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ABSTRACT

Housing Demolition and Occupational Mobility: Evidence from China*

We identify the causal impact of housing demolition on employment and occupational mobility of working-age individuals in China. We exploit housing demolition events as a quasi-natural experiment and apply a two-way fixed effects approach to overcome the potential endogeneity problem. Using data from the CHFS, we find that on the extensive margin, housing demolition creates skill waste by making individuals less likely to work; while on the intensive margin, housing demolition leads to occupational upward mobility, especially among low-skilled workers. We do not find any empirical evidence that housing demolition influences internal migration flow or migrant workers' occupational mobility.

JEL Classification: J24, J62
Keywords: housing demolition, occupational mobility, skill, migrant, China

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1 Introduction

During the past two to three decades, China has experienced a rapid urbanization process that has been accompanied by unprecedented economic growth. In the process of rapid urbanization in China, there has been a massive demolition of old buildings in both rural and urban areas. A lot of existing housing has been expropriated and demolished for public interests, such as infrastructure planning, renovation of old towns and urban villages, and rural-urban integration projects (Ju et al., 2016; Shi and He, 2022). Meanwhile, higher economic growth in urban areas attracts migrants from rural areas, creating strong demand for land that can be used for construction. The booming real estate and skyrocketing housing prices since the 2000s have accelerated the pace of housing demolition to provide more land for real estate development (Chai, 2014). The scale of housing demolition in China is unprecedented. According to data from the Chinese Household Income Project (CHIP), 4.6% of Chinese rural households and 13.3% of Chinese urban households had undergone housing demolition as of the year 2013. The overall number of affected households has increased continuously from 9.79% in 2013 to 15.67% in 2019, based on estimates from a recent study by Shi and He (2022).

Understanding the impacts of housing demolition on the Chinese economy has become increasingly important for both academia and policy makers, given the unprecedented urbanization process in China. The empirical literature in economics on this topic covers a variety of economic outcomes and has documented the effects of housing demolition on life satisfaction (Wang and Wang, 2020), human capital investment in children (Li and Xiao, 2020), household consumption (Yuan et al., 2021), and household financial decisions (Shi and He, 2022). Focusing on the interaction between housing demolition and labor markets in China, recent studies have explored how housing demolition affects individual employment decisions and wages (Zhou, 2020; Zhao and Liu, 2022; Yu et al., 2022). Most studies focus on urban housing demolition and its impact on urban residents. One exception along the line of research focusing on the impact of urbanization and institutional changes on labor market outcomes of households is Wang et al. (2020) who study the effects of expropriation with *hukou* changes on a variety of labor market outcomes among rural Chinese households. They find that the expropriation with *hukou* changes helps the relocated rural household heads to work under better employment contracts, work in better positions, and earn higher wages. Still, less is known about how housing demolition affects labor mobility for the relocated urban residents in modern China. The rapid urbanization process in China has witnessed large-scale geographical labor mobility (e.g., the rural-urban labor migration) as well as occupational movement within labor market. Labor market mobility serves as an important signal of the effectiveness of skill utilization in the labor market. Understanding how housing demolition impacts labor market mobility can provide key insight into the degree of skill utilization in the Chinese labor market. Our paper fills this gap in the literature by focusing on one important measure of labor market mobility – occupational mobility – and documents the causal effect of housing demolition on occupational mobility in China. We further explore the link between the two types of labor market mobility: geographical labor mobility (internal labor migration) and occupational mobility. We then show how housing demolition has influenced migrant workers' occupational mobility differently.

Intuitively an increase in household wealth due to housing demolition compensation could result in decreased labor supply because of the income effects, i.e., individuals become wealthier from a windfall and consequently choose to buy more leisure (Li et al., 2019).[1] Alternatively, a forward-looking rational individual could choose to invest in their own skill accumulation to benefit longer from the positive wealth shock by trying to move to/search for more promising job positions using the extra resources. It remains an empirical question to see which one of the two effects dominates.

