Urbanization and Structural Transformation in the British Cattle Industry

Zekuan Dong
K. Aleks Schaefer

Selected Paper prepared for presentation at the 2022 Agricultural & Applied Economics Association Annual Meeting, Anaheim, CA; July 31-August 2

Urbanization and Structural Transformation in the British Cattle Industry

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., 2006; Thornton, 2010). Moreover, urbanization could stimulate

---

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

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 2008-2018 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.

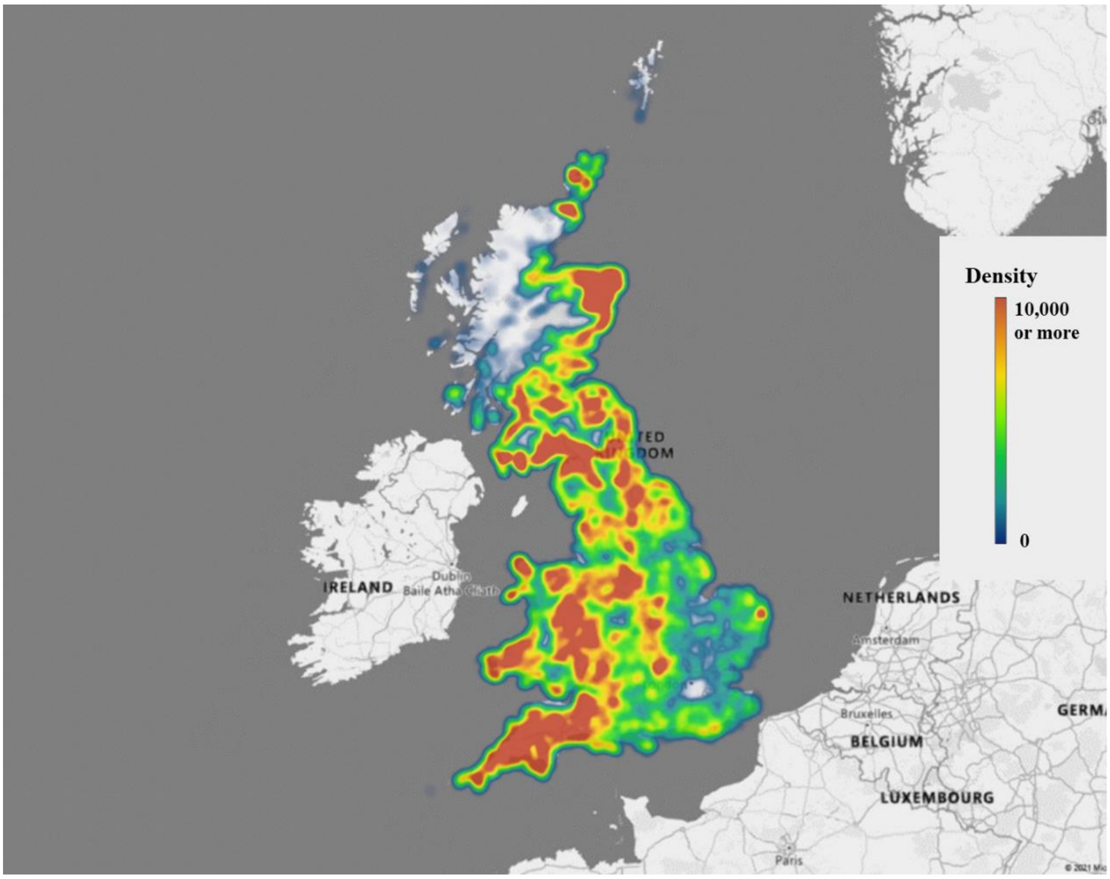
Our empirical results indicate that house price could produce heterogenous impacts on herds with different sizes or areas with different cattle densities. Specifically, the increase of house price would make herds with small sizes smaller or even disappear, and make large herds larger. Similarly, the 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 5.5 million beef cattle distribute in approximately 100,000 herds. Figure 1 displays the spatial distribution of beef cattle in Great Britain in January, 2008. 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, 2008)



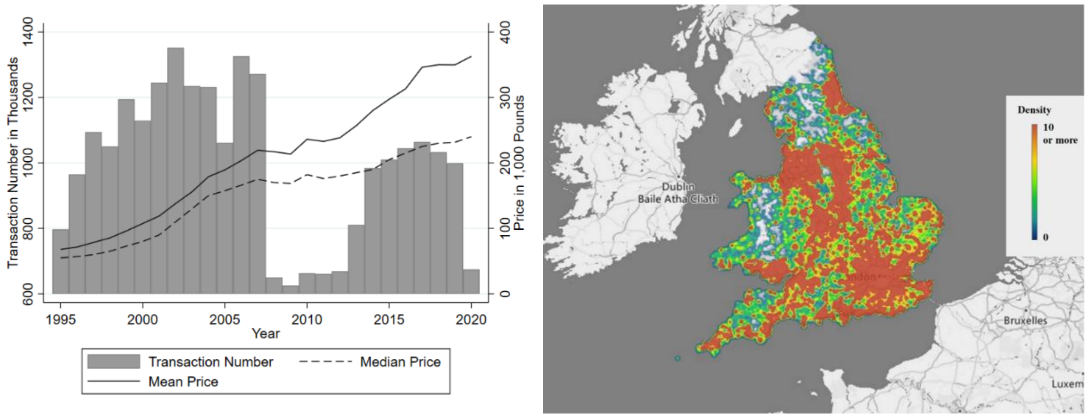
Great Britain has a long history of urbanization. It was the first country to experience rapid and large-scale urbanization, which started in the Mid-18 century and completed by the First World War (Law,1967). During this period, the ratio of urban population in England and Wales increase rapidly from 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 (2018) 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 72,837 beef cattle herds with a total of 9,614,484 observations in England and Wales from 2008 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 different empirical methods of testing the impact of house prices on herds' sizes and existence separately. Section 4.5 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)

---

[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.

