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Housing Wealth and Online Consumer Behavior: Evidence from Xiong'an New Area in China

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Abstract

We provide new evidence on the causal effects of housing wealth on consumer behavior. To overcome the empirical challenge of non-random housing wealth changes, we exploit the unexpected announcement of China's newest national-level new area –Xiong'an New Area–on April 1, 2017 as an exogenous shock to housing prices. We use a proprietary dataset of individual-level online consumption from the largest e-commerce company in China to measure various aspects of consumer behavior, such as consumption patterns, purchase hesitation, tolerance to unsatisfied products, and shirking (proxied by making online purchases during work hours). We explore the underlying mechanisms through which the housing shock affects consumer behavior; in particular, we attempt to disentangle the realizable and unrealizable housing wealth effects.

Keywords: Housing price, wealth effects, consumer behavior, online consumption
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1 Introduction

How does housing wealth affect consumer behavior? The answer to this question is of great interest to policymakers who aim to manage the aggregate consumption demand, to sellers who try to maximize profits, and to academics who attempt to understand the underlying mechanisms. The key empirical challenge to answer this question is that housing wealth changes are typically related to business cycles and other regional changes in the economic development, which makes it difficult to find credibly exogenous variations in housing wealth. Moreover, when investigating the underlying mechanisms, it is particularly challenging to find a clean setting to distinguish between the effects of *realizable* and *unrealizable* housing wealth.[1]

Nonetheless, a large literature has examined the relationship between housing price changes and household consumption patterns using a variety of identification strategies (see, for example, Campbell and Cocco (2007); Agarwal and Qian (2014); Aladangady (2017); Bunn et al. (2018); Waxman et al. (2019); Guren et al. (2021) among others.) In this paper, we make several contributions to the existing literature. First, we exploit the unexpected announcement of China's newest national-level new area, Xiong'an, on April 1, 2017 as an exogenous shock to the housing price and use it as sources of exogenous variations for identification; second, we use a unique transaction-level dataset from a large e-commerce retailer to capture high-quality measures of consumer behavior, including expenditures, shopping hesitation, product return, and whether shopping occurred during working hours (which indicates shirking, following (Gu et al., 2019)); third, we design novel and credible empirical strategies based on policy interventions following the Xiong'an announcement to disentangle the *realizable* and *unrealizable* wealth effects, which affect consumer behavior differently; fourth, we utilize information on delivery addresses in the dataset to examine the behavioral differences between consumers with a single property and those with multiple properties.

Though online consumption is a subset of all consumption expenditures, e-commerce has increasingly replaced offline retail and become an indispensable component of the global retail framework over the last decade, and the unprecedented COVID-19 pandemic further accelerated its rise. In 2020, over two billion people purchased goods or services online, and e-commerce sales have exceeded 4.2 trillion U.S. dollars worldwide.[2] Particularly, China plays a leading role in global digital transformation. China's e-commerce market grew at an average annual rate of 30% from 2004 to 2017 and has now established the world's largest e-commerce market.[3] There are strengths and weaknesses of online consumption data relative to traditional offline consumption data, either based on consumer diaries (e.g., Consumer Expenditure Survey in the United States), or survey data (e.g., Urban Household Survey in China), or more recently, bank/credit card transactions. First, relative to the offline consumption data, the online transaction data is administrative data, and thus it is

[1] By "realizable" housing wealth, we mean housing equity that can be readily realized by the homeowner.

[2] Source: `www.imf.org/-/media/Files/Publications/WEO/2020/October/English/Ch1.ashx`.

[3] According to the Chinese National Bureau of Statistics, approximately 20.7% of the total retail sales of consumer goods were purchased online. Source: `www.jpmorgan.com/merchant-services/insights/reports/china-2020#`; `www.statista.com/statistics/277391/number-of-online-buyers-in-china/`. The number of online shoppers in China has been increasing exponentially from less than 34 million in 2006 to over 700 million by December 2020.

less subject to measurement error bias than offline consumption data; second, online transaction data can capture more facets of consumer behavior than the traditional offline consumption data. In addition, relative to the bank/credit card transaction data, which capture every transaction a consumer pays at a store or online, our online consumption data from a large e-commerce retailer has the advantage that it is not restricted by the payment format used by the buyers.[4] Although a large and growing literature has documented that housing wealth could affect consumption level either positively or negatively (Sinai and Souleles, 2005; Buiter, 2010; Aladangady, 2017; Berger et al., 2018), none has explored the effect of housing wealth on a range of consumer behavior in detail (e.g., hesitation, regret, and shirking) due to the lack of highly-detailed micro data. This study fills this research gap by using a high-frequency and granular panel dataset of online consumption, which contains exceptionally detailed information on orders, products, and consumers.

The housing market serves as a great laboratory for examining the effects of wealth on consumption (Campbell and Cocco, 2007; Gan, 2010; Attanasio et al., 2011; Mian et al., 2013; Aladangady, 2017; Agarwal and Qian, 2017; Waxman et al., 2019; Painter et al., 2020; Kaplan et al., 2020). First, housing wealth accounts for a significant part of household net worth, and housing prices are strongly correlated with household borrowing and consumption over time (Cloyne et al., 2019). Second, many countries have recently witnessed drastic and prolonged housing booms in recent years (Fang et al., 2016; Glaeser et al., 2017; Aladangady, 2017; Badarinza and Ramadorai, 2018; Somerville et al., 2020; Wang and Yang, 2021). Third, significant windfall gains are commonly observed in the housing market. For instance, substantial windfall gains can accrue to homeowners when the value of properties increases substantially due to the introduction of new development plans or tax changes, or when they receive compensation packages from demolished properties. The reverse is also true. As the Chinese housing market enters a period of downward corrections, it is important to know the effect of housing wealth decrease on consumption to estimate the multiplier effect on the economy. Thus, it is crucial to understand the effects of housing price appreciation on consumer behavior, particularly in the e-commerce era. However, the housing price appreciation is endogenous to the changes of economic outcomes most of the time, which creates challenges for causal inferences. Fortunately, China, with its tremendous changes in the housing market over the last decades, provides us with numerous opportunities to identify exogenous variations in housing wealth.

To shed light on the causal impacts of housing wealth on consumer behavior, this paper exploits a unique policy event and a proprietary online consumption dataset provided by the largest e-commerce company in China. Specifically, we study the establishment of the Xiong'an New Area, which is the 19^{th} state-level new area in China and was jointly announced by the Central Committee of the Communist Party of China and the State Council on April 1, 2017. As a millennium plan, the Xiong'an New Area project in China is the first New Area to be established with national significance in the 21st century. The announcement of Xiong'an New Area creates a clean and exogenous shock to housing wealth (see details in Section 2). The level of housing wealth before

[4] Consumers in China increasingly rely on third-party online payment platforms such as Alipay, WeChat Pay, or JD Pay for consumption on the internet, instead of using bank/credit cards.

the announcement is considered orthogonal to the announcement because the exact announcement date and geographic coverage of the new area are plausibly exogenous and unanticipated. In this study, we answer four research questions. First, what are the impacts of the housing price changes on various online consumer behaviors? Second, do the impacts change over time? Third, what are the underlying mechanisms? In particular, what are the differential impacts on consumption behaviors between the realizable and unrealizable housing wealth effect? And fourth, are the impacts different across different types of consumers and product categories?

We begin the analysis by quantifying housing market responses to the announcement of the Xiong'an New Area using a difference-in-differences (DID) approach. Specifically, as shown in Figure 1, we create three groups of counties that are subject to the announcement at different levels: three counties in the Xiong'an New Area proper (C3 hereafter), nine counties that are adjacent to theXiong'an New Area (C9 hereafter), and 37 counties that are non-adjacent to Xiong'an (C37 hereafter). It should also be emphasized that the government immediately imposed a ban on real estate transactions on April 2, 2017 in C3 counties, but not in C9 and C37 counties. With property prices in C3 and C9 skyrocketing overnight following the announcement (as shown in Figure 2), both residents within and around the new area were overjoyed to find themselves sitting on a potential "goldmine." Thus, we define consumers in C3 and C9 as different treatment groups, whereas those in C37 serve as a control group. The results show that the announcement causes the listing prices of properties in C3 and C9 to increase by 65.70% and 24.86%, respectively, relative to the housing prices in C37. Additionally, we provide some suggestive evidence that, during our sample period, the announcement of Xiong'an has a significant effect on the housing market but not on other aspects of counties, such as growth in disposable income, GDP, population, local tax revenue, fiscal revenues, and the number of large firms (see details in Figure A2). This further strengthens our case for using the announcement of the Xiong'an New Area as a shock to the housing wealth.

We then implement the DID strategy to examine the responses of consumer behavior to the housing wealth shock using the online consumption data, which contain the universe of transactions of 0.1% randomly selected active sellers from the e-commerce company between October 2016 and December 2018. The estimation sample in the baseline analyses includes around 3.65 million online orders made by 44,496 local consumers in C3, 230,148 local consumers in C9, and 683,548 local consumers in C37. The local consumers are those with delivery addresses located only in a specific county during our sample period. A critical assumption of the study is that customers with delivery addresses located only in a particular county throughout our sample period are homeowners in that county. Therefore, the data enable us to distinguish consumers who own a single property and those who own multiple properties.

The existing research has examined a variety of possible mechanisms through which housing prices affect consumption, and has suggested three main effects. The first one is *wealth effect*, which can further be categorized into a *realizable* wealth effect and an *unrealizable* wealth effect. Specifically, following a housing price increase, homeowners may consequently feel wealthier through a *realizable* wealth effect since they can take out equity by selling their properties, or through an *unrealizable* wealth effect, according to which even if homeowners cannot sell their properties, they adjust consumption today due to a higher discounted value of wealth. The second one is *collateral effect*, according to which there is a mechanism from housing prices to consumption via the use of home equity loans. Of course, we would also like to control for the effect of *common confounding unobserved factors*, such as expected productive potentials and economic expectations, that can simultaneously affect housing pieces and consumption. Typically, disentangling the *realizable* and *unrealizable* wealth effects is challenging because it demands an empirical setting that could cancel out the collateral effects and the effect of the common confounding factors. Fortunately, the strict ban on housing transactions in Xiong'an from April 2, 2017 and the absence of the restriction on housing transactions in the counties outside of Xiong'an provide us with a unique opportunity to distinguish between the *realizable* and *unrealizable* wealth effects. Moreover, based on the number of delivery addresses (properties) of a consumer owns throughout the sample period, we classify consumers into two groups: consumers with only one address and consumers with multiple addresses. Doing so allows us not only to isolate the wealth effects, but also to estimate the differential effects of the realizable and unrealizable wealth for each group.

The great granularity of our online transaction data also enables us to examine several dimensions of online consumer behavior: consumer hesitation or delay in payment, willingness to return purchased goods, propensity to make online purchases during work hours, preference for discounted products, and tendency to upgrade consumption level. Using the transaction level online consumption data, we are able to produce among the first estimates of the causal effects of wealth on direct measures of consumer behavior. The DID estimation results reveal that the surge in housing prices triggered by the Xiong'an announcement significantly changes various measures of consumer behavior. First, after the announcement, consumers with a single address in C3 (C9) upgraded their consumption by spending 10.62% (5.65%) more per item and 9.75% (5.23%) more per order, on average. Second, consumers with a single address in C3 (C9) became 10.68% (6.29%) less hesitant to make payments, and 6.50% (4.40%) less inclined to request returns. This suggests that consumers who have experienced a wealth windfall would reduce their processing time before making the purchase decision and lower the propensity to return unsatisfactory products. Third, after benefiting from a large and unexpected increase in housing wealth, consumers with a single address in C3 (C9) became 8.2% (4.7%) more likely to make online purchases during work hours, which is consistent with the findings in Henley (2004) and Gu et al. (2019). Fourth, although we do not find significant differences of behavioral responses between consumers with a single address and those with multiple addresses in C3, the behavioral responses appear to be significantly stronger for consumers with multiple addresses in C9 relative to those with a single address in C9. This suggests that the realizable housing wealth has a greater impact than does the unrealizable housing wealth on the consumer behaviors when the consumers have multiple homes.

After estimating the housing market and the consumer behavioral responses to the announcement, we compute the elasticities of consumer behavior with respect to housing prices. Our results show that the elasticities of the combined effects are slightly greater for consumers with multiple addresses in C3, relative to those with a single address in C3. For consumers in C9, we reveal that the elasticities of the combined effects are substantially larger for those with multiple addresses than for single address consumers. When we look at the difference of realizable wealth effect and unrealizable wealth effect, we show that the difference is stronger for consumers with multiple addresses, relative to those with one address.

We also perform a dynamic analysis and, to validate our research design, we explicitly test the parallel trend assumption of the DID approach. The dynamic paths demonstrate that the parallel trend assumption is satisfied and the effects of the announcement on payment hesitation, product return, shirking, and consumption upgrading persist in the long run. To deal with the fact that our sample may include both homeowners and renters, we relax the assumption that a consumer with the same delivery address both before and after the shock is a homeowner in later analysis. Specifically, we restrict the sample to consumers whose birth counties and delivery counties are identical based on the first six digits of their national identity card numbers. Moreover, to strengthen our identification and to create treatment and control groups that are more comparable, we restrict the sample to transactions occurring within 3km of the border between C3 and C9, as well as between C9 and C37. Using either of the two restricted samples for estimation, we still find consistent results. In addition, we find the results are robust when we control for a county-year fixed effect to eliminate potential local shocks and when we control for a seller-month fixed effect to absorb potential omitted shocks at the seller level.

