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Article

Modeling Influence of Agricultural and Non-Agricultural Factors on Texas Rural Land Market Values

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Abstract: Rural land provides physical qualities that affect agricultural production, and space, rural culture, and biodiversity to non-agricultural entities. Texas rural land values have increased substantially in recent years, expanding transactions and prices received. The increase of land price caused expansion of related business operations. Therefore, concerns of volatilities in land price put finding the determinants of land value at the forefront of research. Land use patterns in Texas are numerous as much as they are complicated in terms of interactions and pricing. Therefore, rural land values are determined by factors that differ from the conventional belief that farm income drives values. Identifying alternative determinants of price enables practitioners to make informed decisions. Using county level data, this study estimates a comprehensive spatial panel hedonic model to discover determinants of rural land prices in Texas. Both county-level variation across multiple periods and spatial contribution to the price variability measured by a spatial weighted matrix are considered. The results show that besides the modest influence of traditional farm returns, non-farm factors are crucial in determining Texas rural land values.

Keywords: rural land value; Texas; agriculture; non-agriculture

1. Introduction

Rural land plays a vital role in agriculture. Endowed by its location, rural land provides not only physical qualities that impact agricultural production, but also provides space, rural culture, and biodiversity to non-agricultural entities (Borchers et al. 2014). The resulting demand for rural land reflects more diverse buyer motivations than simply production of food or natural amenities. (Wasson et al. 2013). Rural land uses and values indicate the distribution of benefits from relevant economic activities and provide information to guide business decisions.

Various studies have modeled the determinants of land values along with their merits and challenges. The early agricultural land literature applying the basic capitalization model has not successfully explained the dramatic changes of land values during 1970s-1980s (Nickerson and Zhang 2014). Therefore, the focus of land value studies has shifted over time to find a better explanation. Recent empirical literature on land value determination examines a complex set of factors beyond agricultural returns. One alternative that has been well accepted by most researchers includes the value of non-farm real estate in the model. Many empirical studies have indicated urban influences such as demand for developable land for residential or commercial uses is the most significant determinant of land values (Hardie et al. 2001; Ma and Swinton 2012; Nickerson and Zhang 2015). Another consensus is that specific amenities such as wildlife habitats, river/lake access, and scenic views are also significant determinants of land price (Wasson et al. 2013). Although each of these models offers economic insight into the relationship between land values and its major drivers, the robustness is restricted by certain limitations or constraining assumptions. For example, According to Pope et al. (1979), updating some of these models leads to changes in sign and loss of

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significance in the coefficients of the variables. These results of Pope's regression address the shortcomings of previous models.

With the largest rural land area among contiguous United States, Texas provides great opportunities for a high volume of land transactions. In recent years, Texas rural land values have increased substantially (see Figure 15). Texas also witnesses the most recent major boom-and -bust cycles of the 1970s and 1980s. Texas rural land prices[1] grew over 285% (from $209/acre to $804/acre) in the most recent cycle from 1971 to 1985 based on the price data provided by Texas Real Estate Research Center. The land market expansion is associated with an increase in transactions and prices received. The increase of land price caused expansion of related business operations and thus put the operators in risky positions. When the business sector failed to cover all the debts, it began to contract with a downturn in prices. Afterwards, the agricultural economy experienced one of its greatest recessions in 1980s. As the farm sector faces challenges such as declining crop prices in 1980s, the ability to generate sufficient income to service the debt becomes strained. In such situations, farmers struggled to meet their financial obligations, leading to financial stress and potential economic downturns (Hardin 2017).

Once again, from 2000 to 2020, Texas rural land prices grew 341% (from $694/acre to $3064/acre) with an average increase of 7.75%. Similarly, USDA' report has seen the largest increase rate in cropland prices after 2000s in The Midwestern states (Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Ohio, and Wisconsin). Therefore, concerns of volatilities in land price put finding the determinants of land value once again at the forefront of research.

A varied landscape that supports diverse land uses for Texas land markets creates competition among competing users. Land use patterns in Texas are numerous as much as they are complicated in terms of interactions and pricing of each type of land (for example: cropland production, livestock, residential and recreational activities, timber production). As a result, rural land values are determined by factors that differ from the conventional belief that farm income drives values. Identifying alternative determinants of Texas rural land markets enables practitioners to make better informed decisions. For instance, the excess value of rural land over the value of use in agricultural production provides a measure of non-agricultural return. Understanding the driving factors of rural land value may enhance efforts to preserve natural open space through agricultural conservation easements. However, due to inadequate data, such studies are rarely available in Texas rural land markets. This study sheds light on a comprehensive spatial panel hedonic model to discover determinants of rural land prices in the state of Texas.

The value of rural land has been dependent upon diverse uses such as recreation, investment, second homes other than farm production factors or physical attributes (Nickerson and Zhang 2014). These demands lead to complex market situations since the value of land may be a function of various factors including economic conditions and futures usage. Previous classic land valuation models have failed to capture the relevant underlying attributes of rural land markets and data limitations in Texas rural land markets have constricted the development of related studies. Moreover, the record increase rate of rural land prices in recent years has raised concerns about the overall stability of the land market as well as agricultural economy. Because the situation now is if the market begins to contract, will another bust come. Big drop in land prices can result in financial stress for farmers who own land as a significant asset. If land values drop, farmers may experience a decrease in their net worth, potentially impacting their ability to access credit or secure loans. Furthermore, reduced farm income can lead to decreased spending on inputs, machinery, and labor, potentially impacting the overall profitability of agricultural operations. Lower land prices can also impact land market activities. Farmers and landowners may be less inclined to sell their land at lower prices, preferring to hold onto their properties and wait for future recovery. This can result in reduced transaction volumes and limited liquidity in the land market. The expansion of operations or investment in land

[1] Data available at https://www.recenter.tamu.edu/data/rural-land/#!/state/Texas.The growth rates calculated by the authors are based on nominal prices. Real prices have observed similar trending.