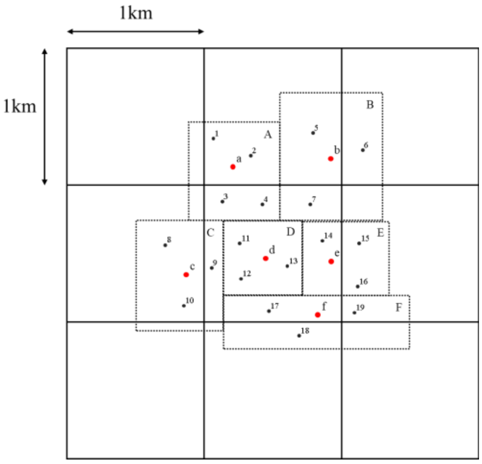
[5] Shepard (1968) propose this method to do two-dimensional interpolation in a geographic system, based on Shepard's method, the basic function of interpolation used in this paper is:

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

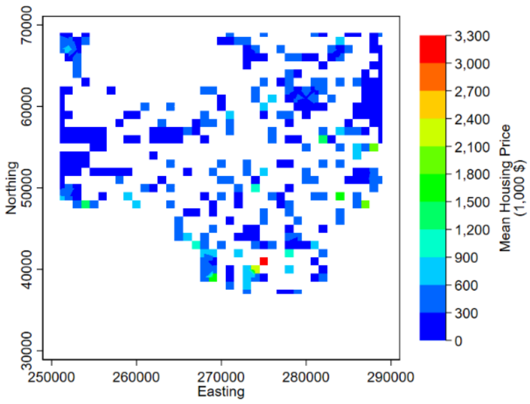
Where z is the house price of a square's central point, x and y are the easting and northing of a square's central point. Thus, the function above can help estimate the unknown house prices of some squares' central points, which are regarded as the average house prices of the square.

shows the visualization 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.

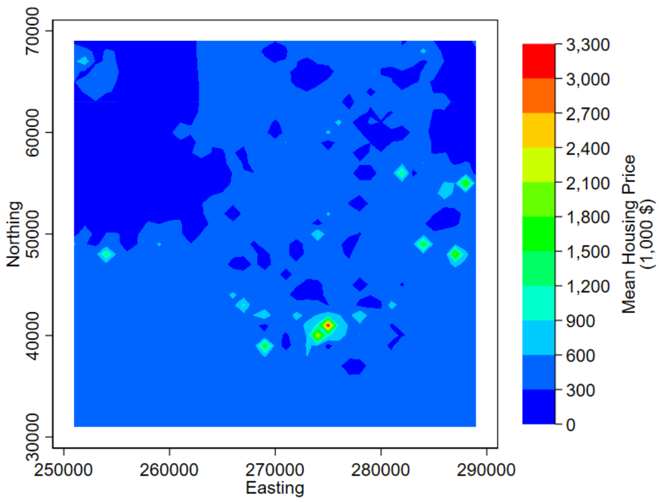
Figure 4 Construction Methods of House Prices heatmaps



Panel(a)



Panel(b)



Panel(c)

4.2 Herds' Existence and Sizes Analyses (Analyses A and B)

To investigate the impact of house prices on herds' existence and size, we consider the following analyses. Firstly, 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' existence (analysis A) and sizes (analysis B):

$$y_{it} = \alpha + \beta_0 H_{t,S_{it}} + \gamma_i + \delta_t + \varepsilon_{it} \quad (1)$$

For analysis A, y_{it} is a dummy variable that indicates if herd i still exists in month t For analysis B, 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 t 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. We employ the two-way fixed effect model to control unobserved factors, γ_i is the herd-level fixed effect, and δ_t is the monthly level fixed effect. ε_{it} is the error term. Thus β_0 is the estimator that carries the impact of house prices on herds' size.

4.3 Heterogeneous Impacts on Herds' existence (Analysis C)

Based on our conceptual model, we consider that house prices might generate different impacts on heterogeneous herds or areas. Thus, we construct analysis C to figure out if herds with different sizes are affected by house prices differently. The empirical model of analysis C is:

$$y_{it} = \alpha + \beta_0 H_{t,S_{it}} + \sum_{Q} \left(\alpha_Q \iota_{Q,it} + \beta_Q \iota_{Q,it} H_{t,S_{it}} \right) + \gamma_i + \delta_t + \varepsilon_{it} \quad (5)$$

Where y_{it} is a dummy variable that indicates if herd i still exists in month t. $\iota_{Q,it}$ is a serious of dummy variables represents the "size" categories that herd i in period t belongs to. For robustness, we use two methods to construct "size" categories. In first method, we only keep those herds that exist at the beginning of our time region (specifically, in Jan 2008). Based on the herds' relative size in Jan 2008, we separate herds into 10 even groups. Thus, $Q \in (1,2,\dots,10)$. The second method is, we separate the herds into 11 groups based on its size in time $t-12$ (one year before), group 0 will contain all the "0" observations, and group 1-10 will contain all the non-zero observations. Thus $Q \in (0,1,2,\dots,10)$ and the current existence will be influenced by the herds' group of one year before[6]. We interact $\iota_{Q,it}$ with $H_{t,S_{it}}$ to allow responses to urbanization (variable $H_{t,S_{it}}$) to differ based on the size of the herd.

4.4 Heterogeneous Impacts on Herds' sizes (Analysis D)

The empirical of analysis D is the similar with analysis C, but y_{it} is the natural logarithm of the number of animals in the herd i in month t. And we change the methods we define $\iota_{Q,it}$ to handle the problems generated by no-cattle herds.