We conduct a series of heterogeneity tests to gain more insights into who respond more and how their responses differ across product categories. Specifically, we find that elderly and female consumers are more responsive in consumption upgrading. The results are in line with the findings in Campbell and Cocco (2007), which indicate that older homeowners are more sensitive to changes in housing wealth than younger homeowners are. In addition, consumers in C9 appear to upgrade their consumption in five out of six product categories following the announcement, while consumers in C3 appear to purchase more expensive products only in the home appliances and clothing categories.

This paper adds to the broad literature on behavioral responses to changes in wealth. As documented by Jappelli and Pistaferri (2010), the primary challenge of establishing causality between consumption and wealth or income is to identify instances of genuine exogenous and unanticipated changes in wealth or income. In the existing literature, the plausibly exogenous shocks to wealth and income include lottery winnings (Imbens et al., 2001; Kuhn et al., 2011), disability (Gertler and Gruber, 2002; Meyer and Mok, 2019), weather changes (Wolpin, 1982; Paxson, 1993), and unanticipated government policies (Parker et al., 2013; Agarwal and Qian, 2014; Jappelli and Pistaferri, 2014; Haushofer and Shapiro, 2016). Along with examining the impact of wealth on consumption (Waxman et al., 2019), the existing work investigates other aspects of behavioral responses. For instance, Haushofer and Shapiro (2016), Blattman et al. (2017), Cesarini et al. (2017), and Li et al. (2020) study the impact of income shocks on labor supply, with mixed results. 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), criminal behaviour (Bignon et al., 2017), and psychological well-being (Stevenson and Wolfers, 2013; Schwandt, 2018; Lindqvist et al., 2020). Our contribution to this strand of literature is twofold. First, we establish a causal inference by utilizing a plausibly exogenous policy that generates spatial and temporal variation in housing wealth. Second, we focus on a set of novel measures of consumer behavior, which are difficult and sometimes impossible to measure using the traditional offline consumption data or survey data.

This paper is also related to the literature on housing wealth. Recent empirical research reveals conflicting findings about the effect of increasing housing prices on household consumption. For instance, some studies show that rising housing prices stimulate consumption by increasing households' perceived wealth (Campbell and Cocco, 2007; Mian et al., 2013; Aladangady, 2017), while others demonstrate that housing price appreciation leads to negative consumption responses (Waxman et al., 2019) and lower productivity (Henley, 2004; Gu et al., 2019). Although our study utilizes a unique housing policy in China and focuses on a specific region, the causal interpretation in this paper is fundamental for household finance and consumption. The new evidence provided in our study has important implications for how wealth shocks impact consumer behavior and how policymakers should respond when housing prices surge, and the findings are generalizable to other countries.

Additionally, this study contributes to a growing literature on online consumption. Relative to the extensive studies on offline consumption, few research investigates online consumption. One reason for the scarcity of the research on the matter has been data limitations. There are a few notable exceptions. 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. Fan et al. (2018) also use Alibaba's e-commerce data and find a negative correlation between online purchasing intensity and market size. In a randomized control trial, Couture et al. (2020) exploit the universe of e-commerce purchases from five provinces that cover 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 offline trade. Einav et al. (2014) also use the eBay data, but focus their study on the sensitivity of e-commerce purchases to sales taxes. Our study provides new insights on how online consumption responds to housing wealth shock in a developing country.

Nevertheless, we should keep several caveats in mind. First, although this paper focuses on online consumer behaviors that are difficult to measure by offline consumption data, it does not offer a full picture of total spending responses. Our findings complement the research on the relationship between consumer behavior and housing wealth, and it is the first study that links housing wealth shock to online consumption. Second, because our data do not include information on homeownership, we are unable to precisely distinguish between treated homeowners and treated renters. However, we believe that this data constraint has negligible effect, given the exceptionally high homeownership rate in regions such as the Xiong'an New Area.[5] Moreover, we deal with this issue by restricting our sample consumers to those with delivery addresses in a specific county both

[5] According to Section 9.4 of the Sixth National Population Census of China Database, homeownership in Hebei Province is 94.13% in towns and 99.25% in villages. Source: `http://www.stats.gov.cn/tjsj/pcsj/rkpc/6rp/indexch.htm`

before and after the shock and using a sample of consumers who are more likely to be homeowners. This alleviates our concern that the imprecise measurement of homeownership may induce spurious regression results. Third, although the geographical randomization of the housing wealth enhances our argument for exogeneity, this study, as with many other natural experiments, has possible bias due to 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. In Section 3, we describe the datasets and provide descriptive statistics. In Section 4, we use various DID estimations to evaluate the impact of the Xiong'an announcement on online consumption. In Section 5, we provide a battery of heterogeneity tests and verify the robustness of our main results. Finally, in section 6 we conclude.

2 Background of the Xiong'an New Area

In China, "new areas" that receive "preferential" treatment from the central and local governments are classified into three levels: state, province, and prefecture. The preferential funding and policy privileges the new areas receive are expected to stimulate and attract new developments to speed up economic growth. The most prominent new area in China is the Pudong New Area in Shanghai, which was the first state-level new area established by the central government in October 1992. Over the last three decades, the model has been replicated in many other major cities. On April 1, 2017, the central government unexpectedly announced plans to develop the Xiong'an New Area. Although the Xiong'an New Area is the 19^{th} state-level new area in China, it is the *first* one that was jointly announced by the Central Committee of the Communist Party of China (CPC) and the State Council, highlighting its national significance and strategic importance. This innovative development zone has been positioned as a critical component of the "Millennium Development Goals". It is part of an effort to solidify China's position 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, approximately 100km southwest of Beijing and 50km from downtown Baoding. As highlighted in red in Figure 1, the new area spans three counties, namely *Xiong, Rongcheng,* and *Anxin*, with a population target of 2.5 million at a density of 1,250 people/km^2. The average per capita GDP of the three counties was 19,227 CNY (around 3,000 US dollars) in 2016.[6] The Xiong'an New Area is planned to serve as a development hub for the Beijing-Tianjin-Hebei economic triangle, and to provide non-capital functions for Beijing, such as schools, hospitals, headquarters of some state-owned firms, public services, and financial institutions. In addition, the central government of China plans to invest RMB 4 trillion (around US$ 624 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 center 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 About Here]

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

Estimating wealth effects is challenging because exogenous changes in wealth are rare to find. This study focuses on the case of the Xiong'an New Area because the announcement, which was unanticipated and kept strictly confidential to the public, provides an excellent opportunity to address the empirical challenges. The planning of Xiong'an was under the direct oversight of the central government. Until April 1, 2017, all pertinent information, including the geographic coverage, the administrative committee members, and the announcement date, was kept in the strictest confidence. Even municipal governments in Hebei province were unaware of the announcement of the new area in advance. Our thorough search of the newspaper articles related to the announcement of the new area finds no discussion before the official announcement on April 1, 2017. In particular, although President Xi Jinping visited *Anxin* County on February 23, 2017, the news was not made public until the new area was announced; moreover, the visit took the cover of the typical visits by top leaders to less developed areas around the Chinese Newe Year.

The highlighted importance and the expected influx of investments created optimism about the future of the new area, and Xiong'an experienced an unprecedented surge in housing prices on the very day of the announcement. The excitement following the announcement was prompted by property investors in anticipation of a price spike due to the future infrastructure boom and a positive economic outlook. Right after the new area was announced, thousands of non-local investors rushed to Xiong'an to purchase properties. As a result, on the second day following the Xiong'an announcement, the local government imposed an emergent suspension of all real estate transactions within the Xiong'an New Area.[7] Although property transactions in Xiong'an are currently prohibited, the market expects that the government will soon ease the restriction. However, the suspension policy hardly deterred investors, who shifted their focus to areas just outside Xiong'an, driving up housing prices in adjacent counties as well. It is worth noting that properties outside of Xiong'an are not subject to the transaction restriction policy. Therefore, the unique policy setting provides us with a great laboratory to analyze the difference between the realizable and unrealizable housing wealth effects on consumer behavior.

3 Data

3.1 Data Source and Summary Statistics

We use a proprietary dataset obtained from a leading e-commerce company in China, which has a market share of approximately 60 percent, with 636 million active consumers and 4 million active sellers on its online shopping platforms as of 2018. Particularly, the company provides a *random* sample of 0.1% active sellers between October 1, 2016 and December 31, 2018; this random sample contains 4,441 active sellers.[8] We then obtain the universe of transactions of these active sellers

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

[8]According to the E-Commerce Report 2018 published by the Ministry of Commerce, the e-commerce company has more than 10 million registered sellers. Of these, however, only 4 million are active sellers, with the remaining sellers classified as inactive sellers who have not had a transaction for 30 consecutive days. Source: `http://dzsws.mofcom.gov.cn/article/ztxx/ndbg/201905/20190502868244.shtml`

during the sample period.

To examine the impact of housing price changes resulting from the announcement of Xiong'an on the consumption behavior of online consumers, we construct three groups of consumers that span 49 sample counties in three prefecture-level cities (Baoding, Cangzhou, and Langfang).[9] The geographical distribution of the 49 sample counties is depicted in Figure 1. Specifically, Groups 1, 2, and 3 respectively consist of consumers whose delivery addresses are in C3 (shaded in red) only, in C9 (shaded in blue) only, and in C37 (shaded in grey) only, both before and after the announcement.[10] This way of sample construction excludes non-local consumers with multiple addresses across counties (e.g., consumers who live in other cities purchase products for their relatives/friends in Xiong'an or migrant workers who move into/out of Xiong'an after the shock), allowing us to focus on local consumers who are more likely to be the homeowners and to distinguish between the realizable and unrealizable wealth effects. Finally, our sample contains 3,646,294 orders (or transactions), 7,349,369 purchased items, purchased from 3,827 active sellers by 44,496 consumers in C3, 230,148 consumers in C9, and 683,548 consumers in C37.

The data contain detailed transaction information including order id, buyer id, seller id, delivery address, the total amount paid in an order, number of purchased items in an order, order creation time, order payment time, item name, item price, the amount paid for each item, discounted amount for each item, return status of a purchased item, delivery fee, and the delivery company. The data also provide information on three demographic characteristics of consumers, namely birth place, gender, and age. Table 1 reports the summary statistics of variables at the item level (Panel A) and the order level (Panel B) for three different buyer groups, both before and after the policy announcement date.

[Table 1 About Here]

Our data offer several advantages. First and foremost, our data are representative and random. In terms of representativeness, the e-commerce company is the market leader in China's e-commerce industry, and it provides the universe of transactions of the randomly selected active sellers. In terms of randomness, the sellers are randomly chosen from the pool of active sellers on the online platform. Second, the data provide detailed information that allows us to construct several unique measures of consumer behavior (see detailed definitions in Section 3.2), which are difficult and sometimes impossible to construct using traditional offline consumption data or survey data. Third, the data span a long period and include detailed descriptions of the purchased items and the demographic information of consumers, allowing us to carry out robustness checks and heterogeneity tests and gain further insights into the consumer responses to the positive wealth shock. Fourth, the detailed information on delivery addresses enables us to distinguish consumers with a single property from those with multiple properties and investigate the differences in their behavioral responses.

We also obtain a supplementary dataset that includes the monthly housing listing prices in

[9] China has a five-level sub-national government hierarchy: province, prefecture city, county, township and villages.

[10] One point regarding the sample groups worth emphasizing is that we exclude those consumers whose delivery addresses fall outside of the respective groups. For instance, buyer A (B or C) is excluded if his/her delivery addresses include not only the Xiong'an New Area (C9 or C37), but also areas outside of Xiong'an (C9 or C37).

each county from *Anjuke*. We report the monthly-level housing market statistics in Panel C of Table 1.[11] Notably, we use the listing price rather than the actual transaction price to measure the fluctuations of local housing prices because real estate transactions in Xiong'an are prohibited after the announcement, making it impossible to observe the post-announcement housing transaction prices in Xiong'an. Nevertheless, the listing price is considered to effectively reflect home sellers' expectations and contain useful information for forecasting future transaction prices (Allen and Dare, 2004).

Figure 2 illustrates the trends of housing listing prices in C3 (solid lines), C9 (dotted lines), and C37 (dashed lines) during the study period. More specifically, the graphs in the top and the bottom panels respectively illustrate the trends of unit price and total price. The red vertical line denotes the announcement month of Xiong'an New Area. As seen in Figure 2, the listing prices in the Xiong'an New Area surge immediately following the announcement.

Alarmed by the skyrocketing prices, the government stepped in on April 2, 2017 to deter speculative behavior by suspending all real estate transactions in Xiong'an. However, despite the restrictions on property purchases, the financial prospects for the future residents of Xiong'an have improved considerably, which has subsequently shifted investors' focus to areas just outside Xiong'an. This is verified by the soaring home prices in nine adjacent counties during the post-announcement period, as indicated by the dotted lines in Figure 2.

[**Figure 2 About Here**]

3.2 Measures of Consumer Behavior

When housing wealth increases, consumers may increase their consumption of certain products, purchase better quality products, or change their preference to products with fewer discounts. We examine whether consumers upgrade their consumption after experiencing positive wealth shocks using the following measures: payment per order, # of items per order, payment per item, and price discounts per item.

Consumers may delay payment for a variety of reasons, such as tight budgets, choice overload, or even internet connectivity issues; nevertheless, one critical reason for the delay is the increase in "perceived risk" or "uncertainty" about the purchase (Corbin, 1980; Cho et al., 2006). Cho et al. (2006) define online shopping hesitation or delay as postponing or deferring product purchases by allowing for more processing time before making a final purchase online. In this study, *Payment hesitation* is a continuous variable that measures the time interval between the order creation time and order payment time. In addition, consumers may regret their online purchases and choose to return products for similar reasons. Consumer tolerance for unsatisfied products should change when housing prices increase and consumers feel wealthier. To capture the effect of housing wealth changes on consumers' tolerance for unsatisfied purchases, we create a dummy variable, *return propensity*, which equals 1 if an item has been returned to a seller and a refund is requested, and

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

0 otherwise.