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improvements may be delayed as well since farmers perceive a decline in land values. This could result in a reduced incentive for agricultural innovation, or conservation practices, impacting long-term productivity and sustainability in the agricultural sector. These challenges may require supportive measures from land participants as well as policymakers. Therefore, the determinants of rural land prices are important references for these measures.

This study tries to solve these three problems (shortcomings of previous models, limited comprehensive rural land study in Texas , and the concern of price volatility in Texas rural land market) by developing a land valuation model for Texas rural land markets. By employing a panel spatial error specification to the classic hedonic modeling framework, this study addresses the potential autocorrelation of unobserved variables. The county level aggregated transactional data provided by Texas Real Estate Research Center makes a comprehensive land value study possible in Texas and helps to improve the estimations. Explanatory variables evaluated in the model help to build the characteristics profile of determinants of Texas rural land market.

The primary objective of this work is to explain Texas rural land value fluctuations in terms of both agricultural and non-agricultural related factors. Both county-level variation across multiple time periods and spatial contribution to the price variability measured by a spatial weighted matrix are considered. Specific objectives are to (1) identify characteristics that determine Texas rural land market prices; (2) determine marginal contribution of each characteristic to rural land prices; (3) estimate the contribution of spatial factors to the rural land prices; (4) develop a characteristic profile of determinants of land values in the state of Texas that can be used by practitioners in land transactions.

Because land comprises a significant component of the farms' balance sheet in the United States, understanding factors of land values has been the subject of numerous land valuation studies. The earliest land studies date back more than 100 years while most advances have not occurred until the more recent decades (Nickerson and Zhang 2014). In early 1960s, Herdt and Cochrane (1966) and Tweeten and Martin (1966) used classic market framework to explain the land values by incorporating simultaneous equation models. Both of these studies proposed land valuation models based on a classic economic framework, which requires strict assumptions to build a supply and demand system. However, Pope et al. (1979) tests Herdt and Cochrane' model with updated data. They find that many variables have lost significance or changed signs.

Since land is considered a unique "product" (or asset) and therefore, difficult to be modeled in the traditional supply and demand framework, the income capitalization model has become a popular alternative method in land valuation studies. As discussed, more researchers agree that land values are influenced by a complex set of factors. An extensive empirical literature has investigated the determinants of land value from a wide range of perspectives (Raup 2003). The typical approach to modeling land value is to link net present value of future returns to current land price – a capitalization model (Ricardo 2005; Burt 1986; Featherstone and Baker 1987; Drozd and Johnson 2004; Guiling et al. 2009). Specifically, Ricardo's theory of rent has been an important milestone in the land value models. One of his main ideas is that land is a unique asset that varies in quality and has limited supply. Therefore, land generates rent that derives from activity conducted on it. Rent varies due to differences in productivity based on the quality of land or its location. (Ricardo 2005). The basic model is written as follows,

$$P_t = \sum_{i=1}^{\infty} \frac{E_t(R_{t+i})}{(1+r)^i} \tag{1}$$

where P_t is the value of land parcel at time t, R_t is the net returns to land in t, r denotes a discount rate, and $E_t(.)$ represents the expectation operator. Burt (1986) applies net rent data and land value data obtained from farm survey in Illinois to this simple model. By addressing the distributed lags, he finds two components of rent returns are the major explanation of land prices. One is the previous year's rent and land price and the other is the expected change in rent and land price for the next year. Although this simple model is a popular framework for investigating land values, the limitations have been recognized widely since net rent fails to capture all of land values based on

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more recent studies (Borchers et al. 2014). The explanation for this failure arises from the fact that in many regions in United States, land values also reflect non-farm factors such as economic opportunities and natural amenities farmland provides for neighboring urban populations (Shi, Phipps, and Colyer 1997; Kuethe, Ifft, and Morehart 2011; Delbecq et al. 2014).

As a result, more recent land studies center around the theoretical framework of urban growth model developed by Capozza and Helsley's (1989). Land values are represented as follows,

$$P_t = \sum_{i=1}^{u} \frac{E_t(R_{t+i})}{(1+r)^{i-u}} + \sum_{u}^{\infty} \frac{E_t(V_{t+u})}{(1+r)^{u}} \tag{2}$$

where P_t is the value of land parcel at time t, R_t is the net returns to land in t, V_t is the conversion cost of farmland to urban use land at time u, r denotes a discount rate, and $E_t(.)$ represents the expectation operator. Their work shows that land conversion occurs when farm returns no longer earn more than urban use activities and the expected future rent can be quite large in rapidly growing cities.