In first method, we only keep those herds that exist in every period of our time region (specifically, from Jan 2008 to Dec 2018). Thus no-cattle samples will all be dropped. Based on the herds' relative size in every month, we separate herds into 10 even groups. Thus, $Q \in (1,2,\dots,10)$. The second method is, we separate the herds into 11 groups based on its size in time t, group 0 will contain all the "0" observations, and group 1-10 will contain all the non-zero observations, thus $Q \in (0,1,2,\dots,10)$. We interact $\iota_{Q,it}$ with $H_{t,S_{it}}$ to allow responses to urbanization (variable $H_{t,S_{it}}$) to differ based on the size of the herd.

4.6 Summary Statistics

Table 1 reports the summary statistics. Our panel dataset is strong balanced and includes 72837 beef herds' information in 132 months. Then the total observations are about 9.6 million. And about 3.4 million observations report no cattle. We further distribute these herds into 46998 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.

---

[6] We shouldn't use the current group of a herd as independent variable because there are strong collinearity current existence and current group.

Table 1 Summary Statistics

Sample		Variable	Mean	Std. Dev	Min	Max
Whole ($n = 9614484$)						
		$\exp(y_{it})$: $Number\ of\ cattle$	52.04159	110.0278	0	5956
		y_{it}: $Existence$	0.6413044	0.4796176	0	1
		$\exp(H_{t,S_{it}})$	312753.7	400022.7	200	111000000
Jan 2008 ($n = 72837$)						
		$\exp(y_{it})$: $Number\ of\ cattle$	55.12745	109.0138	0	3083
		y_{it}: $Existence$	0.6828672	0.4653628	0	1
		$\exp(H_{t,S_{it}})$	279258.4	130749.6	27000	4183500
	$Q = 0 (n = 23099)$					
		$\exp(y_{it})$: $Number\ of\ cattle$	0	0	0	0
		$\exp(H_{t,S_{it}})$	282338.5	141753.3	27500	4183500
	$Q = 1\ (n = 5638)$					
		$\exp(y_{it})$: $Number\ of\ cattle$	2.509046	1.049345	1	4
		$\exp(H_{t,S_{it}})$	285518.1	141497.9	40360	2737500
	$Q = 2\ (n = 4595)$					
		$\exp(y_{it})$: $Number\ of\ cattle$	6.843961	1.402243	5	9
		$\exp(H_{t,S_{it}})$	278430.2	136140.5	46000	2510000
	$Q = 3 (n = 5018)$					
		$\exp(y_{it})$: $Number\ of\ cattle$	13.20925	2.287415	10	17
		$\exp(H_{t,S_{it}})$	277009	142298.1	43750	3000000
	$Q = 4 (n = 4735)$					
		$\exp(y_{it})$: $Number\ of\ cattle$	22.20993	2.870142	18	27
		$\exp(H_{t,S_{it}})$	274453.4	127106.2	52200	2774000
	$Q = 5 (n = 4948)$					
		$\exp(y_{it})$: $Number\ of\ cattle$	34.25748	4.015584	28	41
		$\exp(H_{t,S_{it}})$	275076.7	122037.7	38000	2857999
	$Q = 6 (n = 508)$					
		$\exp(y_{it})$: $Number\ of\ cattle$	50.5757	5.5246	42	60
		$\exp(H_{t,S_{it}})$	271736.3	108424.3	50000	2000000
	$Q = 7 (n = 4900)$					
		$\exp(y_{it})$: $Number\ of\ cattle$	72.21082	7.181677	61	85
		$\exp(H_{t,S_{it}})$	277141	119315.7	59000	2665000
	$Q = 8 (n = 4973)$					
		$\exp(y_{it})$: $Number\ of\ cattle$	103.1661	10.83325	86	123
		$\exp(H_{t,S_{it}})$	275512.2	116943.6	40000	2337500
	$Q = 9 (n = 4874)$					
		$\exp(y_{it})$: $Number\ of\ cattle$	154.7259	20.2866	124	195
		$\exp(H_{t,S_{it}})$	279833.8	123274.8	27000	4058796
	$Q = 10 (n = 4971)$					
		$\exp(y_{it})$: $Number\ of\ cattle$	352.2414	224.1135	196	3083
		$\exp(H_{t,S_{it}})$	282126.1	106473.3	42500	1680000

5 Results

Section 5.1, 5.2 and 5.3 provides estimations of the homogenous impacts of house prices on herds' existence and size (Analyses A and B), and heterogenous impacts on herds' existence and size (Analyses C and D). And serial-correlation-heteroskedasticity-robust standard errors are provided.

5.1 Herds' Existence and Size (Analyses A and B)

Table 2 reports the estimators from Equation (1) for Analysis A and B with inference robust to heteroskedasticity and serial correlation. The estimators of $H_{t,S_{it}}$ shown in the first row capture the effect of house prices on herds. The result indicates that, although house price might have negative impact on herd's existence and size, the estimators are not statistically significant enough.

Table 2 Impact of House Price on Herd Existence and Size

	(1) Existence	(2) Log (number of animals in herd)
$H_{t,S_{it}}$	-0.0019	-0.0054
	(0.0012)	(0.0041)
_cons	0.6651^{***}	2.3735^{***}
	(0.0155)	(0.0508)
Year-month fixed effect	Yes	Yes
Herd fixed effect	Yes	Yes
Month	132	132
Panel groups	72837	72837
N	9614484	9614484

