Housing Shock and Online Consumption

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Abstract

To establish the causal relationship between housing price appreciation and online consumption behavior, this study exploits a unique and comprehensive dataset assembled from October 1, 2016 to December 31, 2018 by the largest e-commerce company in China. In order to overcome the empirical challenges faced by existing literature due to the non-random nature of housing price changes, this study investigates a unique institutional setting in China, namely the announcement of the newest national-level special economic zone, Xiong'an New Area, as an exogenous shock to the housing price. The study focuses on three areas of interest. First, we examine how exogenous and unanticipated wealth shocks impact household online consumption behaviors. Second, we study the dynamic change of online consumption behaviors before and after the housing shock, and determine whether the behavioral responses persist in the long run. Third, we explore the underlying mechanisms through which the housing shock affects consumption behaviors. In particular, we attempt to disentangle the *collateral effects* from the housing *wealth effects*.

Keywords: Housing price, wealth effects, collateral effects, online consumption

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1 Introduction

Substantial evidence indicates that changes in wealth, whether anticipated or unanticipated, transitory or permanent, can significantly affect household consumption (Campbell and Cocco, 2007; Agarwal and Qian, 2014; Aladangady, 2017; Bunn et al., 2018; Waxman et al., 2019), labor supply (Cesarini et al., 2017; Li et al., 2020), health condition (Cesarini et al., 2016; Erixson, 2017), psychological well-being (Frijters et al., 2004; Haushofer and Shapiro, 2016; Lindqvist et al., 2020) and many other areas (Bignon et al., 2017; Briggs et al., 2020). The rapid expansion of e-commerce in all countries in recent years and its important role makes it crucial for policymakers and researchers to understand how e-commerce consumers respond to wealth shocks. However, interpretation of these responses is challenging due to the potential endogeneity and reverse causality issues. More specifically, lack of micro-level data related to online consumption as well as to exogenous and unanticipated changes in wealth has created difficulties in identifying a causal link between changes in wealth and online consumer behaviors. This paper exploits a truly exogenous variation in housing wealth caused by the announcement of a state-level special economic-development zone, and employs high-quality datasets to examine the causal effects of housing price changes on online consumption behaviors.

The housing market provides an excellent laboratory for analyzing the effects of wealth on consumption (Campbell and Cocco, 2007; Gan, 2010; Aladangady, 2017; Agarwal and Qian, 2017; Waxman et al., 2019). In the last few decades, many countries have experienced dramatic, long-lasting housing price increases (Fang et al., 2016; Glaeser et al., 2017; Aladangady, 2017), making it important to understand the effects of housing price appreciation on household consumption, especially in the e-commerce era. While positive consumption responses to housing price appreciation have been well established in the US and the UK contexts, similar evidence is lacking in other countries. This gap matters, and especially so in emerging markets, where the household saving pattern and the relative importance of housing in total household wealth differ. Compared to 30% for US households in the 2010 Census, housing accounts for 77.7% of the total household wealth of urban households in China, and in 2017, homeownership was over 80% in cities (Glaeser et al., 2017). Thus, the magnitude and the volatility of housing prices provide important channels to an understanding of the causal effects of wealth on consumption behavior.

Meanwhile, the rapid development of e-commerce has made online consumption increasingly important in the past decade. In achieving an average annual growth rate of 30% from 2004 to 2017, China has developed the world's largest e-commerce market. After showing a 14.14% year-on-year growth, the number of online shoppers in China reached 610 million, and the penetration rate of online shoppers reached 76% by December 2018. In 2019, the added value of the digital economy accounted for more than one-third of the country's GDP ($14.4 trillion). According to the public report by the National Bureau of Statistics, around 20.7% of the total retail sales of consumer goods were purchased online.[1]

[1] Online shopping in Beijing and Shanghai accounted for about 45% and 40% respectively of total consumer goods purchased. Source: `http://www.stats.gov.cn/tjsj/zxfb/202002/t20200228_1728913.html`

To develop a causal interpretation, we utilize a proprietary and comprehensive online consumption dataset provided by the largest e-commerce company in China, together with the announcement of plans to develop the Xiong'an New Area (see Section 2 for details) and its significant effects on housing wealth. The level of housing wealth before the announcement is orthogonal to the announcement since the exact announcement date and geographic coverage of the state-level special economic-development zone are plausibly exogenous and unanticipated. We take advantage of the differences in the cross-sectional and temporal variation of the establishment of the Xiong'an New Area to construct treatment and control groups. With their property values skyrocketing overnight, homeowners in the Xiong'an New Area were overjoyed to find themselves sitting on potential goldmines; thus, we define households who reside in areas that experience this massive housing price appreciation as treated. The shock to housing wealth is economically significant. Specifically, the difference-in-differences (DID) estimations reveal that after the announcement of the Xiong'an New Area, the listing price of properties in three Xiong'an counties and nine adjacent counties respectively increases by 62.26% and 15.72%, relative to 40 non-adjacent control counties.

We further implement the DID strategy to study the responses of consumption behaviors to the announcement of Xiong'an using the online consumption data that contains the universe of transactions of 4,441 randomly selected active sellers between October 2016 and December 2018. Specifically, we focus on several dimensions of individuals' behavioral response: consumer hesitation or delay in payment, the willingness to return purchased goods, the propensity to make online purchases during work hours, the preference for products with discounts, and the tendency to upgrade consumption. In this paper, we study four research questions. First, does the housing shock have positive or negative impacts on various online consumption behaviors? Second, do the responses change over time and will they persist in the long run? Third, what are the underlying mechanisms? In other words, how can the consumption behavior response to the increasing housing wealth (*wealth effects*) be distinguished from the increasing access to home equity (*collateral effects*)? And fourth, are the responses different across various types of consumers and categories of merchandise?

We find that after the positive shock to housing price, the treated consumers exhibit significant changes in various consumption behaviors relative to the control consumers. First, individuals in the three counties of the Xiong'an New Area (nine adjacent counties to the new area) became 14.2% (6.0%) less hesitant in making payments, and 8.1% (3.1%) less likely to request returns. This suggests that a higher level of housing price effectively reduces the additional processing time before making the purchase decision and lowers the propensity to return unsatisfactory products. Second, after benefiting from a large windfall of housing wealth, individuals in the three treated counties (nine adjacent counties) became 8.7% (3.5%) more likely to use work hours to make online purchases, which is consistent with the findings in Gu et al. (2019). Third, after the positive shock to housing wealth, individuals in the three treated counties (nine adjacent counties) upgraded their consumption habits by spending 10.2% (4.8%) more on an item and 11.6% (4.3%) more on an order, on average.

It is worth emphasizing that we cannot precisely identify the home-ownership of consumers due to data limitations. Instead, to explore the underlying mechanisms, and more specifically, to tease out the pure housing price appreciation (*wealth effect*) from the increased access to home equity (*collateral effect*), we exploit another policy that varies by geographic coverage. Notably, on the second day after the announcement of the Xiong'an New Area, the government suspended all housing transactions in three counties located in Xiong'an, while real estate outside Xiong'an remain tradable. Thus, after the announcement, the residents in Xiong'an can only resort to home equity loans, while residents outside Xiong'an can either sell their properties or borrow against the value of home equity. Comparing consumers in Xiong'an with those outside Xiong'an, we can disentangle the housing wealth effect from the collateral effect. We show that the pure housing wealth effect leads to a 10.85% decrease in payment hesitation, a 3.67% decrease in return intention, a 6.14% increase in shirking propensity, and a 6.04% increase in average payment per order.

We also perform the dynamic analysis and, to validate our research design, we explicitly test the parallel trends in consumption behaviors before the announcement of the Xiong'an New Area. The dynamic paths show that the sizable and unanticipated wealth effects on payment hesitation, shirking, and consumption upgrade persist in the long run. Regarding the willingness to return a product, we observe a U-shape response in which the most significant drop in return propensity occurs seventh months after the wealth shock. To gain further insights into those who respond and the extent to which their responses vary across item categories, we carry out a battery of heterogeneity tests across types of consumers and categories of products. Specifically, older and female consumers are more responsive in consumption upgrades, which are in line with the findings in Campbell and Cocco (2007), who reveal that older homeowners respond more to housing wealth changes than younger homeowners. In addition, after the announcement, consumers in the nine adjacent counties upgrade their consumption in five out of six product categories, while consumers in the three Xiong'an counties appear to purchase more expensive products only in the categories of home appliances and clothing.

This paper adds to the broad literature on consumption response to changes in economic resources. Jappelli and Pistaferri (2010) provide a comprehensive review of empirical approaches employed by researchers and point out that the quasi-experimental approach is useful to establish the causality, while the key challenge is to identify episodes of genuine exogenous and unanticipated changes. The plausibly exogenous shocks to wealth and income used in the existing literature include lottery gambling (Imbens et al., 2001; Kuhn et al., 2011), disability (Gertler and Gruber, 2002; Meyer and Mok, 2019), weather shocks (Wolpin, 1982; Paxson, 1993), and unanticipated government policies (Parker et al., 2013; Agarwal and Qian, 2014; Jappelli and Pistaferri, 2014; Haushofer and Shapiro, 2016). We contribute to this strand of literature by exploiting a unique and truly exogenous policy that creates spatial and temporal variation in housing price. Moreover, instead of focusing on offline consumption, which has been studied both extensively and intensively, we directly contribute to the literature by providing the first empirical analysis of the effect of housing shock on online consumption. The fast-growing global e-commerce market makes the findings of this study important.

This study also relates to another strand of literature on the behavioral responses to wealth shocks. Haushofer and Shapiro (2016), Blattman et al. (2017), Cesarini et al. (2017), and Li et al. (2020) examine the impact of income shocks on labor supply, for which the findings are mixed. Some other studies investigate the influence of income changes on stock market participation (Barberis et al., 2006; Andersen and Nielsen, 2011; Briggs et al., 2020), household consumption (Waxman et al., 2019; Gu et al., 2019), criminal behaviour (Bignon et al., 2017), and psychological well-being (Stevenson and Wolfers, 2013; Schwandt, 2018; Lindqvist et al., 2020). Our paper contributes to this stream of literature by looking at new outcome variables, which are difficult and sometimes impossible to measure by using the traditional offline consumption data.

This study also contributes to a growing literature on online consumption. Relative to the extensive studies carried out on offline consumption, very few papers investigate online consumption. Using Alibaba's e-commerce data to construct the county-level e-commerce development measures, Luo et al. (2019) reveal a positive correlation between e-commerce development and consumption growth. In a randomized control trial, Couture et al. (2020) exploit the universe of e-commerce purchases from 5 provinces and about 12,000 villages in China, and find little evidence of consumption response to an e-commerce expansion program in China. Hortaçsu et al. (2009) use eBay's transaction data to show that e-commerce reduces the trade barrier observed in off-line trade. Einav et al. (2014) also use the eBay data, but focus their study on the sensitivity of e-commerce purchasing to sales taxes.

Nevertheless, we should keep two caveats in mind. First, because our data do not cover homeownership information, we cannot precisely identify the treated home owners and treated renters. However, we believe that the influence of this data limitation is only slight, mainly because homeownership in China, especially in the regions like the pre-announcement Xiong'an New Area, is exceptionally high. Moreover, we restrict our sample buyers to those whose receiving addresses are only in Xiong'an both before and after the shock. This helps us to mitigate the concern that the blurriness of ownership may induce spurious regression results. Second, although the geographical randomization of the housing wealth strengthens our case for exogeneity, a limitation of this study, as with many other natural experiments, is its possible bias from the lack of representativeness of the entire population.