This model has been expanded to estimate other sources of nonfarm income—government payments, for example—that generate a stream of payments that are earned in addition to agricultural returns (Weersink et al.1999; Goodwin et.al 2011). A few studies are discussed here in explaining why government payments are included in the modeling of rural land prices. Featherstone & Baker (1988) examine two different land price scenarios in Indiana prior to the 1996 Farm Bill. One scenario is under the 1985 farm program, and the other is under a free market scenario. At that time, the government programs were linked to commodity prices. As a result, the realized commodity price can be changed by the government programs, which, in turn, affects the level of rent charged and results in changes of land prices. The authors generate a grain price distribution under the alternative policies to investigate how rental rates are set based on varying market commodity prices. According to their results, under the market scenario, land prices are low and more volatile. Specifically, Featherstone & Baker (1988) conclude that there would be a 16% decrease in land prices over a four-year period under the market scenario. Barnard et al. (1997) agree on how government payments contribute to cash rental rate. They developed a regional analysis by dividing United States into 20 regions. Parts of Texas, Georgia, Alabama, the southern Corn Belt, and parts of North Carolina are found to be the regions with largest elasticities or affected most by government payments. Weersink et.al (1999) examine the extent to which agricultural support programs have been captured in farmland prices. The returns have been decomposed to two sources: farm production and government subsidies. This study collects data from the province of Ontario, Canada. The results show that government payments are a more stable source of income than the production-based returns from 1950 to 1993. Goodwin et.al (2011) has also confirmed the importance of government programs. They considered a large sample period by utilizing data of Agricultural Resource Management Survey (ARMS) project, which contain detailed payment information for individual farm program from year 1998 to 2001. Goodwin et.al (2011) find different programs have different effects on land prices (either positive or negative). Moreover, the effects also differ across regions and vary from year to year. Based on the conclusions in previous studies, government payments add value to land price and should be considered as an important variable in land valuation. However, it is worth noticing that as a source of income, government payments may have been considered in determining the rental rates, and thus would be redundant when rental rate is included already.

Natural amenity characteristics (for example: close to lakes, hunting spaces) attract competitors to traditional agricultural operations (Henderson and Moore 2006). Researchers also realize urban fringe land determinants fail to explain land values accurately in more rural setting areas. As discussed by Wasson et al. (2013), in states with few metropolitan area (for example, Colorado), the residential development which utilizes agriculture land is unlikely to resemble the suburban sprawl analysis in prevalent literature. As a result, a unique set of land values and conversion risks are determined by the western public lands, wildlife and demand for recreation.

Another stream of studies explores the relationship between land values and debt or credit conditions. Limited credit access can pose challenges in land investments and farm productivity. For

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example, Ciaian, Falkowski, and Kancs (2012) identify the positive relationship between credit, input use, capital investments, and total factor productivity. In their study, farm credit is represented as total farm loans and increase in farm credit increase farm productivity. Rajan and Ramcharan (2015) introduce a unique method of measuring credit availability. They employ data from the 1900s to 1930s and conduct multiple regression analyses along with graphical assessments, using total bank deposits and number of bank branches as indicators for credit availability. They take advantage of the common and constant board influences in early twentieth century farm lending since the lending is local within counties in each state. They consider the county as the relevant local market for credit. By focusing on counties, they correct for state fixed effects, which in turn, removes the confounding effects of myriad state banking regulations. Their estimation suggests a positive effect of credit availability on land prices. Moreover, they discover that areas with greater credit availability during the commodity price boom have led to land prices decline and long term of lower credit availability after the bust. Devadoss and Manchu (2007) also agree that credit availability play a significant role in land sales and price determination. Their proxy of credit availability is the amount of loans obtained from the Farm Service Agency of USDA. In their county-level analysis, a 1% increase in credit availability results in a 1.40% increase in farmland values in Idaho. Sant' Anna et al. (2021) provide a fix effect regression of counties in the Kansas City and Minneapolis Federal Reserve Districts by controlling land value determinants, credit availability factors and county and macroeconomic factors such as unemployment rate, debt-to-income ratio, annual population growth rate. They include several credit access and credit availability variables applied in previous studies. Meanwhile, they build an index of increased credit availability (a function of available funds, repayment rates and collateral requirements) using Federal Reserve and Federal Deposit Insurance Corporation data. They find that if credit availability index goes up by 0.1, transitioning from an environment where credit availability remains the same or decreases, land price will rise about 1.96% or 1.64% depending on the index used. Therefore, understanding the impacts of credit availability on land values helps agricultural lenders to predict future changes in land prices.

Taking advantages of spatially disaggregated data and geographical application, economists can model determinants of land values with data that matches the economic behavioral decisions better than before (Irwin et al. 2010). Examples include using GIS to collect spatial measures and distance indicators that capture the amenities more precisely (Huang et al. 2006; Ready and Abdalla 2005). Huang et al. (2006) discuss factors driving Illinois farmland values and find that land values decline with parcel size, ruralness, distance to Chicago and several other population centers measured by GIS. They estimate the model using county-level cross-section time-series data. Combining multiple sources of urban influences, Zhang and Nickerson (2015) develop an "urban premium" using parcel-level data from 2001 to 2010 to explain the relationship between urban residential housing market and farmland markets. Instead of analyzing impacts of housing boom and bust on land markets using residential land and structure values, their study focuses on quantifying the residential housing markets' impacts of surrounding farmland values. A parcel-level measure namely, *"urban premium"*, is created by the authors to quantify the magnitude of urban influences on surrounding farmland values. This urban premium declined significantly after 2008 while farmland price remained relatively stable as the increase in commodity demand during the study period obscured the influence of depression of housing market on land values.

The modeling approach favored most by extensive of empirical land studies is the *hedonic price model* (Kennedy et al. 1997; Dillard et al. 2013; Hanson et al. 2018; Tsoodle, Golden, and Featherstone 2006). This method allows analysis of various characteristics of a heterogeneous good as an element of a hedonic function. For instance, Kennedy et al. (1997) conducted a comprehensive analysis of Louisiana rural land markets using a two-stage hedonic pricing method. In their research, they used four groups of independent variables: continuous variables, discrete variables, discrete soil variables and socio-economic variables to estimate the price of rural land.