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

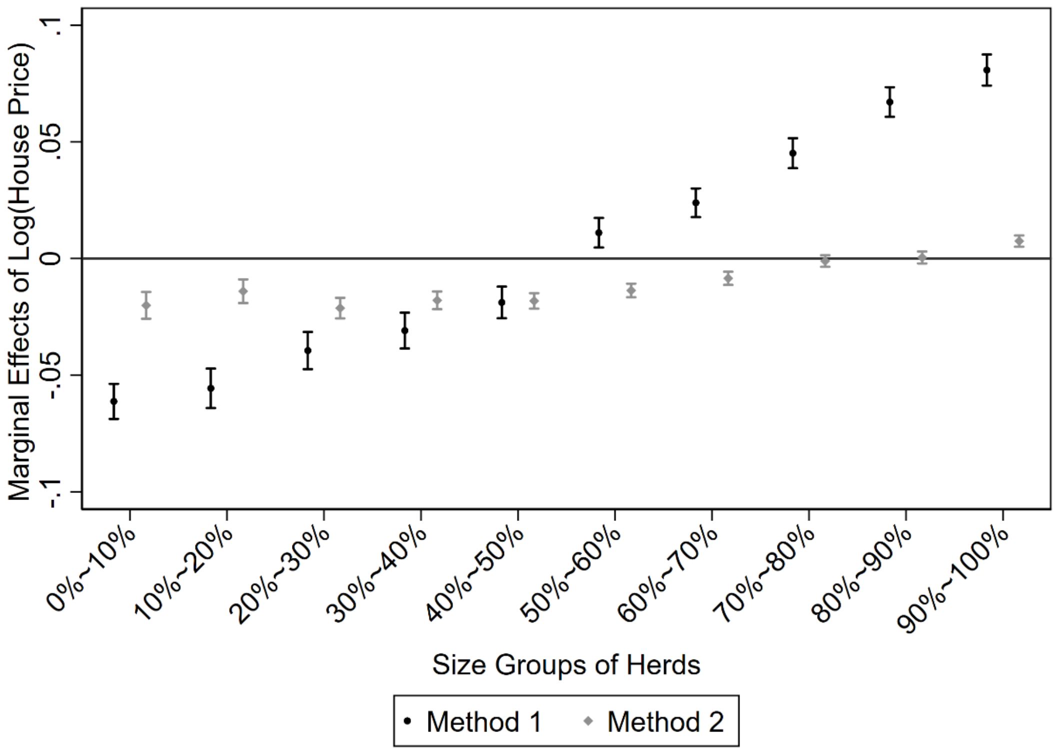
Serial-correlation-heteroskedasticity-robust standard errors are reported in the parentheses. Standard errors are clustered at herd-year level.

5.2 Heterogeneous Impacts on Herds' Existence

In previous section, we don't find strong evidence of the relationship between house price and herds' existence or size. Based on our theoretical model, this issue may be a result of, instead of an irrelevance between house prices and several herds' characteristics, the heterogeneity impacts on different herds. Then analyses C and D are applied to test this hypothesis.

Figure 5 shows the heterogenous impacts of house price on herds' existence with the two classification methods mentioned in section 4.3. And the details are included in the Appendix 1. We can observe strong evidence that house prices have statistically significant and heterogenous impacts on herds with different sizes. Specifically, negative impacts on small herds and positive impacts on big herds. For example, with method 1 of category, we find that for the smallest 10% herds, if house price increase by 10%, the herd will be 0.6% more likely to exit. And for those biggest 10% herds, if house price increase by 10%, they will be 0.8% more likely to stay in the market.

Figure 5 Heterogenous Impacts of House Price on Herds' Existence

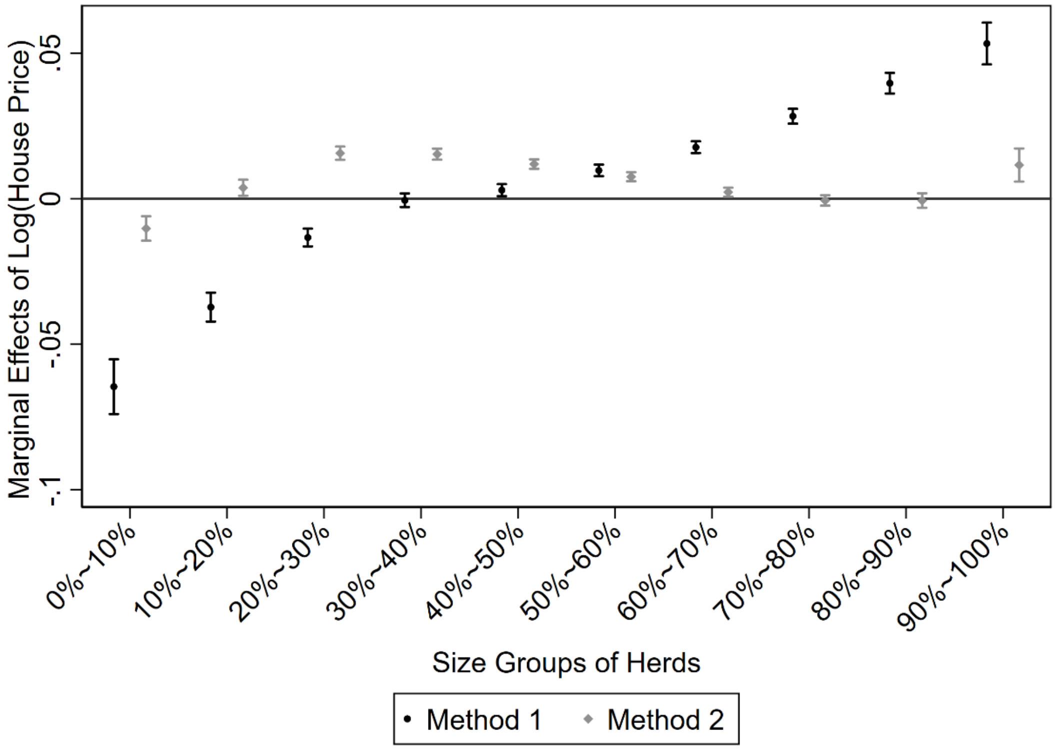


With the conceptual model given in previous section and some economical intuitive, we proposed some explanations about this result. Firstly, small herds, usually with lower productivity, can't generate positive profit under the pressure of increasing house price. So they have to quit the market. Secondly, 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. Exiting the market or moving 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. Thirdly, according to the conceptual model we developed, when house price increase, small herds will exit the market and beef price will increase, which generate a more “comfortable” and “profitable” market circumstance for big herds, they will naturally stay in.

