# Priced Out: Housing Costs, Gendered Migration, and the Geography of Crime in China*

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**Abstract**

Housing-price shocks can reallocate crime across space by changing who moves. Using millions of Chinese court judgments from 2014–2018, we construct city-level measures of criminal participation and show that rising housing costs reshape the geography of crime, with the largest responses in male-perpetrated and male-intensive offenses. We argue that marriage-market norms place disproportionate home-purchase burdens on men; as a result, higher housing costs induce male-skewed out-migration from expensive cities, altering local sex ratios and the supply of potential offenders. Instrumenting housing prices with land prices and differential exposure to regional housing cycles, we find that a 1% increase in housing prices reduces crime in origin cities by about 1.3%, with partially offsetting increases in destination cities. A spatial-equilibrium model calibrated to Chinese migration and crime data identifies two elasticities governing aggregate effects: how criminal payoffs vary with offender concentration and with the scale of the legal economy. The calibration implies weak effects of offender dispersion but strong effects of local economic scale, suggesting that male-selective outflows primarily relocate crime across cities while modestly reducing aggregate criminal participation as high-cost origins contract.

**Keywords:** housing prices; crime; internal migration; gender differences
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# 1 Introduction

Housing prices have risen sharply in China over the past two decades and remain highly uneven across cities (Sun and Zhang, 2020). A growing literature shows that housing-price shocks spill far beyond real estate markets: they reshape local economic activity, reallocate labor and capital, and generate heterogeneous welfare effects across residents.[1] Yet we know much less about how housing-cost shocks affect social outcomes such as crime, even though housing prices are a first-order determinant of who can afford to live where and, therefore, of the local composition of potential offenders.

This paper studies how housing-price shocks reshape the *geography* of crime through gendered mobility. The mechanism is grounded in a salient institutional feature of the Chinese marriage market: norms frequently place the burden of securing a home on men prior to marriage, and housing characteristics affect men's perceived marriage-market prospects (Wei and Zhang, 2011; Du and Wei, 2013; Wrenn et al., 2019). As a consequence, rising housing costs tighten a constraint that is disproportionately borne by men and can induce male-skewed out-migration from expensive cities toward lower-cost destinations. Because offending is overwhelmingly male (Campaniello and Gavrilova, 2018; Khanna et al., 2021), such gendered sorting can affect crime both mechanically, by changing the local supply of potential offenders, and behaviorally by shifting local sex ratios and consequently altering male incentives (Cameron et al., 2019; Edlund et al., 2013).[2] Whether housing-cost shocks ultimately reduce crime or mainly reallocate it across cities is therefore an equilibrium question that depends on how criminal opportunities scale with local conditions.

We bring new data to this question by using millions of criminal court judgments from China Judgments Online (CJO) for 2014–2018. We construct city-year measures of criminal participation and document three core facts. First, increases in housing prices predict a statistically and economically meaningful decline in crime in the cities experiencing the price increase. Second, the response is sharply gendered: the decline is concentrated in male-perpetrated and male-intensive offenses. Third, the crime response is strongest in settings where the marriage-market housing burden is plausibly higher for men, consistent

[1] Evidence from the United States (Chinco and Mayer, 2016; DeFusco et al., 2018; Gao et al., 2020; Baum-Snow and Duranton, 2025), the United Kingdom (Badarinza and Ramadorai, 2018), France (Cvijanović and Spaenjers, 2021), and Singapore (Agarwal et al., 2020) documents that demand-driven housing booms affect not only prices but also industry structure, employment, and welfare (e.g., Gorback and Keys, 2020; Gao et al., 2020; Favilukis and Van Nieuwerburgh, 2021; DeFusco et al., 2022; Diamond and Gaubert, 2022). The broader costs can be substantial: housing booms distort investment and balance sheets (Bayer et al., 2021; Campello et al., 2022), misallocate capital (Basco et al., 2025; Bednarek et al., 2021), and strain affordability and financial stability (Glaeser, 2013; Martín et al., 2021; DeFusco et al., 2022; Mian and Sufi, 2022).

[2] Campaniello and Gavrilova (2018) document a large gender gap in crime and relate it to incentive differences, including expected illegal earnings and arrest risk, and show that men respond more strongly to changes in illicit returns.

with a mobility-driven mechanism rather than a generic income or policing channel.

Our empirical strategy exploits plausibly exogenous variation in city housing prices. We instrument for housing prices using land prices (Saiz, 2010) and differential exposure to regional housing cycles—an instrument that leverages systematic cross-city differences in sensitivity to aggregate housing demand conditions (Guren et al., 2021). In our preferred specification, a 1% increase in housing prices lowers the local crime rate by about 1.3%. The reduced-form effect does not imply that higher housing costs are socially beneficial. Instead, it reflects compositional change induced by gendered mobility. Consistent with this interpretation, housing-price increases predict male-selective out-migration, and the crime decline is disproportionately concentrated in categories with higher male participation.

A central implication of this mechanism is that the local crime effect may not be a city-level "treatment" effect in isolation: when male offenders leave expensive origin cities, crime pressure may rise in destination cities. We therefore study spatial spillovers directly. We show that crime declines in cities experiencing housing-cost increases but rises in cities that are more exposed to housing-cost increases elsewhere, consistent with cross-city displacement through migration. Accounting for these spillovers implies that housing-price shocks primarily *reallocate* crime across space, while leaving open the question of how much aggregate criminal participation changes in equilibrium.

We conduct a series of tests to distinguish the mobility-and-composition channel from competing explanations. The estimates are robust to alternative measures and timing of housing prices and crime, sample restrictions, and controls for other shocks, including export shocks. The relationship disappears in placebo exercises that randomly reshuffle housing prices across cities. Moreover, we find little support for alternative mechanisms centered on contemporaneous labor-market conditions, fiscal capacity, community cohesion, mental health, or skill-selective sorting. The heterogeneity of the effects further supports the mechanism: the estimates are stronger in cities with larger youth shares, higher baseline male shares, more secondary-industry-oriented employment, and stronger transport capacity that lowers moving costs and facilitates relocation.

To quantify the aggregate consequences of housing-cost-induced, male-selective mobility, we embed the mechanism in a tractable spatial equilibrium model in which men and women choose where to live and whether to work in the legal or illegal sector. The model highlights two elasticities that govern whether crime is mostly displaced or also changes in aggregate. The first is an *offender-density elasticity*: how the payoff to offending responds to the local concentration of offenders. When returns are increasing in offender density, dispersal disrupts networks and coordination, lowering marginal payoffs and participation. When returns are decreasing, dispersal reduces congestion among offenders, raising marginal payoffs for those

who remain and making crime more likely to be displaced than eliminated. The second is a *legal-scale elasticity*: how criminal opportunities co-move with the scale of legitimate economic activity. With increasing returns to legal scale, out-migration reduces formal activity and criminal opportunities, amplifying the decline; with decreasing returns, formal activity provides deterrence and informal control, so out-migration relaxes constraints and partially offsets the decline.

We calibrate the model to Chinese migration and crime moments and then feed in the 2015–2018 housing-price shocks. The model implies that these shocks reduce the equilibrium number of criminal participants by 145 cases, corresponding to roughly 5 billion USD per year in incarceration-cost savings. The adjustment is highly uneven across space: high-cost origin cities with net labor outflows experience declines in criminal participation, while lower-cost destination cities with net inflows experience increases. The estimated crime technology rationalizes this pattern: returns respond weakly to offender density but strongly to the scale of the legal economy. Thus, migration primarily reallocates crime across cities and only modestly reduces aggregate participation through the contraction of high-cost origins. These results imply that agglomeration is not crime-neutral.

**Related Literature** Our work speaks to four strands of literature. First, it contributes to research on the link between housing and crime. A large body of evidence shows that neighborhood upgrading, improvements in the built environment, and higher homeownership are associated with lower crime (Freedman and Owens, 2011; Diamond and McQuade, 2019; MacDonald, 2015; Gill et al., 2022; González-Pampillón, 2022; Disney et al., 2020). Two broad mechanisms are emphasized. One is a composition channel, in which rising housing costs induce the out-migration of lower-income and more crime-prone residents, thereby changing the local population mix (Guerrieri et al., 2013; Diamond, 2016; Diamond et al., 2019). The other is a behavior channel, in which crime falls among those who remain as incentives, social interactions, and informal enforcement respond to neighborhood change (Cameron et al., 2019; Edlund et al., 2013). Despite this progress, the relative importance of these channels remains unsettled, especially in settings where housing costs are tightly linked to household formation. We document a robust negative relationship between housing prices and crime in China and trace it to male-selective out-migration, which reduces the local supply of potential offenders and reallocates crime pressure across cities.

Second, we contribute to work on the broader social consequences of housing booms and speculative housing markets. Prior research links housing booms to affordability pressures, capital misallocation, and macroeconomic volatility (e.g., Gao et al., 2020; Favilukis and Van Nieuwerburgh, 2021; Bayer et al., 2021; DeFusco et al., 2022), and to outcomes

such as education, fertility, and health (e.g., Lovenheim, 2011; Dettling and Kearney, 2014; Daysal et al., 2021; Hu et al., 2024b). We add crime to this set of externalities. In our setting, housing-price increases reduce crime in booming cities by inducing male-selective out-migration, but they also shift crime pressure toward lower-cost destinations. This evidence highlights an overlooked social margin through which housing-market cycles shape local outcomes: by changing who lives where, housing booms can alter both the level and the geography of criminal activity.

Third, we contribute to research linking housing costs to marriage-market incentives and, through gendered sorting, to local crime. In China, marriage-market norms make housing a distinctly gendered constraint. Families with sons raise savings in a competitive effort to improve their sons' relative attractiveness in the marriage market (Wei and Zhang, 2011), and norms that often require homeownership prior to marriage imply that rising housing prices can delay or deter entry into first marriage (Du and Wei, 2013; Wrenn et al., 2019). Complementing these studies, we show that higher housing prices disproportionately induce men to leave their origin cities, consistent with marriage-market–driven mobility. This mobility margin matters for crime because offending is overwhelmingly male, and men tend to respond more strongly to incentives, consistent with greater risk-taking and aggression (Wilson and Daly, 1985; Wilson and Herrnstein, 1998; Zuckerman and Kuhlman, 2000; Campaniello and Gavrilova, 2018). Relatedly, Cameron et al. (2019) find that higher sex ratios are associated with greater risk-taking, impatience, and neuroticism among men. Exploiting housing-price shocks as plausibly exogenous variation in marriage-market pressure, we identify a male-biased crime response: the estimated crime reductions are larger in offense categories with higher male participation and stronger in provinces where men bear a larger share of the marital housing burden. By emphasizing male-selective migration, we also connect to work linking gender heterogeneity in labor markets and marriage markets (Autor et al., 2019).[3]

Finally, we contribute to the growing literature on spatial equilibrium models by adapting these frameworks to study the geography of criminal activity (Ahlfeldt et al., 2015; Diamond and Gaubert, 2022; Donaldson and Hornbeck, 2016; Donaldson, 2018; Hu et al., 2024a). While much of the recent literature emphasizes crime's negative externalities on the legal economy and neighborhood amenities (Rozo, 2018; Khanna et al., 2022; Melnikov et al., 2025), we instead treat crime as an economic sector with endogenous payoffs: incentives and returns move with conditions in both legal and illegal activities. Our analysis is closest to Khanna et al. (2022) but adds two gender-specific margins: housing enters utility with

[3] Autor et al. (2019) show that gender differences in industry and household specialization help explain how labor-demand shocks affect young men's marriage-market value. In a similar spirit, we show that gender differences in marital housing burdens and in criminal participation help explain how housing-price shocks translate into changes in local crime rates.

gender-specific expenditure shares, and the expected return to crime differs by gender. These features link migration and crime in a disciplined way. Cities experiencing housing-cost increases generate male-selective net out-migration and sharper declines in male-perpetrated crime, while lower-cost destinations see the mirror-image pattern. The model then lets us quantify both the spatial redistribution of crime and the aggregate change in criminal participation.

The remainder of the paper is organized as follows. Section 2 develops a simple analytical framework that links housing costs, gendered migration, and crime. Section 3 describes the data and empirical strategy and presents the causal estimates and mechanism tests, including spatial spillovers. Section 4 introduces the spatial equilibrium model, and Section 5 presents the calibration and counterfactual exercises. Section 6 concludes.

# 2 A Simple Framework of Crime and Spatial Sorting

We begin with a simple analytical framework to study how crime is distributed across space when migration is shaped by gender. The key mechanism is that gender-biased migration reallocates crime across locations: when differences in housing burdens push men and women to move differently, the resulting imbalance alters local crime rates. We then turn to the data, presenting empirical evidence that matches the model's predictions and underscores the importance of gender-based sorting in shaping the geography of crime.

## 2.1 Model Setting

We consider an economy with $N$ cities, indexed by $d$. Moving to city $d$ entails a migration cost $\tau_d$. For tractability, we impose a symmetry assumption: migration costs depend only on the destination, not on the origin.[4] The population is divided into two gender groups: males ($\theta = M$) and females ($\theta = F$). Each city hosts two sectors: a legitimate sector ($s = \ell$) and a crime sector ($s = c$). We allow for gender heterogeneity along two key dimensions. First, males devote a larger share of income to housing expenditure than females, reflecting cultural norms in China surrounding household formation and home purchase (Wei and Zhang, 2011; Du and Wei, 2013; Wrenn et al., 2019). Second, in the crime sector, males earn higher returns than females, consistent with evidence that men tend to be more risk-taking and aggressive in criminal activity (Wilson and Daly, 1985; Wilson and Herrnstein, 1998; Zuckerman and Kuhlman, 2000; Campaniello and Gavrilova, 2018; Khanna et al., 2021).

[4]This assumption abstracts from birthplace heterogeneity and highlights that migration frictions are destination-specific. In later extensions, we relax this restriction and allow for full bilateral heterogeneity between origin and destination.

**Preferences** Each worker $\omega$ of gender $\theta$ chooses a city $d$ in which to live and work. The total labor endowment of each gender, $\bar{L}^\theta$, is given exogenously. The indirect utility of a worker $\omega$ of gender $\theta$ residing in city $d$ is

$$v_d^\theta(\omega) = \frac{y_d^\theta B_d}{Q_d^{\alpha^\theta} \tau_d} \epsilon_d^\theta(\omega),$$

where $y_d^\theta$ denotes the expected wage income in city $d$, reflecting the fact that individuals also choose between the legitimate and crime sectors, a decision detailed in the next subsection. The parameter $B_d$ denotes city-specific amenities, $Q_d$ is the local housing price, $\alpha^\theta$ is the gender-specific housing expenditure share, $\tau_d$ is the migration costs of moving to $d$, and $\epsilon_d^\theta(\omega)$ is an idiosyncratic taste shock. As $\alpha^M > \alpha^F$, males bear a greater housing burden than females in the Chinese context, making their location choices more sensitive to differences in housing costs across cities. To capture idiosyncratic heterogeneity in location preferences, following Ahlfeldt et al. (2015), we assume that the taste shock $\epsilon_d^\theta(\omega)$ is drawn i.i.d. from a Fréchet distribution with shape parameter $\kappa$. Under this assumption, the resulting migration probabilities take the familiar logit form:

$$\lambda_d^\theta = \left( \frac{y_d^\theta B_d}{Q_d^{\alpha^\theta} \tau_d} \right)^\kappa \Big/ \sum_{d'} \left( \frac{y_{d'}^\theta B_{d'}}{Q_{d'}^{\alpha^\theta} \tau_{d'}} \right)^\kappa. \tag{1}$$

This expression shows that the probability a worker of gender $\theta$ chooses city $d$ increases with the wage and amenities available there, and decreases with both local housing costs and migration frictions. The parameter $\kappa$ governs the sensitivity of migration choices to these relative payoffs: a higher $\kappa$ implies that small differences across cities translate into stronger sorting responses.

**Production** We consider three sectors: a legitimate sector, a crime sector, and a housing sector. In the legitimate sector ($\ell$), a homogeneous final good is produced under perfect competition and constant returns to scale. We assume wages are gender-neutral, abstracting from wage discrimination.[5] In the crime sector ($c$), the expected return to offending in city $d$ is

$$w_{d,c}^\theta = (1 - p_d)\, A_{d,c} m^\theta, \tag{2}$$

where $p_d$ is the probability of detection, $A_{d,c}$ is city-specific criminal productivity, and $m^\theta$ is a gender-specific shifter. We assume $m^M > m^F$, capturing higher expected payoffs for men

[5]Evidence from standardized-pay settings suggests that residual male–female earnings differences largely reflect hours and leave rather than wage rates (Bolotnyy and Emanuel, 2022). Broader evidence finds a declining, though still present, average gap (Blau and Kahn, 2017).

due to greater risk tolerance and physical advantage in many offenses.[6] Finally, housing is produced under perfect competition with constant returns to scale, using a Cobb–Douglas technology in land and capital.[7] To keep the focus on how housing costs shape migration and crime incentives, we take the local housing price as exogenous.[8]

**Sector Choice, Crime, and Spatial Sorting** Within each city, workers choose between the legitimate sector ($\ell$) and the crime sector ($c$). Following the Roy framework (Roy, 1951), productivity in sector $s$ is denoted by $z_{d,s}^{\theta}$, drawn from a Fréchet distribution with shape parameter $\epsilon > 1$ and scale parameter $E_{d,s}$. Given wages per efficiency unit $(w_{d,\ell}^{\theta}, w_{d,c}^{\theta})$, each worker selects the sector offering the higher income. The implied share of workers of gender $\theta$ in sector $s \in \{\ell, c\}$ is

$$\delta_{d,s}^{\theta} = \frac{E_{d,s}(w_{d,s}^{\theta})^{\epsilon}}{E_{d,\ell}(w_{d,\ell}^{\theta})^{\epsilon} + E_{d,c}(w_{d,c}^{\theta})^{\epsilon}}, \tag{3}$$

so that labor market clearing requires $L_{d,s}^{\theta} = L_{d}^{\theta}\delta_{d,s}^{\theta}$. Expected wage income in city $d$ is then

$$y_{d}^{\theta} = \xi_{i}\left[E_{d,\ell}(w_{d,\ell}^{\theta})^{\epsilon} + E_{d,c}(w_{d,c}^{\theta})^{\epsilon}\right]^{1/\epsilon},$$

where $\xi = \Gamma(1 - 1/\epsilon)$ is a constant. When combined with differences in housing expenditure shares, these assumptions generate a clear spatial sorting pattern. In particular, since males devote a larger share of income to housing, they are more sensitive to differences in local housing costs. This yields the following result:

**Proposition 1** (Spatial Sorting by Gender)**.** *Cities with lower housing prices attract a relatively larger share of males. Formally,*

$$\frac{\partial \ln(L_{d,s}^{M}/L_{d,s}^{F})}{\partial \ln Q_{d}} \propto \kappa(\alpha^{F} - \alpha^{M}) < 0,$$

[6] This assumption matches a basic fact in the data: Panel (b) of Figure 2 shows that, over 2014–2018, roughly 90 percent of cases involve at least one male defendant, and this share rises over time. Related evidence attributes such gender gaps in offending to differences in incentives and returns in illicit activities (Campaniello and Gavrilova, 2018).

[7] Combes et al. (2021) propose a nonparametric approach to estimating housing production functions and provide a theoretical rationale for modeling housing supply as constant-returns-to-scale and Cobb–Douglas in land and capital.

[8] This assumption is a tractable shortcut rather than a substantive restriction. In a richer model, housing prices would be endogenous, pinned down by local housing supply (land and construction) and demand. The key source of variation we study is plausibly supply-driven—arising from predetermined land endowments and regulatory or planning constraints that shift the marginal cost of housing—so treating prices as exogenous captures the reduced-form effect of these supply-side forces on households' location choices and crime participation.

where $\kappa > 0$ is the migration elasticity and $\alpha^M > \alpha^F$ denotes the larger housing expenditure share for males. Because housing absorbs a larger share of men's income, they respond more to differences in $Q_d$: as $Q_d$ rises, the male-to-female ratio falls within each sector. This sorting effect is stronger when migration is more elastic (higher $\kappa$).