The remainder of the paper is structured as follows. In Section 2, we provide a brief introduction to the Xiong'an New Area. Section 3 describes the datasets and provides descriptive statistics. In Section 4, we use various DID estimations to evaluate the impact of the establishment of Xiong'an on online consumption. 5 provides a battery of heterogeneity tests and additional tests to generalize the results. Section 6 summarizes the findings of the study.

2 A Brief Introduction of the Xiong'an New Area

In China, new areas are urban districts that receive preferential treatment from the central and local governments and are divided into three levels: state-level, province-level, and prefecture-level. In particular, new areas receive many preferential funding and policy privileges, which are designed to encourage and attract new developments in order to speed up their economic growth. In October

1992, the central government established the Pudong New Area in Shanghai as the first state-level new area, and over the last two decades, the model has been replicated in many other major cities. On April 1, 2017, the central government suddenly announced plans to create the Xiong'an New Area. Although the Xiong'an New Area is the 19th state-level new area, it is the *first* new area that was announced by both the Central Committee of the Communist Party of China (CPC) and the State Council. This innovative development zone has been cast as an integral piece of the "crucial strategy for the millennium to come", and is part of a drive to cement China's credentials as a leader in urban development and to incorporate new technologies into infrastructure.

The Xiong'an New Area is located in the center of Hebei province, 100km southwest of Beijing and around 50km from downtown Baoding. As highlighted in dark blue in Figure 1, the New Area spans the three counties, namely *Xiongxian, Rongcheng,* and *Anxin*, and the population target is 2.5 million with a population density of 1250 people/km^2. The average per capita GDP of the three counties as of 2016 is 19,227 CNY (3,000 US dollars).[2] The main function of Xiong'an New Area is to serve as a development hub for the Beijing-Tianjin-Hebei economic triangle, and to provide non-capital functions in Beijing, such as schools, hospitals, headquarters of some state-owned enterprises, public services, and financial institutions. In addition, the central government of China plans to invest RMB 4 trillion (US$ 580 billion) over the next two decades as part of its "millennium strategy" for the Xiong'an New Area, which will become a major new economic centre similar to the Pudong New Area in Shanghai and the Shenzhen Special Economic Zone in Guangdong province, both of which have proved to be great successes.

[Figure 1 inserted here]

Existing studies that estimate wealth or income effects are challenged by the fact that the amounts of wealth or income are not randomly assigned, and exogenous changes in wealth or income are difficult to identify. The establishment of the Xiong'an New Area creates an exogenous and sizeable shock because the announcement is unanticipated and strictly confidential. The planning and development of Xiong'an is under the direct oversight of China Central Government. Specifically, on March 5, 2016, the location and name of the New Area were confirmed in a meeting of the Politburo Standing Committee of China. All the related information, including the geographic coverage, the members of administrative committee, and the announcement date, was kept in strictest confidence until April 1, 2017. Even the local governments in Hebei province was unaware of the establishment of the New Area in advance. Our thorough search of the newspaper articles related to the establishment of Xiong'an finds no discussion before the official announcement on April 1, 2017. In particular, although Chairman Xi visited in *Anxin* County on February 23, 2017, the news was only revealed to the public one month after the announcement of the New Area.

The highlighted importance and the expected pouring in of investment and funding for the counties created optimism about the future of the New Area, and Xiong'an experienced an unprecedented boom in housing prices on the day of the announcement. The excitement following the announcement was prompted by property investors in anticipation of a jump in prices ahead of an expected infrastructure boom. Right after the announcement of the New Area, thousands

[2]Source: `http://xiongan.gov.cn/2017-12/18/c_129769127.htm`

of non-local property investors rushed to Xiong'an to purchase properties. For this reason, on the second day of the establishment of Xiong'an, the local government imposed an emergency suspension of all real estate sales.[3] However, that hardly deterred investors, who simply redirected their attention to areas just outside Xiong'an, causing home prices in neighboring counties to soar also.

3 Data and Descriptive Statistics

3.1 Data

We use a unique and proprietary dataset obtained from a leading e-commerce company in China, which held a market share of around 60 percent and had 636 million active consumers on its online shopping platforms as of 2018. The dataset contains randomly selected 0.1%, which is 4,441, of active sellers in the period from October 1, 2016 to December 31, 2018.[4] We then obtain the universe of transactions of these 4,441 active sellers during the sample period. This random sampling of sellers guarantees the representativeness and practicality of our data.

To study the impact of the establishment of Xiong'an on the online consumption behaviors of consumers, we restrict the sample to include only three groups of buyers, which span 52 sample counties in three cities (Baoding, Cangzhou, and Langfang). Figure 1 plots the geographical distribution of the 52 sample counties. Specifically, Groups 1, 2, and 3 respectively consist of buyers whose receiving addresses are located *only* in the three counties of the Xiong'an New Area (dark blue areas), nine adjacent counties to the new area (light blue areas), and 40 non-adjacent counties (grey areas), both before and after the announcement.[5] This way of constructing data leaves us a final sample with 1,893,062 transactions/orders, 2,498,745 items, 4,441 active sellers, 10,738 buyers in the three counties in Xiong'an, 60,719 buyers in the nine adjacent counties, and 187,629 buyers in the 40 non-adjacent counties.

[Figure 1 inserted here]

The data contains detailed transaction information including order id, buyer id, seller id, receiving address, amount paid in an order, number of purchased items in an order, order created time, order payment time, item name, item price, amount paid for each item, discounted amount for each item, return status of purchased item, delivery fee, as well as delivery company. In addition, over 70 percent of the transaction data contains the last 12 digits of identity card number, which allows us to identify two key demographic characteristics of buyers, namely gender and age. Table 1 reports the summary statistics of key variables at the item level and at the order level for three different buyer groups, both before and after the policy announcement date.

[3] Source: `https://www.wsj.com/articles/china-looks-to-build-a-major-city-from-scratch-1492428602`

[4] According to the E-Commerce Report 2018 published by the Ministry of Commerce, PRC, the e-commerce company has more than 10 million registered sellers. Of these, however, only 4 million are active sellers, the rest being considered inactive sellers who have had no transactions for 30 consecutive days. Source: `http://dzsws.mofcom.gov.cn/article/ztxx/ndbg/201905/20190502868244.shtml`

[5] One point regarding the sample groups worth emphasizing is that we exclude those buyers whose receiving addresses lie outside the respective groups. For example, buyer A (B or C) is excluded if his/her receiving addresses cover not only Xiong'an new area (9 adjacent counties or 40 non-adjacent counties), but also those areas outside Xiong'an (9 adjacent counties or 40 non-adjacent counties).

[Table 1 inserted here]

Our data offers several advantages. First and foremost, our data guarantees representativeness and randomness. In terms of representativeness, the e-commerce company studied plays a dominant role in the e-commerce market in China. More importantly, the e-commerce company provides the universe of transactions of the sample sellers. In terms of randomness, the sellers are randomly selected from the pool of active sellers on the online platform. Second, the data provides rich information about consumers' online consumption behavior, which is unlikely and sometimes impossible to be observed from traditional offline consumption data. In addition to the amount of payment, we create two order-level and two item-level measures of consumers' online consumption behavior. The two order-level measures are hesitation and shirking; and the two item-level measures include discount fee and return propensity. Such precision and resolution of the data provide insights into behavior that are obscured by conventional data sources. Third, the data covers a long sample period and provides a detailed description of the purchased item as well as the last 12 digits of the identity card number, all of which allow us to carry out several heterogeneity tests and gain further insights into the responses of consumers to the positive housing shock.

We also obtain a supplementary dataset that includes the dynamic changes on average housing listing price and rental price per month in each county from *Anjuke*.[6] Figure 2 illustrates the trends of housing listing price and rental price in three Xiong'an counties (solid lines), nine adjacent counties (dotted lines), and 40 non-adjacent counties (dashed lines) during the study period. More specifically, the three graphs in the top panel of Figure 2 show the trends of unit price, total price, and number of listing units in the housing sales market, while the three graphs in the bottom panel present the trends of respective features in the housing rental market. The red vertical line indicates the announcement date of Xiong'an. Figure 2 clearly shows that both the listing and rental prices in the Xiong'an New Area skyrocket rapidly after the announcement. Since the high granular housing transaction data is not available for the study regions, we use micro-level land transaction data and construct alternative measures to provide additional support for the exogenous nature of the announcement. As shown in Figure A1, land transactions in the Xiong'an New Area remained low in the pre-announcement period, and there were no transactions after October 2016.

Alarmed by the rocketing prices, the government moved in on April 2, 2017 to burst the nascent property bubble by suspending all real estate transactions in Xiong'an, which is reflected by the plunging housing supply as shown in the top right graph. In the meantime, the rental housing market in the Xiong'an New Area presents a sustained boom, as shown in the bottom right graph. Despite these home purchase restrictions, the financial outlook for the future residents of Xiong'an has improved considerably, which subsequently redirected investors' attention to areas just outside Xiong'an. This is verified by the soaring home prices in nine neighboring counties in the post-announcement period, as indicated by the dotted lines in the left and middle graphs.

[Figure 2 inserted here]

[6] *Anjuke* is one of the most influential online real estate platforms in China. Source: `https://baoding.anjuke.com/`

3.2 Measures of Consumption Behavior

We construct several unique measures of consumption behaviors. Consumers may have different reasons for delaying payment, such as tight budget, overchoice, or even internet problems. One critical reason for delay is the increase in "perceived risk" or "uncertainty" (Corbin, 1980; Cho et al., 2006). According to Cho et al. (2006), online shopping hesitation or delay is defined as "postponing or deferring product purchases by having additional processing time before making final product-purchase decisions on the Internet." For similar reasons, consumers may also regret their online purchases and request return of products. We define two measures of consumption behaviors that reflect the perceived risk or uncertainty regarding the purchase: *payment hesitation* and *return propensity*. *Payment hesitation* is a continuous variable that measures the time difference between order time and payment time. *Return propensity* is a dummy variable equal to 1 if an item has been returned to a seller and a refund requested, and 0 otherwise.

Consumers may exert less effort in their jobs and spend more unproductive time on non-work activities when their financial wealth increases sharply, which decreases their fear of losing their jobs due to unproductive behavior. Since our data records the exact timestamp of making an order, we can identify work-time shirking if an order was created during work hours. We follow Gu et al. (2019) and define *shirking* as a dummy variable equal to 1 if the order is created during the work hours, and 0 otherwise. Work-hours are defined as those from 9am – 12pm and 2pm – 5pm from Monday to Friday that do not fall on the public holidays included in the official holiday calendar between 2016 and 2018. This measure directly captures the work-hour shirking behavior with high accuracy and frequency.

Consumers may also increase their consumption of certain products, choose to purchase better quality products, or change their preference to products with discounts. We examine whether individuals upgrade their consumption after experiencing wealth shock by using the following measures: *item payment, order payment, # of items*, and *item discount*. Specifically, *item or order payment* measures the payment per item or per order, and *# of items* measures the number of items purchased in an order. *item discount* is a continuous variable that measures the difference between the list price and the sale price of an item. *item discount* examines whether consumers prefer price promotions after the positive wealth shock.

4 Empirical Methodologies and Main Results

4.1 Housing Market Response

To address the identification challenge, we exploit a unique institutional setting in China and use the announcement of the Xiong'an New Area that triggers an immediate upward adjustment and expectation in housing prices. Therefore, the announcement of the new area serves as an exogenous shock to the housing prices. Moreover, a key identification assumption lies in the exogenous nature of the announcement. The exogenous variation arises from the impossibility of predicting the precise timing of the announcement and the geographic coverage of the new area. In addition, the treatment and control counties are similar across a wide range of geographical characteristics and socio-economic conditions.