5.3 Heterogeneous Impacts on Herds’ Size

Given the conceptual model and the heterogenous impacts on herds’ existence, we then test if house price has heterogenous impacts on those herds survived. The results based on Analysis D and its two methods are shown in Figure 6. Details about regressors are included in the Appendix 1

Figure 6 Heterogenous Impacts of House Price on Herds’ Size



Our empirical results are congenial with our expectation that herds with different sizes response heterogeneously to house price change. In detail, with method 1, we find that if house price increase by 10%, the smallest 10% herds' size will shirk about 0.65%. On the other hand, the biggest 10% herds will increase about 0.53%. Similar reasons can explain these empirical results. Further, in method 1, because we only keep those herds exist in all the periods, thus the heterogenous results can show that for those herds survive the house price change, there are still heterogenous impacts on herds with different sizes.

With the empirical results in Section 5.2 and 5.3, we can fulfill and verify our theory: when house price increase, herds with lower productivity (usually smallest ones) will exit the market, and for those herds survive, those with relative lower productivity will shirk their size to reach a new optimal point and those with highest productivity (usually biggest ones) will increase their sizes and generate more profit.

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 7. 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 of Method 1 in Section 5.3 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 8. 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 7 Forecasting of House price

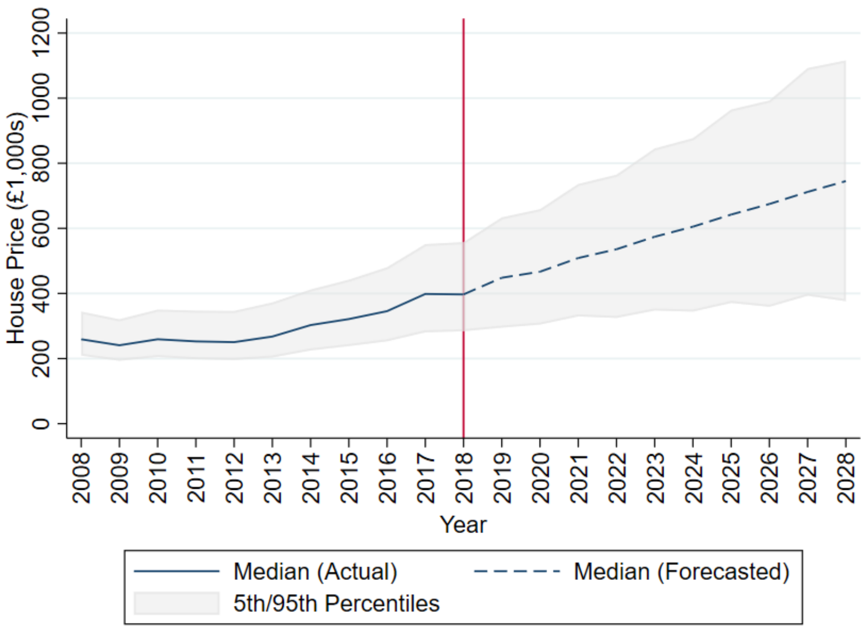
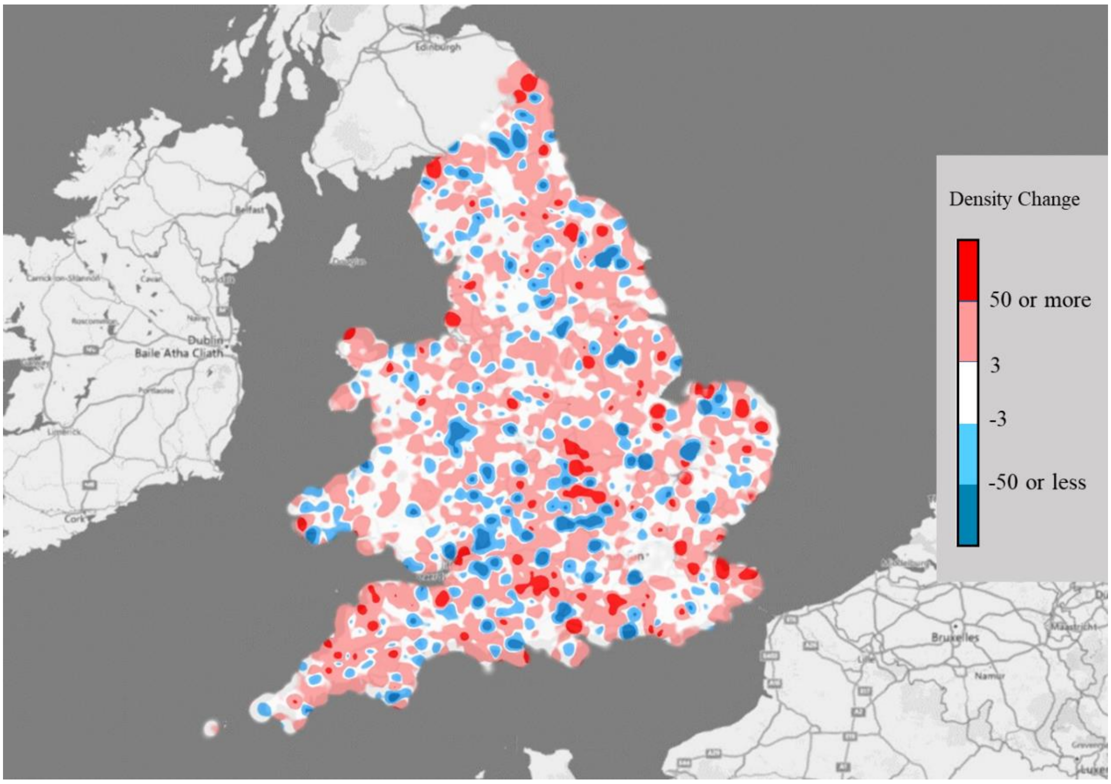


Figure 8 Forecasting of Herds' Density Change



7.Conclusion

Reference

The format hasn't been transferred to AJAE's

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

Appendix 1

Table A1 shows the original regression results for Section 5.2 and 5.3.

