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The Effects of Tornadoes on Housing Prices in Moore, Oklahoma*

Whoi Cho[a], Brian E. Whitacre[a], and Claudia A. Rhoades[a]

[a]*Department of Agricultural Economics, Oklahoma State University, USA*

Abstract: This paper examines the effects of four significant tornadoes on housing prices in Moore, Oklahoma. We use a hedonic difference-in-difference approach by considering transactions made preceding and following major tornadic events in Moore (occurring in 1999, 2003, 2010, and 2013). Our dataset spans nearly 30,000 housing transactions between 1990 and 2020. The length of tornado impacts is evaluated using a set of time indicators for the years leading up to (and after) the tornadoes. We find a 2-5% decrease in housing prices during the first year after a tornado for houses in the destructive path. However, no such impacts exist in years 2-7. We also employ three different specifications (OLS, spatial lag, and spatial error) to find the most appropriate model for considering the potential spatial processes at work. The results are largely similar across specifications.

Keywords: tornado, natural disaster, housing price
JEL Codes: R23, R30, R32

1. INTRODUCTION

Every year, tornadoes cause tremendous damage to property and loss of life in the United States. Oklahoma is one of the states struck more frequently by tornadoes, as it is located in "Tornado Alley", an area where tornadoes are disproportionately frequent (National Oceanic and Atmospheric Administration National Weather Service, National Centers for Environmental Information, 2020b). In particular, the city of Moore, Oklahoma has experienced several damaging tornadoes in the recent past, with the most destructive one taking place in 2013[1]. According to Romanic et al. (2016) who constructed a model for tornado loss

*Acknowledgements. Whoi Cho and Claudia A. Rhoades are graduate students in the Department of Agricultural Economics at Oklahoma State University, Stillwater, OK. Brian Whitacre is a professor and the Jean & Pasty Neustadt Chair in the Department of Agricultural Economics at Oklahoma State University, Stillwater, OK. *Corresponding Author:* Whoi Cho E-mail: whoi@okstate.edu

[1]The 2013 Moore tornado was recorded to be a 5 on the 6-level Enhanced Fujita scale (EF5), which is an indicator of the significant damage caused (National Oceanic and Atmospheric Administration National Weather Service, 2020). The tornado killed 24 people and injured 207, with an estimated property damage of $2 billion. More than 300 homes were damaged by the EF5 tornado (National Oceanic and Atmospheric Administration National Weather Service, National Centers for Environmental Information, 2020a).

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assessment based on historical tornado footprints in Oklahoma, a tornado as destructive as the 2013 tornado in Moore could take place in the state of Oklahoma every 10-12.5 years. Tornadoes not only cause immediate physical damage to the cities they strike, they may also instill a sense of fear in the residents (or prospective residents) of the area. The fear that tornadoes could strike again lingers in the collective memory, potentially influencing residents' future housing decisions and sometimes prompting them to move in order to find a "safer" place to live. The physical damage caused by tornadoes and the sense of insecurity that prompts people to leave the affected areas can result in home buyers and sellers decreasing the value of homes in the affected areas, reflected by lower house prices.

Regardless of the sense of insecurity caused by a natural disaster such as a tornado, making the decision to move to a different city or state is not always an immediately viable option. Housing accounts for a large portion of household finances (Simmons and Sutter, 2007), and moving to a different city or state involves high opportunity costs – including those associated with work and family/friends (Graif, 2016). Moving to a different city or state often entails giving up a job and finding a new job closer to the updated residence. Even moving to a different location within the same city could prove difficult, with housing prices in neighborhoods considered "safer" rising due to a shortage of housing supply in the city as a whole (Malagarie, 2019). Because of the difficulties associated with moving to a different neighborhood, city, or even state imply, many people end up staying in their original properties regardless of the sense of fear instilled by a tornado. Therefore, the housing prices in the affected areas could remain relatively stable in the aftermath of a tornado, even when there was an immediate impact on the resident's sense of security.

The existing literature offers little empirical evidence on the effects of tornadoes on housing prices. The limited studies on this general topic focus on the impact of historical tornadoes on future housing development locations (Hall and Ashley, 2008) or impacts at the city level (Donadelli et al., 2020). Hall and Ashley (2008) used panel data to show that new urban areas in Northeastern Illinois avoided past tornado tracks as they developed, even though urban sprawl continued to increase the median value of homes in areas affected by tornadoes. Donadelli et al. (2020) also used panel data and found negative effects of tornadoes on city-level housing prices using United States housing price index data and tornado records from five different regions. The frequency of historical tornadoes was counted and incorporated into Ordinary Least Squares (OLS) models as dummy variables (Donadelli et al., 2020). Notably, neither of these papers incorporates a hedonic approach that can capture the impact of specific housing characteristics. There is also research estimating property losses from tornadoes. In particular, Elsner et al. (2018) combine data on 3,233 tornado reports across Florida from 1950 through 2015 with property assessments at the time of the event, but do not consider future housing sales as part of their analysis.

Alternatively, there is a fair amount of literature on the effects of other natural disasters such as floods, storms, wildfires, rising sea levels, hurricanes and earthquakes on housing prices. Most of these studies found that natural disasters have discounting effects on housing prices (Murdoch et al., 1993; Pompe and Rinehart, 1995; Mueller et al., 2009; Beltrán et al., 2018; Beck and Lin, 2020; Graff Zivin et al., 2020). Hedonic models are also more common in this field; these models control for the impacts of housing characteristics such as square footage and the number of bathrooms on the price. For example, several studies used OLS models with dummy variables that accounted for the potential impact of wildfires (Mueller et al., 2009), floods (Beltrán et al., 2018), sea level rise (Beck and Lin, 2020), and hurricanes (Graff Zivin et al., 2020) on local housing values. Notably, Graff Zivin et al. (2020) – whose methodology we follow in this paper – finds a *positive* impact on housing prices for houses sold in locations impacted by Florida hurricanes in the following 1-3 years. They argue that this positive relationship is due to the cost of reconstructing houses in desirable areas, and is the result of a negative supply shock. However, they also find a significant decrease in the number of housing transactions made in the affected areas in the year following a hurricane event.