When consumers' financial wealth improves dramatically, they may put in less effort at work and spend more time doing things that are not job-related. Since our data record the precise timestamp an order was placed, we can detect work-time shirking if an order is placed during working hours. We follow Gu et al. (2019) and define *shirking* as a dummy variable equal to 1 if an order is created during the work hours, and 0 otherwise. Work-hours are defined as those from 9am – 12pm and 2pm – 5pm on Mondays through Fridays that do not fall on public holidays included in the official holiday calendar between 2016 and 2018. This measure accurately and directly captures the shirking behavior during work hours.

4 Empirical Methodologies and Main Results

4.1 The Post-shock Response of the Housing Market

The announcement of the Xiong'an New Area on April 1, 2017 immediately resulted in a large upward adjustment in local housing prices. We believe that the announcement satisfies the exogeneity assumption for three reasons. First, as discussed in Section 2, the precise date of the announcement and the geographic coverage of the new area were completely unexpected to the public. Second, Figure 2 shows that the sharp and immediate jump in housing prices in C3 occurred only in the post-announcement period. Third, as shown in Figure A1, we do not observe abnormal land transactions in C3 during the pre-announcement period, providing suggestive evidence that there was no leakage of information and verifying the exogenous nature of the announcement.

We begin the analysis by quantifying the housing market response to the announcement of Xiong'an by estimating the following specification:

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

where the dependent variable $Price_{j,m}$ denotes the logarithm of the average listing 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 with a value of 1 for the treatment counties, and 0 for the control counties.[12] $After_m$ 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 denote the county fixed effect and year-month fixed effect, respectively, and the standard errors are clustered at the county level.

[Table 2 About Here]

Table 2 reports the results of estimating Eq. (1), with Panels A and B using different treatment and control counties. Specifically, in Panel A, C3 and C37 correspond to the treatment counties and control counties, respectively; in Panel B, C9 and C37 correspond to the treatment counties and control counties, respectively. Panel C further compares the housing price responses between

[12] As shown in Table A1, the treatment and control counties are similar across a wide range of geographical characteristics and socio-economic conditions.

C3 and C9. More specifically, the results indicate that the average listing price in C3 increases by 65.70% ($= \exp(0.505) - 1$) more than that in C37 during the post-announcement period. This corresponds to an average estimate of 392,755 CNY (61,661 USD) per $100m^2$ in housing value based on the mean listing housing price shown in Table 1.[13] When we compare the housing market dynamics between C9 and C37, a significant increase in average listing price is also found in the nine adjacent counties of the Xiong'an New Area, but at a lower magnitude of 24.86% ($= \exp(0.222) - 1$). The results reveal that homeowners in C3 and C9 benefit significantly from the increasing housing wealth caused by the unexpected announcement of the Xiong'an New Area.

We also provide some suggestive evidence that, at least during our sample period, the announcement of Xiong'an has an immediate and significant effect on the housing market, but not on other economic characteristics of the counties, which may also influence consumer behavior. As illustrated in Figure A2, none of the six economic characteristics, including the growth of disposable income, GDP, population, tax revenue, fiscal revenue, and the number of large firms, exhibits a *sudden* change as observed in the housing markets of C3 and C9. This lends us strong support that the immediate impact of Xiong'an New Area announcement would be observed mainly in the real estate market, but not in other economic characteristics during our study period. Therefore, it is reasonable to consider the announcement of Xiong'an New Area as a housing wealth shock to the area during the sample period.

4.2 The Post-shock Response of Online Consumer Behavior

4.2.1 Empirical Challenges

There are two main challenges in identifying the causal impact of housing prices on consumer behavior. First, housing prices and economic prospects are jointly determined, and causation may also go in either direction, resulting in an upward bias of OLS estimates. Second, the channels through which changes in housing prices could lead to changes in consumer behavior are difficult to identify due to both a lack of micro-level data that capture consumer behavior and an appropriate setting that generates exogenous variations in housing wealth. As shown in Section 4.1, the Xiong'an New Area announcement triggers a steep surge in housing prices; in addition, the subsequent prohibition of real estate transactions in the new area creates variations in homeowners' ability to sell assets. These variations allow us to distinguish several mechanisms that may underline the relationship between housing prices and consumption, including the *collateral effect*, which refers to increases in housing prices relaxing the collateral constraint, allowing for additional borrowing that can be used to finance spending; and the *wealth effect*, according to which households adjust their consumption patterns and behavior when housing wealth unexpectedly changes. In both the life-cycle model and the model with collateralized lending, higher housing prices can have substantial effects on consumption (Sinai and Souleles, 2005; Berger et al., 2018). More specifically, there are two types of housing wealth effects: a *realizable* wealth effect - household can take out equity through selling the property, and an *unrealizable* wealth effect - even if households in the new area

[13] $5,978 * 65.70\% * 100 = 392,755$.

are not allowed to sell their home, they may still change their consumption behavior due to a higher discounted value of wealth. Of course, we need to properly control for the *common confounding unobservable factors* that may simultaneously affect both housing prices and consumption, for instance, the expected productive potentials, and expectations about future economic conditions.

We overcome these critical challenges by employing a unique policy setting, which is crucial for disentangling the realizable and unrealizable wealth effects, and by using a micro-level panel dataset of online consumption. Specifically, to address the endogeneity concern, we employ a DID approach, with consumers who have experienced a housing wealth shock as the treatment group (i.e., local consumers in C3 and C9) and those who have been relatively unaffected by the shock as the control group (i.e., local consumers in C37). Moreover, to understand the underlying mechanisms, we exploit the housing transaction restriction policy in Xiong'an and attempt to distinguish the realizable and unrealizable wealth effects on consumption behavior. We also categorize consumers into two groups: consumers with only one delivery address and consumers with multiple addresses in a specific county.[14] Notably, an underlying assumption in the baseline analysis is that consumers with delivery addresses restricted to a single county throughout our sample period are homeowners of that county. Under this assumption, these two groups of consumers are treated as homeowners with a single property and homeowners with multiple properties, respectively. We relax the assumption in later analysis to test the robustness of the findings.

Notably, consumers differ in terms of the number of properties/addresses owned or their ability to sell properties because housing transaction restrictions in the area. Table A2 in the appendix illustrates several mechanisms through which housing wealth might influence consumption behavior. First, for consumers in C3 and C9, changes in housing prices could bring all three effects, including the collateral effect, the wealth effect and the common confounding unobservable factors, relative to those in C37. Second, because consumers in C3 cannot sell their properties due to the transaction restriction, the wealth effects of C3 consumers is the *unrealizable wealth effect*; in contrast, consumers in C9 can sell their properties, thus an increase in housing prices can affect their consumption through a *realizable wealth effect*. Third, we expect greater magnitudes of the wealth effect to be observed from homeowners with multiple properties than those with only one property. Therefore, by comparing consumers in C9 to those in C3, we can net out the collateral effect and common confounding unobservable factors, and distinguish between the realizable wealth effect and the unrealizable wealth effect for each group of homeowners (i.e., homeowners with a single property and those with multiple properties).

[14] For example, a single-address buyer in C3 has only one delivery address in the three Xiong'an counties throughout our sample period, while a multiple-addresses buyer in C3 has at least two delivery addresses in the three Xiong'an counties.

4.2.2 Estimation Results on Average Behavioral Response

We examine the response of online consumer behavior to the announcement of Xiong'an using the following specification:

$$\begin{aligned} Y_{o/i,b,s,d} = & \alpha + \beta_1 Treat_b * After_d + \beta_2 Treat_b * After_d * Multiple_b + \\ & \Delta Income_{j(b),y} + \theta_b + \delta_s + \gamma_d + \epsilon_{o/i,b,s,d} \end{aligned} \tag{2}$$

where o/i, b, s, and d respectively index the order (o) or item (i), buyer, seller and date. $Treat_b$ is dummy variable equal to 1 for consumers in the treatment counties, and 0 for consumers in the control counties. $After_d$ is a dummy variable equal to 1 for the period after April 1, 2017, and 0 otherwise. To gain further insights into the impact of rising housing prices on consumption behavior of different types of homeowners, we distinguish between homeowners with a single property and those with multiple properties by including a dummy variable $Multiple_b$, which equals 1 if a consumer has multiple addresses, and 0 if a consumer has only one delivery address in a county. β_1 captures the average response of online consumer behavior for consumers with only one address, and β_2 measures the difference in responses between consumers with only one address and those with multiple addresses. Notably, we include the county-level disposable income growth rate ($\Delta Income_{j(b),y}$), where $j(b)$ denotes the county of buyer b, to control for the potential non-housing-related income effects: the announcement of Xiong'an may attract a large amount of investment and create plenty of new job opportunities, leading to a growth of labor income for the local residents. θ_b stands for buyer fixed effects that absorb the time-invariant factors at the buyer level. δ_s represents seller fixed effects to absorb the time-invariant factors at the seller level, which also mitigates the concern that the consumer behavior may differ across different types of products. We also control for the date fixed effects γ_d to eliminate the date-specific impact that is common to consumers in the treatment and control groups. The standard errors are clustered at the date level.

The dependent variable $Y_{o/i,b,s,d}$ takes different forms at the order or item level, which are categorized into three sets. The first set contains four traditional variables that reveal changes in consumption level: the logarithm of payment and the logarithm of item quantity at the order level, as well as the logarithm of payment and the logarithm of discount amount at the item level. The second set includes two variables that reflect the perceived risk or uncertainty about the purchase: the logarithm of payment hesitation at the order level and the return propensity at the item level. The third one refers to the shirking propensity at the order level, which captures the change in labor supply when individuals benefit from a large windfall of housing wealth.

Table 3 reports the baseline results of Eq. (2), with Panels A, B, and C respectively examining each of the three sets of consumer behavior. The subscript o and i respectively indicate the order-level and item-level outcome variables. We implement three models that differ in the estimation sample, and the definition of the treatment group.

[Table 3 About Here]

Model 1: C3 vs. C37 (Column 1 - Column 4). In Model 1, we compare consumption behaviors of consumers in C3 to those in C37 before and after the Xiong'an announcement. $Treat_b$ takes the value 1 for consumers with delivery addresses only in C3 and 0 for those with delivery addresses only in C37. Specifically, the estimated coefficients of $Treat * After$ are significantly positive at 1% level for both $Payment_o$ and $Payment_i$ in Panel A. The estimates suggest that consumers with only one address in C3, on average, respond to the announcement by increasing their order payments (Column 1) and payments per item (Column 3) by 9.75% (=exp(0.093)-1) and 10.63% (=exp(0.101)-1), respectively, relative to consumers from C37. The results are consistent with the findings in prior studies, which demonstrate that consumption increases in response to windfall gains (Agarwal and Qian, 2014; Haushofer and Shapiro, 2016). For the number of items per order (Column 2) and discount amount per item (Column 4), we find no evidence that consumers purchase more items per order or that they dislike discounted products.

As suggested by Greenleaf and Lehmann (1995) and Cho et al. (2006), online shopping hesitation or delay are related mainly to consumers' "perceived risk" or "uncertainty". Therefore, we hypothesize that consumers who experience positive housing wealth shocks are less concerned about "perceived risk" or "uncertainty", and become more decisive or impulsive while making online purchases.[15] Panel B presents interesting findings. With the large windfall of housing wealth, consumers with one address in the Xiong'an New Area reduce their payment hesitation (Column 1) by 10.68% (=1-exp(-0.113)) more than those in the control group. To put the results into context, a 10.68% decrease in payment hesitation is equivalent to approximately 37.54 seconds in reduction of delay when making payment.[16] Another reason that consumers delay payment at the final stage is their wish to avoid regrets over making wrong purchase decisions. Since most products on the e-commerce website could be returned within seven days from the date of purchase, our data allow us to directly examine the impact on return propensity. As shown in Column 2 of Panel B, the coefficient of $Treat * After$ appears to be significantly negative at -0.065, implying that consumers with only one address in C3 are less likely to return the online purchased items following a positive housing wealth shock. Thus, the results suggest that changes in housing wealth play a significant role in shaping online consumer behavior by reducing the perceived risk associated with online shopping. In addition, following Cho et al. (2006), we control for the logarithm of order (item) payment amount in the regressions in Panel B. The estimated coefficients on $\ln(Payment)$ are significantly positive in Column (1) and significantly negative in Column (2), indicating that payment reluctance is positively associated with the payment value, while return propensity is negatively correlated with the item value.

Panel C estimates the impact of the Xiong'an announcement on shirking propensity. We find the coefficient of the interaction term $Treat * After$ to be economically and statistically significant at 0.082, implying that the Xiong'an announcement increases the shirking behavior of single ad-

[15] Payment hesitation occurs at the final stage of a transaction when consumers 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.

[16] Given that the mean value of hesitation for consumers in C3 before the announcement is 351.35 seconds, a 10.68% decrease in payment hesitation is equal to 10.68%*351.35=37.54 seconds.

dress consumers in C3. This estimated average response is equivalent to a 24.85% increase in the shirking propensity given the pre-announcement mean value (i.e., 0.33) of C3 consumers' shirking propensity. This finding is consistent with that of Gu et al. (2019), which show that consumers become 1.7% more likely to make non-work-related transactions using credit cards during work hours after positive shocks to house prices. In our study, the greater magnitude of the response on shirking tendency suggests that online transaction is likely to capture a more prevalent and salient shirking behavior during work hours than credit card purchases.

