in logarithms, which is equivalent to (7) in levels:

(6) $$y_i = -\alpha_i/\beta_y - \beta_x/\beta_y\, x.$$

(7) $$Y_i = A_i\ X^{-\beta_x/\beta_y}\ .$$

According to these expressions, $-\beta_x/\beta_y$ is the long-run elasticity of the experts’ estimates with respect to the prevailing land price. Ideally, such elasticity should be characterized by $-\beta_x/\beta_y = 1$. The magnitude of the lagged response coefficient β_y represents the speed at which the expert’s response innovation moves to restore the equilibrium relationship. Thus, the gap between the expert’s subjective valuation and its equilibrium value (i.e., the right-hand side of equation (6)) is expected to be reduced by $-100\ \beta_y$% in each period.

Note also that if the expert’s estimate at time (t – 1) satisfies equilibrium condition (6), the time-t expected expert innovation from ECM (5) consists of

$$(8) \qquad \Delta y_{i,t} = \gamma \Delta x_t + \Sigma_{n_y=1}^{N_y} \delta_{y,n_y} \Delta y_{i,t-n_y} + \Sigma_{n_x=1}^{N_x} \delta_{x,n_x} \Delta x_{t-n_x}$$

This means all of the first-difference terms on the right-hand side of ECM (5) represent short-term dynamics in the expert's estimates.

2.2. Drivers of Experts' Estimates Other Than Land Values

As noted earlier, key characteristics of farmland markets is that they are quite thin and that the traded asset is heterogeneous. Hence, it is reasonable to hypothesize that experts may resort to other sources of information in addition to actual trades to enhance the quality of their estimated values. If this were the case, interest rates and farmland rental rates are the most likely candidate sources of additional information. This is true because the asset capitalization model posits that there should be a long-run relationship between land values (X), land rental rates (*RENT*), and the interest rate (*INTEREST*).

More specifically, according to the asset capitalization model, there is a long-run relationship $X = RENT/INTEREST$ in levels, or $x = rent - interest$ in logarithms. This means there would also be a long-run relationship among experts' estimates, rental rates, and the interest rate if the asset capitalization model holds. Importantly, however, if the expert knew the true farmland value, information on rental rates or interest rates would be redundant. That is, conditional on true land values, neither rental rates or interest rates (or any other related variables) should provide relevant information to experts when they respond to the land value survey.

To test whether expert estimates are affected by rental rates and interest rates conditional on land values, we fit the following ECM regression:

$$(9) \qquad \Delta y_{i,t} = \alpha_i + \beta_y\, y_{i,t-1} + \beta_x\, x_{t-1} + \gamma\, \Delta x_t + \Sigma_{n_y=1}^{N_y} \delta_{y,n_y} \Delta y_{i,t-n_y} + \Sigma_{n_x=1}^{N_x} \delta_{x,n_x} \Delta x_{t-n_x}$$

$$+ \phi_{rent} \perp rent_{t-1} + \phi_{rate} \perp interest_{t-1} + \theta_{rent} \perp \Delta rent_t + \theta_{interest} \perp \Delta interest_t$$

$$+ \Sigma_{n_{rent}=1}^{N_{rent}} \psi_{rent,n_{rent}} \perp \Delta rent_{t-n_{rent}} + \Sigma_{n_{interest}=1}^{N_{interest}} \psi_{interest,n_{interest}} \perp \Delta interest_{t-n_{interest}} + u_{i,t}.$$

In this equation, $\perp z$ is defined as the component of variable z orthogonal to the set of regressors in ECM (5), and $\Delta rent_t$ and $\Delta interest_t$ denote the first differences in the logarithms of rental rates and interest rates, respectively. Given a set of variables V, one can decompose variable z as the sum $z = \mu\, V + \perp z(V)$, where μ is a conformable vector and $\perp z(V)$ is orthogonal to V.[2] That is, $\perp z(V)$ can be interpreted as the additional information contained in z, conditional on V. Therefore, if the $\perp z$ regressors in ECM (9) are significant, it means that rental rates and/or the interest rates have an impact on expert responses above and beyond the effect they may have on true values.[3,4]

[2] By construction, using the ordinary least squares estimator $(V^{\mathrm{T}}\, V)^{-1}\, V^{\mathrm{T}}\, z$ as μ yields the desired decomposition. We use this fact to obtain the $\perp z$ regressors in ECM (9), by computing each of them as the residual of an ordinary least squares regression of the corresponding variable z on the entire set of ECM (5) regressors.

[3] An alternative approach to fitting regression (9) would be to use the original variables z instead of their corresponding orthogonal components $\perp z$ as regressors. It is straightforward to demonstrate that the residuals of the resulting regression are identical to the ones in ECM (9) ($u_{i,t}$), so that as a whole the explanatory power of the respective set of regressors is identical under the two alternative formulations. However, the regression with the original variables z exhibits clear multi-collinearity problems, due to the fact that land values, rental rates, and interest rates are very highly correlated, and makes it difficult to test the hypothesis under investigation. Thus, and especially given that the present objective is to test whether rental rates and interest rates provide information conditional on true land values, regression (9) is better suited for the task at hand.

[4] Note that the coefficients for the regressors based on the own expert responses (y) and the true land values (x) should be the same in ECMs (5) and (9), because by construction such regressors are orthogonal to the $\perp z$ variables. In essence, the proposed regression (9) is equivalent to postulating that the residual in ECM (5) behaves according to

$$e_{i,t} = \phi_{rent} \perp rent_{t-1} + \phi_{rate} \perp interest_{t-1} + \theta_{rent} \perp \Delta rent_t + \theta_{interest} \perp \Delta interest_t$$

Finding that the coefficients associated with the orthogonal components of land rents or interest rates are different from zero suggests that experts supplement their knowledge about land values with information on land rents and interest rates to estimate land values. If experts felt sufficiently confident about their knowledge about land values when responding to the survey, their responses (conditional on such values) should not be affected by the rental rates or the interest rate.[5] As explained above, the true land values for low-quality land is more difficult to observe due to its heterogeneous quality and land use, as well as less publicity in land auctions. As a result, with a noisier market signal, experts would rely on other information such as rental rates and interest rates when providing land value estimates for lower quality land. In other words, we hypothesize that the coefficients associated with these orthogonal components of land rents or interest rates, ϕ, ψ, and θ, would be larger in magnitude for low-quality land than high-quality land.

3. Data

Table 1 reports summary statistics for key variables used in the study. Our main data source consists of the expert responses to the annual Iowa State University farmland value opinion

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$$+ \sum_{n_{rent}=1}^{N_{rent}} \psi_{rent,n_{rent}} \perp\Delta rent_{t-n_{rent}} + \sum_{n_{interest}=1}^{N_{interest}} \psi_{interest,n_{interest}} \perp\Delta interest_{t-n_{interest}} + u_{i,t}.$$

[5] Importantly, the survey asks experts what the land value is, not what it should be. To illustrate the importance of this distinction, consider the hypothetical example of ECM (5) satisfying the ideal conditions $\{\alpha_i, \beta_y, \beta_x, \gamma, \delta_y, \delta_x\} = \{0, -1, 1, 1, 0, 0\}$, and that conditions at period t are such that $(y_{i,t-1} - x_{t-1}) = \Delta x_t = 0$. Hence, from the ith expert's perspective her time-$(t-1)$ estimate was in equilibrium with the true land value, and since there is no innovation in the true value her expected response innovation should be $\Delta y_{i,t} = 0$. However, if the coefficients for the $\perp z$ variables in regression (9) are not zero, then the expert's expected response innovation need not be zero. For example, if $\perp\Delta rent_t > 0$, $\theta_{rent} > 0$, and all other $\perp z$ coefficients in (9) are zero, the expert's expected response innovation will be positive ($\Delta y_{i,t} = \theta_{rent}\, \Delta rent_t > 0$) rather than zero. It may be argued that this expert response is warranted because in this scenario the capitalization model indicates that the land value could be expected to adjust upward in the future in response to the orthogonal increase in land rents. The fallacy in this argument is that experts are asked to report their estimates of the true land value x_t, not what the land value should be according to the capitalization model (i.e., $rent_t - interest_t$), or any other theoretical valuation model for that matter. Finding coefficients $\{\phi, \theta, \psi\}$ significantly different from zero in suggests that experts rely on information about rents and interest rates to gauge the value of land when they respond to the survey.

survey conducted every November from 2005 through 2015. This survey was initiated in the 1940s and was one of the most widely used expert opinion surveys in the Midwest; and it is the only source that reports an annual farmland value in dollars for each of the 99 Iowa counties mid-December (Zhang and Duffy 2017). Stinn and Duffy (2012) compare the ISU survey results with sales prices for 20 Iowa counties, and find that the sales results were not significantly different than the survey averages for any year from 2005 to 2011. Figure 1 shows a sample of the survey questions sent to experts in 2015. Every year survey respondents are asked to identify their main professional background, and to provide estimates of the value of high-, medium-, and low-quality land for average-sized farms in their primary county as of November 1. Importantly, the survey respondents are mainly agricultural professionals knowledgeable about the land market, such as farm managers, rural appraisers, agricultural lenders, real estate brokers, and county assessors.