We begin the analysis by quantifying the response of the housing market to the announcement of Xiong'an. The specification is given as follows:

$$Y_{j,m} = \alpha + \lambda \cdot Treat_j \cdot After_m + \theta_j + \gamma_m + \epsilon_{j,m} \tag{1}$$

where the dependent variable $Y_{j,m}$ takes two forms: listing unit price (CNY/sq^2) and rental unit price (CNY/sq^2) for county j in year-month m. The sample period is from October 2016 to December 2018. $Treat_j$ is a dummy variable equal to 1 for the treatment counties, and 0 for the control counties. $After_m$ is a dummy variable equal to 1 for the periods after April 2017, and 0 otherwise. The coefficient λ on the interaction term of $Treat_j$ and $After_m$ is the standard difference-in-differences estimator. θ_j and γ_m refer to the county fixed effects and year-month fixed effects; and the standard errors are clustered at the county level.

[Table 2 inserted here]

Table 2 reports the results of estimating Eq. (1), with Panels A and B using different treatment and control counties. Specifically, three counties in the Xiong'an New Area (C3 hereafter) and 40 non-adjacent counties to the Xiong'an New Area (C40 hereafter) consist of the treatment group and control group, respectively, in Panel A; nine adjacent counties (C9 hereafter) and C40 comprise the treatment group and control group, respectively, in Panel B.

We find that during the post-announcement period, the listing price and the rental price in C3 increase by 62.26% ($= exp(0.484) - 1$) and 79.68% ($= exp(0.586) - 1$), respectively, more than in C40. When we compare the housing market dynamics in C9 and C40, we also see significant increases of listing price and rental price in the nine adjacent counties of the Xiong'an New Area, at lower magnitudes of 15.72% ($= exp(0.146) - 1$) and 31.78% ($= exp(0.276) - 1$), respectively. The results indicate that the homeowners in both the Xiong'an New Areas and the adjacent counties benefit from the unexpected positive housing market shock.

4.2 The Post-shock Response of Consumer Behavior

4.2.1 Empirical Specifications

To examine the consumption behaviors at the order-level and item-level, we use the following specification:

$$Y_{o,b,s,d} = \alpha + \beta \cdot Treat_b \cdot After_d + \Delta GDP_{j,y} + \delta_s + \theta_b + \gamma_d + \epsilon_{o,b,s,d} \tag{2}$$

where o, b, s, and d respectively index the order/item, buyer, seller and date. $After_d$ is a dummy variable equal to 1 for the period after April 1, 2017. The β coefficients capture the average difference in the dependent variables of the treatment group relative to the control group. Notably, we include county-level GDP growth rate to control for the income effects. δ_s represents seller fixed effects to absorb the time-invariant factors at the seller level, which also mitigates the concern that the consumption behavior may differ across different types of products. θ_b stands for buyer fixed effects that absorb the time-invariant factors at the buyer level. We also control for the date fixed effects γ_d to eliminate the time-specific impact. The standard errors are clustered at the seller level.

The dependent variable $Y_{o,b,s,d}$ takes different forms at the order or item level, which we categorize into three sets. The first set includes two variables that reflect the perceived risk: the logarithm of hesitation at the order level and the return dummy at the item level. The second set consists of one outcome variable, the shirking dummy at the order level, which is related to the change of labor supply when individuals benefit from large windfall of housing wealth. The last set contains four variables that reveal changes in consumption level: the logarithm of quantity and payment at the order level, as well as the logarithm of payment and discount amount at the item level.

Equations (1) and (2) estimate the housing market response and consumption behavior response to the exogenous announcement of the Xiong'an New Area, respectively. We unite the estimations from the two specifications to interpret the estimated coefficients of various consumption behaviors in the context of positive housing price shock. Specifically, we calculate the elasticities of consumption behaviors with respect to housing price by dividing the β in Eq. (2) by the λ in Eq. (1).

In addition, we study the dynamics of the behavior response by estimating the following distributed lag model:

$$Y_{o,b,s,d} = \alpha + \sum_{s=-5}^{19} \beta_s \cdot Treat_b \cdot 1\{d \in Month_s\} + \Delta GDP_{j,y} + \delta_s + \theta_b + \gamma_d + \epsilon_{o,b,s,d} \quad (3)$$

where $d \in Month_s$ is a binary indicator that takes value 1 if the transaction date d is in month $s \in \{-5, -4, -3, -2, ..., 0, ..., 17, 18, 19\}$ before/after April 1, 2017. The coefficient β_s captures the difference in the response of consumption behavior measures compared with the benchmark month (between October 1, 2016 and October 31, 2016) in our sample period between the treatment and control groups. More specifically, the coefficient β_0 measures the immediate response in consumption behavior during the month (April 2017) of the Xiong'an announcement. The coefficients $\beta_1, \ldots, \beta_{19}$ measure the responses in the first to the nineteenth month following the Xiong'an announcement, respectively. Similarly, coefficients $\beta_{-5}, \ldots, \beta_{-1}$ measure the different trends of consumption behavior response between the treatment and control buyers in each of the five pre-treatment months; and these coefficients examine whether the parallel trend assumption for DID is satisfied.

4.2.2 Estimation Results on Average Behavioral Response

Table 3 reports the regression results of Eq. (2) for two models that differ in the estimation sample, as well as the definitions of the treatment and control groups. Specifically, we construct the treatment and control groups based on individuals' receiving addresses located either in C3, C9, or C40. Panel A examines behavioral responses that reflect consumers' perceived risk regarding the purchase decision, namely the payment hesitation and the return propensity. Panel B shows a behavioral response related to individuals' effort choices due to increased housing wealth, namely their shirking propensity. Panel C shows outcome variables related to consumption level, such as the payment and the number of items of an order, and the payment and discount of an item. Specifically, we indicate the order-level and item-level outcome variables by subscript o and i, respectively.

[Table 3 inserted here]

In Model 1, we compare the consumption behavior of individuals in C3 to C40 before and after the announcement on April 1, 2017. More specifically, $Treat_b$ takes the value 1 if an individual's *only* receiving address is located in C3, which refers to the three counties in the Xiong'an New Area; and 0 if an individual's *only* receiving address is located in C40, which refers to 40 non-adjacent counties. Although a policy of freezing housing transactions prevents homeowners in C3 from selling their properties to realize housing wealth, the average household experiences increased access to refinancing against their home equity after the shock. We refer to the increased access to refinancing as the *collateral effect* in Model 1. In the meantime, the establishment of Xiong'an may attract large-scale investments and create more employment opportunities, which would result in positive income shocks to the local population in C3 and could confound the interpretation of our estimation on the *collateral effect.* Therefore, we include the county-level GDP growth rate to capture the possible *income effects* during the sample period and to tease out the *collateral effect* ultimately.[7] We thus interpret the coefficient estimate of $Treat * After$ in Model 1 as measuring the *collateral effect* on consumption behavior.

Model 2 compares the consumption behavior of individuals in C9 to C40 before and after the shock. Similarly, in Model 2, $Treat_b$ takes the value 1 if an individual's *only* receiving address is located in C9, which refers to the nine adjacent counties of the Xiong'an New Area. Individuals in C9 can gain access to the housing wealth through direct selling or mortgage refinancing. That is, the increase in housing price in C9 leads to two effects: *wealth effect* and *collateral effect.* Therefore, after controlling for the GDP growth that captures the *income effect*, the coefficient of $Treat*After$ in Model 2 measures the combined effects of *wealth effect* and *collateral effect.*

Panel A of Model 1 presents interesting findings: with the large windfall of housing wealth, individuals in the Xiong'an New Area reduce their payment hesitation by 14.2% (=exp(-0.153)-1) more than those in the control group. To put the results into context, a 14.2% decrease in payment hesitation is equivalent to approximately 51.1 seconds in reduction of delay in making payment. Greenleaf and Lehmann (1995) and Cho et al. (2006) show that online shopping hesitation or delay are related mainly to buyers' "perceived risk" or "uncertainty"; we therefore conjecture that buyers experiencing yet unrealized increases in housing wealth nonetheless have fewer concerns about "perceived risk" or "uncertainty", and become more decisive or impulsive when purchasing

[7] Since we do not have individual-level income measures, we use the county-level GDP growth rate as a proxy for the income changes. We acknowledge that controlling for the county-level GPD growth rate does not fully capture the impact of income changes due to the exogenous shock.

online.[8] Moreover, we follow Cho et al. (2006) and control for the logarithm of order payment value in the regression. The estimated coefficient on $ln(Payment)$ is significantly positive at 0.122, suggesting that individuals show greater shopping hesitation when purchasing high-value goods.

Another reason that individuals delay payment at the final stage is their wish to avoid regrets over making wrong decisions. Since in most cases, items on the e-commerce website can be exchanged or returned within 7 days from the date of purchase, our data allows us to directly examine the impact on return intention. Considering the return propensity, we find that the coefficient of *Treat* $*$ *After* is significantly negative at -0.085, implying that the treatment individuals are less likely to return the online purchased items after the positive housing wealth shock. The results indicate that housing wealth plays a significant role in shaping online consumption behavior by reducing the perceived risk.

Panel B estimates the shirking propensity. We find the interaction term *Treat* $*$ *After* to be economically and statistically significant at 0.083, indicating that the Xiong'an announcement increases consumers' propensity to use work hours for online shopping. Since the estimated average response is equivalent to a 25.1% increase in the propensity compared to the treatment group's pre-shock mean of 0.33, the effect is economically meaningful. This finding is consistent with those in Gu et al. (2019), which show that individuals become 1.7% more likely to use credit cards for non-work-related transactions during work hours after positive shocks to house prices. This suggests that online transaction is likely to capture a more prevalent and salient unproductive behavior than credit card transactions, because individuals who make online purchases do not have to be absent from work.

Panel C examines changes in consumption level. In response to the positive house price shock, individuals on average increase their order payments by 11.6% (=exp(0.110)-1), and the average payment per item increases by 10.2% (=exp(0.097)-1). The results are consistent with prior studies that document the positive responses of consumption to windfall gains (Agarwal and Qian, 2014; Haushofer and Shapiro, 2016). Indeed, the results show that within sellers, the treated consumers upgrade consumption by purchasing more expensive products. In addition, we test the hypothesis that treated consumers may upgrade their consumption by switching to higher-end sellers and present the results in Table A2. Based on the average item price, we create an ordinal dependent variable by dividing the sellers into five categories and then implement an ordinal logistic regression model. If individuals upgrade consumption across sellers, then we expect to see the coefficient on $Treat*After$ in the ordinal logistic regression to be significantly positive. However, we find that the interaction term statistically insignificant in Table A2, implying that the Xiong'an announcement does not drive the treated consumers to upgrade their consumption by purchasing products from higher-end sellers. For the number of items per order and discounted amount per item, as shown in Panel C of Table 3, we find no evidence that individuals purchase more items per order or that they dislike discounted products.

[8] Payment hesitation occurs at the final stage of a transaction when individuals hesitate to complete the order by clicking the final payment button. Price comparison, cost consciousness, and choice overload are major factors contributing to payment hesitation.