Because wages are assumed to be gender-neutral in the legitimate sector, while the crime sector offers higher expected returns to men, gender differences in criminal productivity naturally generate disproportionate male participation in crime. This relationship is summarized in the following result:

**Proposition 2** (Sectoral Sorting by Gender)**.** *The male-to-female ratio is higher in the crime sector than in the legitimate sector. Formally,*

$$\ln \frac{L^M_{d,c}/L^M_{d,\ell}}{L^F_{d,c}/L^F_{d,\ell}} = \epsilon(\ln m^M - \ln m^F) > 0,$$

where $\epsilon > 0$ is the elasticity of sectoral choice with respect to relative wages and $m^\theta$ is the gender-specific productivity shifter in crime (with $m^M > m^F$). Since $m^M > m^F$ implies higher expected crime returns for men, men are more likely to select into the crime sector, so the male intensity of crime exceeds that of legitimate work; the gap is larger when sectoral choice is more responsive (higher $\epsilon$).

## 2.2 The Effect of Housing Regulations on Crime

To illustrate the core mechanisms of the model, we focus on a housing shock that induces gender-biased migration flows. As shown in Proposition 1, differences in housing expenditure shares between males and females imply that a unilateral increase in housing prices generates systematically gendered migration responses. At the same time, as Proposition 2 establishes, men and women differ in their relative propensity to engage in crime. These two forces imply that housing shocks not only affect the overall level of crime but also reshape its spatial distribution across cities.

**Proposition 3** (Housing Shocks and Crime Rates)**.** *Crime rates, measured as the ratio of criminal to legitimate employment ($CrimeRatio_d$), rise in response to a negative housing price shock. Formally,*

$$\frac{\partial CrimeRate_d}{\partial \ln Q_d} \propto \kappa(\alpha^F - \alpha^M)\left[\left(\frac{m^M}{m^F}\right)^\epsilon - 1\right] < 0.$$

Since $\alpha^M > \alpha^F$ and $m^M > m^F$, lower housing prices draw relatively more males into cities, raising the share of workers engaged in crime relative to legitimate employment. The strength

of this effect depends on the degree of gender heterogeneity in both housing expenditure and returns to crime. These mechanisms imply that housing policies, by altering local price levels, can have unintended consequences for crime rates and ultimately for social stability. This forms the basis for our empirical analysis, with detailed proofs provided in Appendix A.1.

This simple framework, however, should be viewed only as a first step, offering an intuitive benchmark rather than a complete description. While it highlights how housing price changes generate gender-biased migration flows and alter local crime rates, it does not capture how crime is redistributed more broadly across space. Because migration links cities together, a policy intervention in one location may have unintended consequences for the social stability of other regions through these networks. In what follows, we provide empirical evidence on these spillovers and examine how local housing shocks propagate across space to affect crime in other areas. Moreover, the framework also abstracts from the technology of criminal activity. We have assumed constant returns to scale, yet the degree of scale is critical: it determines whether migration leads to a net creation or destruction of crime overall.[9] Fully addressing these issues requires a richer structural model and a careful calibration of the crime production function. This motivates not only the empirical analysis but also the quantitative exercises that follow, which aim to provide a more complete understanding of the links between housing policy, migration, and social stability.

# 3 Empirical Evidence

We now turn to the data to test the channel linking gender-biased migration and crime. Our empirical strategy exploits variation across a large set of Chinese cities, focusing on how external housing regulation shocks shift gender-specific migration patterns and, through this mechanism, reshape the spatial distribution of crime. We first describe the key datasets on housing prices and crime that provide the foundation for causal identification, and then present the regression framework together with the instrumental-variable (IV) strategy used to estimate the causal effect of housing prices on crime.

## 3.1 Background, Data Sources and Measures

The analysis draws on two primary sources of city-level data: housing prices and crime. Cities serve as the geographic unit of observation throughout the study.[10]

[9] For instance, if crime exhibits increasing returns to scale, then a rise in housing prices in one city may reduce crime locally by inducing male out-migration, while the inflow of males elsewhere could generate an even larger increase in crime in receiving cities.

[10] China's administrative system has four tiers. At the top are provincial units, which include provinces (e.g., Zhejiang), autonomous regions (e.g., Tibet), and municipalities directly governed by the central government (e.g., Beijing, Shanghai, Chongqing, Tianjin). Below the provincial level are prefectures, which

### 3.1.1 Housing Market and Housing Price Data

**Housing Market and Housing Price Change in China** Over the past several decades, China's housing market has undergone a profound transformation from a welfare-based allocation system to one of the world's largest marketized asset sectors. Before 1978, Chinese housing was state-owned and collectively assigned to employees of state-owned enterprises as part of their compensation (Fang et al., 2016). Market reforms gradually unfolded since then, culminating in 1994 when workers gained the right to purchase their housing units (Wang, 2011; Fang et al., 2016). In 1998, the allocation system was fully abolished and a market-based housing sector was established (Fang et al., 2016; Wrenn et al., 2019). State-owned housing units were privatized, urban residents obtained property rights, and local governments gained authority to lease land for development. Since the late 1990s, housing reform has not only provided urban households with private property rights but also redefined housing as both a consumption good and a financial asset. This dual character has generated rapid urban growth and wealth accumulation, which triggered rapid growth in demand (Wrenn et al., 2019).

Our primary measure of housing prices comes from the China Real Estate Information website, compiled by the State Information Center.[11] The dataset reports city-level information on commodity residential housing, including both transaction prices and sales volumes. For the purpose of our analysis, we use the average unit transaction price (measured in RMB per square meter) as the housing price variable. All values are converted to real terms by deflating nominal prices with the Consumer Price Index (CPI), using 2000 as the base year.[12] Figure 1 illustrates the national average price of commodity residential housing from 2000 to 2021, together with the annual growth rate. Housing prices in China have risen dramatically over this period, growing at an average rate of 11.2 percent per year. This trend reflects both institutional reforms and policy shifts. The 2008 global financial crisis marked a sharp inflection point. In response, the Chinese government adopted expansionary monetary and fiscal policies that stimulated home purchases (Sun and Zhang, 2020). Prices surged by 25.6 percent between 2008 and 2009. Credit supply surged, land revenue became a dominant source of local fiscal income, and real estate investment became a major driver

are subdivided into counties, autonomous counties, and county-level cities. The fourth tier consists of townships and towns. Missing values in the figure correspond to counties or county-level cities that report directly to provinces. Because our analysis focuses on the four municipalities and on prefecture-level cities, these county-level units are excluded from the sample. Further details are available at http://xzqh.mca.gov.cn/statistics/2018.html.

[11] CREI provides systematic information on China's real estate market and the dataset has been widely used in both policy reports and academic studies as an authoritative source on housing market dynamics. Further details are available at http://www.crei.cn/.

[12] CPI data are from the National Bureau of Statistics of China.

of GDP growth.

**Housing Regulation in China** After the global financial crisis, the rapid appreciation of housing prices has raised increasing concerns about possible financial instability and excessive household leverage, particularly among younger cohorts. This gradually turned the Chinese government's attitude over the housing market to macroprudential tightening (Chen and Wen, 2017). On 4 December 2016, the Chinese leader launched the famous principle that 'houses are for living, not for speculation' at the Central Economic Work Conference. On the demand side, housing regulation has primarily targeted credit availability, eligibility criteria, and speculative demand. The central bank and financial regulators have adjusted loan-to-value (LTV) ratios, minimum down-payment requirements, and mortgage rates in response to market conditions. On the supply side, China's housing market is uniquely shaped by its land system and the fiscal structure of local governments. Urban land remains legally state-owned and can be transferred to real estate usage through leasehold auctions. Local governments thus rely heavily on land sales revenue, which creates a fiscal incentive to promote development but also to restrict land release strategically to maintain prices.

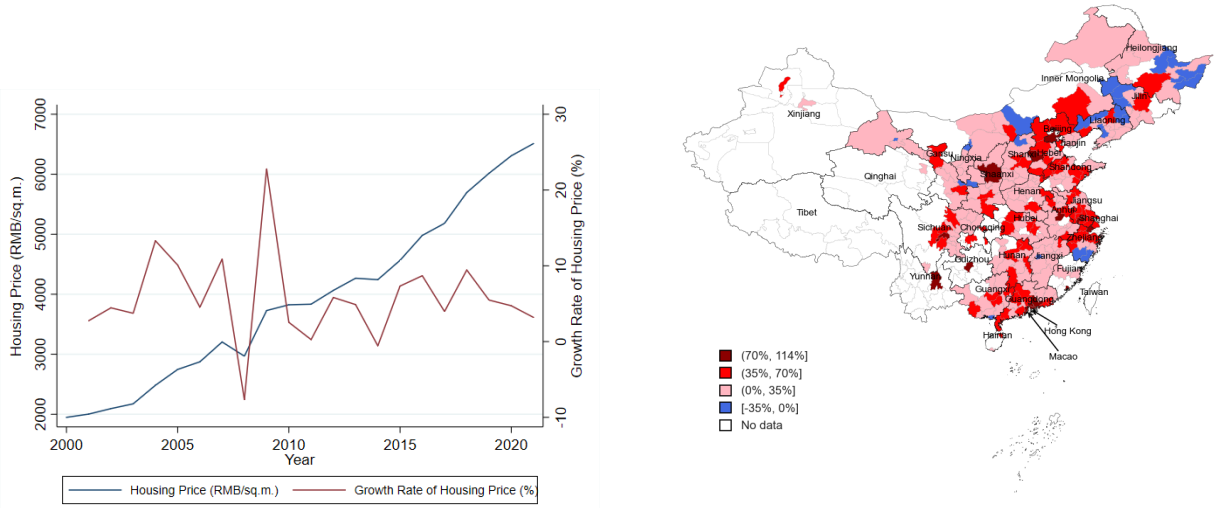
Despite government intervention aimed at cooling the housing market, Chinese housing prices still appreciated at an average annual rate of 6.4 per cent between 2010 and 2021. The sustained demand from rural-urban migrants, the attractive returns on real estate investment, and the tightening supply of land all contributed to this persistent upward trend (Liang et al., 2016; Glaeser and Gyourko, 2018). Meanwhile, proper control groups are hard to match in most of those policy shocks due to the unclear heterogeneity over Chinese cities under the decision making process. Consequently, we eschew reliance on city-specific housing-regulation policies for identification. Instead, following the established literature (Guren et al., 2021), we exploit systematic heterogeneity in how cities respond to regional housing-price cycles and use this variation as an instrumental variable in a two-stage least-squares (2SLS) framework to secure credible causal inference.

### 3.1.2 Crime Rate Measures

We follow Ma et al. (2022) in constructing city-level measures of crime. The primary data source is the China Judgments Online (CJO) database, which contains detailed judgment documents officially released between 2011 and 2018. The Supreme People's Court (SPC) first issued regulations on the online publication of judgment documents in November 2010, requiring courts to disclose their rulings.[13] Each judgment document records detailed

[13]The rules were revised in 2013 (effective January 1, 2014) and again in 2016 (effective October 1, 2016), progressively expanding the coverage of cases available online. Under these regulations, all levels of people's courts are required to publish judgment documents on CJO, with the exception of sensitive cases involving

Figure 1: Housing Prices in China




(a) Trends in Housing Prices and Growth Rates (b) Change in Housing Prices, 2014-2018

Note: Panel (a) shows the national average unit price of commodity residential housing in China (in RMB per square meter, deflated by the CPI with 2000 as the base year) and its annual growth rate from 2000 to 2021. The growth rate is calculated as the year-over-year change in the logarithm of real housing prices. Housing price data are taken from the China Real Estate Information (CREI) database, compiled and maintained by the State Information Center.

information, including the date of the case, the location of the court, and the nature of the offense. We restrict attention to criminal cases, which account for roughly 20 percent of all published judgments (Ma et al., 2016). Unlike civil or administrative disputes, criminal cases are of particular social and policy relevance because of their high economic and social costs (Fajnzylber et al., 2000; Brand and Price, 2000; Heeks et al., 2018; Chalfin, 2015).

**Variable Construction** Our crime measures are based on a systematic textual analysis of judgment documents. Each case is classified into one or more crime categories using keywords drawn from the Criminal Law of the People's Republic of China and standard judicial terminology. For example, documents containing the terms "抢劫," "抢夺," or "哄抢" are coded as robbery. When a case involves multiple offenses, it is assigned to all relevant categories. Appendix Table A.1 provides the full mapping of keywords to the fourteen crime types analyzed in this study.

In addition to crime categories, we extract information on offender characteristics and case outcomes. Specifically, the gender of defendants is identified from explicit mentions in

state secrets, juvenile crime, divorce proceedings, child custody, mediation settlements, or other cases deemed unsuitable for disclosure.

the documents. If both male and female offenders are involved in a single case, the case is counted under both groups. We also extract information on the monetary value associated with each crime, which is used to calibrate the estimated economic returns to crime across different locations. All case-level information is aggregated to the city–crime type–gender level, forming a panel that captures the distribution of offenses across space, categories, and offender groups. To account for differences in city size, we normalize the number of cases by the population at end of year from China City Statistical Yearbook. Our dependent variable is thus defined as the number of criminal cases per thousand population by city, crime type, and gender.

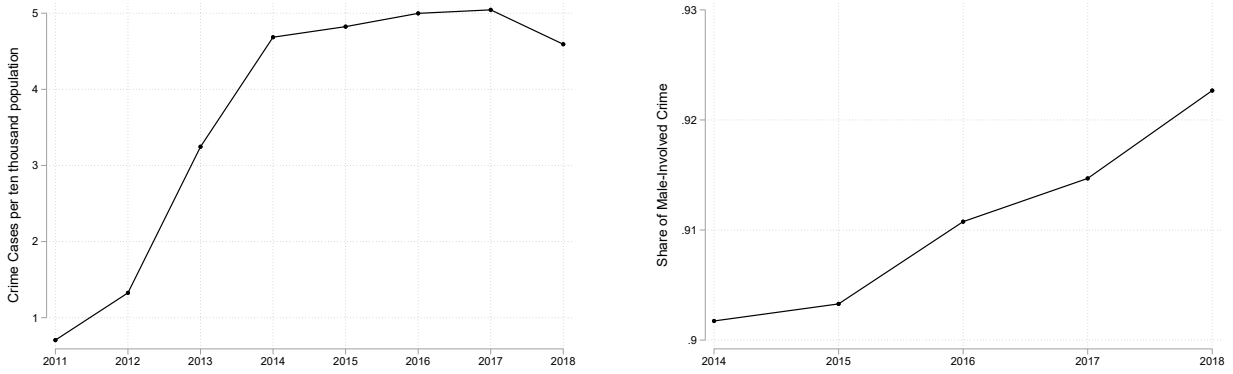
To assess the representativeness of the crime data, Ma et al. (2022) aggregate case-level information from CJO to the national level and compare it with official statistics released by the SPC. They report that the number of judgment documents available on CJO between 2014 and 2015 is roughly half of the number of closed cases published by the SPC. Given that certain categories of cases (such as those involving state secrets) are never disclosed and that there is often a time lag before judgments appear on CJO (Ma et al., 2022), the actual disclosure rate is likely to be considerably higher. Moreover, criminal cases have the highest disclosure rate among all case types, since mediation settlements are rare in criminal proceedings (Ma et al., 2016).

Panel (a) of Figure 2 plots the average crime rate across Chinese cities from 2011 to 2018, measured as the number of criminal cases published on China Judgments Online (CJO) per 10,000 residents. The series exhibits a clear level break in 2014: crime rates in 2011–2013 are mechanically lower because online posting of judgments was not yet comprehensive, whereas a 2014 regulatory revision made publication largely mandatory. We therefore focus on the 2014–2018 window, where coverage is stable and comparable over time. Panel (b) reports the average share of cases involving at least one male defendant over 2014–2018. This share is about 0.9 and trends upward, highlighting the strongly male-intensive nature of criminal participation, consistent with the incentive-based patterns emphasized by Campaniello and Gavrilova (2018).

### 3.1.3 Other Covariates

City-level socioeconomic covariates are obtained primarily from the China City Statistical Yearbook, published by the National Bureau of Statistics of China. These include GDP per capita, fiscal expenditure per capita, average wages, the unemployment rate, the number of teachers, and the employment shares of the secondary and tertiary sectors. Demographic covariates are constructed from nationally representative surveys conducted by the National Bureau of Statistics, including the 2005 and 2015 one-percent population surveys. From

Figure 2: Crime Rate and Male Participation in China




(a) Crime Rate

(b) Male Share of Crime

Note: The figure plots China's crime rate from 2011 to 2018 and share of male-involved crime from 2014 to 2018. Crime date comes from China Judgments Online Database (CJO) and crime rate is defined as the number of criminal cases released on CJO per ten thousand population.

these data, we compute the male-to-female ratio and the migration rate for each city in the two sample periods.

To capture institutional and cultural factors relevant for migration and housing decisions, we include several additional covariates. Following Tian (2019), we construct a migrant-friendliness index that summarizes local variation in migration-related policies. Information on the opening dates of high-speed rail connections is drawn from the Special Issue on Railway Passenger and Freight Transport published by the Ministry of Railways. The likelihood of parents purchasing marital housing for their children is extracted from the China Health and Retirement Longitudinal Study (CHARLS), conducted by Peking University, using textual responses on household transfers for marriage-related expenses. Finally, we draw on the China Family Panel Studies (CFPS), also organized by Peking University, to construct a city-level depression index, based on standardized coding of mental health questions across survey waves. More details on the construction of each covariate are provided in the relevant sections of the paper. Appendix Table A.2 reports descriptive statistics for the main variables used in the empirical analysis.

## 3.2 Empirical Strategy

This section sets out our causal inference strategy. The key idea is that exogenous housing policy shocks serve as natural experiments: by pushing up local housing costs, they generate migration flows, which then alter the distribution of crime across cities. We use these shocks to isolate exogenous variation in housing prices and, through this channel, identify their causal effect on crime.

**Baseline Specification** Our goal is to estimate the causal effect of housing prices on local crime rates over the 2014–2018 period. To this end, we regress the city-level crime rate on housing prices using the following specification:

$$\ln(Crime/L)_{ct} = \alpha + \beta \ln HP_{ct} + \gamma X_{ct} + \lambda_t + \lambda_c + \epsilon_{ct}, \tag{4}$$

where the dependent variable $\ln(Crime/L)_{ct}$ is the logarithm of criminal cases per capita in city $c$ and year $t$. The key regressor, $\ln HP_{ct}$, is the logarithm of the average housing price in city $c$ and year $t$, deflated by the provincial Consumer Price Index (CPI, base year 2000).[14] The vector $X_{ct}$ contains city-level controls that may also affect crime, including GDP per capita, fiscal expenditure per capita, and the employment shares of the secondary and tertiary sectors, all drawn from the China City Statistical Yearbook. Year fixed effects $\lambda_t$ capture common shocks across all cities in a given year, while city fixed effects $\lambda_c$ absorb time-invariant local characteristics. Standard errors are clustered at the city level to allow for arbitrary correlation within cities. Overall, the baseline sample covers 263 cities between 2014 and 2018. Missing values in housing prices are concentrated in cities in Yunnan Province, which accounts for the small variation in coverage across years.

**Instrumental Variables** Estimating equation (4) directly may yield biased estimates, since unobserved city–year shocks are likely to affect both housing prices and crime. For instance, a surge in local technology that boosts labor demand could increase wages and housing demand, thereby driving up housing prices. At the same time, higher employment opportunities may reduce crime, since criminal activity often serves as an informal occupation for the unemployed (Khanna et al., 2023). Reverse causality may also pose a problem: households may avoid living in high-crime neighborhoods, which depresses housing demand and lowers prices in those areas (Tita et al., 2006).

