Urbanization and Structural Transformation in the British Cattle Industry

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1 Introduction

Urbanization is an invariable accompaniment of economic growth (Kuznet, 1955). The world has experienced and are expected to continue urbanization. According to the United Nations[1], in 2018, 55% of the world's population reside in urban areas, back to 1950, this number is only 30%. They also estimated that 68% of world's population will be urban by 2050. Nevertheless, the levels of urbanization diverse by different regions. By 2018, highly urbanized regions include Northern America (with 82% of population residents in urban areas), Latin America and the Caribbean (81%), Europe (74%) and Oceania (68%)[1]. Less urbanized regions contain Asia (50%) and Africa (43%). The world will see unparalleled urban growth in next few decades, particularly in those underdeveloped countries in Africa and Asia (Thornton, 2010). Since underdeveloped countries have been patterning after British, German, and American models in the process of urbanization (Hoselitz, 1955), study the developed countries' urbanization patterns and influences could be referential significant to the ongoing urban growth in developing countries.

The inevitable urbanization trend could generate both risks and opportunities for livestock systems (Delgado, 2001). Especially, Seto and Ramankutty (2016) systematically establish a bilateral linkages structure between urbanization and food systems, they indicate that urbanization could affect food systems through land use and built environment, household and demography, economy and development, lifestyle and culture, and innovation. Urbanization, by boosting population growth and income growth, could naturally generate more demand for livestock products (Steinfeld et al.,

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[1] United nations (2018). World Urbanization Prospects: The 2018 Revision

2006; Thornton, 2010). Moreover, urbanization could stimulate livestock products' consumptions by diversify people's diets (Seto and Ramankutty, 2016; Kastner, 2012; Li, Zhao, and Cui, 2013; Delgado, 2003; Huang and Bouis, 2001; Huang and Rozelle, 1998; Reardon et al., 2014). Seto and Ramankutty (2016) believes that highly urbanized areas would consume more animal protein—pork, poultry, beef, and dairy products than the world average. Delgado (2003) finds that people in urban areas consume more milk and meat, and the rapid urbanization in developing countries would cause much demand of livestock products in next decades. By comparing the urban-rural food consumption differences between in Taiwan, Huang and Bouis (2001) shows that wheat, meat, fish, and fruit consumption is higher in more urbanized areas, this phenomenon may due to the different lifestyles, marketing systems and occupation structures between urban and rural areas. There is also a well-established literature shows that urbanization could promote livestock production growth through technology and food supply chain (Thornton, 2010; Reardon et al., 2014; Seto and Ramankutty, 2016)

A large literature suggests urbanization could exert negative impacts on livestock production through different channel, for instance, environmental channels (e.g. climate change, pollution, land cover changes and disease spreading) and resource channels (e.g. land and water competition) (Abu Hatab, Cavinato, and Lagerkvist, 2019; Thornton and Gerber, 2010; Thornton and Herrero, 2014; Seto and Ramankutty, 2016; Li, Zhao, and Cui, 2013; Thornton, 2010). Among these issues, land competition is a widely expressed concern. Urbanization, which often brings along with population growth, higher incomes and diets change, requires more food, especially animal protein (Abu Hatab, Cavinato, and Lagerkvist, 2019; Seto and Ramankutty, 2016). And this increasing demand of animal protein needs more land resource in livestock systems (Seto and Ramankutty, 2016; Reardon et al. 2014). However, the expanding urban areas could result in pervasive loss of pastures and croplands (Thornton, 2010; Seto and Ramankutty, 2016). Seto and Ramankutty (2016) argues that because most cities are historically allocated in fertile agricultural areas and cities' built-up areas are expanding quickly, urbanization is capturing lands from agricultural use rapidly. Also, urban expansion may increase the land value in nearby rural areas and encourage farmers to sell their lands and move in cities, and this procedure, in turn, intensifies urbanization (Seto and Ramankutty, 2016). With all these channels, urbanization is exacerbating the disequilibrium between pasture land demands and supplies.

Previous literature suggests that the development of urban areas could remodel the patterns of livestock farming fundamentally. However, in the context of the impacts of urbanization on herds' size and spatial distributions, there seems to be an unbalance between the abundance of theoretical literature and the lack of empirical study. Only a few studies provide statistical evidence for relative but different topics. Some researches show statistically significant linkages of urbanization and rural settlements' patterns (Tan and Li, 2013; Yang, Xu, and Long, 2016), or relationships between urbanization and farm sizes (Masters et al., 2013; Tan et al, 2013; Hazell and Hazell, 2013). Carver et al. (2000) use Geographic Information Systems (GIS) to find that bills, by legally regulating the setback distance of livestock facilities' locations from populated areas, will decrease available rural land for livestock facilities siting to a large extent. Exploring the poorly-understood linkages between urbanization and livestock farming in developed countries could offer a developmental perspective on multiple economic topics, for example, urban-rural relationship, food security and poverty reduction. Thus, this paper would make up the deficiency in relative economics literature by offering empirical evidence of urbanization's externality on herds' sizes and spatial distributions.

In this paper, based on location information, we combine monthly data of all beef cattle herds with all real estate transactions between 2010-2018 in England and Wales. Since it is well verified that urbanization and house prices have strong correlation with each other in many countries, including the United Kingdom (Liu and Roberts, 2013; Awaworyi Churchill, Hailemariam, and Erdiaw-Kwasie, 2020; Wang, Hui, and Sun, 2017; Chen, Guo, and Wu, 2011), we will regard house prices as an indicator of urbanization. This paper uses two combination methods to qualifying the impacts of urbanization on herds' sizes and spatial distributions separately. Firstly, to check the relationship between herds' size and urbanization, we generate the heatmaps of house prices, and denote every herd to its corresponding location on the house-price heatmap.

Secondly, to exam the effect of urbanization on herds' special distribution, besides the house-price heatmap mentioned above, we construct the heatmaps of herds, and make these two serious of heatmaps overlap each other.

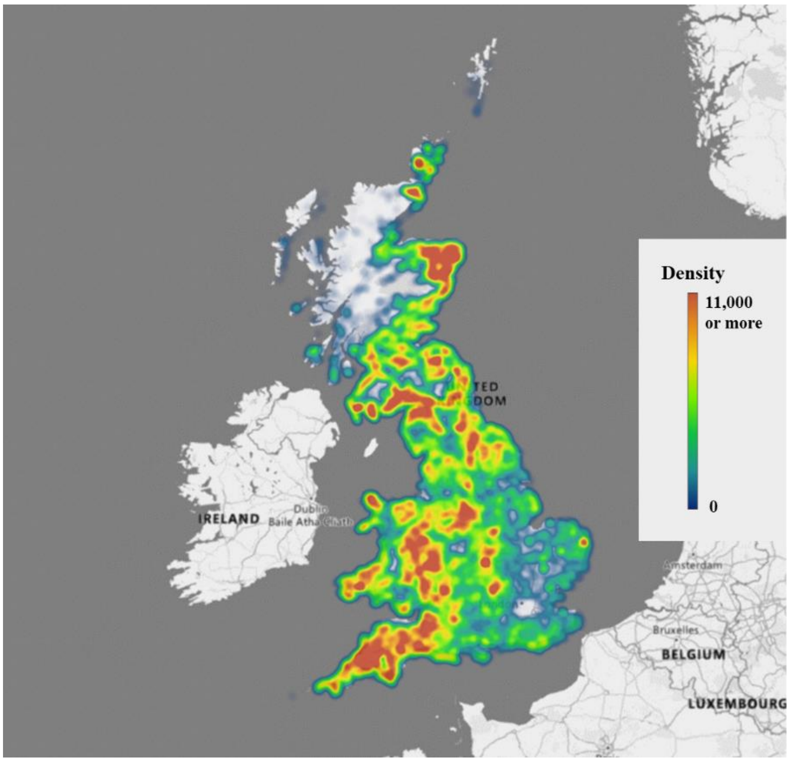
Our empirical results indicate that house price could produce heterogenous impacts on herds with different sizes or areas with different cattle densities. Specifically, the increase of house price would make herds with small sizes smaller or even disappear, and make large herds larger. Similarly, the increase of house price would make the cattle densities of high-cattle-density areas higher, and, on the other hand, cattle densities of low-cattle-density areas lower. The empirical results suggest urbanization could accelerate the concentration of livestock farming.

The remainder of the paper is organized as follows. Section 2 provides background of the urbanization and livestock industry in the United Kingdom. Section 3 introduces the data. Section 4 shows our methodologies and summaries the final dataset. Section 5 examines the impacts of urbanization on cattle farming and discuss our results. Section 6 uses our empirical results to predict the future of livestock productions under the expansion of urban areas. Section 8 concludes.

2 Background

In Great Britain, about 5,300,000 beef cattle distribute in approximately 100,000 herds. Figure 1 displays the spatial distribution of beef cattle in Great Britain in January, 2010. As beef cattle herds widely spread over Great Britain, north-central and west England, Wales, and east Scotland have a higher concentration of beef cattle.

Figure 1 Beef Cattle Spatial Distribution in Great Britain (Jan, 2010)

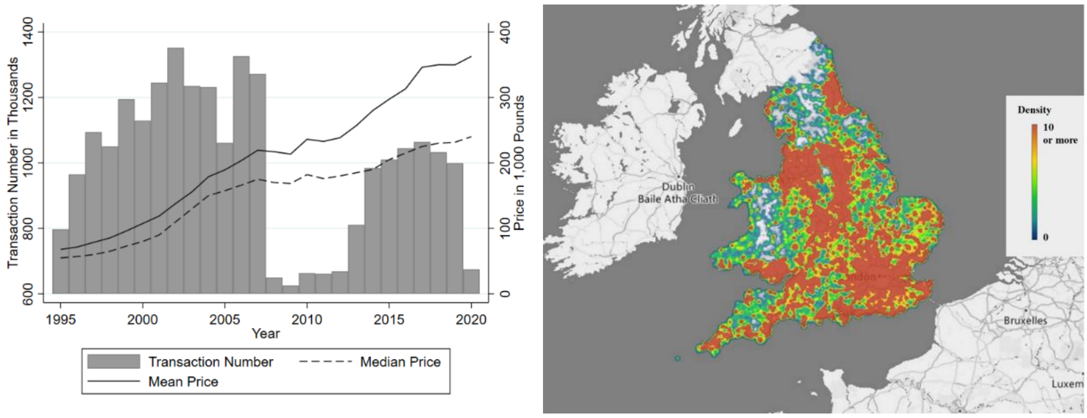


Great Britain has a long history of urbanization. It was the first country to experience rapid and large-scale urbanization, which started in the Mid-18 century and completed by the First World War (Law,1967). During this period, the ratio of urban population in England and Wales increase rapidly from 50.2% in 1851 to 78.1% in 1911(Law,1967). During 1960s-1990s, the urban population ratio of United Kingdom fluctuated between 77%-79%. Since 2000, this rate increased steadily from 78.75% in 2001 to 83.90% 2020.[2]

Along with this recent urban development and population change, house prices continued to rise. In 2008, there are about 650,000 property transactions registered in England and Wales, with a median price of 170,000 pounds. And in 2018, over 1,000,000 transactions in England and Wales were recorded, and the median price is 230,000 pounds. Figure 2 provides an outline and spatial distribution of property transactions in England and Wales.

[2] World Bank, https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS?locations=GB

Figure 2 Overview and Spatial Distribution of Property Transactions in England and Wales



3 Data

We combine three data sets to finish our discussion: APHA Sam Database, Price Paid Data, and National Statistics Postcode Lookup (NSPL) dataset.

3.1 APHA Sam Database

APHA Sam Database contains monthly data for all beef and dairy cattle herds in Great Britain (England, Wales and Scotland). Information like herds' locations, number of animals in the herd, main product that a herd provides. In this paper, our final herd dataset includes 68,113 beef cattle herds with a total of 7,356,204 observations in England and Wales from 2010 to 2018. Other summary statistics are reported in Table 1.