Consistent with the results in Model 1, Model 2 shows that relative to buyers in C40, the combined housing wealth effects and collateral effects decrease the consumption hesitation by 6.1% (=exp(-0.062)-1), reduce the return propensity by 0.031 units, and increase the shirking propensity by 0.034 units for individuals in C9. A similar pattern of consumption upgrade has also been observed in C9. As shown in Panel C, the announcement causes individuals in C9 to purchase more expensive items, as reflected by a 4.3% (=exp(0.042)-1) increase in payment per order and a 4.8% (=exp(0.047)-1) increase in payment per item on average, while the impact on the number of items per order is trivial. Notably, the magnitudes of all the estimated coefficients on $Treat * After$ are much smaller than those in Model 1. This is due mainly to the weaker impact of the announcement on the housing prices of the surrounding counties of Xiong'an: as Panel B of Table 2 indicates, the increase in housing price in the nine adjacent counties is around one-third of that in the Xiong'an New Area.

4.2.3 Estimation Results on Dynamic Behavioral Response

To examine the parallel pre-trend assumption in the DID analysis, as well as the behavioral response in the long-run, we carry out the dynamic tests following Eq. (3). Figure 3 (order level) and Figure 4 (item level) plot the estimated coefficients β_s and their respective 95-percent confidence intervals, with Panel A and Panel B corresponding to C3-vs-C40 and C9-vs-C40 comparisons, respectively. The vertical line indicates the month when the new area was announced. We find that the differences in consumption behavior response between the treatment and control groups during the five-month pre-announcement period are insignificant, both statistically and economically, indicating that the parallel trend assumption is satisfied in all DID estimations.

When we compare the consumption behavior of individuals in C3 to that of individuals in C40 in Panel A, the estimated coefficients on payment hesitation (in Figure 3) and return propensity (in Figure 4) immediately decrease in the month of the new area announcement (S=0), and the effect on shirking (in Figure 3) starts to increase in the first month after the announcement (S=1). The coefficient on hesitation decreases persistently, and the treatment group becomes 23.2% less reluctant in making payment in the third month after the announcement (S=3), although the magnitude declines and stabilizes at around 10% in the long run. The effect on return intention (in Figure 4) keeps decreasing and exhibits the largest response in the seventh month after the shock (S=7). Moreover, the consumption responses on order payment and item payment are statistically significant in most of the post-announcement months, and their largest responses show up in the seventh month. This suggests that the housing shock drives the consumers to upgrade their consumption by purchasing more expensive items, and this pattern persists in the long run. It is worth noting that there is a bell-shaped response for the effect on shirking propensity, suggesting a strong and immediate response in the short run and a tendency toward behavioral reversion in the long run. Besides, we find little effect of the Xiong'an shock on the number of items per order and the amount of discount fees during the whole sample period. We also find similar patterns when we compare C9 to C40 in in Panel B of Figures 3 and 4.

4.3 Discussion

Based on our estimations of housing market response in Table 2 and consumption behavioral response in Table 3, we then estimate the elasticities of consumption behavior with respect to housing price and summarize the results in Table 4. Columns (1) and (2) of Table 4 present respectively the collateral effects and the combined results of collateral effects and wealth effects. We interpret the difference between the estimated effects in column (2) and column (1) as measuring the wealth effects on consumption behavior, and we present the results in column (3). Table 4 helps to pin down the precise mechanism through which the exogenous wealth shock affects online consumption behavior, and to quantify the collateral effects and the wealth effects.

[Table 4 inserted here]

First, comparing columns (1) and (2), we find that the elasticities of consumption behavior related to housing price are greater in magnitude in the nine adjacent counties than those in the three Xiong'an counties. This is because homeowners in the adjacent counties can easily liquidate their housing wealth; however, the emergent imposition of the government restriction significantly limits the options of homeowners in the Xiong'an New Area to liquidate their housing wealth and fund spending needs. Second, comparing columns (1) and (3), we find that the collateral effects on consumption behavior are greater in magnitude than the housing wealth effects. This implies that homeowners may seek the housing collateral channel to fund immediate spending needs, rather than directly sell the property.

Specifically, our analysis shows a large housing price elasticity of consumption: a 100% increase in housing collateral (housing wealth) would lead to a 31.61% (10.85%) reduction in payment hesitation, a 17.56% (3.67%) reduction in return intention, a 17.15% (6.14%) increase in shirking propensity, a 22.73% (6.04%) increase in order payment, and a 20.04% (12.15%) increase in payment per item.

5 Additional Tests

5.1 Heterogeneity Tests

The previous section provides strong evidence of different online consumption behaviors in response to the Xiong'an announcement, while raising two further questions for us: who responds more, and to what extent do the responses vary across product categories?

The richness of the item-level information and demographic information of individual consumers allows us to answer these questions in greater depth. In the first set of heterogeneity analyses, based on the descriptions of items in the data, we classify items into six broad categories: daily goods, home appliances, clothing, entertainment, health-related products, and others. We repeat the estimation of Eq. (2) across the six product categories for the item-level outcome variables, and plot the estimated coefficients in Figure 5.

In terms of item payment, consumers in the three Xiong'an counties and consumers in the nine adjacent counties show distinctly different consumption response patterns across product categories. Specifically, after the announcement, consumers in the nine adjacent counties upgrade their consumption in five out of six item categories, while consumers in the three Xiong'an counties appear to buy more expensive products only in the categories of home appliances and clothing. In terms of item discount and item return, we find similar heterogeneous response patterns across product categories between consumers in the three Xiong'an counties and consumers in the nine adjacent counties.

[**Figure 5 inserted here**]

In the second set of heterogeneity tests, we obtain the information on the gender and age of the consumer based on the last 12 digits of buyers' identity card, and then repeat the estimation of Eq. (2) using four subsamples: female, male, age under 30 years, and age 30 years and over. Figure 6 plots the estimated coefficients of two models. We find that, after the Xiong'an announcement, female consumers prefer more expensive items, and show weaker intention than male consumers to return purchased items. The results also show that in the post-announcement period, older consumers buy more expensive items, compared to their younger counterparts. When we conduct the heterogeneity test in returning intention, we find that the response is larger for older consumers than for younger ones in the three treatment counties, while the opposite pattern is revealed in the nine adjacent counties.

[**Figure 6 inserted here**]

We also conduct the heterogeneity tests at the order level by age groups. As shown in Figure 7, female buyers and buyers above 30 years old are more responsive to the Xiong'an announcement in order payment. In terms of payment hesitation, we see little variation in the estimated responses across genders and age groups for buyers in C3. However, for buyers in C9, the responses of payment hesitation to Xiong'an shock are greater in magnitude for female and younger consumers relative to their respective peers. In terms of shirking propensity, the heterogeneity results for C3 and C9 illustrate clearly opposite patterns in the responses across gender and age groups.

[**Figure 7 inserted here**]

To sum up, we can draw several important conclusions from the heterogeneity tests. First, in order payment and item payment, older consumers and female consumers are more responsive than their respective counterparts to the housing shock. This is in line with Campbell and Cocco (2007), which reveals that older homeowners are more responsive to changes in housing wealth relative to the younger cohorts. Second, the comparisons of responses in hesitation, shirking, and returning intention between female and male, and between young and old consumers, show consistently opposite patterns in the three core counties relative to the nine adjacent counties. Third, across product categories, consumers in the nine adjacent counties upgrade their consumption in almost all item categories, while consumers in the three Xiong'an counties show upgrading responses only in home appliances and clothing.

5.2 Buyer-YearMonth Level Analysis

In the previous analyses, we examine responses of various consumption behaviors at the transaction level. In this section, we aggregate the micro-level data at the *buyer-yearmonth* level to study whether the treated individuals show positive responses in payment amount, order frequency, and the number of items at a monthly interval. The estimation results in Table A3 illustrate that buyers in C3 and C9 respectively increase their monthly online consumption in terms of payment amount by 11.1% (1.3%) and 4.6% (2.2%), comparing to buyers in C40, in the unbalanced (balanced) buyer-yearmonth panel. Nevertheless, we see little response in the number of completed orders and purchased items.

5.3 Robustness Checks

One concern is that, individuals in different counties may have distinct consumption preferences for seasonal products. For instance, buyers in C3 may have a higher demand for comfort levels after the shock and they could be more likely to purchase home appliances (e.g., electronic fans, air conditioners) to increase comfort levels in the summer. To address the concern, we include the buyer-quarter fixed effects in Eq. (2) and rerun the estimations. The results are reported in Table A4, which are consistent with those in Table 3.

Another alternative explanation is that our findings may result from the differences across C3, C9, and C40, rather than the Xiong'an establishment. To address this concern and test for the robustness of different specifications, we conduct border discontinuity regressions using the DID approach. Since the data contain detailed information on receiving addresses at the transaction level, we limit the sample to transactions within 3km of the border between C3 and C9, and between C9 and C40. This approach excludes individuals that are particularly close or far away from the urban centre, therefore reducing the variations in unobserved location characteristics between buyers in the treatment and control counties. Tables A5 represents the results. The differences between the border sample and entire sample in the baseline analysis vary slightly by specification, and the patterns and general magnitudes are consistent across samples.

6 Conclusion

This paper uses a unique dataset of online consumption from the largest e-commerce company in China to analyze how online consumption behaviors respond to an unanticipated housing wealth shock. The unique policy announcement by the Chinese government enables us to exploit the exogenous variation in housing price appreciation across counties, and to use a difference-in-differences approach to estimate the consumption responses. Specifically, we compare consumers who are exposed to the wealth shocks (in 3 Xiong'an counties or 9 adjacent counties) with those who are not exposed (in 40 non-adjacent counties), and we assume that the difference in consumption response arises from the ability to liquidate the housing wealth.

We first show that following the Xiong'an announcement, the housing listing prices (rental price) in three Xiong'an counties and nine adjacent counties increase by 62.26% (79.68%) and 15.72% (31.78%), respectively, relative to 40 non-adjacent counties. Turning to the DID estimations on online consumption behaviors, we find that the treated individuals in three Xiong'an counties accelerate their payment processing time by 14.2% and reduce the return probability by 8.1% more than those in the control group. The announcement also increases consumers' propensity to use work hours for online shopping; the estimated average response is equivalent to a 25.1% increase in the propensity compared to the treatment group's pre-shock mean. Moreover, treated consumers also upgrade consumption by purchasing more expensive items. Individuals increase their order payments and payment per item by 11.6% and 10.2%, respectively, on average. In the dynamic analysis, we reveal that the positive responses in consumption level and shirking propensity, and the negative responses in payment hesitation, are long-lasting. Regarding the returning propensity, we observe a U-shape dynamic response in which the largest drop in returning propensity occurs in the seventh month after the Xiong'an announcement. We also find that the elasticities of consumption behavior relative to housing price are greater in magnitude in the nine adjacent counties than those in the three Xiong'an counties. Moreover, the collateral effects on consumption behavior are greater in magnitude than the housing wealth effects.

Our main contributions to the literature are threefold. First, our study is the first to reveal a positive impact of housing wealth on online consumption. Second, we take advantage of the dataset to examine the responses to the housing wealth shock of consumption behaviors that cannot be easily measured using the traditional offline data, such as hesitation, shirking, and returning intention. Third, the exogenous shock we utilized changed housing wealth rapidly and tremendously, giving us an opportunity to investigate the long-term impact. Lastly, our analysis distinguishes the consumption behavioral response to the increasing housing wealth from the increasing access to home equity.