Finally, under Model 1, the coefficients on $Treat * After * Multiple$ are statistically insignificant in all the regressions, which show that the behavioral responses of C3 consumers with a single delivery address are not substantially different from those with multiple delivery addresses. Given that the housing transaction restriction applies only to properties in C3, these results suggest that as long as homeowners cannot take out equity in the form of selling their properties, their spending patterns and behavior are similar irrespective of how many properties they own.

Model 2: C9 vs. C37 (Column 5 - Column 8). In order to distinguish between the realizable and unrealizable wealth effects, we compare consumption behavior of consumers in C9 to that of consumers in C37 before and after the Xiong'an announcement in Model 2. Specifically, $Treat_b$ takes the value 1 for consumers with delivery addresses only in C9 and 0 for those with delivery addresses only in C37. Since the transaction restriction is not applicable to properties outside of C3, homeowners in both C9 and C37 can cash out equity by either refinancing or selling their properties.

Comparing Model 2 to Model 1, we find similar patterns of behavioral responses of homeowners with a single address in C9 to those in C3. As shown in Panel A, the announcement causes homeowners with a single address in C9 to increase their online spending by 5.23% (=exp(0.051)-1) in payment per order (in Column 5) and 5.65% (=exp(0.055)-1) in payment per item (in Column 7), on average, respectively. The impacts on the number of items per order (in Column 6) and the discounted amount per item (in Column 8) remain trivial. Panels B and C demonstrate that the announcement decreases purchase hesitation by 6.29% (=1-exp(-0.065)), reduces return propensity by 4.4%, and increases shirking propensity by 4.70% for homeowners with a single address in C9, relative to the control group. Notably, the magnitudes of all the estimated coefficients on $Treat * After$ are smaller in Model 2 relative to those in Model 1. This is mostly due to the relatively weaker impact of the announcement on the housing prices in the C9 counties than in C3 counties. As shown in Table 2, the increase of housing prices in C9 is roughly 40% of the increase in C3.

More interestingly, in Model 2, the reported coefficients of the triple interaction term $Treat * After * Multiple$ for $Payment_o$, $Payment_i$, $Hesitation_o$, $Return_i$, and $Shirking_o$ are statistically significant. This suggests that consumers with multiple addresses in C9 are more responsive on these measures to the positive housing shock than those with a single address in C9. In particular, following the Xiong'an announcement, consumers with multiple addresses in C9 increase their payment at the order (item) level by 8.98% (9.20%); reduce their payment hesitation and return intention by

10.51% and 7.3%, respectively; and increase their likelihood of using work hours for online shopping by 7.3%. Taken together, in contrast to the findings in Model 1, the statistical significance and economic magnitudes on $Treat * After * Multiple$ in Model 2 suggest that the differential effects of increasing housing prices on consumption behavior between consumers with a single address and those with multiple addresses are amplified when consumers can sell their homes to fund spending needs.

Model 3: C3+C9 vs. C37. To directly explore the differential effects of realizable and unrealizable housing wealth on consumption behavior, we analyze the behavioral differences between consumers in counties with purchase restrictions (C3) and those without (C9). The difference is captured in the triple interaction term $Treat_b * After_d * C3$, formally:

$$\begin{aligned} Y_{o/i,b,s,d} =& \alpha + \beta_1 Treat_b * After_d + \beta_2 Treat_b * After_d * C3 + \\ & \Delta Income_{j(b),y} + \theta_b + \delta_s + \gamma_d + \epsilon_{o/i,b,s,d} \end{aligned} \quad (3)$$

where $Treat_b$ takes value 1 for consumers in both C3 and C9, and takes value 0 for consumers in C37. $C3$ is a binary variable equal to 1 for consumers in C3. Other variables are the same as in Eq.(2).

The results are reported in Table 4. We want to highlight that the treatment group in Columns (1)-(4) are consumers with a single delivery address, while the treatment group in Columns (5)-(8) consists of consumers with multiple delivery addresses. Therefore, the coefficient of $Treat_b * After_d * C3$ captures the differential responses between consumers in C3 (where the housing transaction restrictions are imposed) and C9 (where people can take out equity by selling their properties) for different groups of consumers. There are two major observations from Table 4. First, the estimated coefficients of $Treat * After$ are statistically significant for $Payment_o$, $Payment_i$, $Hesitation_o$, $Return_i$, and $Shirking_o$ for both single address and multiple addresses consumers, which are in line with the results in Table 3. Second, the coefficients of $Treat * After * C3$ are statistically significant for the five behavioral measures, indicating that consumers in C3 are more responsive to the housing shock than those from C9.

[Table 4 About Here]

4.3 Elasticities of Consumer Behavior with respect to Housing Price

Based on our estimations of housing market responses in Table 2 and consumer behavioral responses in Table 3, we then estimate the elasticities of consumer behavior with respect to housing price by dividing the β in Eq.(2) by the λ in Eq.(1). A critical assumption to compare the elasticities across counties is that the housing markets of C3 and C9 are homogeneous. Table 5 summarizes the elasticities for the five behavioral measures - $Payment_o$, $Payment_i$, $Hesitation_o$, $Return_i$, and $Shirking_o$, all of which have statistically significant coefficients of $Treat * After$ in Table 3.

As shown in Columns (1) and (2) of Table 5, the elasticities of the combined effects in C3, which include the unrealizable wealth effect, the collateral effect, and the effect of the common confounding unobservable factors, are slightly larger for consumers with multiple addresses, relative to those with only one address. Similarly, results in Columns (3) and (4) show that the elasticities of the combined effects for consumers in C9, are substantially higher for consumers with multiple addresses when compared with consumers with a single address. We then interpret the difference between the elasticities in Columns (3) and (1) as measuring the difference between the realizable and unrealizable wealth effects for consumers with one address. Similarly, the last column measures the difference between the realizable and unrealizable wealth effects for consumers with multiple addresses. The results suggest that, the realizable wealth effect is greater than the unrealizable wealth effect on various measures of consumer behavior, and the differences in responses are magnified for homeowners with multiple properties.

[Table 5 About Here]

4.3.1 Estimation Results on Dynamic Behavioral Response

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

$$Y_{o/i,b,s,d} = \alpha + \sum_{s=-5}^{19} \beta_s * Treat_b * 1\{d \in Month_s\} + \Delta Income_{j(b),y} + \theta_b + \delta_s + \gamma_d + \epsilon_{o/i,b,s,d} \tag{4}$$

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 consumer 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 consumer behavior in the month (April 2017) of the Xiong'an announcement. The coefficients $\beta_1, \dots, \beta_{19}$ measure the responses in the first to the nineteenth month following the Xiong'an announcement, respectively. Similarly, coefficients $\beta_{-5}, \dots, \beta_{-1}$ measure the different trends of consumer behavior response between the treatment and control consumers in each of the five pre-treatment months; and these coefficients examine whether the parallel trend assumption for DID is satisfied.

Figure 3 (order level) and Figure 4 (item level) depict the estimated coefficients β_s and their respective 95 percent confidence intervals, with Panel A and Panel B corresponding to C3-vs.-C37 and C9-vs.-C37 comparisons, respectively. The vertical line represents the month in which the new area was announced. We find that the differences in consumer behavior responses between the treatment and control groups during the five-month pre-announcement period are insignificant, both statistically and economically, validating that the parallel trend assumptions are satisfied in all DID estimations.

[Figure 3 About Here]

[Figure 4 About Here]

When we compare the consumption behavior of consumers in C3 to that of consumers in C37 in Panel A, we observe that 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 ($s = 0$), while the effect on shirking (in Figure 3) starts to increase in the announcement month ($s = 0$). The coefficient on payment hesitation decreases persistently, and the treatment group becomes 21.2% less reluctant in making payment in the second month after the announcement ($s = 2$), although the magnitude declines and stabilizes at approximately 10% in the long run. The significantly negative effect on return propensity (in Figure 4) also persists during our sample period. Moreover, the consumption responses on order and item payments are statistically significant in most post-announcement months, with the largest responses occurring in the second month after the announcement. This suggests that the positive housing shock induces the consumers to upgrade their consumption by purchasing items that are more expensive, and this pattern persists over time. Additionally, the effects on shirking are immediate and strong in the short term and remain persistent throughout the 20-month post-shock period, allowing for an interpretation of a decline in work effort incentives after an unanticipated, positive wealth shock. Besides, we find that the housing shock has a negligible influence on the quantity of products per order and price discounts. Similar patterns are also revealed in in Panel B of Figures 3 and 4 when comparing C9 to C37.

5 Additional Tests

5.1 Robustness Checks

We carry out various tests to study the robustness of our results, including border discontinuity regressions, a subsample analysis, and controlling for more conservative sets of fixed effects.

5.1.1 Border Discontinuity Regressions

An alternative explanation is that our findings might be explained by the *region-specific*, as opposed to common, observed or unobserved differences among C3, C9, and C37 counties, rather than by the Xiong'an New Area announcement. To address this concern and assess the robustness of various specifications, we conduct border discontinuity regressions using the DID approach. Using detailed information on delivery addresses at the transaction level, we restrict the sample to transactions within a 3-km band on each side of the border between C3 and C9, as well as between C9 and C37. This approach excludes consumers who are particularly close to or far away from the urban center and reduces the variations in unobserved location characteristics across consumers in the treatment and control counties.

Table A3 presents the results. In Model 1, we limit the sample to transactions within 3km of the border between counties that have transaction restrictions (C3) and those that do not (C9). We find that after the announcement of Xiong'an, individuals in C3 increase their consumption online, on average, leading to positive treatment effects on $Payment_o$ and $Payment_i$, and become less hesitant when making payments, compared to those in C9. However, none of the coefficients on $Treat * After * Multiple$ are statistically different from zero, suggesting that consumers with a single property and those with multiple properties behave similarly in the 3 km band between C3 and C9 after the positive wealth shock.

Model 2 restricts the sample to transactions occurring within 3 km of the boundary between C9 and C37. Again, we find statistically significant increases in $Payment_o$ and $Shirking_o$, and declines in $Hesitation_o$ and $Return_i$ in the 3km band of C9 relative to those just across the county border in C37 within the same 3km band. Moreover, after the announcement, individuals with multiple addresses increase the average payment per order and per item, are less likely to return products, and are more likely to shop online during work hours than those with a single address. However, we find that the coefficients of $Treat * After$ are insignificant for $Return_i$ and $Shirking_o$ in Model 1 and for $Payment_i$ in Model 2. This could be explained by the relatively small samples in the border discontinuity regressions.

5.1.2 Subsample Analysis

The previous analyses are based on the assumption that consumers with delivery addresses located only in a particular county throughout our sample period are homeowners in that county. Although the homeownership rate in Hebei Province is around 95.99%, our sample of buyers may still include some buyers who rent the same property and thus their delivery addresses remain unchanged during the sample period.[17] While we do not directly observe homeownership in the data, we construct a subsample to deal with this concern. Specifically, we restrict the consumers to those whose birth counties (based on the first six digits of their national identity card numbers) and delivery counties are identical. The subsample thus contains *local* consumers who are more likely to be homeowners compared to the full sample. Table A4 presents the results of estimating Eq.(2) using this restricted sample, and we find the results are consistent with the baseline estimations.

5.1.3 Inclusion of Additional Fixed Effects

Although our main specifications have included disposable income growth at the county level to account for local income changes, one concern about the results is that some potential unobserved time-varying regional shocks could affect expectations about the future permanent income. For instance, following the announcement of Xiong'an, there could be local policies to support entrepreneurs by making it easier to do business in the area, or initiating alternative funding schemes to encourage businesses to create more job opportunities, or developing local infrastructure (roads and shipping ports) to make online shopping experiences more convenient and thus attract more online consumers. In this case, the housing wealth effect and consumer behavior may be spuriously correlated due to such omitted variables. To dispel this concern, we include the county-year fixed effect in Eq.(2). The results are reported in Table A5, which are consistent with those in Table 3.

Moreover, one might be concerned that sellers may launch seasonal deals or special promotions from time to time, such as the Single's Day (November 11) and the 618 Shopping Festivals (June

[17] According to Section 9.4 of the Sixth National Population Census of China Database, homeownership in Hebei Province is 89.23% in cities, 94.13% in towns and 99.25% in villages, respectively. Source: `http://www.stats.gov.cn/tjsj/pcsj/rkpc/6rp/indexch.htm`

18), which might drastically alter consumers' shopping patterns and behavior. To account for potential omitted shocks at the seller level, we include a seller-month fixed effect in Eq.(2) and re-estimate the specifications. The results are presented in Table A6, which are in line with those in Table 3.

5.2 Heterogeneity Tests

Our results present compelling evidence that various online consumer behavior responds significantly to the housing wealth shock caused by the Xiong'an announcement. This raises two further questions: who responds more, and to what extent do the responses differ by product category?

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

$$Y_{o/i,b,s,d} = \alpha + \beta Treat_b * After_d + \Delta Income_{j(b),y} + \theta_b + \delta_s + \gamma_d + \epsilon_{o/i,b,s,d} \tag{5}$$

As we can see in Figure 5, in terms of item payment, consumers in C3 and C9 show diverse consumption response patterns across product categories. Consumers in C9 upgrade their consumption in five out of six item categories following the announcement, while consumers in C3 appear to increase their consumption just in the categories of home appliances, clothing and others. In terms of price discount and item returns, we find comparable heterogeneous response patterns across product categories between C3 and C9 consumers.

