Disamenity or Premium: Do Electricity Transmission Lines Affect Farmland Values and Housing Prices Differently?†

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Disamenity or Premium: Do Electricity Transmission Lines Affect Farmland Values and Housing Prices Differently?

Abstract: A substantial increase in electricity demand has triggered a rising investment in energy infrastructure in the U.S. over the last decade. This paper examines the capitalization effects of electricity transmission lines (TMLs) on nearby farmland values and housing prices in the Midwest from 2015 to 2019, based on 16,026 parcel-level farmland sales data from FarmlandFinder and 1,905,280 housing transaction data from the Zillow Transaction and Assessment Dataset database. Our estimation results reaffirm the disamenity effects of TMLs on housing property values and find that the disamenity effects are larger on houses in urban areas than in rural areas. Nearby TMLs generate premiums for surrounding farmland, which contrasts with the disamenity evidence due to aesthetics (either visual or audible) in the literature. We further show that farmland parcels within 0-2 km of TMLs in high-wind areas are approximately 3.10% more expensive than comparable parcels in low-wind areas. Our paper provides novel and contrarian evidence on the effects of TMLs on property values amid rising investment in energy infrastructure.

Keywords: Transmission lines (TMLs), Property values, Wind resources, Disamenity, Option values

JEL Codes: Q15, R14, R31

1 Introduction

A reliable electric transmission grid is critical for a renewable and low-carbon energy future in the U.S.(Perera et al., 2020; Sugimoto, 2021). New investments in transmission lines (TMLs), especially in rural America (The White House, 2021), generate renewed interest in the impacts of TMLs on nearby residential and agricultural properties. Previous studies have provided extensive and consistent evidence of disamenity effects of TMLs on nearby residential housing prices (Priestley and Evans, 1996; Hamilton and Schwann, 1995; François, 2002; Chalmers and Voorvaart, 2009; Jackson and Pitts, 2010), leading to 5% to 20% price declines. Visual aesthetics deterioration, possible health risks and safety hazards, and impacts on culture are often cited as reasons.

The literature on the impacts on farmland values of TMLs is limited, inconclusive, and mostly outdated. Existing literature suggests null effects from TMLs on farmland values in the U.S. (Brown, 1976; Jackson, 2010; Jackson and Pitts, 2010). Sardaro et al. (2018) find that the overhead TMLs depressed nearby farmland values in Italy due to concerns about low TMLs disrupting agricultural production and fewer production acres converted to TML buffer zones. On the other hand, a recent study shows that proximity to TMLs for farmland parcels is positively valued after the construction of utility-scale solar facilities (Abashidze and Taylor, 2022). This could be because renewable energy facilities are typically located on land close to TMLs to conveniently connect to the existing grid and thus reduce the startup cost (Lamy et al., 2016; Pechan, 2017; Deng et al., 2022). This is consistent with the evidence of large wind lease payments to landowners (Mcelroy, 2020). In addition, TMLs could facilitate the adoption of precision agriculture equipment that requires electricity (Mitra et al., 2022), and can improve quality of life by enabling telemedicine, virtual communications, and remote work. In sum, more research is needed to pin down the impacts of TMLs on nearby farmland values. In particular, we will examine whether TMLs' disamenity effects discovered in the residential housing market would apply to farmland prices and whether proximity to TMLs facilitates energy infrastructure investments.

This paper examines the capitalization effects of TMLs on nearby farmland and housing values in the U.S. Midwest, focusing on (i) how the TMLs impact nearby farmland prices and housing property values with rapid renewable energy development, and (ii) whether the growing demand for renewable energy challenges the conventional wisdom that TMLs are disamenities. This research is based on 16,026 arm's length farmland sales data from a startup company called FarmlandFinder[1] and 1,905,280 single-family housing transaction data from the ZTRAX/Zillow database in 12 Midwestern states from 2016 to 2019. We focus on the Midwest for its abundant wind resources, and wind energy accounted for the largest share (42.4%) of renewable energy in 2020 (U.S. Energy Information Administration, 2021). Also, due to the high electricity demand in the coastal areas, there is a high demand for electricity transportation via TMLs.

The availability of comprehensive and up-to-date data from ZTRAX/Zillow and FarmlandFinder is instrumental in exploring our research question, as it provides unique advantages compared to other data sources. First, Zillow stands out as the most extensive and accessible platform for housing market data, offering a comprehensive dataset that includes housing price and transaction information. This wealth of data, which is not easily obtainable from other sources, allows for a thorough analysis of housing prices and transactions, enabling us to capture a more accurate and nuanced understanding of the market dynamics. Second, previous studies on the farmland market often relied on survey data or transactions limited to a specific state, resulting in a fragmented and limited view of the market. However, our database incorporates arm's length transactions from 12 core agricultural states, covering a wider geographical scope. This regional coverage enables a more accurate and robust depiction of the farmland market, surpassing the limitations of previous studies and providing a more comprehensive assessment of the factors influencing regional farmland prices and transactions.

We rely on the hedonic house price regressions as our main empirical models. We run separate regressions to quantify the capitalization effects of proximity to TMLs on nearby farmland values and housing prices. Moreover, we add an interaction term of proximity to TMLs with measures for wind resources to examine the premium of being close to a TML and in a high-wind area to explore the possible treatment effect mechanism. Finally, we explore heterogeneities by comparing estimates across whether in urban counties/areas, whether there are two or more TMLs, and across different subsamples. We reaffirm disamenity effects of TMLs on housing property values. Housing prices decline by 2.74% on average for every 1 km closer to the nearest TML, and the disamenity

[1] FarmlandFinder is now acquired by Growers Edge, and rebranded as `https://app.range.ag`.

effects are stronger in urban areas. We further show that the higher wind resources in the farmland market at least partially drive the price premiums, as they offset or even reverse the disamenity effect. In particular, for farmland parcels with TMLs in the range of 0-2 km, the prices of those farmlands in high-wind areas are 3.10% higher than comparable parcels in low-wind areas. Our heterogeneity analyses reveal that the premium is larger for Great Plain states' farmland where energy infrastructure investment is higher. The disamenity effects for housing prices in I-states and Lakes states with more natural amenities are stronger.

This research contributes to the literature in two ways. First, we provide novel and contrarian evidence regarding the differential effects of TMLs on farmland values and residential housing prices. Our results show that close proximity to TMLs yields positive premiums for nearby farmland parcels, different from the null or negative capitalization effects of TML. We also confirm the TMLs' disamenity effects on residential housing prices, and this disamenity effect is larger for urban houses than rural houses. Second, we firstly demonstrate TMLs have a synergy with local wind resources on farmland values, consistent with recent findings on the capitalization effects of renewable energy (Abashidze and Taylor, 2022). Overall, this article demonstrates the capitalization effects of TMLs amid rising investment in renewable energy infrastructure, and reveals important trade-offs that owners of different types of properties face in urban or rural areas when siting TMLs.

This paper is structured as follows. Section 2 provides an overview of the data sources, while Section 3 outlines the empirical model. Section 4 presents the empirical results, and Section 5 discusses the findings from the heterogeneity and robustness checks. Finally, the last section concludes the paper.

2 Data Description

We compiled multiple datasets to generate the farmland and housing property datasets for regression analyses. The farmland dataset includes 16,026 farmland sales from 2016 to 2019 in 12 Midwestern states, measures of TMLs influences, land characteristics, and proximity to urban areas and other infrastructure and facilities.[2] The housing property dataset covers 1,905,280 single-family housing

[2]The farmland sales data are limited to 2016-2019 because the Farmlandfinder company was established in 2016. Farmland data prior to 2016 are not available. Using a relatively short sample period has certain advantages (Kuminoff

sales from 2015 to 2019 in the same 12 states in the Midwest, and other variables such as TML measures, housing characteristics, and location. Below we explain each dataset and the merging process in detail.

2.1 Farmland data

We obtained farmland value data from FarmlandFinder, a start-up company (since acquired by Growers Edge) that scrapes thousands of auction and real estate companies' sites for land sales information. The data include the land parcel characteristics as well as landowner information; its main function is to facilitate transactions involving absentee landowners. In addition to the detailed information on farmland centroid location, acreage, and transaction date, the dataset also provides information on sales history, soil survey results, crop history, etc. A screenshot of the website interface is provided in Figure A1 to illustrate how the land value and other related information of each parcel is displayed. FarmlandFinder offers both auction data (including both public auction and seal-bid auction) and real estate listing data; these two types of data account for more than two-thirds of all arm's length farmland transactions (Zhang, 2016). The farmland value data cover 12 Midwestern states including North Dakota, South Dakota, Wisconsin, Michigan, Indiana, Ohio, Iowa, Illinois, Kansas, Nebraska, Missouri, and Minnesota. The distribution of arm's length farmland transactions is shown in Panel A of Figure 1.

The summary statistics for variables used in the farmland value analysis are presented in Panel A of Table 1. The transaction price ranges between \$520/acre and \$28,500/acre with a mean \$5,668/acre.[3] The average distance from the farmland boundary to the nearest TML is 3.66 km with the minimum close to zero and the maximum at 11.00 km.[4] Approximately 38% of farmlands are situated within 0-2 km of their nearest TML, while approximately 33% and 18% of these farmlands have their closest TML located in the distance bands of 2-5 km and 5-8 km, respectively. The remaining 11% of farmlands have their nearest TML within the range of 8-11 km. Around 28% of farmland parcels are in the high-wind region and the other 72% are in the low-wind region based

et al., 2010; Bishop et al., 2020) since the hedonic equilibrium may evolve over time due to changes in macroeconomic factors that influence homebuyers' willingness to pay for amenities over a long time period. The housing transaction data follows a similar time window for consistency.

[3]These numbers are in real terms based on the first year of each dataset.

[4]We excluded the observations with the nearest TML out of 11 km due to the identified extent of TMLs on farmland values in Section 3.1. We thank the Editor for this valuable suggestion.

on the 7 m/s cutoff (Xu and Zha, 2021).[5] For the farmland-related characteristics, the average farmland area is 127 acres and almost 77% are tillable lands. Almost a quarter (23%) of farmland parcels in the sample consist of prime land, with an average of 12% loam soil. The average land slope is 7.95 degrees. In addition, more than half of the farmland parcels are in urban areas and the average population size is around 61,000. The average distance from the farmland to the highway, railway, waterbody, biodiesel, and grain warehouse ranges from 0.39 to 10.88 km. We construct a dummy variable to capture whether there are two or more TMLs within each distance band for each farmland parcel. We find that 20% of the farmlands are close to two or more TMLs within 2 km, while 36% and 47% of the farmlands are close to two or more TMLs in the distance band 2-5 km and 5-8 km, respectively.