An interesting component of this analysis is the mechanism by which historical tornado paths could influence housing prices. If there were evidence of path dependency for tornadoes – that is, if future tornadoes were more likely to occur in the same paths as prior events – then confirmation of a price decline in those locations would demonstrate a rational response. In this case, the potential risk would be incorporated into the sales price; buyers of such properties receive a discount due to their willingness to accept a higher probability of future tornado damage. Alternatively, if there is no evidence that tornadoes are likely to follow the same historical path, then pricing in risk into houses on those paths is irrational. In this case, even though tornadoes are equally likely to hit other parts of the city, the fear of history repeating itself influences the housing market equilibrium.

The science regarding tornado path dependency is relatively straightforward. While some regions (and even specific cities) are more likely to see tornadoes than others, there is no evidence to suggest tornadoes will follow the direct paths of their predecessors (Brooks et al., 2003; Strader et al., 2017; Pillion, 2021).[2] Thus, any pricing impact uncovered in this analysis – which considers only a single city identified as having a high likelihood of events – represents an intriguing form of irrationality where house buyers and sellers settle on a price influenced by expectations that are not grounded in reality.

The aim of this paper is to examine the effects of four significant tornadoes on housing prices in Moore, Oklahoma. We use a difference-in-difference approach by considering transactions made preceding and following major tornadic events in Moore. Our data includes nearly 30,000 housing sales from 1990 – 2020, and studies the impacts of tornadoes occurring in 1999, 2003, 2010, and 2013. Our econometric specification isolates transactions along the destructive paths of the four major tornadoes under evaluation. A set of time indicator variables for the years leading up to (and after) the tornadoes allows us to document the length of impact in these locations. Our focus on a single city is unique in the existing literature, and our examination adds to the small body of evidence on this topic. In particular, because tornadoes typically affect only relatively small swaths of land (as opposed to other natural disasters like hurricanes or earthquakes), our intra-city focus can document the degree to which proximity to a historical tornado path matters for future housing purchases in locations prone to such events.

When measuring the effects of natural disasters on housing values, it may be important to account for spatial autocorrelation. A significant amount of the previous literature on this

[2]Pillion (2021) cites leading researcher Harold Brooks: "The evidence mostly points to random chance as to why some communities are leveled and some are spared."

subject has failed to do so, and has used OLS models that are ineffective in forming unbiased and efficient estimates when spatial patterns are present (Loftin and Ward, 1983; Anselin, 2010). Dubin (1992), for instance, found that housing prices were frequently impacted by neighborhood or other extrinsic characteristics of the properties, such as accessibility from urban areas. Underlying spatial patterns need to be tested and accounted for. Two simple spatial models can successfully account for spatial autocorrelation or heterogeneity: the spatial lag model and the spatial error model (Can, 1992; Anselin, 2010).

The spatial lag model has been frequently used when analyzing the effects of natural disasters on housing prices. This model assumes that the dependent variable, in this case, housing prices, is not only affected by the specific characteristics of the home itself, but also by the value of *neighboring* house prices (LeSage and Pace, 2009). In essence, the spatial lag model allows for the estimation of spillover effects, as it assumes that the spatially weighted average of housing prices in a neighborhood affects the price of each house directly (Kim et al., 2003). For instance, the spatial lag model has been used to analyze how housing prices are affected by receiving a flood risk designation (Posey and Rogers, 2010), to demonstrate a negative impact of perceived flood risk on local housing prices (O'Neill et al., 2016), and to explore whether there is a "broadband premium" in the rural housing market (Conley and Whitacre, 2020).

The spatial error model, on the other hand, assumes the spatial effects are included in the error term of the specification. This means that instead of directly affecting the dependent variable, the spatial process at work influences shocks to unobserved terms (the errors). Even though this model does not explicitly account for spillover effects, it is useful when analyzing variables that likely have spatial patterns, but whose spatial effects are difficult to quantify or measure (Anselin, 2003). There is no previous literature that we are aware of that uses spatial error models to analyze the impact of tornadoes on housing prices. In a broader scope, several studies use spatial error models in a hedonic house pricing context. Bin et al. (2011) used a spatial error model to consider spatial heterogeneity while measuring the impact of sea-level rise on housings in coastal regions. Baltagi and Bresson (2011) also used spatial error models to handle (and test) the spatial effects and potential heterogeneity for housing prices in Paris. Thus, the hedonic house pricing literature has incorporated OLS, spatial lag, and spatial error specifications. This paper uses the Lagrange multiplier test to find the most appropriate model to estimate the underlying spatial effects at work (Anselin, 1988), while also considering the theoretical rationale for why a particular specification might be preferred.

2. DATA

This study uses 31 years (1990-2020) of housing transaction data provided by the county assessor's office from Cleveland County, Oklahoma. Cleveland County has a median household income of $62,863, which is higher than the median household income of $54,449 for the state of Oklahoma (United States Census Bureau, 2020). The city of Moore was chosen as the subject of this study because of its history with significant tornadoes, and because it is one of the representative cities in Cleveland county. Moore has a similar median household income to Cleveland county ($64,810) and accounts for about 22 percent of the county's

Table 1: Summary Statistics of Four Tornadoes over Fujita Scale 4 in Moore, OK.

Year	Classification	Length (miles)	Width (miles)	Killed	Injured	# Impacted Future House Sales
1999	EF5	38	1.0	36	583	5,412
2003	EF4	17	0.4	0	134	1,641
2010	EF4	24	1.1	2	49	4,290
2013	EF4	14	1.1	24	212	3,235

Source: Storm Prediction Center, National Oceanic and Atmospheric Administration (NOAA).