The data structure consists of an unbalanced panel, because not every expert participated in the survey each year. To avoid having too few time series observations for any individual, expert estimate variables used in the regressions (e.g., $\Delta y_{i,t}$ and $y_{i,t-1}$) correspond to experts who participated in at least seven out of the eleven surveys conducted from 2005 through 2015. Thus, the study involved responses from 311 experts, with 36% participating in all surveys during the period under study, and 12%, 16%, 18%, and 18% providing responses in ten, nine, eight, and seven of the surveys, respectively.

In general, there were more expert respondents in northern and central Iowa than in southern Iowa, which is consistent with the distribution of farms and farmland across the state. In particular, the Northwest Iowa and Northeast Iowa CRDs each boast more than 14% of respondents, whereas the East-Central Iowa, Southwest Iowa, South-Central Iowa, and Southeast

Iowa CRDs each account for less than 10% of respondents. Each expert could report land estimates for more than one county; however, the vast majority (82%) of respondents only gave land value estimates for one county, with only 7% of respondents furnishing estimates for more than three counties. As a result, if an expert provided land value estimates for more than one county, only the estimates for the primary county were used for our analysis.

Importantly, there is no objective, readily available measure of the prevailing land price (X_t), especially at the county level. Given such limitation, the analysis is performed using the following alternative proxies for the unobserved prevailing price corresponding to expert *i*'s estimate for high-, medium-, and low-quality land, respectively:

(a) Others' county median: Defined as the median of the estimates from all experts for the county other than expert *i*.

(b) Others' CRD median: Computed as the median of the median county estimates for expert *i*'s CRD. For this purpose, a median county estimate is calculated as (*i*) the "others' county median" defined in (a) above for expert *i*'s county, and (*ii*) the median of the estimates from all experts in the respective county for the rest of the CRD's counties.

(c) Farm Credit Service (FCS) county average sales price: Defined as the average price from the county's sales records for 85% tillable cropland reported by FCS.

(d) FCS CRD median price: Calculated as the median of the FCS county prices defined in (c) above for the CRD corresponding to expert *i*.

(e) RLI CRD value: Defined as the tillable cropland value estimates released each September from a survey of 80-odd farm manager and appraiser members of the Iowa Chapter of the Realtor Land Institute for expert *i*'s CRD.

(f) ISU CRD value: Defined as the ISU farmland value result released mid-December after the survey, corresponding to the CRD for expert *i*.

To extract as much information as possible from the data, the medians for cases (a) and (b) above are constructed using the entire set of experts (i.e., attention is not restricted to experts who participated in at least seven of the eleven surveys). Note also that a given expert's estimate is explicitly excluded from the sample used to compute others' median, which is used to represent the corresponding true land value. This approach is adopted to prevent the expert's estimate from having any influence on the respective median, thus ensuring the exogeneity of the true value regressors. The rationale for using medians instead of averages to construct the variables representing the prevailing prices is to avoid having the latter unduly affected by outliers. This concern is especially strong at the county level because the number of experts for any given county is relatively small, which makes the average more vulnerable to extreme values. The number of other experts' responses used to construct the other's county median land values ranged from a low of two to a high of eleven, with an average of five other expert's responses for each of the 99 Iowa counties.

In cases (b), (d), (e), and (f) the variables constructed are aimed at representing true values at the CRD level rather than the county level. In contrast, the ISU survey asks experts for the estimates of land values in their counties. While this discrepancy might seem problematic, using variables to represent CRD-level true values is relevant for at least three reasons. First, models (6) and (7) can accommodate this scenario if county-level estimates are proportional to CRD-level true values. Second, the CRD-level variables are based on larger samples; hence, they are subject to less sample variability (i.e., the resulting representative true values contain less noise). The CRD-level others' median relies on an average of 34 other experts' responses for

Iowa’s nine crop reporting districts as opposed to an average of five other experts’ responses for the 99 Iowa counties. Third, given the potential difficulties experts may face in formulating their subjective land valuation estimates due to heterogeneity and the thinness of the market, it is reasonable to hypothesize that they are likely to consider information on land values beyond their own counties.

Unlike the other series used to represent the prevailing prices, the FCS price series does not discriminate among high-, medium-, and low-quality land but rather represents the average prices for arm’s length transactions for 85% tillable cropland (Zhang 2016). This database not only includes land sales financed by FCS, but all arm’s length transactions across the state. In this instance, one may appeal again to models (6) and (7) to justify the use of (c) and (d) above to represent the prevailing prices by hypothesizing that expert estimates for different qualities are proportional to the prevailing price of a representative land quality.

We also use two other official releases of commonly used survey results as proxies of the prevailing prices at the CRD level. In particular, the Realtors Land Institute (RLI) Iowa Chapter publishes semiannual survey results of Iowa farmland markets and provides CRD-level estimates for tillable cropland, pastureland, and timberland in March and September (Hansen 2018). A key difference between the RLI and ISU survey is that the RLI survey directly asks farm managers and brokers land value estimates at the CRD level rather than at the county level. The series (e) are the RLI September average estimates for tillable cropland at the CRD level. Since the RLI sample mainly consists of farm managers, which also represents 15% of our respondents, it is not irrational to assume that the land value estimates our survey respondents provided were influenced by the RLI September releases. Variable (f) above is simply the average expert’s response of land value estimates for high-, medium- and low-quality in their primary county across all respondents to the ISU survey with primary counties located within a particular CRD. This is released every year during mid-December and represents the land value as of November 1 for that particular survey year. Variable (f) is different from (b) because (f) is the simple average across all raw responses, which include expert $i's$ own estimate, while (b) is the exogenous median of other experts not influenced by the expert's own response.

Finally, the land rent used in the regressions is the average cash rent at the CRD and county level published every May from the ISU Cash Rent Survey (Plastina 2018), while the interest rate is the state-average interest rates on farm real estate published each October from the Federal Reserve Bank of Chicago quarterly Land Values and Credit Conditions Survey (Oppedahl 2018).

4. Econometric Estimation

We estimate regression (5) by means of Bayesian methods. The main reason for resorting to Bayesian estimation is that it allows us to avoid a number of issues that would arise if we were to perform inference under classical methods for the case of nonstationary farmland values.[6] Regardless of whether farmland values are stationary or not, given the ECM structure of regression (5), Bayesian methods allow us to estimate in a straightforward manner the full posterior distributions for its parameters, conditional on the initial set of observations of the

[6] Importantly, even though ECMs are typically used in conjunction with nonstationary variables to represent (and test) co-integrating relationships, ECMs can also be used to represent the dynamics of stationary variables (De Boef and Keele 2008). However, in the case of classical econometrics, appropriate inference requires determining whether farmland values are stationary or not. This assertion is true because if farmland values are nonstationary, which is most likely to be the case (see, e.g., Lence 2001, 2004), standard classical inference methods no longer apply to conduct hypothesis testing in regression (5). Thus, under a classical approach, one must first test whether farmland values are stationary or not. This can be done by means of the test proposed by Harris and Tzavalis (1999), which is designed for testing the null hypothesis of nonstationarity using panel data characterized by short time series and large cross sections. If farmland values are found to be nonstationary, the significance of the lagged land value coefficient can be tested using a homogeneous panel ECM co-integration test. A popular test for this purpose is the one introduced by Westerlund (2007), whose null hypothesis is no co-integration (i.e., that the lagged expert estimate coefficient equals zero).

model variables (Gelman et al. 2013). Such posterior distributions can then be employed to test the various hypothesis of interest, as desired.