[Figure 5 About Here]

In the second set of heterogeneity tests, we repeat the estimation of Eq.(5) by gender and age groups (there are six subsamples of consumers: female, male, age under 30, age of 30-40, age of 40-50, and age above 50). Figure 6 plots the estimated coefficients. We find that, after the Xiong'an announcement, the products purchased by female consumers in C3 and male consumers in C9 become more expensive; the response in return propensity does not vary significantly across gender. The results also show that products purchased by older consumers appear to be more expensive after the shock, compared to the purchases of their younger counterparts. This is in line with Campbell and Cocco (2007), which reveal that older homeowners are more responsive to changes in housing wealth relative to the younger cohorts. When we conduct the heterogeneity tests in return propensity across age groups, we find that the response is stronger for older consumers than for younger ones in C3, while the opposite pattern is revealed in C9.

[Figure 6 About Here]

We also conduct the heterogeneity tests at the order level by gender and age group. As shown in Figure 7, female consumers and elderly consumers are more responsive to the Xiong'an announcement in terms of order payment. In terms of payment hesitation, we observe homogeneous responses across gender and age groups for consumers in C3. However, for consumers in C9, the responses of payment hesitation to the shock are larger 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 similar patterns in the responses across gender and age groups. The comparisons of responses in hesitation, shirking, and return intention between female and male, and between young and older consumers, demonstrate consistently divergent patterns in C3 relative to C9.

[Figure 7 About Here]

5.3 Aggregate Level Analysis

In the previous analyses, we examine responses of various consumer behaviors at the transaction level. In this section, we aggregate the micro-level data at the Buyer-YearMonth level to study whether the treated consumers exhibit positive responses in terms of payment amount, order frequency, and the number of items on a monthly basis. The estimation results in Table A7 indicate that consumers in C3 and C9 respectively increase their monthly online consumption in terms of payment amount by 10.3% and 6.08%, compared to consumers in C37, in the unbalanced buyer-year-month panel. Nevertheless, we see little response in the number of completed orders and purchased items.

6 Conclusion

This paper examines how consumer behavior responds to an unanticipated housing wealth shock using a proprietary dataset of online consumption from the largest e-commerce company in China. The unique and surprising policy announcement by the Chinese government enables us to exploit the exogenous variation in housing price appreciation across counties and utilize a difference-in-differences approach to estimate the consumption and behavioral responses. Specifically, we compare consumers who are exposed to the wealth shocks (in C3 and C9) with those who are less likely to be affected (in C37), assuming that the difference in consumption responses arises from the ability to use the changing housing wealth. Moreover, the implementation of the housing transaction in the new area offers us an opportunity to distinguish between the realizable and unrealizable wealth effects. In addition, rich information provided in the dataset enables us to group consumers based on the number of properties/addresses owned and examine their differential behavioral responses to the positive housing wealth shock.

We first show that following the Xiong'an announcement, the housing listing prices in C3 and C9 increase by 65.70% and 24.86%, respectively, compared to the changes in C37. Turning to the DID estimations on online consumer behavior, we find that treated consumers with a single address in C3 (C9) upgraded their consumption by spending 10.62% (5.65%) more per item and 9.75% (5.23%) more per order, on average. Moreover, consumers with a single address in C3 (C9) became 10.68% (6.29%) less hesitant to make payments, and 6.50% (4.40%) less inclined to request returns. In terms of shirking, we show that consumers with a single address in C3 (C9) became 8.2%

(4.7%) more likely to make online purchases during work hours. More importantly, we do not find significant differences in behavioral responses between consumers with a single address and those with multiple addresses in C3, while the behavioral responses turn out to be stronger for multiple addresses consumers in C9, relative to consumers with only one address in C9. Furthermore, the results show that the elasticities of realizable wealth are greater in magnitude than those of unrealizable wealth irrespective of the number of properties owned. And the differences are stronger for consumers with multiple addresses than those with only one address.

To ensure that our estimated results are robust, we carry out a battery of robustness checks, including birth counties matching, border discontinuity regression, and controlling for a more conservative set of fixed effects. In the dynamic analysis, we show that the parallel trend assumption is satisfied for the DID estimation, and the positive responses in consumption level and shirking propensity, as well as the negative responses in payment hesitation and return intention are long-lasting. We also find that the elasticities of consumer behaviors with respect to housing prices are greater in magnitude in the nine adjacent counties than those in the three Xiong'an counties.

This study makes several contributions to the existing literature. First, our study is the first to reveal a causal impact of housing wealth on a variety of online consumer behaviors, such as hesitation, shirking, and returning intention, which are difficult to quantify using the traditional offline consumption data or survey data. Second, the exogenous shock changes housing wealth rapidly and tremendously, allowing us to establish a clean causal relationship between housing wealth and online consumer behavior and to investigate the long-term impact. Third, our analysis identifies the difference between realizable wealth effect and unrealizable wealth effect.

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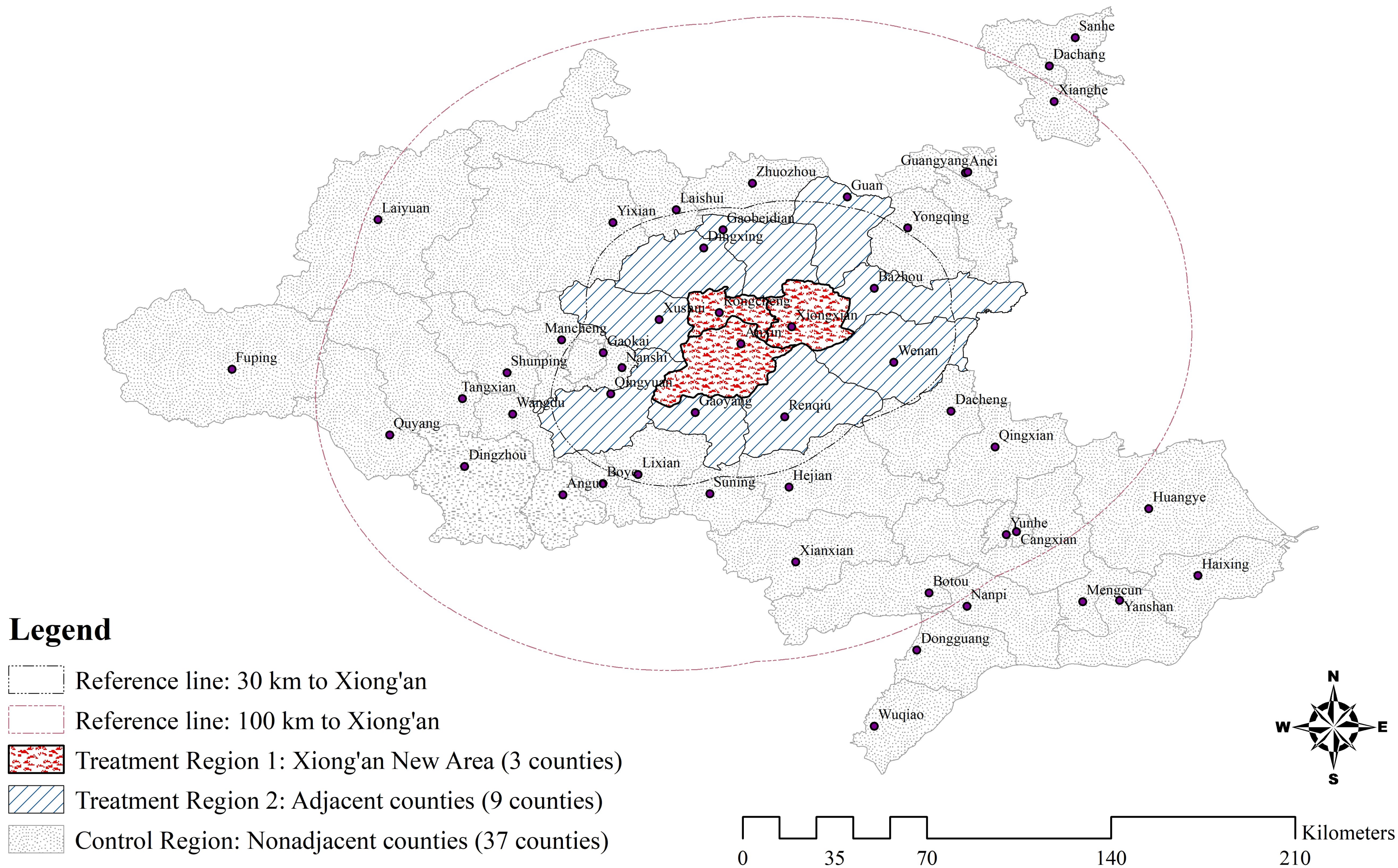
Figure 1: The Geographic Coverage of Treatment and Control Counties



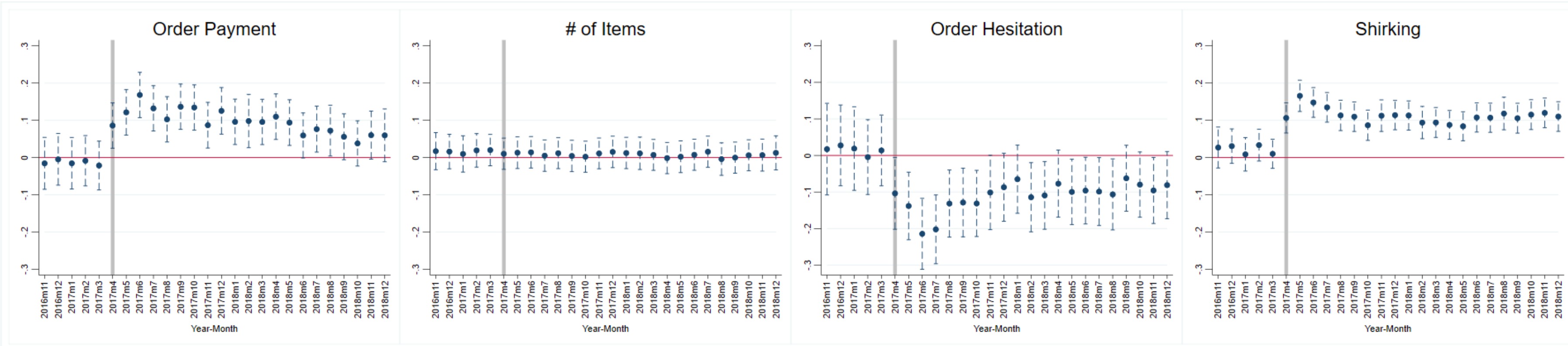
Notes: This figure shows the geographic coverage of the sample counties in this study. There are three counties (shaded in red) in Xiong'an, nine adjacent counties (shaded in blue) of Xiong'an, and 37 non-adjacent counties (shaded in grey) of Xiong'an. The 49 counties span in three cities: Baoding, Cangzhou, and Langfang.

Figure 2: Housing Market Trends in C3, C9, and C37

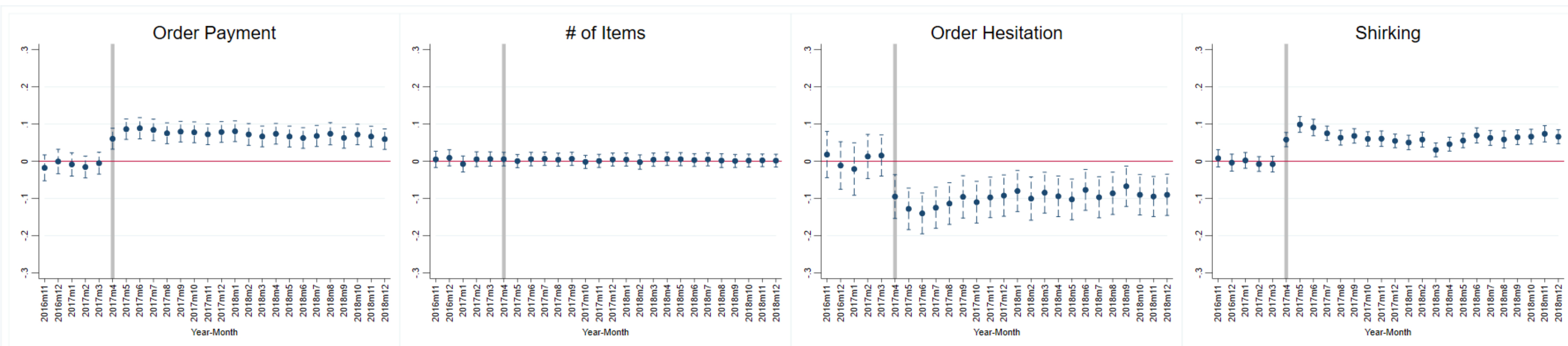
Notes: This figure shows the trends of listing unit price and listing total price in the three Xiong'an counties (solid line), nine adjacent counties (dotted line), and 37 non-adjacent counties (dashed line) from October 2016 to December 2018. The verticle red line indicates the announcement month.

Figure 3: Dynamic Behavioral Responses: Order-Level Estimation

Panel A: C3 vs. C37



Panel B: C9 vs. C37



Notes: This figure plots the estimated coefficients and their respective 95-percent confidence intervals from estimating Eq. (4) using the order level data, with Panel A and Panel B corresponding to C3-vs.-C37 and C9-vs.-C37 comparisons, respectively.