Detailed explanations of the theoretical foundation of hedonic property value models can be found in Freeman (2014) and Palmquist (2005). However, several empirical issues may arise when using a hedonic model. The geographic extent of the farmland markets is a significant common concern in this area. One assumption of the equilibrium hedonic price that transactions are drawn from a single market might be challenged since the land study usually use farmland price data that has restrictive number of transactions as well as narrowly defined geographic areas (Nickerson and Zhang 2014). The application of hedonic model also suffers from choice of data (Henderson and Gloy 2009) and the construction of dependent variables (Zhang et al. 2012). Potential spatial correlations of unobserved variables and attributes cause biased estimates and thus become a prominent econometric issue in hedonic settings. To solve this problem, recent literatures apply different spatial models (Anselin and Arribas-Bel 2013; Hardie et al. 2001; Zhang and Nickerson 2015).

As a result, this study has at least two contributions to the land valuation work. First, this paper provides a more comprehensive analysis of Texas land markets by examining several factors that have been used in most previous studies in other states. Second, the results offer empirical insights on how land market and housing market interact with each other.

2. Data and Analytical Framework

Texas Real Estate Research Center (REC) at Texas A&M University collects vast amounts of the state's land transactional data provided by a network of corresponding market observers and thus creates an excellent laboratory to study land value determinants. The data contains sales of rural land in Texas including information about price per acre, size of tract per sale, financing condition, total land values, previous land use, etc. This rural land database includes all reported sales not involved in urban-style developments, greater than regional minimum acreages ranging from 45 to 160 acres, and with prices less than $30,000 per acre. This study uses a county-level panel data set for the years 2007, 2012, and 2017 (Table 1). Although specific disaggregated level land parcels would provide a larger and more varied database, we lack data for most of our key variables for such parcels, notably agricultural return data and the value of land in alternative residential use. One hundred and forty-seven counties out of 254 counties in Texas are selected without missing values to construct a balanced panel.

The dependent variable, sale price per acre, is the median price of the county's annual transaction sales data in each of the three periods. Housing price is also obtained from REC's housing activity database that generates listing data from over 50 MLS (Multiple Listing Service) systems in Texas[2]. Returns to agricultural production (proxied by market value of agricultural products and machinery costs) and government payments are obtained from the Census of Agriculture (Data are collected from https://quickstats.nass.usda.gov/.). The three monetary variables are divided by the total land in farms in each respective county such that values are in dollars per acre. Information about median household income comes from American Community Survey (ACS) of U.S. Census Bureau that can be found on Census Bureau's website (available at https://data.census.gov/table?q=DP03&t=Income+(Households,+Families,+Individuals). Following Rajan and Ramcharan (2015), credit availability variables include number of banks representing more competition for depositor funds and greater credit supply and total deposited in banks as proxy for liquidity and lending capacity. Data comes from the FDIC Summary of Deposits (SOD). As used in Huang et al. (2006), rural-urban continuum codes published by USDA Economic Research Service are used (available at https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/) The rural-urban continuum codes distinguish between metropolitan and rural counties by population size of their metro area as well as degree of urbanization and adjacency to a metro area. The value ranges between 0 to 9 and measures the urbaneness/ruralness of a county. The lower the number, the more urban the county. Both 2003's and 2013's codes are applied to the three years period data to capture the possible population movement change of a county. Table 2 gives description and summary statistics for all variables in the regression. The average land price of the three years is

[2] For more discussion of the housing data, readers may also see the information from REC's website: https://www.recenter.tamu.edu/data/housing-activity/.

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\$3,950/acre among 147 counties and housing price is \$118.67 in thousand dollars with a large volatility shown by standard deviation of 65.06. There are a few counties that receive no government payments in at least one of the three periods. Specifically, Titus County did not receive any program payments during 2007, 2012, and 2017. The number of bank branches recorded by FDIC ranges from 1 to 105 and the average total deposits is \$3 million/ square mile while the median is only \$0.45 million/ square mile indicating the data is more towards the lower side so more counties have lower deposits in the 147 counties selected. The mean of rural urban code is 4.56, almost half of nine while the median is six, which indicates a more rural counties classification in the analysis. Standard deviation of agricultural return variables is high indicating the variance of agricultural activity in different counties.

As discussed, researchers have shown that land values are affected by both farm and non-farm factors. Recent empirical studies include additional factors such as recreational activities, urbanization pressures, and financial incentives (Sant'Anna et al. 2021; Mishra and Ortalo-Magné 2011: Devadoss and Manchu 2007). The strategy in this work is to combine variables used in several previous studies based on equation (1) and equation (2) explained in the literature review section and apply it to a hedonic model setting. In a hedonic model, the land value can be approximated by a set of related attributes. As a result, land value is considered as a differentiated product with a combination of agricultural and non-agricultural characteristics, and each characteristic is valued by its implicit price. Since both applied and theoretical econometric work have increasingly recognized the existence of spatial effects (spatial heterogeneity and spatial dependence), this study also demonstrates this problem following Anselin (2010), (2013), Baltagi et al. (2007), Pinkse and Slade (2010). A common challenge in empirical applications is the presence of unobserved local or regional variables that could lead to spatial error correlation. In this county-level study, for example, measurement errors may occur if spatial effects on land prices do not correspond to counties as units of observation. To address the potential spatial correlation problem, this work first incorporates into the hedonic model a spatial error term to control the spatial dependence. Intuitively speaking, a spatial error model addresses the spatial dependence by incorporating a spatial weight matrix in modeling the error term. The hedonic model for this study is as follows,

$$\begin{gathered} P_{l(i,t)} = \beta_0 + \beta_1 P_{h(i,t)} + \beta_2 G_{(i,t)} + \beta_3 Y_{(i,t)} + \beta_4 C_{(i,t)} + \beta_6 D_{(i,t)} \\ + \beta_7 R_{(i,t)} + \beta_8 V_{(i,t)} + \beta_9 M_{(i,t)} + \delta_i + \tau_t + \varepsilon_{l(i,t)} \\ \varepsilon = \rho \boldsymbol{W} \varepsilon + u \text{ , where } i=1,2\ldots,147;\ t=2007,2012,2017 \end{gathered} \tag{3}$$