Table A1 Heterogenous Impacts of House Price on Herds' Existence and Size

	(1)	(2)	(3)	(4)
	Existence	Existence	Log (number of animals in the herd)	Log (number of animals in the herd)
	Method 1	Method 2	Method 1	Method 2
$H_{t,s_{it}}$	-0.0612***	0.0117***	-0.0646***	-0.0091***
	(0.0038)	(0.0015)	(0.0048)	(0.0005)
$\iota_{1,it} \times H_{t,s_{it}}$	-	-0.0318***	-	-0.0012
	-	(0.0031)	-	(0.0021)
$\iota_{2,it} \times H_{t,s_{it}}$	0.0056	-0.0257***	0.0273***	0.0128***
	(0.0057)	(0.0028)	(0.0050)	(0.0014)
$\iota_{3,it} \times H_{t,s_{it}}$	0.0218***	-0.0330***	0.0513***	0.0247***
	(0.0055)	(0.0026)	(0.0050)	(0.0012)
$\iota_{4,it} \times H_{t,s_{it}}$	0.0303***	-0.0296***	0.0641***	0.0244***
	(0.0054)	(0.0023)	(0.0049)	(0.0010)
$\iota_{5,it} \times H_{t,s_{it}}$	0.0424***	-0.0299***	0.0676***	0.0210***
	(0.0051)	(0.0021)	(0.0049)	(0.0009)
$\iota_{6,it} \times H_{t,s_{it}}$	0.0723***	-0.0254***	0.0743***	0.0166***
	(0.0050)	(0.0020)	(0.0049)	(0.0009)
$\iota_{7,it} \times H_{t,s_{it}}$	0.0851***	-0.0202***	0.0823***	0.0113***
	(0.0049)	(0.0020)	(0.0049)	(0.0009)
$\iota_{8,it} \times H_{t,s_{it}}$	0.1064***	-0.0128***	0.0930***	0.0085***
	(0.0050)	(0.0018)	(0.0049)	(0.0010)
$\iota_{9,it} \times H_{t,s_{it}}$	0.1283***	-0.0113***	0.1043***	0.0084***
	(0.0049)	(0.0019)	(0.0051)	(0.0013)
$\iota_{10,it} \times H_{t,s_{it}}$	0.1420***	-0.0042**	0.1179***	0.0206***
	(0.0050)	(0.0018)	(0.0060)	(0.0029)

$\iota_{1,it}=1$	-	0.8347***	-	1.2597***
	-	(0.0384)	-	(0.0261)
$\iota_{2,it}=1$	-	0.8488***	0.4303***	1.8857***
	-	(0.0354)	(0.0632)	(0.0175)
$\iota_{3,it}=1$	-	0.9913***	0.6216***	2.3198***
	-	(0.0321)	(0.0620)	(0.0147)
$\iota_{4,it}=1$	-	0.9883***	0.8175***	2.8121***
	-	(0.0292)	(0.0616)	(0.0125)
$\iota_{5,it}=1$	-	1.0204***	1.0703***	3.2749***
	-	(0.0268)	(0.0615)	(0.0110)
$\iota_{6,it}=1$	-	0.9850***	1.2551***	3.6997***
	-	(0.0251)	(0.0613)	(0.0107)
$\iota_{7,it}=1$	-	0.9368***	1.4124***	4.1152***
	-	(0.0247)	(0.0611)	(0.0108)
$\iota_{8,it}=1$	-	0.8562***	1.5473***	4.5020***
		(0.0232)	(0.0619)	(0.0123)
$\iota_{9,it}=1$		0.8504***	1.7124***	4.8901***
		(0.0236)	(0.0639)	(0.0166)
$\iota_{10,it}=1$		0.7743***	1.9339***	5.2338***
		(0.0230)	(0.0761)	(0.0370)
_cons	0.7619***	0.0866***	2.9897***	0.1360***
	(0.0160)	(0.0183)	(0.0601)	(0.0061)
Year-month fixed effect	Yes	Yes	Yes	Yes
Herd fixed effect	Yes	Yes	Yes	Yes
Month	132	120	132	132
Panel groups	49738	72837	27550	72837
N	6565416	8740440	3636600	9614484

Appendix 2

For robustness concern, we further construct empirical regressions over every 1 km by 1 km squares to analysis how house prices effect cattle's' spatial distribution. We first distribute the cattle in every herd into its correspond 1 km^2 square, and total up the cattle number in every square. Then, similar with the regressions on individual herd, we employ following regression model to test the impact of house prices on cattle's density in every square:

$$y_{st}=\alpha+H_{st}\beta_1+\gamma_s+\delta_t+\varepsilon_{st}$$

Where variable y_{st} is the natural logarithm of the number of total animals in the square s in month t ,or y_{st} is a dummy variable that indicates if square s in month t still has cattle. 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. ε_{st} is the error term. Thus β_1 is the estimator that carries the impact of average house prices on herds' distribution.

Table A2.1 shows the basic regression results without separate squares into different groups. We still can't find any statistically significant relationship between house price and cattle distributions.