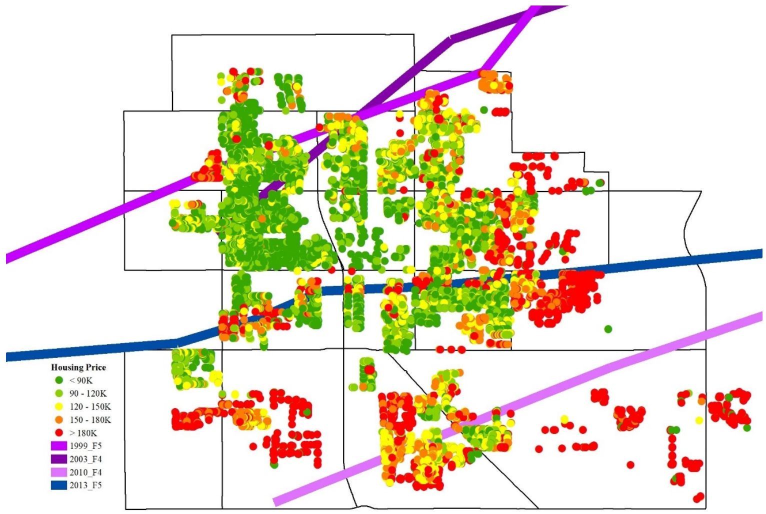
population (United States Census Bureau, 2020). There were 28,969 home sales transactions made during 1990 - 2020. We include all of these transactions as part of our OLS specification. However, constructing spatial weight matrices does not allow using multiple points with the same location, so we follow the approach used in Hoen et al. (2015) and keep only the most recent transacted record. This resulted in 15,066 housing sales transactions for the spatial models (including tests of whether OLS by itself is appropriate). Our datasets contain the sales price of the house, the date of sale, and the associated physical characteristics of the property. These characteristics include the house area in square feet, the number of bedrooms and bathrooms, the year the house was built, the square footage associated with any existing garage, and the location of the house in latitude and longitude. The age of the house was calculated by subtracting the sales transacted year from the year it was built.

Historical tornado records were collected from the National Oceanic and Atmospheric Administration National Weather Service (NOAA). Tornadoes have hit Moore nine times since 1998, and four of them have been Fujita scale 4 (or Enhanced Fujita scale 4) or over. The Fujita (or Enhanced Fujita) scale consists of six categories, ranging from zero to six, with categories four or above considered devastating or incredibly damaging (National Oceanic and Atmospheric Administration National Weather Service, 2020). We focus only on the four out of the nine tornado events in Moore since 1998 that were evaluated as four or above on the Fujita scale. This was done because the main objective of this paper is to assess the impacts of historical tornadoes that have caused significant property damage – and have likely lived on in residents' memories. The four tornadoes in Moore, Oklahoma included in the study took place in 1999, 2003, 2010, and 2013. Figure 1 demonstrates the paths of these four tornadoes, and shows the distribution of the values of housing sales transactions in Moore, OK during the 1990 – 2020 period. Table 1 provides details on the lengths, widths, and number of people killed/injured due to these events.

Distances were calculated from each house to the closest point of each tornado's path.[3] Following Graff Zivin et al. (2020), we use this distance to construct a dummy variable for whether a house was considered to be in the destructive path of the tornado. The length and width of each tornado varied (Table 1), with several being over 1 mile wide. Houses within 1.25 times the documented width of each tornado are considered as inside the

[3]As shown in Figure 1, the tracks of tornadoes are somewhat random across the town. However, the tracks of older tornadoes (1999 and 2003) passed the northwest side of Moore, Oklahoma. Unlike these two previous tornadoes, the 2010 tornado passed through the southeast side, and the 2013 tornado moved through the middle of the city.

Figure 1: Distribution of Housing Values in Moore, OK and Historical Tornadoes Track That Had Over Four (4) Fujita Scale in 1999, 2003, 2010, and 2013.



destructive path. The number of houses impacted by each event is shown in Table 1. As the methodology section below details, we use the date and location of each transaction to construct a difference-in-difference framework that allows for comparisons of sales before and after a tornado occurs. The approach also allows us to estimate the length of the potential impacts on housing prices by considering the amount of time elapsed since the last tornadic event.

3. METHODS

3.1. Hedonic Pricing Model

According to Rosen (1974), hedonic prices are determined based on the various associated characteristics of a product. The literature on housing prices frequently uses hedonic models to estimate prices as a function of housing attributes or characteristics such as square feet, the number of rooms, building age, etc.(Can, 1992; Sirmans et al., 2005; Ottensmann et al., 2008). The literature on the effects of natural disasters on housing prices builds on these models to estimate how such disasters might affect sales prices, after controlling for the characteristics of the house (Murdoch et al., 1993; Mueller et al., 2009; Beltrán et al., 2018). These studies have used different ways to quantify the effects of natural disasters on housing prices. Most of them have used the distance from the hazardous area and the frequency of damage as hedonic variables affecting housing prices (Posey and Rogers, 2010; O'Neill et al., 2016; Donadelli et al., 2020).

We build on these efforts to develop a hedonic price model estimating the effects of historical tornadoes on housing prices in Moore. Our specifications control for the physical characteristics of the house, allow for year-over-year price shifts (year fixed effects), and ultimately estimate the impacts of being located in the path of a prior damaging tornado. We begin by running our hedonic housing price model using ordinary least squares (OLS), ignoring any potential spatial effects as much of the prior literature has done. We then assess the Moran's I statistic on the residuals and consider an alternative spatial error model to address these issues as a robustness check.

As noted above, the present study focuses on four tornado events, which took place in 1999, 2003, 2010 and 2013. It is important to note that although tornado paths are random, unlike many other natural disasters, there have often been times when tornado paths have overlapped and moved in the same direction (Donadelli et al., 2020). Therefore, instead of using four different distances from the tornado path, we use an indicator variable before and after the tornado for houses located within 1.25 times the width of each tornado path. We follow Graff Zivin et al. (2020) and estimate the OLS model as:

$$lnP_{itq} = \sum_{k} \alpha_k X_{kitq} + \sum_{\tau=-9}^{7} \beta_\tau Tor_{itq}^{\tau} + \gamma_t + \delta_q + \varepsilon_{itq} \tag{1}$$

where lnP_{itq} is a logarithm of the housing price for location i in year t and the quarter of the year q. X_{kitq} are the housing characteristics k such as the number of bathrooms, house and garage size, and age of house i;[4] Tor_{itq}^{τ} is a set of indicators documenting the time dimension of the transaction in relation to a tornadic event (for example, Tor_{itq}^{τ}= 1 if the transaction takes place within a tornado path. $\tau = 0$ indicates the sales transaction in the first twelve months after a tornado, $\tau = 1$ the next twelve months, and so on; a negative τ indicates a transaction made *before* the tornado); γ_t are fixed year effects. $\delta_q$are quarter-of-year fixed effects capturing seasonality in the housing market. And ε_{itq} is error term which is assumed to be independent and identically distributed (i.i.d.): $\varepsilon_{itq} \sim N(0, \sigma^2)$. Our indicator variables run from 9 years prior to a tornado to 7 years after[5], allowing for the set of β_τ estimates to document the impact on housing prices both before (where we expect no impact) and after an event (where one may exist). Houses that were never in the path of a destructive tornado have 0's for all Tor_{itq}^{τ} measures. As a simple robustness check, we also estimate a standard difference-in-difference model where all of the year indicators Tor_{itq}^{τ} are replaced by a single dummy variable taking value 1 if the sale took place up to three years following a tornado (event years 0-2).