2.2 Housing data

The house transaction data were compiled from the ZTRAX database. The ZTRAX database contains almost 2.5 million transactions across 12 U.S. states from 2015 to 2019. Panel B of Figure 1 shows the distribution of houses in the 12 states. In addition to detailed information on the sales amount and the date of transaction, the housing dataset includes house structural characteristics, such as the year of build, lot size, the number of bathrooms, the number of bedrooms, the number of stories, and the number of full baths.

In the data cleaning process, we remove transactions with sale prices lower than $1,000, as well as those in the top 1% of prices. We only use single-family house transactions and deflate the sale prices to 2000 dollars using the Federal Housing Finance Agency's (FHFA) state-quarter house price index.[6] Properties with lot sizes below 1,000 square feet and those in the top 1% are also excluded. Moreover, we exclude houses with an unusually large number of house characteristics. Specifically, we remove houses with less than 0.5 stories (7,947 observations) or more than 5 stories (1,016 observations). Additionally, we exclude properties with a total number of rooms exceeding 14 (2,457 observations) or more than 8 bedrooms (246 observations) or 4 bathrooms (6,210 observations). Notably, our main results remain robust even when we retain these extreme value observations.

[5] Further justifications for selecting a 7 m/s cutoff are provided in Section 4.1.

[6] More details see `https://www.fhfa.gov/`.

The housing dataset includes a large portion of missing values for house characteristics. Table B1 shows the missing percentage for housing characteristics; for example, the number of total rooms is missing for approximately 51% of the observations. Table B2 indicates the number of block groups and census tracts with the corresponding housing characteristics missing and shows that the number of total rooms is missing more frequently on both block group and census tract levels. When categorized by states, Michigan has the largest number of missing values, followed by Wisconsin, Illinois, Ohio, Minnesota, Nebraska, Iowa, Missouri, North Dakota, Indiana, South Dakota, and Kansas. Using observations with all house characteristics available shrinks the sample size from 1.9 million to around 0.8 million (see Column (7) in Table B3), which significantly reduces the representativeness of our analysis if the housing characteristic information is not missing at random.[7] Indeed, many characteristics are missing in a whole census tract or block group.

To mitigate the missing value concern, we apply an imputation method that involves averaging the house characteristics at a higher geographic level to impute. For example, if the block level information is missing, we use the census average to impute the missing block level variables; if the census tract level information is missing, we impute it using the county average. Table B1 indicates that imputation does not result in a significant difference of means between covariates, reinforcing the reliability of our imputation method.

There are 1,905,280 house transactions in the merged housing value dataset. The summary statistics for variables used in analyses of the housing property prices are presented in Panel B of Table 1. The average transaction price is \$181,680 with a minimum of \$1,000 and a maximum of \$1,900,000. The mean of the distance to the nearest TML is around 1.2 km.[8] Approximately 24% of houses are situated within the distance band of 0-0.5 km from their nearest TML, while approximately 23%, 19%, and 15% of these houses have their nearest TML located in the distance bands of 0.5-1 km, 1-1.5 km, and 1.5-2 km, respectively. The remaining 19% of houses have their nearest TML within the range of 2-3 km. The percentage of houses in the high-wind regions is around 8%. Approximately 84% of houses are in the urban areas. The average age of the properties

[7] We also provide a robustness check in the appendix to show the results of using the data without imputation. Table B3 Columns (7)-(9) show that the coefficients of all pooled, urban, and rural samples are not obviously different as after imputation, an indication of the reliability of our imputation procedures.

[8] Similar to the "Farmland data" section, we excluded the observations with the nearest TML out of 3 km due to the identified extent of TMLs on farmland values in Section 3.1.

is 55.48 years. The average lot size is approximately 43,57 square feet. The properties have an average of 1.39 stories, 4.99 total rooms, 2.84 total bedrooms, and 1.51 full baths. We construct a dummy variable to present if there are two or more TMLs within each distance band for each house. Our results suggest that only 16% of the houses are close to two or more TMLs within 0.5 km; this figure is 15%, 24%, and 28%, for the distance band 0.5-1 km, 1-1.5 km, and 1.5-2 km, respectively.

2.3 TMLs data

To construct the proximity of properties to TMLs, we obtained publicly available shapefiles of TMLs from the U.S. Department of Homeland Security's Homeland Infrastructure Foundation-Level Data (HIFLD), which includes detailed information on TML location, voltage, whether the line is overhead or not, and the line owner. The exact locations of farmland centroids, houses, and TMLs allow us to calculate the distance from each farmland parcel and house to the nearest TML, respectively.[9]

2.4 Supplementary data

The wind speed data is compiled from the National Renewable Energy Lab, which provides the annual average wind speed at a 100-meter altitude above sea level for each 2-km × 2-km grid cell in the continental U.S. for the years 2007-2013. According to Xu and Zha (2021), experimental data indicates that seven meters per second (7 m/s) wind speed achieves optimal efficiency. To test whether the cutoff value is consistent with real-world scenarios, we overlap the distribution of wind turbines and the wind speed in the U.S. in Figure 2, where most of the wind turbines are constructed in areas with wind speeds higher than 7 m/s. Thus, we define 7 m/s as the cutoff value in the baseline analysis. Regions with an average wind speed higher than 7 m/s are defined as having abundant wind resources.

We match farmland location to the nearest wind speed grid and use the nearest wind speed as the speed of the farmland. Since the wind speed resolution is 2-km by 2-km, a larger farmland (i.e. farmland area is over 4 square kilometers) may be matched to different wind speed grids.[10]

[9]This dataset was accessed through `https://hifld-geoplatform.opendata.arcgis.com/datasets/electric-power-transmission-lines`; we last accessed it in December, 2021.

[10]Similarly, we also match the houses to the nearest wind speed grid and use 7 m/s as the cutoff to assign houses

Farmland characteristics were obtained from several different datasets. Soil texture variables and proportion of prime land come from the Soil Survey Spatial Data (SSURGO). Specifically, the farmland suitable for field crops is prime land. We obtained the average land slope and National Commodity Crop Productivity Index (NCCPI) from the USDA Natural Resources Conservation Service. The NCCPI is used to measure the potential inherent productivity of soil. Higher NCCPI values indicate the innate ability of soil, landscape, and climate conditions to foster higher crop productivity. Based on these datasets, we use ArcGIS to match these attributes to each farmland parcel.

We use two variables to measure the urban influences, including (i) whether the farmland is in an urban area, which captures the future rent due to urban development; and (ii) the population of the nearby urban areas, which captures the option value from the transition from farmland to urban utilization. Note that we have used the National Center for Health Statistics' urban-rural classification scheme for counties provided in 2013 for the farmland value analysis.[11] This classification system categorizes U.S. counties and county-equivalent entities into six levels of urban-rural classification, including large central metro, large fringe metro, medium metro, small metro, micropolitan, and non-core. The first five categories are considered urban counties, while the last category is designated as rural counties. The spatial distribution of these two urban and rural classifications are shown in Figure A2.

We calculate the distance variables from each farmland to the nearest biodiesel plant, waterbody, railway, and highways in ArcGIS using Census Bureau TigerLine datasets.[12] Distances to the nearest highway and the railway station are included to control for additional values conferred by the convenience for transporting agricultural goods. Distances to other agricultural facilities such as grain warehouses and biodiesel are also included to measure the value of accessing these facilities. Distance to the waterbody captures the capitalization effects of irrigation.

into either high-wind or low-wind areas.

[11] It could be found at https://www.cdc.gov/nchs/data_access/urban_rural.htm.

[12] The data link is https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html.

3 Empirical Models

To explore the capitalization effects of TMLs on property values, we adopt a hedonic regression model to estimate the influence of transmission lines by primarily using the proximity of farmland parcel or house to the nearest TML. The hedonic pricing model developed by (Rosen, 1974) is one of the most used revealed-preference approaches to value owners' willingness to pay for housing characteristics, environmental amenities, and other neighborhood attributes (Murphy, 2018; Bishop et al., 2020; Koster and Pinchbeck, 2022). We first identify the spatial extent of TMLs impacts and then apply two separate regression models to examine the effects of transmission lines on farmland and housing property values.

3.1 Identifying the spatial extent of TML influences on property values

Before measuring the impacts of proximity to TMLs on farmland values and housing prices, we first identify the spatial extent of TML influences on these two types of property values based on a data-driven approach. This helps guide our sample selection for estimation in Section 3.2 and Section 3.3.

In the farmland value analysis, we introduced a sequence of distance bands spanning up to 11 km with a 1 km increment (i.e., 0-1 km, 1-2 km, 2-3 km, $\cdots$, 10-11 km) to explore at which distance TMLs' influence disappear.[13] The base group is the distance band that goes beyond 11 km. Binary variables were constructed to indicate the proximity of farmland to TMLs, categorized by distance bands. For instance, if the nearest TML distance falls within the 1 km range, the corresponding binary variable for the 0-1 km interval assumes a value of 1, and 0 for other distance bands. Regression analyses were performed on these distance bands to identify the point at which the estimated coefficient loses statistical significance. The effects of proximity to TMLs on farmland values display a nonlinear trend as indicated in Panel A of Figure 3, which suggests that the positive impact weakens as the distance to the nearest TML increases, and vanishes once the distance surpasses 8 km.

[13] For all distance bands, note that the lower bound is inclusive, while the upper bound is exclusive. To illustrate, this convention is exemplified by intervals such as [0, 1), [1, 2), and [10, 11). The same principle applies to the intervals below.

Similarly, the effect of proximity to TMLs on housing prices can exhibit a non-linear pattern and may disappear beyond a certain distance threshold. We incorporated a set of distance bands within 3 km at a 0.5 km increment (e.g., 0-0.5 km, 0.5-1 km, $\cdots$, and 2.5-3 km), and the base group is the distance band that goes beyond 3 km. Similarly, if the distance to the nearest TML falls within the range of 0.5-1 km, the dummy variable corresponding to the 0.5-1 km interval is assigned a value of 1, while the dummy variables for other distance intervals are set to 0. We then analyzed the point at which the estimated coefficient becomes statistically insignificant. We found that a closer distance band has a more pronounced negative impact on housing values in Panel B of Figure 3. Compared to distance bands beyond 3 km, TMLs located within a 0.5 km radius of houses were associated with a significant devaluation of housing prices. The impact diminished and then became near-zero and statistically insignificant as the distance bands increased after 1.5-2 km. Our results demonstrate a nonlinear relationship between proximity to TMLs and housing prices, highlighting the importance of considering distance thresholds in understanding the effects of TMLs on the housing market. Below we introduce the farm value and housing value model and explain how we specify proximity to TMLs based on the thresholds we identified above.