3.2 Price Paid Data

Price Paid Data tracks all property sales in England and Wales submitted to HM Land Registry for registration. It is based on the raw data released each month. Each record provides information like sale price stated on the transfer deed, address of the property, date of transfer and postcode of the property. The final database used for regression or forecasting in this paper includes 10,886,943 observations for all registered property transactions in England and Wales from 2008 to 2020. Other summary statistics are reported in Table 1.

3.3 National Statistics Postcode Lookup (NSPL)

The National Statistics Postcode Look-up (NSPL) relates both current and terminated postcodes in the United Kingdom to a range of current statutory administrative, electoral, health and other statistical geographies via 'best-fit' allocation from Census Output Areas. The NSPL is produced by ONS Geography, which is the executive office of the UK Statistics Authority and provides geographic support to the Office for National Statistics (ONS).

We use NSPL to spatially link Price Paid Data and APHA Sam Database. This is because the location information in APHA Sam Database is northing and easting of a specific herd, and the location information of a house transaction in Price Paid Data is postcode. So NSPL, which provides distinct linkages between postcodes and other location information like easting & northing, longitude & latitude, can be a vital bond of Price Paid Data and APHA Sam Database.

Also, considering the time range of our database, we choose NSPL (Aug, 2011) based on 2011 Census Output Areas as the dataset we use. This dataset includes 2,523,327 postcodes within the United Kingdom, the Channel Islands and the Isle of Man with their corresponding statistical geographies.

4 Methodology

In this section, we will introduce several methodologies that we construct for further empirical study. In section 4.1, we describe the spatial methodology about generating a heat map of property prices. Section 4.2, 4.3 and 4.4 shows the empirical method of testing the impact of house prices on herds' sizes, spatial distribution and existence separately. In section 4.5, we provide the empirical method of perceiving the heterogenous impacts of house price on herds' structure. Section 4.6 provides a statistical summary of data.

4.1 Spatial Methodology of House Prices

Herds are located at different geographic points, and we want to test the impact of the corresponding locations' house prices on herds' structures, as a result, a spatial methodology that generates heatmaps of house prices is constructed.

Price Paid Data is a database that contains all property sales in England and Wales, and it provides the postcode information of every sold property. Further, National Statistics Postcode Lookup (NSPL) links every postcode's area with a 'best-fit' allocation, and provides vital geographical information like easting and northing to 1-meter resolution. Thus, by merging these two databases, we construct a spatial methodology to generate heatmaps of house prices over England and Wales for further discussions.

Figure 4 illustrate the construction methods of house prices annul heatmaps, this method includes three procedures. Panel(a) shows the first procedure about how we distribute property transaction to 1km by 1km squares. Firstly, we separate the land area of England and Wales into 1km by 1km squares. And for specific square, say the middle square of Panel(a), we have several involved postcode areas, which in Panel(a) represented by rectangle A, B, C, D, E, and F. For every postcode area, we have its corresponding "best-fit" allocation point given by NSPL, which in Panel(a) represented by red point a, b, c, d, e, and f. Within every postcode area, there are several property transactions, which in Panel(a) represented by black point with numeric. Thus, for every "best-fit" allocation point with easting and northing information, we will distribute it, along with its postcode area, to the square it belongs. For example, in Panel(a), we will distribute postcode areas D, E and F to the center 1km by 1km square. And all the transactions with in area D, E and F will be distributed in the center square, even though some transactions (black point 15,16,18 and 19) don't actually occur in this1km by 1km center square. This method is efficient and credible given the characters of our data.

Consider that there are about 2,500,000 postcodes within the United Kingdom given by NSPL, and the land area of the United Kingdom is 241,930 square kilometers[3], there are averagely more than 10 postcode areas within every 1km by 1km square. As a result, most transactions would actually occur within the1km by 1km square that they are distributed to. Mispairing problems, i.e. transitions happen out of a specific square are distribute to the square (like black points 15,16,18 and 19) and transitions happen within a specific square are distribute to other squares (like black points 3,4,7 and 9), will be infrequent.

After allocate every transaction to its corresponding 1km by 1km square, the second procedure is computing the average transaction price as the house price of the square. Panel(b) shows a visualization of this procedure based on partial of Great Britain's land area[4]. Notice that there are some blank squares on the heatmap, this is because there aren't any transactions registered within specific square, so the house prices of these squares are unknown. However, there might be some herds locates within these blank squares, and it's common knowledge that the average housing price of these squares can't be zero. Naturally, we consider about estimating the average house prices of these unknown-price squares based on known-price squares. For this third procedure, this paper uses a well-known and widely used interpolation method, Shepard's method[5], to estimate the average housing price of blank squares. Panel(c) shows the visualization

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[3] World bank, https://data.worldbank.org/indicator/AG.LND.TOTL.K2?locations=GB

[4] This is because if the graph contains all 1 sq.km squares, the heatmap will exceed Stata's ability in visualization and the map would be too vague to show details about how following step works.

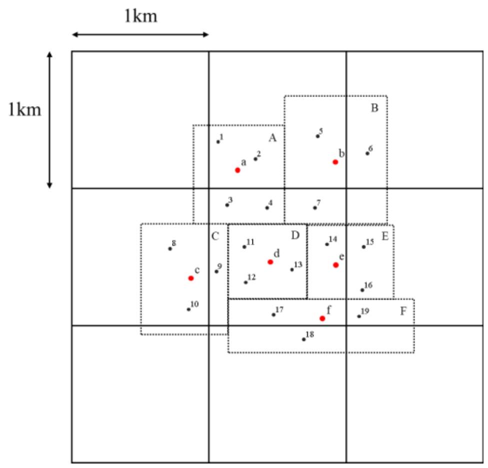
[5] Shepard (1968) propose this method to do two-dimensional interpolation in a geographic system, based on Shepard's method, the basic function of interpolation used in this paper is:

$$z_i = \begin{cases} \dfrac{\sum_{j=1,j\neq i}^{n} \dfrac{z_j}{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sum_{j=1,j\neq i}^{n} \dfrac{1}{(x_i - x_j)^2 + (y_i - y_j)^2}} & if\ (x_i - x_j)^2 + (y_i - y_j)^2 \neq 0\ for\ all\ j \\ z_i & if\ (x_i - x_j)^2 + (y_i - y_j)^2 = 0\ for\ some\ j \end{cases}$$

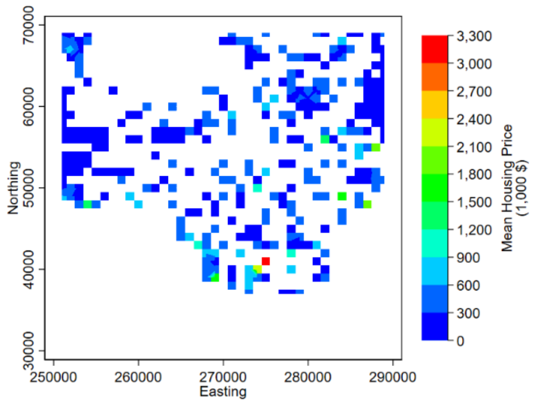
Where z is the house price of a square's central point, x and y are the easting and northing of a square's central point. Thus, the function above can help estimate the unknown house prices of some squares' central points, which are regarded as the average house prices of the square.

of house prices distribution after impose the third procedure to Panel(b). With these procedures, we can generate the average housing prices distribution over England and Wales.

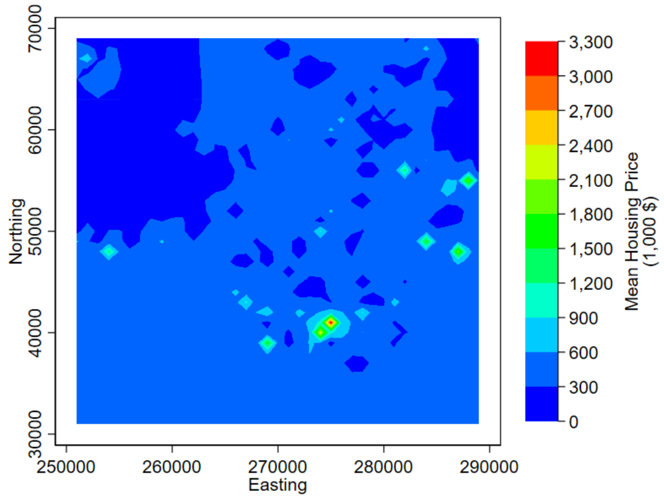
Figure 4 Construction Methods of House Prices heatmaps



Panel(a)



Panel(b)



Panel(c)

4.2 Empirical Method on Herds' Sizes Analyses (Analyses A and B)

To investigate the impact of house prices on herds' size, we consider two analyses. Firstly, for all the two analyses, we just allocate every herd to its corresponding 1km by 1km square based on the easting and northing of the herd. Thus, we know the average house price of where a specific herd locates.

Secondly, we use the following empirical method to test the impact of current house prices on herds' sizes (analysis A):

$$y_{it} = \alpha + H_{t,S_{it}}\beta_1 + P_{it}\beta_2 + \gamma_i + \delta_t + \varepsilon_{it} \tag{1}$$

Where variable y_{it} is the natural logarithm of the number of animals in the herd i in month t, which is a measurement of herd's size. S_{it} is the corresponding 1km by 1km square that herd i in month m locates in. $H_{t,S_{it}}$ is the natural logarithm of annul average house price of square S_{it} in the year that month t belongs to. γ_i is the herd-level fixed effect, and δ_t is the monthly level fixed effect. Because we control fixed effect into monthly level, the only meaningful economic control variable that available is P_{it}, which is the beef price of month t and varies in England or Wales. ε_{it} is the error term. Thus β_1 is the estimator that carries the impact of house prices on herds' size.

Thirdly, we run the following model to test the impact of the rate of house price change on herds' size (analysis B):

$$y_{it} = \alpha + \beta_1 C_{t,S_{it}} + \beta_2 P_{it} + \gamma_i + \delta_t + \varepsilon_{it} \tag{2}$$

Different from equation (1), we use $C_{t,S_{it}}$ as the independent variable. $C_{t,S_{it}}$ is the rate of annual house price change in square S_{it} and is expressed as a percentage. To calculate $C_{t,S_{it}}$, we use the annual average house price of square S_{it} in the year that month t belongs to, to minus the annual average house price of square S_{it} in the year that month $t-12$ belongs to, and divided by the annual average house price of square S_{it} in the year that month t belongs to, i.e. $C_{t,S_{it}} = \frac{\exp\left(H_{t,S_{it}}\right) - \exp\left(H_{t-12,S_{it}}\right)}{\exp\left(H_{t,S_{it}}\right)} \times 100\%$. In this model, β_1 carries the impacts of the speed that house prices change on herds' size.

4.3 Empirical Method on Herds' spatial Distribution (analyses C and D)

This paper also tests the effects of house prices on herd's spatial distribution. To capture their spatial characteristics, we construct monthly heatmaps for herds to with methodology similar to the spatial method for house transactions describe in section 4.1. The only difference is that, since we already have the northing and easting information for every herd in APHA Sam Database, we can directly allocate them into corresponding 1km by 1km squares without NSPL as a linkage. Spatial heatmaps of herds are then constructed by totaling the animals of all herds within a same square. Finally, by overlapping herds' heatmaps on house price heatmaps, we can use empirical models to capture the relationship between their spatial distribution.

Similar with analyses A and B, we test the impact of average house prices (analysis C) and rate of house price change (analysis D) on herds' distribution. The empirical model of analysis C is:

$$y_{st} = \alpha + H_{st}\beta_1 + P_{st}\beta_2 + \gamma_s + \delta_t + \varepsilon_{st} \tag{3}$$

Where variable y_{st} is the natural logarithm of the number of total animals in the square s in month t. H_{st} is the natural logarithm of annul average house price of square s in the year that month t belongs to. γ_s is the square-level fixed effect, and δ_t is the monthly level fixed effect. Similar, we control P_{st}, which is the beef price of month t and varies in England or Wales. ε_{st} is the error term. Thus β_1 is the estimator that carries the impact of average house prices on herds' distribution.