The Moran's I statistic (Cliff and Ord, 1981) of the residuals from these OLS models are also obtained in order to measure the presence of spatial dependence in the residuals.[6] This type of Moran's I test is typically used to explore whether or not using a spatial model is appropriate. If the Moran's I statistic suggests that the residuals of the OLS model exhibit spatial dependence, the conclusion is that the OLS model is not the appropriate model to use. Lagrangian Multipliers (LM) associated with the residuals can suggest alternative

[4]Some hedonic housing models include variables such as income levels or racial characteristics of the neighborhood. These are not available annually for the full 30-year period under analysis here.

[5]We choose these years because they allow for all observations to be included (i.e., housing transactions in 1990 are 9 years prior to the first 1999 tornado and transactions in 2020 are 7 years after the last 2013 tornado).

[6]Recall, however, this test can only be run on a subset using the most recent transactions (i.e., removing earlier sales of the same house). This significantly reduces our sample size.

spatial models that could potentially capture the spatial patterns present (Anselin, 1988; Anselin et al., 1996).

We use two simple spatial models as alternatives to the OLS specification: spatial lag and spatial error models. The spatial lag model acknowledges that the dependent variable (housing price) in one location may be impacted by neighboring values, and it explicitly models this relationship. The spatial lag model, therefore, assumes that endogenous feedback effects between neighbors are present, and the spatial parameter represents the magnitude and direction of that feedback. On the other hand, the spatial error model estimates the effects of spatial processes in the error term. The resulting spatial parameter value is not as easy to interpret compared to the spatial lag model. However, the spatial error model has the advantage of accounting for potential missing variables that could be difficult to quantify.

We use both spatial models in our analysis since we believe that the appropriate way to capture the spatial processes at work is an open question. On the one hand, tornadoes can be damaging and destructive, directly affecting housing prices in the affected areas. These lowered prices could then directly affect their neighbors in a spatial lag model. On the other hand, tornadoes can indirectly affect housing prices by increasing the perceived risk of the residents of the affected areas (i.e., spatial heterogeneity may exist). This may prompt the value of the properties in such areas to decrease over time, and a spatial error model could be more appropriate to capture this indirect effect.

Both spatial models include an inverse distance weight matrix with a 2 km threshold (i.e., all households outside of the threshold receive zero weight). We estimate spatial lag and error models as extensions of the main specification in (1). The spatial lag model is:

$$lnP_{itq} = \rho \mathbf{W} lnP_{itq} + \sum_{k} \alpha_k X_{kitq} + \sum_{\tau=-9}^{7} \beta_\tau Tor_{itq}^{\tau} + \gamma_t + \delta_q + \varepsilon_{itq} \tag{2}$$

and the spatial error model is:

$$lnP_{itq} = \sum_{k} \alpha_k X_{kitq} + \sum_{\tau=-9}^{7} \beta_\tau Tor_{itq}^{\tau} + \gamma_t + \delta_q + u_{itq}; u_{itq} = \lambda \mathbf{W} u_{itq} + \varepsilon_{itq} \tag{3}$$

where ρ is a spatial autocorrelation parameter for the spatial lag models; $\mathbf{W}$ is an n x n inverse distance spatial weight matrix (n is the number of observations); λ is the spatial parameter for the spatial error models; u_{itq} is the error term for spatial error models that assumed to have correlated errors; and ε_{itq} is assumed to be a vector of i.i.d. errors. We recognize that using only the last home transaction may bias our data, particularly if houses impacted by an earlier tornado are sold again later – in which case they would be dropped. Thus, we argue that our "full-sample" difference-in-difference specification is the most suitable for identification, and include the reduced-sample OLS and spatial models only as a robustness check.

Table 2: Summary Statistics of Housing Sales Transactions by Moore, OK, 1990-2020.

	Obs.	Mean	Std. Dev.	Min	Max
Housing Price	28,969	118,657	75,397	30,000	1,930,500
Bedrooms	28,969	3	0	1	7
Bathrooms	28,969	2	1	1	6
Building Age	28,969	20	17	1	97
Square Feet	28,969	1,558	480	480	7,030
Garage Square Feet	28,969	481	144	0	1,785

4. RESULTS

Table 2 displays the summary statistics for the housing transactions during 1990-2020 in Moore, Oklahoma. The total number of housing sales is 28,969, with an average house price of \$118,657. The average area of the property is 1,558 ft^2, and an average garage size is 481 ft^2. On average, the number of bedrooms and bathrooms are three and two, respectively. In addition, the average building age is 20 years, but the range of ages is large going from a minimum of 1 year to a maximum of 97 years, with a standard deviation of 17 years. These statistics are largely similar to our reduced sample of 15,066 used in the spatial specifications.

The results of our main OLS specifications (both full and reduced sample) are in Table 3. The effects of housing characteristics on housing price were similar regardless of the model and generally had the expected signs and magnitudes. The area of the property (square feet) and garage (garage square feet) positively impact the housing price, while building age is associated with a decrease in housing price. Housing square footage displays diminishing marginal returns as evidenced by the opposite sign on its squared term; this also holds for building age in the reduced sample. The number of bathrooms shows a positive coefficient but no statistical significance. The quarter of sale is highly significant with quarters 2-4 resulting in higher sales prices than quarter one. These results are in line with intuition regarding the real estate industry, and reflect relationships demonstrated in the previous literature (Can, 1992; Ottensmann et al., 2008).