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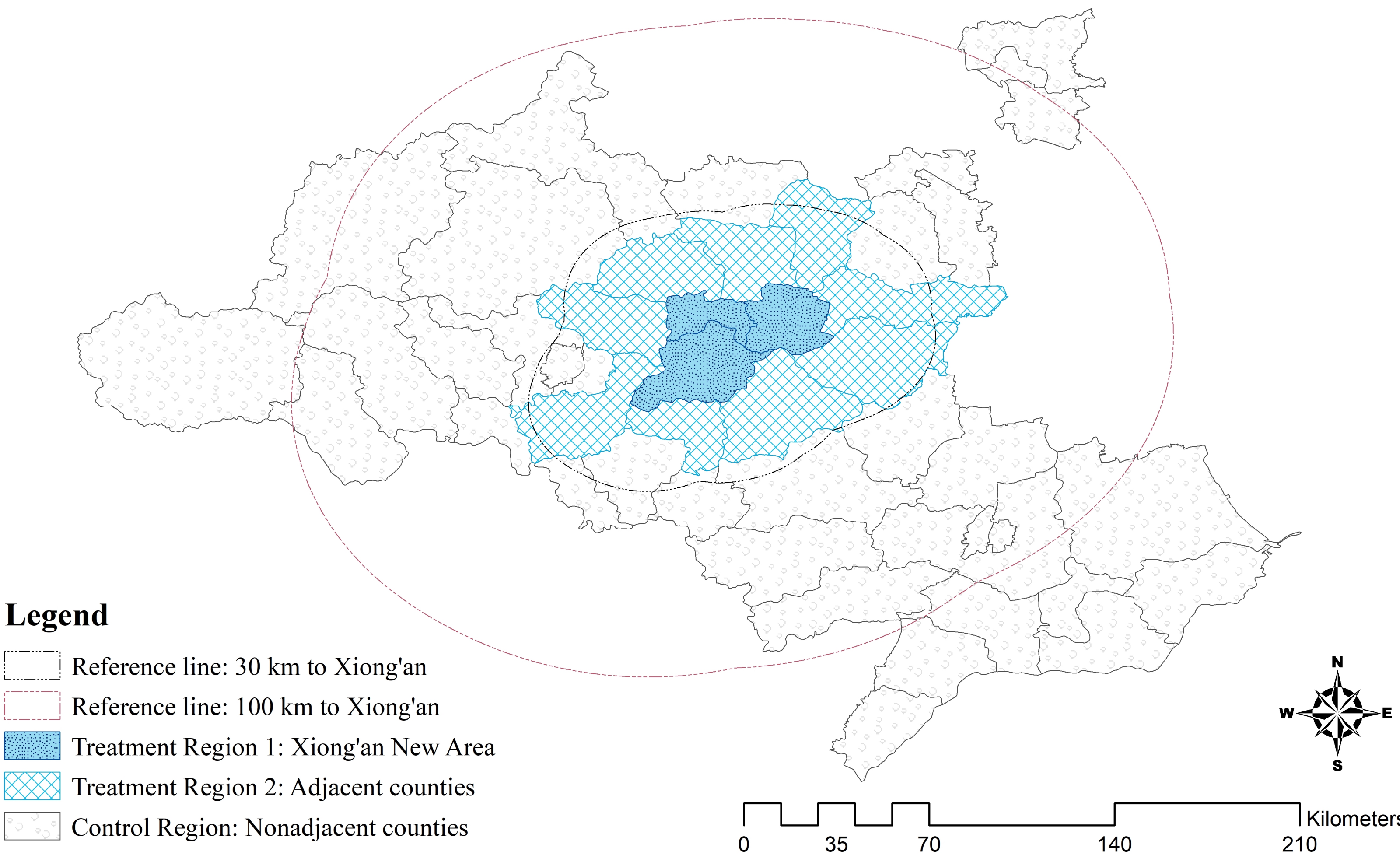
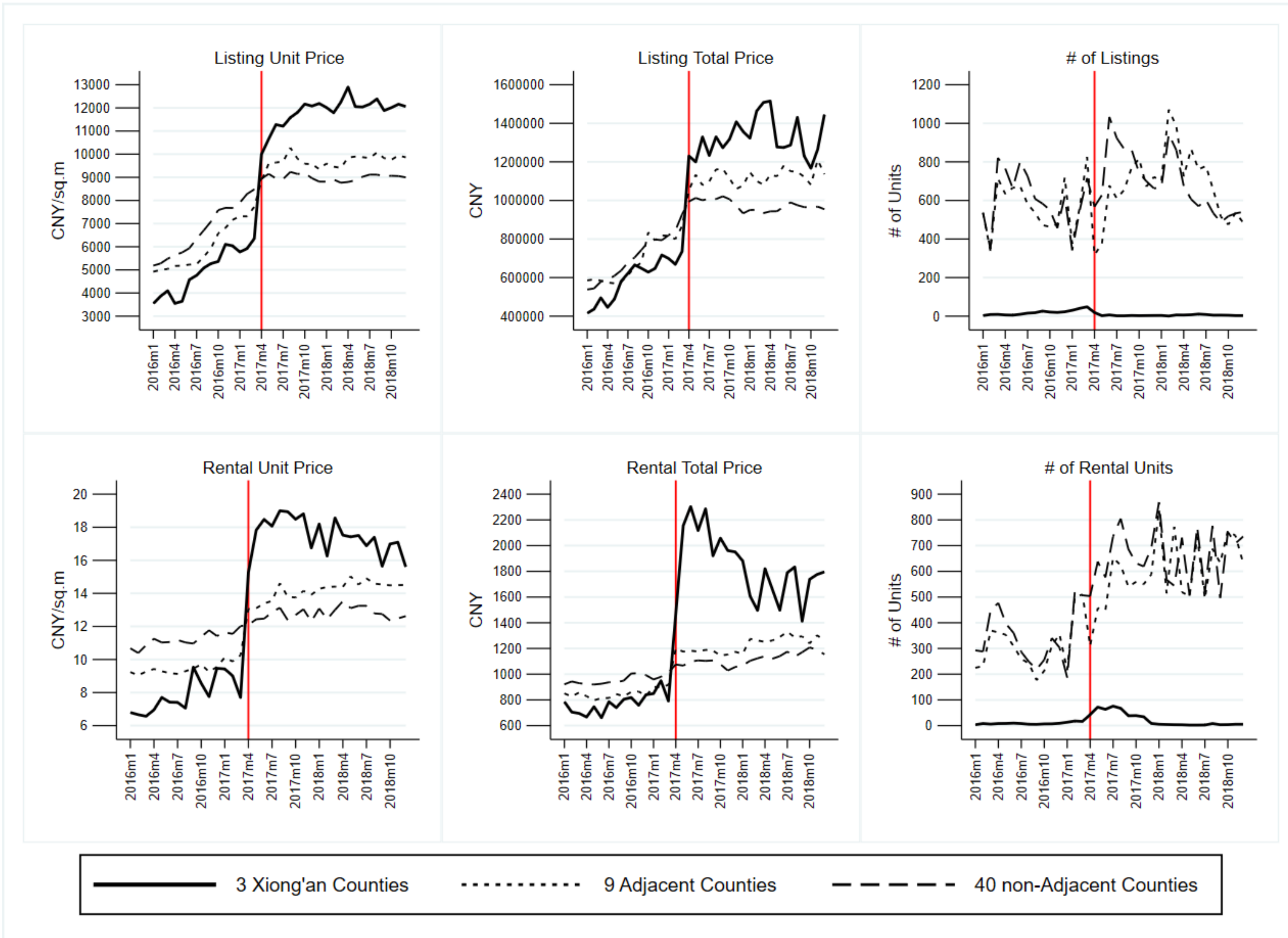
Figure 1: The Geographic Coverage of Treatment and Control counties



Notes: This figure shows the geographic coverage of the treatment and control counties in this study.

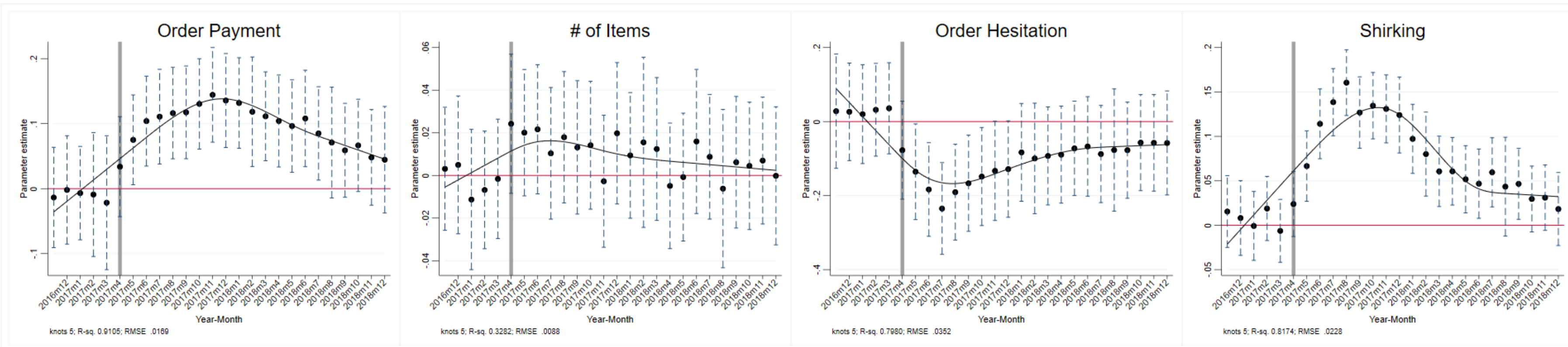
Figure 2: Housing Market Trends in Baoding, Cangzhou, and Langfang



Notes: This figure shows the trends of listing unit price, total price, and number of transaction of properties in Baoding, Cangzhou, and Langfang from Jan 2016 to Dec 2018. The solid line represented the trends of the treatment county, and dotted and dashed lines represent the trends in the control counties.