Another advantage of the Bayesian approach is that it yields full posterior distributions for functions of such parameters. This feature is especially useful here, because the long-run elasticity $-\beta_x/\beta_y$ is a nonlinear function of the original regression parameters. In this instance, the Bayesian approach allows us to compute the elasticity posterior in a straightforward manner (i.e., it is not necessary to use approximations like the delta method).

Bayesian estimations are conducted using RStan (https://cran.r-project.org/web/packages/rstan/vignettes/rstan.html), the R interface to Stan in the R version 3.4.1 programming language and software environment (https://www.r-project.org). Stan 2.14.0 is employed to implement Hamiltonian Monte Carlo (HMC) sampling with the No-U-Turn sampler (Stan Development Team 2016). Estimation is conditioned on the initial set of observations (i.e., the initial condition consists of the observed values in the year 2005), assuming that the residuals in regression (5) are normally distributed as $e_{i,c,t} \sim \text{Normal}(0, \sigma_e^2)$. To ensure proper posteriors, weakly informative proper priors are adopted for all of the estimated parameters following the typical parameterizations reported in Stan's user guide (Stan Development Team 2016). More concretely, the priors for all of the slope coefficients in regression (5) (i.e., β_y, β_x, γ, $\delta_{y,n}$, $\delta_{x,n}$) and the demeaned experts' intercepts are Normal(0, 5^2),[7]

[7] Following standard practice in Bayesian estimation, the regressions are conducted using demeaned variables. This procedure enhances efficiency because it greatly facilitates achieving convergence in the Monte Carlo chains, by eliminating the correlation between the estimates of the slope and the intercept. More concretely, consider a generic regression $y = a + b\,x + e$ with dependent variable y, explanatory variable x, intercept a, slope b, and residual e. Then, the demeaned regression consists of $\hat{y} = a' + b'\,\hat{x} + e'$, where $\hat{y} \equiv y - mean(y)$ and $\hat{x} \equiv x - mean(x)$ are the demeaned dependent and explanatory variables, and the intercept a' is centered at zero. Clearly, the residuals and the slope of the original regression are identical to the residuals and the slope of the demeaned regression (i.e., $e = e'$ and $b = b'$, respectively), whereas the intercept of the original regression can be recovered from the coefficients of the demeaned regression as $a = a' + mean(y) - b'\,mean(x)$ (Stan Development Team 2016, Section 26.11)

whereas the prior corresponding to the variance of the residuals (σ_e^2) consists of σ_e ~ Cauchy(0, 2.5). The generalized regression (9) is estimated in a similar manner, with Normal(0, 5^2) priors for all of the slope coefficients, and a σ_u ~ Cauchy(0, 2.5) prior associated with the variance of the residuals (σ_u^2).

For each of the estimated regressions, the HMC procedure is conducted using four chains, each of them consisting of 2,000 iterations. The first 1,000 iterations of each chain are discarded as a burn-in period. The Gelman-Rubin test (Gelman and Rubin 1992) is then applied to check the convergence of the remaining part of the chains for each of the parameters. The Gelman-Rubin test checks the convergence of a parameter's Markov chain to its posterior distribution (i.e., whether the parameter estimates are stationary) by comparing the variances both within the chains and between the chains. The Gelman-Rubin test statistics are smaller than 1.001 for all of the estimated models, providing strong evidence of convergence for all parameters. Upon convergence, the 4,000 simulated values for each parameter are taken to be draws from the parameter's posterior marginal distribution. The 4,000 sets of simulated parameters are also used to obtain the posterior distributions for some values of interest, such as the long-run elasticity $-\beta_x/\beta_y$, which should equal one if $\beta_y = -\beta_x$, as hypothesized by the restricted ECM. The 2.5% and 97.5% quantiles of the posterior distributions are then used to construct, respectively, the upper and lower bounds of the 95% credible intervals (CIs) for the corresponding parameter (or function of parameters). CIs are the Bayesian analogs of the classical method's confidence intervals.

5. Results and Discussion

Table 2 presents the strawman results of the ECM regressions shown in equation (5) with one lag estimated using the pooled OLS model. The first three columns in table 2 showcase the results for high-, medium-, and low-quality land using the prevailing prices proxied by other experts' median subjective valuations at the county level, while columns IV-VI replicate these pooled OLS regressions using the others' median estimates at the CRD level. It is important to note that the regression coefficients exhibit expected signs as explained in the methodology section. For example, the positive coefficient on Δx_t suggests that experts will increase their land value estimates following an increase in current land market signals, while the negative coefficient on $y_{i,t-1}$ implied that respondents would correct 20%–30% of prior errors as measured by their deviation between the experts' estimate last year with the lagged prevailing price. However, the OLS model assumes a common intercept for all respondents, which is not necessarily consistent with the fact that participants of farmland markets often possess different subjective beliefs over the true land values due to heterogeneous knowledge, experience, and perceptions of market and other relevant signals. In addition, the Wald test for the individual fixed-effects model reveals that individual intercepts are statistically significant, and we also prefer the individual fixed-effects model over the pooled OLS model due to the better goodness-of-fit measure such as higher log-likelihood.

As a result, table 3 presents the results of our preferred specification and ECM regressions estimated using the individual fixed-effects model. These estimations replicate the models shown in table 2 but were estimated using the fixed-effects model as opposed to pooled OLS model. Table 3 provides strong evidence that agricultural professionals do self-correct their prior errors in their previous land estimates, and their behaviors conform to an ECM with instantaneous adjustments where they not only promptly self-correct prior errors but also immediately respond to changes in current land market movements. In particular, holding other characteristics constant, column I shows that for every one percent prior error in the respondent's land value estimate a year ago compared to the prevailing price proxied by others' median at county level, experts will almost fully correct a prior error by 0.97% when providing an estimate for high-quality land the same year. In addition, our results show that agricultural professionals respond to contemporaneous land market changes or innovations in the current prevailing price. For example, column IV shows that a one percent increase in the district level prevailing price for high-quality land proxied by others' median leads to a 0.80% uptick in the estimated land value reported by an agricultural professional. Comparatively, the three OLS models show only 23%–25% of self-correction of prior errors as opposed to the full amount. This may result from the difficulty to gauge the "true" value of farmland for any individual respondent given the limited land supply and the heterogeneous land quality, or results from the inability of OLS model to account for individual heterogeneity across experts.

Table 3 also reveals a declining magnitude of coefficients for the prevailing price and self-correction when we move from high-quality land to medium- and low-quality land. This suggests that the land market signals are more informative in explaining respondents' land value estimates for high- and medium-quality land as opposed to that for low-quality land. In particular, the long-run elasticity of experts' responses with respect to the current market signals decreases from 0.91 for high-quality land to 0.82 for low-quality land using county-level estimation, and similarly, it decreases from 0.97 for high-quality land to 0.93 for low-quality land using district-level estimation. This declining magnitude also reflects a greater departure from the theoretically consistent coefficient of one for the true land market trends as we move from high-quality land to lower quality land classes. As explained in section 3, these changes likely reflect the empirical observation that the land market trend signals are more difficult to gauge for lower quality land due to its more heterogeneous land quality, mix between lower quality cropland, pasture, and timberland, and less high-profile auction sales and thus less discussion and publicity when compared to high-quality land. It is highly plausible that respondents are more likely to remember the higher-priced land auction sales, and the wider range for the productivity index associated with the lower-quality land from the ISU survey also confirms that respondents tend to agree as to what high-quality land is in their respective region as opposed to more heterogeneous lower-quality grounds (Zhang and Duffy 2017). Using the coefficients from table 3 columns IV and VI, figure 2 graphically illustrates the different speed in the error-correction process for high- and low-quality land, and shows that for high-quality land, respondents almost instantaneously respond to the innovation in true land market changes in just one period, while it would take two or more periods to fully adjust to shocks to the underlying true land values for low-quality land.

Furthermore, table 3 also compares the results using others' median at the county level versus others' median at the CRD level. As discussed above, the key difference between the county and district level model is that the CRD measure utilizes much more other the pool of respondents when constructing the others' median compared to the county measure, which arguably will be noisier and less precise in signaling the land market trends. Interestingly, we find that respondents respond or self-correct more to regional land market changes at the crop reporting level as opposed to the county level. Specifically, a one percent increase in district level high-quality land value proxied by others' median on average would lead to a 0.90% increase in the respondent's land value estimate for high-quality land, while the corresponding change using a county-level estimation shown in column I is only 0.66%. This is likely due to the fact that regional land market signals at the district level are more salient and informative for respondents even when asked to provide land value estimates for their primary county. Yet it is also likely this is due to the statistical artifact that the county-level proxy “true” land value is noisier and less precise due to lack of observations.