To address these endogeneity concerns, we instrument housing prices with one-year lagged land prices. This strategy builds on Saiz (2010), who rely on geographic constraints and land-use regulations to construct instruments. In the Chinese context, land use is tightly regulated to preserve farmland (Han et al., 2020). Urban construction land is allocated through a top-down quota system spanning five administrative levels, where each local Bureau of Land and Resources must prepare land-supply plans in line with directives from higher authorities (Tian and Ma, 2009; Liang et al., 2016; Han et al., 2020). These regulatory constraints limit the supply of developable land, pushing up land prices. Because land is a key component of construction costs, higher land prices feed directly into higher housing prices (Pollakowski

[14] CPI data are obtained from the National Bureau of Statistics of China.

and Wachter, 1990). Land prices are measured using micro-level transaction data on urban land transfers from the China Land Market website.[15] The validity of this instrument rests on the exclusion restriction: conditional on city and year fixed effects and observable controls, land prices should affect local crime rates only through their impact on housing prices. In other words, while land prices capture regulatory constraints and supply-side conditions in the housing market, they are not expected to directly influence criminal behavior once economic fundamentals are held constant.

As a second source of exogenous variation, we follow Guren et al. (2021) in constructing a "sensitivity instrument" that exploits systematic differences in how cities respond to regional housing price cycles. Provincial housing markets in China display pronounced boom–bust dynamics, but the degree of comovement with these cycles varies markedly across cities. Importantly, these differences are persistent over time, providing a stable source of variation in local housing prices that can be used for identification.[16] Formally, we estimate city-specific sensitivities by regressing city-level housing price growth on provincial growth and then use the estimated sensitivities to construct the instrument:

$$Z_{ct} = HP_{c,2005} \prod_{\tau=2006}^{t} (1 + \hat{\delta}_c \Delta \ln HP_{p\tau}), \quad \text{where} \quad \Delta \ln HP_{cpt} = \gamma_c + \delta_c \Delta \ln HP_{pt} + v_{cpt}, \quad (5)$$

where $\Delta \ln HP_{cpt}$ denotes the housing price growth rate in city $c$ of province $p$ and year $t$, and $\Delta \ln HP_{pt}$ is the corresponding provincial growth rate. The coefficient $\hat{\delta}_c$ measures the extent to which city $c$ responds to provincial fluctuations. To reinforce the validity of the sensitivity instrument, we implement several safeguards. First, provincial housing prices are computed as the leave-one-out mean of city-level prices to mitigate the reflection problem (Manski, 1993). Under this procedure, the instrument cannot be constructed for the four municipalities (Beijing, Tianjin, Shanghai, and Chongqing) and for Kunming, the only city in Yunnan with complete housing price data from 2014–2018. Second, when generating the instrument for year $t$, the estimate of $\hat{\delta}_c$ is obtained excluding observations from that year, thereby reducing the possibility that contemporaneous shocks bias the instrument. Finally, whether $HP_{c,2005}$ is included or excluded has no bearing on the results, since $\ln HP_{c,2005}$ is

[15] The China Land Market website (https://www.landchina.com/ ) is the official platform operated by the Ministry of Natural Resources, covering all transactions of state-owned land across Chinese cities. Each record provides detailed information on the date of transfer, location, land parcel size, designated usage (e.g., residential, commercial, or industrial), lease term, and the transaction price. We use residential land transfers to construct average land prices at the city–year level.

[16] Appendix Figure A.1 illustrates the case of Jiangsu Province. While provincial housing prices exhibit clear cyclical fluctuations, the amplitude of these fluctuations differs across cities. Nanjing, for example, consistently co-moves more strongly with provincial cycles than Xuzhou, and this relative sensitivity remains stable over time. Similar patterns hold in other provinces, underscoring the empirical relevance of the instrument.

absorbed by city fixed effects.

## 3.3 Baseline Results

Table 1 presents the baseline estimates of the effect of housing prices on crime rates from equation (4). Columns (1) and (2) report OLS results without and with city-level controls ($X_{ct}$). In both specifications, the coefficient on housing prices is negative but statistically insignificant, a pattern suggestive of endogeneity bias. Columns (3) to (5) turn to the IV estimates, using lagged land prices, the sensitivity-based instrument, and a combination of the two. In every case, the coefficient on housing prices is negative and statistically significant, indicating that increases in housing costs reduce crime. This pattern is consistent with the idea that rising housing prices deter potential offenders by raising the opportunity cost of crime and altering the composition of local populations. The first-stage Kleibergen–Paap rk Wald $F$ statistics all exceed 10, ruling out weak-instrument concerns.

Table 1: Impact of Housing Prices on Crime Rates

| Dependent variable: $\ln(Crime/L)_{ct}$ | (1) OLS | (2) OLS | (3) Land Price IV | (4) Sensitivity IV | (5) Combined IV |
|---|---|---|---|---|---|
| $\ln HP_{ct}$ | -0.065 | -0.109 | -1.283** | -0.801* | -1.048** |
| | (0.069) | (0.071) | (0.560) | (0.432) | (0.414) |
| Observation | 1,315 | 1,282 | 1,271 | 1,258 | 1,247 |
| First-stage F-statistics | - | - | 21.17 | 14.79 | 17.32 |
| City Controls | - | Y | Y | Y | Y |
| City Fixed Effects | Y | Y | Y | Y | Y |
| Year Fixed Effects | Y | Y | Y | Y | Y |

Note: The sample covers 263 cities observed annually from 2014 to 2018. The dependent variable is the logarithm of crime cases per capita. The main explanatory variable is the logarithm of housing prices, deflated using the provincial CPI (base year 2000). City-level controls include GDP per capita, fiscal expenditure per capita, and the employment shares of the secondary and tertiary sectors. Column (1) reports OLS estimates without city controls; column (2) adds these controls. Columns (3)–(5) report IV estimates using the same controls, instrumenting housing prices with lagged land prices, the sensitivity-based instrument, and the two instruments combined, respectively. Kleibergen–Paap rk Wald F-statistics are reported for the first stage in columns (3)–(5). Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The magnitudes are substantial. Column (3) implies that a 1% increase in housing prices lowers crime rates by about 1.3%. Column (4), using the sensitivity instrument, delivers a slightly smaller but still significant effect. When both instruments are combined in column (5), the effect remains negative and is significant at the 1% level. These findings suggest an economically important channel: rising housing prices make crime less attractive, either by raising the opportunity cost of criminal activity or by reducing the relative concentration of high-risk groups in cities.[17]

[17]The IV estimates are consistently larger in magnitude than their OLS counterparts. This divergence

## 3.4 Robustness Checks

We test the robustness of our results by using alternative measures of housing prices and crime, restricting the sample, examining spillover effects across cities, and implementing a falsification test for unobserved shocks. All specifications include city-level controls and, unless noted otherwise, use IV estimation with both lagged land prices and the sensitivity-based instrument.

**Alternative Measures of Housing Prices and Crime Rates** In the baseline analysis, the key regressor is the logarithm of housing prices, and the crime rate is measured as cases per capita. Table A.4 examines the robustness of our findings to alternative definitions of both variables. Column (1) replaces contemporaneous housing prices with their one-year lag to account for the fact that criminal cases may take time to be formally registered. The coefficient remains negative and statistically significant, with a magnitude larger than in column (5) of Table 1, consistent with a lagged response of crime to housing shocks. Column (2) addresses the close correlation between housing prices and wages. Following Moretti (2013), who emphasize that wage comparisons across skill groups should account for differences in local housing costs, we construct a wage-normalized housing price measure defined as the ratio of housing prices to per capita disposable income of urban residents, using data from the China Real Estate Information Website. The coefficient remains negative and statistically significant, with a magnitude comparable to the baseline. Finally, column (3) redefines the dependent variable. Rather than measuring the crime rate per capita, we use employment at year-end as the denominator to better capture the population at risk of committing crimes. Results again remain robust: housing prices continue to exert a negative and statistically significant effect on crime.

**Excluding Provincial Capitals** As noted in section 3.2, construction of the sensitivity-based instrument requires excluding the four municipalities, since provincial housing price growth is computed as the leave-one-out mean of city-level growth rates. These municipalities are already omitted from the baseline estimates, and their exclusion is appropriate given that both housing markets and crime patterns may differ systematically from other cities due to their unique administrative status. A similar concern arises for provincial capitals more broadly. These cities often receive preferential policy treatment and greater resource

suggests that OLS understates the true effect of housing prices on crime. A likely explanation is omitted variables: unobserved technological shocks, such as automation, may raise housing prices through local economic growth while simultaneously pushing some workers into criminal activity (Khanna et al., 2023). In the absence of adequate controls, OLS will bias the coefficient toward zero, obscuring the true negative relationship between housing prices and crime.

allocations, which could make them outliers relative to the rest of the sample. To account for this possibility, we re-estimate the regressions excluding all provincial capitals. Column (4) of Table A.4 shows that the results remain robust.

**Effects of Export Shocks** China's rapid export-led transformation (Brandt and Rawski, 2008; Feenstra and Wei, 2010) raises a natural concern: city-level forces tied to exports may move both housing prices and crime. Export shocks can affect housing demand and local wages, and they may also shift crime through labor-market conditions (Khanna et al., 2023). To address this possibility, we follow Ma et al. (2022) and construct a city-level export shock, $ExportShock_{ct} = \frac{\Delta Export_{ct}}{L_{c,2010}} = \frac{Export_{ct} - Export_{ct-1}}{L_{c,2010}}$, where $Export_{ct}$ is city $c$'s total exports in year $t$, $Export_{c,t-1}$ is the corresponding value in the previous year, and $L_{c,2010}$ is the city's 2010 working-age population used for normalization. Column (5) of Table A.4 adds $ExportShock_{ct}$ as an additional control. The housing-price coefficient is essentially unchanged, suggesting that contemporaneous export shocks are unlikely to be driving our baseline relationship between housing prices and crime.

**Falsification Test** As a further robustness check, we implement a falsification test to assess whether the negative effect of housing prices on crime could simply reflect unobserved stochastic trends or omitted variables. We randomly reassign housing prices across cities and re-estimate the baseline IV specification from column (5) of Table 1. This procedure—consisting of reshuffling housing price data and re-running the IV regression—is repeated 500 times. If the observed effect is spurious, the simulated coefficients should cluster around zero and show no systematic significance.

Appendix Figure A.2 plots the kernel density of the 500 simulated estimates and their associated p-values, alongside the benchmark IV estimate of –1.048 from column (5). The simulated coefficients are tightly centered around zero, with the vast majority of p-values well above conventional significance thresholds, consistent with the null of no effect. By contrast, the actual estimate stands out as a pronounced negative outlier relative to the simulated distribution. This pattern reinforces the interpretation that the observed negative effect of housing prices on crime reflects a genuine causal relationship, rather than spurious correlations driven by unobserved shocks.

## 3.5 Heterogeneity Analysis

The richness of the crime data makes it possible to examine how the effect of housing price shocks varies across different city contexts. In particular, we investigate heterogeneity along three dimensions that shed light on potential mechanisms: the demographic composi-

tion of the local population, the structure of industrial activity, and the capacity of urban transportation systems. All regressions include city-level controls and are estimated by IV, with housing prices instrumented by land prices and the sensitivity-based instrument unless otherwise noted.

**Youth Composition** First, given that a large proportion of crimes are committed by young individuals (Hu, 2006; Edlund et al., 2013), we examine whether the effect of housing prices on crime rates differs across cities with varying shares of youth population. Using data from the 2010 Population Census provided by the National Bureau of Statistics, we restrict the sample to the working-age population aged 16–64. Following the *Medium- and Long-Term Youth Development Plan (2016–2025)* issued by the State Council of China, we define youth as individuals under the age of 35 and compute the youth ratio as their share within the working-age population at the city level. Then, we split the sample at the median youth ratio and estimate the effects separately for cities above and below this threshold. The results, reported in columns (1) and (2) of Table 2, indicate that housing prices significantly reduce crime rates only in cities with a high youth ratio.

**Crime Gender Gap** Second, according to our crime data, over 90 percent of criminal cases involve male offenders.[18] Given this pronounced gender imbalance, we examine whether the effect of housing prices on crime rates varies across cities with different male population shares. Specifically, we define the male ratio as the proportion of residential males within the working-age population at the city level, based on the 2010 Population Census. We then split the sample at the median male ratio and estimate the effects separately for cities above and below this threshold. As reported in columns (3) and (4) of Table 2, the negative effect of housing prices on crime rates is statistically significant in cities with a high male ratio, whereas the effect becomes insignificant in cities with a lower male share. This pattern is consistent with the mechanism outlined in section 3.6: as housing costs rise, men are more likely than women to migrate out, reducing the pool of potential offenders and contributing to lower local crime rates.

**Industrial Structure** Third, we examine whether a city's industrial structure influences the effect of housing prices on crime rates. Specifically, we divide the sample based on the median employment share in the secondary and tertiary sectors in 2014, using data from the China City Statistical Yearbook. Columns (5) and (6) of Table 2 show how the impact

[18] Appendix Figure A.3 shows that this pattern is pervasive geographically: in 2014, every city had a male involvement share above 80 percent (measured as the fraction of cases with at least one male defendant).

of housing prices on crime rates differs across cities with varying industrial compositions. We find that housing prices have a significantly negative effect on crime rates in cities with a high employment share in the secondary industry, while the effect becomes statistically insignificant in cities dominated by the tertiary sector. A possible explanation is that male employment shares are generally higher in the secondary sector than in the tertiary sector.[19]

**Transportation Ridership Capacity** Finally, we examine whether the effect of housing prices on crime depends on the development of public transport. Well-developed transport systems lower migration costs (Baum-Snow, 2007; Baum-Snow et al., 2017), making it easier for residents to relocate when housing becomes more expensive. This increased mobility can reshape local demographics and, in turn, crime dynamics. To capture transport development, we use per capita highway passenger volume from the China City Statistical Yearbook and divide cities at the median level. The estimates, reported in columns (7) and (8) of Table 2, show that rising housing prices reduce crime significantly only in cities with stronger transport capacity, while the effect is negligible where mobility is more limited. When housing costs rise, better transport networks accelerate population outflows that contribute to lower local crime rates.

Table 2: Heterogeneous Effects of Housing Prices on City Crime Rates

| Dep var: $\ln(Crime/L)_{ct}$ | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Youth Ratio | | Male Ratio | | SecShare | TerShare | Highway Ridership | |
| | High | Low | High | Low | High | High | High | Low |
| $\ln HP_{ct}$ | -1.379* | -0.110 | -1.306** | -0.425 | -1.384*** | -0.663 | -1.672** | 0.211 |
| | (0.800) | (0.439) | (0.636) | (0.465) | (0.298) | (1.136) | (0.688) | (0.473) |
| Observation | 478 | 764 | 502 | 740 | 648 | 590 | 617 | 587 |
| First-stage F-statistics | 12.99 | 4.62 | 14.84 | 4.76 | 15.36 | 7.25 | 16.25 | 11.33 |
| City Controls | Y | Y | Y | Y | Y | Y | Y | Y |
| City Fixed Effects | Y | Y | Y | Y | Y | Y | Y | Y |
| Year Fixed Effects | Y | Y | Y | Y | Y | Y | Y | Y |

Note: The sample consists of city-year observations from 2014 to 2018. The dependent variable is the log of crime cases per capita, and the main explanatory variable is the log of housing prices. Columns (1) and (2) report results for cities with youth population ratios above and below the median, respectively. Columns (3) and (4) present results for cities with male population ratios above and below the median, respectively. Columns (5) and (6) restrict the sample to cities with employment shares in the secondary and tertiary sectors above the median, respectively. Columns (7) and (8) show results for cities with highway passenger volume per capita above and below the median, respectively. City-level controls include the logarithm of GDP per capita, the logarithm of fiscal expenditure per capita, and the employment shares of the secondary and tertiary sectors. In all regressions, housing prices are instrumented using a combination of land prices and a sensitivity-based instrument. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[19] According to the 2015 1% Population Survey, the male employment share in the secondary industry is 68 percent, compared to 55 percent in the tertiary industry.

## 3.6 Suggestive Mechanism

We next turn to the mechanisms through which rising housing prices may reduce crime. Several channels are plausible, including migration responses, shifts in the provision of local public services, and changes in labor market conditions that affect individuals' incentives to participate in criminal activity.

### 3.6.1 Crime Effects of Male-Selective Migration

In Chinese tradition, men are generally expected to purchase a home before marriage. This norm places men under disproportionate economic and social pressure when housing costs rise (Xu and Wang, 2022; Wei and Zhang, 2011; Du and Wei, 2013; Wrenn et al., 2019). Faced with these pressures, men are more likely than women to relocate from high- to low-cost areas in search of affordable housing and improved marriage prospects. Since men also constitute the overwhelming majority of criminal offenders (Campaniello and Gavrilova, 2018), this pattern generates the crime effects of male-selective migration: origin cities losing male residents may experience relative declines in crime, while destination cities may face new pressures.

**Gender Composition of Crime** Across countries and historical contexts, crime has been overwhelmingly male-dominated, and China is no exception. Judgment documents from the CJO database show that in every one of the 263 cities in our sample, more than 80 percent of criminal cases involve at least one male offender. Appendix Figure A.3 illustrates the pattern for 2014, with Zhejiang Province standing out slightly, where crimes such as financial fraud and counterfeiting tend to involve relatively more female participation.

Disaggregating by offense type reveals a pronounced asymmetry in gender composition. For each crime category, we compile all judgment records from 2014, count the number of cases, identify those with at least one male defendant, and compute the male share as the ratio of male-involved cases to total cases nationwide. Appendix Table A.3 shows that traffic offenses and robbery are overwhelmingly male-dominated, with roughly 97 percent of cases involving men. Most other crime categories also exceed a 75 percent male share, while only a few—notably financial crimes, counterfeiting, and prostitution-related offenses—fall below this threshold, with male participation ranging from 58 to 70 percent.[20] This systematic male dominance is consistent with Campaniello and Gavrilova (2018), who attribute gender differences in criminal activity to incentives such as expected earnings and the likelihood of

[20]Repeating the exercise at the individual level, by dividing the number of male offenders by the total number of offenders within each category, yields nearly identical rankings and magnitudes.

arrest.[21] Because offending is male-intensive across categories, housing prices mechanically have more scope to move crime in male-heavy places, consistent with the larger negative effects estimated for cities with higher male ratios in columns (3) and (4) of Table 2.

**Male-biased Migration** We test whether rising housing prices induce male-biased migration by estimating gender-specific regressions of migration rates between 2010 and 2015 on housing prices and their interaction with a male indicator:

$$OutMig_{cs,2015} = \gamma_0 + \gamma_1 \ln HP_{c,2010} + \gamma_2 \ln HP_{c,2010} \times \mathbb{I}\{s = \text{Male}\} + \Gamma X_{c,2010} + \eta_{p(c)} + \epsilon_c, \quad (6)$$

where $OutMig_{cs,2015}$ denotes the cumulative out-migration rate from origin city $c$ for gender $s \in \{\text{Male}, \text{Female}\}$, measured using the 2015 1% Population Survey and normalized by the number of registered residents of gender $s$ in city $c$. The sample is restricted to the working-age population ages 16–64. The coefficients of interest are $\gamma_1$, which captures the effect of housing prices on female out-migration, and $\gamma_2$, which identifies the differential effect for males relative to females. To mitigate endogeneity concerns, we employ the sensitivity-based instrument from the baseline analysis, as land price data are unavailable in 2010. City-level controls $X_{c,2010}$ include log per capita GDP, per capita fiscal expenditure, and employment shares in the secondary and tertiary sectors; province fixed effects $\eta_{p(c)}$ are included, and standard errors are clustered at the province level. The estimates, reported in column (1) of Table 3, show that housing prices have little effect on female out-migration, while the interaction term indicates a significant positive response for males. Quantitatively, rising housing prices increase the male out-migration rate by about 0.5 percentage points more than the corresponding effect for females. This male-biased pattern suggests that rising housing costs disproportionately encourage men to leave their origin cities, a mechanism that may help account for the observed decline in crime given that the overwhelming majority of offenders are male.