3.2 Farmland value model

To explore the effects of proximity to TMLs on farmland values, we use a parcel-level dataset to investigate this research question and index farmland parcel by i and year by t. The outcome variable is the log of farmland sales price per acre, F_{it}. The explanatory variable $line_{it}$ represents the exposure to the TMLs, measured by the distance from farmland parcel boundary to the nearest transmission line in km in the baseline analysis. We restrict the farmland sampe to those with the nearest TML in the radius of 11 km based on the results in Panel A of Figure 3. The baseline model that estimates effects of TMLs on farmland values is specified as follows:

$$\log(F_{it}) = \alpha_0 + \alpha_1 line_{it} + \mathbf{X}_i\gamma + \delta_c + \phi_t + \varepsilon_{it} \tag{1}$$

where δ_c represents county fixed effects and ϕ_t stands for year fixed effects. We also use an alternative TML measure with a binary dummy indicating whether TMLs cross farmlands. The vector

$\mathbf{X}_i$ controls for a series of variables that might influence farmland values, including (i) farmland locations: distance to the nearest highway, railway, waterbody, biodiesel, and grain warehouses; (ii) farmland quality: land percentage tillable, average NCCPI for agriculture, percentage of prime farmland; (iii) farmland characteristics: gross acres, average slope, percentage of clay/silt/loam; and (iv) urban influence: whether in the urban area and population size in urban areas.

In the farmland value regression, we control county fixed effects δ_c to control for time-invariant unobservables that vary between counties, and year fixed effects ϕ_t to capture price variations over years. The farmland market is a tight market with limited transactions (Zhang, 2016). In our dataset, across all 12 states, the average annual count of farmland transactions per census tract is around 5. Consequently, to allow enough within variations after fixed effects controls, we employ county fixed effects instead of census tract fixed effects in our estimation. ε_{it} is the error term. The standard errors are clustered at the county level to account for the potential spatial correlation between farmland parcels within one county.

Imposing a linear specification can be misleading considering that the impacts of proximity to TMLs decay as the distance to the nearest TML increases. Based on the results of Panel A of Figure 3, we use the distance bands of 0-2 km, 2-5 km, and 5-8 km in one regression since the impacts vary at these distance bands, with the distance band 8-11 km as the base group.[14] The regression model is specified as follows:

$$\log\left(F_{it}\right) = \beta_0 + \beta_1 B_{0-2km,it} + \beta_2 B_{2-5km,it} + \beta_3 B_{5-8km,it} + \mathbf{X}_i\gamma + \delta_c + \phi_t + \varepsilon_{it} \tag{2}$$

where the $B_{0-2km,it}$, $B_{2-5km,it}$, and $B_{5-8km,it}$ are the distance bands of 0-2 km, 2-5 km, and 5-8 km, respectively. For example, if the distance to the nearest TML is 1.6, then $B_{0-2km,it} = 1$, and other distance bands equal to zero. The other variables in Equation (2) are same as those in Equation (1).

[14] We thank the editor for this valuable suggestion.

3.3 Housing value model

The location of TMLs may be endogenous (Shokri Gazafroudi et al., 2022) especially in the housing value regressions. The endogeneity of TMLs sitings would cause downward bias because of the disproportionate siting of TMLs in poorer neighborhoods. To mitigate this concern, we add fine-scale spatial fixed effects and only leverage variations in the same neighborhood[15] where "neighborhood quality" is relatively homogeneous within the spatial unit controlled by the fixed effects model (Ciccone, 2002; Von Graevenitz and Panduro, 2015; Addison et al., 2022). The time-invariant price differences between different neighborhood communities are then absorbed by the fixed effects. The plausibility of the fixed effects estimator depends on there being no unobserved time-varying confounders after the set of controls is included.

Specifically, our fixed effects regressions control for time-invariant neighborhood characteristics at the census tract level. A census tract is small enough that residents are more or less similar in important social-economic characteristics. Nonetheless, the fixed effects control still retains significant variations in the proximity to TMLs. Our samples show that the minimum and maximum distance to the TMLs could be quite different across different census tracts. For example, in some tracts most houses are located within a 2 km radius of a TML while in others most houses are located over 10 km away. When checking variations in the proximity to TMLs within census tracts, the average difference between the maximum and the minimum distances to TMLs is around 2.5 km with a standard deviation of 2.6 km, which provides enough variations for estimation.[16]

We restrict the sample to limit houses within 3 km of TMLs based on results in Panel B of Figure 3. The baseline model that estimates the effects of TMLs on housing property values is specified as:

$$\log(H_{it}) = \alpha_0 + \alpha_1 line_{it} + \mathbf{Z}_i\eta + \delta_s + \phi_t + \varepsilon_{it} \tag{3}$$

[15]The neighborhood means census tract in our context. The census tract data come from Census Bureau and can be found at `https://www.census.gov`. According to its definition, a census tract is a small, relatively permanent statistical subdivision of a county delineated by a local committee of census data users for the purpose of presenting data. Designed to be relatively homogeneous units with respect to population characteristics, economic status, and living conditions at the time of establishment, census tracts average about 4,000 inhabitants. Literature such as Tang et al. (2020) also applied census tracts as spatial fixed effects for analysis.

[16]Although our pooled regressions results using block group fixed effects remain robust as shown in Columns (1)-(3) of Table B3 in the appendix, we did not add block group fixed effect because (i) the average number of observations within block groups is around 100, which is far less than the 300 average in census tracts; (ii) the within variation in block groups is much smaller than in census tracts, as the difference of maximum and minimum distances to TMLs is only around 1 km with standard deviation 1.3 km, which may not give us enough variations to precisely estimate the effect.

Similar to Equation (2), we specify the distance bands to capture the nonlinear effects of TMLs on housing prices based on the results in Panel B of Figure 3. We use the distance bands of 0-0.5 km, 0.5-1 km, 1-1.5 km, and 1.5-2 km, with the distance band 2-3 km as the base group. The regression model is specified as follows:

$$\log(H_{it}) = \beta_0 + \beta_1 B_{0-0.5km,it} + \beta_2 B_{0.5-1km,it} + \beta_3 B_{1-1.5km,it} + \beta_4 B_{1.5-2km,it} + \mathbf{Z}_i \eta + \delta_s + \phi_t + \varepsilon_{it} \quad (4)$$

where the $B_{0-0.5km,it}$, $B_{0.5-1km,it}$, $B_{1-1.5km,it}$, and $B_{1.5-2km,it}$ are the distance bands of 0-0.5 km, 0.5-1 km, 1-1.5 km, and 1.5-2 km, respectively. For example, if the distance to the nearest TML is 1.6, then $B_{1.5-2km,it} = 1$, and other distance bands equal to zero. The other variables in Equation (4) are same as those in Equation (3).

4 Empirical Results

In this section, we first report the estimates of the impacts of TMLs on property values, and then explore nonlinear relationship by adding distance bands based on the spatial extent identified in Section 3.1 and test whether the effects of TMLs depend on the local potential of constructing renewable energy facilities by using wind resources as a proxy variable for the potential.

4.1 Effects on farmland values

As shown in Column (1) of Table 2, proximity to transmission lines significantly increases farmland sales prices. On average, being 1 km closer to the nearest TML in the radius of the spatial extent (i.e., 11 km) increases values by approximately 1.04%(=exp(-0.0105)-1), holding everything else constant. The average distance for the 25$^{\text{th}}$ percentile and 75$^{\text{th}}$ percentile is 1.21 km and 5.59 km, with a difference of 4.38 km.[17] This difference suggests that holding everything else constant, if a farmland parcel located at the 75$^{\text{th}}$ percentile of the distance to TMLs (5.59 km) moved to the 25$^{\text{th}}$ percentile (1.21 km), its value increases by 4.71%(=exp((-0.0105)$\times$(-4.38))-1). Several factors might explain this positive effect. First, farmers might expect the option values from the construction of renewable energy facilities and receive compensation, as renewable energy facilities

[17] Additional statistics for these distance variables are displayed in Table B5.

are generally built near TMLs.[18] Second, proximity to transmission lines is crucial for adopting new technologies, particularly for agricultural operations in rural areas with limited power grid support. Grid failures can leave these operations without power for hours or days.[19] To integrate innovative equipment, such as precision agriculture tools, into the power grid, they must be connected via transmission lines (Wall, 2001). Farms located far from transmission lines may not have sufficient power for certain technologies and installing TMLs can be prohibitively expensive. Therefore, farms in close proximity to TMLs are better placed to adopt new technology due to convenient grid access.

The nonlinear estimates pertaining to the impacts of TMLs on farmland values within the spatial extent, identified in Section 3.1, are presented in Column (2) of Table 2. The findings reveal that, in comparison to the prices of farmland parcels in proximity to the nearest TML within the 8-11 km range, farmland prices located closest to TMLs in the 0-2 km range exhibit a premium of 10.98% (=exp(0.1042)-1). This premium gradually attenuates to 8.58% (=exp(0.0823)-1) as the distance band extends to 2-5 km and further decreases to 5.57% (=exp(0.0542)-1) as the distance increases to 5-8 km.

Most control variables are correlated with farmland values, consistent with our expectations as shown in Column (1) of Table B4. Being close to urban areas and the larger population in the urban areas creates a premium for farmland, which confirms findings in the existing literature (Chicoine, 1981; Huang et al., 2006; Kuethe et al., 2011; Zhang and Nickerson, 2015). Not surprisingly, land quality measures, including land percentage tillable and average NCCPI for agriculture, are positively associated with farmland sale prices. Locating near a highway or railway could increase farmland values due to lower transportation costs. Being close to biodiesel or a grain warehouse could also reduce transportation costs, thus increasing farmland values. However, being close to a body of water may have a high risk of flooding (Chicoine, 1981; Wang, 2021) and lowers farmland values.

We further explore the synergy of TMLs and the construction potential of renewable energy because TMLs may interact with renewable energy facilities and have a synergy effect on farmland prices. We utilize wind resources to capture the potential of renewable energy because of two

[18] Examples of farmers who received compensation from solar and wind turbine construction projects can be found in the following sources: https://tinyurl.com/47bvuzyf and https://www.gao.gov/assets/gao-04-756.pdf.

[19] For more details, see https://cpower.com/2021/11/30/reliable-power-is-critical-for-agriculture/.

reasons. First, the Midwest is one of the major suppliers of wind energy, accounting for 27% in the U.S. due to the region's open plains and the high wind speed. Second, existing literature shows that wind potential is an effective instrument for capturing the potential of wind energies (Kaffine, 2019; Zou, 2017). We do not choose solar resources because the adoption of agrivoltaics and utility-scale solar farms in the Midwest is still low (Hoff and DeVilbiss, 2017). To test whether the TMLs effects differ depending on the wind potential, we add to Equation (1) a set of interaction terms between the three distance bands with a dummy denoting whether located at high wind areas.

We define high-wind areas as places with 7 meter/second of wind or above at an elevation of 100 meters. As well as aligning with the fact that experimental data indicates that seven meters per second achieves optimal efficiency (Xu and Zha, 2021), this speed cutoff is consistent with our empirical observation that 83.2% of all wind turbines in the Corn Belt are installed in an area with a wind speed above it. This practice enables us to obtain an estimated farmland sales price differential among these four categories based on proximity to the TMLs and wind resources.