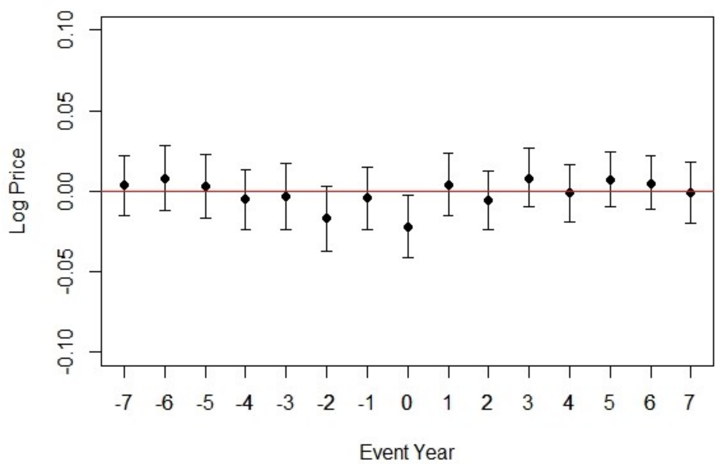
The main variables of interest are the annual indicator variables based on whether the house was in the path of a tornado. The full OLS model shows no impact of being in the path of a tornado in the years leading up to a tornadic event, as expected (Table 3; coefficients with 95% confidence intervals in Figure 2). It also documents a 2.2% reduction in sales price the year immediately following a tornado. Notably, these impacts disappear after the first year, and remain indistinguishable from zero for event years $1-7$. The standard difference-in-difference specification in column (2) finds a marginally significant and smaller effect of a 0.9% price reduction for sales taking place in years 0-2 following a tornado.

Table 3: Results of OLS Model with Including (and Excluding) Repeated Sales

	Full Sample				Reduced Sample (Last Sale Only)			
	(1)		(2)		(3)		(4)	
Intercept	9.978***	(0.021)	9.979***	(0.020)	9.872***	(0.027)	9.877***	(0.026)
Square Feet[a]	0.685***	(0.013)	0.684***	(0.013)	0.732***	(0.015)	0.731***	(0.015)
Square Feet^2	−0.079***	(0.003)	−0.079***	(0.003)	−0.084***	(0.003)	−0.083***	(0.003)
Building Age[b]	−0.084***	(0.003)	−0.084***	(0.003)	−0.113***	(0.004)	−0.113***	(0.004)
Building Age^2	−0.001**	(0.001)	−0.001**	(0.001)	0.004***	(0.001)	0.004***	(0.001)
Bathrooms	0.004	(0.004)	0.004	(0.004)	0.007	(0.004)	0.007	(0.004)
Garage Square Feet[a]	0.258***	(0.015)	0.257***	(0.015)	0.375***	(0.017)	0.374***	(0.017)
Sales Quarter 2	0.024***	(0.005)	0.024***	(0.005)	0.030***	(0.006)	0.029***	(0.006)
Sales Quarter 3	0.019***	(0.005)	0.018***	(0.005)	0.027***	(0.006)	0.027***	(0.006)
Sales Quarter 4	0.033***	(0.005)	0.033***	(0.005)	0.036***	(0.006)	0.036***	(0.006)
Tornado Event Year 0-2[c]			−0.009*	(0.005)			−0.022***	(0.006)
-9	−0.001	(0.010)			0.016	(0.015)		
-8	0.004	(0.010)			0.014	(0.014)		
-7	0.004	(0.009)			−0.005	(0.013)		
-6	0.008	(0.010)			−0.025*	(0.014)		
-5	0.003	(0.010)			−0.013	(0.014)		
-4	−0.005	(0.009)			0.018	(0.013)		
-3	−0.003	(0.010)			0.032**	(0.014)		
-2	−0.017	(0.010)			0.011	(0.013)		
-1	−0.004	(0.010)			0.013	(0.012)		
0	−0.022**	(0.010)			−0.053***	(0.012)		
1	0.004	(0.010)			−0.016	(0.012)		
2	−0.006	(0.009)			−0.015	(0.011)		
3	0.008	(0.009)			0.005	(0.010)		
4	−0.001	(0.009)			−0.001	(0.011)		
5	0.007	(0.009)			−0.001	(0.009)		
6	0.005	(0.008)			0.006	(0.009)		
7	−0.001	(0.010)			−0.010	(0.010)		
Year Fixed Effects	Yes		Yes		Yes		Yes	
N	28,969		28,969		15,066		15,066	
R^2	0.7038		0.7037		0.7811		0.7807	

Notes: The 1%, 5%, and 10% levels of significance are given as ***, **, and *, respectively.
[a] House and garage square footage measured in 1,000 square feet.
[b] Age measured in 10 year increments.
[c] This estimates from an OLS model, where the set of event indicators are replaced by a single indicator of whether the transaction occurs in years 0-2 following exposure to the tornadoes.

Figure 2: Tornado Effects on Housing Values – Full Sample



Notes: Estimates from the OLS model including repeated sales transactions are plotted with their 95% confidence interv
sample of Moore housing sales (N=28,969).

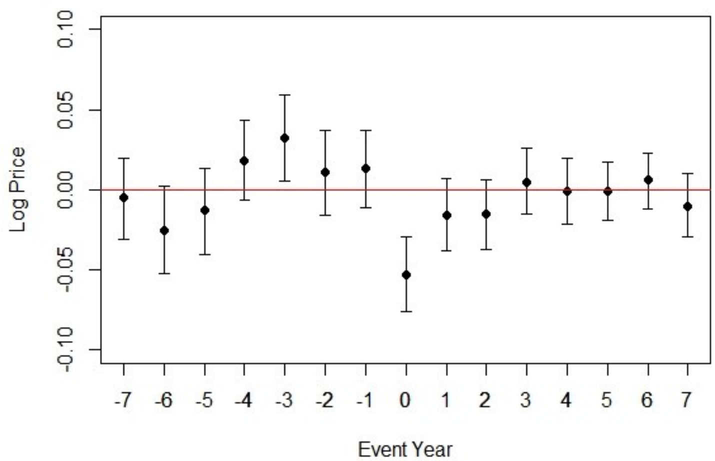
For the reduced-sample OLS model (that only includes the most recent sale for all houses), the returns to housing characteristics are similar (Column 3). The estimates of tornado impacts are even stronger, although with a surprisingly significant (and likely spurious) effect 3 years before an event.[7] Here, the price penalty for a house in the path of a tornado occurring less than one year (event year 0) prior is 5.3%, more than double the estimate from the full sample. The year-event indicator coefficients and their 95% confidence intervals are shown in Figure 3. The standard difference-in-difference specification for the reduced sample (Column 4) shows a highly significant price reduction of 2.2% in event years 0-2.