$P_{l(i,t)}$ is the median price of rural land sales (in thousand dollars per acre), $P_{h(i,t)}$ is the median value of single family housing (in thousands of dollars), G is government payments received per acre excluding conservation payments, Y is median household income (in thousand dollars), C is one of the two credit availability variables, representing number of different bank companies in a county and D is the other one, representing total deposits in banks in the county per \$1 Million/square mile, and R is Rural–urban continuum code based on 2003 and 2013 Census service. $R_{i,2007}$ is from 2003 Census service using the 2003 Rural-urban Continuum Code, while $R_{i,2012}$ and $R_{i,2017}$ is from 2013 Census service using the 2013 Rural-urban Continuum Code. V is the per-acre market value of agricultural products sold, M is the per-acre value of machinery reported in the Census of Agriculture (a measure of non-land capital). The reason to include M along with V is the availability of more capital can increase V by the marginal product of capital. For a given level of V, more capital per acre may be an indicator of larger permanent net returns per acre, and thus add more value to land (Hardie et al., 2001). $\boldsymbol{W}$ is an $n \times n$ spatial weight matrix and since this model is a panel for three years, the matrix is defined as follows,

$$\boldsymbol{W} = \begin{bmatrix} \boldsymbol{W_1} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{W_2} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{W_3} \end{bmatrix} \tag{4}$$

The contiguity matrix for each year, $\boldsymbol{W_t}$, can differ across years in the number of observed counties. $\boldsymbol{W}$ is constructed in a way that the (i, j) element of $\boldsymbol{W_t}$ is 1 if a county is k-nearest-neighbor

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of county i and zero if it is not (k=5 in this paper). The k-nearest neighbor spatial matrix assumes that spatial dependency decreases as distance between two observations increases (Nickerson and Zhang 2015). ρ is a scalar measuring spatial autocorrelation, and u is a spatially uncorrelated error term. The model also controls for county-level fixed effect (δ_i) and year fixed effect (τ_t). Although this weighted matrix error term may correct biased results by better controlling the spatial correlation, it has been challenged by its strong and *a priori* assumptions about the error structure (Gibbons and Overman 2012). An alternative method that has simpler assumptions about the error structure is the spatial fixed effects model (Kuminoff, Parameter and Pope 2010). This model incorporates fixed effects that correspond to the scale of the unobserved variables that leads to spatial correlation, such as census tracts (Anselin 2013). However, it has limitations in that it does not control unobserved spatial correlation that varies within spaces and may cause spurious spatial errors if delineation of spatial groups is not reasonable. As a result, in this study, only the spatial error model is considered to fix any potential misspecification related to space. A fixed effect regression without spatial error correction is also provided for reference purposes. A package called "splm"[3] ,which designed for the estimation and testing of various spatial panel data specifications in R (Millo and Piras 2012), is employed to run the spatial panel regression model.

3. Results and Discussion

Table 3 reports the estimation results of the spatial-error panel regression model in a hedonic setting under fixed effects assumption, controlling for both county and time effects. The significance of the spatial autoregressive coefficient, which is below 1% significant level, confirms the existence of spatial correlation between counties. It confirms the land value dependence among neighboring counties and this dependency is not captured by explanatory variables in the model. It is evident that, when controlled for the spatial error, several variables that were not significant in the unadjusted model become significant (they are rural urban code and agricultural production sold). Therefore, spatial clustering of residuals exists in model, thereby demonstrating the importance of effect of neighboring counties on the land value of a given county. and controlling of this effect does help to improve statistical inference of any determinants for land values in this study. The benefit could also be improvements of efficiency according to previous studies (Benirschka and Binkley 1994; Hardie et al. 2001; Zhang and Nickerson 2015).

The unit of measurement for rural land price is thousand dollars per acre and the single-family housing price is also in thousands of dollars. Thus, the coefficient of 0.00329 for house value indicates that a $1000 increase in housing price generates $3.29 / per acre increase in price of rural land value with other things are equal. This housing market effect is expected but minor since the land sales in the REC database are the more rural sales rather than urban sales. In other words, urban influence of transition to urban usage is smaller in rural land market than that in urban rural fringe. The coefficient of 0.7317 means a $1,000 increase in median household income is associated with a $73.17 /per acre increase in land value. The indicated greater purchasing power support land prices. The unit of total deposits is $1 million /square mile and each additional $1 million increase in deposits implies $67.61 per acre increase in land price. This suggests that increases in credit availability positively but minimally impact land values. A possible explanation could be that when banks have high availability of funds, they will grant more loans to land participants and increase the supply of credit. As a result, this increase of liquidity can put upward pressure on land prices. The Rural–urban continuum code, which also represents one of neighborhood characteristics, has a negative effect on rural land values. The interpretation behind this is straightforward. The larger the code is, the more rural the county. The further away from metropolitan cities (based on population classification), the less the demand for commercial land. The coefficient of per-acre market value of agricultural products is significant. It means that $1.2 land price increase for a $1 increase in output value per acre. This result also helps to explain that agricultural factors do contribute to the land values of Texas

[3] Details of the package can be found in https://cran.r-project.org/web/packages/splm/splm.pdf

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rural land market. However, due to limitation of data, this study does not provide estimates on any recreational impact.