Figure 3: Dynamic Results of Order Tests

Panel A: C3 vs C40



Panel B: C9 vs C40

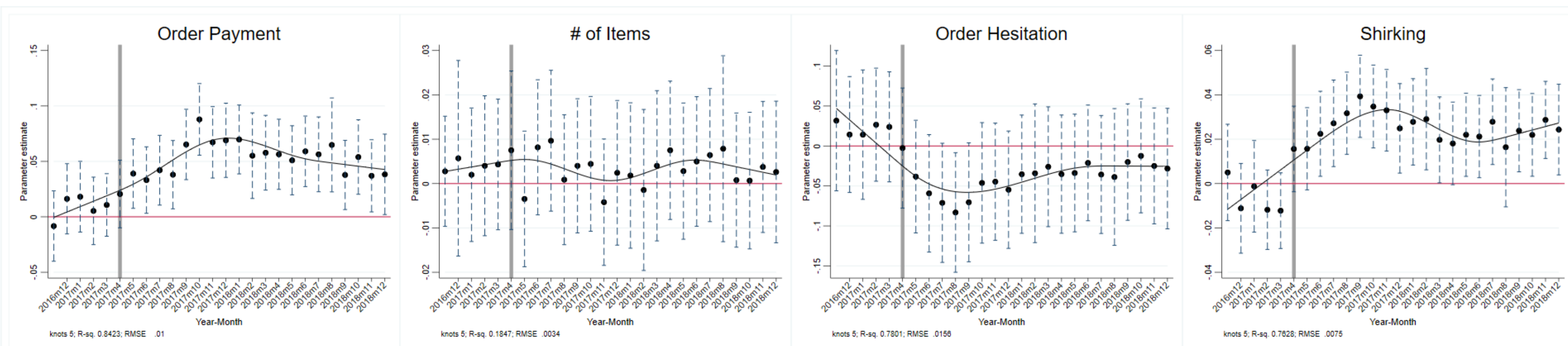
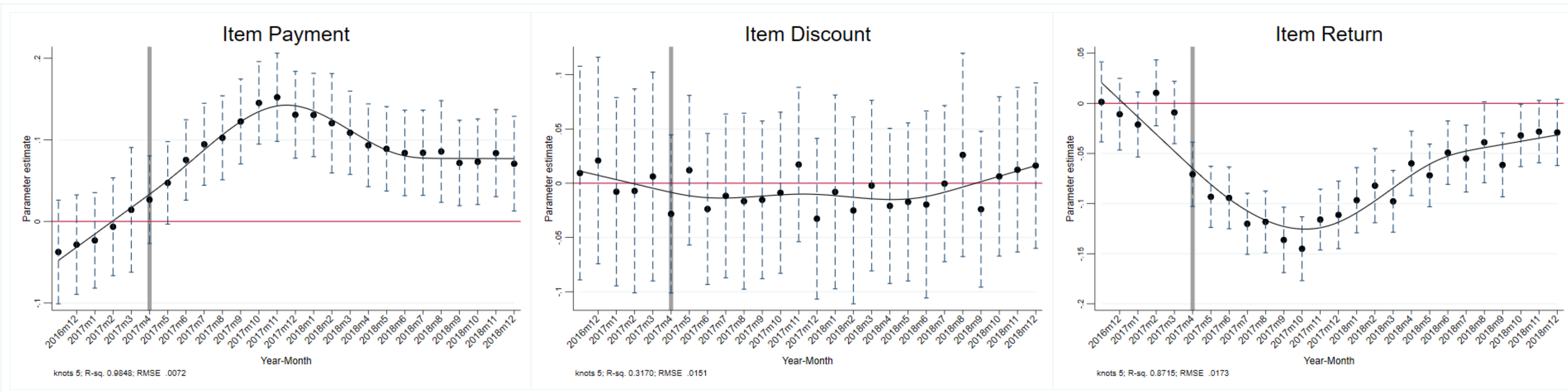


Figure 4: Dynamic Results of Item Tests

Panel A: C3 vs C40



Panel B: C9 vs C40

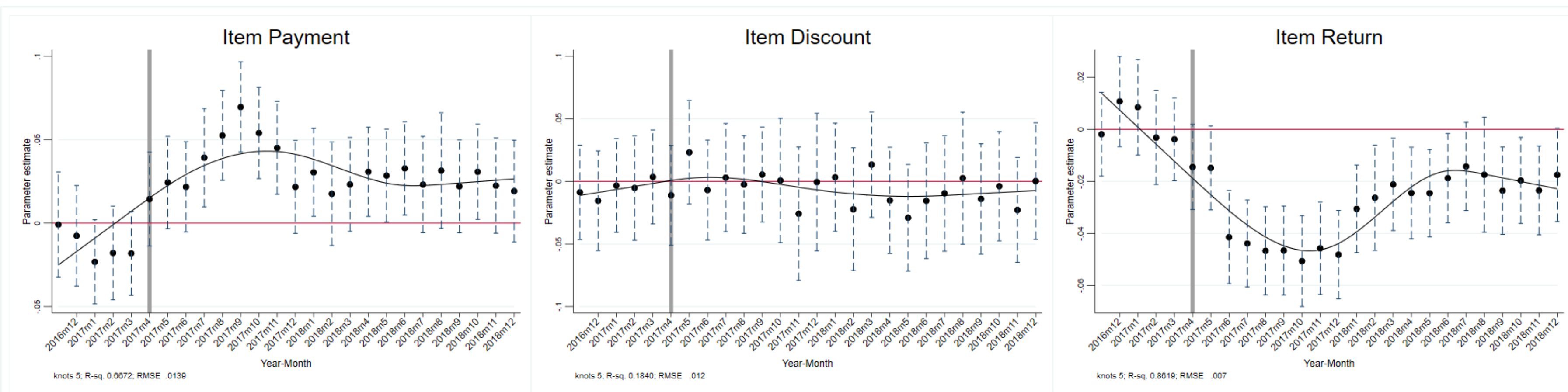
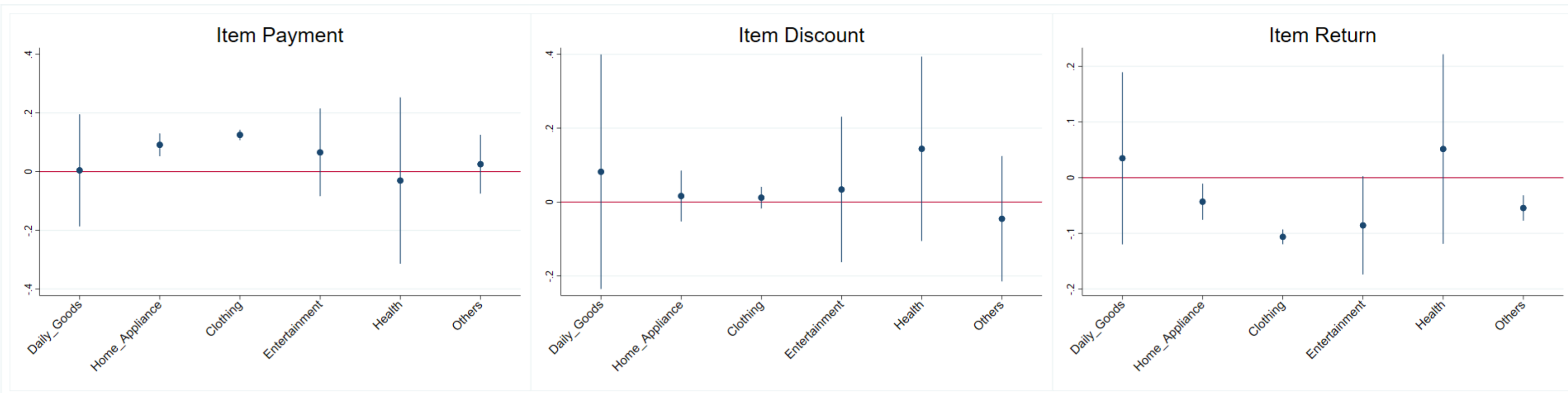


Figure 5: Heterogeneity Test Across Item Categories: Item-Level Estimation

Panel A: C3 vs C40



Panel B: C9 vs C40

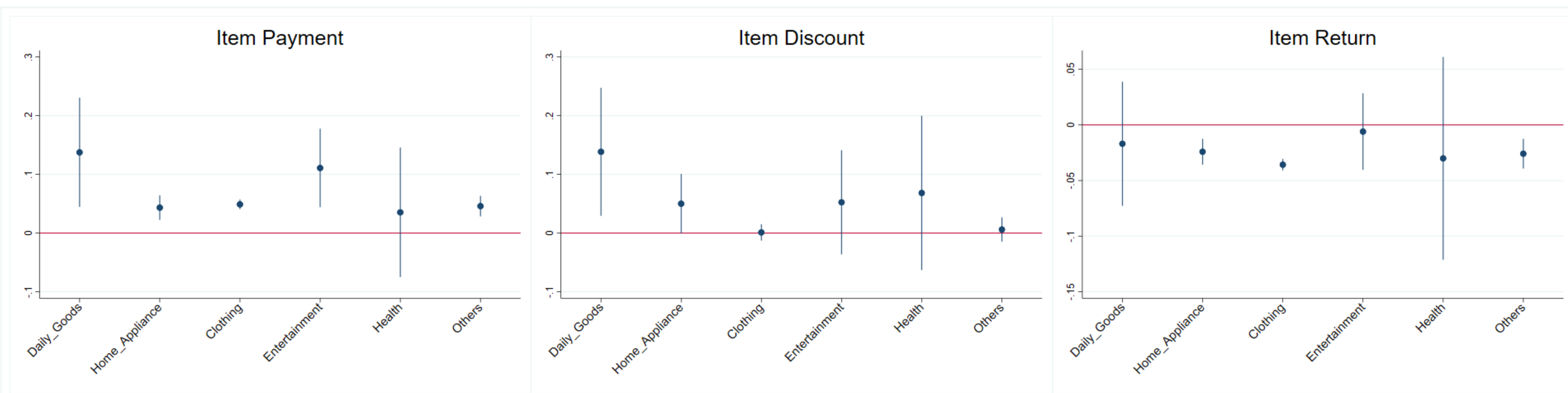
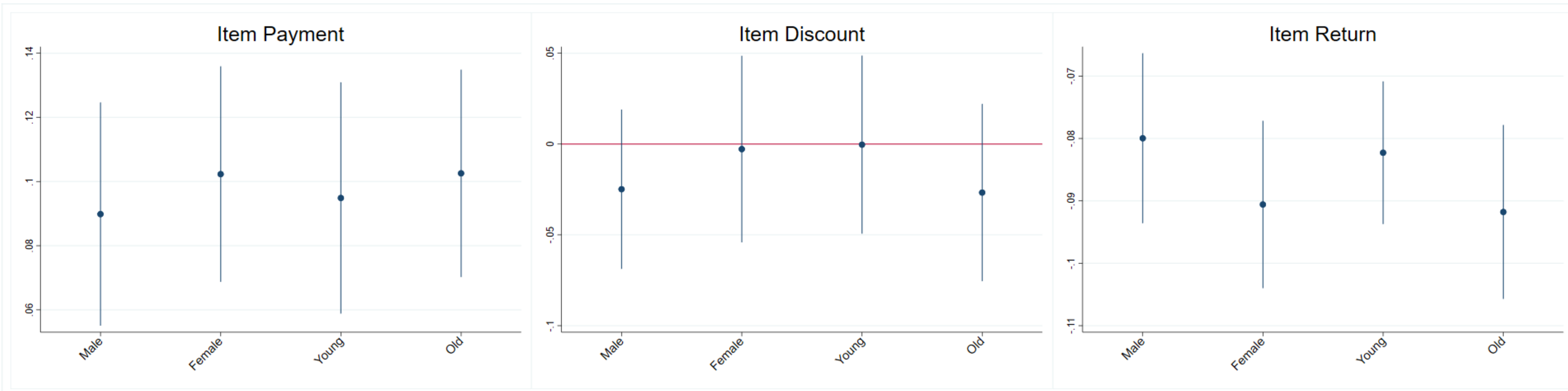