Next, we present a set of robustness checks to assess the stability of our results based on how the prevailing land prices were calculated or proxied rather than the others’ median response used in the main specification. First, table 4 presents several robustness checks that make use of the average sales prices for 85% tillable cropland at the district and county level for arm’s length transactions collected by the Farm Credit Services of America, the dominant agricultural lender in Iowa, which we use to replace the others’ median measure. In particular, for high-, medium-, and low-quality land, we use the average CRD-level or county-level average sales prices for 85% tillable cropland, as opposed to others’ median response for a particular land quality class used in tables 2 and 3. Several recent studies examine the similarity between reported average estimates from opinion surveys, such as the ISU land value survey, with sales prices and find that, in general, these two data sources are comparable (Stinn and Duffy 2012). The comparison between tables 3 and 4 shows that our main results on experts’ error correction behavior with instantaneous adjustments remain qualitatively similar.

Table 5 presents additional robustness checks using publically released land value estimates from two expert opinion surveys. Although the ISU land value survey is so far the only source that provides an annual county-level farmland value estimate, it is not the only data agricultural professionals watch for to gauge the pulse of land market movements. In particular, the RLI publishes a semiannual survey that provides CRD-level estimates for cropland, pastureland, and timberland every September. Table 5 columns I-III use the RLI CRD-level cropland value estimates for high-, medium-, and low-quality land as the proxy for the true value as opposed to others' median. In contrast, columns IV-VI use the average land value estimates from the ISU survey at the CRD level publically released in mid-December as the proxy to the true land values, roughly six weeks after the survey data collection started. As a result, these measures are simple average estimates across all respondents as opposed to others' median at the CRD level as shown in the main specifications in table 3, and thus contain a respondent's own estimate. These robustness checks yield similar results as the main specification—the respondents seem to self-correct prior errors in one period, and the instantaneous error-correction behavior is more obvious for high-quality land than for lower quality land. A comparison with table 3 shows that the long-run elasticities implied from these robustness checks are even higher than those for the main specifications, which may result from the fact that the average value estimates were publically released and widely covered in the media and thus might be perceived as more transparent and salient than the others' median measure that a particular respondent does not actually observe.

The next set of robustness checks concern the construction of samples and the main specifications. In particular, table 6 presents three models that essentially replicate the main model for high quality land for three different subsamples, including only respondents who have responded at least eight out of eleven years, omitting observations from 2014 to 2015, which is characterized by a decline in the land market, and also including only informed land market experts such as farm managers, rural appraisers, and agricultural lenders. In general, they yield qualitatively similar results with the main specification. Furthermore, in order to assess the impact on the preciseness of the others' median measure due to changing the number of responses, we conduct an additional set of robustness checks by breaking the sample into counties in the top-third versus bottom-third quantile based on number of expert responses. Intuitively, we expect the counties with more expert responses would yield more precise measures of the prevailing land prices, and as a result exhibit a more theoretically-consistent error-correction behavior. Table 7 contrasts the results between the high-response counties and low-response counties, and finds precisely that the coefficients for y_{t-1} and Δx_t from the error-correction for counties with ample responses is significantly higher than that for counties with less responses. Interestingly, we only find higher long-run elasticity for high-response subsamples than low-response subsamples for the high-quality land.

Table 8 further presents robustness checks incorporating orthogonal components of interest rates and cash rents into the key specification. A comparison with table 3 shows that the coefficients for y_{t-1} and Δx_t are largely similar, and more importantly, table 8 columns IV and VI reveal that the effects for interest rate changes and cash rents are more pronounced for medium- and low-quality land compared to that for high-quality land; and, similarly, they are also more significant for county-level estimation as opposed to district-level models. This is consistent with our earlier discussion that respondents use interest rate and cash rent fluctuations to supplement and refine the land market signals especially when the land market signals are noisier in the case of lower quality land and county-level estimation that relies on less observations when constructing true land market trends. In fact, a comparison between high- and low-quality land in table 3 also shows that changes in lagged land values $\boldsymbol{\Delta y_{t-1}}$ and $\boldsymbol{\Delta x_{t-1}}$ also play a greater role in explaining the experts' land value responses for low-quality land than that for high-quality land. Furthermore, we find that the respondents seem to respond more disproportionally to interest rate changes compared to similar changes in cash rents, especially when county-level others' median was used to proxy the prevailing land price. In particular, a one percent increase in interest rate would leads to a corresponding half-percent reduction in land value on average, while a one percent increase in cash rent would at best lead to 0.4% increase in land value. This could also result from the fact that interest rate is more uniform across the nation and thus is arguably a more salient signal to all respondents, while cash rents are more sticky in nature, often with more than one year in lease, and may not reflect the actual crop and livestock market fundamentals that drive land market changes.

6. Conclusions

Using a panel data of 311 agricultural experts to the ISU land value survey from 2005 to 2015, we develop an ECM to examine how these surveyed agricultural experts update their responses over time, and more specifically, how they self-correct prior errors and adjust their estimates following changes in the prevailing land prices. We employ Bayesian methods to estimate a series of ECM panel fixed-effects models, and because of the lack of true, observable market values for farmland we construct several measures to proxy the prevailing land prices, including the median response of other experts at the county or district level. Our main results provide strong evidence that agricultural professionals' responses to expert opinion surveys over time exhibit error-correction behavior with instantaneous adjustments—in particular, experts self-correct deviations away from true market values proxied using others' median in just one or two periods, and adjust to changes in underlying true market values almost immediately. We also find that the error-correction behavior is more pronounced and more theoretically consistent for high-quality land than that for lower quality land due to noisier land market signals for more heterogeneous low-quality land, and consequentially cash rents and interest rates also play a bigger role in determining experts' responses for lower quality land.

To the best of our knowledge, our article is the first to empirically document the error-correction behavior in expert opinion surveys of farmland values, and our Bayesian estimation approach allows us to more easily conduct causal inference in the presence of nonstationary farmland values. Of course, our research is not without limitations. First, because the true market values for farmland is not readily available and in many cases essentially unknown, we have to rely on measures such as others' median to proxy the true market values. To the extent these proxies misrepresent the true farmland values, this may introduce errors in our estimation. To address this, our Bayesian approach essentially uses the true value as an unknown parameter with these proxies being its signals or measurements, which partially mitigates the problem. Second, although we use others' median as proxy for true value, at the time of the survey each year, a respondent may also see her own lagged response from last year, but do not directly observe others' median. Instead, they could potentially see the publically released land value estimates from the ISU survey, RLI survey and to a lesser extent the FCS cropland prices. Various robustness checks show that our main conclusions of error-correction behavior with instantaneous adjustments remain robust to these alternative specifications and samples. Finally, the magnitude of error-correction behavior is somewhat dependent on the experience and knowledge of agricultural professionals to the opinion surveys, and the conclusions of our research are arguably more transferrable for expert opinion surveys rather than producer or consumer surveys.

Our research has important implications for policymakers, agricultural professionals, and researchers of farmland markets in general, especially given the pervasive use of opinion surveys to gauge land market movements. By providing empirical evidence that agricultural experts in opinion surveys exhibit theoretically-consistent error-correction behavior with instantaneous adjustments to land market signals, our analysis lends credence to the expert opinion surveys of land values commonly employed by land grant universities and the Federal Reserve Bank. This is important given the pervasive usage of the expert opinion surveys by agricultural professionals, researchers and policymakers. Our quantification of the roles of non-land-market signals, such as cash rents and interest rates, in determining experts' responses, especially for low-quality land, also offers new insights regarding the relative role of different characteristics in shaping farmland values, and the rationality of respondents to land value surveys. Future research should examine the saliency of land market signals across different land quality classes, and investigate when and how much interest rates affect farmland values relative to other factors. Our analysis uses an expert opinion survey of farmland values as an example, but we conjecture that the error-correction behavior we uncovered in this article should be noticeable in other opinion surveys of consumers, voters, producers, and other professionals, which is left for future studies to examine.

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Figure 1. Example land value question from 2015 ISU land value survey.