Table 1. Definition and source for Variables.

Variable	Description	Source
Land value	Sale price per acre (in thousand dollars per acre)	REC
House value	Closing price per acre (in thousand-dollar units)	REC
Government payments	Total government payments received per acre less any conservation payments ($/acre)	Agricultural Census
Household Income	median household income (in thousand dollars)	U.S. Census Bureau
Bank	Number of different bank companies in a county	FDIC
Deposits	Total deposits in banks in the county $1 million/sq. mile	FDIC
Rural Urban Code	Rural–urban continuum code, measure of ruralness, value between 1 and 9	USDA survey
Agriculture production value	Market value of farm production sold ($/acre)	Agricultural Census
Machinery Costs	Farmer-owned farm machinery ($/acre)	Agricultural Census

Note: REC represents Texas Real Estate Research Center. FDIC: represents Federal Deposit Insurance Corporation. USDA represents U.S. Department of Agriculture.

Table 2. Summary of descriptive statistics.

Variable	*Mean*	*Standard Deviation*	*Min*	*Max*	*Count*
Land value	3.95	3.34	0.38	17.93	441
House value	118.67	65.06	12.21	480.00	441
Government payments	5.60	6.11	0.00	30.52	441
Household Income	45.55	11.21	25.80	95.39	441
Bank	9.79	12.63	1.00	105.00	441
Deposits	3.00	14.39	0.02	203.36	441
Rural Urban Code	4.56	2.45	1.00	9.00	441
Agriculture production value	235.84	342.31	3.99	2401.08	441
Machinery Costs	211.19	124.14	19.07	660.64	441

Sources: Author's calculations.

Table 3. Regression results.

	Non spatial fixed effect model		Spatial error model-Fixed Effect	
	Coef.	p-values	Coef.	p-values
House value	0.0064***	-0.0007	0.0033**	-0.0148
Government payments	0.007	-0.708	0.0018	-0.9044
Household Income	0.0861***	-0.0007	0.0732***	-0.0001
Bank	0.0715	-0.2539	-0.0066	-0.8832
Deposits	0.0610***	-9.10E-10	0.0676***	(< 2.2e-16)
Rural Urban Code	-0.0300	-0.7914	-0.1547*	-0.06
Agriculture production value	0.0008	-0.2465	0.0012**	-0.018
Machinery Costs	0.0052**	-0.0127	-0.0003	-0.837
Spatial autoregressive coefficient			0.545	(< 2.2e-16)
Intercept			0.5582	-0.5904
Archer	-4.0541	n/a	-2.488597	0.0239
Armstrong	-4.6658	n/a	-3.450238	0.0008
Austin	2.0364	n/a	5.365789	0.0000

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Bailey	-4.3562	n/a	-2.428578	0.0207
Bandera	1.3369	n/a	3.342726	0.0007
Bastrop	-1.4431	n/a	1.586453	0.1658
Baylor	-2.3140	n/a	-0.887239	0.3522
Bee	-1.6648	n/a	0.212874	0.8216
Bell	-3.2649	n/a	0.687003	0.6008
Bexar	-6.3924	n/a	-1.135128	0.5865
Blanco	4.2786	n/a	7.045488	0.0000
Bosque	-0.7489	n/a	1.433082	0.1811
Bowie	-5.0041	n/a	-1.45562	0.2135
Brazoria	-4.7144	n/a	0.15714	0.9303
Brazos	1.7567	n/a	5.541541	0.0000
Briscoe	-3.1059	n/a	-1.339639	0.2349
Brown	-2.7272	n/a	-0.42024	0.6793
Burleson	-1.5833	n/a	0.93682	0.3380
Burnet	-0.5679	n/a	2.903337	0.0300
Caldwell	-0.7256	n/a	1.711359	0.0785
Callahan	-2.9217	n/a	-1.416202	0.1195
Camp	-5.7831	n/a	-2.572458	0.0609
Carson	-5.3585	n/a	-3.441236	0.0016
Cass	-4.1317	n/a	-0.877563	0.4257
Castro	-5.7730	n/a	-3.515218	0.0135
Chambers	-4.2679	n/a	-1.480846	0.2738
Childress	-2.6534	n/a	-1.011027	0.3160
Clay	-3.5265	n/a	-1.998173	0.0558

	Non spatial fixed effect model		Spatial error model-Fixed Effect	
	Coef.	p-values	Coef.	p-values
Cochran	-3.7740	n/a	-1.689635	0.1269
Coke	-2.5774	n/a	-0.968626	0.3682
Coleman	-1.9826	n/a	-0.427835	0.6396
Collin	-7.9807	n/a	0.123779	0.9676
Colorado	1.8082	n/a	4.870109	0.0000
Comanche	-2.6025	n/a	-0.079205	0.9413
Cooke	-0.1702	n/a	3.169108	0.0095
Coryell	-3.0468	n/a	-0.742034	0.4689
Crosby	-3.8128	n/a	-2.269079	0.0055
Dallas	-17.8742	n/a	-7.171087	0.1313
Deaf Smith	-5.2040	n/a	-3.448212	0.0056
Delta	-3.7804	n/a	-1.567235	0.0773
Denton	-3.7724	n/a	2.672716	0.2266
Dickens	-2.5649	n/a	-1.084369	0.2869
Dimmit	-1.0721	n/a	0.20524	0.8176
Donley	-2.8512	n/a	-1.267883	0.2377
Duval	-1.8591	n/a	-0.258679	0.7889
Eastland	-2.3778	n/a	-0.359045	0.7127
Ellis	-4.1332	n/a	-0.102642	0.9409
Erath	-2.2994	n/a	0.943524	0.4013
Fannin	-2.9744	n/a	0.039628	0.9713
Fayette	-0.1821	n/a	3.468099	0.0045
Floyd	-4.1212	n/a	-2.195321	0.0237
Fort Bend	-5.6690	n/a	0.524433	0.8257
Franklin	-3.7239	n/a	-0.472904	0.6999
Garza	-3.3287	n/a	-1.897814	0.0599