The empirical model of analysis D is:

$$y_{st} = \alpha + C_{st}\beta_1 + P_{st}\beta_2 + \gamma_s + \delta_t + \varepsilon_{st} \tag{4}$$

We can see that the only difference comparing analysis C is that we use C_{st} as the independent variable. C_{st} is the calculated by $C_{st} = \frac{\exp(H_{st}) - \exp(H_{s,t-12})}{\exp(H_{st})} \times 100\%$.

4.4 Empirical Method on Herds' Existence (Analysis E)

Analyses E is designed to test if house prices would affect cattle farmer's choice on keep farming and keep a herd existing. The analysis is based on similar empirical models in Equation (1). The difference is that y_{it} is a dummy variable that indicates if herd i still exists in month t. So $y_{it} = 0$ if there are no cattle within herd i in month t, which means the herd disappear in this period, and $y_{it} = 1$ means there is at least one animal in the herd, which indicates herd existence.

4.5 Empirical Method of Heterogeneous Impacts on Herds (Analyses F, G and H)

Another intuition of the paper is that house prices might generate different impacts on heterogeneous herds or areas. Thus, we construct analysis F to figure out if herds with different sizes are affected by house prices differently. The empirical model of analysis F is:

$$y_{it} = \alpha + H_{t,S_{it}}\beta_1 + P_{it}\beta_2 + \mathbf{G}_{it}\boldsymbol{\beta}_3 + \mathbf{G}_{it} * H_{t,S_{it}}^{dm}\boldsymbol{\beta}_4 + \mathbf{G}_{it} * P_{it}^{dm}\boldsymbol{\beta}_5 + \gamma_i + \delta_t + \varepsilon_{it} \quad (5)$$

Where $\mathbf{G}_{it}$[6] is an indicator that represents the group herd i in time t belongs to base on their relative sizes among all the herds in the same period t. Specifically, we separate herds into 7 groups, which with size at bottom 40%[7] ($\mathbf{G}_{it} = 0$), between 40% to 50%($\mathbf{G}_{it} = 1$), between 50% to 60%($\mathbf{G}_{it} = 2$), between 60% to 70%($\mathbf{G}_{it} = 3$), between 70% to 80%($\mathbf{G}_{it} = 4$), between 80% to 90%($\mathbf{G}_{it} = 5$) and between 90% to 100%($\mathbf{G}_{it} = 6$) of all herds in time t. Thus, the coefficient matrix $\boldsymbol{\beta}_3$ carries the general sizes difference between different groups. And $\boldsymbol{\beta}_4$, which is the coefficient of the intersection of $\mathbf{G}_{it}$ and $H_{t,S_{it}}$, captures the heterogeneous impacts of house prices on different herds. Besides, we use demeaned variables $H_{t,S_{it}}^{dm}$ and P_{it}^{dm}, where $H_{t,S_{it}}^{dm} = H_{t,S_{it}} - \bar{H}$ and $P_{it}^{dm} = P_{it} - \bar{P}$, to construct interactions so we can obtain difference-in-means estimates.

Similarly, analysis G is designed to find whether areas with higher and lower densities of cattle are affected by house prices heterogeneously. The empirical model of analysis H is:

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[6] When applying the model, $\mathbf{G}_{it}$ would be a serious of dummy variables, that's why we use matrix form here.

[7] This is because for every time t, about 30% herds are recorded with zero cattle, so it's meaningless to further separate this group.

$$y_{st} = \alpha + H_{st}\beta_1 + P_{st}\beta_2 + \mathbf{D_{st}}\boldsymbol{\beta_3} + \mathbf{D_{st}} * H^{dm}_{t,S_{it}}\boldsymbol{\beta_4} + \mathbf{D_{st}} * P^{dm}_{st}\boldsymbol{\beta_5} + \gamma_i + \delta_t + \varepsilon_{it} \quad (6)$$

Where $\mathbf{D_{st}}$ is an indicator that represents the group square i in time t belongs to base on its relative cattle density among all the squares in the same period t. Specifically, we separate squares into 8 groups, which with the number of cattle in a square at bottom 30%($\mathbf{D_{st}} = 0$)[8], between 30% to 40%($\mathbf{D_{st}} = 1$), between 40% to 50%($\mathbf{D_{st}} = 2$), between 50% to 60%($\mathbf{D_{st}} = 3$), between 60% to 70%($\mathbf{D_{st}} = 4$), between 70% to 80%($\mathbf{D_{st}} = 5$), between 80% to 90%($\mathbf{D_{st}} = 6$) and top 10%($\mathbf{D_{st}} = 7$) of all squares in time t. Thus, $\boldsymbol{\beta_4}$ captures the heterogeneous impacts of house prices on different areas with different cattle densities. Other settings are similar as models before.

Considering that the impact of housing price on herds' existence might also be heterogeneous, we further employ the analysis H with model shown as below to capture the impacts:

$$y_{it} = \alpha + H_{t,S_{it}}\beta_1 + P_{it}\beta_2 + \mathbf{G}_{i,t-1}\boldsymbol{\beta}_3 + \mathbf{G}_{i,t-1} * H^{dm}_{t,S_{it}}\boldsymbol{\beta}_4 + \mathbf{G}_{i,t-1} * P^{dm}_{it}\boldsymbol{\beta}_5 + \gamma_i + \delta_t + \varepsilon_{it} \quad (7)$$

Where y_{it} is a dummy variable indicates if a herd i still exists (contains more than one cattle) in time t. $\mathbf{G}_{i,t-1}$ is an indicator that represents the group herd i in time $t-1$ belongs to base on their relative sizes among all the herds in the same period t. Specifically, we separate herds into 7 groups, which with size at bottom 40% ($\mathbf{G}_{i,t-1} = 0$), between 40% to 50%($\mathbf{G}_{i,t-1} = 1$), between 50% to 60%($\mathbf{G}_{i,t-1} = 2$), between 60% to 70%($\mathbf{G}_{i,t-1} = 3$), between 70% to 80%($\mathbf{G}_{i,t-1} = 4$), between 80% to 90%($\mathbf{G}_{i,t-1} = 5$) and between 90% to 100%($\mathbf{G}_{i,t-1} = 6$) of all herds in time t. Thus, the coefficient matrix $\boldsymbol{\beta}_4$, which is the coefficient of the intersection of $\mathbf{G}_{i,t-1}$ and $H_{t,S_{it}}$, can show the difference of a herd's relative size in last period could generate different impacts of housing price on herds' existence in current period. Besides, we use demeaned variables $H^{dm}_{t,S_{it}}$ and P^{dm}_{it}, where $H^{dm}_{t,S_{it}} = H_{t,S_{it}} - \bar{H}$ and $P^{dm}_{it} = P_{it} - \bar{P}$, to construct interactions

[8] This is because for every time t, about 20% squares are recorded with zero cattle, so it's meaningless to further separate this group.

so we can obtain difference-in-means estimates.

4.6 Summary Statistics

Table 1 reports the summary statistics. Our final herd level analyses include 68113 beef herds' information in 108 months. Then the total observations are about 7.4 million. We further distribute these herds into 44903 1 km^2 squares according to their easting and northing. By calculating or estimating the annual average transaction prices of all the squares, we obtain the corresponding housing prices of all the squares. Thus, herds, squares and housing prices are well related.

Table 1 Summary Statistics

Sample	Variable	Mean	Std. Dev	Min	Max
All herds ($n = 7356204$)					
	$\exp(y_{it}):Number\ of\ cattle$	54.93	112.64	0	5956
	$y_{it}: Existence$	0.68	0.47	0	1
	$\exp\ (H_{t,s_{it}})$	322096.5	424605.2	200	111000000
	$C_{t,s_{it}}$	17.9708	664.3877	-99.97813	304943.5
	P_{it}	179.0255	16.99958	137.8232	212.1318
$\mathbf{G}_{it} = 0$ ($n = 2{,}996{,}385$)					
	$\exp(y_{it}):Number\ of\ cattle$	0.5898925	1.328648	0	7
	$\exp\ (H_{t,s_{it}})$	325903.4	368581.9	200	111000000
$\mathbf{G}_{it} = 1$ ($n = 712{,}913$)					
	$\exp(y_{it}):Number\ of\ cattle$	9.040416	2.914576	3	17
	$\exp\ (H_{t,s_{it}})$	319503.1	348760.7	250	111000000
$\mathbf{G}_{it} = 2$ ($n = 723{,}781$)					
	$\exp(y_{it}):Number\ of\ cattle$	20.71025	4.641317	11	34
	$\exp\ (H_{t,s_{it}})$	316406.8	485641.6	250	111000000
$\mathbf{G}_{it} = 3$ ($n = 729{,}764$)					
	$\exp(y_{it}):Number\ of\ cattle$	38.9208	6.76721	25	57
	$\exp\ (H_{t,s_{it}})$	318537	672763.1	200	111000000
$\mathbf{G}_{it} = 4$ ($n = 730{,}406$)					
	$\exp(y_{it}):Number\ of\ cattle$	66.59063	10.43335	47	94
	$\exp\ (H_{t,s_{it}})$	319248.3	584746.4	200	111000000
$\mathbf{G}_{it} = 5$ ($n = 731{,}020$)					
	$\exp(y_{it}):Number\ of\ cattle$	114.2801	19.45972	81	165
	$\exp\ (H_{t,s_{it}})$	317296	223445	910	21100000
$\mathbf{G}_{it} = 6$ ($n = 731{,}935$)					

	$\exp(y_{it}): Number\ of\ cattle$	301.0195	217.1606	144	5956
	$\exp(H_{t,s_{it}})$	325816.9	247811.3	910	21100000
All squares ($n = 4849524$)					
	$\exp(y_{st}): Number\ of\ cattle$	84.21969	172.6563	0	18005
	$\exp(H_{st})$	325694	383954.5	200	111000000
	C_{st}	18.74721	790.4971	-99.97813	304943.5
	P_{st}	179.0238	17.00075	137.8232	212.1318
$\mathbf{D}_{it} = 0$ ($n = 1{,}485{,}366$)					
	$\exp(y_{st}): Number\ of\ cattle$	0.7449753	1.537521	0	8
	$\exp(H_{st})$	334563.4	324237.9	200	52200000
$\mathbf{D}_{it} = 1$ ($n = 471{,}826$)					
	$\exp(y_{st}): Number\ of\ cattle$	10.28913	3.583184	3	21
	$\exp(H_{st})$	326641.1	333010.9	250	42000000
$\mathbf{D}_{it} = 2$ ($n = 479{,}905$)					
	$\exp(y_{st}): Number\ of\ cattle$	23.82902	5.381115	13	39
	$\exp(H_{st})$	321556.6	334804.5	200	52200000
$\mathbf{D}_{it} = 3$ ($n = 482{,}465$)					
	$\exp(y_{st}): Number\ of\ cattle$	43.07633	7.06837	28	62
	$\exp(H_{st})$	319677.6	429386.3	200	111000000
$\mathbf{D}_{it} = 4$ ($n = 481{,}709$)					
	$\exp(y_{st}): Number\ of\ cattle$	69.02928	9.468464	50	95
	$\exp(H_{st})$	320394.9	562581.7	200	111000000
$\mathbf{D}_{it} = 5$($n = 482{,}504$)					
	$\exp(y_{st}): Number\ of\ cattle$	106.1904	13.6635	80	143
	$\exp(H_{st})$	319736.8	574292	910	111000000
$\mathbf{D}_{it} = 6$ ($n = 482{,}556$)					
	$\exp(y_{st}): Number\ of\ cattle$	168.4808	25.35483	123	234
	$\exp(H_{st})$	317593	208024.5	1000	18800000
$\mathbf{D}_{it} = 7$ ($n = 483{,}193$)					
	$\exp(y_{st}): Number\ of\ cattle$	423.133	378.7306	206	18005
	$\exp(H_{st})$	326942.3	253336.3	250	21100000

5 Results

Section 5.1, 5.2 and 5.3 provides estimations of the impacts of house prices on herds' sizes (Analyses A and B), spatial distribution (Analyses C and D) and existence (Analysis E). Further, section 5.4, 5.5 and 5.6 shows the empirical results of heterogeneous impacts of house price on herds' sizes (Analysis F), spatial distribution (Analysis G) and existence (Analysis H). For robustness purposes, in every analysis, we run the regressions with economic variables, if applicable, specified contemporaneously or lagged, and deflated or not deflated by annual GDP deflators[9]. And robust standard errors are provided under different inferences.