We mirror the analysis on the in-migration margin by studying $InMig_{cs,2015}$, the inflow rate of gender $s$ into city $c$ over 2010–2015. The key regressor is $ExpoHP_{c,2010}$, city $c$'s exposure to housing-price shocks elsewhere. Following Imbert et al. (2022), we construct the Bartik-style measure

$$ExpoHP_{ct} = \ln\left(\sum_{o \neq c} m_{oc} \times HP_{ot}\right), \quad (7)$$

where $m_{oc}$ is the pre-2005 migrant share from origin $o$ to destination $c$, capturing persistent

[21] Their analysis shows that men, on average, earn 13 percent more than women in criminal activities and respond more strongly to changes in illegal earnings.

origin–destination links.[22] Column (2) of Table 3 shows that higher $ExpoHP_{c,2010}$ predicts disproportionately larger male inflows, reinforcing the out-migration evidence and pointing to a demographic channel through which housing costs reshape crime. Given that $ExpoHP_{ct}$ predicts male-skewed inflows, we further include it in the crime regression to assess whether the baseline housing-price effect is confounded by contemporaneous shocks elsewhere. Column (3) of Table 3 shows that the coefficient on local housing prices remains significantly negative and becomes larger in magnitude, while the coefficient on $ExpoHP_{ct}$ is significantly positive. This is consistent with external housing-price increases generating male-selective inflows that partially offset the crime-reducing effect of higher local housing costs.

**Male-biased Criminal Participation** The evidence on male-biased migration implies that rising housing prices should disproportionately reduce crime committed by men. To evaluate this prediction, we use city–gender–year level crime data from 2014 to 2018 and estimate a regression specification analogous to (4). The dependent variable is $\ln(Crime/L)_{cst}$, the logarithm of crime cases per capita in city $c$ and year $t$ involving offenders of gender $s$, with the baseline strategy described in section 3.2. The key regressors are the logarithm of housing prices, $\ln HP_{ct}$, which captures the effect on female crime rates, and its interaction with a male indicator, $\ln HP_{ct} \times \mathbb{I}\{s = \text{Male}\}$, which measures the differential response of male crime relative to female crime. We include gender–year fixed effects to absorb common shocks specific to each gender-year, and city fixed effects to control for time- and gender-invariant heterogeneity. Standard errors are clustered at the city level, and housing prices are instrumented with land prices and the sensitivity-based instrument introduced earlier.

As reported in column (3) of Table 3, rising housing prices are associated with a significant decline in crime committed by men, while the effect on women is small and statistically insignificant. This gender-differentiated response highlights that the overall reduction in crime is driven primarily by men.[23] These findings are consistent with the mechanism proposed earlier: male-biased migration reduces the pool of potential male offenders, thereby linking housing costs to lower crime rates.

To reinforce the conclusion that men drive the relationship between housing prices and crime, we examine whether the response to housing costs differs systematically across crime types according to their male intensity. Since rising housing prices reduce crime primarily by lowering male participation, crime categories with a higher share of male offenders should

[22] Using pre-determined migration shares mitigates concerns that contemporaneous shocks jointly determine both current migration flows and $HP_{ot}$.

[23] Because some cases involve both male and female offenders, we also construct an alternative measure based on the number of offenders per capita rather than crime cases per capita. The results remain unchanged.

display stronger declines. The analysis relies on a panel of city–crime type–year observations from 2014 to 2018, with crime incidence measured as the logarithm of per capita cases by type. The key regressor is the interaction between housing prices and the male intensity of each crime type, defined as the share of cases involving male offenders: $MaleIntensity_m = \sum_c Crime^{male}_{cm,2014} / \sum_c Crime_{cm,2014}$, as reported in Appendix Table A.3. This interaction provides a direct test of whether male-dominated crimes respond more sharply to housing price increases.[24] The results, reported in column (4) of Table 3, reveal a consistent pattern: crime types with greater male intensity decline disproportionately as housing costs rise. This finding complements the gender-disaggregated evidence and strengthens the central conclusion that the reduction in crime is driven primarily by men, reflecting their greater participation in criminal activity.

Finally, as a further test of the male-driven mechanism, we ask whether the crime-reducing effect of housing prices is stronger in regions where men bear a larger share of the housing burden. To capture regional differences, we construct a province-level measure of the gender gap in housing expenditure shares using the 2010 China Family Panel Survey (CFPS). For each province, we calculate average housing expenditure shares separately for men and women, and define the gender gap as their difference, denoted $AlphaGap_p$.[25] We then extend the baseline specification by interacting housing prices with this province-level gender gap.[26] Column (5) of Table 3 reports a negative and statistically significant coefficient on the interaction, showing that the crime-reducing effect of higher housing costs is amplified in provinces where men bear a larger share of the housing burden. In other words, rising housing prices more effectively deter male participation in crime when local norms assign men a disproportionate responsibility for home-ownership.

### 3.6.2 Alternative Mechanisms

We further examine why rising housing prices may coincide with lower crime rates by testing several alternative explanations. In particular, we assess whether the decline in crime could instead stem from broader social, economic, or psychological adjustments triggered by

[24] The specification follows the similar empirical strategy as before, including city-level controls, crime-type–year fixed effects to absorb common shocks, and city fixed effects to capture persistent local heterogeneity. Standard errors are clustered at the city level, and housing prices are instrumented with land prices and the sensitivity-based instrument.

[25] The CFPS reports housing expenditure at the household level. To attribute expenditures to individuals, we identify the registered property owner(s) on the deed and assign the housing burden accordingly, assuming equal shares when multiple names are listed.

[26] We work at the province level because the mechanisms that allocate the housing burden between men and women are largely shaped by regional norms and institutions, such as marriage-market conventions, local property practices, and hukou-related rules, that vary systematically across provinces but less within them. A province-level measure therefore provides a natural and stable proxy for the environment in which city-level housing price shocks translate into male-specific constraints.

Table 3: Gender-Biased Impact of Housing Price on Migration and Crime

| Dependent variable: | (1) $OutMig_{cs,2015}$ | (2) $InMig_{cs,2015}$ | (3) $\ln(Crime/L)_{ct}$ | (4) $\ln(Crime/L)_{cst}$ | (5) $\ln(Crime/L)_{cmt}$ | (6) $\ln(Crime/L)_{ct}$ |
|---|---|---|---|---|---|---|
| $\ln HP_{c,2010}$ | -0.033 | | | | | |
| | (0.039) | | | | | |
| $\ln HP_{c,2010} \times \mathbb{I}\{s = \text{Male}\}$ | 0.005*** | | | | | |
| | (0.001) | | | | | |
| $ExpoHP_{c,2010}$ | | 0.069*** | | | | |
| | | (0.011) | | | | |
| $ExpoHP_{c,2010} \times \mathbb{I}\{s = \text{Male}\}$ | | 0.004*** | | | | |
| | | (0.001) | | | | |
| $\ln HP_{ct}$ | | | -1.637** | 0.176 | 0.079 | -0.736*** |
| | | | (0.683) | (0.702) | (0.344) | (0.257) |
| $\ln ExpoHP_{ct}$ | | | 1.121** | | | |
| | | | (0.560) | | | |
| $\ln HP_{ct} \times \mathbb{I}\{s = \text{Male}\}$ | | | | -0.258*** | | |
| | | | | (0.042) | | |
| $\ln HP_{ct} \times MaleIntensity_m$ | | | | | -1.563*** | |
| | | | | | (0.211) | |
| $\ln HP_{ct} \times AlphaGap_{p(c)}$ | | | | | | -3.414** |
| | | | | | | (1.699) |
| Observation | 506 | 516 | 1,242 | 2,496 | 19,002 | 1,180 |
| First-stage F-statistics | 20.49 | 13.37 | 9.00 | 17.32 | 9.43 | 10.07 |
| City Controls | Y | Y | Y | Y | Y | Y |
| Province Fixed Effects | Y | Y | Y | Y | Y | Y |
| City Fixed Effects | - | - | Y | Y | Y | Y |
| Year Fixed Effects | - | - | Y | Y | Y | Y |
| Gender-Year Fixed Effects | - | - | - | Y | - | - |
| Crime-Type-Year Fixed Effects | - | - | - | - | Y | - |

Note: Columns (1)–(2) use cross-sectional city–gender data to examine the gender-biased effects of housing prices on migration, focusing on out-migration from origin cities and in-migration to destination cities between 2010 and 2015, respectively. The key explanatory variables are the logarithm of housing prices ($\ln HP_{c,2010}$) and its interaction with a male dummy in column (1), and the logarithm of exposure to housing price shocks in other cities ($ExpoHP_{c,2010}$) and its interaction with a male dummy in column (2). Column (3) use city–year data (2014–2018) to examine how the effect of housing prices are confounded by exposure to contemporaneous housing price shocks in other cities. Columns (4) use city–gender–year data(2014–2018) to study the gender-biased impact of housing prices on crime rates, measured by per capita crime cases. Column (5) employs city–crime-type–year data (2014–2018) to examine how the effect of housing prices varies with the male intensity of different crime types. Column (6) use city–year data (2014–2018) to examine how the effect of housing prices varies with the gender differences in housing burden of different cities. City-level controls include the logarithm of GDP per capita, the logarithm of fiscal expenditure per capita, and the employment shares of the secondary and tertiary sectors. In all regressions, housing prices are instrumented using a combination of land prices and a sensitivity-based instrument. Standard errors are clustered at the province level in columns (1)–(2) and at the city level in columns (3)–(6). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

housing price growth. Each potential mechanism is examined using a regression framework similar to (4), which relates changes in each channel to local housing price fluctuations. The dependent variable captures a possible pathway—fiscal, labor market, or social—through which housing prices may affect crime. Identification comes from within-city variation over time, with city and year fixed effects removing persistent local traits and nationwide shocks.

**Provision of Social Stability Services** A natural explanation for the observed decline in crime is the improved provision of social stability services. In China, this mechanism is intimately connected to the real estate market. Local governments rely heavily on land sales and related fees, both of which rise with housing prices (Ihlanfeldt, 2007). Higher land prices expand fiscal capacity by easing local budget constraints, enabling greater investment in public goods and services (Qun et al., 2015; He et al., 2016; Shu et al., 2018; Gyourko et al., 2022). In practice, revenues from land transfers have long financed key components of local governance, including policing, social security, and community welfare. Consequently, rising housing prices may reduce crime not through demographic or behavioral shifts, but through a fiscal channel: greater revenues allow governments to strengthen law enforcement, improve public security, and expand social programs that deter criminal activity.

To evaluate this mechanism, we examine three categories of local government expenditure most relevant to social stability, drawing on data from the China Fiscal Statistical Yearbooks. The first is public security spending, covering the People's Armed Police, judicial and prosecutorial agencies, and public security departments. The second is social spending, which aggregates expenditures on education, social security, health care, and urban–rural public services. The third measure, total social stability spending, is defined as the sum of the two. All variables are expressed in per-capita logarithmic terms.

Table 4 reports the estimated effects of housing prices on local fiscal outcomes. Column (1) shows that higher housing prices are associated with a significant rise in public security spending, whereas columns (2) and (3) indicate no discernible effects on broader categories of social or total stability expenditures. This pattern suggests that housing price growth may modestly strengthen fiscal support for law enforcement, but there is little evidence of a broader fiscal expansion across social sectors. Hence, while the increase in public security spending could play a limited supporting role, it is unlikely to be the main driver of the observed reduction in crime.[27]

[27]To further support this point, we re-estimate the baseline regression while directly controlling for all three categories of public expenditure. As shown in column (1) of Appendix Table A.5, the estimated effect of housing prices on crime remains virtually unchanged. This result indicates that even after accounting for fiscal spending differences, housing prices continue to exhibit a significant negative association with crime, suggesting that the fiscal channel plays at most a limited role in explaining the observed relationship.

**Labor Market Responses** Another potential mechanism linking housing prices to crime operates through the labor market. Rising housing prices can affect local labor markets in ways that may, in turn, influence crime. As housing becomes more expensive, some workers—especially those with lower incomes—move elsewhere, tightening local labor supply and pushing wages higher (Liang et al., 2016). Higher wages raise the opportunity cost of committing crimes, reducing incentives for illegal activity (Machin and Meghir, 2004). At the same time, housing booms generate jobs directly in construction and indirectly in related sectors (Estevão and Tsounta, 2011; Geerolf et al., 2014), lowering unemployment and further discouraging crime (Raphael and Winter-Ebmer, 2001; Khanna et al., 2023; Britto et al., 2022; Rose, 2018; Dix-Carneiro et al., 2018). These forces suggest that stronger labor market conditions accompanying housing price growth could contribute to lower crime rates.

To examine these channels, we draw on city-level data from the China City Statistical Yearbook and consider three indicators: the logarithm of average wages, the unemployment-to-population ratio, and the employment-to-population ratio. Columns (4)–(6) of Table 4 report the estimated effects of housing prices on these labor market outcomes. None of the coefficients are statistically significant, suggesting that housing price movements have little measurable impact on local wages or employment.[28]

**Education and Community Composition** A more indirect explanation relates to changes in community composition and the local public environment. Rising housing prices can reshape neighborhood demographics by attracting households with greater financial stability and stronger preferences for education and safety. This shift tends to foster communities with higher levels of social capital and informal monitoring, reducing incentives and opportunities for criminal behavior (Guerrieri et al., 2013; Diamond, 2016; Diamond et al., 2019). At the same time, higher property values expand the local fiscal base, enabling local governments to invest more in visible and politically salient public goods—particularly education (Litschig and Morrison, 2013; Jackson et al., 2015).[29]

[28] As in the previous exercise, we re-estimate the baseline regression while controlling for all three labor market variables. As shown in column (2) of Table A.5, the coefficient on housing prices remains stable and statistically significant. This result suggests that even after accounting for local wage and employment conditions, housing prices continue to exert a strong negative association with crime, implying that labor market adjustments are unlikely to drive our main findings.

[29] In China, education-related public expenditure is closely linked to neighborhood desirability. Local governments devote substantial resources to improving school quality and related public services, which strongly influence residential choices among middle- and high-income households. Well-funded schools often become focal points for "school-district housing" (*xuéqū fáng*) demand, attracting more affluent and education-oriented families. As a result, higher education spending not only reflects stronger fiscal capacity and better public service provision but also signals a more stable, higher-income resident base—features

To assess these possibilities, we examine indicators of education and public service quality from the China City Statistical Yearbook, including per capita education spending and the number of teachers. Columns (7)–(9) of Table 4 show no significant effects of housing prices on these measures, and when all these variables are jointly added to the baseline regression (column (3) of Table A.5), the estimated coefficient on housing prices remains stable. These results suggest that while education-oriented public investment and shifts in community composition may accompany housing price growth, they are unlikely to explain the short-run decline in crime rates observed in our data. Future work could extend this analysis by incorporating additional indicators of xuéqū fáng–related investment to better capture how housing demand for school quality shapes neighborhood dynamics.

**Mental Health** Mental health may represent another channel through which housing prices influence crime. Rising housing costs can impose substantial financial pressure on households, particularly for prospective buyers, and such stress may deteriorate psychological well-being.[30] Following Xu and Wang (2022), we use data from the China Family Panel Survey (CFPS 2014, 2016, and 2018) to construct province-level measures of depression based on the Kessler Psychological Distress Scale (K6) (Kessler et al., 2002), a widely used indicator of mental well-being.[31] We aggregate responses across all six questions to construct two indices of psychological distress—one as an equal-weighted average and the other using principal components analysis (PCA). These individual-level indices are then averaged at the province–year level to produce aggregate measures of depression intensity.

Columns (10)–(11) of Table 4 show no significant effect of housing prices on mental health. In column (4) of Table A.5, once these measures are included in the baseline regression, the estimated coefficient on housing prices remains significantly negative and becomes even larger in magnitude. Finally, when all potential mediating variables—those used as dependent variables in Table 4—are jointly included, the estimated effect of housing prices on crime remains virtually unchanged (column (5) of Table A.5). Taken together, these findings indicate that mental health does not mediate the relationship between housing prices and crime, further reinforcing the robustness of our main results.

typically associated with lower crime rates. Moreover, in urban China, education investment serves as a strategic instrument for sustaining real estate values and fostering socially cohesive, low-crime communities.

[30] A large body of research links poor mental health to higher propensities for criminal behavior, as individuals under psychological distress often experience diminished self-control and impaired decision-making (Donnellan et al., 2005; Anderson et al., 2015; Heller et al., 2017).

[31] The K6 scale provides a concise yet comprehensive measure of mental distress across six dimensions: emotional frustration, nervousness, restlessness, hopelessness, difficulty with daily functioning, and feelings of meaninglessness. Respondents report symptom frequency over the past month on a five-point scale ranging from "never" (0) to "almost every day" (4).

Table 4: Mechanisms: The Impact of Housing Prices through Alternative Channels

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Social Stability Expenditure | | | Labor Market Condition | | |
| Dependent variable: | Public Security | Social Spending | Social & Security | Wage | Unemployment | Employment |
| $\ln HP_{ct}$ | 0.517*** | 0.276 | 0.285 | 0.004 | -0.004 | 0.106 |
| | (0.171) | (0.244) | (0.195) | (0.081) | (0.003) | (0.198) |
| Observation | 1,105 | 1,195 | 1,105 | 1,254 | 1,259 | 1,246 |
| City FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |

| | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|
| | Education and Community Composition | | | Depression Index | |
| Dependent variable: | # Teacher ≥Secondary | # Teacher ≥Primary | Spending | Simple Average | PCA |
| $\ln HP_{ct}$ | -0.055 | 0.023 | 0.264 | 0.081 | 0.334 |
| | (0.115) | (0.088) | (0.168) | (0.088) | (0.331) |
| Observation | 1,228 | 1,228 | 1,259 | 722 | 722 |
| City FE | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y |

Note: The sample is composed of observations at the city-year level from 2014 to 2018. The dependent variable is the logarithmic number of criminal cases per ten thousand population. The variable of interest is the logarithmic CPI deflated housing price. Columns (1) through (5) sequentially control for city-level fiscal spending on public security, average wage, fiscal spending on education, the depression index, and export shocks, respectively. In all regressions, housing price is instrumented using the sensitivity IV. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Skill-biased Migration** A final concern is that higher housing prices may reduce crime by altering the skill composition of residents. If rising housing costs disproportionately induce unskilled workers to leave high-price cities, the local population could shift away from individuals who are plausibly closer to the margin of criminal participation. This channel is a priori plausible because housing expenditures take up a larger share of income for less-educated households; an increase in housing costs therefore compresses their real income net of housing by more, making high-price cities relatively less attractive (Chen et al., 2025). Under this mechanism, housing booms would trigger selective out-migration among unskilled workers, shrinking the pool of affordability-constrained residents and mechanically lowering measured crime.

We evaluate this channel by examining whether housing prices differentially predict migration by skill. The outcome of interest is $OutMig_{c,2015}$, the cumulative out-migration rate in city $c$ measured in the 2015 1% Population Survey, constructed separately for (i) unskilled workers with education at or below high school and (ii) skilled workers with education at or above college. Data limitations prevent a panel design with city fixed effects, so we estimate the cross-sectional specification

$$OutMig_{c,2015} = \gamma_0 + \gamma_1 \ln HP_{c,2010} + \Gamma X_{c,2010} + \eta_{p(c)} + \epsilon_c, \tag{8}$$

where $HP_{c,2010}$ is the city's housing price in 2010, $X_{c,2010}$ includes the same city controls as

in (6), and $\eta_{p(c)}$ are province fixed effects. We then estimate the analogous specification for $InMig_{c,2015}$, the cumulative in-migration rate over 2010–2015, using the same skill definitions. In this setting, we replace own-city housing prices with $ExpoHP_{c,2010}$, a Bartik-style exposure measure defined in equation (7) that summarizes housing-price shocks in the places that historically sent migrants to $c$, capturing inflow pressure into $c$ driven by housing costs elsewhere.

Table 5 reports this exercise by estimating migration responses separately for unskilled and skilled workers and testing whether the coefficients differ across groups. Columns (1)–(2) show that $\ln HP_{c,2010}$ has no detectable effect on out-migration for either group, and the estimates are statistically indistinguishable from one another. Columns (3)–(4) turn to in-migration, using exposure to housing-price shocks elsewhere, $\ln ExpoHP_{c,2010}$. More exposed cities attract more migrants, but they attract unskilled and skilled workers in nearly the same proportion: the coefficients are similar in magnitude and Fisher's permutation test fails to reject equality ($p = 0.35$). More generally, following Cleary (1999), the permutation-test $p$-values exceed 0.10 for both out- and in-migration, providing no evidence of differential sensitivity by skill. Therefore, housing-price shocks do not appear to systematically tilt migration toward or away from unskilled workers, making a skill-composition mechanism an unlikely explanation for the crime declines we document.