As presented in Column (3) of Table 2, a comparison between farmland properties in the reference group, located within a range of 8-11 km from the nearest TML, and those situated within the 0-2 km radius reveals a noteworthy difference. Farmlands within the 0-2 km proximity exhibit a price premium of 8.26% (=exp(0.0794)-1) when compared to the base group. For farmlands within the 0-2 km range from the nearest TML, the sale price of farmland located in high-wind areas registers an even higher premium, standing at 3.10% (=exp(0.0794+0.0844-0.0539-0.0794)-1), in contrast to those located in low-wind areas, holding all other variables constant. This result underscores the presence of substantial wind option values associated with farmland in close proximity to TMLs, particularly in light of potential wind resources. As expected, the wind option values exhibit a diminishing trend as the distance band expands to 2-5 km and subsequently to 5-8 km. This trend is evident through the reduced magnitude and declining statistical significance of the other two interaction terms as presented in Column (3).

4.2 Effects on housing property values

Our results suggest significant disamenity effects as shown in Column (1) in Table 3. If a house is 1 km closer to the nearest TML in the radius of the spatial extent (i.e., 3 km) identified in Section 3.1, its housing price decreases by 2.74%(=exp(0.0270)-1) on average, holding everything else constant. The distance to the nearest TML for the 25^{th} percentile and 75^{th} percentile is 0.53 km and 1.80 km as shown in Panel B of Table B5, with a difference of 1.27 km, suggesting that holding everything else constant, if a house located at the 25^{th} percentile of the distance to TMLs moved to the 75^{th} percentile, its value increases by 3.49%(= exp(0.0270×1.27)-1).

The influence of TMLs on housing property values reveals nonlinear patterns within the spatial extent, identified in Section 3.1. As presented in Column (2) of Table 3, compared to houses within a 2-3 km radius of TMLs, houses within 0-0.5 km range experience a 5.20% (=exp(-0.0534)-1) price decrease. This negative effect diminishes as the distance band extends to 0.5-1 km, reaching a value of 3.44% (=exp(-0.0350)-1), which further decreases to 1.73% (=exp(-0.0175)-1) as the distance band encompasses the range of 1-1.5 km. As the distance band expands to 1.5-2 km, the disamenity effect becomes considerably attenuated in magnitude, registering a mere 0.92% (exp(-0.0092)-1), and is only marginally significant.

In column (2), Table B4, we find a larger lot size, more stories, rooms, bedrooms, and full baths increase housing property values significantly. The age of housing properties has a negative influence on housing property values, potentially attributable to various factors including escalated maintenance expenses, absence of contemporary amenities, possible safety apprehensions, and outdated architectural designs prevalent in older properties.[20]

As depicted in Column (3) of Table 3, among the four interactions with the high wind dummy, only the interaction between distance band 0-0.5 km and located in a high wind area is statistically significant at 10% level. An examination between houses in the reference group situated within a distance of 2-3 km from the nearest TML, and those positioned within the 0-0.5 km radius exhibit a discernible disamenity effect of 4.95%(=exp(-0.0508)-1) in comparison to the reference group. For

[20] Note that empirical evidence suggests a U-shaped relationship between the age of housing property and housing prices, with a turning point estimated to occur around 500 years. However, the maximum age observed within our sample is 318 years, thereby implying a negative impact of age on housing property prices within the age range examined. Importantly, our findings hold robust when excluding the squared term of age in the analysis.

residences falling within the 0-0.5 km range from the nearest TML, the sale prices of houses situated in high-wind areas exhibit an even more pronounced disamenity effect, totaling 2.83%(=exp(-0.0508-0.0316+0.0029-(-0.0508))-1), relative to their counterparts in low-wind areas, all else being equal. This interaction term implies that the adverse consequences stemming from proximity to TMLs on housing prices are exacerbated in regions characterized by heightened wind speeds. We posit that the amplified disamenity effects observed in high-wind areas may be attributed to an increased susceptibility to wind-related natural disasters. These events, including the potential collapse of TMLs, can have cascading effects on neighboring housing properties. Notably, several states in our study regions are susceptible to tornadoes.[21]

5 Heterogeneity and Robustness Checks

We conducted a series of heterogeneous analyses and robustness checks to test whether our results are sensitive to different econometric specifications and remain robust in subsamples.

5.1 Heterogeneity across urban and rural properties

Urban and rural properties may have different responses to the influence of TMLs. In the farmland case, renewable energy facilities such as wind turbines are generally located in rural areas (Grieser et al., 2015), so the premium related to renewable energy might only show up or dominate in rural farmland parcels. For residential housing prices, although both urban and rural homeowners might have concerns about the aesthetics and visual disamenities of TMLs, we conjecture that rural residents could value the convenience of improved access to electricity and associated energy cost savings.[22] Therefore, we test for the heterogeneous influence of TMLs across urban and rural properties.

As depicted in Column (4) of Table 2, the coefficients associated with the interaction terms

[21] Please refer to a ranking of tornado risks by state at http://www.usa.com/rank/us--tornado-index--state-rank.htm.

[22] American Council for Energy Efficient Economy shows that overall, Americans living in rural areas spend a disproportionally high share of their income on energy bills. Rural households have a median energy burden of 4.4%, compared to the national burden of 3.3% (Ross et al., 2018).Note that the 2010 Census Urban and Rural Classification defines an urban area as an area with a population of 50,000 or more people, while an urban cluster consists of at least 2,500 and less than 50,000 people. This information could be found at https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural/2010-urban-rural.html. The remaining areas are designated as rural.

between distance bands and the urban county dummy variables exhibit a consistently negative sign, although not statistically significant at a 10% level. These results provide weak evidence suggesting that the implementation of renewable energy infrastructure, such as wind turbines, in the Midwest might have the potential to generate additional value for farmers in rural areas. But this premium is not statistically different from farmland parcels located in urban county.

The impact of TMLs on housing sales prices displays substantial variations between urban and rural contexts based on Column (4) of Table 3. For houses located within the 0-0.5 km range from the nearest TML, prices of urban houses decrease by 2.90% (=exp(-0.0294)-1) when compared to their rural counterparts. Similar patterns in urban houses are also observed in the distance bands of 0.5-1 km and 1-1.5 km. The heterogeneous effects of TMLs across urban and rural samples suggest the importance of distinguishing the effects of TMLs in different regions when conducting an impact evaluation. For example, residents in urban areas should be compensated more than those in the rural areas.

5.2 Additional measures of transmission lines

We developed several additional measures for TMLs to enhance our understanding of their impacts on property values. For farmland, we calculate the number of TMLs within each distance band and then generate a dummy variable, indicating whether two or more TMLs exist within each band. Subsequently, we interact these dummy variables with the distance bands to investigate whether the presence of two or more TMLs within the same distance band generates additional premiums for farmlands. The results are summarized in Column (5) of Table 2, revealing that for farmlands with the nearest TML in the 0-2 km range, those with two or more TMLs within this band command prices that are 8.98% higher (=exp(0.0860)-1) than comparable ones with only one TML. Additional premiums stemming from the presence of two or more TMLs are also observed in the distance bands of 2-5 km and 5-8 km with a smaller magnitude. Furthermore, we employ another measure that takes into account whether a transmission line crosses the farmland parcel itself, which could bring challenges for farming activties especially during maintenance and repair of TMLs (Sardaro et al., 2018). Our results indicate that this measure exerts a negative influence on farmland values but does not attain statistical significance, as demonstrated in Column (6) of Table 2.[23]

For housing properties, we calculate the number of TMLs within each distance band and generate a dummy variable, indicating whether two or more TMLs exist within each band. We then interact these dummy variables with the distance bands to investigate whether the presence of two or more TMLs within the same distance band generates additional disamenities for houses. Our results, summarized in Column (5) in Table 3, reveal that having two or more TMLs does not seem to bring additional, statistically significant disamenity effects on housing prices. The coefficient of the interaction term within the band 1-1.5 km is the only significant one among all interactions. However, we note that the same distance band is not significant when we allow for differential impacts due to the presence of two or more TMLs.

5.3 Subsample analysis

We explore whether TMLs' effects on both farmland values and housing prices are heterogeneous across regions. We divide states in the Midwest into three categories by geographic proximity and similarity: (i) I-states (Iowa, Illinois, and Indiana)[24]; (ii) Lake states (Wisconsin, Michigan, Ohio, and Minnesota); and (iii) Great plains states (Nebraska, South Dakota, North Dakota, Missouri, and Kansas). We observe significant heterogeneities in these regions as shown in Columns (1)-(3) in Table 4 and Columns (1)-(3) in Table 5.

Results in Columns (1) to (3) of Table 4 confirm the findings that the premium associated with farmland proximity to TMLs is not uniform across distance bands. For instance, the coefficient associated with the distance band of 0-2 km is estimated at 0.1518 for great plain states, and this figure is 0.1226 and 0.0806 for the band of 2-5 km and 5-8 km, respectively. Moreover, comparing results among columns (1) to (3) also highlight regional disparities in the premium. Specifically, while the premium in the Lake states is relatively small and statistically insignificant, the Great Plains region consistently exhibits higher premiums, indicating that TMLs have a more pronounced

[23]We thank one reviewer for suggesting conducting a regression analysis of bifurcation on plot-level yield would enable us to test whether farmlands with TMLs running through have lower yields. Unfortunately, we do not have access to plot-level yield data for the farmlands in FarmlandFinder at present, which restricts us from conducting such analysis.

[24]"I-states" typically refers to the three Midwestern agricultural states whose names begin with the letter "I": Illinois, Indiana, and Iowa. They are often grouped together due to their proximity and similar agricultural economies, etc. Basha et al. (2021) and Chen et al. (2022) use similar group in their analysis.

positive effect on farmland values. The higher premium for Great Plain states' farmlands could be because energy infrastructure investment is larger in these states.[25] This observation underscores the importance of considering regional variation when assessing the impact of TMLs on farmland prices, with a clear indication that areas with greater energy infrastructure investments tend to experience more substantial premiums.

We observe significant disamenity effects of TMLs on housing prices in both I-states and Lake states. The coefficients of the distance band of 0-0.5 km for I-states and Lake states amount to -0.0612 and -0.0550, respectively, and are both significant at a 1% level. The disamenity effects in I-states and Lake states might stem from the higher population densities within these states compared to great plain states[26], which conceivably lead to greater proximity between residential dwellings and TMLs, thereby intensifying the influence of any potential disamenity effects. The presence of more natural amenities in I-states and Lakes states compared to great plain states might help explain the stronger visual disamenity effects of TMLs. The Major Land Uses database maintained by USDA Economic Research Service shows that I-states and Lakes states have more parks and wilderness areas in percentage of total land use.[27]

Our results suggest disamenity effects of TMLs within the housing market of the Great Plains are not statistically significant, which could be attributed to the sparser population distribution characteristic of the Great Plains, potentially resulting in reduced sensitivity to disamenity effects. Furthermore, great plain states have been a hot spot for other energy infrastructure investments according to U.S. Energy Information Administration (EIA)[28], including intrusive shale gas projects[29], and we conjecture that this potentially makes TMLs less visually disturbing.