5.1 Herds' Sizes Analyses

Table 2 reports the estimators from Equation (1) for Analysis A with inference robust to heteroskedasticity and serial correlation. Column (1), (2), (3) and (4) correspond to the specifications where variables are in present price without deflated. Variables in Column (5), (6), (7) and (8), if applicable, are deflated into real price. Column (1), (2), (5) and (6) correspond to the specifications without lagged variables. Column (3), (4), (7) and (8) correspond to the specifications with lagged beef prices. Panel and time level fixed effects are included in every specification. The estimators of $H_{t,s_{it}}$ shown in the first row capture the effect of house prices on herds' size. Comparing across Column (1) through (8), we can see a strong and robust evidence that annul average house prices have negative impacts on herds' size. There is no significant difference between estimators with or without deflated economic variables. But the estimators seem larger when considering lagged beef prices. And the results are statistically significant with inference robust to heteroskedasticity and serial correlation. The coefficients of $H_{t,s_{it}}$ in Column (2) and (6) are -0.0088, and it's statistically significant in 95% level. And the coefficients of $H_{t,s_{it}}$ in Column (4) and (8), where lagged beef prices are included, are -0.011, and it's also statistically significant in 95% level. The result indicates that, generally, if the average house price of an area increases 10%, the size of every herd in this area will getting small by approximately 0.11%. This result argues that the higher average house price in an area, the smaller herds are distributed here. All the coefficient of market beef price P_{it} is positive and significant in 99% level, this means an 10% increase in the beef price will make herds' size increase by about 2% to 4%. This result is congenial with economics theories and suggests credibility of our models.

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[9] https://www.gov.uk/government/statistics/gdp-deflators-at-market-prices-and-money-gdp-march-2021-budget

Table 2 Impact of House Price on Herd Size

	(1) Log (number of animals in herd)	(2) Log (number of animals in herd)	(3) Log (number of animals in herd)	(4) Log (number of animals in herd)	(5) Log (number of animals in herd)	(6) Log (number of animals in herd)	(7) Log (number of animals in herd)	(8) Log (number of animals in herd)
$H_{t,S_{it}}$	-0.0087***	-0.0088**	-0.0110***	-0.0111***	-0.0087***	-0.0088**	-0.0110***	-0.0111***
	(0.0014)	(0.0043)	(0.0014)	(0.0042)	(0.0014)	(0.0043)	(0.0014)	(0.0042)
P_{it}	0.3929***	0.3938***	0.2301***	0.2293***	0.3929***	0.3937***	0.2299***	0.2292***
	(0.0374)	(0.0652)	(0.0451)	(0.0577)	(0.0373)	(0.0652)	(0.0451)	(0.0576)
_cons	0.5049***	0.5015	-6.2165***	-6.2356***	0.4776**	0.4742	-6.3325***	-6.3518***
	(0.1944)	(0.3424)	(0.5155)	(1.5081)	(0.1970)	(0.3470)	(0.5223)	(1.5285)
Year-month fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Herd fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deflated	No	No	No	No	Yes	Yes	Yes	Yes
Lag	No	No	Yes	Yes	No	No	Yes	Yes
Month	108	108	96	96	108	108	96	96
Panel groups	68113	68113	68113	68113	68113	68113	68113	68113
N	7356204	7356204	6538848	6538848	7356204	7356204	6538848	6538848

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Heteroskedasticity-robust standard errors are reported in the parentheses of column (1), (3), (5), and (7).

Serial-correlation-heteroskedasticity-robust standard errors are reported in the parentheses of column (2), (4), (6), and (8). Standard errors are clustered at herd-year level.

Table 3 reports the estimators from Equation (2) for Analysis B. Other settings are similar with Table (1). The estimated coefficients of variable $C_{t,S_{it}}$ shown in the first row capture the effect of the rate of house prices' change on herds' sizes. The coefficients of $C_{t,S_{it}}$ in column (1), (3), (5) and (7) are significant in 99% level. However, after considering both heteroskedasticity and serial correlation problems and get cluster-robust standard error in column (2), (4), (6) and (8), the coefficients of $C_{t,S_{it}}$ are not significant. The result can't provide enough evidence to suggest the relationship between the speed of house prices increase with herds' size.

Table 3 Impact of House Price Change on Herd Size

	(1) Log (number of animals in herd)	(2) Log (number of animals in herd)	(3) Log (number of animals in herd)	(4) Log (number of animals in herd)	(5) Log (number of animals in herd)	(6) Log (number of animals in herd)	(7) Log (number of animals in herd)	(8) Log (number of animals in herd)

$C_{t,S_{it}}$	-0.0000017***	-0.0000017	-0.0000017***	-0.0000017	-0.0000017***	-0.0000017	-0.0000018***	-0.0000018
	(0.00000042)	(0.00000132)	(0.00000040)	(0.00000122)	(0.00000043)	(0.00000134)	(0.00000041)	(0.00000125)
P_{it}	0.3904942***	0.3912954***	0.2298428***	0.2291213***	0.3904319***	0.3912323***	0.2296842***	0.2289624***
	(0.03735394)	(0.06521563)	(0.04513418)	(0.05765525)	(0.03733787)	(0.06519797)	(0.04511809)	(0.05763706)
_cons	0.4084469**	0.4042858	-6.3e+00***	-6.3e+00***	0.3807300*	0.3765155	-6.4e+00***	-6.4e+00***
	(0.19380609)	(0.33837254)	(0.51550256)	(1.50792518)	(0.19640400)	(0.34296284)	(0.52231201)	(1.52833271)
Year-month fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Herd fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deflated	No	No	No	No	Yes	Yes	Yes	Yes
Lag	No	No	Yes	Yes	No	No	Yes	Yes
Month	108	108	96	96	108	108	96	96
Panel groups	68113	68113	68113	68113	68113	68113	68113	68113
N	7356204	7356204	6538848	6538848	7356204	7356204	6538848	6538848

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Heteroskedasticity-robust standard errors are reported in the parentheses of column (1), (3), (5), and (7).

Serial-correlation-heteroskedasticity-robust standard errors are reported in the parentheses of column (2), (4), (6), and (8). Standard errors are clustered at herd-year level.

5.2 Herds' Spatial Distribution Analyses

Table 4 shows the estimators from Equation (3) for analysis C. The estimated coefficients of H_{st} indicates the impacts of house prices on herds' spatial distribution. Other settings are similar with Table 1 and 2. However, the same problem is that the results are not robust after considering both heteroskedasticity and serial correlation problems. Thus these results can't provide enough evidence for the relationship between house prices and animal densities.

Table 4 Impact of House Price on Herds Spatial Distribution

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log (number of animals in the square)	Log (number of animals in the square)	Log (number of animals in the square)	Log (number of animals in the square)	Log (number of animals in the square)	Log (number of animals in the square)	Log (number of animals in the square)	Log (number of animals in the square)
$H_{t,S_{it}}$	-0.0069***	-0.0069	-0.0080***	-0.0080	-0.0069***	-0.0069	-0.0080***	-0.0080
	(0.00161)	(0.0050)	(0.00161)	(0.0050)	(0.00161)	(0.0050)	(0.00161)	(0.0050)
P_{it}	0.4405***	0.4411***	0.3077***	0.3100***	0.4404***	0.4410***	0.3075***	0.3098***
	(0.04205)	(0.0730)	(0.05077)	(0.0645)	(0.04203)	(0.0730)	(0.05075)	(0.0645)

_cons	0.8060***	0.8029**	-6.2515***	-6.2359***	0.7754***	0.7722**	-6.3746***	-6.3588***
	(0.21891)	(0.3839)	(0.57831)	(1.6847)	(0.22183)	(0.3890)	(0.58596)	(1.7075)
Year-month fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Square fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deflated	No	No	No	No	Yes	Yes	Yes	Yes
Lag	No	No	Yes	Yes	No	No	Yes	Yes
Month	108	108	96	96	108	108	96	96
Panel groups	44903	44903	44903	44903	44903	44903	44903	44903
N	4849524	4849524	4310688	4310688	4849524	4849524	4310688	4310688

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Heteroskedasticity-robust standard errors are reported in the parentheses of column (1), (3), (5), and (7).

Serial-correlation-heteroskedasticity-robust standard errors are reported in the parentheses of column (2), (4), (6), and (8). Standard errors are clustered at square-year level.

Table 5 reports the estimators from Equation (4) for analysis D. The estimated coefficients of C_{st} captures the impacts of the rate of house prices' change on herds' spatial distribution. Settings in Column (1), (2), (3) and (4) are similar with those in Table (3). The estimated coefficients of C_{st} in the columns are between -0.0000019 to -0.000002, and they are all statistically significant in 99% level. This evidence argus that, if the rate of the house prices' growth in a specific area is 10% larger than other areas, the animals distributed here would be generally 0.002% less. This result indicates that the faster house prices increase in an area, the less herds would stay.

Table 5 Impact of House Price Change on Herds Spatial Distribution

	(1) Log (number of animals in the square)	(2) Log (number of animals in the square)	(3) Log (number of animals in the square)	(4) Log (number of animals in the square)	(5) Log (number of animals in the square)	(6) Log (number of animals in the square)	(7) Log (number of animals in the square)	(8) Log (number of animals in the square)
C_{st}	-0.000001884***	-0.0000019	-0.000001916***	-0.0000019	-0.000001923***	-0.0000019	-0.000001956***	-0.0000020
	(0.00000042)	(0.00000129)	(0.00000039)	(0.00000120)	(0.00000042)	(0.00000132)	(0.00000040)	(0.00000122)
P_{st}	0.438426268***	0.4390288***	0.307492087***	0.3097786***	0.438335604***	0.4389375***	0.307302718***	0.3095888***
	(0.04204605)	(0.07304147)	(0.05076671)	(0.06452959)	(0.04202809)	(0.07302212)	(0.05074867)	(0.06450923)
_cons	0.729371068***	0.7262447*	-6.288351436***	-6.3e+00***	0.698360666***	0.6951948*	-6.411099501***	-6.4e+00***
	(0.21814950	(0.37897606	(0.57825589	(1.68452148	(0.22107442	(0.38411947	(0.58589998	(1.70732631

	)	)	)	)	)	)	)	)
Year-month fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Square fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deflated	No	No	No	No	Yes	Yes	Yes	Yes
Lag	No	No	Yes	Yes	No	No	Yes	Yes
Month	108	108	96	96	108	108	96	96
Panel groups	44903	44903	44903	44903	44903	44903	44903	44903
N	4849524	4849524	4310688	4310688	4849524	4849524	4310688	4310688

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Heteroskedasticity-robust standard errors are reported in the parentheses of column (1), (3), (5), and (7).

Serial-correlation-heteroskedasticity-robust standard errors are reported in the parentheses of column (2), (4), (6), and (8). Standard errors are clustered at square-year level.

5.3 Herds' Existence

Table 6 reports the estimators from analysis E. The estimated coefficients of H_{st} indicates the impacts of house prices on herds' existence. Settings for different specification are similar as before. The estimated coefficients of H_{st} in Column (8) is -0.0039. This result is statistically significant in 99% level and it's robust to serial correlation and heteroskedasticity. Based on the result, we observe a statistically significant relationship between house prices and farms' decisions on keep herds. Specifically, if the average house price of an area is 10% higher than others, cattlemen would be 3.9% less willing to keep farming and lead to herds' disappearance.