Table 5: Mechanisms: The Impacts of Housing Prices on Unskilled and Skilled Workers

| Dependent variable: | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Out-migration | | In-migration | |
| | Unskilled workers | Skilled workers | Unskilled workers | Skilled workers |
| $\ln HP_{c,2010}$ | -0.063 | 0.008 | | |
| | (0.058) | (0.023) | | |
| $\ln ExpoHP_{c,2010}$ | | | 0.072*** | 0.065*** |
| | | | (0.016) | (0.008) |
| Observation | 251 | 251 | 251 | 251 |
| City Controls | Y | Y | Y | Y |
| Province Fixed Effects | Y | Y | Y | Y |
| Empirical p-values (Unskilled versus skilled) | 0.13 | | 0.35 | |

Note: This sample uses cross-sectional city-level data. The dependent variables are out-migration from origin cities and in-migration to destination cities over 2010 to 2015, reported separately for unskilled and skilled workers. Columns (1) and (2) report the out-migration regressions, where the key explanatory variable is the log housing price in 2010, $\ln HP_{c,2010}$. Columns (3) and (4) report the in-migration regressions, where the key explanatory variable is the log exposure to housing price shocks in other cities, $ExpoHP_{c,2010}$. City-level controls include the logarithm of GDP per capita, the logarithm of fiscal expenditure per capita, and the employment shares of the secondary and tertiary sectors. In all regressions, housing prices are instrumented using land prices. Standard errors are clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The last row reports empirical two-sided p-values from Fisher's permutation test of the null hypothesis that the coefficients are equal for skilled and unskilled workers.

Overall, under China's male-staked homeownership norm, rising housing costs constrain men more than women and induce male-biased outflows from high-cost origins toward cheaper destinations. Since offending is overwhelmingly male, these movements shift lo-

cal offender pools—thinning them in origins and, mechanically, adding pressure to destinations. Consistent with this mechanism, migration is male-selective; crime falls more in male and male-intensive categories; and the effects are stronger where men face a heavier housing burden, while fiscal, labor-market, community, mental-health, and skill-selective sorting channels receive little support. The aggregate impact, however, is a general-equilibrium object, shaped by how crime returns and participation adjust as populations reallocate. The next section develops a tractable quantitative framework to quantify these interactions and run housing and transfer counterfactuals.

# 4 A Generalized Model of Crime Geography

To quantify the aggregate impact of gender-based migration and broader economic development on crime, this section extends the stylized framework in section 2 into a multi-region quantitative model. The extended model introduces a richer production structure encompassing both legal and illegal sectors, while explicitly modeling migration and occupational choices for male and female individuals. This setup allows the equilibrium allocation of population and crime to emerge endogenously from gender-specific migration incentives and sectoral returns across regions.

## 4.1 Preferences

Each worker $\omega$ of gender $\theta$, born in city $o$, chooses a destination city $d$ in which to live and work. The total labor endowment of each gender group born in city $o$, denoted $\bar{L}_o^\theta$, is exogenously given. Workers are mobile across cities but face migration costs $\tau_{od}$. A worker $\omega$ of gender $\theta$, originating from city $o$ and residing in city $d$, maximizes the following utility function:

$$U_{od}^\theta(\omega) = \left(\frac{C_{od}^\theta}{1-\alpha^\theta}\right)^{1-\alpha^\theta} \left(\frac{H_{od}^\theta}{\alpha^\theta}\right)^{\alpha^\theta} \frac{B_d \epsilon_{od}^\theta(\omega)}{\tau_{od}} \quad \text{s.t.} \quad C_{od}^\theta + Q_d H_{od}^\theta \leq y_d^\theta,$$

where $C_{od}^\theta$ denotes consumption of the final good, taken as the numeraire; $H_{od}^\theta$ is housing consumption at city-specific price $Q_d$; and $B_d$ represents the amenity value of city $d$, capturing environmental quality, public services, and other local attributes. Each worker faces an idiosyncratic preference shock $\epsilon_{od}^\theta(\omega)$, which governs individual heterogeneity in location choices. Income $y_d^\theta$ denotes the wage earned in city $d$, and $\alpha^\theta$ is the gender-specific share of income devoted to housing expenditure. In line with the Chinese cultural norm that males tend to bear greater responsibility for home purchase during marriage formation, we assume $\alpha^M > \alpha^F$. This gender difference implies that housing price variations can generate asymmetric migration responses between men and women, thereby influencing the spatial

distribution of both population and crime. The indirect utility of a worker $\omega$ of gender $\theta$, born in city $o$ and residing in city $d$, is given by:

$$v_{od}^{\theta}(\omega) = \frac{y_d^{\theta} B_d}{Q_d^{\alpha^{\theta}} \tau_{od}} \epsilon_{od}^{\theta}(\omega),$$

where $\tau_{od}$ denotes the bilateral migration cost between cities $o$ and $d$. Following Ahlfeldt et al. (2015), the idiosyncratic term $\epsilon_{od}^{\theta}(\omega)$ is assumed to be i.i.d. across workers, cities, and genders, and follows a Fréchet distribution with shape parameter $\kappa$, which governs the degree of heterogeneity in individual preferences. The probability that a worker of gender $\theta$ born in city $o$ chooses to live in city $d$ is therefore:

$$\lambda_{od}^{\theta} = \frac{L_{od}^{\theta}}{\bar{L}_o^{\theta}} = \left( \frac{y_d^{\theta} B_d}{Q_d^{\alpha^{\theta}} \tau_{od}} \right)^{\kappa} \Big/ \sum_{d'} \left( \frac{y_{d'}^{\theta} B_{d'}}{Q_{d'}^{\alpha^{\theta}} \tau_{od'}} \right)^{\kappa}. \tag{9}$$

Finally, aggregate labor demand in each city must equal the total inflow of workers across all origins, yielding the labor-market clearing condition:

$$L_d^{\theta} = \sum_o L_{od}^{\theta} = \sum_o \lambda_{od}^{\theta} \bar{L}_o^{\theta}. \tag{10}$$

The above labor supply framework captures how men and women sort across cities in response to differences in wages, housing costs, amenities, and migration frictions. The resulting equilibrium distribution of workers by gender forms the basis for analyzing how gender-specific migration patterns—driven by housing affordability and local economic conditions—contribute to spatial variation in crime rates.

## 4.2 Sector Choice

Each city hosts two sectors: a legitimate sector ($\ell$) and a crime sector ($c$). Workers decide between these sectors according to a Roy-style framework (Roy, 1951), where occupational sorting arises from idiosyncratic productivity differences. Each worker of gender $\theta$ residing in city $d$ draws sector-specific productivity levels $(z_{d,\ell}^{\theta}, z_{d,c}^{\theta})$ from a Fréchet distribution with shape parameter $\epsilon > 1$ and scale parameters $(E_{d,\ell}, E_{d,c})$. While all workers are *ex ante* identical, they become *ex post* heterogeneous after drawing their productivity realizations across sectors. Given the wages per efficiency unit $(w_{d,\ell}^{\theta}, w_{d,c}^{\theta})$, a worker chooses the sector offering the higher income potential:

$$\max_{s \in \{\ell, c\}} \left\{ z_{d,s}^{\theta} w_{d,s}^{\theta} \right\}.$$

Aggregating individual decisions, the total employment of workers of gender $\theta$ in sector $s \in \{\ell, c\}$ and city $d$ is given by

$$L_{d,s}^{\theta} = L_{d}^{\theta}\delta_{d,s}^{\theta}, \quad \text{with} \quad \delta_{d,s}^{\theta} = \frac{E_{d,s}(w_{d,s}^{\theta})^{\epsilon}}{E_{d,\ell}(w_{d,\ell}^{\theta})^{\epsilon} + E_{d,c}(w_{d,c}^{\theta})^{\epsilon}}, \tag{11}$$

The term $\delta_{d,s}^{\theta}$ represents the share of workers of gender $\theta$ in city $d$ who choose sector $s$. This share captures how individuals allocate across sectors based on two key determinants. The first is sector-specific productivity ($E_{d,s}$), which summarizes local technological or institutional factors affecting efficiency in each activity. The second is the relative wage incentive $(w_{d,s}^{\theta})^{\epsilon}$, which reflects how differences in returns per efficiency unit attract workers to one sector over another. In equilibrium, a higher wage or productivity level in the crime sector ($c$) raises $\delta_{d,c}^{\theta}$ by increasing the expected payoff from engaging in illegal activities, while stronger performance in the legitimate sector ($\ell$) has the opposite effect. Thus, $\delta_{d,s}^{\theta}$ captures how workers respond to relative economic opportunities, translating city-level differences in productivity and wages into observed patterns of occupational sorting between legal and illegal work. Finally, the expected wage income of workers of gender $\theta$ in city $d$ is given by

$$y_{d}^{\theta} = \xi_{i}\left[E_{d,\ell}(w_{d,\ell}^{\theta})^{\epsilon} + E_{d,c}(w_{d,c}^{\theta})^{\epsilon}\right]^{1/\epsilon}.$$

where $\xi_i = \Gamma(1 - 1/\epsilon)$ is a constant derived from the properties of the Fréchet distribution. This expression aggregates expected earnings across sectors, weighted by the underlying heterogeneity in individual productivity draws.

**Legitimate Sector** In the legitimate sector, the final good is produced under perfect competition and constant returns to scale, with no intrinsic gender bias in technology or institutions. The production function for city $d$ is specified as

$$Y_{d,\ell} = A_{d,\ell}{L_{d,\ell}^{M}}^{\sigma}{L_{d,\ell}^{F}}^{1-\sigma},$$

where $A_{d,\ell}$ denotes city-specific productivity in the legitimate sector, and $\sigma$ represents the share of men in total labor compensation. Both male and female labor contribute symmetrically to output, but their relative productivity and remuneration are endogenously determined by the equilibrium allocation of workers across genders.Under perfect competition, firms hire labor until its marginal product equals the wage per efficiency unit. The

resulting equilibrium wages for men and women are:

$$w_{d,\ell}^{M} = \sigma A_{d,\ell}(\frac{L_{d,\ell}^{M}}{L_{d,\ell}^{F}})^{\sigma-1}, \qquad w_{d,\ell}^{F} = (1-\sigma)A_{d,\ell}(\frac{L_{d,\ell}^{M}}{L_{d,\ell}^{F}})^{\sigma}. \tag{12}$$

These relationships imply that gender wage differences arise naturally from variations in local labor composition. When the share of male workers rises, the marginal product of male labor declines due to congestion in the same production role, while the relative scarcity of female labor pushes up women's wages. The opposite holds when female employment expands. Hence, wage differentials across genders reflect a simple market-clearing logic: cities with a higher concentration of men tend to exhibit lower male wages and higher female wages, and vice versa. This equilibrium mechanism provides a direct link between demographic structure and gender-specific wage outcomes across locations.

**Crime Sector** In the crime sector, individuals engage in illegal activities that yield uncertain and location-specific returns. The expected return to crime for a worker of gender $\theta$ in city $d$ is given by

$$w_{d,c}^{\theta} = (1-p_d)\, A_{d,c} m^{\theta} (L_{d,c})^{\rho} (L_{d,\ell})^{\eta}. \tag{13}$$

Here, $p_d$ denotes the probability of detection and punishment, which varies across cities with differences in policing intensity and institutional effectiveness. The term $A_{d,c}$ reflects city-specific productivity in criminal activities, while $m^{\theta}$ represents a gender-specific shifter capturing behavioral and psychological traits.[32] The returns to crime also depend on the scale and composition of local activities. A larger number of criminals, $L_{d,c} \equiv \sum_{\theta} L_{d,c}^{\theta}$, can either depress or raise individual payoffs depending on the underlying environment. When $\rho < 0$, congestion dominates: competition for illicit opportunities becomes more intense, reducing the average return to crime. When $\rho > 0$, the opposite occurs—criminal networks benefit from agglomeration through coordination, specialization, and mutual protection, leading to higher returns.The broader economic environment, summarized by the size of the legitimate sector, $L_{d,\ell} \equiv \sum_{\theta} L_{d,\ell}^{\theta}$, also shapes the profitability of crime. When $\eta > 0$, a larger legal economy raises criminal returns by expanding targets and illicit demand. When $\eta < 0$, development lowers returns through stronger enforcement and tighter informal monitoring.[33]

[32] Consistent with extensive evidence that men are generally more risk-tolerant and aggressive than women, we assume $m^{M} > m^{F}$, implying higher efficiency and expected returns for men in criminal activities. This asymmetry naturally generates gender differences in both participation and rewards within the crime sector.

[33] Most work stresses crime's damage to legal activity and amenities (Rozo, 2018; Khanna et al., 2022; Melnikov et al., 2025). Here crime is an economic sector with endogenous payoffs. This perspective is particularly apt for China, where both opportunities and enforcement are highly local and scale with market size (Ma et al., 2025).

Rising housing prices can reshape the spatial pattern of crime through gender-specific migration. As housing becomes less affordable, men—who devote a larger share of income to home purchase—are more likely to migrate out of high-cost cities, reducing the local male population and, consequently, the potential pool of offenders. The aggregate impact on crime, however, depends critically on the parameters $\rho$ and $\eta$. When congestion effects dominate ($\rho < 0$), the exit of offenders raises the marginal return to crime for those remaining, offsetting part of the decline in participation. When agglomeration effects prevail ($\rho > 0$), the erosion of criminal networks lowers returns and amplifies the reduction in crime. The interaction with the legitimate sector further modifies this outcome: if formal employment acts as a deterrent ($\eta < 0$), out-migration weakens social control and dampens the overall decline, whereas if it expands opportunities for predation ($\eta > 0$), a shrinking legal economy reinforces the fall in crime. Understanding the net effect therefore requires calibrating these parameters—$\rho$, $\eta$, and the gender-specific migration responses—to quantify the aggregate contribution of housing-induced migration to crime across cities.

## 4.3 Housing Supply

Housing in each city, denoted by $H_d$, is produced under perfect competition using land $K_d$ and capital $M_d$ according to the production function:

$$H_d = M_d^{\mu} K_d^{1-\mu},$$

where $\mu$ represents the capital share in housing production. Capital is freely mobile across regions and supplied perfectly elastically at price $P$, while land is in fixed supply and subject to local regulation with price $R_d$. The representative housing producer solves

$$\max_{M_d, K_d} Q_d M_d^{\mu} K_d^{1-\mu} - P M_d - R_d K_d,$$

which yields the equilibrium housing service price

$$Q_d = R_d^{1-\mu} (1-\mu)^{\mu-1} \mu^{-\mu} P^{\mu}.$$

This baseline expression captures the technological cost of supplying housing given local factor prices. To incorporate policy distortions, we introduce a regulatory wedge $\tau_d$, such that $Q_d = \tau_d R_d^{1-\mu} (1-\mu)^{\mu-1} \mu^{-\mu} P^{\mu}$ where $\tau_d$ reflects city-specific housing regulations or administrative interventions. A higher $\tau_d$ represents more restrictive zoning, price controls, or bureaucratic barriers that raise effective housing costs relative to production costs. In this setup, policy-induced changes in $Q_d$ act as exogenous shifts in housing affordability,

while the housing quantity $H_d$ adjusts endogenously to clear the market. The land market equilibrium condition is given by

$$H_d = \frac{\alpha^M y_d^M}{Q_d} L_d^M + \frac{\alpha^F y_d^F}{Q_d} L_d^F, \tag{14}$$

where the right-hand side denotes total housing demand from male and female residents, consistent with their expenditure shares $\alpha^M$ and $\alpha^F$ in the utility function. An exogenous increase in $Q_d$—for instance, due to tighter housing regulation—reduces local housing demand and induces out-migration, particularly among men, who allocate a larger fraction of income to housing. As shown in the migration and crime mechanisms (9) and (13), this selective migration alters the gender composition of the local labor force, thereby influencing equilibrium crime outcomes. In the quantitative analysis that follows, we treat changes in $Q_d$ as exogenous regulatory shocks and calibrate their magnitudes using reduced-form estimates linking housing regulation intensity to observed price variation, thereby tracing how policy-driven shifts in housing affordability propagate through migration and demographic structure to generate spatial variation in crime across cities.

Finally, a competitive equilibrium consists of a set of prices and allocations such that all agents optimize and all markets clear. Workers of both genders choose their location, sector, and consumption bundle to maximize utility, given wages, housing prices, and migration costs. Firms maximize profits in both the legitimate and crime sectors, while land and labor markets clear simultaneously. These conditions jointly determine the spatial distribution of population and employment across cities. To evaluate the effects of housing price shocks, we solve the model using the exact-hat algebra method, which captures relative changes in equilibrium variables; the full system of equations is presented in Appendix A.2.

# 5 Quantitative Results

This section quantifies how housing price shocks between 2015 and 2018 affected migration and crime participation across Chinese cities. The analysis covers 260 geographic units—the same cities included in our empirical study—that experienced exogenous changes in land and housing prices during this period. We first describe the calibration of key parameters and data inputs used to discipline the model. Using observed bilateral migration flows and crime statistics from 2015 as the baseline, together with the exogenous housing price shocks, we then simulate the implied changes in population distribution and occupational choices between 2015 and 2018.

## 5.1 Model Calibration

**Migration Flow** Bilateral migration flows are constructed using the 2015 1% Population Survey conducted by the National Bureau of Statistics of China. The survey provides detailed information on individuals' registered (*Hukou*) residence, current residence, and gender at the county (or district) level. We restrict the sample to the working-age population (ages 16–64) and aggregate observations to the city level to form origin–destination migration matrices for men and women, denoted by $\lambda_{od}^{M}$ and $\lambda_{od}^{F}$, respectively. These matrices capture the baseline spatial distribution of workers by gender before the housing price shocks.

**Crime Participation** To construct baseline participation rates in criminal activity, we first aggregate total inflows from all origins to obtain the resident population in each destination city by gender. Using the China Judgments Online Database, we identify all recorded criminal cases in 2015 and extract the number of convicted offenders by city and gender. Dividing this count by the total resident population yields the share of individuals engaged in crime for each gender, denoted by $\delta_{d,c}^{M}$ and $\delta_{d,c}^{F}$. The complementary shares, $\delta_{d,\ell}^{M}$ and $\delta_{d,\ell}^{F}$, represent participation in the legitimate sector. These participation shares capture the equilibrium allocation of workers across legal and illegal activities at the city level in 2015.

**Returns to Crime** A central component of the model is how the profitability of crime responds to local conditions. Two parameters govern this mechanism: $\rho$, the elasticity of crime returns with respect to the number of criminals ($L_{d,c}$), and $\eta$, the elasticity with respect to the number of legal-sector workers ($L_{d,\ell}$). These parameters determine whether gendered migration—by altering city-level population composition—amplifies or dampens overall criminal activity. We estimate $\rho$ and $\eta$ using city-level data from the China Judgments Online Database. For each city, we calculate the total monetary amount involved in all adjudicated criminal cases and divide it by the number of offenders to obtain the average monetary return per crime. We then regress the logarithm of this measure on the logarithms of the number of criminals and the number of legal-sector workers, estimating both elasticities jointly. The resulting estimates, $\rho = -0.22$ and $\eta = 0.82$, reveal two key insights. First, the negative value of $\rho$ points to congestion effects among criminals, suggesting that competition for illicit opportunities reduces the average return to crime. Second, the positive $\eta$ implies that crime profitability rises with the scale of the legitimate economy, reflecting greater potential targets or complementary demand for illicit services. These parameters govern how shifts in gender composition, driven by housing-induced migration, propagate through the economy to affect overall crime.