Appendix A contains the results of the reduced-sample OLS model (specification (3) in Table 3) alongside those for the spatial lag and error models. The Moran's I of the residuals from the reduced-sample OLS model demonstrates that spatial autocorrelation exists (p-value ≤ 0.001). However, the value of the Moran's I statistic is not large (0.020). In addition to the Moran's I test, traditional and robust versions of the Lagrange Multiplier tests (Anselin et al., 1996) for both the spatial lag and spatial error models were highly statistically significant (all p-values < 0.0001), leaving us to conclude that either model could be used to analyze the effect of tornadoes on housing prices – and that no strong evidence exists favoring one over the other.

As Appendix A demonstrates, the coefficients on the housing characteristics for both the spatial lag and spatial error models are largely similar to those from the OLS specification. Both models have highly statistically significant coefficients for the resulting spatial parameters (ρ and λ, respectively). The values on square footage (for both building and garage)

[7] We hypothesize that this spurious but significant prior-year coefficient may be the result of house re-sales that were affected by multiple tornadoes. For example, a house sold in 2000 that was impacted both by the 1999 tornado (event year +1) and the 2003 tornado (event year -3).

Figure 3: Tornado effects on housing values – Reduced Sample



Notes: Estimates from the OLS model including repeated sales transactions are plotted with their 95% confidence interv
sample of Moore housing sales (N=28,969).

are slightly lower than the initial OLS estimates, likely due to the bias of omitting relevant spatial characteristics. Additionally, the spatial error model demonstrates a positive impact of bathrooms – an intuitive result that is not observed in the OLS or spatial lag specifications. Overall, however, the omitted variable bias does not appear to be severe; and the differences across specifications are minimal.

The estimates of tornado impacts are again similar to the OLS results for both the spatial lag and error specifications. Years leading up to a tornado are generally not statistically significant, with the exception of a likely spurious 3% *increase* 3 years prior. The findings here reinforce those from our primary, full-sample specification and suggest a highly significant impact of tornadoes on housing prices, but only for the year immediately following the event. The spatial specifications find a price reduction of between 4.4% and 5.1% in the year immediately following a tornado, compared to a 5.3% reduction under OLS.

Even though the spatial lag models have a slightly better fit (lower AIC and larger log-likelihood) of the two specifications presented (Akaike, 1973), we do not have strong evidence on which model is statistically better. From a theoretical perspective, we argue that the spatial error model is preferred because the spillovers in the lag model are global in nature (LeSage, 2014). These types of spillovers have endogenous feedback effects, implying that a change in one region will result in a new long-run steady state equilibrium where not only neighbors but neighbors-of-neighbors (and so on) are affected. LeSage (2014) argues that these global spillovers are rare in regional science situations; in the context of housing prices, it is difficult to make an argument for their existence. Regardless, the takeaways from the two models are essentially the same as for the OLS models – that tornadoes do impact housing prices immediately following the event. The inclusion of spatial parameters seems to overcome a small bias in specific housing characteristic coefficients, but the changes are not economically meaningful.

5. CONCLUSIONS

The objective of this study was to use a hedonic housing price model to examine whether four distinct damaging tornadoes affected future housing prices in Moore, Oklahoma. We use indicator variables for every pre-/post-tornado year associated with four historical tornado paths to account for tornado effects on housing prices, while controlling for household-specific factors like building age, square footage, and garage size. The tornadoes used in the analysis were Fujita scale 4 (or Enhanced Fujita scale 4) or over, considered devastating or incredibly damaging, and took place in 1999, 2003, 2010, and 2013. The OLS model that includes all sales between 1990 and 2020 suggests that recent tornado history does matter, with a price reduction of 2.2% for houses in the path of an event during the following year. When our sample is restricted to only the latest sales of each property (which is required to construct spatial weight matrices), the results become even stronger, with price reductions of over 5% in the event year 0. We find evidence of spatial dependence, suggesting that a spatial lag or spatial error model might be more appropriate. However, the results from these specifications fundamentally mirror those from OLS.

We argue that the sales prices decreases in the year following a tornadic event are primarily driven by an increased perceived risk experienced by the existing (or potential) residents of areas affected by prior tornadoes. A remarkable feature of this perceived risk is that it is inherently irrational, given the randomness with which tornadoes strike. Notably, we did not find any evidence of longer-term or delayed impacts lasting more than a year post-tornado. Further research should attempt to confirm this finding and examine whether a longer-term relationship might hold in other geographies.

Our study adds to the limited body of evidence on how smaller-scale natural disasters such as tornadoes impact housing prices. Recent hedonic work has tended to incorporate spatial lag models more than spatial error ones. However, our results demonstrate that neither is a marked improvement over simple OLS in our specific case. The results here suggest that repercussions from tornadoes impact the local housing market in the year following an event. Replicating this study in a non-tornado-prone region would be an interesting test of whether a similar result is found where the perceived risk is markedly lower.

REFERENCES

Akaike, Htrotugu. (1973) "Maximum Likelihood Identification of Gaussian Autoregressive Moving Average Models," *Biometrika*, 60(2), 255–265. http://doi.org/10.1016/0166-0462(92)90004-K.

Anselin, Luc. (1988) "Lagrange Multiplier Test Diagnostics for Spatial Dependence and Spatial Heterogeneity," *Geographical Analysis*, 20(1), 1–17. http://doi.org/10.1111/j.1538-4632.1988.tb00159.x.

Anselin, Luc. (2003) "Spatial Externalities, Spatial Multipliers, and Spatial Econometrics," *International Regional Science Review*, 26(2), 153–166. http://doi.org/10.1177/0160017602250972.

Anselin, Luc. (2010) "Thirty Years of Spatial Econometrics," *Papers in Regional Science*, 89(1), 3–25. http://doi.org/10.1111/j.1435-5957.2010.00279.x.

Anselin, Luc, Anil K Bera, Raymond Florax, and Mann J Yoon. (1996) "Simple Diagnostic Tests for Spatial Dependence," *Regional Science and Urban Economics*, 26(1), 77–104. http://doi.org/10.1016/0166-0462(95)02111-6.