Please select the ONE category that best describes your primary profession:

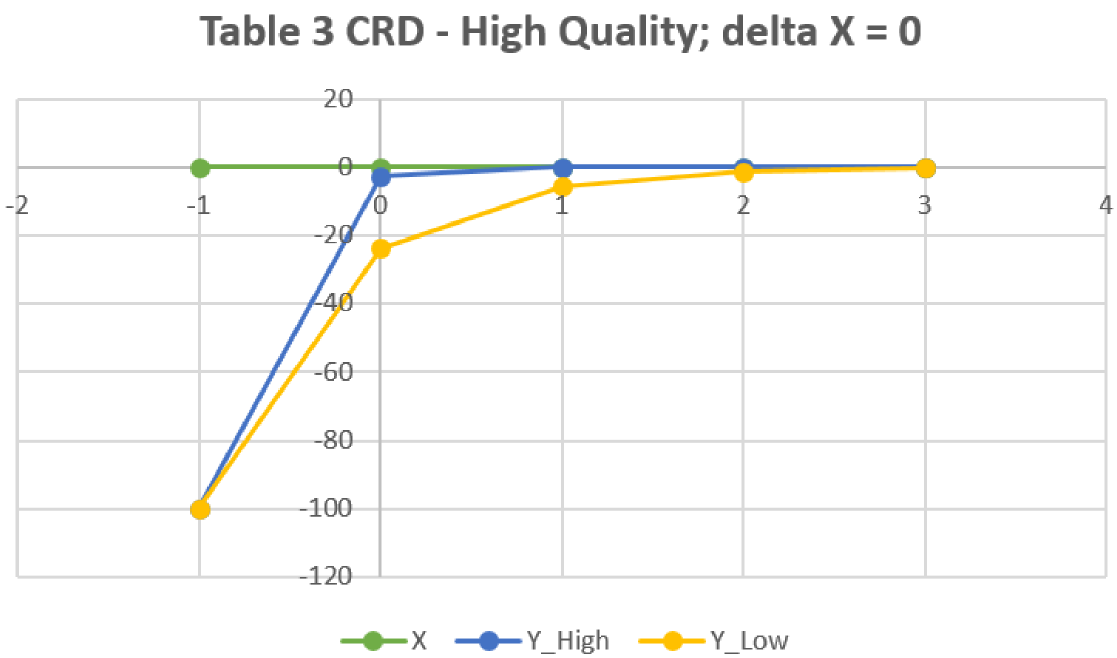
Appraiser	Ag Lender	Professional Farm Manager	Farmer	Extension	FSA	Non-FSA Government	Sales	Other
O	O	O	O	O	O	O	O	O

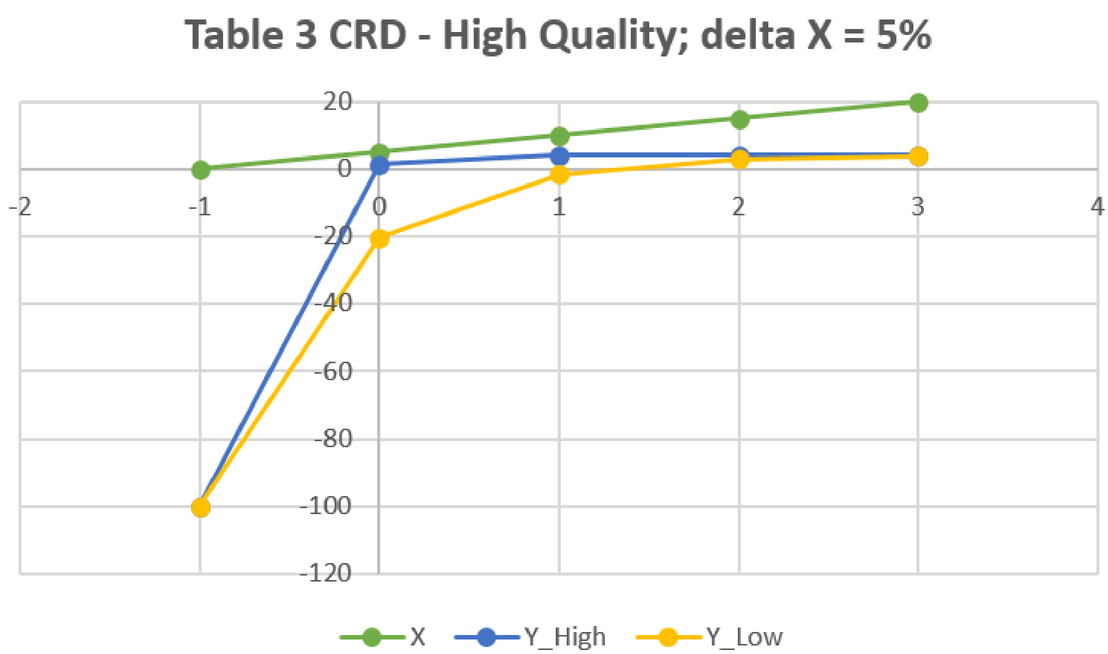
Farmland values in your primary county as of November 1, 2015

1. Land values for average-size farms in <<field/county>> County are:

	Your reported values last year ($/acre)	Your present estimates ($/acre)	Your estimated average CSR1	Your estimated average CSR2
High quality land	<< Value_High>>			
Medium quality land	<< Value_Medium>>			
Low quality land	<< Value_Low>>			

Figure 2. Illustrations of error-correction behavior of experts using CRD-level regressions for high and low quality land shown in table 3.





Panel (a) assumes no changes in underlying true values ($\Delta x_t = 0$); and panel (b) assumes a 5% increase in underlying true values ($\Delta x_t = 5\%$)

Table 1. Summary Statistics of Main Variables used to Perform Regressions

Variable	Description	Average	Std. Dev.	Min	Max	# Obs
HighQualValue	High-quality land value ($/acre)	7232	3335	756	20000	2880
MidQualValue	Medium-quality land value ($/acre)	5582	2633	610	16000	2880
LowQualValue	Low-quality land value ($/acre)	3880	1969	280	12000	2880
HighQualCRDMedian	CRD median of other respondents' values for high-quality land ($/acre)	7180	2843	2275	13455	2880
MidQualCRDMedian	CRD median of other respondents' values for medium-quality land ($/acre)	5497	2184	1450	10000	2880
LowQualCRDMedian	CRD median of other respondents' values for low-quality land ($/acre)	3768	1465	1100	7000	2880
HighQualCountyMedian	County median of other respondents' values for high-quality land ($/acre)	7214	3094	1650	20000	2861
MidQualCountyMedian	County median of other respondents' values for medium-quality land ($/acre)	5554	2385	1125	16000	2860

LowQualCounty Median	County median of other respondents' values for low-quality land ($/acre)	3849	1710	750	12000	2859
No_Years	Number of years that respondents provided land value estimates	10	1	7	11	2880
RENT_CRD	Average cash rent at the CRD level ($/acre)	203	53	110	306	2880
RENT_County	Average cash rent at the county level ($/acre)	204	55	93	363	2880
RATE	Chicago Fed January farmland loan interest rate (% per year)	5.86	1.06	4.61	7.74	2880
HighQual_ISU_CRD	ISU published farmland values for high-quality land at the CRD level as of Nov 1st ($/acre)	7148	2830	2659	12890	2880
MidQual_ISU_CRD	ISU published farmland values for medium-quality land at the CRD level as of Nov 1st ($/acre)	5525	2209	1725	11011	2880
LowQual_ISU_CRD	ISU published farmland values for low-quality land at the CRD level as of Nov 1st ($/acre)	3824	1466	1252	7162	2880
*HighQual_RLI_*	RLI published cropland values	7174	2922	2971	13337	2880

CRD	for high-quality land at the CRD level as of September 1st ($/acre)					
MidQual_RLI_CRD	RLI published cropland values for medium-quality land at the CRD level as of September 1st ($/acre)	5614	2147	2351	10303	2880
LowQual_RLI_CRD	ISU published cropland values for low-quality land at the CRD level as of September 1st ($/acre)	4016	1341	1919	6957	2880
FCS_AvgCRD	Mean sales prices for 85% tillable cropland at the CRD level from Farm Credit Services of America ($/acre)	7152	2228	2927	11289	2102
FCS_AvgCounty	Mean sales prices for 85% tillable cropland at the county level from Farm Credit Services of America ($/acre)	7183	2495	1927	14982	2102

Table 2. Pooled OLS Results of ECM Estimates with no Fixed Effects, Assuming True Land Values are given by Median of Other Experts' Opinions