Figure 4: Dynamic Behavioral Responses: Item-Level Estimation

Panel A: C3 vs. C37

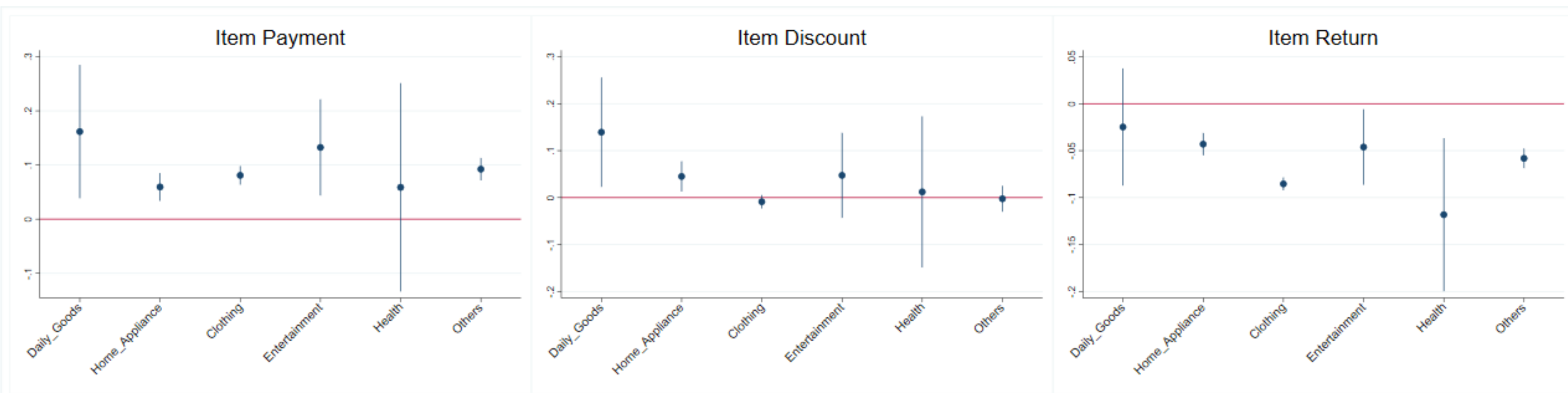
Panel B: C9 vs. C37

Notes: This figure plots the estimated coefficients and their respective 95-percent confidence intervals from estimating Eq.(4) using the item-level data, with Panel A and Panel B corresponding to C3-vs.-C37 and C9-vs.-C37 comparisons, respectively.

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

Panel A: C3 vs. C37

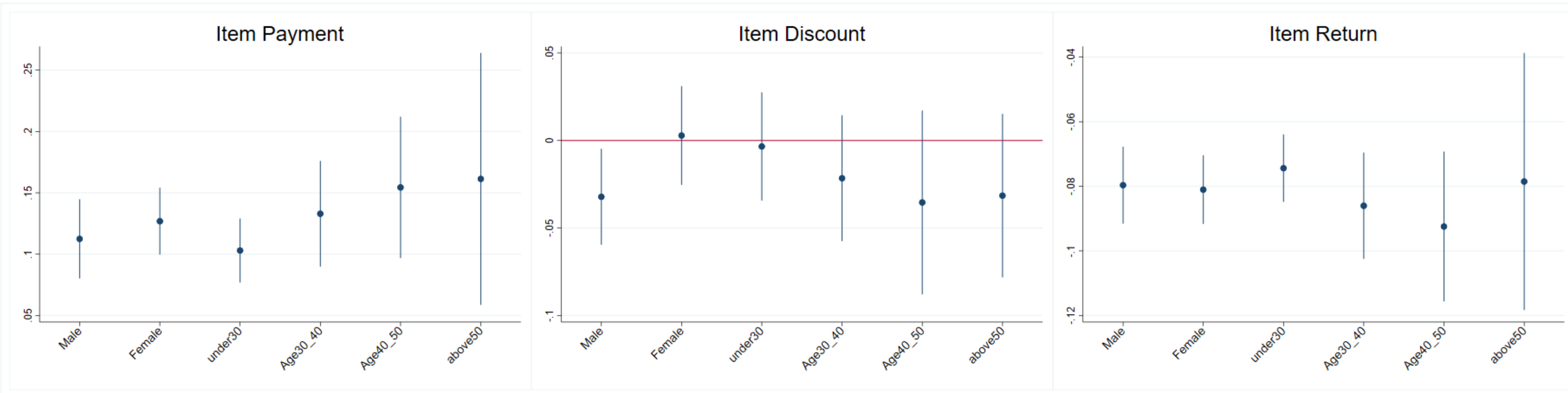
Panel B: C9 vs. C37



Notes: This figure plots the estimated coefficients of estimating Eq.(5) across item categories, with Panel A and Panel B corresponding to C3-vs.-C37 and C9-vs.-C37 comparisons, respectively. The items are divided into six categories: daily goods, home appliances, clothing, entertainment, health-related products, and others.

Figure 6: Heterogeneity Test across Consumer Categories: Item-Level Estimation

Panel A: C3 vs. C37

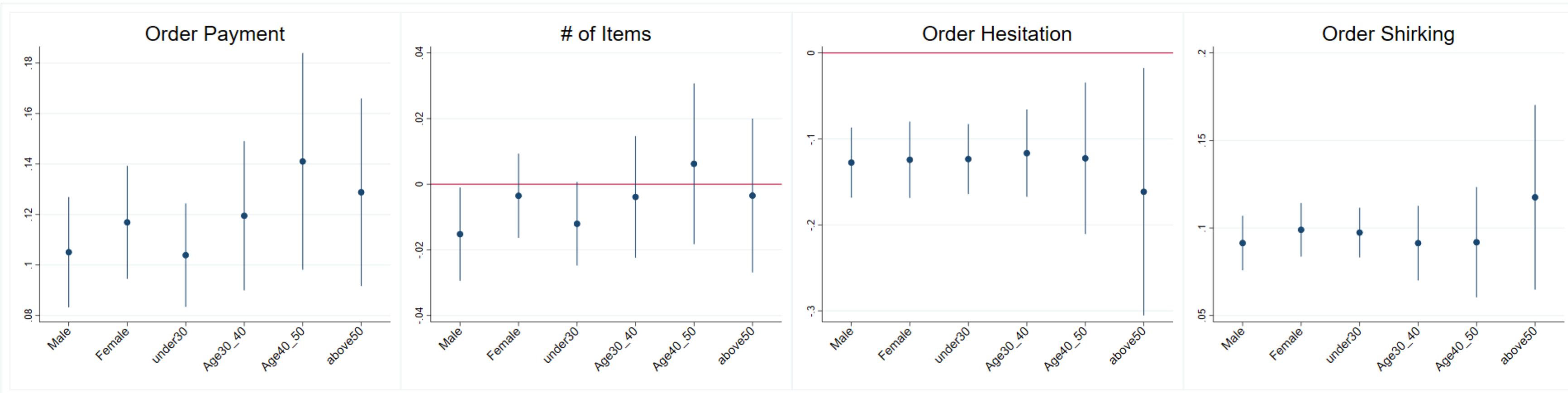


Panel B: C9 vs. C37

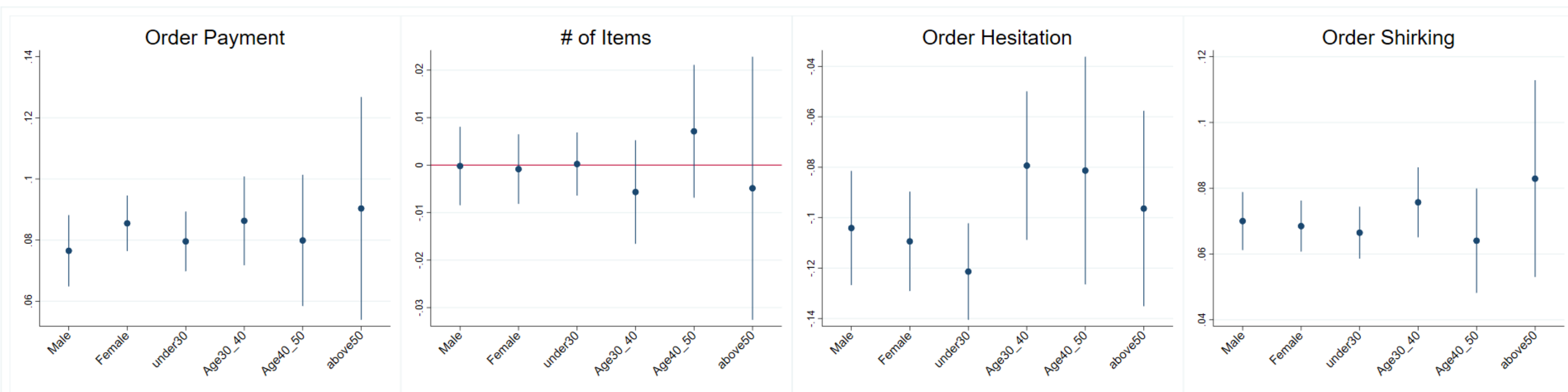
Notes: This figure plots the estimated coefficients of estimating Eq.(5) across consumer categories, with Panel A and Panel B corresponding to C3-vs.-C37 and C9-vs.-C37 comparisons, respectively. The consumers are divided into six categories: female, male, age under 30, age of 30-40, age of 40-50, and age above 50.

Figure 7: Heterogeneity Test Across Consumer Categories: Order-Level Estimation

Panel A: C3 vs. C37



Panel B: C9 vs. C37



Notes: This figure plots the estimated coefficients of estimating Eq.(5) across consumer categories, with Panel A and Panel B corresponding to C3-vs.-C37 and C9-vs.-C37 comparisons, respectively. The consumers are divided into six categories: female, male, age under 30, age of 30-40, age of 40-50, and age above 50.

Table 1: Summary Statistics of Online Consumption Data and Housing Data

	Group 1: 3 Xiong'an Counties (C3)				Group 2: 9 Adjacent Counties (C9)				Group 3: 37 non-Adjacent Counties (C37)			
	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												
Price_i	124.62	308.20	138.73	272.07	126.42	199.37	146.78	328.74	129.70	693.72	144.37	318.55
Payment_i	50.91	176.81	62.04	112.62	52.01	88.68	64.24	128.18	52.12	105.03	59.85	127.58
Return_i	0.34	0.47	0.24	0.43	0.29	0.46	0.22	0.41	0.30	0.46	0.30	0.46
Discount_i	73.71	159.45	76.69	217.85	74.41	139.71	82.54	268.13	77.58	659.10	84.52	256.13
Obs.	369,030				1,801,347				5,178,992			
Panel B: Order-Level Statistics												
Payment_o	59.20	96.69	71.55	111.77	66.69	128.63	76.61	129.10	61.48	116.48	68.79	125.24
Quantity_o	1.55	3.98	1.47	4.83	1.61	6.81	1.54	10.90	1.51	4.19	1.50	9.95
Hesitation_o	351.35	1984.89	225.68	1546.88	189.21	1437.89	134.87	1139.84	179.52	1406.56	141.79	1218.74
Shirking_o	0.33	0.47	0.40	0.49	0.34	0.48	0.39	0.49	0.35	0.48	0.33	0.47
Obs.	175,051				876,652				2,594,591			
Panel C: Monthly-Level Housing Market Statistics												
Unit Price	5,978	682	12,066	1,686	7,126	3,339	10,222	2,582	7,452	4,717	8,396	3,829
Total Price	675,513	92,380	1,361,333	345,490	817,427	377,065	1,173,212	359,715	922,187	536,511	1,004,895	440,103
Obs.	81				243				999			

Notes: This table presents the summary statistics of the online consumption data at the item level (Panel A) and order level (Panel B) for three buyer groups before and after the announcement. The final sample includes transactions of buyers whose delivery addresses are located only in the study counties and contains 3,646,294 transactions/orders, 7,349,369 purchased items, 3,827 active sellers, 44,496 consumers in the three counties in Xiong'an, 230,148 consumers in the nine adjacent counties, and 683,548 consumers in the 37 non-adjacent counties. Panel C reports the summary statistics of the housing market in different county groups. The subscript o and i respectively indicate the order-level and item-level outcome variables.