5.4 Heterogeneity across TML voltages

We also explore the heterogeneous effects of electricity transmission lines across various voltages. According to the EFE-PORTAL, we define transmission lines below 150 KV as low class and the

[25]The state ranking of the energy infrastructure investment in the U.S. refers to https://www.usnews.com/news/best-states/rankings/infrastructure.

[26]The state ranking of the population density in the U.S. refers to https://wisevoter.com/state-rankings/population-density-by-state/.

[27]More details about the database could be found at: https://www.ers.usda.gov/data-products/major-land-uses/maps-and-state-rankings-of-major-land-uses/.

[28]More details related to energy infrastructure investment refers to https://www.eia.gov/maps/maps.php.

[29]A report on the invasiveness of shale gas can be found in https://www.theguardian.com/environment/2013/dec/14/fracking-hell-live-next-shale-gas-well-texas-us.

ones above 150 KV as high class.[30] For farmland values, although both high-voltage and low-voltage TMLs have premiums for farmland values, the low-voltage ones have a larger magnitude (as shown in Column (4)-(5), Table 4) possibly because high-voltage TMLs are generally more noticeable and taller, have more structures, and occupy more land, resulting in a visual disamenity (Devine-Wright and Batel, 2013; Sardaro et al., 2018). In addition, high-voltage TMLs are often associated with perceived risks, including possible adverse health effects (Bickel et al., 2005). Thus, these adverse effects associated with high-voltage TMLs might have offset part of the premium of TMLs for farmland values. As shown in Columns (4) and (5) of Table 5, we do not find a significant difference in the disamenity effects of TMLs on housing values.

5.5 Robustness checks using repeat sales samples

We further explore the repeat sales samples to account for house-specfiic, time-invariant unobservables using house fixed effects. However, the TML dataset lacks information on the installation dates of transmission lines, which prevents us from measuring variations in distance to TMLs for each transaction of the same property. As a result, proximity effects are captured by the time-invariant distance measures to TMLs, making it difficult to use repeat sales to measure the impact of TML proximity. To address this concern, we have searched for information on the average age of TMLs, and find that according to the White House, more than 70% of the U.S. electricity grid is over 25 years old. Additionally, from 2013 to 2020, TML expansion has only grown by approximately 1% per year, which indirectly suggest that the installation of new TMLs during our analysis period is rare, thus minimizing the potential impact of new installations.

Although we cannot conduct the repeat sales analysis linking changes in housing prices with changes in TML proximity, we conduct a robustness check of our main distance bands specification using only houses that comprise the repeat sales samples. The results are summarized in Columns (4)-(6) of Table B3, which shows that our findings remain robust in these samples.

[30]For more details, see https://www.emf-portal.org/en/emf-source/76.

6 Conclusion

The U.S. is making a substantial investment in electricity transmission lines in the next few years. The impacts of TMLs on property values are still opaque, and the renewed efforts to modernize and upgrade the electricity grid might shift property owners' perceptions of nearby TMLs. Existing literature often ignores the effects of TMLs considering the influence of option value from the potential of renewable energy. This paper addresses the research gap by combining multiple datasets including Zillow housing sales data, farmland sales data, satellite data on wind resources, land characteristics data, and some other supplementary datasets to explore the capitalization effects of TMLs on both farmland and housing property values.

We reaffirm the disamenity effects of TMLs on residential property values, which is especially stronger for urban houses than houses located outside urban areas. These results imply that urban residents shoulder a more substantial burden of negative spillover effects arising from the construction and operation of TMLs.

Our paper provides novel and contrarian evidence on the impacts of TMLs on farmland sales prices. Different from the null effects in the literature, we find proximity to transmission lines creates positive values for farmland owners, especially for those owning parcels with abundant wind resources, which can be capitalized into higher land prices. Similar results were also found in Abashidze and Taylor (2022), which explores the effects of the construction of solar farms on agricultural land values; they found the price of farmland near TMLs slightly increases after the construction of solar farms.

The contrarian evidence on farmland values offered here highlights the evolution of TMLs' influence on property values. Existing literature generally finds disamenity effects of TMLs due to their interruption of agricultural production, their unaesthetic appearance, and potential health risks and hazards. Recent literature largely found null effects of TMLs, possibly because of farmers' and residents' adaptation to TMLs in terms of agricultural production, aesthetic adjustment, and scientific cognition. Our results provide new results different from the disamenity and null effects, possibly due to the option value from the renewable energy, convenient and less-costly access to reliable electricity supply for precision agriculture, and more electric appliances like electric cars.

These results inspire us to evaluate TMLs from a dynamic and heterogeneous perspective.

Our results also provide insights into the construction and siting of TMLs. Considering the disamenity effects on urban housing properties, the metropolitan areas are better off adopting underground transmission lines to reduce the strong disamenity effects of TMLs on housing property values. Our results suggest that farmland prices especially in rural counties enjoy premiums from being close to TMLs, so the cheaper overhead TMLs may be a viable option in rural areas.

Our paper suggests two directions for future research. First, many TMLs were constructed before 2015, which marks the start of our study period, and this prevents us from analyzing property values before and after the establishment of TMLs. Therefore, future research could leverage temporal variations to improve the estimation of the treatment effect of TMLs using historical transactions. Second, we did not distinguish the farmland parcels close to existing wind turbines from those without; instead, our estimation focused on the wind resources potential. Incorporating the wind turbines' locations data could separate the anticipation effects of future turbine constructions on farmland values.

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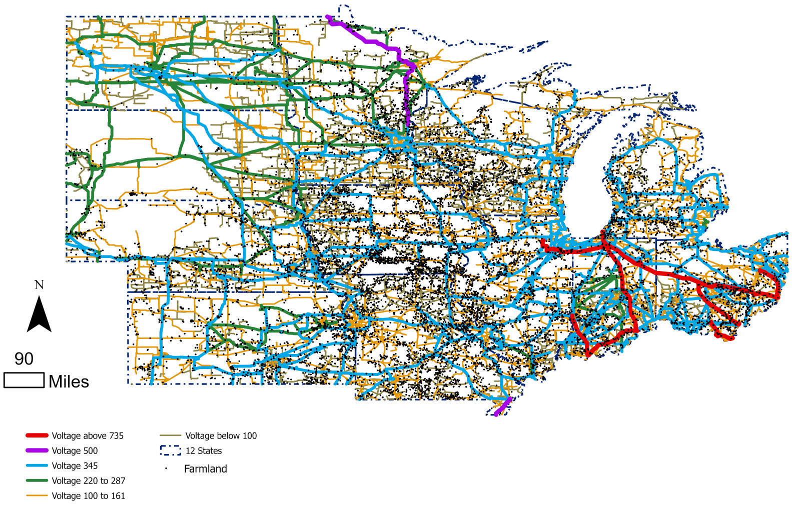
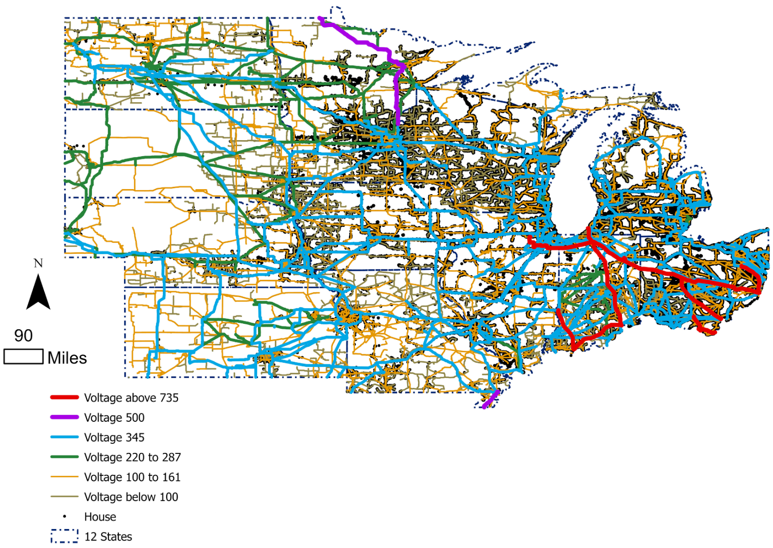
Main Figures

Figure 1: Spatial Distribution of Farmland Sales and Residential Housing Sales in Twelve Midwestern States



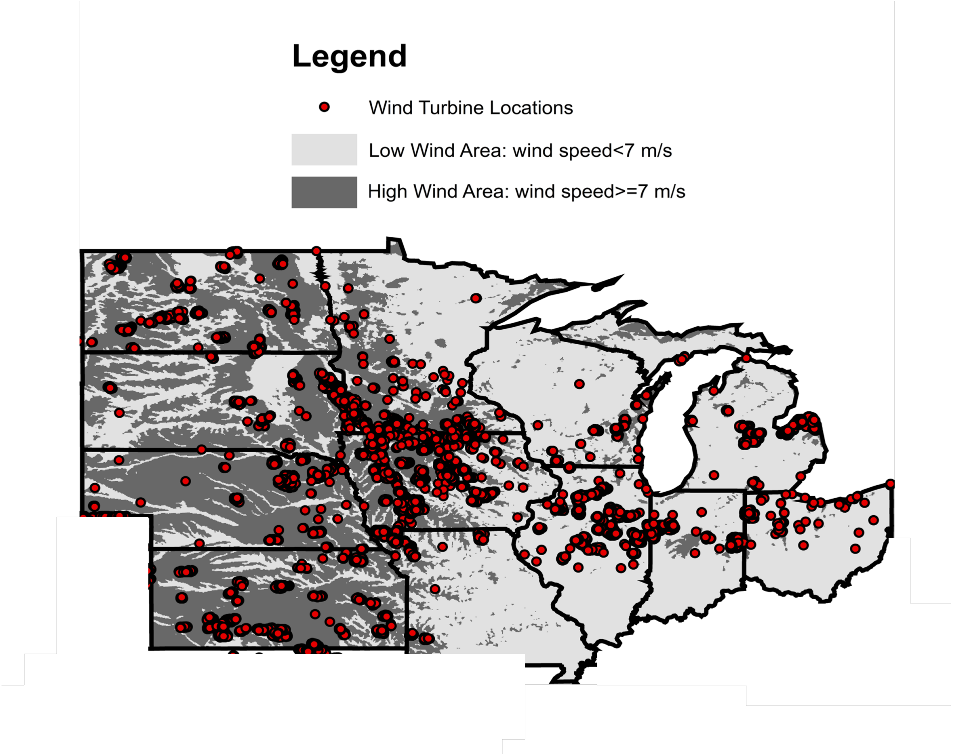
(a) Spatial Distribution of Arm's Length Farmland Sales