Table A2.1 Impact of House Price on Squares

	(1)	(2)
	Existence	Log (number of animals in square)
H_{st}	-0.0007	-0.0019
	(0.0014)	(0.0048)
_cons	0.7508***	2.9267***
	(0.0175)	(0.0609)
Year-month fixed effect	Yes	Yes
Herd fixed effect	Yes	Yes
Month	132	132
Panel groups	46998	46998
N	6203736	6203736

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

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

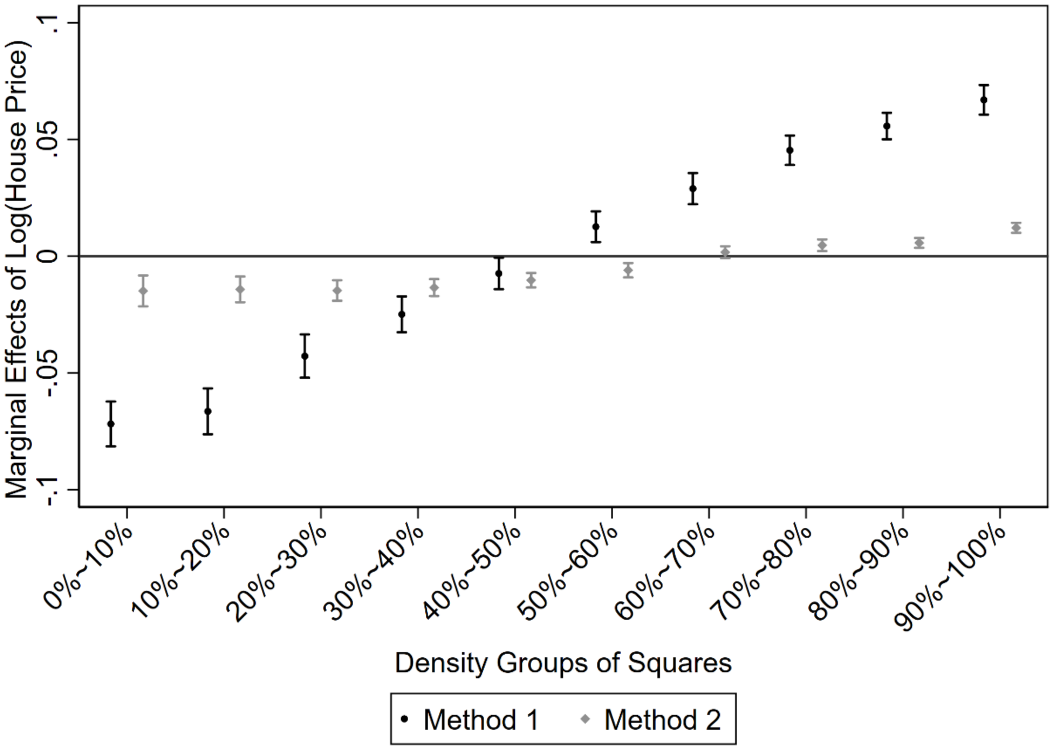
Further, based on the cattle density in every square, we separate them into different groups to test heterogenous impacts. The model for testing impacts on existence is as follow:

$$y_{st} = \alpha + \beta_0 H_{st} + \sum_{Q} \left(\alpha_Q \iota_{Q,st} + \beta_Q \iota_{Q,st} H_{st} \right) + \gamma_i + \delta_t + \varepsilon_{it}$$

Where y_{st} is a dummy variable that indicates if square s still contain some cattle in month t. $\iota_{Q,st}$ is a serious of dummy variables represents the "density" categories that square s in period t belongs to. For robustness, we use two methods to construct "density" categories. In first method, we only keep those squares that contain cattle at the beginning of our time region (specifically, in Jan 2008). Based on the cattle density in Jan 2008, we separate squares into 10 even groups. Thus, $Q \in (1,2, \ldots ,10)$. The second method is, we separate the squares into 11 groups based on its density in time $t - 12$ (one year before), group 0 will contain all the "0" observations, and group 1-10 will contain all the non-zero observations. Thus $Q \in (0,1,2, \ldots ,10)$ and the current existence will be influenced by the squares' group of one year before[7]. We interact $\iota_{Q,st}$ with H_{st} to allow responses to urbanization (variable H_{st}) to differ based on the density within the square.

Then, Figure A2.1 shows how house price impact if there are any cattle within a square. From this result, we can still observe that for squares with original higher density, a higher house price will lead to a higher possibility that the square still contains cattle in the future. And squares with original lower density will be less likely to contain cattle in the future if house price increase.

Figure A2.1 Heterogenous Impacts of House Price on Cattle's Existence in Squares



Using similar model, we change dependent variable y_{st} to the natural logarithm of the number of total cattle in the square s in month t. And the regression results are shown in Figure A2.2. The results future support our solution about the relationship between house price and cattle density.

The detailed regressors of Figure A2.1 and Figure A2.2 are shown in Table A2.

[7] We shouldn't use the current group of a herd as independent variable because there are strong collinearity current existence and current group.