	County Level			**CRD Level**		
	High-Quality	**Medium-Quality**	**Low-Quality**	**High-Quality**	**Medium-Quality**	**Low-Quality**
$\boldsymbol{y_{t-1}}$	$-.242^{***}$ (.019)	$-.235^{***}$ (.019)	$-.236^{***}$ (.019)	$-.199^{***}$ (.017)	$-.199^{***}$ (.017)	$-.203^{***}$ (.018)
	[-.278, -.206]	[-.273, -.198]	[-.274, -.200]	[-.232, -.166]	[-.234, -.165]	[-.238, -.169]
$\boldsymbol{x_{t-1}}$	$.174^{***}$ (.021)	$.163^{***}$ (.021)	$.129^{***}$ (.022)	$.165^{***}$ (.020)	$.169^{***}$ (.022)	$.133^{***}$ (.022)
	[.133, .215]	[.123, .204]	[.086, .173]	[.125, .205]	[.125, .213]	[.089, .177]
$\boldsymbol{\Delta x_t}$	$.582^{***}$ (.026)	$.524^{***}$ (.028)	$.371^{***}$ (.029)	$.726^{***}$ (.033)	$.738^{***}$ (.044)	$.593^{***}$ (.047)
	[.531, .632]	[.469, .578]	[.314, .427]	[.660, .791]	[.652, .822]	[.499, .685]
$\boldsymbol{\Delta y_{t-1}}$	$-.269^{***}$ (.023)	$-.273^{***}$ (.024)	$-.224^{***}$ (.023)	$-.320^{***}$ (.022)	$-.312^{***}$ (.023)	$-.268^{***}$ (.022)
	[-.312, -.224]	[-.3198, -.228]	[-.271, -.178]	[-.363, -.278]	[-.356, -.266]	[-.312, -.223]

Δx_{t-1}	.342*** (.030)	.300*** (.031)	.194*** (.032)	.427*** (.036)	.415*** (.046)	.449*** (.052)
	[.283, .400]	[.239, .362]	[.132, .256]	[.356, .497]	[.323, .507]	[.346, .551]
Intercept	.635*** (.097)	.654*** (.109)	.931*** (.119)	.313*** (.109)	.263** (.120)	.583*** (.128)
	[.445, .826]	[.442, .869]	[.695, 1.165]	[.102, .528]	[.029, .503]	[.334, .836]
Long-Run	.715*** (.049)	.693*** (.056)	.544*** (.068)	.828*** (.063)	.850*** (.072)	.654*** (.081)
Elasticity	[.615, .808]	[.583, .799]	[.406, .670]	[.703, .946]	[.704, .987]	[.485, .806]
Std. Deviation	.187*** (.003)	.211*** (.003)	.259*** (.004)	.182*** (.003)	.207*** (.003)	.251*** (.004)
of Residuals	[.181, .193]	[.205, .218]	[.251, .267]	[.177, .188]	[.201, .214]	[.243, .258]
$\mathbf{R^2}$	.401 (.019)	.340 (.022)	.253 (.024)	.425 (.018)	.360 (.020)	.292 (.022)
Observations	1,958	1,955	1,954	1,990	1,990	1,990
Log-likelihood	2,302 (1.9)	2,059 (1.9)	1,665 (1.9)	2,390 (1.9)	2,137 (1.9)	1,757 (1.9)

*** (**,*) Different from zero at the 1% (5%, 10%) level of significance, based on the respective 99% (95%, 90%) Credible Interval.

Note: Standard deviations are shown within parentheses, and lower and upper bounds of 95% credible intervals are shown within brackets.

Table 3. Results of ECM with Individual Expert Fixed Effects, Assuming True Land Values are given by Median of Other Experts' Opinions

	County Level			CRD Level		
	High-Quality	**Medium-Quality**	**Low-Quality**	**High-Quality**	**Medium-Quality**	**Low-Quality**
$\boldsymbol{y_{t-1}}$	$-.966^{***}$ (.035)	$-.887^{***}$ (.033)	$-.727^{***}$ (.030)	$-.973^{***}$ (.035)	$-.913^{***}$ (.034)	$-.763^{***}$ (.032)
	[-1.034, -.898]	[-.950, -.823]	[-.789, -.668]	[-1.042, -.906]	[-.976, -.847]	[-.825, -.701]
$\boldsymbol{x_{t-1}}$	$.882^{***}$ (.037)	$.804^{***}$ (.037)	$.598^{***}$ (.035)	$.942^{***}$ (.038)	$.884^{***}$ (.038)	$.713^{***}$ (.038)
	[.811, .952]	[.732, .875]	[.530, .668]	[.866, 1.016]	[.812, .958]	[.634, .787]
$\boldsymbol{\Delta x_t}$	$.663^{***}$ (.026)	$.610^{***}$ (.029)	$.460^{***}$ (.030)	$.796^{***}$ (.031)	$.784^{***}$ (.042)	$.645^{***}$ (.049)
	[.612, .713]	[.554, .666]	[.401, .519]	[.735, .857]	[.700, .868]	[.574, .773]
$\boldsymbol{\Delta y_{t-1}}$	$.052^{**}$ (.026)	.007 (.025)	-.029 (.025)	.032 (.025)	.004 (.025)	-.035 (.025)
	[.002, .103]	[-.041, .055]	[-.078, .020]	[-.017, .081]	[-.045, .053]	[-.085, .014]

Δx_{t-1}	-.008 (.031)	-.007 (.034)	-.024 (.034)	.022 (.037)	.035 (.045)	.137*** (.049)
	[-.068, .053]	[-.073, .061]	[-.090, .041]	[-.053, .095]	[-.051, .122]	[.042, .234]
Intercept	310 individual	310 individual	310 individual	310 individual	310 individual	310 individual
	expert intercepts	expert intercepts	expert intercepts	expert intercepts	expert intercepts	expert intercepts
Long-Run	.913*** (.014)	.907*** (.018)	.822*** (.029)	.967*** (.013)	.968*** (.018)	.934*** (.028)
Elasticity	[.886, .940]	[.870, .941]	[.766, .878]	[.941, .993]	[.933, 1.002]	[.878, .987]
Std. Deviation	.170*** (.003)	.195*** (.003)	.243*** (.004)	.165*** (.003)	.188*** (.003)	.232*** (.004)
of Residuals	[.165, .176]	[.188, .201]	[.235, .252]	[.159, .170]	[.182, .194]	[.225, .240]
R^2	.503 (.017)	0.440 (.019)	.340 (.023)	.532 (.016)	.473 (.018)	0.392 (.021)
Observations	1,957	1,954	1,953	1,989	1,989	1,989
Log-likelihood	2,484 (14)	2,217 (14)	1,784 (14)	2,594 (14)	2,328 (14)	1,908 (14)

*** (**,*) Different from zero at the 1% (5%, 10%) level of significance, based on the respective 99% (95%, 90%) Credible Interval.

Note: Standard deviations are shown within parentheses, and lower and upper bounds of 95% credible intervals are shown within brackets.

Table 4. Robustness Checks Assuming True Land Values are given by Average Sales Prices for 85% Tillable Cropland Collected by the Farm Credit Service of America

	County Level			CRD Level		
	High-Quality	**Medium-Quality**	**Low-Quality**	**High-Quality**	**Medium-Quality**	**Low-Quality**
$\boldsymbol{y_{t-1}}$	-1.168*** (.047)	-1.123*** (.045)	-1.049*** (.043)	-1.141*** (.045)	-1.093*** (.042)	-1.011*** (.041)
	[-1.259, -1.077]	[-1.210, -1.035]	[-1.133, -.967]	[-1.228, -1.055]	[-1.174, -1.011]	[-1.091, -.930]
$\boldsymbol{x_{t-1}}$	1.008*** (.059)	.936*** (.056)	.828*** (.053)	1.017*** (.062)	.951*** (.062)	.841*** (.063)
	[.893, 1.120]	[.826, 1.049]	[.723, .932]	[.900, 1.140]	[.830, 1.072]	[.717, .962]
$\boldsymbol{\Delta x_t}$	.624*** (.041)	.563*** (.044)	.471*** (.053)	.758*** (.071)	.711*** (.081)	.622*** (.098)
	[.543, .704]	[.477, .652]	[.369, .574]	[.615, .896]	[.554, .867]	[.431, .814]
$\boldsymbol{\Delta y_{t-1}}$	.144*** (.032)	.091*** (.031)	.083*** (.030)	.097*** (.032)	.049* (.030)	.049 (.030)
	[.082, .206]	[.031, .150]	[.025, .143]	[.037, .159]	[-.011, .106]	[-.011, .109]