Table 6 Impact of House Price on Herds' Existence

	(1) Existence	(2) Existence	(3) Existence	(4) Existence	(5) Existence	(6) Existence	(7) Existence	(8) Existence
$H_{t,s_{it}}$	-0.0032***	-0.0032**	-0.0039***	-0.0039***	-0.0032***	-0.0032**	-0.0039***	-0.0039***
	(0.00043)	(0.0013)	(0.00044)	(0.0013)	(0.00043)	(0.0013)	(0.00044)	(0.0013)
P_{it}	0.1400***	0.1400***	0.0919***	0.0919***	0.1400***	0.1400***	0.0919***	0.0919***
	(0.01200)	(0.0206)	(0.01457)	(0.0180)	(0.01200)	(0.0206)	(0.01457)	(0.0180)
_cons	-0.0090	-0.0091	-0.4547***	-0.4547	-0.0187	-0.0188	-0.4689***	-0.4689
	(0.06247)	(0.1080)	(0.16422)	(0.4732)	(0.06330)	(0.1094)	(0.16638)	(0.4796)
Year-month fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Herd fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deflated	No	No	No	No	Yes	Yes	Yes	Yes
Lag	No	No	Yes	Yes	No	No	Yes	Yes

Month	108	108	96	96	108	108	96	96
Panel groups	68113	68113	68113	68113	68113	68113	68113	68113
N	7356204	7356204	6538848	6538848	7356204	7356204	6538848	6538848

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Heteroskedasticity-robust standard errors are reported in the parentheses of column (1), (3), (5), and (7).

Serial-correlation-heteroskedasticity-robust standard errors are reported in the parentheses of column (2), (4), (6), and (8). Standard errors are clustered at herd-year level.

5.4 Heterogeneous Impacts on Individual Herd's Size

In previous section, we find some evidence of the relationship between housing price and herds' structures or herds' distribution. Nevertheless, for some topics, the impacts are not robust under serial correlation and heteroskedasticity. This issue may be a result of, instead of an irrelevance between house prices and several herds' characteristics, an insufficiency of our model. A vital and potential problem is the effects of housing price might be heterogeneous on herds with different size or areas with different cattle densities. Then analyses G and H are applied to test this hypothesis.

Table 7 and Figure 5, based on analysis F, reports the impacts of housing price on herds with different sizes. All the stand errors are robust to both serial correlation and heteroskedasticity. Herds with sizes at bottom 40% ($\mathbf{G}_{it} = 0$) are omitted as a control group. Other settings are similar as before. The coefficients of $H_{t,S_{it}}$ and $\{\mathbf{G}_{it} = j\} \times H_{t,S_{it}}^{dm}$ (where $j = 1,2 \dots 6$) capture the heterogeneous impacts of house prices on the number of cattle within herds with different sizes. In column (4), after deflating the variables and considering lags, the coefficients of $H_{t,S_{it}}$ equals to -0.033 and it's statistically significant in 99% level. This indicates that, for those herds with relatively smallest sizes (bottom 40%), the higher the housing price, the smaller a herd will be. Specifically, if average house prices increase by 10%, the herds will be 0.33% smaller. The coefficient of $\{\mathbf{G}_{it} = j\} \times H_{t,S_{it}}^{dm}$ (where $j = 1,2 \dots 6$) capture the heterogeneous impacts on herds with relative size between 40%-100% of all herds comparing to that bottom 40% herds. Specifically, these coefficient suggest that, if average house price increase by 10%, the animals number of a herd with size 40%-50% will decrease by 0.34% (-0.0329-0.0012), with size 50%-60% will slight increase by 0.06% (-0.0329+0.0393), with size 60%-70% will increase by 0.23% (-0.0329+0.0563), with size 70%-80% will increase by 0.40% (-0.0329+0.0726), with size 80%-90% will increase by 0.55% (-0.0329+0.0881), with size top 10% will increase by 0.82% (-0.0329+0.1144). And almost all the estimators are statistically significant under 99% level and robust to serial correlation and heteroskedasticity. The results provide strong evidence of the heterogeneous effects of house prices on herds' size. Small herds would prefer to shirk if housing price is higher while big herds prefer to contain more animals. We propose two potential interpretations for this empirical result. Firstly, small herds, usually with lower fixed cost, sunk cost and assets specificity, could quit the market or move to other areas easily and low-costly if the land prices increase. On the contrary, for big herds, usually with higher fixed cost, sunk cost and assets specificity, quit the market or move could be costly. Then if land prices increase, which increase the opportunity costs of farming, the owner of a big herd will try to contain more cattle to generate more profit to hedge the increasing opportunity costs. Thus, the owner of big herds would only quit the market when land prices increase too dramatically for them to adjust to. Secondly, for those areas with higher house prices, the conflicts between urbanization and herds could be more intense and containing small herds seems to be a "waste" of lands. Thus, intensive production with larger herds and higher animal density could be a natural choice.

Figure 5 Heterogenous Impacts of House Price on Herd Size

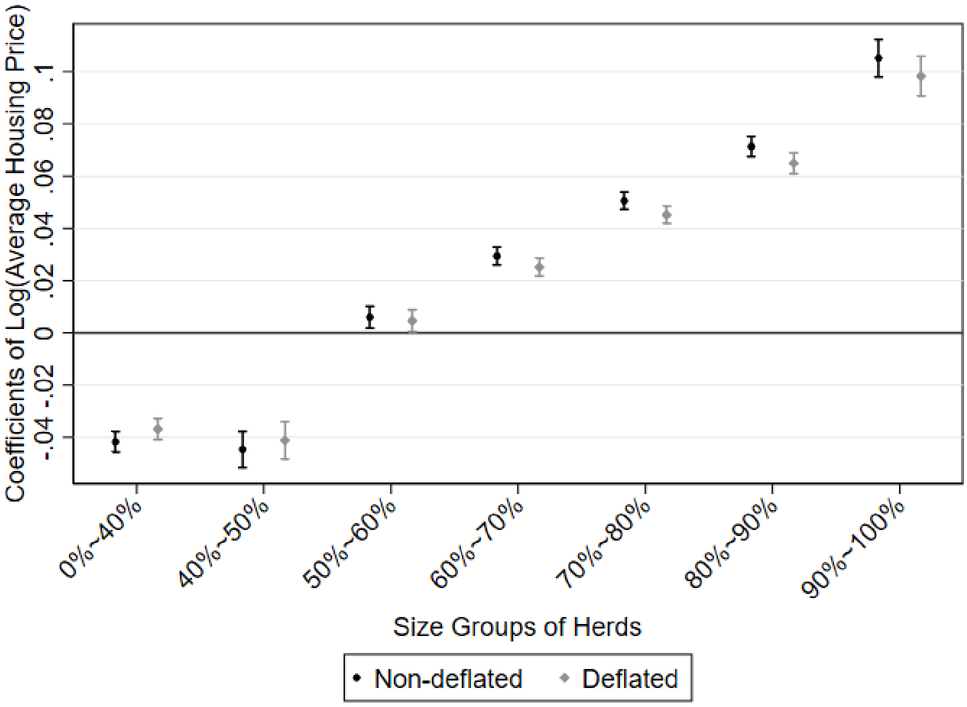


Table 7 Heterogenous Impacts of House Price on Herd Size

	(1)	(2)	(3)	(4)
	Log (number of animals in herd)	Log (number of animals in herd)	Log (number of animals in herd)	Log (number of animals in herd)
$H_{t,S_{it}}$	-0.0417***	-0.0394***	-0.0368***	-0.0329***
	(0.0020)	(0.0020)	(0.0021)	(0.0020)
$\{\mathbf{G}_{it} = 1\} \times H^{dm}_{t,S_{it}}$	-0.0029	-0.0027	-0.0043	-0.0012
	(0.0040)	(0.0042)	(0.0041)	(0.0043)
$\{\mathbf{G}_{it} = 2\} \times H^{dm}_{t,S_{it}}$	0.0477***	0.0462***	0.0415***	0.0393***
	(0.0028)	(0.0028)	(0.0028)	(0.0029)
$\{\mathbf{G}_{it} = 3\} \times H^{dm}_{t,S_{it}}$	0.0710***	0.0683***	0.0619***	0.0563***
	(0.0025)	(0.0025)	(0.0026)	(0.0026)
$\{\mathbf{G}_{it} = 4\} \times H^{dm}_{t,S_{it}}$	0.0922***	0.0876***	0.0820***	0.0726***
	(0.0024)	(0.0025)	(0.0025)	(0.0025)
$\{\mathbf{G}_{it} = 5\} \times H^{dm}_{t,S_{it}}$	0.1131***	0.1060***	0.1018***	0.0881***
	(0.0026)	(0.0027)	(0.0028)	(0.0027)
$\{\mathbf{G}_{it} = 6\} \times H^{dm}_{t,S_{it}}$	0.1468***	0.1349***	0.1350***	0.1144***
	(0.0041)	(0.0041)	(0.0044)	(0.0043)
$\mathbf{G}_{it} = 0$	0.0000	0.0000	0.0000	0.0000
	-	-	-	-
$\mathbf{G}_{it} = 1$	1.8434***	1.8238***	1.8431***	1.8204***
	(0.0023)	(0.0025)	(0.0023)	(0.0025)
$\mathbf{G}_{it} = 2$	2.7241***	2.7055***	2.7218***	2.7083***
	(0.0017)	(0.0019)	(0.0017)	(0.0019)
$\mathbf{G}_{it} = 3$	3.3701***	3.3533***	3.3680***	3.3586***
	(0.0016)	(0.0018)	(0.0016)	(0.0017)
$\mathbf{G}_{it} = 4$	3.9079***	3.8914***	3.9063***	3.8978***
	(0.0017)	(0.0019)	(0.0017)	(0.0018)
$\mathbf{G}_{it} = 5$	4.4202***	4.4026***	4.4190***	4.4095***
	(0.0020)	(0.0023)	(0.0021)	(0.0022)

$\mathbf{G}_{it} = 6$	4.9872***	4.9619***	4.9862***	4.9702***
	(0.0033)	(0.0037)	(0.0034)	(0.0036)
P_{it}	-0.0178	-0.0591***	0.0710***	0.0423**
	(0.0210)	(0.0182)	(0.0213)	(0.0182)
$\{\mathbf{G}_{it} = 1\} \times P_{it}^{dm}$	-0.5105***	0.0107	-0.3970***	0.2968***
	(0.0135)	(0.0177)	(0.0148)	(0.0182)
$\{\mathbf{G}_{it} = 2\} \times P_{it}^{dm}$	-0.0487***	0.1615***	-0.1475***	0.0875***
	(0.0104)	(0.0138)	(0.0113)	(0.0138)
$\{\mathbf{G}_{it} = 3\} \times P_{it}^{dm}$	0.1547***	0.2083***	-0.0256**	-0.0043
	(0.0095)	(0.0120)	(0.0104)	(0.0120)
$\{\mathbf{G}_{it} = 4\} \times P_{it}^{dm}$	0.2533***	0.1965***	0.0315***	-0.0860***
	(0.0093)	(0.0113)	(0.0101)	(0.0114)
$\{\mathbf{G}_{it} = 5\} \times P_{it}^{dm}$	0.3142***	0.1843***	0.0637***	-0.1413***
	(0.0094)	(0.0112)	(0.0103)	(0.0113)
$\{\mathbf{G}_{it} = 6\} \times P_{it}^{dm}$	0.3806***	0.2032***	0.0932***	-0.1780***
	(0.0112)	(0.0123)	(0.0121)	(0.0127)
_cons	0.9459***	1.6620***	0.4225***	0.8244*
	(0.1112)	(0.4175)	(0.1154)	(0.4272)
Year-month fixed effect	Yes	Yes	Yes	Yes
Herd fixed effect	Yes	Yes	Yes	Yes
Deflated	No	No	Yes	Yes
Lag	No	Yes	No	Yes
Month	108	96	108	96
Panel groups	68113	68113	68113	68113
N	7356204	6538848	7356204	6538848

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Serial-correlation-heteroskedasticity-robust standard errors are reported in parentheses. Standard errors are clustered at herd-year level.