Figure A2.2 Heterogenous Impacts of House Price on Cattle's Density in Squares

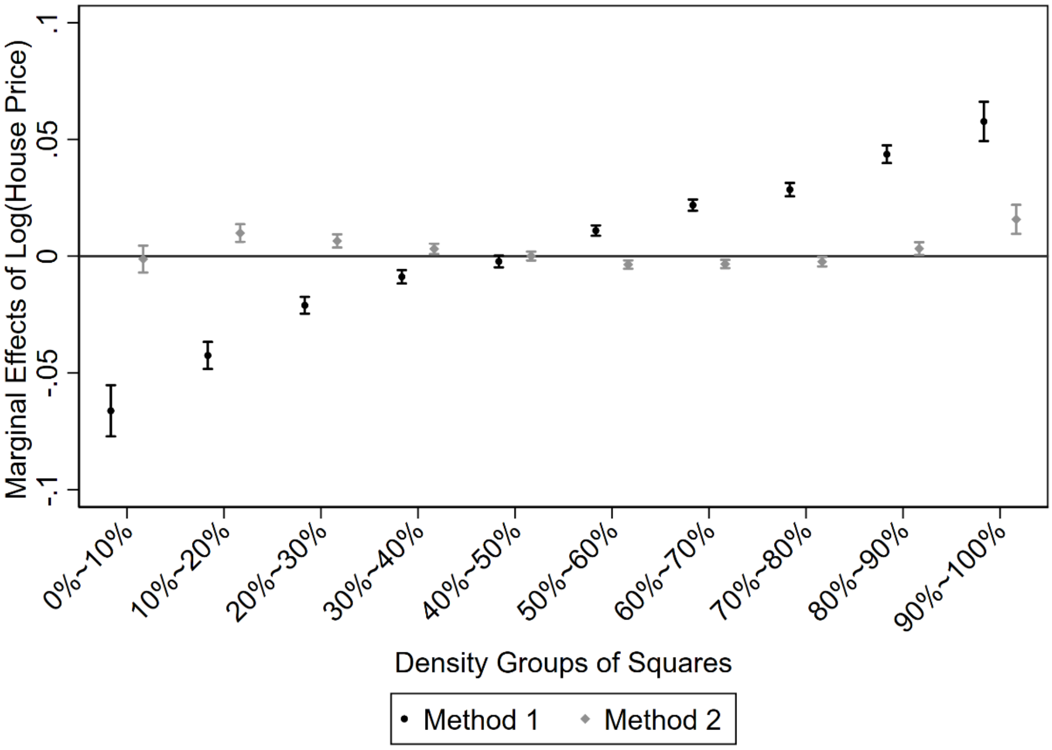


Table A2 Heterogenous Impacts of House Price on Squares

	(1)	(2)	(3)	(4)
	Existence	Existence	Log (number of animals in the square)	Log (number of animals in the square)
	Method 1	Method 2	Method 1	Method 2
H_{st}	-0.0718***	0.0078***	-0.0662***	-0.0048***
	(0.0049)	(0.0022)	(0.0056)	(0.0008)
$\iota_{1,st} \times H_{st}$	-	-0.0227***	-	0.0035
	-	(0.0037)	-	(0.0029)
$\iota_{2,st} \times H_{st}$	0.0054	-0.0220***	0.0237***	0.0147***
	(0.0069)	(0.0034)	(0.0059)	(0.0020)
$\iota_{3,st} \times H_{st}$	0.0290***	-0.0225***	0.0452***	0.0113***
	(0.0067)	(0.0030)	(0.0057)	(0.0015)
$\iota_{4,st} \times H_{st}$	0.0469***	-0.0213***	0.0574***	0.0079***
	(0.0062)	(0.0027)	(0.0058)	(0.0013)
$\iota_{5,st} \times H_{st}$	0.0644***	-0.0181***	0.0640***	0.0048***
	(0.0059)	(0.0026)	(0.0057)	(0.0011)
$\iota_{6,st} \times H_{st}$	0.0845***	-0.0138***	0.0772***	0.0012
	(0.0059)	(0.0026)	(0.0057)	(0.0011)
$\iota_{7,st} \times H_{st}$	0.1008***	-0.0061**	0.0881***	0.0014
	(0.0059)	(0.0024)	(0.0057)	(0.0011)
$\iota_{8,st} \times H_{st}$	0.1172***	-0.0031	0.0947***	0.0024**
	(0.0058)	(0.0024)	(0.0058)	(0.0012)
$\iota_{9,st} \times H_{st}$	0.1276***	-0.0021	0.1099***	0.0080***

	(0.0056)	(0.0023)	(0.0059)	(0.0015)
$\iota_{10,st} \times H_{st}$	0.1388***	0.0043*	0.1239***	0.0206***
	(0.0058)	(0.0023)	(0.0070)	(0.0033)
$\iota_{1,st} = 1$	-	0.7354***	-	1.3628***
	-	(0.0467)	-	(0.0365)
$\iota_{2,st} = 1$	-	0.8152***	0.5271***	2.1502***
	-	(0.0423)	(0.0737)	(0.0246)
$\iota_{3,st} = 1$	-	0.8708***	0.7494***	2.8376***
	-	(0.0374)	(0.0721)	(0.0191)
$\iota_{4,st} = 1$	-	0.8880***	0.9484***	3.3788***
	-	(0.0344)	(0.0722)	(0.0159)
$\iota_{5,st} = 1$	-	0.8661***	1.1579***	3.8150***
	-	(0.0323)	(0.0720)	(0.0145)
$\iota_{6,st} = 1$	-	0.8261***	1.2553***	4.2065***
	-	(0.0324)	(0.0713)	(0.0141)
$\iota_{7,st} = 1$	-	0.7393***	1.3731***	4.5272***
	-	(0.0305)	(0.0715)	(0.0141)
$\iota_{8,st} = 1$	-	0.7095***	1.5575***	4.8367***
		(0.0303)	(0.0722)	(0.0156)
$\iota_{9,st} = 1$		0.7027***	1.6748***	5.1271***
		(0.0292)	(0.0737)	(0.0195)
$\iota_{10,st} = 1$		0.6261***	1.8920***	5.4268***
		(0.0294)	(0.0881)	(0.0408)
_cons	0.8573***	0.1799***	3.2146***	0.1094***
	(0.0175)	(0.0271)	(0.0701)	(0.0102)
Year-month fixed effect	Yes	Yes	Yes	Yes
Herd fixed effect	Yes	Yes	Yes	Yes
Month	132	120	132	132
Panel groups	36768	46998	24046	46998
N	4853376	5639760	3174072	6203736