Δx_{t-1}	.045 (.043)	.050 (.044)	.073 (.050)	.105* (.060)	.089 (.065)	.089 (.077)
	[-.038, .133]	[-.038, .134]	[-.025, .173]	[-.013, .219]	[.047, .217]	[-.061, .239]
Intercept	286 individual expert intercepts	286 individual expert intercepts	286 individual expert intercepts	286 individual expert intercepts	286 individual expert intercepts	286 individual expert intercepts
Long-Run Elasticity	.862*** (.026)	.833*** (.029)	.789*** (.035)	.891*** (.033)	.870*** (.039)	.832*** (.050)
	[.810, .913]	[.777, .888]	[.717, .858]	[.825, .954]	[.792, .948]	[.734, .928]
Std. Deviation of Residuals	.176*** (.004)	.192*** (.004)	.232*** (.005)	.170*** (.004)	.188*** (.004)	.230*** (.005)
	[.168, .184]	[.184, .201]	[.222, .242]	[.163, .178]	[.180, .196]	[.220, .240]
R^2	.551 (.020)	.524 (.021)	.470 (.023)	.579 (.019)	.546 (.020)	.479 (.023)
Observations	1,312	1,312	1,312	1,312	1,312	1,312
Log-likelihood	1,622 (14)	1,506 (14)	1,260 (14)	1,664 (14)	1,537 (14)	1,271 (14)

*** (**,*) Different from zero at the 1% (5%, 10%) level of significance, based on the respective 99% (95%, 90%) Credible Interval.

Note: Standard deviations are shown within parentheses, and lower and upper bounds of 95% credible intervals are shown within brackets.

Table 5. Robustness Checks Assuming True Land Values are given by Either the Realtor Land Institute CRD Cropland Values or Iowa State University's CRD Farmland Value Estimates

	Realtor Land Institute			**Iowa State University**		
	High-Quality	**Medium-Quality**	**Low-Quality**	**High-Quality**	**Medium-Quality**	**Low-Quality**
y_{t-1}	$-.940^{***}$ (.037)	$-.869^{***}$ (.036)	$-.692^{***}$ (.031)	$-.966^{***}$ (.035)	$-.919^{***}$ (.034)	$-.792^{***}$ (.032)
	[-1.014, -.868]	[-.940, -.799]	[-.752, -.631]	[-1.033, -.898]	[-.986, -.852]	[-.855, -.731]
x_{t-1}	$.879^{***}$ (.041)	$.823^{***}$ (.043)	$.676^{***}$ (.047)	$.986^{***}$ (.039)	$.889^{***}$ (.037)	$.692^{***}$ (.035)
	[.800, .961]	[.741, .909]	[.583, .768]	[.908, 1.064]	[.815, .965]	[.624, .763]
Δx_t	1.125^{***} (.037)	$.986^{***}$ (.041)	$.779^{***}$ (.047)	$.873^{***}$ (.039)	$.788^{***}$ (.044)	$.671^{***}$ (.056)
	[1.052, 1.199]	[.908, 1.066]	[.687, .871]	[.797, .950]	[.702, .873]	[.564, .780]
Δy_{t-1}	.034 (.028)	-.018 (.027)	$-.066^{***}$ (.025)	.018 (.025)	-.012 (.026)	-.024 (.025)
	[-.019, .087]	[-.070, .034]	[-.116, -.017]	[-.029, .067]	[-.063, .039]	[-.072, .024]

Δx_{t-1}	$-.094^{**}$ (.042)	-.068 (.047)	-.008 (.050)	$.104^{**}$ (.045)	$.096^{*}$ (.050)	$.146^{***}$ (.055)
	[-.176, -.012]	[-.161, .025]	[-.103, .089]	[.016, .193]	[-.001, .193]	[.042, .254]
Intercept	310 individual expert intercepts	310 individual expert intercepts	310 individual expert intercepts	310 individual expert intercepts	310 individual expert intercepts	310 individual expert intercepts
Long-Run Elasticity	$.935^{***}$ (.016)	$.947^{***}$ (.020)	$.976^{***}$ (.040)	1.021^{***} (.014)	$.968^{***}$ (.016)	$.874^{***}$ (.024)
	[.903, .964]	[.907, .987]	[.893, 1.053]	[.993, 1.049]	[.935, 1.000]	[.826, .920]
Std. Deviation of Residuals	$.173^{***}$ (.003)	$.193^{***}$ (.003)	$.241^{***}$ (.004)	$.163^{***}$ (.003)	$.184^{***}$ (.003)	$.228^{***}$ (.004)
	[.167, .179]	[.187, .200]	[.233, .249]	[.157, .168]	[.179, .191]	[.220, .236]
$\mathbf{R^2}$	.486 (.019)	.445 (.019)	.345 (.023)	.543 (.016)	.494 (.017)	.414 (.021)
Observations	1,989	1,989	1,989	1,989	1,989	1,989
Log-likelihood	2,500 (14)	2,276 (14)	1,835 (14)	2,615 (14)	2,368 (14)	1,944 (14)

*** (**,*) Different from zero at the 1% (5%, 10%) level of significance, based on the respective 99% (95%, 90%) Credible Interval.

Note: Standard deviations are shown within parentheses, and lower and upper bounds of 95% credible intervals are shown within brackets.

Table 6. Robustness Checks for High-quality Land under Selected Types of Experts and Periods

	County Level			CRD Level		
	Experts with 11 Annual Responses	**Farm managers, rural appraisers and ag lenders only**	**2005-2013**	**Experts with 11 Annual Responses**	**Farm managers, rural appraisers and ag lenders only**	**2005-2013**
y_{t-1}	-.981*** (.049)	-.849*** (.056)	-1.047*** (.044)	-1.024*** (.050)	-.833*** (.057)	-1.046*** (.045)
	[-1.076, -.885]	[-.961, -.737]	[-1.134, -.963]	[-1.123, -.928]	[-.943, -.722]	[-1.135, -.959]
x_{t-1}	.896*** (.054)	.746*** (.059)	1.029*** (.045)	1.000*** (.056)	.778*** (.059)	1.044*** (.047)
	[.791, 1.002]	[.632, .862]	[.941, 1.118]	[.891, 1.111]	[.663, .892]	[.953, 1.134]
Δx_t	.665*** (.041)	.610*** (.038)	.649*** (.029)	.785*** (.051)	.806*** (.046)	.794*** (.035)
	[.588, .745]	[.535, .683]	[.591, .707]	[.686, .884]	[.716, .892]	[.726, .862]
Δy_{t-1}	.015** (.035)	.021 (.044)	.077** (.033)	.029 (.034)	-.010 (.044)	.065** (.032)
	[-.053, .084]	[-.064, .107]	[.011, .142]	[-.038, .099]	[-.099, .074]	[.003, .128]

Δx_{t-1}	.069 (.049)	-.007 (.047)	-.164*** (.043)	.084 (.058)	-.074 (.055)	-.091* (.053)
	[-.029, .166]	[-.099, .085]	[-.246, -.081]	[-.028, .202]	[-.182, .036]	[-.197, .014]
Intercept	113 individual expert intercepts	107 individual expert intercepts	296 individual expert intercepts	113 individual expert intercepts	107 individual expert intercepts	297 individual expert intercepts
Long-Run Elasticity	.913*** (.021)	.878*** (.023)	.983*** (.016)	.976*** (.020)	.934*** (.023)	.998*** (.017)
	[.872, .954]	[.830, .922]	[.951, 1.015]	[.936, 1.016]	[.888, .977]	[.966, 1.031]
Std. Deviation of Residuals	.204*** (.005)	.144*** (.004)	.168*** (.003)	.197*** (.005)	.135*** (.004)	.164*** (.003)
	[.195, .214]	[.136, 153]	[.162, .175]	[.188, .207]	[.128, .143]	[.157, .170]
R^2	.516 (.023)	.477 (.032)	.423 (.023)	.538 (.022)	.535 (.027)	.448 (.022)
Observations	963	691	1,560	990	717	1,583
Log-likelihood	1,048 (8.0)	992 (8.3)	2,001 (14)	1,110 (8.1)	1,078 (8.3)	2,073 (14)

*** (**,*) Different from zero at the 1% (5%, 10%) level of significance, based on the respective 99% (95%, 90%) Credible Interval.