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Gillespie	2.2646	n/a	5.841454	0.0000
Goliad	-2.0868	n/a	-0.071549	0.9424
Gonzales	-1.8186	n/a	0.539311	0.6176
Gray	-4.5755	n/a	-2.709749	0.0137
Grayson	-1.8653	n/a	2.110187	0.0880
Grimes	0.4425	n/a	3.564902	0.0011
Guadalupe	-2.6097	n/a	1.256382	0.3556
Hale	-5.6352	n/a	-2.782209	0.0091
Hamilton	-2.0567	n/a	0.0571	0.9550
Haskell	-3.0949	n/a	-1.21531	0.1836
Hays	4.2464	n/a	7.762506	0.0000
	Non spatial fixed effect model		Spatial error model-Fixed Effect	
	Coef.	p-values	Coef.	p-values
Henderson	-3.4028	n/a	-0.039825	0.9694
Hidalgo	-1.6046	n/a	2.043984	0.0947
Hill	-3.1474	n/a	0.105125	0.9243
Hockley	-5.2607	n/a	-2.165697	0.0589
Hood	0.4584	n/a	4.040787	0.0013
Hopkins	-4.3039	n/a	-0.957718	0.3938
Houston	-2.0917	n/a	0.751064	0.4775
Howard	-4.5172	n/a	-2.577508	0.0107
Hunt	-4.5674	n/a	-0.974692	0.3811
Hutchinson	-3.6524	n/a	-1.959697	0.0863
Jack	-2.2641	n/a	-0.377159	0.7267
Jackson	-3.3051	n/a	-0.476338	0.6764
Jefferson	-1.2121	n/a	1.442985	0.1862
Jim Hogg	-1.7082	n/a	-0.422515	0.6465
Jim Wells	-3.1981	n/a	-0.878005	0.3659
Johnson	-2.1106	n/a	2.212196	0.1152
Jones	-3.9225	n/a	-2.122065	0.0174
Karnes	-2.0130	n/a	0.349452	0.7273
Kaufman	-4.6533	n/a	-1.100827	0.3881
Kendall	1.7473	n/a	4.724269	0.0014
Kerr	0.3346	n/a	2.76622	0.0105
Kleberg	-1.9407	n/a	-0.339657	0.7171
Knox	-2.8269	n/a	-1.02778	0.3413
Lamar	-3.9069	n/a	-0.983535	0.3338
Lamb	-5.2771	n/a	-2.283535	0.0417
Lampasas	-1.6115	n/a	0.352438	0.7291
Lavaca	-0.9093	n/a	2.138185	0.0527
Lee	-1.7445	n/a	1.413602	0.2286
Liberty	-3.0153	n/a	0.19328	0.8575
Limestone	-2.8894	n/a	-0.534411	0.5947
Live Oak	-2.5134	n/a	-0.345685	0.7525
Lubbock	-6.4678	n/a	-2.051125	0.1597
Lynn	-4.4528	n/a	-2.038148	0.0298
Madison	-1.6172	n/a	1.10638	0.2750
Martin	-5.4554	n/a	-3.112122	0.0042
Matagorda	-2.8984	n/a	-0.37229	0.7101
Medina	-2.0459	n/a	0.246889	0.8152