Baltagi, Badi H and Georges Bresson. (2011) "Maximum Likelihood Estimation and Lagrange Multiplier Tests for Panel Seemingly Unrelated Regressions with Spatial Lag and Spatial Errors: An Application to Hedonic Housing Prices in Paris," *Journal of Urban Economics*, 69(1), 24–42. http://doi.org/10.1016/j.jue.2010.08.007.

Beck, Jason and Meimei Lin. (2020) "The Impact of Sea Level Rise on Real Estate Prices in Coastal Georgia," *Review of Regional Studies*, 50(1), 43–52. http://doi.org/10.52324/001c.11643.

Beltrán, Allan, David Maddison, and Robert JR Elliott. (2018) "Is Flood Risk Capitalised Into Property Values?," *Ecological Economics*, 146, 668–685. http://doi.org/10.1016/j.ecolecon.2017.12.015.

Bin, Okmyung, Ben Poulter, Christopher F Dumas, and John C Whitehead. (2011) "Measuring the Impact of Sea-Level Rise on Coastal Real Estate: A Hedonic Property Model Approach," *Journal of Regional Science*, 51(4), 751–767. http://doi.org/10.1111/j.1467-9787.2010.00706.x.

Brooks, Harold E, Charles A Doswell, and Michael P Kay. (2003) "Climatological Estimates of Local Daily Tornado Probability for the United States," *Weather and Forecasting*, 18(4), 626–640. http://doi.org/10.1175/1520-0434.

Can, Ayse. (1992) "Specification and Estimation of Hedonic Housing Price Models," *Regional Science and Urban Economics*, 22(3), 453–474. http://doi.org/10.1016/0166-0462(92)90039-4.

Cliff, Andrew David and J Keith Ord. (1981) *Spatial Processes: Models & Applications*. Taylor & Francis, London: Pion.

Conley, Kelsey L and Brian E Whitacre. (2020) "Home Is Where the Internet Is? High-speed Internet's Impact on Rural Housing Values," *International Regional Science Review*, 43(5), 501–530. http://doi.org/10.1177/0160017620918652.

Donadelli, Michael, Marcus Jüppner, Antonio Paradiso, and M Ghisletti. (2020) "Tornado Activity, House Prices, and Stock Returns," *The North American Journal of Economics and Finance*, 52, 101162. http://doi.org/10.1016/j.najef.2020.101162.

Dubin, Robin A. (1992) "Spatial Autocorrelation and Neighborhood Quality," *Regional*

Science and Urban Economics, 22(3), 433–452. http://doi.org/10.1016/0166-0462(92)90038-3.

Elsner, James B, Emily Ryan, and Georgianna Strode. (2018) “Structural Property Losses from Tornadoes in Florida,” *Weather, Climate, and Society*, 10(2), 253–258. http://doi.org/10.1175/WCAS-D-17-0055.1.

Graff Zivin, Joshua S, Yanjun Liao, and Yann Panassie. (2020) “How Hurricanes Sweep Up Housing Markets: Evidence from Florida,” National Bureau of Economic Research: https://www.nber.org/system/files/working_papers/w27542/w27542.pdf.

Graif, Corina. (2016) “(Un)natural Disaster: Vulnerability, Long-Distance Displacement, and the Extended Geography of Neighborhood Distress and Attainment After Katrina,” *Population and Environment*, 37(3), 288–318. http://doi.org/10.1007/s11111-015-0243-6.

Hall, Soren G and Walker S Ashley. (2008) “Effects of Urban Sprawl on the Vulnerability to a Significant Tornado Impact in Northeastern Illinois,” *Natural Hazards Review*, 9(4), 209–219. http://doi.org/10.1061/(ASCE)1527-6988(2008)9:4(209).

Hoen, Ben, Jason P Brown, Thomas Jackson, Mark A Thayer, Ryan Wiser, and Peter Cappers. (2015) “Spatial Hedonic Analysis of the Effects of US Wind Energy Facilities on Surrounding Property Values,” *The Journal of Real Estate Finance and Economics*, 51(1), 22–51. http://doi.org/10.1007/s11146-014-9477-9.

Kim, Chong Won, Tim T Phipps, and Luc Anselin. (2003) “Measuring the Benefits of Air Quality Improvement: A Spatial Hedonic Approach,” *Journal of Environmental Economics and Management*, 45(1), 24–39. http://doi.org/10.1016/S0095-0696(02)00013-X.

LeSage, James and Robert Kelley Pace. (2009) *Introduction to Spatial Econometrics*. Chapman and Hall/CRC. http://doi.org/10.1201/9781420064254.

LeSage, James P. (2014) “What Regional Scientists Need to Know About Spatial Econometrics,” *Available at SSRN 2420725*. http://doi.org/10.2139/ssrn.2420725.

Loftin, Colin and Sally K Ward. (1983) “A Spatial Autocorrelation Model of the Effects of Population Density on Fertility,” *American Sociological Review*, pp. 121–128. http://doi.org/10.2307/2095150.

Malagarie, Danielle. (2019) Tornado Impact on the Housing Market. https://dayton247now.com/news/local/tornado-impact-on-the-housing-market. Accessed 21 Apr 2020.

Mueller, Julie, John Loomis, and Armando González-Cabán. (2009) “Do Repeated Wildfires Change Homebuyers’ Demand for Homes in High-Risk Areas? A Hedonic Analysis of the Short and Long-Term Effects of Repeated Wildfires on House Prices in Southern California,” *The Journal of Real Estate Finance and Economics*, 38(2), 155–172. http://doi.org/10.1007/s11146-007-9083-1.

Murdoch, James C, Harinder Singh, and Mark Thayer. (1993) “The Impact of Natural Hazards on Housing Values: The Loma Prieta Earthquake,” *Real Estate Economics*, 21(2), 167–184. http://doi.org/10.1111/1540-6229.00606.

National Oceanic and Atmospheric Administration National Weather Service. (2020) Enhanced F Scale for Tornado Damage. Available online at https://www.spc.noaa.gov/faq/tornado/ef-scale.html. Accessed 24 Feb 2020.

National Oceanic and Atmospheric Administration National Weather Service, National Centers for Environmental Information. (2020a) Storm Events Database. https://www.ncdc.noaa.gov/stormevents/eventdetails.jsp?id=451572.

National Oceanic and Atmospheric Administration National Weather Service, National Centers for Environmental Information. (2020b) Tornado Alley. Asheville, NC. Available online at https://www.ncdc.noaa.gov/climate-information/extreme-events/us-tornado-climatology/tornado-alley. Accessed 20 Mar 2020.