**Exogenous Housing Price Shocks** To obtain plausibly exogenous variation in local housing prices over 2015–2018, we exploit the lagged pass-through from land markets to housing markets. Following the IV strategy in section 3.2 and the logic in Saiz (2010), we instrument current housing prices with one-year-lagged land prices.[34] The identifying idea is that land prices largely reflect earlier government auctions and planning cycles, which are predetermined relative to contemporaneous local demand or speculative conditions. This timing helps isolate supply-driven movements in housing prices, rather than shocks that directly shift crime. Formally, we use the fitted component of housing prices from the first stage as

$$\ln HP_{dt} = \gamma_0 + \gamma_1 \ln LandPrice_{dt-1} + \lambda_t + \lambda_d + \epsilon_{dt}, \tag{15}$$

where $\lambda_t$ and $\lambda_d$ are year and city fixed effects. The fitted values $\widetilde{HP}_{dt}$ capture variation in housing prices explained by exogenous changes in land supply conditions—reflecting, for example, regulatory release of land or geographic constraints on expansion—while abstracting from contemporaneous demand pressures. We then compute the predicted cumulative housing-price growth between 2015 and 2018 as

$$\hat{Q}_d = \widetilde{HP}_{d,2018} / \widetilde{HP}_{d,2015}. \tag{16}$$

This ratio measures the component of local housing-price changes that stems from predetermined land-market forces rather than from demand-driven feedbacks such as migration or investment surges. Because the timing and administrative nature of land-price adjustments precede and constrain housing development decisions, $\hat{Q}_d$ provides a credible source of exogenous cross-city variation in housing-price shocks. The final sample consists of 260 cities, which form the spatial units for the quantitative analysis.

**Other Model Parameters** Other parameters used in the model are calibrated from national survey data and existing studies to ensure consistency with observed behavior and prior empirical estimates. In particular, the gender-specific housing expenditure share, $\alpha^\theta$, is obtained from the 2010 China Family Panel Survey. We compute the national averages separately for males and females, yielding values of 0.30 and 0.15, respectively.[35] The parameter $\sigma$ represents the male share of total labor compensation in the legal sector and is

[34] The first-stage Kleibergen–Paap rk Wald $F$ statistic is 21 in column (3) of Table 1, mitigating weak-instrument concerns.

[35] These estimates are close to the benchmark value of 0.25 reported by Chen et al. (2025) for China and fall within the range documented for other advanced economies. For reference, estimates for other countries include the United States (0.23–0.32), France (0.27-0.33), the United Kingdom (0.15–0.31), and Germany (0.25–0.33) (Ahlfeldt et al., 2015; Combes et al., 2019; Ahlfeldt and Pietrostefani, 2019; Ahlfeldt et al., 2020; Overman and Xu, 2024).

set to 0.63, calculated from the 2015 1% Population Survey based on aggregated male and female wage income. In addition, the shape parameter $\epsilon$, which governs the elasticity of workers' sectoral choice with respect to relative wages, is fixed at 1.5, following Gould et al. (2002) and Machin and Meghir (2004). The migration elasticity parameter $\kappa$ is likewise set to 1.5, in line with Tombe and Zhu (2019). A summary of all parameter values is displayed in Table 6.

Table 6: Summary of Key Parameter Calibration in the Model

| Parameter | Description | Source | Value |
|---|---|---|---|
| $\lambda_{od}^{\theta}$ | Migration flow by gender | 2015 1% Population Survey | |
| $\delta_{d,c}^{\theta}$ | Crime participation rates by gender | China Judgments Online Database | |
| $\hat{Q}_d$ | Hat change in housing prices | China Land Market website | |
| $\rho$ | Congestion elasticty w.r.t offenders | Authors' own calculation | -0.22 |
| $\eta$ | Agglomeration elasticity w.r.t. workers | Authors' own calculation | 0.82 |
| $\alpha^M$, $\alpha^F$ | Housing expenditure share by gender | 2010 China Family Panel Survey | 0.35, 0.15 |
| $\sigma$ | Male share of total labor compensation | 2015 1% Population Survey | 0.63 |
| $\epsilon$ | Elasticity of workers' sectoral choice | Gould et al. (2002), Machin et al. (2004) | 1.5 |
| $\kappa$ | Migration elasticity | Tombe and Zhu (2019) | 1.5 |

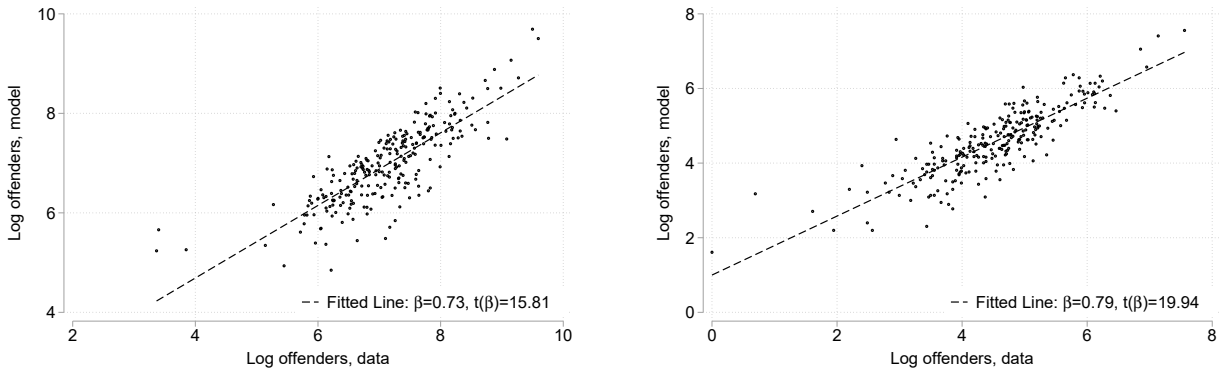
## 5.2 Model Fit

We begin by assessing how well the model replicates key empirical moments, with particular attention to crime participation. Figure 3 compares the model-predicted number of offenders—driven entirely by exogenous housing price shocks—with the actual number of offenders recorded across 260 cities. Panel (a) reports the results for males. The fitted line between predicted and observed values has a slope of 0.73 ($t = 15.81$) and an $R^2$ of 0.67, indicating that the model explains more than half of the observed cross-city variation in male crime participation. Cities with larger positive housing price shocks tend to have higher predicted and observed crime rates, consistent with the model's mechanism linking housing-induced income pressure to criminal incentives. Panel (b) shows the corresponding comparison for females, suggesting that the model performs similarly well in capturing spatial differences in female crime participation. The close correspondence between predicted and observed outcomes demonstrates that the model not only reproduces the aggregate level of crime participation but also translates housing-market shocks into quantitatively realistic behavioral responses across gender and location.

## 5.3 Housing Shocks and Crime

**Redistributional Pattern and the Role of Selective Migration** We begin by examining how housing price shocks reshape the spatial distribution of crime. Panel (a) of

Figure 3: Model Fit: Predicted versus Observed Crime Participation in 2018



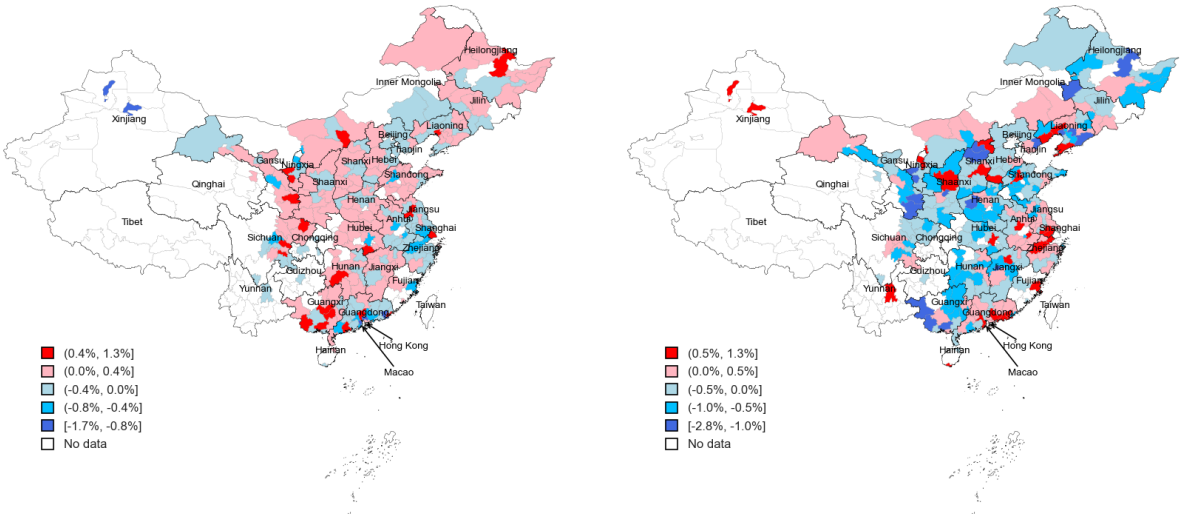

(a) Males (b) Females

Note: Each dot represents one city. The horizontal axis plots the observed number of criminal offenders in 2018, while the vertical axis plots the model-predicted number of offenders generated by exogenous housing price shocks between 2015 and 2018. The fitted solid line corresponds to the best linear fit across cities. In panel (a), the slope of 0.73 ($t = 15.81$, $R^2 = 0.67$) indicates that the model explains more than half of the cross-city variation in male crime participation. In panel (b), the slope of 0.79 ($t = 19.94$, $R^2 = 0.74$) suggests a similarly strong correspondence for females. The diagonal 45-degree line represents perfect prediction. Deviations from this line capture city-specific residuals not explained by the model. Together, the panels illustrate that the model successfully reproduces the spatial distribution of crime participation across genders.

Figure 4 depicts the geographic pattern of changes in total crime participation, where warm colors (red) indicate increases and cool colors (blue) denote declines. Crime reductions are concentrated in coastal cities and provincial capitals—areas that experienced the steepest housing price appreciation between 2015 and 2018. In contrast, crime increases are most pronounced in inland and northeastern regions, where housing markets remained relatively stagnant. This spatial divergence reflects a redistribution of population pressure from high-cost to low-cost areas. Rising housing prices reduce local affordability and disproportionately displace males, who are generally more mobile and more sensitive to changes in the cost of living. As these workers leave high-cost cities, local crime participation tends to fall; conversely, crime may rise in the destinations that absorb them. Migration thus serves as a key transmission channel through which housing shocks propagate across regions. Panel (b) of Figure 4 provides supporting evidence by showing the corresponding changes in out-migration rates. The pattern closely mirrors that of crime participation: cities with higher out-migration experience sharper declines in crime, whereas those attracting more residents show rising crime rates. The negative spatial correlation between migration and crime offers direct empirical support for the model's mechanism—housing price shocks affect crime not only through local income pressures but also by reshaping migration flows and, in turn, the demographic composition of the urban labor force.

To illustrate the underlying mechanism, we examine gender-specific responses to housing price shocks. Figure 5 plots the relationship between city-level housing price shocks and

Figure 4: Crime and Migration Responses to Housing Price Shocks, 2015–2018



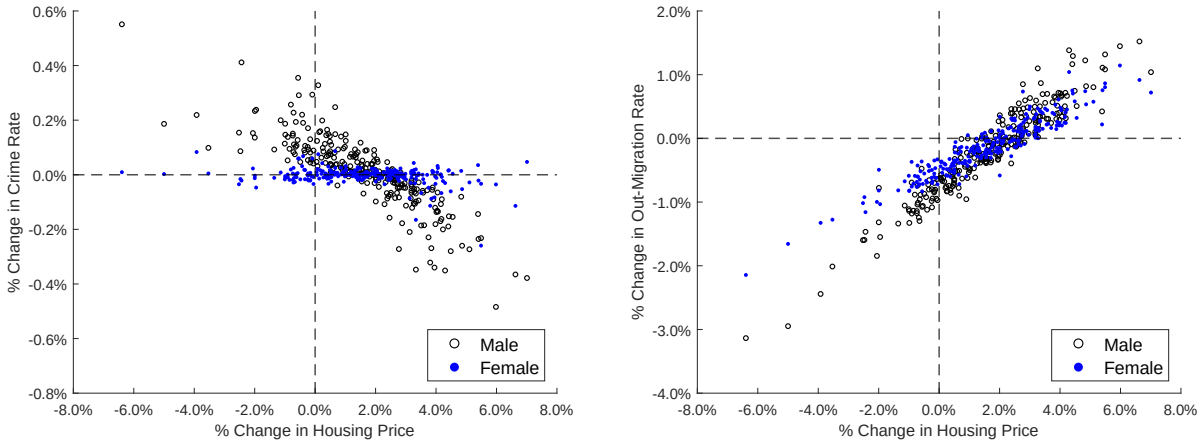

(a) Change in Crime Rate

(b) Change in Out-Migration Rate

Note: Each map displays city-level percentage changes between 2015 and 2018 predicted by the model, where the underlying variation is driven by exogenous housing price shocks. Panel (a) shows the predicted change in total crime participation, defined as the percentage change in the number of offenders per 10,000 residents. Panel (b) displays the corresponding change in out-migration rates, measured as the percentage change in the number of residents migrating out of each city relative to its population. Color intensity represents the magnitude of change: warm colors (red) indicate increases and cool colors (blue) indicate declines. Cities with missing or incomplete data are shaded in gray. The housing price shocks are constructed as predicted values from the first-stage regression described in section 3.2, where housing prices are instrumented using one-year-lagged land prices. All variables are standardized by city population to ensure comparability across regions.

the corresponding changes in crime and out-migration rates by gender. Panel (a) reveals a pronounced negative relationship between housing price shocks and male crime rates: cities experiencing larger housing price increases tend to exhibit sharper reductions in male crime participation. In contrast, female crime rates show no systematic relationship with housing price changes, suggesting that women's engagement in criminal activity is far less sensitive to housing market fluctuations. Panel (b) shows that rising housing prices are associated with higher out-migration, particularly among males. The stronger male response reflects both higher mobility and greater exposure to the financial burden of rising living costs. These patterns indicate that housing price shocks induce selective migration: males are more likely to move out of high-cost cities, leading to a compositional decline in male crime participation. This mechanism is consistent with the empirical estimates reported in Table 3.

Figure 5: Gender Differences in the Response to Housing Price Shocks




(a) Change in Crime Rate

(b) Change in Out-Migration Rate

Note: Each dot represents a city. The horizontal axis reports the exogenous change in housing prices. The vertical axes show the corresponding percentage changes in (a) the crime rate (number of offenders per 10,000 residents) and (b) the out-migration rate. Both measures are expressed in "hat" form, $\hat{x}_d = x_{d,2018}/x_{d,2015} - 1$, capturing the cumulative proportional change over the period. Blue dots denote female outcomes and black dots denote male outcomes. The fitted solid lines represent gender-specific linear trends.

**Net Crime Effects and Fiscal Implications** To quantify the aggregate impact of housing price shocks, we decompose the change in the number of criminal workers in each city $d$ into shift–share form:

$$\Delta L_{d,c} = \Delta L_d \delta_{d,c} + L'_d \Delta \delta_{d,c}. \tag{17}$$

The first term, $\Delta L_d \delta_{d,c}$, captures the shift effect—the impact of changes in the overall labor force holding the crime participation rate constant. The second term, $L'_d \Delta \delta_{d,c}$, captures the share effect—changes in the crime participation rate conditional on the new labor force

size. Panel (a) of Table 7 reports this decomposition. Column (1) shows the total change in criminal workers, while columns (2) and (3) report the shift and share contributions. We also split cities into net outflow and net inflow groups after the housing-price shocks.

Table 7: Decomposition of Crime Participation Changes Induced by Housing Price Shocks

| | (1) Total Change in Criminal Workers $\Delta L_{d,c}$ | (2) Shift Change $\Delta L_d \delta_{d,c}$ | (3) Share Change $L'_d \Delta \delta_{d,c}$ |
|---|---|---|---|
| *Panel (a): Baseline results* | | | |
| Net Outflow Cities | -619 | -351 | -268 |
| Net Inflow Cities | 475 | 279 | 196 |
| All Cities | -145 | -72 | -72 |
| *Panel (b): The role of technology parameters* | | | |
| Congestion parameter ($\rho$) | | | |
| $0.5 \times \rho_0$ | -165 | -72 | -92 |
| $2 \times \rho_0$ | -116 | -72 | -44 |
| Agglomeration parameter ($\eta$) | | | |
| $0.5 \times \eta_0$ | -108 | -72 | -35 |
| $2 \times \eta_0$ | -218 | -72 | -145 |

Note: Panel (a) quantifies the aggregate change in the number of criminal workers induced by exogenous housing price shocks between 2015 and 2018, and decomposes the change into shift and share components as defined in Equation (17). The variable $\Delta L_{d,c}$ measures the total change in the number of criminal workers in city $d$. The first term, $\Delta L_d \delta_{d,c}$, represents the *shift component*—the effect of changes in the total labor force holding the crime participation rate constant—while the second term, $L'_d \Delta \delta_{d,c}$, represents the *share component*—the effect of changes in crime participation conditional on the new labor force size. The decomposition is implemented for each city using model-predicted values under the estimated housing price shocks, where housing prices are instrumented by one-year-lagged land prices following the specification described in Section 3.2. Results are then aggregated into two groups: cities with net labor outflows (where rising housing costs push workers to migrate out) and cities with net labor inflows (which absorb these migrants). The final row reports the nationwide total across all cities. A negative value indicates a decline in the number of criminal workers relative to the 2015 baseline. Panel (b) reports counterfactual outcomes for the nationwide total change in the number of criminal workers induced by exogenous housing price shocks, where the congestion parameter ($\rho$) and the agglomeration parameter ($\eta$) are varied around their baseline values ($\rho_0 = -0.22$, $\eta_0 = 0.82$).

In cities facing net labor outflows, typically high-cost regions where housing prices rose sharply, the number of criminal workers declines by a total of 619. This reduction reflects two reinforcing forces: a shrinking local labor force and a lower crime participation rate, as the returns to crime fall with a smaller market size and reduced opportunities for illegal activity. In contrast, net inflow cities—generally lower-cost inland regions—see an increase of 474 criminal workers. Although migration redistributes crime across space, the reduction in outflow cities more than offsets the rise in inflow cities, producing a nationwide net decline of 145 criminal workers. To gauge the fiscal consequences of crime redistribution, we follow Di Tella and Schargrodsky (2013) and use incarceration costs as a benchmark. Their estimates place the daily cost of imprisonment at approximately USD 34 per inmate, or about USD 12,410 per year. Applying this figure, we convert the net change in criminal participation associated with housing price shocks into fiscal terms. The estimated nationwide decline of 145 offenders translates into annual government savings of roughly USD 5 billion

in prison expenditures.[36] This result shows that housing-induced selective migration does more than reallocate crime: it reduces crime in the aggregate. By contracting activity in high-cost origin cities, the shock shrinks the effective market for crime, lowering equilibrium participation and easing the fiscal and social burdens of offending.

How housing-induced migration translates into a national change in crime depends on how local conditions shift the relative payoff to offending. The key objects are the technology parameters governing city-size effects in the legitimate sector: congestion ($\rho < 0$) and agglomeration ($\eta > 0$). Panel (b) of Table 7 varies $(\rho, \eta)$ around their baseline values and reports the implied nationwide change in criminal workers. The shift component is essentially fixed at $-72$ across all cases, so the variation in the aggregate effect comes entirely from the share component, that is, changes in the crime participation rate. When congestion is stronger (more negative $\rho$), the national decline shrinks (from $-165$ at $0.5 \times \rho_0$ to $-116$ at $2 \times \rho_0$). When agglomeration is stronger (higher $\eta$), the decline grows sharply (from $-108$ at $0.5 \times \eta_0$ to $-218$ at $2 \times \eta_0$).

These results show that crime technology matters because it governs how migration changes the *return to legal work*, and thus the participation margin, not because people are mechanically reallocated across space. The policy implication is conditional. If inflow cities convert density into higher legal productivity and wages (high $\eta$), housing-driven concentration tends to *reduce* crime, and policies that ease mobility while expanding housing supply in productive cities are likely to deliver net crime reductions. If instead legal agglomeration is weak and illicit returns are not competed away in dense markets (low $\eta$ and weak congestion), concentration can *raise* crime in destination cities even as it falls in origin cities. In that environment, mobility and housing reforms should be paired with place-based interventions in receiving cities that strengthen legal opportunities or compress criminal returns.