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	Non spatial fixed effect model		Spatial error model-Fixed Effect	
	Coef.	p-values	Coef.	p-values
Menard	-0.8477	n/a	0.564402	0.5850
Milam	-2.2584	n/a	0.516819	0.6204
Mills	-1.4009	n/a	0.706331	0.5377
Mitchell	-3.0499	n/a	-1.426597	0.1590
Montague	-1.9954	n/a	0.547972	0.6166
Montgomery	-0.8260	n/a	5.509213	0.0044
Moore	-4.7759	n/a	-2.64561	0.0338
Navarro	-3.7831	n/a	-0.737925	0.4804
Nolan	-3.2334	n/a	-1.573994	0.0988
Nueces	-4.7959	n/a	-1.413164	0.2549
Palo Pinto	-0.6970	n/a	1.722936	0.1103
Parker	-2.4673	n/a	2.200367	0.1431
Parmer	-6.2041	n/a	-3.979936	0.0061
Potter	-3.4126	n/a	-1.571378	0.1273
Randall	-7.1416	n/a	-4.750644	0.0004
Real	-0.7949	n/a	1.185095	0.2763
Red River	-2.8178	n/a	-0.593166	0.5307
Runnels	-3.4210	n/a	-1.303756	0.1910
San Patricio	-4.7504	n/a	-1.596878	0.1406
San Saba	-0.8916	n/a	0.845631	0.4107
Scurry	-4.7878	n/a	-2.50153	0.0331
Shackelford	-3.6662	n/a	-1.835356	0.1384
Sherman	-5.2041	n/a	-2.815481	0.0332
Stephens	-2.5147	n/a	-0.697664	0.5088
Swisher	-4.8542	n/a	-2.961484	0.0071
Tarrant	-2.0981	n/a	5.399491	0.0769
Taylor	-4.2281	n/a	-1.464843	0.2059
Terry	-4.6461	n/a	-1.961857	0.0497
Titus	-2.7364	n/a	0.44624	0.7056
Tom Green	-4.0483	n/a	-1.49149	0.2016
Travis	-1.4527	n/a	4.757941	0.0497
Tyler	-4.0730	n/a	-0.059341	0.9588
Uvalde	-1.5904	n/a	0.435221	0.6617
Van Zandt	-3.6317	n/a	0.536019	0.6640
Victoria	-3.8137	n/a	-0.942199	0.4025
Waller	4.0502	n/a	7.56676	0.0000
Washington	3.5587	n/a	7.871225	0.0000
	Non spatial fixed effect model		Spatial error model-Fixed Effect	
	Coef.	p-values	Coef.	p-values
Webb	-2.7186	n/a	-1.065757	0.2685
Wharton	-3.3843	n/a	0.181878	0.8729
Wichita	-5.0403	n/a	-2.409377	0.0331
Williamson	-4.1360	n/a	1.103085	0.5833
Wilson	-3.1648	n/a	0.010971	0.9928
Wise	-2.2079	n/a	1.271424	0.2841
Yoakum	-5.2299	n/a	-2.686111	0.0310
Young	-3.1631	n/a	-1.013679	0.3516
2007	-4.0541		-0.2884	0.7682
2012	-4.2956		-0.3545	0.7303
2017	-3.6974		0.6429	0.5626
Number of observations (141*3)			441	
Number of counties			147	

Note: *p< 0.1.**p< 0.05.***p< 0.01.

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4. Conclusions, Implications, and Future Research

As an important source of value on landowners' balance sheet as well as index of farm health, the future of land real estate receives constant attention from different land participants and policymakers. The rapid increase in Texas rural land price from 2000 to 2020 has raised questions and concerns about the causes and sustainability of current land values. While studies on land value determinants exist across United States with various data frames and econometric methodologies, research specifically in Texas is rare. This analysis focuses on obtaining a better understanding of determinants (either agricultural or non-agricultural factors) of rural land market values in Texas. Aggregated county-level panel data are used for estimating possible factors. Similar findings could be expected in other large states with similar complex of geographic, population densities and usage of lands.

Using a spatial-error panel regression hedonic modeling approach, this study finds non-agricultural factors that contribute to rural land values in Texas. Among those, single family housing price, which can represent the capital gains in area capturing more non-farm pressure, has a significant positive effect on land values. One possible implication is that housing price increases often reflect expectations of future economic growth and development in an area. If an area is expected to experience population growth, job opportunities, or infrastructure improvements, it creates a positive outlook for the housing market. Buyers and investors anticipate these growth prospects and are willing to pay higher prices for land, anticipating future appreciation. These expectations of future growth contribute to the increase in land values. The estimation result of housing price indicates that a $1,000 increase in housing price generates $3.29 / per acre increase in price of rural land value while other things are equal. This housing market effect is expected but minor since the land sales in the REC database are the more rural sales rather than urban sales. The study also finds the coefficient of median household income is 0.7317, which means a $1,000 increase in median household income is associated with a $73.17 /per acre increase in land value. This is consistent with Gilliland (2005), whose findings indicate the growing association between personal income and land prices. Moreover, credit availability measured by total deposits also has a positive effect on land values which is consistent with previous literature (Sant'Anna et al. 2021). Lenders can assess and mitigate loan risks and better manage their investment portfolios if they are aware of these positive impacts and thus the future change in land values. Government programs aimed at increasing credit availability for land acquisition may inadvertently push up land values and result in an even harder acquisition environment. The rural urban code variable shows the urban pressure still exists on Texas rural land markets. The model specification, spatial-error model has slightly different results from the classic fixed effect model, suggesting that the unobserved spatial related characteristics have been well controlled by the approach. Agricultural returns are shown to be important as well since the coefficient of agriculture production sold is significant. In all, this study finds several non-agricultural factors that drive Texas rural land values. This conclusion has also been discussed more in recent land value studies. The return from agriculture also plays a critical role as the bottom line of support most rural land values. Therefore, a characteristic profile of determinants of land values of Texas rural land markets includes housing values, credit availability, ruralness/urbaneness, household income according to the empirical analysis results and variable related to agriculture return.

There are a few improvements that can be made to the study. Recreation demands on land have a positive effect on rural to land values (Pope1985; Wasson et al. 2013) but was not included in the model. Further analysis may include fish or hunting license report data issued at county level to measure the effect. A full analysis should incorporate the value of land in alternative commercial uses other than just residential housing (for example, retail business). The insignificance of the government programs in the model also raises the question about how and what magnitude such policies can be captured by land values. As discussed by Goodwin et.al (2003), the standard model assumption of long-term expected return fails to capture the policy benefits annually since the observation values are not necessarily the valid expectations. Moreover, this study cannot fully account for all credit lenders as only the FDIC data are available for this study. If more data (for

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example, the Ag Credit Survey conducted by Federal Reserve Bank (Sant'Anna et al. 2021)) are provided in the future, the results would be more informative. Nonetheless, with the development of more spatially rich data, a future study would have more possibilities in identifying determinants of land values at parcel-level as well.

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