(b) Spatial Distribution of ZTRAX Single-Family Residential Housing Sales

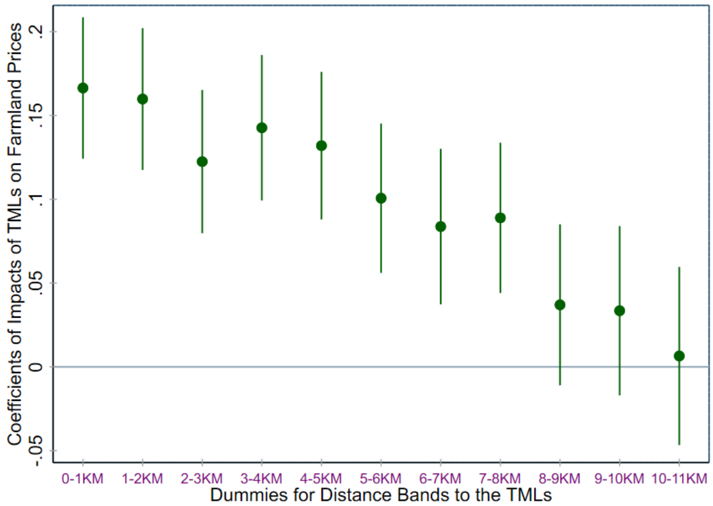
Note: Panel (a) of this figure indicates the geographical location of farmland parcels in 12 Midwestern states and the transmission lines by voltages. The black dot represents the farmland and the lines are transmission lines. The red lines indicate the transmission lines with the highest voltage while the brown ones have the lowest voltage. This dataset is from FarmlandFinder, a startup company now acquired by Growers Edge. Panel (b) of this figure indicates the geographical location of houses in 12 states and the transmission lines by voltages. The black dot represents the house and the lines are transmission lines. The red lines indicate the transmission lines with the highest voltage while the brown ones have the lowest voltage. This dataset is from the Zillow ZTRAX database.

Figure 2: Spatial Distribution of Wind Speed at 100-meter Hub Height with Existing Wind Turbines

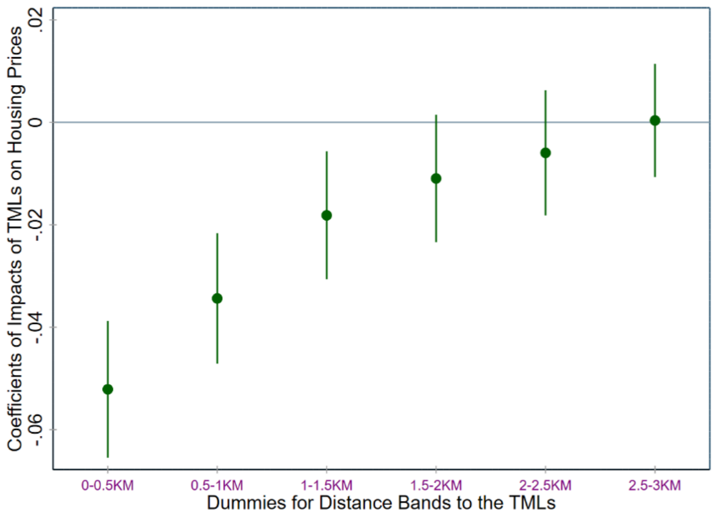


Note: This figure presents the geographical location of wind turbines and the wind speed spatial distribution in the Midwest. The red dot indicates the wind turbine. The light gray area represents the low-wind area with wind speed lower than 7 m/s. The dark gray is the high-wind area with wind speed above 7 m/s.

Figure 3: Nonlinear Effects of Proximity to TMLs on Farmland Values and Housing Property Values



(a) Nonlinear Effects of Proximity to TMLs on Farmland Prices



(b) Nonlinear Effects of Proximity to TMLs on Housing Prices

Note: Panel (a) of this figure depicts the impact of proximity to electricity transmission lines (TMLs) on farmland prices, highlighting a nonlinear pattern. The x-axis represents distance bands to TMLs, ranging from 0-1 km to 10-11 km, with the base band being beyond 11 km. The y-axis displays the coefficients indicating the impact of proximity to TMLs on farmland prices. This figure shows that closer proximity to TMLs has a stronger positive impact on farmland values. The magnitude of the positive impact diminishes as the distance from TMLs increases; the positive effect disappears when the distance goes beyond 8 km. Panel (b) of this figure depicts the impact of proximity to TMLs on housing prices, exhibiting a nonlinear pattern as well. The x-axis represents distance bands to TMLs, ranging from 0-0.5 km to 2.5-3 km, with the base band being beyond 3 km. The y-axis displays the coefficients indicating the impact of proximity to TMLs on housing prices. This figure shows that closer proximity to TMLs has a stronger negative impact on housing values. The magnitude of the negative impact diminishes as the distance from TMLs increases. This negative effect is only significant at the 90% level when the distance is within 1.5 km.

Main Tables

Table 1: Summary Statistics

Variables	Unit	Mean	Std.dev.	Min	Max
Panel A: Farmland					
Farmland price	dollars/acre	5,667.90	3,988.30	520.00	28,500.00
Distance to the nearest TML	km	3.66	2.92	0.00	11.00
Distance band (0-2 km)	1=yes; 0=no	0.38	0.48	0.00	1.00
Distance band (2-5 km)	1=yes; 0=no	0.33	0.47	0.00	1.00
Distance band (5-8 km)	1=yes; 0=no	0.18	0.39	0.00	1.00
Located in high wind areas (>7 m/s)	1=yes; 0=no	0.28	0.45	0.00	1.00
Gross acres	×100	1.27	2.48	0.10	99.21
Land percentage tillable	[0,1]	0.77	0.41	0.00	1.00
Average NCCPI for agriculture	[0,1]	0.42	0.18	0.00	0.81
% of prime farmland	[0,1]	0.23	0.27	0.00	1.00
Soil texture: % of clay	[0,1]	0.00	0.04	0.00	1.00
Soil texture: % of silt	[0,1]	0.00	0.02	0.00	0.83
Soil texture: % of loam	[0,1]	0.12	0.24	0.00	1.00
Average land slope	degree	7.95	7.83	0.00	55.00
Whether in urban county	1=yes; 0=no	0.53	0.50	0.00	1.00
Population in urban areas	count (×10000)	6.10	15.88	0.00	263.74
Distance to highway	m (×10000)	0.39	0.39	0.00	3.80
Distance to railway	m (×10000)	0.95	0.95	0.00	9.93
Distance to body of water	m (×10000)	0.32	0.29	0.00	2.56
Distance to biodiesel	m (×10000)	10.88	6.78	0.05	44.88
Distance to grain warehouse	m (×10000)	1.43	1.70	0.01	19.81
If TMLs across farmland	1=yes; 0=no	0.07	0.26	0.00	1.00
Two or more TMLs (0-2 km)	1=yes; 0=no	0.20	0.40	0.00	1.00
Two or more TMLs (2-5 km)	1=yes; 0=no	0.36	0.48	0.00	1.00
Two or more TMLs (5-8 km)	1=yes; 0=no	0.47	0.50	0.00	1.00
Panel B: Housing					
House transaction price	dollars (×1000)	181.68	157.84	1.00	1900.00
Distance to the nearest TML	km	1.20	0.80	0.00	3.00
Distance band (0-0.5 km)	1=yes; 0=no	0.24	0.43	0.00	1.00
Distance band (0.5-1 km)	1=yes; 0=no	0.23	0.42	0.00	1.00
Distance band (1-1.5 km)	1=yes; 0=no	0.19	0.39	0.00	1.00
Distance band (1.5-2 km)	1=yes; 0=no	0.15	0.35	0.00	1.00
Located in high wind areas (> 7 m/s)	1=yes; 0=no	0.08	0.27	0.00	1.00
Whether in urban area	1=yes; 0=no	0.84	0.37	0.00	1.00
Age	years	55.48	28.90	0.00	318.00
Lot size	square feet (x1000)	43.57	143.56	1.00	1,742.40
No. of stories	count	1.39	0.50	0.50	5.00
No. of total rooms	count	4.99	2.78	0.00	14.00
No. of total bedrooms	count	2.84	1.02	0.00	8.00
No. of full bath	count	1.51	0.63	0.00	4.00
Two or more TMLs (0-0.5 km)	1=yes; 0=no	0.16	0.37	0.00	1.00
Two or more TMLs (0.5-1 km)	1=yes; 0=no	0.15	0.36	0.00	1.00
Two or more TMLs (1-1.5 km)	1=yes; 0=no	0.24	0.43	0.00	1.00
Two or more TMLs (1.5-2 km)	1=yes; 0=no	0.28	0.45	0.00	1.00

Note: This table presents the descriptive statistics for farmland and housing samples. In total, there are 16,026 observations in the farmland dataset and 1,905,280 observations in the housing dataset.

Table 2: Effects of Proximity to TMLs on Farmland Values

Dependent variable	Log of farmland prices					
	(1)	(2)	(3)	(4)	(5)	(6)
Distance to the nearest TML	-0.0105***					
	(0.0022)					
Distance band (0-2 km)		0.1042***	0.0794***	0.1085***	0.0681***	
		(0.0209)	(0.0237)	(0.0283)	(0.0224)	
Distance band (2-5 km)		0.0823***	0.0635***	0.0846***	0.0520**	
		(0.0194)	(0.0218)	(0.0262)	(0.0209)	
Distance band (5-8 km)		0.0542***	0.0310	0.0715***	0.0267	
		(0.0193)	(0.0224)	(0.0245)	(0.0229)	
Distance band (0-2 km) × High wind			0.0844*			
			(0.0464)			
Distance band (2-5 km) × High wind			0.0612			
			(0.0442)			
Distance band (5-8 km) × High wind			0.0757*			
			(0.0440)			
Located at high wind areas			-0.0539			
			(0.0409)			
Distance band (0-2 km) × Urban county dummy				-0.0128		
				(0.0425)		
Distance band (2-5 km) × Urban county dummy				-0.0091		
				(0.0383)		
Distance band (5-8 km) × Urban county dummy				-0.0411		
				(0.0394)		
Distance band (0-2 km) × Two or more TMLs (0-2 km)					0.0860***	
					(0.0175)	
Distance band (2-5 km) × Two or more TMLs (2-5 km)					0.0625***	
					(0.0179)	
Distance band (5-8 km) × Two or more TMLs (5-8 km)					0.0516**	
					(0.0226)	
Whether TMLs across farmland						-0.0231
						(0.0180)
Adj. R-sq	0.424	0.429	0.429	0.429	0.431	0.427
No. of obs.	16,026	16,026	16,026	16,026	16,026	16,026

Note: This table shows the results for the effects of proximity to TMLs on farmland values. The dependent variable is the logarithm of farmland sales prices for all regressions. Column (1) presents the effects of distance to the nearest TML on farmland prices. Column (2) replaces the major explanatory variable with three distance bands based on the results in Panel A of Figure 3. Columns (3)-(5) report the heterogeneous results of impacts of TMLs across wind potential, whether on urban counties, and whether there exist two or more TMLs within each distance band, respectively. Column (6) summarizes the results of an alternative measure (i.e., whether TMLs across farmland) of TMLs' influence on farmland values. We controlled for farmland characteristics, urban influence variables, agricultural profitability influence variables, county fixed effects, and year fixed effects in all regressions. Significance: $* < 0.1, ** < 0.05, *** < 0.01$.