Our empirical strategy explores the exogenous variation in the incidence of housing demolition among a representative sample of Chinese households drawn from the China Household Finance Survey (CHFS). The CHFS contains a rich set of individual-level information on labor supply, occupational choices, job characteristics, as well as other key demographic characteristics. More importantly, it contains information on housing demolition experienced by the surveyed households over multiple years.[2] The CHFS panel design allows us to use the fixed-effects regression method to control for any unobserved individual or time-invariant characteristics that could have otherwise biased our results. Using the incidence of housing demolition in China as an exogenous wealth shock we

[1]The average compensation value is around 270,884 Yuan (2010 CPI adjusted) and the average disposable income per capita in urban China was 18,779 Yuan in 2010. The amount of housing demolition compensation is calculated with our sample drawn from the China Household Finance Survey for years 2013, 2017, and 2019. The average disposable per capita income is taken from CEIC: https://www.ceicdata.com/en/china/disposable-income-per-capita-urban.

[2]We use the self-reported housing demolition information for years 2013, 2017, and 2019.

first find that the affected individuals are less likely to work compared to those who have not experienced housing demolition, which confirms what the literature has found.[3] This suggests that on the extensive margin, housing demolition creates skill waste and the economy suffers from not utilizing part of the impacted labor. Our paper then moves beyond the extensive margin and finds that conditional on working, individuals who experienced housing demolition are more likely to experience upward occupational mobility (by 10.8 percentage points). This is a novel finding and highlights the fact that on the intensive margin, housing demolition can help workers improve their career choices, bettering the utilization of skills in the labor market. Further heterogeneity analysis reveals that the effect on upward occupational mobility is mainly driven by low-skilled workers, young males, and individuals living in relatively poorer households. Our empirical results are robust towards a series of specification and sample selection tests.

Our identification strategy relies on the exogeneity of the incidence of housing demolition. We assume that the treatment status i.e., the incidence of housing demolition, cannot be determined by the households, and therefore the households cannot take advantage of it by selecting into housing demolition. Concerns can be raised to challenge the validity of this assumption. Some households could self-select themselves into the neighborhood where the housing demolition is more likely to happen, and if these households are systematically different from those who have otherwise not experienced housing demolition, our causal analysis can be threatened because there are potential unobserved factors that jointly determine the housing demolition status and the labor market outcomes. For example, our causal effect estimates on occupational mobility would be biased if individuals with certain unobserved characteristics moved to demolition-prone areas to take advantage of the compensation from the upcoming housing demolition.[4] Another example on the extensive margin of labor supply could be that individuals who are on the margin of participating in the labor market seek housing demolition opportunities to enjoy the income shock in order to leave the labor market afterwards. To empirically capture such cases, we would need more detailed data on household migration history and

[3]There are many missing observations on housing demolition compensation in our estimation sample (about 40% of those who report having experienced housing demolition), which prevents us from quantifying the pure wealth effects (value-based) caused by the housing demolition. Our estimated causal effect, however, provides a local average treatment effect (LATE) from being relocated due to housing demolition and includes mainly the wealth effect.

[4]We control for a rich set of observed individual characteristics to minimize the space of unobserved selection. The descriptive statistics for these controls can be found in Table 1.

labor supply history before the actual housing demolition takes place. Unfortunately, the CHFS we use in this paper does not provide us with such information. We therefore leave this further exploration into the endogeneity issues about housing demolition in China to our future research.

To ease the concern of the endogeneity of housing demolition, we apply an approach developed by Oster (2019) to formally test whether the unobserved self-selection (as occurring if instead the treated individual had a choice) undermines the validity of our causal estimates.[5] We show in Section 5.2 that our results are not driven by the selection on unobservable characteristics, which supports our causal interpretation.

We also test the hypothesis on whether the process of housing demolition has any impact on the migrant workers in China. We do not find any empirical evidence that suggests either of the following: 1) areas that experienced more housing demolition attract more internal migrant workers; or 2) any impact on the occupational mobility of migrant workers. These findings suggest that housing demolition primarily affects local households.