Figure 6: Heterogeneity Test Across Buyer Groups: Item-Level Estimation

Panel A: C3 vs C40



Panel B: C9 vs C40

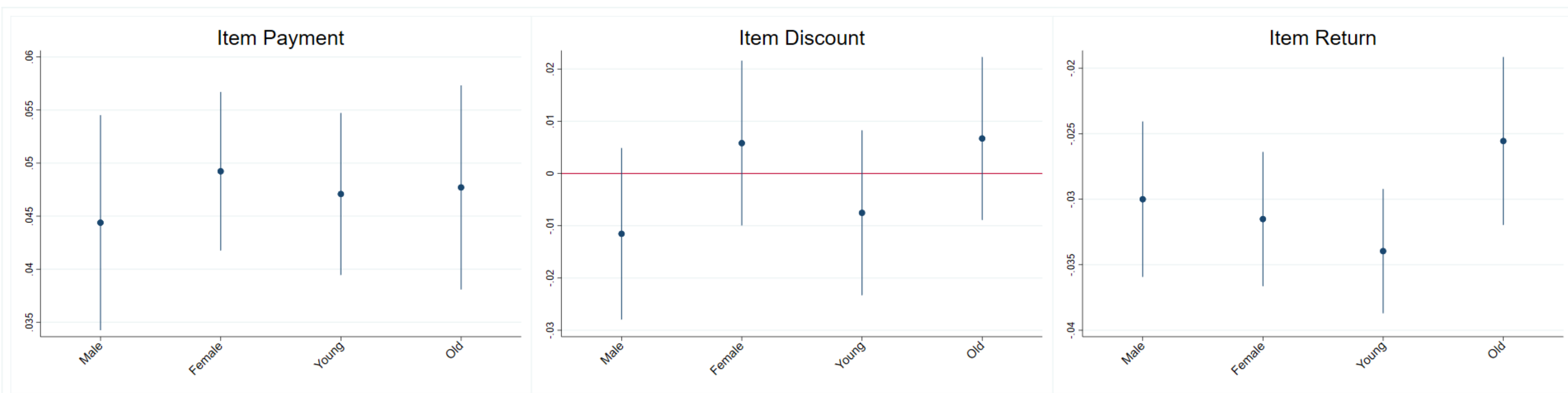
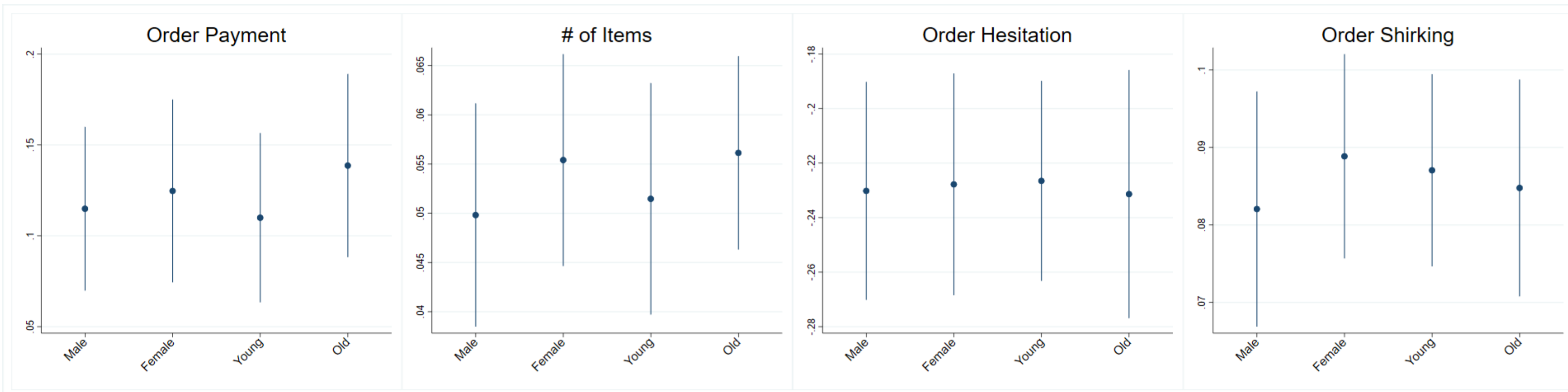


Figure 7: Heterogeneity Test Across Buyer Groups: Order-Level Estimation

Panel A: C3 vs C40



Panel B: C9 vs C40

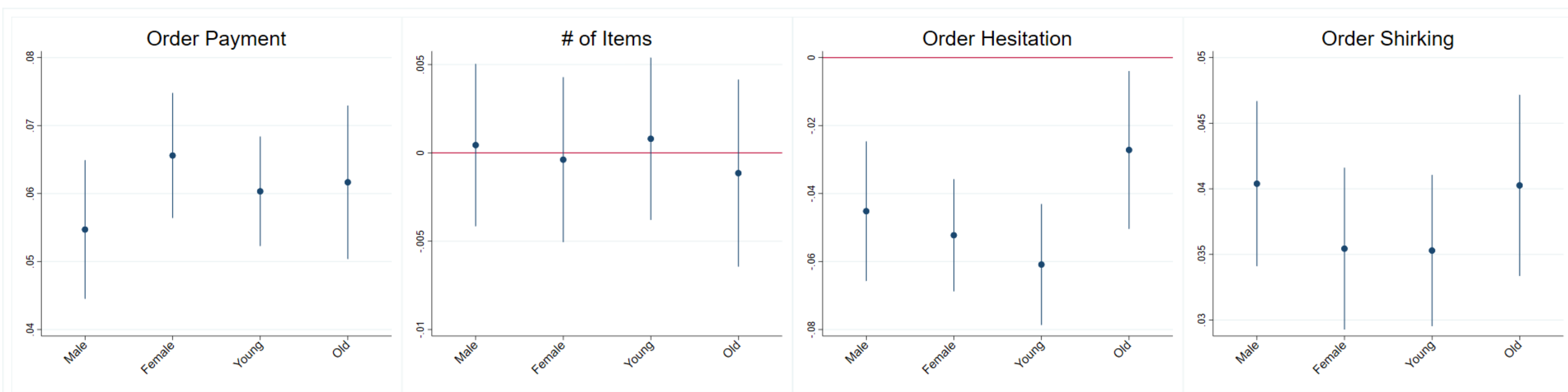


Table 1: Summary Statistics of Online Consumption Data

	Group 1: 3 Xiong'an Counties (C3)				Group 2: 9 Adjacent Counties (C9)				Group 3: 40 non-Adjacent Counties (C40)			
	Before		After		Before		After		Before		After	
	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D
Panel A: Item Level Statistics												
Item Price	126.07	213.74	136.95	242.18	128.6	220.18	138.49	253.79	132.45	724.15	139.46	278.48
Item Payment	52.79	94.67	65.35	95.26	54.2	89.13	64.57	105.74	54.61	102.56	62.89	118.42
Item Return	0.27	0.44	0.14	0.35	0.25	0.44	0.23	0.42	0.25	0.43	0.25	0.43
Discount Fee	73.28	142.63	71.6	194.95	74.4	159.94	73.92	194.94	77.84	689.02	76.57	211.26
Observations	92,373				507,042				1,422,904			
Panel B: Order Level Statistics												
# of Items	1.43	3.18	1.6	2.46	1.59	7.13	1.56	6.03	1.5	4.17	1.57	12.35
Order Payment	61.05	110.61	75.11	108.08	65.92	124.79	77.11	117.28	62.64	126.62	70.36	118.58
Hesitation	359.7	1,990.00	222.09	1,483.62	194.63	1,476.86	176.04	1,393.53	177.96	1,403.44	158.98	1,332.90
Shirking	0.33	0.47	0.4	0.49	0.34	0.47	0.36	0.48	0.35	0.48	0.33	0.47
Observations	52,605				289,886				836,725			

Notes: Table 1 presents the summary statistics of the online consumption data at the order level and item level for three buyer groups before and after the announcement. The final sample includes transactions of buyers whose receiving addresses are located only in the study counties and consists of 1,893,062 orders / 2,498,745 items purchased by 10,738 buyers from 4,4441 active sellers.

Table 2: Housing Price at County-month Level

Model	Panel A: C3 vs. C40		Panel B: C9 vs. C40	
Dep. Variable	Listing Price	Rental Price	Listing Price	Rental Price
Model	(1)	(2)	(3)	(4)
Treat*After	0.484***	0.586***	0.146*	0.276***
	(0.082)	(0.142)	(0.077)	(0.023)
Observations	1,107	1,107	1,269	1,269
R-squared	0.927	0.811	0.922	0.841
County FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes

Notes: Table 2 examines the impact of the announcement on housing listing price and rental price and reports the results of estimating Eq. (1), with Panels A and B using different treatment and control counties. Panels A and B use individuals in the Xiong'an New Area and those in nine adjacent counties as treatment groups, respectively. The control group refers to individuals in the 40 non-adjacent counties. Standard errors are clustered at the county level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3: The Post-shock Response of Consumer Behavior

Model	(1) C3 vs. C40		(2) C9 vs. C40	
Panel A. perceived risk or uncertainty				
Dep. Variable	hesitation_o	return_i	hesitation_o	return_i
ln(Payment)	0.122***	0.045***	0.123***	0.044***
	(0.004)	(0.003)	(0.005)	(0.003)
ΔPerGDP	0.127*	0.074***	0.132**	0.050***
	(0.068)	(0.003)	(0.064)	(0.003)
Treat*After	-0.153***	-0.085***	-0.062***	-0.031***
	(0.016)	(0.005)	(0.007)	(0.002)
Observations	858,168	1,521,755	1,089,782	1,940,499
R-squared	0.511	0.469	0.504	0.463

Panel B. labor supply

Dep. Variable	shirking_o	shirking_o
ΔPerGDP	-0.097***	-0.003
	(0.023)	(0.022)
Treat*After	0.083***	0.034***
	(0.005)	(0.002)
Observations	872,493	1,107,859
R-squared	0.543	0.54

Panel C. consumption

Dep. Variable	payment_o	quantity_o	payment_i	discount_i	payment_o	quantity_o	payment_i	discount_i
ΔPerGDP	0.017	0.005	0.004	0.139***	0.062*	0.022	-0.009	0.141***
	(0.037)	(0.016)	(0.032)	(0.048)	(0.036)	(0.017)	(0.033)	(0.053)
Treat*After	0.110***	0.015	0.097***	-0.013	0.042***	0.002	0.047***	-0.002
	(0.022)	(0.016)	(0.017)	(0.022)	(0.006)	(0.003)	(0.003)	(0.007)
Observations	872,493	872,493	1,521,755	1,610,536	1,107,859	1,107,859	1,940,499	2,055,165
R-squared	0.781	0.544	0.837	0.821	0.778	0.543	0.835	0.821
Buyer FE	Yes				Yes			
Seller FE	Yes				Yes			
Daily FE	Yes				Yes			