Table 2: Estimation Results of Housing Market Response

Sample	Panel A: C3 vs. C37	Panel B: C9 vs. C37	Panel C: C3 vs. C9
Model	(1)	(2)	(3)
Treat*After	0.505***	0.222***	0.284**
	(0.082)	(0.077)	(0.108)
Observations	1,080	1,242	324
R-squared	0.922	0.918	0.881
County FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes

Notes: This table reports the results of estimating Eq. (1), with Panels A, B, and C using different treatment and control counties. Three counties in the Xiong'an new area and 37 non-adjacent counties to the Xiong'an new area consist of the treatment group and control group, respectively, in Panel A; nine adjacent counties and 37 non-adjacent counties to the Xiong'an new area comprise the treatment group and control group, respectively, in Panel B; three counties in the Xiong'an new area and nine adjacent counties comprise the treatment group and control group, respectively, in Panel C. Fixed effects of county and year-month are included in all columns. 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. C37				Model 2: C9 vs. C37			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Consumption								
Dep. Variable	Payment_o	Quantity_o	Payment_i	Discount_i	Payment_o	Quantity_o	Payment_i	Discount_i
Treat*After	0.093***	-0.009	0.101***	-0.027	0.051***	-0.011	0.055***	-0.003
	(0.022)	(0.014)	(0.026)	(0.029)	(0.009)	(0.007)	(0.013)	(0.011)
Treat*After*Multiple	0.022	0.001	0.022	0.016	0.035***	0.011	0.033**	-0.008
	(0.023)	(0.015)	(0.028)	(0.030)	(0.010)	(0.008)	(0.014)	(0.012)
Observations	2,769,642	2,769,642	5,548,022	5,548,022	3,471,243	3,471,243	6,980,339	6,980,339
R-squared	0.778	0.484	0.597	0.801	0.777	0.484	0.594	0.801
Panel B. Perceived Risk and the Tolerance Level								
Dep. Variable	Hesitation_o	Return_i			Hesitation_o	Return_i		
Treat*After	-0.113***	-0.065***			-0.065***	-0.044***		
	(0.043)	(0.012)			(0.019)	(0.005)		
Treat*After*Multiple	-0.014	-0.017			-0.046**	-0.029***		
	(0.043)	(0.012)			(0.021)	(0.005)		
ln(Payment)	0.124***	-0.097***			0.124***	-0.093***		
	(0.002)	(0.001)			(0.002)	(0.001)		
Observations	2,769,642	5,548,022			3,471,243	6,980,339		
R-squared	0.446	0.429			0.438	0.418		
Panel C. Labor Supply								
Dep. Variable	Shirking_o				Shirking_o			
Treat*After	0.082***				0.047***			
	(0.015)				(0.007)			
Treat*After*Multiple	0.015				0.026***			
	(0.016)				(0.007)			
Observations	2,769,642				3,471,243			
R-squared	0.483				0.475			
Fixed Effects	Buyer FE, Seller FE, Date FE							

Notes: This table 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 using the full sample. In Model 1, we compare the behaviors of consumers in C3 to C37; and in Model 2, we compare the behaviors of consumers in C9 to C37. Panel A reports results using four traditional variables that reveal changes in consumption level: the logarithm of payment and item quantity at the order level, as well as the logarithm of payment and discount amount at the item level. Panel B reports results using two variables that reflect the perceived risk about a purchase and the tolerance level of unsatisfied products: the logarithm of hesitation at the order level and the return propensity at the item level. Panel C reports results using the shirking propensity at the order level. We indicate the order-level and item-level outcome variables by subscript o and i, respectively. Fixed effects of buyer, seller, and date are included in all columns. Standard errors are clustered at the date level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: The Post-shock Response of Consumer Behavior (Model 3: C3+C9 vs. C37.)

# of addresses	Single				Multiple			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Consumption								
Dep. Variable	Payment_o	Quantity_o	Payment_i	Discount_i	Payment_o	Quantity_o	Payment_i	Discount_i
Treat*After	0.051***	-0.011	0.056***	-0.003	0.086***	0.001	0.088***	-0.011**
	(0.009)	(0.007)	(0.013)	(0.011)	(0.004)	(0.003)	(0.005)	(0.005)
Treat*After*C3	0.041*	0.002	0.045**	-0.025	0.029***	-0.009	0.035***	0.000
	(0.024)	(0.015)	(0.020)	(0.032)	(0.010)	(0.006)	(0.012)	(0.012)
Observations	2,725,733	2,725,733	5,449,433	5,449,433	3,515,156	3,515,156	7,078,928	7,078,928
R-squared	0.778	0.484	0.598	0.801	0.777	0.484	0.594	0.801
Panel B. Perceived Risk and the Tolerance Level								
Dep. Variable	Hesitation_o	Return_i			Hesitation_o	Return_i		
Treat*After	-0.065***	-0.044***			-0.112***	-0.073***		
	(0.019)	(0.005)			(0.008)	(0.002)		
Treat*After*C3	-0.047**	-0.021*			-0.016	-0.010**		
	(0.019)	(0.010)			(0.016)	(0.005)		
ln(Payment)	0.124***	-0.098***			0.125***	-0.092***		
	(0.002)	(0.001)			(0.002)	(0.001)		
Observations	2,725,733	5,449,433			3,515,156	7,078,928		
R-squared	0.44	0.43			0.443	0.417		
Panel C. Labor Supply								
Dep. Variable	Shirking_o				Shirking_o			
Treat*After	0.047***				0.072***			
	(0.007)				(0.004)			
Treat*After*C3	0.035**				0.025***			
	(0.016)				(0.007)			
Observations	2,725,733				3,515,156			
R-squared	0.486				0.473			
Fixed Effects	Buyer FE, Seller FE, Date FE							

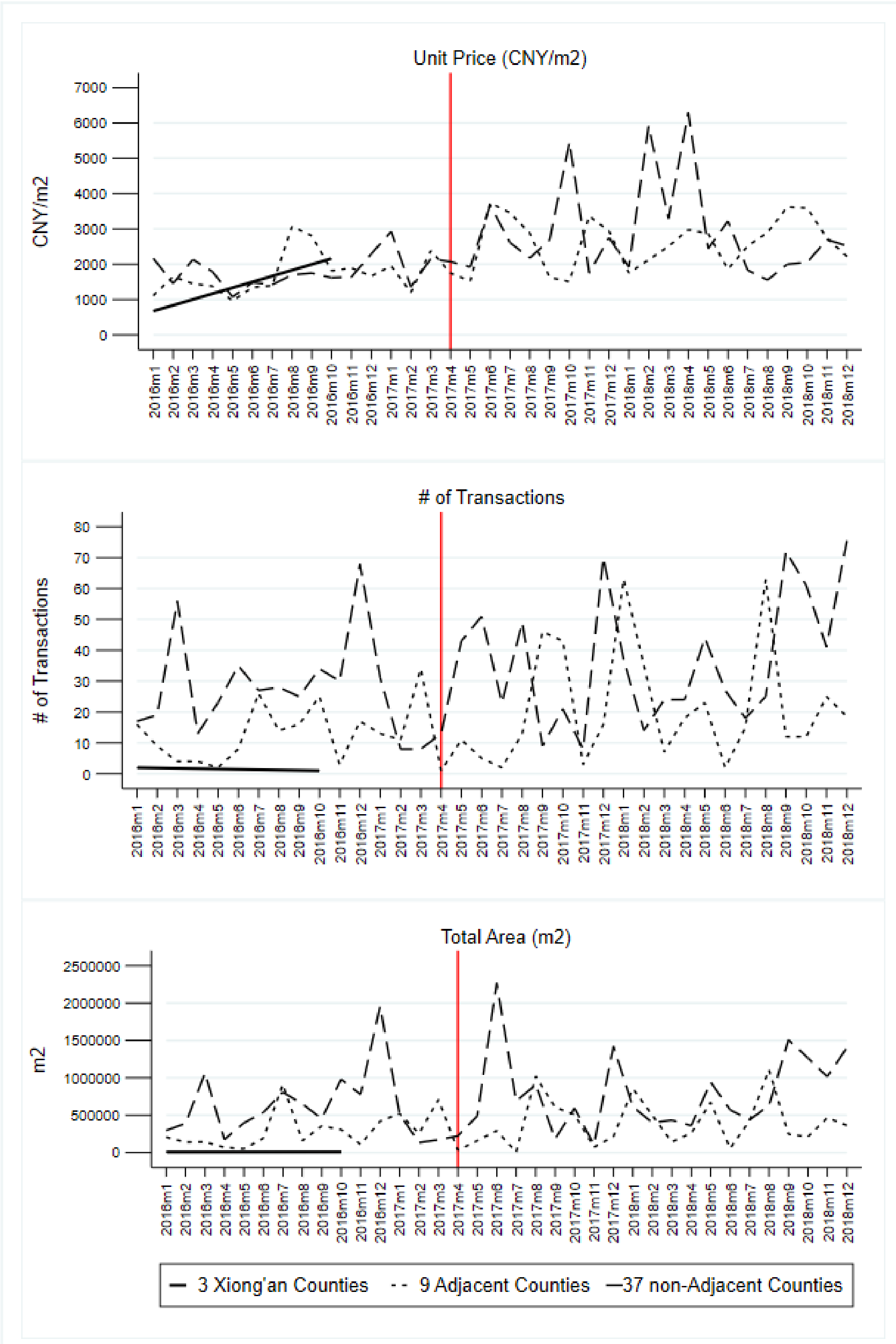
Notes: This table reports the regression results of Eq.(2), with consumers in both C3 and C9 being the treatment group and consumers in C37 being the control group. The treatment group in Columns (1)-(4) are consumers with a single delivery address, and the treatment group in Columns (5)-(8) consists of consumers with multiple delivery addresses. Panel A reports results using four traditional variables that reveal changes in consumption level: the logarithm of payment and item quantity at the order level, as well as the logarithm of payment and discount amount at the item level. Panel B reports results using two variables that reflect the perceived risk about a purchase and the tolerance level of unsatisfied products: the logarithm of hesitation at the order level and the return propensity at the item level. Panel C reports results using the shirking propensity at the order level. We indicate the order-level and item-level outcome variables by subscript o and i, respectively. Fixed effects of buyer, seller, and date are included in all columns. Standard errors are clustered at the date level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Elasticity of Consumer Behavior to Housing Price

Model	(1)	(2)	(3)	(4)	(5)	(6)
Sample	C3 vs. C37		C9 vs. C37		(3)-(1)	(4)-(2)
# of addresses	Single	Multiple	Single	Multiple	Single	Multiple
Effects	unrealizable wealth +collateral +common unobs.	unrealizable wealth +collateral +common unobs.	realizable wealth +collateral +common unobs.	realizable wealth +collateral +common unobs.	realizable wealth - unrealizable wealth	realizable wealth - unrealizable wealth
Payment_o	0.184	0.228	0.230	0.387	0.046	0.160
Payment_i	0.200	0.244	0.248	0.396	0.048	0.153
Hesitation_o	-0.224	-0.251	-0.293	-0.500	-0.069	-0.249
Return_i	-0.129	-0.162	-0.198	-0.329	-0.069	-0.166
Shirking_o	0.163	0.192	0.212	0.329	0.049	0.137

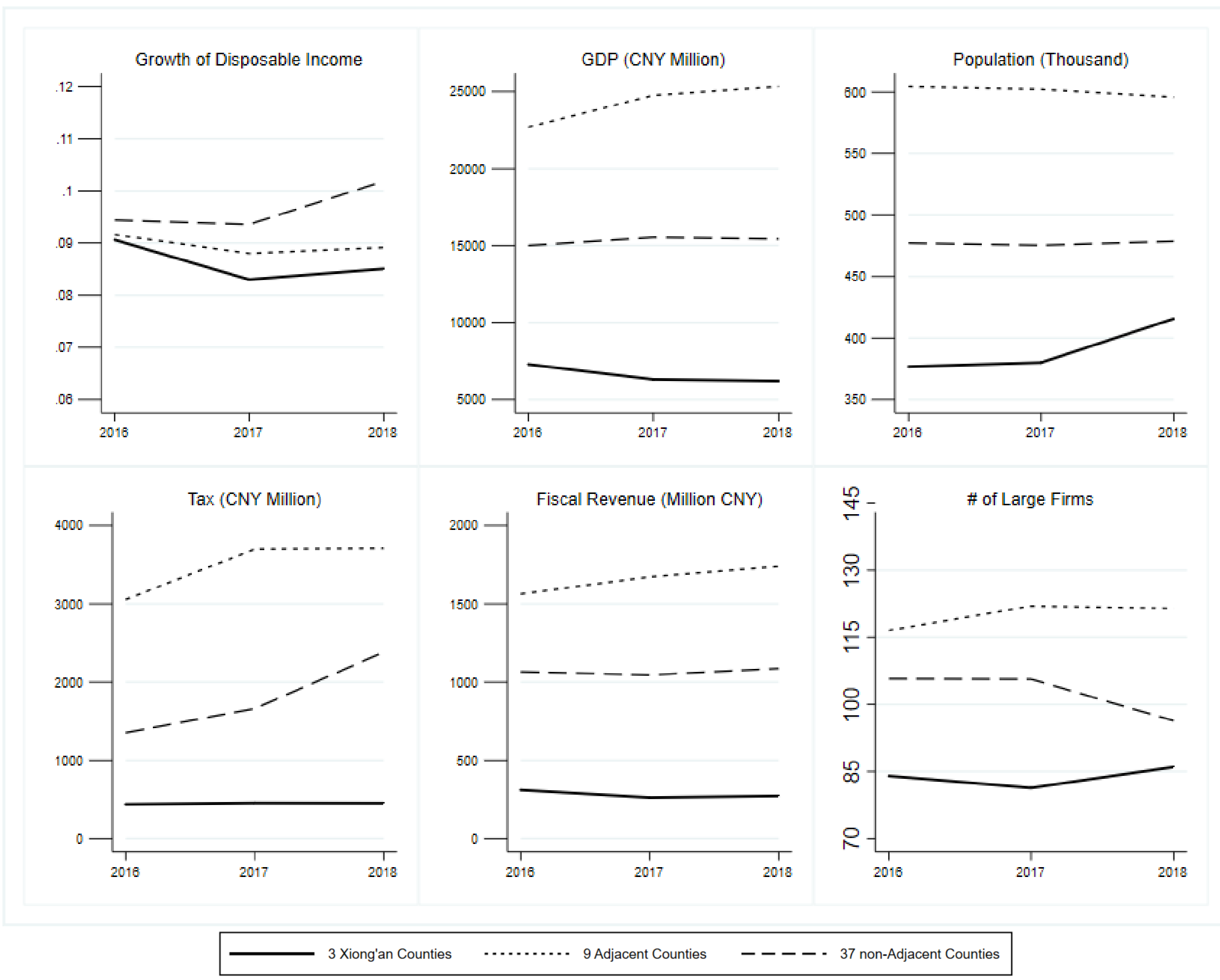
Notes: This table summarizes the elasticities of five measures of consumption behavior with respect to housing price. Columns (1) to (2) present the results of C3-vs.-C37 comparison; Columns (3) to (4) present the results of C9-vs.-C37 comparison; Column (5) presents the difference between Column (3) and Column (1); and Column (6) presents the difference between Column (4) and Column (2). Headers in the third row indicate the count of delivery addresses of the treatment buyers. Headers in the fourth row show the combined effects from the estimations.