**How Migration Costs Shape Crime Patterns** Appendix C studies how mobility frictions mediate the crime response to housing-price shocks.[37] Lower migration costs increase mobility and shift population toward larger, higher-income cities; because men are more mobile and more responsive to economic incentives in the model, the resulting adjustment in criminal participation is disproportionately male. Mobility also affects where crime con-

[36] Crime imposes substantial economic and social costs (Detotto and Vannini, 2010; Chalfin, 2015; Heeks et al., 2018). Beyond direct losses to victims, criminal activity generates indirect costs through heightened fear, deteriorating mental health, and increased household spending on precautionary measures such as security systems. Governments also face significant fiscal burdens, as maintaining public safety requires sustained expenditures on policing, courts, and correctional facilities (Welsh et al., 2015; Morris and Tweeten, 1971).

[37] Holding all other parameters fixed, we vary domestic migration costs symmetrically by $\pm 10\%$ around the baseline and recompute the equilibrium under the same housing shocks; Appendix C describes the procedure in detail.

centrates: as migration costs fall, the Herfindahl–Hirschman Index of criminal workers rises, indicating that criminal activity becomes more concentrated in a smaller set of large urban centers. The key takeaway is not that easing mobility mechanically "raises crime," but that it changes both the level and the spatial concentration of criminal participation by strengthening migration toward locations where the returns to crime are highest.

# 6 Conclusion

Gender-biased internal migration can reshape the geography of crime. Using crime measures from millions of court judgment documents, this paper studies how housing-price shocks, a defining feature of China's urban economy and a key driver of local conditions, induce male-selective migration and thereby reallocate criminal activity across cities.

Our first contribution is to show that rising housing prices in a city reduce its crime rate. We interpret this decline through a marriage-market mechanism: norms that place a disproportionate housing burden on men make housing costs a binding constraint on male household formation, so higher prices induce male-selective out-migration from high-cost cities. Because offending is overwhelmingly male, this sorting shrinks the local supply of potential offenders in origin cities and shifts crime pressure toward destination cities, consistent with the spillover patterns in the data.

Our second contribution is to move beyond reduced-form evidence by developing a spatial general-equilibrium model that quantifies the aggregate and distributional crime effects of housing-cost-induced, male-selective migration. The model features gender-specific location and sector choices, with men and women differing in housing expenditure shares and expected criminal returns. Calibrated to match the pre-shock equilibrium, it implies that housing-price increases over 2015–2018 reduce nationwide criminal participation, with gains concentrated in high-cost net outflow cities and partly offset by higher participation in lower-cost destinations. The model clarifies why housing shocks can generate large cross-city reallocation yet only a modest aggregate change: crime payoffs are only weakly checked by local offender density but rise strongly with legal scale, so mobility shifts both the supply of potential offenders and local crime opportunities.

These results have direct policy implications. Housing shocks generate cross-city spillovers in crime through migration, so place-based public-safety policy must account for displacement toward receiving cities. Reforms that ease mobility and improve the portability of public services can further mitigate both the level and concentration of crime induced by housing shocks. More broadly, housing policy, migration frictions, and local public safety are tightly linked, and policies that improve affordability and reduce mobility barriers can deliver social gains beyond standard labor-market and welfare outcomes.

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# A Theoretical Appendix

## A.1 Derivation of Comparative Statics

**Spatial Sorting by Gender.** The probability that a worker chooses to live in city $d$ is:

$$\lambda_d^\theta = \left(\frac{y_d^\theta B_d}{Q_d^{\alpha^\theta}\tau_d}\right)^\kappa \Big/ \sum_{d'}\left(\frac{y_{d'}^\theta B_{d'}}{Q_{d'}^{\alpha^\theta}\tau_{d'}}\right)^\kappa. \tag{A.1}$$

Within each city, share of workers in sector $s \in \ell, c$ is:

$$\delta_{d,s}^\theta = \frac{E_{d,s}(w_{d,s}^\theta)^\epsilon}{E_{d,\ell}(w_{d,\ell}^\theta)^\epsilon + E_{d,c}(w_{d,c}^\theta)^\epsilon}. \tag{A.2}$$

Accordingly, the total labor supply of gender $\theta$ in sector $s$ and city $d$ is:

$$L_{d,s}^\theta = \bar{L}^\theta \lambda_d^\theta \delta_{d,s}^\theta. \tag{A.3}$$

Taking the derivative of the relative labor supply with respect to the logarithm of the housing price $Q_d$, we obtain:

$$\frac{\partial}{\partial \ln Q_d}(\ln \frac{L_{d,s}^M}{L_{d,s}^F}) \propto \frac{\partial}{\partial \ln Q_d}(\ln \frac{\lambda_d^M}{\lambda_d^F}) \propto \kappa(\alpha^F - \alpha^M). \tag{A.4}$$

**Sector Sorting by Gender** In the legitimate sector, wages are gender-neutral, $w_{d,\ell}^M = w_{d,\ell}^F$. In the crime sector, males enjoy higher expected returns, reflecting gender-based productivity differences:

$$\ln \frac{w_{d,c}^M}{w_{d,c}^F} = \ln \frac{m^M}{m^F}, \quad \text{with } m^M > m^F,$$

where $m^\theta$ denotes gender-specific productivity in crime. Equations (A.2) and (A.3) imply:

$$\ln \frac{L_{d,c}^M/L_{d,\ell}^M}{L_{d,c}^F/L_{d,\ell}^F} = \ln \frac{\delta_{d,c}^M}{\delta_{d,c}^F} - \ln \frac{\delta_{d,\ell}^M}{\delta_{d,\ell}^F} = \epsilon(\ln \frac{w_{d,c}^M}{w_{d,\ell}^M} - \ln \frac{w_{d,c}^F}{w_{d,\ell}^F}) = \epsilon \ln(m^M/m^F). \tag{A.5}$$

**Housing Price and Crime Rate** The crime rate in city $d$ is defined as:

$$\text{CrimeRatio}_d \equiv \frac{L_{d,c}^M + L_{d,c}^F}{L_{d,\ell}^M + L_{d,\ell}^F} = \xi_{d,\ell}\frac{L_{d,c}^M}{L_{d,\ell}^M} + (1-\xi_{d,\ell})\frac{L_{d,c}^F}{L_{d,\ell}^F}, \tag{A.6}$$

where $\xi_{d,\ell} \equiv \frac{L_{d,\ell}^M}{L_{d,\ell}^M + L_{d,\ell}^F}$ denotes the share of males in the legitimate labor force. This expression shows that the overall crime rate is a weighted average of gender-specific crime ratios with

weights corresponding to the gender composition of the legitimate workforce—$\xi_{d,\ell}$ for males and $1-\xi_{d,\ell}$ for females.

Using equations (A.2) and (A.3), the female crime ratio can be expressed as:

$$\frac{L^F_{d,c}}{L^F_{d,\ell}} = \frac{E_{d,c}(w^F_{d,c})^\epsilon}{E_{d,\ell}(w^F_{d,\ell})^\epsilon}. \tag{A.7}$$

Combining this with equation (A.5), the male crime ratio can be written as

$$\frac{L^M_{d,c}}{L^M_{d,\ell}} = (\frac{m^M}{m^F})^\epsilon \frac{L^F_{d,c}}{L^F_{d,\ell}}. \tag{A.8}$$

Hence, the crime rate is given by:

$$\text{CrimeRatio}_d = \xi_{d,\ell}\left((\frac{m^M}{m^F})^\epsilon - 1\right)\frac{L^F_{d,c}}{L^F_{d,\ell}} + \frac{L^F_{d,c}}{L^F_{d,\ell}}. \tag{A.9}$$

Taking the derivative of the crime rate with respect to the logarithm of housing prices $Q_d$, we obtain:

$$\frac{\partial}{\partial \ln Q_d}\text{CrimeRatio}_d \propto \frac{\partial}{\partial \ln Q_d}\xi_{d,\ell}\left((\frac{m^M}{m^F})^\epsilon - 1\right) \tag{A.10}$$

Note that $\xi_{d,\ell} = \frac{L^M_{d,\ell}}{L^M_{d,\ell}+L^F_{d,\ell}} = 1 - \left(1+\frac{L^M_{d,\ell}}{L^F_{d,\ell}}\right)^{-1}$. Applying equation (A.4), we derive:

$$\frac{\partial}{\partial \ln Q_d}\text{CrimeRatio}_d \propto \kappa(\alpha^F - \alpha^M)\left((\frac{m^M}{m^F})^\epsilon - 1\right). \tag{A.11}$$

## A.2 Equilibrium and Hat Algebra

Given the parameter set $\{\alpha^\theta, \sigma, \mu, \kappa, \epsilon, \rho, \eta\}$ and the exogenously location- and sector-specific characteristics $\{\bar{L}^\theta_o, A_{d,s}, B_d, E_{d,s}, M_d, K_d, \tau_{od}, p_d\}$, the general equilibrium of the model above is vectors of $\{\lambda^\theta_{od}, \delta^\theta_{d,s}, L^\theta_{d,s}, w^\theta_{d,s}, Q_d\}$ that satisfies the following system of equations:

$$\lambda^\theta_{od} = \frac{L^\theta_{od}}{\bar{L}^\theta_o} = \frac{\left(\frac{y^\theta_d B_d}{Q_d^{\alpha^\theta}\tau_{od}}\right)^\kappa}{\sum_{d'}\left(\frac{y^\theta_{d'} B_{d'}}{Q_{d'}^{\alpha^\theta}\tau_{od'}}\right)^\kappa} \tag{A.12}$$

$$y^\theta_d = \xi_i\left[E_{d,\ell}(w^\theta_{d,\ell})^\epsilon + E_{d,c}(w^\theta_{d,c})^\epsilon\right]^{1/\epsilon} \tag{A.13}$$

$$\delta^\theta_{d,s} = \frac{E_{d,s}(w^\theta_{d,s})^\epsilon}{E_{d,\ell}(w^\theta_{d,\ell})^\epsilon + E_{d,c}(w^\theta_{d,c})^\epsilon} \tag{A.14}$$

$$L_d^\theta = \sum_o L_{od}^\theta = \sum_o \lambda_{od}^\theta \bar{L}_o^\theta \tag{A.15}$$

$$L_{d,s}^\theta = L_d^\theta \delta_{d,s}^\theta \tag{A.16}$$

$$L_{d,s} = L_{d,s}^M + L_{d,s}^F \tag{A.17}$$

$$w_{d,\ell}^M = \sigma A_{d,\ell} (\frac{L_{d,\ell}^M}{L_{d,\ell}^F})^{\sigma-1} \tag{A.18}$$

$$w_{d,\ell}^F = (1-\sigma) A_{d,\ell} (\frac{L_{d,\ell}^M}{L_{d,\ell}^F})^{\sigma} \tag{A.19}$$

$$w_{d,c}^\theta = (1-p_d)\, A_{d,c} m^\theta (L_{d,c})^\rho (L_{d,\ell})^\eta \tag{A.20}$$

$$H_d = \frac{\alpha^M y_d^M}{Q_d} L_d^M + \frac{\alpha^F y_d^F}{Q_d} L_d^F \tag{A.21}$$

To quantify the effects of housing price shocks, denoted by $\hat{Q}_d$, we apply the exact hat algebra method. A variable with a hat, $\hat{x}$, represents a relative change, defined as $\hat{x} = x'/x$. Accordingly, the relative changes in equilibrium are characterized by the following system of equations:

$$\hat{\lambda}_{od}^\theta = \frac{\left(\hat{y}_d^\theta (\hat{Q}_d)^{-\alpha^\theta} \hat{\tau}_{od}^{-1}\right)^\kappa}{\sum_{d'} \lambda_{od'}^\theta \left(\hat{y}_{d'}^\theta (\hat{Q}_{d'})^{-\alpha^\theta} \hat{\tau}_{od'}^{-1}\right)^\kappa} \tag{A.22}$$

$$\hat{y}_d^\theta = \left[(\hat{w}_{d,\ell}^\theta)^\epsilon \delta_{d,\ell}^\theta + (\hat{w}_{d,c}^\theta)^\epsilon \delta_{d,c}^\theta\right]^{1/\epsilon} \tag{A.23}$$

$$\hat{\delta}_{d,s}^\theta = \frac{(\hat{w}_{d,s}^\theta)^\epsilon}{(\hat{w}_{d,\ell}^\theta)^\epsilon \delta_{d,\ell}^\theta + (\hat{w}_{d,c}^\theta)^\epsilon \delta_{d,c}^\theta} \tag{A.24}$$

$$\hat{L}_d^\theta = \sum_o \hat{\lambda}_{od}^\theta \frac{L_{od}^\theta}{L_d^\theta} \tag{A.25}$$

$$\hat{L}_{d,s}^\theta = \hat{L}_d^\theta \hat{\delta}_{d,s}^\theta \tag{A.26}$$

$$\hat{L}_{d,s} = \hat{L}_{d,s}^M \frac{L_{d,s}^M}{L_{d,s}} + \hat{L}_{d,s}^F \frac{L_{d,s}^F}{L_{d,s}} \tag{A.27}$$

$$\hat{w}_{d,\ell}^M = (\frac{\hat{L}_{d,\ell}^M}{\hat{L}_{d,\ell}^F})^{\sigma-1} \tag{A.28}$$

$$\hat{w}_{d,\ell}^F = (\frac{\hat{L}_{d,\ell}^M}{\hat{L}_{d,\ell}^F})^{\sigma} \tag{A.29}$$

$$\hat{w}_{d,c}^\theta = (\hat{L}_{d,c})^\rho (\hat{L}_{d,\ell})^\eta \tag{A.30}$$

$$\hat{H}_d = \frac{\hat{y}_d^M}{\hat{Q}_d}\hat{L}_d^M HS_d^M + \frac{\hat{y}_d^F}{\hat{Q}_d}\hat{L}_d^F HS_d^F \tag{A.31}$$

# B Empirical Appendix

## B.1 Tables

Table A.1: Keywords in Criminal Case Classification

| Types | Chinese | English |
|---|---|---|
| 1 Public security | 失火 | negligent arson |
| | 决水 | breaching a dike |
| | 投放危险物质 | spreading dangerous materials |
| | 破坏交通工具 | sabotaging transportation vehicle |
| | 破坏交通设施 | sabotaging transportation facility |
| | 破坏电力设备 | sabotaging any electric power or gas facility |
| | 破坏易燃易爆设备 | sabotaging any inflammable or explosive equipment |
| | 破坏广播电视设施, 公用电信设施 | sabotaging any broadcasting, television or public telecommunications facility |
| | 重大飞行事故 | causing a grave air accident |
| | 铁路运营安全事故 | causing a railway operational accident |
| | 危险物品肇事 | violating the regulations on the control of dangerous materials and thereby causing a serious accident |
| | 工程重大安全事故 | lowering the quality standard of a construction project and thereby causing a serious accident |
| | 教育设施重大安全事故 | failing to adopt measures against dangers in educational facilities and thereby causing a serious accident |
| | 消防责任事故 | violating the regulations on fire prevention and causing a serious accident |
| | 不报, 谎报安全事故 | not reporting or not truly reporting when accident happens |
| | 非法制造, 买卖, 运输, 邮寄, 储存枪支, 弹药, 爆炸物 | illegally manufacturing, trading in, transporting, mailing or storing any guns, ammunition or explosives |
| | 非法制造, 买卖, 运输, 储存危险物质 | illegally manufacturing, trading in, transporting, mailing or storing any dangerous materials |
| | 违规制造, 销售枪支 | violating the regulations on manufacturing or selling guns |
| | 非法持有, 私藏枪支, 弹药 | illegally possessing or concealing any guns or ammunition |
| | 非法出租, 出借枪支 | illegally leasing or loaning guns |
| | 丢失枪支不报 | failing to report about the lost guns |
| | 非法携带枪支, 弹药, 管制刀具, 危险物品危及公共安全 | illegally entering a public place with any gun, ammunition, controlled cutting tool or any other dangerous tools and thereby endangering public security |
| 2 Traffic offence | 交通肇事 | violating regulations governing traffic and transportation and thereby causing a serious accident |
| | 危险驾驶 | driving dangerously |
| 3 Violence | 暴力危及飞行安全 | using violence against any person on board an aircraft and thereby endangers air safety |
| | 抗税 | refusing to pay taxes by means of violence or threat |
| | 强迫交易 | buying or selling commodities by violence or intimidation |
| | 强奸 | raping a woman or a child by violence, coercion or any other means |
| | 猥亵 | acting indecently against a woman or a child by violence, coercion or any other forcible means |
| | 侮辱 | publicly humiliating another person by violence or other methods |
| | 暴力干涉婚姻自由 | using violence to interfere with another person's freedom of marriage |
| | 妨害公务 | obstructing a functionary of a state organ from carrying out his functions by means of violence or threat |
| | 妨害作证 | coercing the witness by means of violence or threat |
| | 强迫卖血 | forcing another person to sell blood by means of violence or threat |
| | 武装叛乱, 暴乱 | organizing or carrying out armed rebellion or armed riot |
| | 强制 | forcing by means of violence or threat |
| | 绑架 | kidnapping |
| | 殴打 | beating |
| | 聚众扰乱 | gathering people to disturb public order |

| Types | Chinese | English |
|---|---|---|
| | 聚众斗殴 | gathering people to engage in affrays |
| | 劫夺被押解人员 | rescuing the criminal, defendant or criminal suspect under escort |
| | 暴动越狱 | instigating a riot to escape from prison |
| | 聚众持械劫狱 | gathering people to raid a prison with weapons |
| | 爆炸罪 | causing explosion |
| | 放火 | arson |
| | 故意杀人 | intentionally committing homicide |
| | 故意伤害 | intentionally inflicting injury upon another person |
| | 恐怖组织 | terrorist organization |
| | 恐怖活动 | terrorist activities |
| | 恐怖主义 | terrorism |
| | 极端主义 | extremism |
| | 武装掩护走私 | shielding smuggling with arms |
| | 抗拒缉私 | resisting the seizure of smuggled goods by means of violence or threat |
| | 非法拘禁 | unlawfully detaining another person |
| | 拐卖妇女 | abducting and trafficking in a woman |
| | 拐卖儿童 | abducting and trafficking in a child |
| | 收买被拐卖的妇女 | buying an abducted woman |
| | 收买被拐卖的儿童 | buying an abducted child |
| | 聚众阻碍解救被收买的妇女 | gathering people to prevent functionaries of a state organ from rescuing a sold woman |
| | 聚众阻碍解救被收买的儿童 | gathering people to prevent functionaries of a state organ from rescuing a sold child |
| | 劫持航空器 | hijacking an aircraft |
| | 劫持船只 | hijacking a ship |
| | 劫持汽车 | hijacking a motor |
| | 过失致人死亡 | negligently causing death to another person |
| | 非法搜查 | unlawfully subjecting another person to a body search or a search of his residence |
| | 非法侵入住宅 | unlawfully intruding into another person's residence |
| | 诽谤 | inventing stories to defame another person by violence or other methods |
| | 刑讯逼供 | extorting confession from a criminal suspect or defendant by torture |
| | 暴力取证 | extorting testimony from a witness by violence |
| | 虐待 | abuse |
| | 煽动暴力抗拒法律实施 | incites people to resist by violence the implementation of the laws and administrative rules and regulations of the state |
| | 寻衅滋事 | creating disturbances |
| | 组织, 领导, 参加黑社会组织 | forming, leading or taking an active part in organizations in the nature of criminal syndicate |
| | 非法集会, 游行, 示威 | illegally holding an assembly, a procession or a demonstration |
| | 强迫劳动 | compelling employees to work by restricting their personal freedom in violation of the laws and regulations on labour administration |
| | 雇用童工从事危重劳动 | hiring child labor to engaging in dangerous or hard work |
| | 报复陷害 | retaliation or circumvention |
| 4 Robbery | 抢劫 | robbing public or private property |
| | 抢夺 | forcibly seizing public or private property |
| | 聚众哄抢 | gathering people to forcibly seize public or private property |
| 5 Stealing | 盗窃 | stealing a relatively large amount of public or private property or committing theft repeatedly |
| | 盗掘 | excavating a site of ancient culture or ancient tomb of historical, artistic or scientific value |
| | 盗伐 | stealthily felling trees, bamboo, etc. in forest or woods |
| 6 Defrauduation | 诈骗 | swindling public or private property |
| 7 Extortion | 敲诈勒索 | extorting public or private money or property by blackmail |
| 8 Drugs | 毒品 | drugs related |
| 9 Prostitution | 聚众淫乱 | gathering to engage in licentious activities |
| | 组织卖淫 | arranging for another to engage in prostitution |
| | 强迫卖淫 | forcing another person to engage in prostitution |
| | 引诱, 容留, 介绍卖淫 | luring other persons into or sheltering prostitution or procuring other persons to engage in prostitution |
| | 引诱幼女卖淫 | luring a girl under the age of 14 to engage in prostitution |