Table 3: Effects of Proximity to TMLs on Housing Property Values

Dependent variable	Log of housing prices				
	(1)	(2)	(3)	(4)	(5)
Distance to the nearest TML	0.0270***				
	(0.0027)				
Distance band (0-0.5 km)		-0.0534***	-0.0508***	-0.0343***	-0.0524***
		(0.0059)	(0.0062)	(0.0077)	(0.0064)
Distance band (0.5-1 km)		-0.0350***	-0.0334***	-0.0152**	-0.0324***
		(0.0055)	(0.0057)	(0.0075)	(0.0057)
Distance band (1-1.5 km)		-0.0175***	-0.0158***	-0.0007	-0.0070
		(0.0051)	(0.0054)	(0.0080)	(0.0061)
Distance band (1.5-2 km)		-0.0092**	-0.0083*	-0.0012	-0.0117**
		(0.0045)	(0.0079)	(0.0047)	(0.0057)
Distance band (0-0.5 km) × High wind			-0.0316*		
			(0.0185)		
Distance band (0.5-1 km) × High wind			-0.0204		
			(0.0175)		
Distance band (1-1.5 km) × High wind			-0.0213		
			(0.0163)		
Distance band (1.5-2 km) × High wind			-0.0124		
			(0.0145)		
Located at high wind areas			0.0029		
			(0.0163)		
Distance band (0-0.5 km) × Urban area dummy				-0.0294***	
				(0.0085)	
Distance band (0.5-1 km) × Urban area dummy				-0.0296***	
				(0.0082)	
Distance band (1-1.5 km) × Urban area dummy				-0.0250***	
				(0.0086)	
Distance band (1.5-2 km) × Urban area dummy				-0.0123	
				(0.0085)	
Distance band (0-0.5 km) × Two or more TMLs (0-0.5 km)					-0.0027
					(0.0057)
Distance band (0.5-1 km) × Two or more TMLs (0.5-1 km)					-0.0068
					(0.0046)
Distance band (1-1.5 km) × Two or more TMLs (1-1.5 km)					-0.0172***
					(0.0056)
Distance band (1.5-2 km) × Two or more TMLs (1.5-2 km)					0.0036
					(0.0061)
Adj. R-sq	0.550	0.550	0.550	0.550	0.550
No. of obs.	1,905,280	1,905,280	1,905,280	1,905,280	1,905,280

Note: This table displays the results for the effects of proximity to TMLs on housing values. The dependent variable is the logarithm of housing property sales prices for all regressions. Column (1) reports the impacts of distance to the nearest TML on housing prices. Column (2) replaces the explanatory variable with distance bands based on the results in Panel B of Figure 3. Columns (3)-(5) present the heterogeneous impacts of TMLs across wind potential, whether in urban areas, and whether there exist two or more TMLs within each band, respectively. We controlled for housing characteristics, census tract fixed effects, and year-quarter fixed effects in all regressions. Significance: $* < 0.1, ** < 0.05, *** < 0.01$.

Table 4: Additional Heterogeneous Analysis of the Impacts of TMLs on Farmland Values

	Regions			Voltage	
Dependent variable	Log of farmland prices				
Subsample	I-states	Lake states	Great plains	$\leq$ 150V	>150V
	(1)	(2)	(3)	(4)	(5)
Distance band (0-2 km)	0.0636***	0.0003	0.1518***	0.1240***	0.0549*
	(0.0216)	(0.0407)	(0.0332)	(0.0244)	(0.0306)
Distance band (2-5 km)	0.0385**	0.0105	0.1226***	0.0824***	0.0599**
	(0.0191)	(0.0383)	(0.0310)	(0.0241)	(0.0289)
Distance band (5-8 km)	0.0240	-0.0224	0.0806**	0.0629***	0.0227
	(0.0221)	(0.0372)	(0.0322)	(0.0222)	(0.0307)
Adj. R-sq	0.394	0.519	0.408	0.432	0.427
No. of obs.	5,744	4,940	5,342	9,072	6,954

Note: This table shows the heterogeneous analysis for farmland values using subsamples categorized by region and voltage, respectively. We controlled for farmland characteristics, urban influence variables, agricultural profitability influence variables, county fixed effects, and year fixed effects in all regressions. Significance: $* < 0.1, ** < 0.05, *** < 0.01$.

Table 5: Additional Heterogeneous Analysis of the Impacts of TMLs on Housing Prices

	Regions			Voltage	
Dependent variable	Log of housing prices				
Subsample	I-states	Lake States	Great Plains	≤150V	>150V
	(1)	(2)	(3)	(4)	(5)
Distance band (0-0.5 km)	-0.0612***	-0.0550***	-0.0324	-0.0561***	-0.0365***
	(0.0134)	(0.0070)	(0.0199)	(0.0061)	(0.0099)
Distance band (0.5-1 km)	-0.0385***	-0.0351***	-0.0247	-0.0369***	-0.0237***
	(0.0119)	(0.0065)	(0.0188)	(0.0056)	(0.0090)
Distance band (1-1.5 km)	-0.0253**	-0.0181***	0.0046	-0.0194***	-0.0058
	(0.0108)	(0.0061)	(0.0175)	(0.0053)	(0.0083)
Distance band (1.5-2 km)	-0.0059	-0.0114**	-0.0031	-0.0093**	-0.0086
	(0.0100)	(0.0052)	(0.0161)	(0.0047)	(0.0075)
Adj. R-sq	0.554	0.537	0.616	0.550	0.551
No. of observations	387,071	1,285,914	232,294	1,665,614	238,551

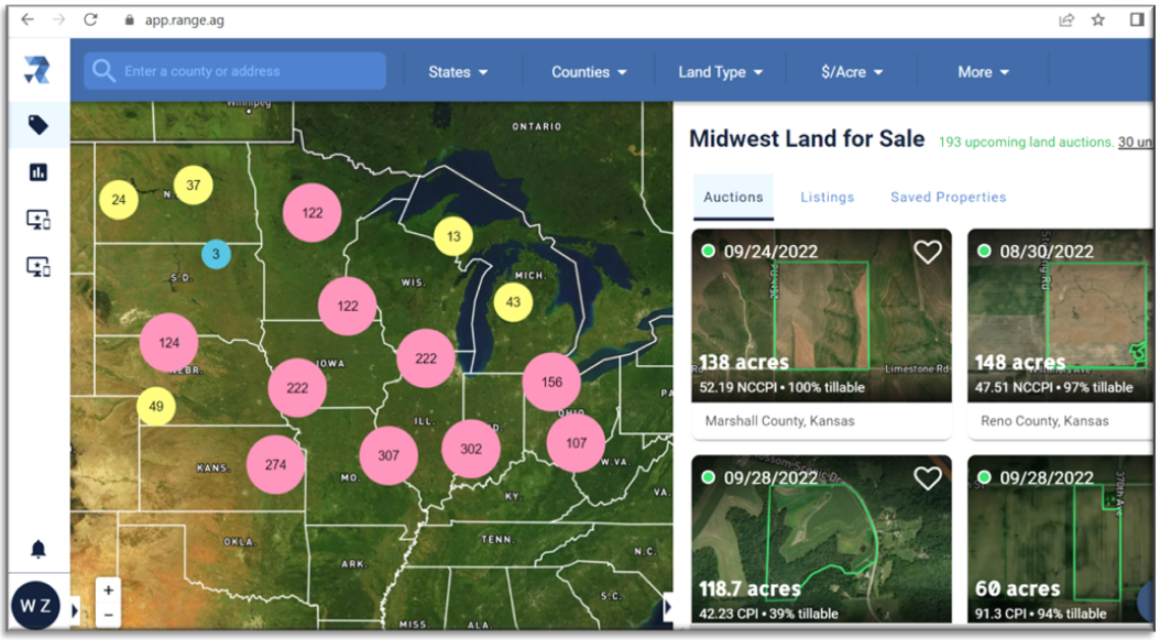
Note: This table shows the heterogeneous analysis for housing prices using subsamples categorized by region and voltage, respectively. We controlled for housing characteristics, census tract fixed effects, and year-quarter fixed effects in all regressions. Significance: $* < 0.1, ** < 0.05, *** < 0.01$.

Online Supporting Information

Disamenity or Premium: Do Electricity Transmission Lines Affect Farmland Values and Housing Prices Differently?

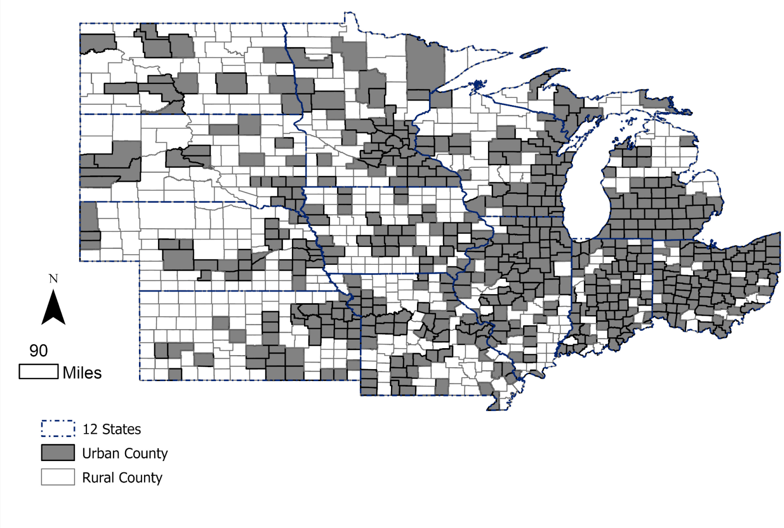
Appendix A: Additional Figures

Figure A1: Screenshot of the FarmlandFinder Website

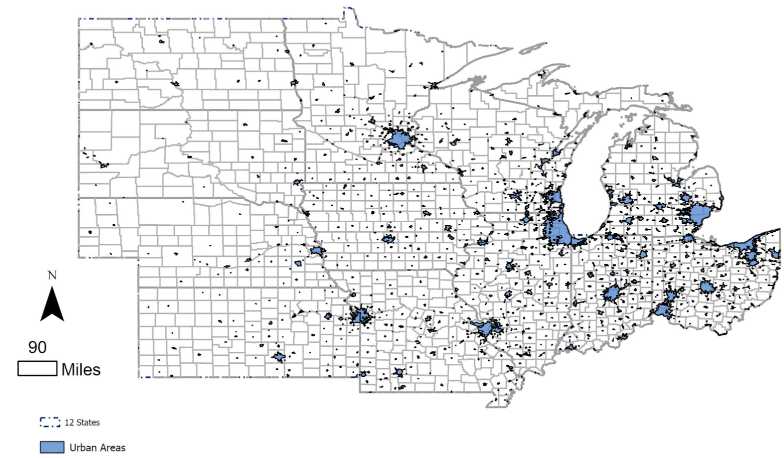


Note: This figure presents the FarmlandFinder website, which is the source of farmland value dataset. It has been acquired by Growers Edge, and is accessible at https://app.range.ag/. It provides detailed information on auction or listing farmland acres, percent of tillables, crop history, and soil productivity index. It also shows the number of farmland parcels for sale in almost all of the Midwest (i.e. 12 states).