5.5 Heterogeneous Impacts on Herds' Spatial Distributions

Based on previous discussion, we are now considering potential heterogeneous impacts on areas with different animal densities. Table 8 and Figure 6, based on analysis G, reports the impacts of housing price on squares with different cattle densities. All the stand errors are robust to both serial correlation and heteroskedasticity. Squares with cattle densities at bottom 30% ($\mathbf{D}_{it} = 0$) are omitted as a control group. Other settings are similar as before. The coefficients of $H_{t,S_{it}}$ and $\{\mathbf{D}_{it} = j\} \times H_{t,S_{it}}^{dm}$ (where $j = 1,2 \ldots 7$) capture the heterogeneous impacts. In column (4), after deflating the variables and considering lags, the coefficients of $H_{t,S_{it}}$ equals to -0.0482 and it's statistically significant in 99% level. This indicates that, for those squares with relatively lowest cattle densities (bottom 30%), the higher the housing price, the less cattle will be.

Specifically, if average house prices increase by 10%, the number of cattle will decrease by 0.48%. The coefficient of $\{\mathbf{D}_{it} = j\} \times H^{dm}_{t,s_{it}}$ (where $j = 1,2 \dots 7$) capture the heterogeneous impacts on squares with relative higher animal densities between 30%-100% of all squares comparing to that bottom 30% squares. Specifically, these coefficients suggest that, if average house price is relatively 10% higher, the cattle number of a square with density level between 30%-40% will decrease by 0.48% (-0.0482+0.0001), 40%-50% will decrease by 0.03% (-0.0482+0.0456), with size 50%-60% will slight increase by 0.15% (-0.0482+0.0632), with size 60%-70% will increase by 0.35% (-0.0482+0.0829), with size 70%-80% will increase by 0.49% (-0.0482+0.0970), with size 80%-90% will increase by 0.57% (-0.0482+0.1048), with size top 10% will increase by 0.77% (-0.0482+0.1254). And almost all the estimators are statistically significant under 99% level and robust to serial correlation and heteroskedasticity. These results suggest strong evidence about the heterogeneity of house prices on herds' distribution. For those areas with lower cattle densities, there would be a negative relationship between housing price and cattle density, on the contrary, for those areas with higher animal densities, the relationship seems to be positive. We think this phenomenon is a result of the difference in resistance power over urbanization. Those areas with higher cattle densities can gain more advantages in resisting the pressure of urbanization because they usually have higher scale effect, more powerful agricultural institutions and more beneficial agricultural policies. Thus when land price increase, they could stay in the market and change the marginal rate of substitution between cattle and lands to reach a new optimal point. However, for those areas with lower cattle densities, farmers would have lower bargaining power over urbanization, thus an increase in housing price could easily crowds herds out.

Figure 6 Heterogenous Impacts of House Price on Herds' Distribution

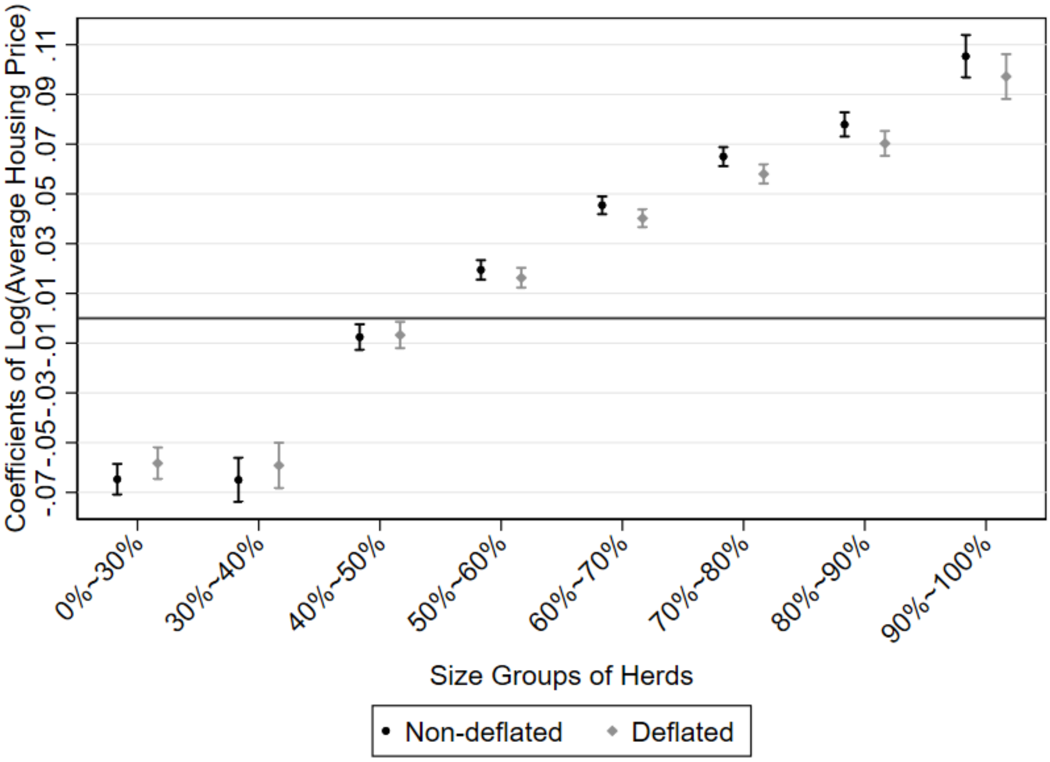


Table 8 Heterogenous Impacts of House Price on Herds' Distribution

	(1) Log (number of animals in the square)	(2) Log (number of animals in the square)	(3) Log (number of animals in the square)	(4) Log (number of animals in the square)
$H_{t,S_{it}}$	-0.0647***	-0.0587***	-0.0583***	-0.0482***
	(0.0031)	(0.0031)	(0.0032)	(0.0032)
$\{\mathbf{D}_{it}=1\}\times H^{dm}_{t,S_{it}}$	-0.0002	-0.0031	-0.0009	0.0001
	(0.0054)	(0.0056)	(0.0056)	(0.0057)
$\{\mathbf{D}_{it}=2\}\times H^{dm}_{t,S_{it}}$	0.0572***	0.0529***	0.0515***	0.0456***
	(0.0039)	(0.0039)	(0.0040)	(0.0040)
$\{\mathbf{D}_{it}=3\}\times H^{dm}_{t,S_{it}}$	0.0842***	0.0779***	0.0746***	0.0632***
	(0.0035)	(0.0035)	(0.0036)	(0.0036)
$\{\mathbf{D}_{it}=4\}\times H^{dm}_{t,S_{it}}$	0.1102***	0.1017***	0.0985***	0.0829***
	(0.0034)	(0.0034)	(0.0035)	(0.0035)
$\{\mathbf{D}_{it}=5\}\times H^{dm}_{t,S_{it}}$	0.1297***	0.1194***	0.1163***	0.0970***
	(0.0035)	(0.0035)	(0.0036)	(0.0035)
$\{\mathbf{D}_{it}=6\}\times H^{dm}_{t,S_{it}}$	0.1427***	0.1297***	0.1286***	0.1048***
	(0.0038)	(0.0038)	(0.0040)	(0.0039)
$\{\mathbf{D}_{it}=7\}\times H^{dm}_{t,S_{it}}$	0.1701***	0.1528***	0.1554***	0.1254***
	(0.0052)	(0.0052)	(0.0055)	(0.0053)
$\mathbf{D}_{it}=0$	0.0000	0.0000	0.0000	0.0000
	-	-	-	-
$\mathbf{D}_{it}=1$	1.8679***	1.8492***	1.8674***	1.8458***
	(0.0031)	(0.0034)	(0.0031)	(0.0034)
$\mathbf{D}_{it}=2$	2.7467***	2.7305***	2.7440***	2.7338***
	(0.0025)	(0.0027)	(0.0025)	(0.0027)
$\mathbf{D}_{it}=3$	3.3463***	3.3344***	3.3435***	3.3402***
	(0.0024)	(0.0026)	(0.0024)	(0.0026)
$\mathbf{D}_{it}=4$	3.8179***	3.8079***	3.8155***	3.8145***

	(0.0025)	(0.0027)	(0.0025)	(0.0026)
$\mathbf{D}_{it} = 5$	4.2390***	4.2292***	4.2370***	4.2367***
	(0.0027)	(0.0029)	(0.0027)	(0.0028)
$\mathbf{D}_{it} = 6$	4.6583***	4.6467***	4.6565***	4.6546***
	(0.0030)	(0.0033)	(0.0031)	(0.0033)
$\mathbf{D}_{it} = 7$	5.1427***	5.1237***	5.1409***	5.1332***
	(0.0043)	(0.0047)	(0.0043)	(0.0047)
P_{it}	-0.1103***	-0.0866***	0.0304	0.1010***
	(0.0259)	(0.0231)	(0.0266)	(0.0230)
$\{\mathbf{D}_{it} = 1\} \times P_{it}^{dm}$	-0.4401***	-0.0239	-0.3246***	0.2401***
	(0.0187)	(0.0237)	(0.0205)	(0.0243)
$\{\mathbf{D}_{it} = 2\} \times P_{it}^{dm}$	0.0222	0.2049***	-0.0858***	0.0915***
	(0.0148)	(0.0186)	(0.0161)	(0.0187)
$\{\mathbf{D}_{it} = 3\} \times P_{it}^{dm}$	0.2301***	0.2628***	0.0103	-0.0130
	(0.0139)	(0.0164)	(0.0150)	(0.0164)
$\{\mathbf{D}_{it} = 4\} \times P_{it}^{dm}$	0.3285***	0.2422***	0.0594***	-0.1066***
	(0.0136)	(0.0156)	(0.0146)	(0.0156)
$\{\mathbf{D}_{it} = 5\} \times P_{it}^{dm}$	0.4000***	0.2327***	0.0903***	-0.1787***
	(0.0135)	(0.0153)	(0.0146)	(0.0153)
$\{\mathbf{D}_{it} = 6\} \times P_{it}^{dm}$	0.4633***	0.2433***	0.1292***	-0.2051***
	(0.0137)	(0.0156)	(0.0149)	(0.0156)
$\{\mathbf{D}_{it} = 7\} \times P_{it}^{dm}$	0.5357***	0.2784***	0.1617***	-0.2252***
	(0.0155)	(0.0167)	(0.0168)	(0.0171)
_cons	1.8272***	2.3231***	1.0190***	0.9486*
	(0.1386)	(0.4915)	(0.1466)	(0.5060)
Year-month fixed effect	Yes	Yes	Yes	Yes
Square fixed effect	Yes	Yes	Yes	Yes
Deflated	No	No	Yes	Yes
Lag	No	Yes	No	Yes
Month	108	96	108	96
Panel groups	44903	44903	44903	44903
N	4849524	4310688	4849524	4310688

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Serial-correlation-heteroskedasticity-robust standard errors are reported in parentheses. Standard errors are clustered at square-year level.

5.6 Heterogeneous Impacts on Herds' Existence

We proposed some explanations about the heterogeneous impacts on herds. One of them is that small herds, comparing to big herds, might be more incentive to quit the market if under the pressure from urbanization. To test this hypothesis, we employ a model shown in Section 4.5 Equation (7). The results are shown in Figure 7 and Table 9. From the results, we obtain a strong evidence that housing price has heterogeneous impacts on herds with different sizes. Small herds are more likely to quit the market if housing price increases while larger herds are more likely to stay. Specifically, for those smallest herds (bottom 40%), if the average housing price of an area increase by 10%, the possibility of these herds exist till next period will decrease by 0.29%. However, for biggest herds (top 10%), if the average housing price increase by 10%, the possibility of these herds exist till next period will increase by 0.33%.