| Types | Chinese | English |
|---|---|---|
| | 卖淫, 嫖娼 | prostitution |
| | 传播性病 | spreading serious venereal diseases such as syphilis and gonorrhea |
| | 淫秽 | pornography |
| 10 Gambling | 赌博 | gambling |
| 11 Counterfeiting | 生产, 销售伪劣产品 | producing or selling fake products |
| | 生产, 销售假药 | producing or selling fake medicines |
| | 生产, 销售劣药 | producing or selling medicines of inferior quality |
| | 生产, 销售不符合安全标准的食品 | producing or selling food that is not up to hygiene standards |
| | 生产, 销售有毒, 有害食品 | producing or selling food with toxic or harmful non-food raw materials |
| | 生产, 销售不符合标准的医用器材 | producing or selling medical apparatus and instruments or medical hygiene materials that are not up to the national or trade standards |
| | 生产, 销售不符合安全标准的产品 | producing or selling products that are not up to the national or trade standards |
| | 生产, 销售伪劣农药, 兽药, 化肥, 种子 | producing or selling fake pesticides, fake animal pharmaceuticals or fake chemical fertilizers |
| | 生产, 销售不符合卫生标准的化妆品 | producing or selling cosmetics that are not up to hygiene standards |
| 12 IP infringement | 假冒注册商标 | using a trademark which is identical with the registered trademark on the same kind of commodities without permission |
| | 销售假冒注册商标的商品 | selling commodities bearing counterfeit registered trademarks |
| | 非法制造, 销售非法制造的注册商标标识 | making or selling representations of the registered trademarks without authorization |
| | 假冒专利 | counterfeiting the patent of another |
| | 侵犯著作权 | infringing on copyright |
| | 销售侵权复制品 | selling works reproduced by infringing on the copyright of the owners |
| | 侵犯商业秘密 | infringing on business secrets |
| | 侵犯知识产权 | infringing on intellectual property |
| | 损害商业信誉, 商品声誉 | fabricating stories and spreading them to damage another person's business credit or commodity reputation |
| | 虚假广告 | fake advertisement |
| | 串通投标 | bid in collusion |
| | 组织, 领导传销活动 | organizing or leading pyramid scheme |
| | 非法经营 | illegal operation |
| | 伪造, 倒卖伪造的有价票证 | counterfeiting or scalping any negotiable tickets |
| | 非法转让, 倒卖土地使用权 | illegally transferring or scalping land-use right |
| | 提供虚假证明文件 | deliberately providing false testifying papers |
| | 逃避商检 | evading commodity inspection |
| | 扰乱市场秩序 | disturbing market's order |
| | 破坏社会主义市场经济秩序 | disrupting the order of the socialist market economy |
| 13 Finance | 伪造货币 | counterfeiting currencies |
| | 假币 | counterfeit currencies |
| | 变造货币 | altering currencies |
| | 擅自设立金融机构 | establishing a banking institution without the approval of the People's Bank of China |
| | 伪造, 变造, 转让金融机构经营许可证, 批准文件 | forging, altering or transferring the permit for operation of any banking institution |
| | 高利转贷 | fraudulently obtaining credit funds from a banking institution and transferring the funds to another at usury |
| | 骗取贷款, 票据承兑, 金融票证 | fraudulently obtaining loans, bill acceptance, financial securities |
| | 非法吸收公众存款 | illegally taking in deposits from the general public |
| | 伪造, 变造金融票证 | forging or altering financial bills |
| | 妨害信用卡管理 | hindering the management of credit card |
| | 伪造, 变造国家有价证券 | forging or altering treasury certificates or any other negotiable securities issued by the state |
| | 伪造, 变造股票, 公司, 企业债券 | forging or altering stocks or corporate or enterprise bonds |
| | 擅自发行股票, 公司, 企业债券 | issuing stocks or corporate or enterprise bonds without approval |
| | 内幕交易, 泄露内幕信息 | possessing inside information about any stock exchange transactions or illegally releasing such information before publication |
| | 利用未公开信息交易 | using undisclosed information in transactions |
| | 编造并传播证券, 期货交易虚假信息 | fabricating and spreading false information to adversely affect securities exchange |
| | 诱骗投资者买卖证券, 期货合约 | cajoling investors into buying or selling securities |

| Types | Chinese | English |
|---|---|---|
| | 操纵证券, 期货市场 | rigging stock prices |
| | 背信运用受托财产 | using entrusted property in breach of trust |
| | 违法运用资金 | illegally using funds |
| | 违法发放贷款 | illegally granting fiduciary loans |
| | 吸收客户资金不入账 | illegally lending the funds he absorbed from the clients instead of entering them into the account book |
| | 违规出具金融票证 | illegally issuing letters of credit or other letters of guaranty, negotiable instruments, deposit certificates or certificates of financial standing |
| | 对违法票据承兑, 付款, 保证 | accepting, paying or guaranteeing an illegal negotiable instrument |
| | 逃汇 | illegally transferring foreign exchange inside China out |
| | 洗钱 | money laundering |
| 14 Bribery | 贪污 | corruption |
| | 受贿 | accepting bribes |
| | 行贿, 贿赂 | bribery |
| | 巨额财产来源不明 | huge property with unknown source |
| | 隐瞒境外存款 | concealing his bank savings outside the territory of China |
| | 私分国有资产 | dividing up state-owned assets in secret |
| | 私分罚没财物 | dividing up in secret the fines or confiscated property |

Table A.2: Summary Statistics for Key Variables Used in Regressions, 2014-2018

| Variable | Num. Obs. | Mean | Std | Min | Max |
|---|---|---|---|---|---|
| Log number of criminal cases per ten thousand population | 1,315 | 1.41 | 0.54 | -0.58 | 3.28 |
| Log housing price (RMB/sq.m.) | 1,315 | 8.13 | 0.47 | 7.15 | 10.57 |
| Log land price (RMB/sq.m.) | 1,304 | 6.99 | 1.00 | 1.42 | 10.58 |
| Log sensitivity instrument (RMB/sq.m.) | 1,290 | 7.86 | 0.58 | 6.30 | 10.17 |
| Log GDP per capita (RMB) | 1,284 | 10.98 | 0.56 | 8.33 | 15.68 |
| Log fiscal expenditure per per capita (RMB) | 1,315 | 9.10 | 0.50 | 7.90 | 11.60 |
| Employment share of secondary industry | 1,314 | 0.45 | 0.14 | 0.08 | 0.83 |
| Employment share of tertiary industry | 1,313 | 0.53 | 0.13 | 0.17 | 0.90 |

Table A.3: Male Intensity Across Crime Types (Descending Order)

| (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|
| Traffic offense | Robbery | Violence | Public security | Stealing | Extortion | Bribery |
| 97.7% | 97.2% | 92.5% | 92.4% | 91.9% | 90.1% | 87.8% |
| (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| Drugs | Defraudation | Gambling | IP | Finance | Counterfeiting | Prostitution |
| 83.7% | 82.2% | 77.1% | 76.4% | 69.6% | 64.8% | 58.2% |

Table A.4: Robustness: Impact of Housing Prices on Crime Rates

| Dep var: $\ln(Crime/L)_{ct}$ | (1) Lagged Housing Price | (2) Wage-adjusted Housing Price | (3) Crime per Employment | (4) Excluding Capital Cities | (5) Export Shocks |
|---|---|---|---|---|---|
| $\ln HP_{ct}$ | -1.588** | -1.107** | -1.081** | -0.934** | -1.062** |
| | (0.627) | (0.456) | (0.464) | (0.401) | (0.430) |
| $ExportShock_{ct}$ | | | | | 0.007 |
| | | | | | (0.010) |
| Observation | 1,247 | 1,247 | 1,247 | 1,123 | 1,232 |
| City Controls | Y | Y | Y | Y | Y |
| City Fixed Effects | Y | Y | Y | Y | Y |
| Year Fixed Effects | Y | Y | Y | Y | Y |

Note: The sample consists of city–year observations from 2014 to 2018. The dependent variable is the logarithm of crime cases per capita, and the main explanatory variable is the logarithm of housing prices. Column (1) replaces contemporaneous housing prices with their one-year lag, while column (2) employs wage-normalized housing prices, defined as the ratio of housing prices to per capita disposable income of urban residents. Column (3) redefines the crime rate using end-of-year employment as the denominator, and column (4) excludes provincial capital cities from the sample. Column (5) adds a control for each city's export shocks. All specifications include city-level controls—GDP per capita, fiscal expenditure per capita, and the employment shares of the secondary and tertiary sectors—and instrument housing prices with a combination of lagged land prices and the sensitivity-based instrument. Standard errors are clustered at the city level *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

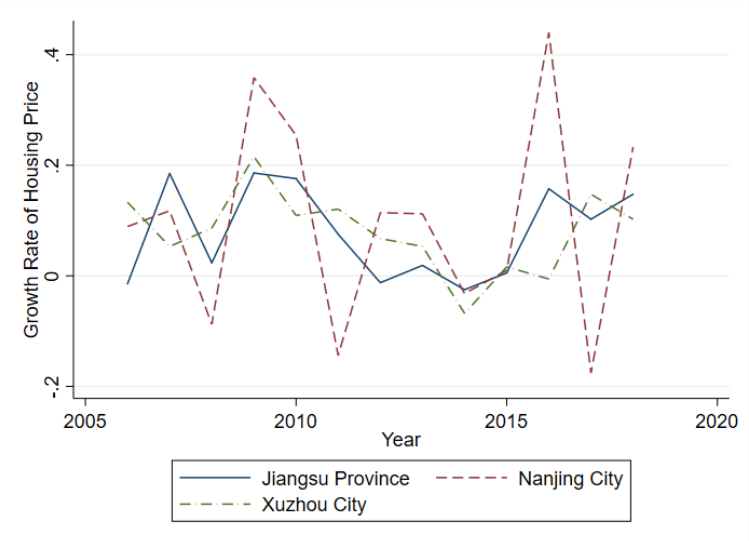
Table A.5: Housing Prices and Crime Rates: Controlling for Alternative Mechanisms

| Dependent variable: $\ln(Crime/L)_{ct}$ | (1) Social Stability | (2) Labor Market | (3) Educational Resources | (4) Mental Health | (5) Combined Controls |
|---|---|---|---|---|---|
| $\ln HP_{ct}$ | -1.078** | -1.068** | -1.093** | -1.176*** | -1.394** |
| | (0.506) | (0.425) | (0.451) | (0.415) | (0.566) |
| Observation | 1,076 | 1,215 | 1,200 | 702 | 596 |
| Alternative Mechanism Controls | Y | Y | Y | Y | Y |
| City Controls | Y | Y | Y | Y | Y |
| City Fixed Effects | Y | Y | Y | Y | Y |
| Year Fixed Effects | Y | Y | Y | Y | Y |

Note: The sample is composed of observations at the city-year level from 2014 to 2018. The dependent variable is the logarithmic number of criminal cases per ten thousand population. The variable of interest is the logarithmic CPI deflated housing price. Columns (1) through (5) sequentially control for city-level fiscal spending on public security, average wage, fiscal spending on education, the depression index, and export shocks, respectively. In all regressions, housing price is instrumented using the sensitivity IV. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

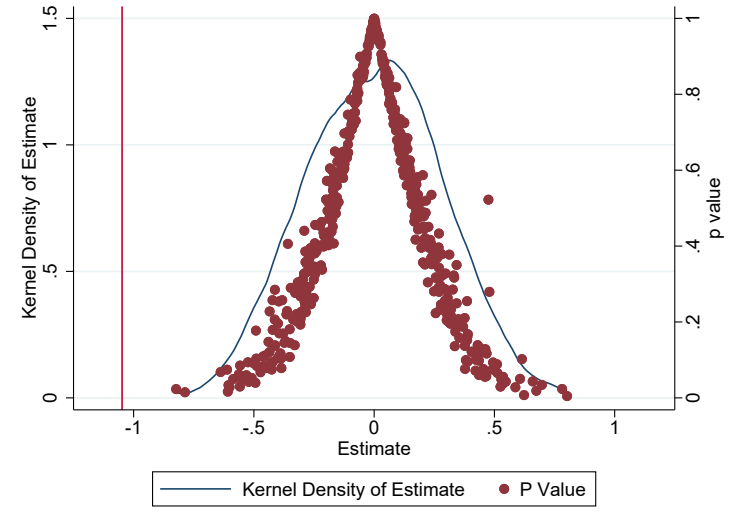
## B.2 Figures

Figure A.1: Housing Prices in Jiangsu Province and Two Selected Cities



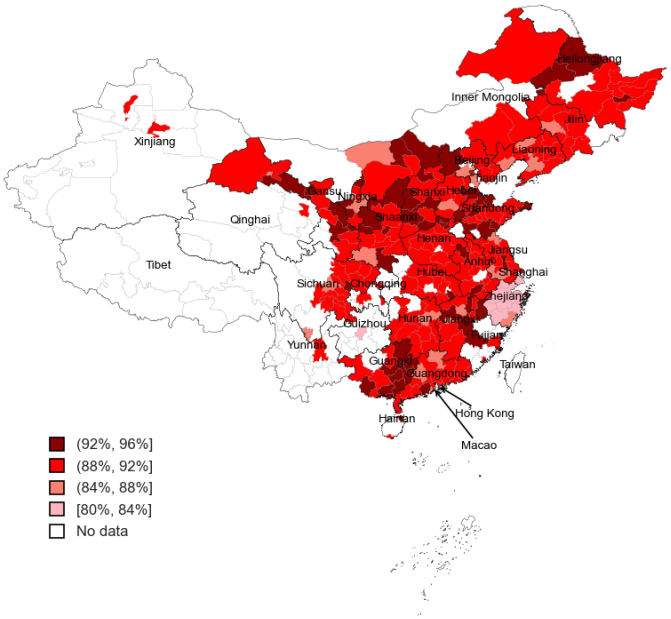

Note: The figure plots housing price growth rates from 2006 to 2018 for Jiangsu Province and its two representative cities, Nanjing and Xuzhou. All data are drawn from the China Real Estate Information website.

Figure A.2: Distribution of Estimated Coefficients in the Falsification Test




Note: The figure displays the kernel distribution of the simulated estimators and their p-values from the 500 simulations randomly assigning housing price to cities. The vertical line shows the benchmark estimator from the column (5) of Table 1.

Figure A.3: Distribution of Male Crime Intensity Across Cities in 2014




Note: Male crime intensity is defined as the share of crimes involving male offenders out of total criminal cases in each city in 2014.

# C Quantitative Appendix

**How Migration Costs Shape Crime Patterns.** This appendix analysis demonstrates that migration can generate nontrivial aggregate effects on the spatial distribution of crime, depending on the relative scale and returns of the criminal sector. This implies that migration policy may have broader social consequences, some of which could be unintended.[38] To assess this mechanism more systematically, we examine how domestic labor mobility influences the relationship between housing price shocks and crime participation. Specifically, we conduct a counterfactual experiment that varies domestic migration costs while holding all other model parameters constant. Migration costs are adjusted symmetrically within a range of $\pm 10\%$, represented as $\hat{\tau}_{od} \in \{0.9, 0.92, \ldots, 1.08, 1.1\}$. This exercise allows us to trace how differences in mobility barriers shape the reallocation of labor and, consequently, the aggregate and spatial effects of housing market shocks on crime.

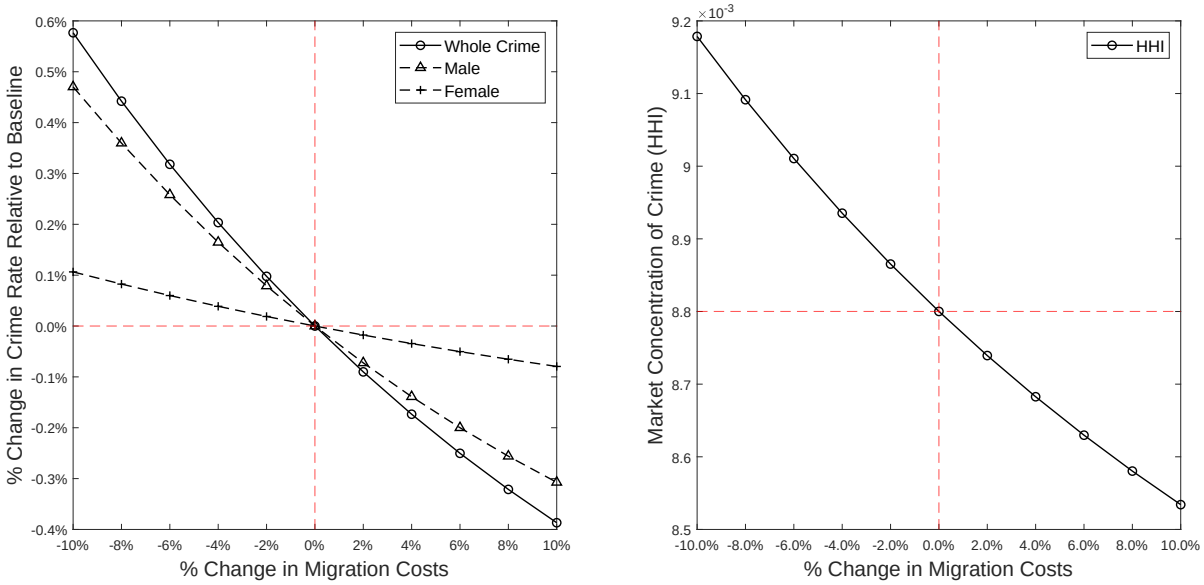
Panel (a) of Figure A.4 shows that lower migration costs raise overall crime participation relative to the baseline, with the effect more pronounced for males than for females. In contrast, higher migration costs—such as those imposed by stricter hukou regulations—help contain crime participation. This gender asymmetry reflects the structure of the model: males face a lower elasticity of migration costs and a higher sensitivity of occupational choice to relative wages. As migration becomes easier, male workers respond more strongly to housing price differentials and relocate toward larger, higher-income cities. This reallocation enlarges the effective market size of destination cities and raises the expected return to crime, leading to a disproportionate increase in male crime participation. Female mobility, by contrast, is constrained by higher effective migration costs and weaker wage responsiveness, resulting in smaller behavioral adjustments and a muted crime response.

Panel (b) provides corroborating evidence using the Herfindahl–Hirschman Index (HHI) of criminal workers, which measures the spatial concentration of crime. The HHI is calculated as the sum of squared city-level shares of total criminal workers, where higher values indicate a more concentrated distribution. The figure shows that as migration costs decline, the HHI rises steadily, implying that easier mobility channels crime into a smaller set of large urban centers. This pattern is consistent with the model's prediction that lower migration frictions amplify spatial inequality in crime by intensifying the relocation of mobile groups—primarily males—toward regions where the returns to criminal activity scale with city size.[39]

[38] For example, reducing migration costs may encourage greater labor mobility toward large cities, where higher population density and increasing returns in the crime sector could amplify overall crime rates.

[39] Cross-country evidence supports this implication. In the United States, where internal mobility is high and institutional barriers to relocation are minimal, crime has become increasingly concentrated in large metropolitan areas (Glaeser and Sacerdote, 1999). Despite a sharp nationwide decline in crime, violent and property offenses remain localized in major cities such as Chicago and Baltimore, with the ten largest

Figure A.4: The Role of Labor Mobility in the Impact of Housing Prices




(a) Crime Rate

(b) Crime Concentration

metropolitan areas accounting for more than half of all homicides (Weisburd, 2015; Sharkey, 2018). By contrast, in developed economies with a lower internal mobility—such as Spain—crime is more evenly distributed across medium-sized cities (Buonanno and Montolio, 2008), while in Latin American countries with weak transport integration, regional crime rates remain persistent and spatial diffusion limited (Gaviria, 2002).