Figure A1: Trends of Land Transactions in 49 counties



Notes: This figure presents the trends of land transactions in the three Xiong'an counties (solid line), nine adjacent counties (dotted line), and 37 non-adjacent counties (dashed line) from October 2016 to December 2018. The top graph, middle graph, and bottom graph respectively show the trends of unid price, total price, and total area in the land market. The red vertical line indicates the announcement month.

Figure A2: Trends of Economic Characteristics in 49 counties



Notes: This figure presents the trends of six economic characteristics, including the growth of disposable income, GDP, population, tax revenue, fiscal revenue, and the number of large firms, in C3, C9, C37 during the study period.

Table A1: Comparisons of Sample Counties

Sample Counties	C3		C9		C37	
	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
Disposable Income	18,924.55	447.47	21,589.89	2,064.71	20,929.30	7,178.29
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 in 2016.

Table A2: Effects in Different Counties

counties	C3		C9		C37	
# of addresses	single	multiple	single	multiple	single	multiple
common unobs.	✓	✓	✓	✓	×	×
collateral effect	✓	✓	✓	✓	×	×
realizable wealth effect	×	×	✓	✓	×	×
unrealizable wealth effect	✓	✓	×	×	×	×

Notes: This table illustrates four mechanisms through which housing wealth might influence consumption behavior. We use ✓and × symbols to indicate whether or not a group of consumers experiences certain effects.

Table A3: The Post-shock Response of Consumer Behavior: Border Discontinuity Regression

	Model 1: C3 vs. C9				Model 2: C9 vs. C37			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Consumption								
Dep. Variable	Payment_o	Quantity_o	Payment_i	Discount_i	Payment_o	Quantity_o	Payment_i	Discount_i
Treat*After	0.035**	-0.004	0.092**	0.030	0.034**	-0.006	0.019	0.003
	(0.014)	(0.027)	(0.045)	(0.043)	(0.015)	(0.012)	(0.021)	(0.019)
Treat*After*Multiple	0.015	0.011	-0.041	-0.028	0.051***	0.005	0.070***	-0.018
	(0.036)	(0.029)	(0.045)	(0.045)	(0.016)	(0.013)	(0.022)	(0.020)
Observations	285,321	285,321	675,030	675,030	1,163,941	1,163,941	2,339,859	2,339,859
R-squared	0.803	0.559	0.614	0.827	0.779	0.485	0.594	0.802
Panel B. Perceived Risk and the Tolerance Level								
Dep. Variable	Hesitation_o	Return_i			Hesitation_o	Return_i		
Treat*After	-0.090**	-0.024			-0.091***	-0.050***		
	(0.040)	(0.019)			(0.034)	(0.009)		
Treat*After*Multiple	0.032	-0.024			-0.026	-0.019**		
	(0.036)	(0.019)			(0.037)	(0.009)		
ln(Payment)	0.131***	-0.059***			0.122***	-0.093***		
	(0.005)	(0.001)			(0.003)	(0.001)		
Observations	285,321	675,030			1,163,941	2,339,859		
R-squared	0.524	0.413			0.439	0.419		
Panel C. Labor Supply								
Dep. Variable	Shirking_o				Shirking_o			
Treat*After	0.031				0.042***			
	(0.028)				(0.012)			
Treat*After*Multiple	-0.030				0.033***			
	(0.031)				(0.012)			
Observations	285,321				1,163,941			
R-squared	0.487				0.477			
Fixed Effects	Buyer FE, Seller FE, Date FE							

Notes: This table 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 using the full sample. In Model 1, we restrict the sample to transactions within a 3-km band on each side of the border between C3 and C9; and in Model 2, we restrict the sample to transactions within a 3-km band on each side of the border between C9 and C37. Panel A reports results using four traditional variables that reveal changes in consumption level: the logarithm of payment and item quantity at the order level, as well as the logarithm of payment and discount amount at the item level. Panel B reports results using two variables that reflect the perceived risk about the purchase and the tolerance level of unsatisfied products: the logarithm of hesitation at the order level and the return propensity at the item level. Panel C reports results using the shirking propensity at the order level. We indicate the order-level and item-level outcome variables by subscript o and i, respectively. Fixed effects of buyer, seller, and date are included in all columns. Standard errors are clustered at the date level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table A4: The Post-shock Response of Consumer Behavior: Subsample Analysis

	Model 1: C3 vs. C37				Model 2: C9 vs. C37			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Consumption								
Dep. Variable	Payment_o	Quantity_o	Payment_i	Discount_i	Payment_o	Quantity_o	Payment_i	Discount_i
Treat*After	0.088***	-0.006	0.097***	-0.037	0.051***	-0.014	0.063***	-0.002
	(0.021)	(0.014)	(0.026)	(0.028)	(0.009)	(0.014)	(0.013)	(0.011)
Treat*After*Multiple	0.028	-0.003	0.029	0.022	0.035***	0.014	0.026*	-0.012
	(0.022)	(0.015)	(0.028)	(0.029)	(0.009)	(0.014)	(0.014)	(0.012)
Observations	704,639	704,639	1,314,674	1,314,674	885,055	885,055	1,661,165	1,661,165
R-squared	0.76	0.435	0.522	0.774	0.758	0.436	0.518	0.774
Panel B. Perceived Risk and the Tolerance Level								
Dep. Variable	Hesitation_o	Return_i			Hesitation_o	Return_i		
Treat*After	-0.130***	-0.066***			-0.076***	-0.041***		
	(0.042)	(0.012)			(0.019)	(0.005)		
Treat*After*Multiple	0.001	-0.013			-0.037*	-0.030***		
	(0.043)	(0.012)			(0.020)	(0.005)		
ln(Payment)	0.128***	-0.099***			0.127***	-0.094***		
	(0.003)	(0.001)			(0.003)	(0.001)		
Observations	704,639	1,314,674			885,055	1,661,165		
R-squared	0.389	0.362			0.377	0.351		
Panel C. Labor Supply								
Dep. Variable	Shirking_o				Shirking_o			
Treat*After	0.082***				0.046***			
	(0.014)				(0.007)			
Treat*After*Multiple	0.015				0.027***			
	(0.016)				(0.007)			
Observations	704,639				885,055			
R-squared	0.432				0.423			
Fixed Effects	Buyer FE, Seller FE, Date FE							

Notes: This table 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 using the full sample. We restrict the consumers to those whose birth coun- ties (based on the first six digits of their national identity card numbers) and delivery counties are identical. In Model 1, we compare the behaviors of consumers in C3 to C37; and in Model 2, we compare the behaviors of consumers in C9 to C37. Panel A reports results using four traditional variables that reveal changes in consumption level: the logarithm of payment and item quantity at the order level, as well as the logarithm of payment and discount amount at the item level. Panel B reports results using two variables that reflect the perceived risk about the purchase and the tolerance level of unsatisfied products: the logarithm of hesitation at the order level and the return propensity at the item level. Panel C reports results using the shirking propensity at the order level. We indicate the order-level and item-level outcome variables by subscript o and i, respectively. Fixed effects of buyer, seller, and date are included in all columns. Standard errors are clustered at the date level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table A5: The Post-shock Response of Consumer Behavior: County-Year Fixed Effect

	Model 1: C3 vs. C37				Model 2: C9 vs. C37			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Consumption								
Dep. Variable	Payment_o	Quantity_o	Payment_i	Discount_i	Payment_o	Quantity_o	Payment_i	Discount_i
Treat*After	0.117***	-0.009	0.116***	-0.026	0.057***	-0.010	0.061***	-0.009
	(0.023)	(0.014)	(0.027)	(0.030)	(0.009)	(0.007)	(0.014)	(0.012)
Treat*After*Multiple	0.023	0.001	0.022	0.016	0.035***	0.011	0.033**	-0.008
	(0.023)	(0.015)	(0.028)	(0.030)	(0.010)	(0.008)	(0.014)	(0.012)
Observations	2,769,642	2,769,642	5,548,022	5,548,022	3,471,243	3,471,243	6,980,339	6,980,339
R-squared	0.778	0.484	0.597	0.801	0.777	0.484	0.594	0.801
Panel B. Perceived Risk and the Tolerance Level								
Dep. Variable	Hesitation_o	Return_i			Hesitation_o	Return_i		
Treat*After	-0.133***	-0.079***			-0.078***	-0.061***		
	(0.044)	(0.012)			(0.020)	(0.006)		
Treat*After*Multiple	-0.015	-0.016			-0.046**	-0.029***		
	(0.043)	(0.012)			(0.021)	(0.005)		
ln(Payment)	0.124***	-0.097***			0.124***	-0.093***		
	(0.002)	(0.001)			(0.002)	(0.001)		
Observations	2,769,642	5,548,022			3,471,243	6,980,339		
R-squared	0.446	0.429			0.438	0.418		
Panel C. Labor Supply								
Dep. Variable	Shirking_o				Shirking_o			
Treat*After	0.090***				0.054***			
	(0.015)				(0.008)			
Treat*After*Multiple	0.016				0.026***			
	(0.016)				(0.007)			
Observations	2,769,642				3,471,243			
R-squared	0.484				0.475			
Fixed Effects	Buyer FE, Seller FE, Date FE, County-Year FE							

Notes: This table 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 using the full sample. In Model 1, we compare the behaviors of consumers in C3 to C37; and in Model 2, we compare the behaviors of consumers in C9 to C37. Panel A reports results using four traditional variables that reveal changes in consumption level: the logarithm of payment and item quantity at the order level, as well as the logarithm of payment and discount amount at the item level. Panel B reports results using two variables that reflect the perceived risk about the purchase and the tolerance level of unsatisfied products: the logarithm of hesitation at the order level and the return propensity at the item level. Panel C reports results using the shirking propensity at the order level. We indicate the order-level and item-level outcome variables by subscript o and i, respectively. Fixed effects of buyer, seller, date, and county-year are included in all columns. Standard errors are clustered at the date level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table A6: The Post-shock Response of Consumer Behavior: Seller-Month Fixed Effect

	Model 1: C3 vs. C37				Model 2: C9 vs. C37			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Consumption								
Dep. Variable	Payment_o	Quantity_o	Payment_i	Discount_i	Payment_o	Quantity_o	Payment_i	Discount_i
Treat*After	0.111***	-0.012	0.122***	-0.030	0.054***	-0.010	0.057***	0.003
	(0.022)	(0.014)	(0.026)	(0.028)	(0.009)	(0.007)	(0.013)	(0.011)
Treat*After*Multiple	0.008	0.004	0.005	0.018	0.032***	0.009	0.030**	-0.018
	(0.023)	(0.015)	(0.028)	(0.029)	(0.009)	(0.007)	(0.014)	(0.011)
Observations	2,766,178	2,766,178	5,545,727	5,545,727	3,468,021	3,468,021	6,978,180	6,978,180
R-squared	0.799	0.505	0.611	0.819	0.797	0.504	0.607	0.818
Panel B. Perceived Risk and the Tolerance Level								
Dep. Variable	Hesitation_o	Return_i			Hesitation_o	Return_i		
Treat*After	-0.115***	-0.060***			-0.067***	-0.045***		
	(0.043)	(0.012)			(0.019)	(0.005)		
Treat*After*Multiple	-0.013	-0.020			-0.045**	-0.028***		
	(0.043)	(0.012)			(0.020)	(0.005)		
ln(Payment)	0.125***	-0.100***			0.125***	-0.096***		
	(0.002)	(0.001)			(0.002)	(0.001)		
Observations	2,766,178	5,545,727			3,468,021	6,978,180		
R-squared	0.454	0.438			0.445	0.427		
Panel C. Labor Supply								
Dep. Variable	Shirking_o				Shirking_o			
Treat*After	0.081***				0.045***			
	(0.015)				(0.007)			
Treat*After*Multiple	0.017				0.027***			
	(0.016)				(0.008)			
Observations	2,766,178				3,468,021			
R-squared	0.492				0.482			
Fixed Effects	Buyer FE, Seller-Month FE, Date FE							

Notes: This table 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 using the full sample. In Model 1, we compare the behaviors of consumers in C3 to C37; and in Model 2, we compare the behaviors of consumers in C9 to C37. Panel A reports results using four traditional variables that reveal changes in consumption level: the logarithm of payment and item quantity at the order level, as well as the logarithm of payment and discount amount at the item level. Panel B reports results using two variables that reflect the perceived risk about the purchase and the tolerance level of unsatisfied products: the logarithm of hesitation at the order level and the return propensity at the item level. Panel C reports results using the shirking propensity at the order level. We indicate the order-level and item-level outcome variables by subscript o and i, respectively. Fixed effects of buyer, seller-month, and date are included in all columns. Standard errors are clustered at the date level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table A7: Consumption at Buyer-YearMonth Level

Dep. Variable	Model 1: C3 vs. C37			Model 2: C9 vs. C37		
	Payment	# of Orders	# of Items	Payment	# of Orders	# of Items
	(1)	(2)	(3)	(4)	(5)	(6)
Treat*After	0.098***	-0.001	-0.005	0.059***	0.001	0.000
	(0.012)	(0.003)	(0.005)	(0.006)	(0.001)	(0.003)
Observations	2,135,546	2,135,546	2,135,546	2,677,761	2,677,761	2,677,761
R-squared	0.532	0.375	0.412	0.532	0.372	0.413
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 at the Buyer-YearMonth level. Fixed effects of buyer and year-month are included in all columns. Standard errors are clustered at the buyer level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.