Figure 7 Heterogenous Impacts of House Price on Herds' Existence

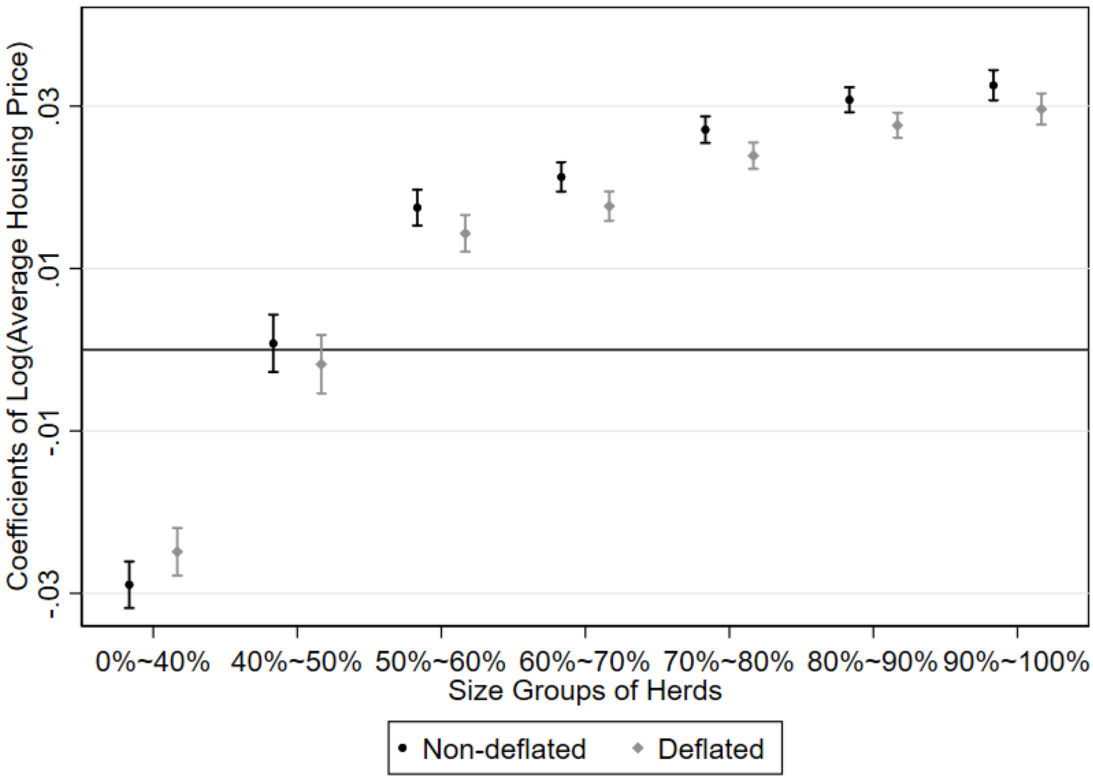


Table 9 Heterogenous Impacts of House Price on Herds' Existence

	(1)	(2)	(3)	(4)
	Existence	Existence	Existence	Existence
$H_{t,S_{it}}$	-0.0290***		-0.0249***	
	(0.0015)		(0.0015)	
$\{\mathbf{G}_{i,t-1}=1\}\times H_{t,S_{it}}^{dm}$	0.0298***		0.0232***	
	(0.0021)		(0.0022)	
$\{\mathbf{G}_{i,t-1}=2\}\times H_{t,S_{it}}^{dm}$	0.0465***		0.0393***	
	(0.0017)		(0.0017)	
$\{\mathbf{G}_{i,t-1}=3\}\times H_{t,S_{it}}^{dm}$	0.0502***		0.0426***	
	(0.0016)		(0.0016)	
$\{\mathbf{G}_{i,t-1}=4\}\times H_{t,S_{it}}^{dm}$	0.0561***		0.0488***	
	(0.0015)		(0.0016)	
$\{\mathbf{G}_{i,t-1}=5\}\times H_{t,S_{it}}^{dm}$	0.0597***		0.0525***	
	(0.0015)		(0.0016)	
$\{\mathbf{G}_{i,t-1}=6\}\times H_{t,S_{it}}^{dm}$	0.0615***		0.0545***	
	(0.0016)		(0.0017)	
$\mathbf{G}_{i,t-1}=0$	0.0000		0.0000	
	-		-	
$\mathbf{G}_{i,t-1}=1$	0.6500***		0.6490***	

	(0.0012)	(0.0012)
$\mathbf{G}_{i,t-1} = 2$	0.7427***	0.7419***
	(0.0010)	(0.0010)
$\mathbf{G}_{i,t-1} = 3$	0.7787***	0.7784***
	(0.0010)	(0.0010)
$\mathbf{G}_{i,t-1} = 4$	0.7995***	0.7995***
	(0.0010)	(0.0010)
$\mathbf{G}_{i,t-1} = 5$	0.8136***	0.8137***
	(0.0011)	(0.0011)
$\mathbf{G}_{i,t-1} = 6$	0.8258***	0.8259***
	(0.0012)	(0.0012)
P_{it}	-0.0940***	-0.0047
	(0.0135)	(0.0137)
$\{\mathbf{G}_{i,t-1} = 1\} \times P_{it}^{dm}$	0.0662***	-0.0782***
	(0.0075)	(0.0082)
$\{\mathbf{G}_{i,t-1} = 2\} \times P_{it}^{dm}$	0.1930***	0.0248***
	(0.0063)	(0.0068)
$\{\mathbf{G}_{i,t-1} = 3\} \times P_{it}^{dm}$	0.2287***	0.0509***
	(0.0060)	(0.0064)
$\{\mathbf{G}_{i,t-1} = 4\} \times P_{it}^{dm}$	0.2426***	0.0645***
	(0.0058)	(0.0063)
$\{\mathbf{G}_{i,t-1} = 5\} \times P_{it}^{dm}$	0.2484***	0.0712***
	(0.0057)	(0.0062)
$\{\mathbf{G}_{i,t-1} = 6\} \times P_{it}^{dm}$	0.2521***	0.0735***
	(0.0057)	(0.0061)
_cons	1.0732***	0.5611***
	(0.0721)	(0.0747)
Year-month fixed effect	Yes	Yes
Herd fixed effect	Yes	Yes
Deflated	No	Yes
Lag	No	No
Month	107	107
Panel groups	68113	68113
N	7288091	7288091

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Serial-correlation-heteroskedasticity-robust standard errors are reported in parentheses. Standard errors are clustered at herd-year level.

6 Forecasting

In this section, we use our heterogenous herd's spatial distribution results from Section 5.5 to forecast the herds density evolution from 2018 to 2028 under the effect of house price change.

Firstly, we employ an ARIMA model to derive the house price after 2018 of every 1 sq.km. square separately by using the data between 2008 and 2018. The forecasting result is shown in Figure 8. The results indicate a long-lasting decreasing of house prices and the median house price would double in the following decade. Based on the herds' dataset of January 2018, we then simulate the herds' distribution in January 2028 by employing our empirical results in Section 5.5 and, ceteris paribus, changing the house prices of 2018 to our forecasting house prices in 2028. Finally, by comparing the herds' distribution in January of 2018 and 2028, we generate a heatmap that capture the herds' density changes. The heatmap is shown in Figure 9. The areas where the average number of cattle increase more than 50, increase between 3 to 50, change between -3 to 3, decrease between 3 to 50, and decrease more than 50 are painted by red, light red, light blue and blue respectively.

Figure 8 Forecasting of House price

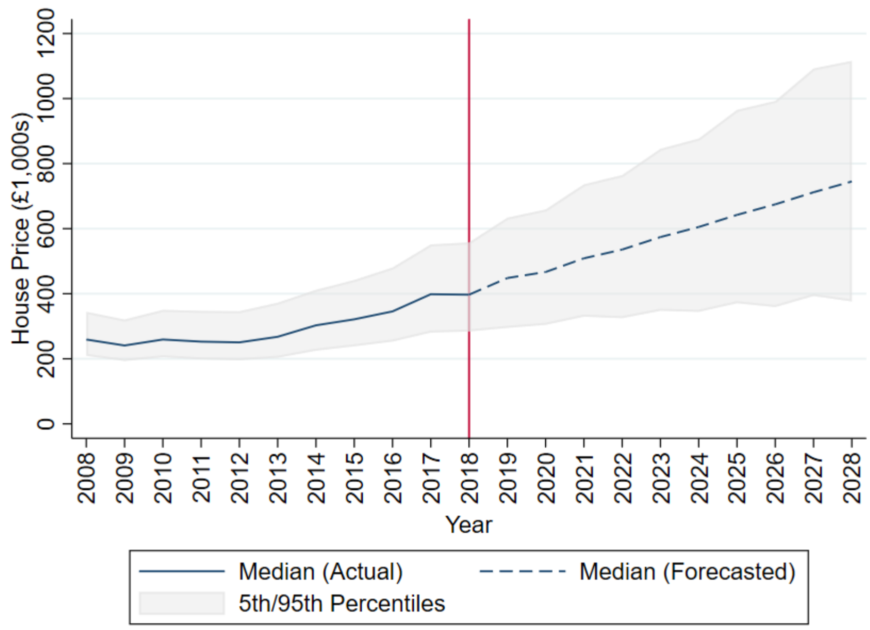
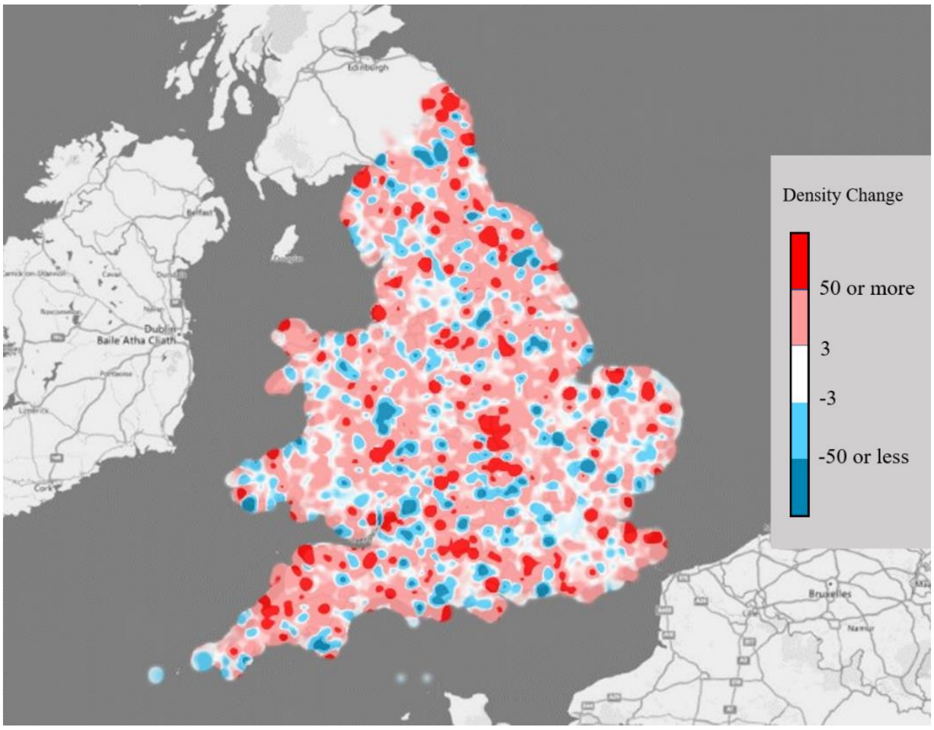


Figure 9 Forecasting of Herds' Density Change



7.Conclusion

Reference

(Need to be retreat)

Kuznets, Simon. “Economic Growth and Income Inequality.” The American Economic Review, vol. 45, no. 1, 1955, pp. 1–28. JSTOR, www.jstor.org/stable/1811581. Accessed 29 Aug. 2021.

United Nations (2018). World Urbanization Prospects: The 2018 Revision

The State of World Population 2018 UNFPA

United Nations (2018). World Urbanization Prospects: The 2018 Revision, Methodology, Working Paper No.
ESA/P/WP.252. UN DESA

Thornton, P. K. (2010). Livestock production: Recent trends, future prospects. Philosophical Transactions of the Royal Society of London B: Biological Sciences, 365(1554), 2853–2867.

Hoselitz, Bert F. “The City, The Factory, and Economic Growth.” The American Economic Review, vol. 45, no. 2, 1955, pp. 166–184. JSTOR, www.jstor.org/stable/1823550. Accessed 31 Aug. 2021.