Figure A2: Spatial Distribution of Urban and Rural Classifications



(a) Urban and Rural Classification for Farmland Values Analysis



(b) Urban and Rural Classification for Housing Prices Analysis

Note: This figure illustrates the spatial distribution of urban areas within the selected states. Panel A showcases the urban/rural classification for analyzing farmland values, where the dark regions correspond to urban counties, while the white regions correspond to rural counties. Panel B presents the urban/rural classification for analyzing housing prices, with the blue regions representing urban areas and the remaining white regions designated as rural areas.

Appendix B: Additional Tables

Table B1: Housing Characteristics Comparison before and after Imputation

	Before				After			Standardized Difference
	No. of Obs.	Mean	SD	Missing %	No. of Obs.	Mean	SD	
Age	1,234,433	54.59	32.62	35.22	1,905,468	55.48	28.90	0.03
No. of stories	1,094,143	1.38	0.54	42.58	1,905,468	1.39	0.50	0.02
No. of total rooms	939,499	5.00	3.14	50.69	1,905,468	4.99	2.78	0.00
No. of total bedrooms	1,169,295	2.85	1.17	38.63	1,905,468	2.84	1.02	-0.01
No. of full baths	1,101,577	1.53	0.74	42.19	1,905,468	1.51	0.63	-0.03

Note: This table shows the housing characteristics comparisons before and after imputation. Before imputation, data is missing at least 35% for each characteristic. We use block group average, census tract average, county average and state average to impute the missing values. There are no significant differences between samples before and after imputation, and thus there is no obvious data structure change, which implies our imputation method is reliable.

Table B2: The Number of Houses with Missing Housing Characteristics by Spatial Scales and States

Panel A: By area levels			
	Block	Census Tract	County
Age	6,249	2,503	182
No. of stories	7,508	2,874	210
No. of total rooms	18,525	7,181	320
No. of total bedrooms	8,973	3,425	220
No. of full bath	10,570	4,156	307
Total number of obs.	40,564	15,464	686
Panel B: By states			
	MN	IA	IL
Age	62,553	21,700	116,080
No. of stories	94,485	31,782	132,737
No. of total rooms	94,825	35,520	162,075
No. of total bedrooms	54,864	23,698	148,850
No. of full bath	89,185	25,358	131,968
Total number of obs.	212,183	99,510	235,940
	NE	KS	MO
Age	14,080	1,319	17,351
No. of stories	18,605	4,495	29,687
No. of total rooms	59,689	4,239	27,873
No. of total bedrooms	19,632	1,290	27,675
No. of full bath	47,089	1,293	27,675
Total number of obs.	96,460	12,556	93,444
	MI	WI	SD
Age	140,036	194,080	2,495
No. of stories	189,032	195,832	7,147
No. of total rooms	243,692	210,559	2,592
No. of total bedrooms	156,032	188,021	2,549
No. of full bath	158,538	194,058	9,377
Total number of obs.	432,428	239,502	9,428
	ND	IN	OH
Age	6,297	8,608	86,325
No. of stories	9,827	10,396	87,178
No. of total rooms	11,229	12,624	100,923
No. of total bedrooms	10,948	11,898	90,601
No. of full bath	16,301	15,070	85,609
Total number of obs.	18,158	51,622	401,801

Note: This table presents the number of complete missing cells from two different perspectives. Panel A indicates the number of totally missing block group/census tract/county by house characteristics. Panel B shows the number of missing observations in each state by house characteristics. For comparing the number of missing values with total observations in each area/state, we list the total number of observations in the last row of each section.

Table B3: Additional Robustness Check for Housing Prices

	Block group fixed effect			Repeat sales sample			No imputation		
Dependent variable	Log of housing prices								
Sample	Pooled (1)	Urban areas (2)	Rural areas (3)	Pooled (4)	Urban areas (5)	Rural areas (6)	Pooled (7)	Urban areas (8)	Rural areas (9)
Distance band (0-0.5 km)	-0.0514***	-0.0546***	-0.0435***	-0.0475***	-0.0489***	-0.0328**	-0.0506***	-0.0606***	-0.0133
	(0.0057)	(0.0076)	(0.0088)	(0.0082)	(0.0098)	(0.0129)	(0.0072)	(0.0085)	(0.0114)
Distance band (0.5-1 km)	-0.0352***	-0.0391***	-0.0261***	-0.0267***	-0.0275***	-0.0241*	-0.0253***	-0.0318***	-0.0035
	(0.0052)	(0.0068)	(0.0082)	(0.0076)	(0.0091)	(0.0127)	(0.0065)	(0.0077)	(0.0113)
Distance band (1-1.5 km)	-0.0199***	-0.0226***	-0.0124	-0.0119*	-0.0112	-0.0215	-0.0067	-0.0094	-0.0018
	(0.0049)	(0.0060)	(0.0087)	(0.0071)	(0.0083)	(0.0134)	(0.0061)	(0.0070)	(0.0116)
Distance band (1.5-2 km)	-0.0099**	-0.0100**	-0.0103	-0.0059	-0.0037	-0.0236*	-0.0062	-0.0070	-0.0072
	(0.0041)	(0.0047)	(0.0081)	(0.0061)	(0.0069)	(0.0124)	(0.0053)	(0.0059)	(0.0116)
Housing characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Block group fixed effect	Yes	Yes	Yes						
Census tract FE				Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-sq	0.571	0.624	0.315	0.539	0.565	0.345	0.693	0.714	0.450
No. of observations	1,903,527	1,595,184	307,027	992,014	893,838	98,176	801,698	724,553	76,798

Note: This table presents supplementary robustness analyses, wherein Columns (1)-(3) execute tests by substituting block group fixed effects, Columns (4)-(6) perform tests in repeat sales samples and the number of observations for these three columns present the number of houses involving repeated sales, and Columns (7)-(9) perform tests in samples that do not undergo imputation. The housing regressions incorporate variables related to housing characteristics. Columns (1)-(3) utilize block group fixed effects with standard errors clustered at the block-group level, while columns (4)-(9) employ census tract fixed effects. Significance: $* < 0.1, ** < 0.05, *** < 0.01$.

Table B4: Baseline Results of the Impacts of TMLs on Nearby Farmland Values and Housing Prices with Control Variables

	Farmland Values		Housing Prices	
Dependent variable	Log of farmland prices		Log of housing prices	
All sample	(1)		(2)	
Distance band (0-2 km)	0.1042***	(0.0209)		
Distance band (2-5 km)	0.0823***	(0.0194)		
Distance band (5-8 km)	0.0542***	(0.0193)		
Distance band (0-0.5 km)			-0.0534***	(0.0059)
Distance band (0.5-1 km)			-0.0350***	(0.0055)
Distance band (1-1.5 km)			-0.0175***	(0.0051)
Distance band (1.5-2 km)			-0.0092**	(0.0045)
Gross acres	-0.0798***	(0.0067)		
Gross acres^2	0.0010***	(0.0002)		
Land percentage tillable	0.2203***	(0.0204)		
Average NCCPI for agriculture	0.7200***	(0.0663)		
% of prime farmland	0.0586	(0.0394)		
Soil texture: % of clay	0.2395	(0.2050)		
Soil texture: % of silt	-0.2140	(0.1451)		
Soil texture: % of loam	-0.0324	(0.0364)		
Average land slope	0.0017	(0.0013)		
Population in urban areas	0.0063***	(0.0006)		
Whether in urban county	0.1787***	(0.0260)		
Distance to highway	-0.1186***	(0.0210)		
Distance to railway	-0.0430***	(0.0104)		
Distance to body of water	0.1163***	(0.0285)		
Distance to biodiesel	-0.0171***	(0.0021)		
Distance to grain warehouse	-0.0494***	(0.0078)		
Age			-0.0065***	(0.0002)
Age^2(/100)			0.0006***	(0.0001)
Lot size			0.0003***	(0.0000)
No. of stories			0.1099***	(0.0032)
No. of total rooms			0.0129***	(0.0015)
No. of total bedrooms			0.0585***	(0.0021)
No. of full bath			0.1722***	(0.0026)
County FE	Yes			
Year FE	Yes			
Census tract FE			Yes	
Year-quarter FE			Yes	
Adj. R-sq	0.429		0.550	
No. of obs.	16,026		1,905,280	

Note: This table shows complete baseline results for both farmland values and housing prices. In each column, the coefficients are in the left and the standard errors are in the parentheses. Significance: $* < 0.1, ** < 0.05, *** < 0.01$.

Table B5: Detailed Summary Statistics for Distance Variables

Variables	Sample	Unit	Mean	Std. dev.	Min	P10	P25	P50	P75	P90	Max
Panel A: Farmland											
Distance to the nearest TML	Whole sample	km	3.66	2.92	0.00	0.40	1.21	2.93	5.59	8.30	11.00
	I-states	km	3.85	2.94	0.00	0.46	1.38	3.23	5.82	8.49	11.00
	Lake-states	km	3.34	2.80	0.00	0.36	1.01	2.58	5.12	7.74	11.00
	Great plain states	km	3.76	2.98	0.00	0.41	1.31	2.96	5.75	8.54	11.00
Panel B: Housing											
Distance to the nearest TML	Whole sample	km	1.20	0.80	0.00	0.23	0.53	1.07	1.80	2.42	3.00
	I-states	km	1.34	0.80	0.00	0.31	0.66	1.25	1.96	2.53	3.00
	Lake-states	km	1.19	0.80	0.00	0.22	0.51	1.06	1.78	2.41	3.00
	Great plain states	km	1.05	0.75	0.00	0.20	0.43	0.88	1.53	2.21	3.00

Note: This table presents the complete summary statistics for the distance variables used in this paper. Panel A provides statistics for farmland-related distance variables, while Panel B provides statistics for housing-related distance variables. Specifically, we report the mean, standard deviation, minimum value, 10^{th} percentile, 25^{th} percentile, 50^{th} percentile, 75^{th} percentile, 90^{th} percentile, and maximum value of these variables.