This paper makes several contributions to the literature. First, it contributes to the literature on the impact of housing demolition on labor supply by moving beyond the extensive margin and providing novel evidence on the causal impact of housing demolition on occupational mobility. The results add to the literature by showing that on the extensive margin, housing demolition generates negative effects on employment, while on the intensive margin, housing demolition generates positive effects on occupational mobility, especially among low-skilled workers. Secondly, the paper shows that housing demolition mainly affects local households and does not have any impact on either the internal migration flow or the migrant workers' occupational mobility. Our study extends our current understanding of the interaction between fast urbanization and labor markets as well as skill utilization in China. Housing demolition in China, on one hand, produces skill waste by pushing otherwise employable workers out of labor markets, but on the other hand, it helps those who are closely attached to labor markets by allowing for

[5]This methodology, which relies on the assumption that unobserved selection correlates with the selection observed in the explanatory variables, quantifies the magnitude of the unobserved selection that makes beta, the coefficient of a treatment variable (e.g., experienced housing demolition), equal to zero. Oster (2019) suggests that if the estimated amount of unobserved selection is at least as much or more than the amount of observed selection, then unobserved selection does not compromise the validity of the treatment coefficient estimated by the OLS.

upward occupational mobility. It offers important implications for policy makers who are interested in balancing economic efficiency with wealth inequality while designing housing demolition policies in the future.

The rest of the paper is organized as follows. Section 2 provides the policy background of housing demolition in China and some related literature on the effects of this policy. Section 3 describes the data and provides variable definitions and statistics. Section 4 explains our empirical strategy and section 5 reports the results. Section 6 discusses the mechanism behind our results. Section 7 concludes.

2 Background

In the process of rapid urbanization in China, there has been a massive demolition of old buildings in rural areas, urban villages, and suburbs. A lot of existing housing has been expropriated and demolished for public interests, such as infrastructure planning, renovation of old towns and urban villages, and rural-urban integration projects (Ju et al., 2016; Shi and He, 2022). Meanwhile, higher economic growth in urban areas triggered a huge flow of rural-to-urban migrants, creating strong demand for housing. The real estate boom since the 2000s accelerated the pace of housing demolition to provide land for real estate development, a phenomenon driven by local governments and real estate developers in the name of "urban renewal" (Chai, 2014).

The land in China is publicly owned – thus the local government is the sole decision maker over housing demolition (Zhao and Liu, 2022).[6] Relocated homeowners cannot refuse to move out and must vacate their property by the deadline, but they have the right to negotiate compensation during the demolition procedures. The compensation brought by housing demolition leads to substantial wealth growth for Chinese households, especially thanks to housing value appreciation during the real estate boom (Wu et al., 2013; Li et al., 2019).[7] Even if there are rare and isolated cases of what the media calls "nail households" – homeowners who try to prevent demolition and ask for more compensation – they ultimately reach an agreement with the local government (Deng,

[6]The land in urban districts is owned by the State, while village members collectively own farmland and home premises in rural areas.

[7]China has implemented a series of laws and regulations to ensure fair compensation for evicted homeowners by stipulating that compensation for expropriated homes should not be lower than the market prices of similar properties (Cao and Zhang, 2018; Shi and He, 2022).

2017).

Starting from the market-oriented housing reform in 1998, a large quantity of public rental houses has changed into private ownership. The urban public housing has declined from 75% in the 1980s to about 16.3% in the early 2000s (Huang, 2004; Logan et al., 2010). Housing units with private ownerships started to dominate in urban areas. Providing affordable dwelling with ownership in urban areas tends to be the most common approach to accommodate displaced households from housing demolitions. Local governments are responsible for managing and supervising the entire process of housing demolition. They should develop a preliminary relocation and compensation scheme, and subsequently negotiate with relocated residents to finalize specific compensation packages for each relocated household. Relocated residents must move to other places either by purchasing new homes from the market or by moving to the designated residential units by the local governments (Hu et al., 2015).

The residential relocation is a rather lengthy and complicated process that involves the interests of the displaced households, of the local government, and of the real estate developers. Due to historical reasons, in many cases, the households do not have ownership of their to-be-demolished/redeveloped residential units. Some of these households are employees of large workplaces who offer them the entitlement to workplace-based housing. In such cases, the employers are representing the households to negotiate with the local government and developers on the terms of relocation. Relocation methods and compensation terms are negotiated between the households, local governments, and developers. There are large variations in these terms between regions and even between households in the same area. For most urban housing demolitions that happened after 2001, usually households are given the options of moving to designated new residential units or collecting monetary compensations to buy housing units from the market. The compensation amount depends on many factors that reflect the bargaining power of the household. Such factors could include but not limited to the housing conditions before the demolition; number of residents lived in the house with local *hukou* registration; location and market price of the demolished area. The option of receiving monetary compensation to purchase homes from the market was only made available after the implementation of "Regulation on the Dismantlement of Urban Houses" (Order of the State Council No. 305) in 2001. According to this regulation, compensation for displacement could be in the form of property exchange (in-kind compensation) as well as monetary compensation.