Delgado, C., Rosegrant, M., Steinfeld, H., Ehui, S., and Courbois, C. (2001). Livestock to 2020: The next food revolution. Outlook on Agriculture, 30(1), 27–29

Steinfeld, H., Gerber, P., Wassenaar, T., Castel, V., Rosales, M. and de Haan, C. 2006 Livestock’s long shadow: environmental issues and options. Rome, Italy: FAO

Delgado, C. 2005 Rising demand for meat and milk in developing countries: implications for grasslands-based livestock production. In Grassland: a global resource (ed. D. A. McGilloway), pp. 29–39. The Netherlands: Wageningen Academic Publishers.

Huang, J. and Bouis, H. (2001), Structural changes in the demand for food in Asia: empirical evidence from Taiwan. Agricultural Economics, 26: 57-69. https://doi.org/10.1111/j.1574-0862.2001.tb00054.x

Anderson K, Dimaranan B, Hertel T, et al. Asia–Pacific food markets and trade in 2005: a global, economy-wide perspective[M]//WORLD SCIENTIFIC REFERENCE ON

ASIA-PACIFIC TRADE POLICIES: 1: Political Economy of Agricultural Protection in East Asia. 1997: 431-456.

Kastner T, Rivas M J I, Koch W, et al. Global changes in diets and the consequences for land requirements for food[J]. Proceedings of the National Academy of Sciences, 2012, 109(18): 6868-6872.

Li, G., Zhao, Y. and Cui, S. Effects of urbanization on arable land requirements in China, based on food consumption patterns. Food Sec. 5, 439–449 (2013). https://doi.org/10.1007/s12571-013-0265-9

Li, G.-L., Bai, X., Yu, S., Zhang, H. and Zhu, Y.-G. (2012), Urban Phosphorus Metabolism through Food Consumption. Journal of Industrial Ecology, 16: 588-599. https://doi.org/10.1111/j.1530-9290.2011.00402.x

Pandey B, Reba M, Joshi P K, et al. Urbanization and food consumption in India[J]. Scientific reports, 2020, 10(1): 1-12.

Delgado C L. Rising consumption of meat and milk in developing countries has created a new food revolution[J]. The Journal of nutrition, 2003, 133(11): 3907S-3910S.

Reardon T, Tschirley D, Dolislager M, et al. Urbanization, diet change, and transformation of food supply chains in Asia[J]. Michigan: Global Center for Food Systems Innovation, 2014: 46.

Reardon, T. and C.P. Timmer. 2014. “Five Inter-Linked Transformations in the Asian Agrifood Economy: Food Security Implications,” Global Food Security. 3(2).

Reardon T, Tschirley D, Dolislager M, et al. Urbanization, diet change, and transformation of food supply chains in Asia[J]. Michigan: Global Center for Food

Systems Innovation, 2014: 46.

Seto K C, Ramankutty N. Hidden linkages between urbanization and food systems[J]. Science, 2016, 352(6288): 943-945.

Thornton, P. K. and Gerber, P. 2010 Climate change and the growth of the livestock sector in developing countries. Mitigation Adapt. Strateg. Glob. Change 15, 169 –184.

Satterthwaite D. The implications of population growth and urbanization for climate change[J]. Environment and urbanization, 2009, 21(2): 545-567.

Thornton, P. K., and Herrero, M. (2014). Climate change adaptation in mixed crop–livestock systems in developing countries. Global Food Security, 3(2), 99–107.

Chapman S, Watson J E M, Salazar A, et al. The impact of urbanization and climate change on urban temperatures: a systematic review[J]. Landscape Ecology, 2017, 32(10): 1921-1935.

Abu Hatab, A., Cavinato, M.E.R. and Lagerkvist, C.J. Urbanization, livestock systems and food security in developing countries: A systematic review of the literature. Food Sec. 11, 279–299 (2019). https://doi.org/10.1007/s12571-019-00906-1

Carver A D, Arthur R D, Beck R J, et al. The Effects of Urbanization on the Siting and Expansion of Livestock Facilities in Illinois Under Proposed Legislation: A Spatial Analysis[J]. The Professional Animal Scientist, 2000, 16(2): 100-104.

Tan M, Li X. The changing settlements in rural areas under urban pressure in China: Patterns, driving forces and policy implications[J]. Landscape and Urban Planning, 2013, 120: 170-177.

Yang R, Xu Q, Long H. Spatial distribution characteristics and optimized reconstruction analysis of China's rural settlements during the process of rapid urbanization[J]. Journal of rural studies, 2016, 47: 413-424.

Masters W A, Djurfeldt A A, De Haan C, et al. Urbanization and farm size in Asia and Africa: Implications for food security and agricultural research[J]. Global Food Security, 2013, 2(3): 156-165.

Tan M, Robinson G M, Li X, et al. Spatial and temporal variability of farm size in China in context of rapid urbanization[J]. Chinese Geographical Science, 2013, 23(5): 607-619.

Hazell P, Hazell P B R. Comparative study of trends in urbanization and changes in farm size in Africa and Asia: implications for agricultural research[J]. 2013.

Awaworyi Churchill S, Hailemariam A, Erdiaw-Kwasie M O. Urbanization and Housing Prices in OECD Countries: 1870 to 2016[J]. Available at SSRN 3673260, 2020.

Wang X R, Hui E C M, Sun J X. Population migration, urbanization and housing prices: Evidence from the cities in China[J]. Habitat International, 2017, 66: 49-56.

Chen J, Guo F, Wu Y. One decade of urban housing reform in China: Urban housing price dynamics and the role of migration and urbanization, 1995–2005[J]. Habitat International, 2011, 35(1): 1-8.

Liu, N., and Roberts, D. (2013). Counter-urbanisation, planning and house prices: an analysis of the Aberdeen Housing Market Area, 1984-2010. Town Planning Review, 84(1), 81-105.

Law C M. The growth of urban population in England and Wales, 1801-1911[J]. Transactions of the Institute of British Geographers, 1967: 125-143.

Shepard, Donald (1968). "A two-dimensional interpolation function for irregularly-spaced data". Proceedings of the 1968 ACM National Conference. pp. 517–524. doi:10.1145/800186.810616.

Appendix

Table 8, based on analysis X, reports the impacts of house prices' increase rates on herds' animals with different sizes. All the stand errors are robust to both serial correlation and heteroskedasticity. Herds with sizes at bottom 40% ($\mathbf{G}_{it} = 0$) are omitted as a control group. Other settings are similar as before. The coefficients of $C_{t,S_{it}}$ and $\{\mathbf{G}_{it} = j\} \times C_{t,S_{it}}^{dm}$ (where $j = 1,2 \dots 6$) capture the heterogeneous impacts of house prices growth rates on the number of cattle within herds with different sizes. In column (4), after deflating the variables and considering lags, the coefficients of $C_{t,S_{it}}$ equals to -0.00000044 but it's not statistically significant.

Table 8

	(1)	(2)	(3)	(4)
	Log (number of animals in herd)	Log (number of animals in herd)	Log (number of animals in herd)	Log (number of animals in herd)
$C_{t,S_{it}}$	-0.000000435	-0.000000372	-0.000000476	-0.000000368
	(0.000000550)	(0.000000581)	(0.000000566)	(0.000000597)
$\{\mathbf{G}_{it} = 1\} \times C_{t,S_{it}}^{dm}$	0.000003064	0.000003005	0.000001405	0.000002280
	(0.000003369)	(0.000003370)	(0.000003421)	(0.000003404)
$\{\mathbf{G}_{it} = 2\} \times C_{t,S_{it}}^{dm}$	-0.000002392**	-0.000002638**	-0.000002602**	-0.000002765**
	(0.000001205)	(0.000001211)	(0.000001277)	(0.000001256)

$\{\mathbf{G}_{it}=3\}\times C^{dm}_{t,s_{it}}$	0.000001039	0.000000959	0.000001177	0.000000994
	(0.000000726)	(0.000000707)	(0.000000750)	(0.000000731)
$\{\mathbf{G}_{it}=4\}\times C^{dm}_{t,s_{it}}$	0.000000518	0.000000327	0.000000758	0.000000402
	(0.000000698)	(0.000000696)	(0.000000750)	(0.000000729)
$\{\mathbf{G}_{it}=5\}\times C^{dm}_{t,s_{it}}$	0.000005748**	0.000005057**	0.000006934***	0.000005593**
	(0.000002346)	(0.000002058)	(0.000002599)	(0.000002214)
$\{\mathbf{G}_{it}=6\}\times C^{dm}_{t,s_{it}}$	0.000002747*	0.000002122	0.000003287*	0.000002357
	(0.000001668)	(0.000001332)	(0.000001865)	(0.000001465)
$\mathbf{G}_{it}=0$	0.0000	0.0000	0.0000	0.0000
	-	-	-	-
$\mathbf{G}_{it}=1$	1.844213783***	1.824591042***	1.843779878***	1.820940076***
	(0.002272788)	(0.002491134)	(0.002286601)	(0.002472774)
$\mathbf{G}_{it}=2$	2.724941524***	2.707173410***	2.722375741***	2.709345127***
	(0.001734656)	(0.001899751)	(0.001740562)	(0.001866753)
$\mathbf{G}_{it}=3$	3.372237078***	3.356677173***	3.369524232***	3.360785857***
	(0.001623095)	(0.001776527)	(0.001627169)	(0.001743620)
$\mathbf{G}_{it}=4$	3.911714457***	3.896654552***	3.909140454***	3.901367209***
	(0.001695003)	(0.001859647)	(0.001700077)	(0.001830111)
$\mathbf{G}_{it}=5$	4.425653305***	4.409600773***	4.423158719***	4.414369555***
	(0.002049951)	(0.002251777)	(0.002057469)	(0.002226732)
$\mathbf{G}_{it}=6$	4.994460138***	4.971032677***	4.992013667***	4.976684600***
	(0.003358104)	(0.003668600)	(0.003367049)	(0.003660684)
P_{it}	-0.037123816*	-0.048460367***	0.081440989***	0.064037359***
	(0.021031167)	(0.018196774)	(0.021363669)	(0.018172639)
$\{\mathbf{G}_{it}=1\}\times P^{dm}_{it}$	-0.513009662***	0.010506530	-0.396276226***	0.297722005***
	(0.013480752)	(0.017671013)	(0.014788065)	(0.018195798)
$\{\mathbf{G}_{it}=2\}\times P^{dm}_{it}$	-0.034174329***	0.149260950***	-0.159747456***	0.064273997***
	(0.010371774)	(0.013858295)	(0.011312530)	(0.013829497)
$\{\mathbf{G}_{it}=3\}\times P^{dm}_{it}$	0.177631641***	0.190070728***	-0.043396147***	-0.038003560***
	(0.009539397)	(0.012019623)	(0.010324705)	(0.012007709)
$\{\mathbf{G}_{it}=4\}\times P^{dm}_{it}$	0.285017715***	0.174304446***	0.008168541	-0.129709741***
	(0.009289828)	(0.011356546)	(0.010037366)	(0.011376337)
$\{\mathbf{G}_{it}=5\}\times P^{dm}_{it}$	0.353196055***	0.156051239***	0.033676137***	-0.196306173***
	(0.009397105)	(0.011278639)	(0.010219304)	(0.011305162)
$\{\mathbf{G}_{it}=6\}\times P^{dm}_{it}$	0.434234137***	0.167087100***	0.054632796***	-0.251623481***
	(0.011146790)	(0.012303862)	(0.012084991)	(0.012525351)
_cons	0.520594230***	1.390177593***	-0.099091559	0.395227106
	(0.109153658)	(0.417619880)	(0.112397709)	(0.427346217)
Year-month fixed effect	Yes	Yes	Yes	Yes
Herd fixed effect	Yes	Yes	Yes	Yes
Deflated	No	No	Yes	Yes
Lag	No	Yes	No	Yes
Month	108	96	108	96
Panel groups	68113	68113	68113	68113
N	7356204	6538848	7356204	6538848