O'Neill, Eoin, Finbarr Brereton, Harutyun Shahumyan, and J Peter Clinch. (2016) "The Impact of Perceived Flood Exposure on Flood-Risk Perception: The Role of Distance," *Risk Analysis*, 36(11), 2158–2186. http://doi.org/10.1111/risa.12597.

Ottensmann, John R, Seth Payton, and Joyce Man. (2008) "Urban Location and Housing Prices within a Hedonic Model," *Journal of Regional Analysis and Policy*, 38(1100-2016-89822). http://doi.org/10.22004/ag.econ.132338.

Pillion, Dennis. (2021) Do Tornadoes Strike the Same Place Twice? Researchers Say It's 'Random Chance'. Available online: https://www.al.com/news/2021/03/do-tornadoes-strike-the-same-place-twice-researchers-say-its-random-chance.html. Accessed 27 Mar 2021.

Pompe, Jeffrey J and James R Rinehart. (1995) "The Value of Beach Nourishment to Property Owners: Storm Damage Reduction Benefits," *Review of Regional Studies*, 25(3), 271–286. http://doi.org/10.52324/001c.9010.

Posey, John and William H Rogers. (2010) "The Impact of Special Flood Hazard Area Designation on Residential Property Values," *Public Works Management and Policy*, 15(2), 81–90. http://doi.org/10.1177/1087724X10380275.

Romanic, Djordje, Maryam Refan, Chieh-Hsun Wu, and Gero Michel. (2016) "Oklahoma Tornado Risk and Variability: A Statistical Model," *International Journal of Disaster Risk Reduction*, 16, 19–32. http://doi.org/10.1016/j.ijdrr.2016.01.011.

Rosen, Sherwin. (1974) "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition," *Journal of Political Economy*, 82(1), 34–55. http://doi.org/10.1086/260169.

Simmons, Kevin M and Daniel Sutter. (2007) "Tornado Shelters and the Housing Market," *Construction Management and Economics*, 25(11), 1119–1126. http://doi.org/10.1080/01446190701618299.

Sirmans, Stacy, David Macpherson, and Emily Zietz. (2005) "The Composition of Hedonic Pricing Models," *Journal of Real Estate Literature*, 13(1), 1–44. http://doi.org/10.1080/10835547.2005.12090154.

Strader, Stephen M, Walker S Ashley, Thomas J Pingel, and Andrew J Krmenec. (2017) "Projected 21st Century Changes in Tornado Exposure, Risk, and Disaster Potential," *Climatic Change*, 141(2), 301–313.

United States Census Bureau. (2020) American Community Survey. https://data.census.gov/cedsci/profile?g=1600000US4049200. Accessed 19 June 2020.

A. APPENDIX A

Table A1: Results of OLS, Spatial Lag, and Spatial Error Models with Reduced Sample

	OLS (1)		**Spatial Lag** (2)		**Spatial Error** (3)	
Intercept	9.872***	(0.027)	7.561***	(0.138)	9.943***	(0.028)
Square Feet[a]	0.732***	(0.015)	0.690***	(0.015)	0.691***	(0.016)
Square Feet^2	−0.084***	(0.003)	−0.081***	(0.003)	−0.080***	(0.003)
Building Age[b]	−0.113***	(0.004)	−0.096***	(0.004)	−0.113***	(0.004)
Building Age^2	0.004***	(0.001)	0.004**	(0.001)	0.004***	(0.001)
Bathrooms	0.007	(0.004)	0.006	(0.004)	0.010	(0.005)
Garage Square Feet[a]	0.375***	(0.017)	0.318***	(0.017)	0.335***	(0.018)
Sales Quarter 2	0.030***	(0.006)	0.031***	(0.006)	0.030***	(0.006)
Sales Quarter 3	0.027***	(0.006)	0.027***	(0.006)	0.026***	(0.006)
Sales Quarter 4	0.036***	(0.006)	0.036***	(0.006)	0.035***	(0.006)
Rho (ρ)			0.206***	(0.012)		
Lambda (λ)					0.586***	(0.035)
Tornado Event Year 0-2						
-9	0.016	(0.015)	0.021	(0.014)	0.015	(0.015)
-8	0.014	(0.014)	0.019	(0.014)	0.013	(0.014)
-7	−0.005	(0.013)	0.003	(0.013)	−0.004	(0.013)
-6	−0.025*	(0.014)	−0.021	(0.014)	−0.027*	(0.014)
-5	−0.013	(0.014)	−0.001	(0.014)	−0.017	(0.014)
-4	0.018	(0.013)	0.02	(0.013)	0.017	(0.013)
-3	0.032**	(0.014)	0.032**	(0.014)	0.030**	(0.014)
-2	0.011	(0.013)	0.015	(0.013)	0.010	(0.013)
-1	0.013	(0.012)	0.018	(0.012)	0.012	(0.012)
0	−0.053***	(0.012)	−0.044***	(0.012)	−0.051***	(0.012)
1	−0.016	(0.012)	−0.007	(0.012)	−0.016	(0.012)
2	−0.015	(0.011)	−0.008	(0.011)	−0.015	(0.011)
3	0.005	(0.010)	0.009	(0.010)	0.005	(0.010)
4	−0.001	(0.011)	0.006	(0.010)	−0.001	(0.011)
5	−0.001	(0.009)	0.010	(0.009)	−0.001	(0.009)
6	0.006	(0.009)	0.017*	(0.009)	0.006	(0.009)
7	−0.010	(0.010)	−0.001	(0.010)	−0.009	(0.010)
Year Fixed Effects	Yes		Yes		Yes	
Moran's I Residuals	0.020***					
Log Likelihood			443.475		408.925	
AIC	-531.580		-748.93		-699.85	
N	15.066		15,066		15,066	
R^2	0.781					
LM Lag[c]	243.750***					
Robust Lag[c]	74.130***					
LM Error	171.290***					
Robust Error	146.590***					

Notes: The 1%, 5%, and 10% levels of significance are given as ***, **, and *, respectively.

[a] House and garage square footage measured in 1,000 square feet.

[b] Age measured in 10 year increments.

[c] Lagrange multiplier (LM) and robust LM test statistics are reported for the reduced-sample OLS model.