The value of monetary compensation should be determined on the basis of the displaced housing location, the housing purpose, and the construction area. The compensation rules were maintained in an updated regulation "Regulation on the Expropriation of Buildings on State-owned land and Compensation" (Order of the State Council No. 590) in 2011.

Our data does not contain information on the forms of compensation from housing demolition chosen by the households.[8] It is also unclear whether the households who experienced housing demolition have relocated in a different region. However, we believe that there are large variations in terms of the compensation amount and affordable housing provisions across regions as well as between households in the same region. For example, using self-collected survey data from Nanjing in 2011 (a major city in southeast China), Hu et al. (2015) find that residents from collectively owned land holding urban *hukous* are more likely to receive in-kind compensation, because they had relatively larger homes and many of them were landlords in urban villages before the housing demolition happened. They also find that those with high school education or above are more likely to receive higher discount in purchasing affordable housing than residents with lower education, because the higher educated residents have strong negotiation powers. Almost all dislocated residents relocated in the inner circle of Nanjing. Another study presents similar evidence from Shanghai. Using self-collected survey data on a sample of randomly selected households from Shanghai in 2006, Li and Song (2009) document that 57.4% of displaced residents purchased affordable housing at heavily discounted prices from the municipal housing bureau, while another 30.7% of displaced households took the compensation housing offered by developers. Most of the relocated residents ended up in homes that are within the Shanghai city area and about 26.5% of them located in the central city area. They also find that the relocated residents are on average better off with their current living conditions.

Importantly, housing demolition, urban renewal, and real estate development have jointly contributed to the rapid growth of the Chinese economy and to the changing behaviors of individuals and households.

[8] The CHFS contains a question that asks the amount of compensation including both in-kind and cash collected from housing demolition, but we have nearly half of the households who experienced housing demolition not responding to this question.

3 Data

We use data from the China Household Finance Survey (CHFS), a nationally representative survey conducted biennially by the Survey and Research Center for China Household Finance of Southwestern University of Finance and Economics since 2011 (see Gan et al. (2014) for a technical description of this dataset). The CHFS provides detailed information on individual labor supply, occupational characteristics, skill levels, housing demolition, as well as other relevant information. The first round of surveys in 2011 interviewed around 8,500 households in 25 provinces, and the subsequent waves covered more households in 29 provinces. There are more than 28,000 households in the 2013 wave and approximately 40,000 households in each wave between 2015 and 2019. Due to observation constraints and the availability of information on occupations, we employ the 2013, 2017, and 2019 waves of the CHFS data.

We restrict our analysis to economically active people aged between 16 and 64 years and exclude students in school. We also exclude observations with missing values in any of the required variables used in the empirical analysis.[9] Since the identification strategy requires individuals to be observed at least twice during the panel, we then retain individuals who are in the survey for two or three periods.[10] The final sample is an unbalanced panel of 33,265 observations, corresponding to 12,066 individuals and 5,725 households.

The core independent variable is obtained from the survey question: "Has the household ever experienced a housing demolition (*chaiqian*)?" We use a dummy variable to measure housing demolition at the extensive margin, which takes the value of one if the

[9]It is important to note that we also exclude from our analysis individuals who received an extreme amount of housing demolition compensation. However, our results are also robust when we included such outliers.