Note: Standard deviations are shown within parentheses, and lower and upper bounds of 95% credible intervals are shown within brackets.

Table 7. Robustness Checks for Subsamples based on the Number of Expert Responses

	CRDs in the Top-Third Quantile Based on Number of Expert Responses			**CRDs in the Bottom-Third Quantile Based on Number of Expert Responses**		
	High-Quality	**Medium-Quality**	**Low-Quality**	**High-Quality**	**Medium-Quality**	**Low-Quality**
y_{t-1}	-1.034*** (.066)	-1.001*** (.062)	-.861*** (.059)	-.991*** (.060)	-.968*** (.059)	-.803*** (.055)
	[-1.161, -.903]	[-1.126, -.884]	[-.973, -.745]	[-1.111, -.874]	[-1.082, -.853]	[-.911, -.694]
x_{t-1}	1.016*** (.069)	.978*** (.064)	.777*** (.068)	.937*** (.067)	.994*** (.073)	.850*** (.075)
	[.876, 1.152]	[.855, 1.104]	[.644, .908]	[.803, 1.070]	[.852, 1.136]	[.702, .997]
Δx_t	.856*** (.051)	.786*** (.063)	.797*** (.074)	.699*** (.055)	.848*** (.089)	.703*** (.099)
	[.760, .954]	[.665, .908]	[.654, .942]	[.590, .806]	[.674, 1.021]	[.510, .897]
Δy_{t-1}	.073 (.048)	.114** (.048)	-.007 (.051)	.022 (.043)	-.004 (.044)	-.047 (.042)
	[-.023, .169]	[.022, .210]	[-.106, .093]	[-.061, .105]	[-.091, .082]	[-.127, .037]

Δx_{t-1}	-.071 (.074)	-.093 (.085)	-.074 (.089)	-.002 (.064)	.014 (.096)	.083 (.098)
	[-.220, .082]	[-.262, .077]	[-.251, .103]	[-.127, .122]	[-.174, .202]	[-.104, .279]
Intercept	171 individual expert intercepts	171 individual expert intercepts	171 individual expert intercepts	97 individual expert intercepts	97 individual expert intercepts	97 individual expert intercepts
Long-Run Elasticity	.983*** (.021)	.977*** (.027)	.903*** (.044)	.945*** (.027)	1.027*** (.036)	1.059*** (.057)
	[.941, 1.023]	[.923, 1.030]	[.817, .989]	[.890, .997]	[.956, 1.097]	[.948, 1.170]
Std. Deviation of Residuals	.152*** (.005)	.166*** (.005)	.213*** (.007)	.189*** (.006)	.220*** (.007)	.258*** (.008)
	[.143, .162]	[.155, .177]	[.199, .227]	[.178, .201]	[.207, .233]	[.243, .274]
R^2	.557 (.029)	.496 (.033)	0.416 (.038)	.487 (.031)	.445 (.034)	0.394 (.038)
Observations	654	654	654	617	617	617
Log-likelihood	904 (11)	847 (11)	684 (11)	718 (7.8)	625 (7.6)	527 (7.9)

*** (**,*) Different from zero at the 1% (5%, 10%) level of significance, based on the respective 99% (95%, 90%) Credible Interval.

Note: Standard deviations are shown within parentheses, and lower and upper bounds of 95% credible intervals are shown within brackets.

Table 8. Results of ECM Incorporating Orthogonal Components of Interest Rates and Rental Rates

	County Level			CRD Level		
	High-Quality	**Medium-Quality**	**Low-Quality**	**High-Quality**	**Medium-Quality**	**Low-Quality**
y_{t-1}	-.965*** (.033)	-.887*** (.032)	-.726*** (.029)	-.974*** (.034)	-.914*** (.032)	-.763*** (.030)
	[-1.028, -.901]	[-.950, -.824]	[-.784, -.669]	[-1.041, -.908]	[-.976, -.851]	[-.820, -.706]
x_{t-1}	.881*** (.035)	.805*** (.036)	.597*** (.035)	.942*** (.037)	.884*** (.036)	.713*** (.037)
	[.813, .948]	[.735, .877]	[.530, .665]	[.872, 1.012]	[.814, .954]	[.642, .785]
Δx_t	.663*** (.024)	.611*** (.026)	.460*** (.029)	.797*** (.030)	.783*** (.042)	.676*** (.048)
	[.617, .710]	[.561, .663]	[.403, .517]	[.736, .858]	[.701, .861]	[.585, .770]
Δy_{t-1}	.051** (.024)	.008 (.025)	-.030 (.023)	.032 (.025)	.005 (.024)	-.035 (.023)
	[.003, .099]	[-.040, .056]	[-.074, .015]	[-.017, .081]	[-.041, .053]	[-.081, .011]
Δx_{t-1}	-.007 (.030)	-.007 (.032)	-.023 (.032)	.021 (.037)	.035 (.047)	.137*** (.049)

	[-.066, .054]	[-.070, .056]	[-.084, .038]	[-.049, .092]	[-.058, .127]	[.040, .234]
$\perp$***rent***$_{t-1}$	.118 (.111)	.108 (.127)	-.122 (.157)	.184 (.183)	-.049 (.249)	-.646** (.306)
	[-.098, .334]	[-.142, .357]	[-.431, .189]	[-.184, .540]	[-.526, .425]	[-1.230, -.055]
$\perp$***interest***$_{t-1}$	-1.259*** (.165)	-1.367*** (.174)	-1.436*** (.200)	-1.098*** (.236)	-1.335*** (.259)	-1.753*** (.292)
	[-1.581, -.936]	[-1.714, -1.021]	[-1.833, -1.047]	[-1.555, -.646]	[-1.852, -.819]	[-2.322, -1.184]
$\Delta\perp$***rent***$_t$	.372*** (.068)	.413*** (.076)	.421*** (.098)	.512*** (.130)	.412** (.169)	.204 (.173)
	[.237, .501]	[.262, .564]	[.234, .606]	[.266, .771]	[.077, .736]	[-.137, .538]
$\Delta\perp$***interest***$_t$	-.492*** (.102)	-.501*** (.118)	-.479*** (.140)	-.203* (.123)	-.248* (.134)	-.402** (.168)
	[-.691, -.290]	[-.734, -.268]	[-.750, -.205]	[-.437, .038]	[-.508, .019]	[-.736, -.073]
$\Delta\perp$***rent***$_{t-1}$	.205*** (.063)	.229*** (.070)	.332*** (.085)	.090 (.094)	.218* (.120)	.184 (.139)
	[.078, .328]	[.091, .368]	[.164, .502]	[-.093, .277]	[-.011, .448]	[-.092, .457]
$\Delta\perp$***interest***$_{t-1}$	.613*** (.107)	.683*** (.112)	.691*** (.133)	.686*** (.127)	.799*** (.151)	.848*** (.161)

	[.394, .826]	[.465, .904]	[.426, .959]	[.436, .937]	[.502, 1.104]	[.528, 1.164]
Intercept	310 individual expert intercepts	310 individual expert intercepts	310 individual expert intercepts	310 individual expert intercepts	310 individual expert intercepts	310 individual expert intercepts
Long-Run Elasticity	.913*** (.013) [.888, .938]	.908*** (.017) [.874, .941]	.821*** (.028) [.767, .875]	.968*** (.013) [.940, .994]	.968*** (.018) [.934, 1.002]	.935*** (.027) [.881, .988]
Std. Deviation of Residuals	.164*** (.003) [.158, .170]	.186*** (.003) [.180, .1931]	.231*** (.004) [.224, .239]	.162*** (.003) [.157, .168]	.186*** (.003) [.180, .192]	.229*** (.004) [.221, .237]
R^2	.541 (.016)	0.490 (.018)	.402 (.021)	.546 (.016)	.484 (.018)	0.411 (.021)
Observations	1,957	1,954	1,953	1,989	1,989	1,989
Log-likelihood	2,566 (14)	2,308 (14)	1,882 (14)	2,622 (14)	2,348 (14)	1,939 (14)

*** (**,*) Different from zero at the 1% (5%, 10%) level of significance, based on the respective 99% (95%, 90%) Credible Interval.

Note: Standard deviations are shown within parentheses, and lower and upper bounds of 95% credible intervals are shown within brackets.