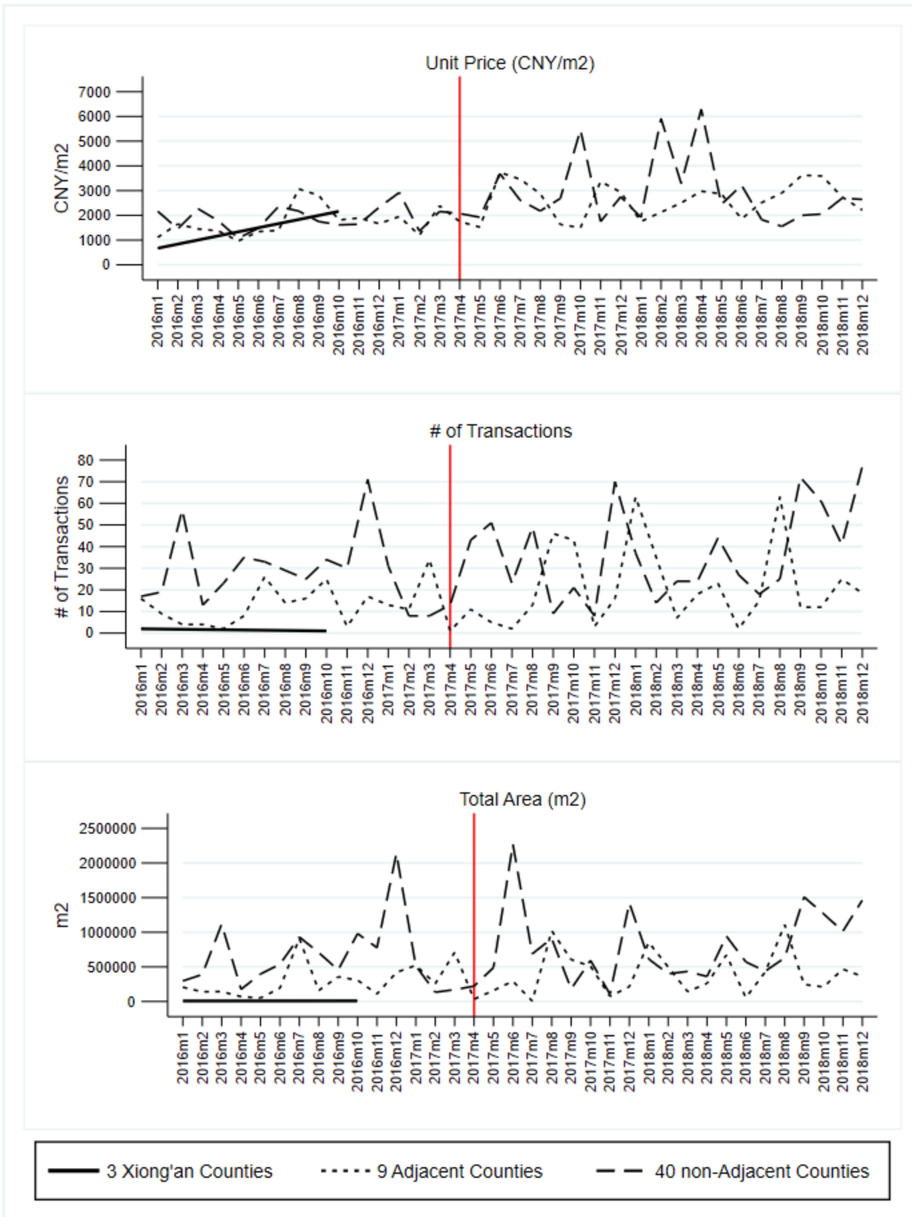
Notes: Table 3 reports the regression results of Eq. (2) for two models that differ in the estimation sample and the definition of the treatment and control groups. Panel A examines behavioral responses that reflect consumers' perceived future financial risk in the context of consumer decision making, namely the payment hesitation and the return propensity. Panel B shows a behavioral response that is related to the effort choice of individuals due to increased housing prices, namely their shirking propensity. Panel C shows outcome variables that are related to consumption level, such as the payment and the number of items of an order, and the payment and discount of an item. The subscript of an outcome variable indicates whether the variable is at the order level or item level. Standard errors are clustered at the seller level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Elasticity of Consumption Behavior to Housing Price

Model	(1) C3 vs. C40	(2) C9 vs. C40	(2)-(1)
Effects	collateral effects	collateral and wealth effects	wealth effects
Payment hesitation	-31.61%******	-42.47%***	-10.85%***
Return intention	-17.56%***	-21.23%***	-3.67%***
Shirking propensity	17.15%***	23.29%***	6.14%***
Order payment	22.73%***	28.77%***	6.04%***
Number of items per order	3.10%	1.37%	-1.73%
Payment per item	20.04%***	32.19%***	12.15%***
Discount fees	-2.69%	-1.37%	1.32%

Notes: This table summarizes the elasticities of consumption behavior related to housing price. Column 1 estimates the collateral effects. Column 2 provides the combined wealth effects and collateral effects. Column 3 takes the difference between the estimations in column 2 and column 1.

Figure A1: Trends of Land Transactions in 52 Counties



Notes: This figure presents the trends of land transactions in the 52 counties during the study period. The red vertical line indicates the announcement date.

Table A1: Comparisons of Sample Counties

Sample Counties	C3		C9		C40	
	Mean	S.D	Mean	S.D	Mean	S.D
# of Towns	9.67	2.08	12.50	3.66	12.77	4.96
Area	518.67	207.04	781.00	187.34	993.33	606.95
Population	380,000	101,488	600,000	153,994	479,696	223,767
GDP (Mill.)	6,310	1,470	18,600	18,000	15,900	10,700
Per_GDP	17,198.16	4,561.64	31,000.00	19,576.01	33,179.61	16,609.76
Saving (Mill.)	12,400	1,900	15,900	11,200	17,200	10,600
# of Firms	81.33	33.26	100.00	84.31	104.21	72.83
Middle School Population	14,768.67	4,505.84	18,526.88	7,843.08	22,916.52	13,292.26
Primary School Population	34,276.67	10,712.59	39,515.63	18,867.58	41,199.27	20,988.31

Notes: This table presents the summary statistics of key economic variables at the county level.

Table A2: The Post-shock Response of Consumption Upgrade across Sellers

Dep. Variable	Seller Ranking	
Model	C3 vs C40	C9 vs C40
ΔPerGDP	0.131	0.219
	(0.154)	(0.138)
Treat*After	-0.023	-0.035
	(0.069)	(0.045)
Observations	872,735	1,108,062
R-squared	0.457	0.457
Buyer FE	Yes	Yes
Daily FE	Yes	Yes

Notes: This table tests the hypothesis that treated consumers may upgrade their consumption by switching to higher end sellers. The dependent variable is an ordinal value from 1 to 5 that based on the average item price of each seller. Standard errors are clustered at the seller level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table A3: Consumption at Buyer-YearMonth Level

Model	(1) C3 vs. C40			(2) C9 vs. C40		
Panel A. Unbalanced Buyer-YearMonth Panel						
Dep. Variable	Payment	# of Orders	# of Items	Payment	# of Orders	# of Items
Treat*After	0.111***	-0.002	0.010**	0.046***	0.001	-0.002
	(0.012)	(0.003)	(0.005)	(0.006)	(0.001)	(0.002)
Observations	678,538	678,538	678,538	863,122	863,122	863,122
R-squared	0.477	0.346	0.360	0.477	0.337	0.359
Panel B. Balanced Buyer-YearMonth Panel						
Treat*After	0.013**	0.001	0.001	0.022***	0.002	0.002
	(0.006)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)
Observations	5,355,909	5,355,909	5,355,909	6,705,396	6,705,396	6,705,396
R-squared	0.110	0.121	0.117	0.109	0.119	0.117
Buyer FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table examines responses of various consumption behavior the Buyer-YearMonth level. Panels A and B present results using unbalanced and balanced samples, respectively. Standard errors are clustered at the buyer level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table A4: The Post-shock Response of Consumer Behavior (Controlling for Buyer-Quarter Fixed Effect)

Model	(1) C3 vs. C40		(2) C9 vs. C40	
Panel A. perceived future financial risk				
Dep. Variable	hesitation_o	return_i	hesitation_o	return_i
ln(Payment)	0.115***	0.041***	0.116***	0.040***
	(0.004)	(0.003)	(0.005)	(0.003)
ΔPerGDP	0.171	0.104***	0.087	0.079***
	(0.105)	(0.030)	(0.101)	(0.027)
Treat*After	-0.116***	-0.092***	-0.052***	-0.036***
	(0.027)	(0.009)	(0.011)	(0.003)
Observations	617,818	1,307,169	786,323	1,670,232
R-squared	0.511	0.469	0.504	0.463

Panel B. labor supply		
Dep. Variable	shirking_o	shirking_o
ΔPerGDP	-0.120***	-0.013
	(0.023)	(0.022)
Treat*After	0.071***	0.034***
	(0.009)	(0.002)
Observations	630,486	802,446
R-squared	0.543	0.54

Panel C. consumption								
Dep. Variable	payment_o	quantity_o	payment_i	discount_i	payment_o	quantity_o	payment_i	discount_i
ΔPerGDP	-0.020	0.005	-0.031	0.117*	0.022	0.022	-0.014	0.173***
	(0.037)	(0.016)	(0.039)	(0.061)	(0.036)	(0.017)	(0.033)	(0.053)
Treat*After	0.118***	0.013	0.126***	-0.011	0.056***	0.002	0.043***	0.003
	(0.022)	(0.016)	(0.017)	(0.022)	(0.006)	(0.003)	(0.003)	(0.007)
Observations	630,486	872,493	1,307,169	1,400,328	802,446	802,446	1,670,232	1,790,388
R-squared	0.781	0.544	0.837	0.821	0.778	0.543	0.835	0.821
Buyer-Quarter FE	Yes				Yes			
Seller FE	Yes				Yes			
Daily FE	Yes				Yes			

Notes: Table 3 reports the regression results of Eq. (2) for two models that differ in the estimation sample and the definition of the treatment and control groups. Panel A examines behavioral responses that reflect consumers' perceived future financial risk in the context of consumer decision making, namely the payment hesitation and the return propensity. Panel B shows a behavioral response that is related to the effort choice of individuals due to increased housing prices, namely their shirking propensity. Panel C shows outcome variables that are related to consumption level, such as the payment and the number of items of an order, and the payment and discount of an item. The subscript of an outcome variable indicates whether the variable is at the order level or item level. Standard errors are clustered at the seller level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table A5: The Post-shock Response of Consumer Behavior (3-km Boundary)

Model	(1) C3 vs. C9				(2) C9 vs. C40			
Panel A. perceived future financial risk								
Dep. Variable	hesitation$_o$		return$_i$		hesitation$_o$		return$_i$	
ln(Payment)	0.118***		0.036***		0.119***		0.043***	
	(0.009)		(0.003)		(0.005)		(0.003)	
ΔPerGDP	0.171		0.104***		0.087		0.079***	
	(0.105)		(0.030)		(0.101)		(0.027)	
Treat*After	-0.053**		-0.063***		-0.072***		-0.031***	
	(0.026)		(0.007)		(0.012)		(0.003)	
Observations	110,161		199,503		366,877		651,431	
R-squared	0.404		0.322		0.384		0.337	
Panel B. labor supply								
Dep. Variable	shirking$_o$				shirking$_o$			
ΔPerGDP	-0.120***				-0.013			
	(0.023)				(0.022)			
Treat*After	0.053***				0.033***			
	(0.010)				(0.004)			
Observations	112,227				373,021			
R-squared	0.416				0.428			
Panel C. consumption								
Dep. Variable	payment$_o$	quantity$_o$	payment$_i$	discount$_i$	payment$_o$	quantity$_o$	payment$_i$	discount$_i$
ΔPerGDP	-0.020	0.005	-0.031	0.117*	0.022	0.022	-0.014	0.173***
	(0.037)	(0.016)	(0.039)	(0.061)	(0.036)	(0.017)	(0.033)	(0.053)
Treat*After	0.079***	0.011	0.044**	-0.016	0.040***	0.002	0.048***	0.002
	(0.025)	(0.012)	(0.019)	(0.027)	(0.006)	(0.002)	(0.005)	(0.003)
Observations	112,227	112,227	199,503	212,015	373,021	373,021	651,431	690,293
R-squared	0.734	0.451	0.795	0.779	0.738	0.437	0.796	0.776
Buyer FE	Yes				Yes			
Seller FE	Yes				Yes			
Daily FE	Yes				Yes			

Notes: Table 3 reports the regression results of Eq. (2) for two models that differ in the estimation sample and the definition of the treatment and control groups. Panel A examines behavioral responses that reflect consumers' perceived future financial risk in the context of consumer decision making, namely the payment hesitation and the return propensity. Panel B shows a behavioral response that is related to the effort choice of individuals due to increased housing prices, namely their shirking propensity. Panel C shows outcome variables that are related to consumption level, such as the payment and the number of items of an order, and the payment and discount of an item. The subscript of an outcome variable indicates whether the variable is at the order level or item level. Standard errors are clustered at the seller level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.