[10]To investigate whether the results are compromised by possible panel attrition issues, we first compare the baseline characteristics between the "attritors" (individuals who are observed once) and the "non-attritors" (individuals who are observed more than once). We find that the attritor group does in fact display observable differences when compared with the non-attritor group. While we cannot run the panel analysis on the sample of individuals observed only once, we can gauge the extent to which this is likely to be a concern by considering the results for the sample of individuals that never attrit, that is, those who stay in the survey for all three waves possible, and compare them with individuals who attrit at some point but appear in the survey at least twice. The estimation results for these two groups provide supportive evidence that the changes in employment and occupational mobility observed in this study are not driven by sample attrition. Relevant descriptive statistics and regression results are available upon request from the authors. We thank an anonymous referee for raising this point.

answer is "yes" and zero otherwise. Table 1 shows that 3,871 (11.6%) individuals in our sample have ever experienced housing demolition.

The main outcome variables of interest include employment and occupational mobility. Participation in employment is defined by whether an individual is currently working. This broad definition includes individuals who are temporarily out of work, e.g., on vacation, sick leave, or maternity/paternity leave. In order to capture occupational mobility, we compare each individual's previous occupation in 2017 or 2013 to her current occupation in 2019. We employ two occupational mobility measures so we can estimate the housing demolition effect in both the short and medium term. We define any occupation changes from 2017 to 2019 as *short-term* and from 2013 to 2019 as *medium-term*. According to the ISCO-88 classification, we divide the occupational categories into four distinct categories, namely, low-skilled blue collar, high-skilled blue collar, low-skilled white collar, and high-skilled white collar.[11] These four occupational categories are ranked one to four, with higher ranks representing higher skills demanded by the job. Upward mobility is a dummy variable equal to one if an individual's occupation in 2019 is ranked higher than her previous job occupation in 2017 or 2013, while the opposite is true for downward mobility.

Descriptive statistics for the sample of individuals with/without housing demolition experience are presented in Table 1. Individuals who experienced housing demolition are older (by 1.45 years), while they are less likely to be married and have dependent children than those without such experience. In terms of human capital, they have a higher level of education and a higher probability of staying in good health compared to their non-demolished counterparts. In terms of household conditions, individuals whose homes were demolished tend to reside in households with fewer members (including fewer working-age adults) and more wealth. We also find a higher incidence of urban residency and urban *hukou* (household registration) holding among individuals who have experienced housing demolition relative to those who have not. This is not surprising as one of the aims of housing demolition in China is "urban renewal" which mainly targets demolition and reconstruction of older buildings in urban areas (Li and Xiao, 2020). Importantly, there

[11] Low-skilled blue collar includes farmers and agricultural, forestry, animal husbandry, and fishery workers; high-skilled blue collar includes production or transportation machine operators and related personnel; low-skilled white collar includes clerical support workers and service and sales workers; high-skilled white collar includes managers, professionals, technicians, and associate professionals. Armed forces occupations are excluded from the study.

are observable differences in the employment probability between individuals with and without housing demolition experience. Individuals who experienced housing demolition are less likely to be employed relative to those without such experience, with the t-statistic strongly rejecting their similarity at 1 percent significance level.

Table 2 shows descriptive statistics for occupational characteristics by demolished and non-demolished groups, conditional on being employed. We find that individuals with and without housing demolition experience exhibit very different occupational distributions. In particular, individuals in the non-demolished group are significantly more likely to work in low-skilled blue-collar occupations, while individuals in the demolished group are more likely to work in high-skilled blue-collar occupations and white-collar occupations of either skill level. We also find that the probability of occupational mobility is significantly higher among individuals who experienced home demolition, though the direction of mobility is ambiguous.

4 Empirical Strategy

The primary goal of this study is to investigate the causal impact of housing demolition on occupational mobility. Our identification strategy relies on the variation in housing demolition events that generate exogenous shocks to individual and household choices, since housing demolition and relocation are typically exogenously determined by local governments. Refusing to move out of houses facing demolition or self-selecting to experience housing demolition is not possible. We consequently treat housing demolition as a quasi-natural experiment and use this assumption to overcome the potential endogeneity problem. Individuals living in households that experience housing demolition are categorized as the treated group and those without such experience as the comparison group.

4.1 Employment

To provide a complete picture of how housing demolition influences individual labor market outcomes, we first analyze the effect of housing demolition on the probability of employment using a pooled probit model:

$$Employed_{it} = \pi + \theta HD_{it} + X_{it}^{'}\gamma + Prov + Year + \epsilon_{it} \tag{4.1}$$

where the dependent variable, $Employed_{it}$, denotes the employment status of individual i at time t, a dummy variable indicating whether the individual is currently working. HD_{it} is a binary indicator equal to one if the individual resides in households who experienced housing demolition and zero otherwise. X_{it} is a vector of individual and household characteristics and includes: age and its squared term, gender, marital status, education years, a dummy variable for good health,[12] a dummy variable for urban *hukou* status, household size, presence of dependent children (aged 0 to 15) in the household, presence of dependent elderly (aged 65 and above) in the household, number of adults (aged 16 to 64) in the household, the natural logarithm of household income, the natural logarithm of household assets, a dummy for whether the household gets compensation for demolition, and a dummy for whether the household is located in rural areas. Moreover, we control for province fixed effects $Prov$ and year fixed effects $Year$ to account for confounding factors. ϵ_{it} is an error term. Since our estimation approach involves using repeated observations of individuals from the same household in different time periods, we cluster the standard errors at the household level to allow for arbitrary correlation within households and across time.

4.2 Occupational mobility

We next examine the impact of housing demolition on occupational mobility, focusing on individuals who are employed. For each individual, we compare her previous occupation in 2017 or 2013 to her current occupation in 2019. The simplest pooled ordinary least square (henceforth, OLS) regression model takes the following form:

$$Y_{it} = \alpha + \beta HD_{it} + X_{it}^{'}\gamma + Prov + u_{it} \tag{4.2}$$

[12]There is evidence that health status influences people's labor market outcomes and occupational choices. For instance, Zhou (2020) finds that good health condition positively impacts upon employment, working hours, and wages using the same CHFS dataset. Strulik (2022) shows that healthy individuals are more likely to do health-demanding jobs by proposing a life cycle model of occupational choice.

where Y_{it} is a binary indicator of upward or downward occupational mobility for individual i at time t. The key regressor, HD_{it}, is the same as that in equation 4.1. Time-varying control variable X_{it} and province fixed effects $Prov$ are also included in the regression equation.[13] u_{it} is an error term. Robust standard errors are calculated and estimations have been clustered over the household level in order to account for correlation within repeated observations. The effect of interest is captured by the coefficient (β) on the HD_{it} variable. Equation 4.2 is estimated using a linear probability model.[14] One concern with estimating this equation is that OLS estimation methods will yield biased estimates of β if housing demolition is endogenous. We take the viewpoint that housing demolitions are random events after conditioning on all observable controls. As discussed above, there might be some threats to this crucial assumption, such as the case where individuals' choices of occupations and demolition sites are shaped by the same unobserved components.

To correct for this type of endogeneity and better identify the causal impact, we employ a two-way fixed effects (henceforth, FE) model that can be expressed as:

$$Y_{it} = \alpha + \beta HD_{it} + X_{it}^{'}\gamma + c_i + \delta_t + v_{it} \tag{4.3}$$

where c_i indicates individual fixed effects and δ_t represents year fixed effects. By including these two terms, we control for individual-specific and time-specific unobservable effects which may plague the causal interpretation of our estimates. The two-way fixed effect model thus provides the most reliable identification strategy among the models we have introduced, so we will refer to the FE model as our preferred specification in the following sections. Nevertheless, there could still be some source of endogeneity that varies both across individuals and over time. To address this problem, we apply an approach introduced in Oster (2019) to test the exogeneity of our treatment status i.e., housing demolition. We assume that the unobserved selection correlates with the selection observed in the explanatory variables. We first quantify the magnitude of the unobserved selection that makes the key estimated parameter, the coefficient of a treatment variable (e.g., experienced housing demolition), equal to zero. Secondly, we further test the stability of the effect of experiencing housing demolition towards various levels of selection on the

[13] We dropped year dummies since the analysis here is based on a two-year short panel and the dependent variable is the change in outcomes between the two years.

[14] The probit model delivers very similar estimates.

unobservables (the delta). The results are presented in Tables 7 and 8 in Section 5.

5 Results

The aim of our empirical analysis is to examine the role of housing demolition in individual employment decisions, as well as their occupational mobility. The tables below report only the parameter estimates of the housing demolition variable. The estimates of additional covariates are reported in the full estimates in Tables A2-A4 in the Appendix.

5.1 Does housing demolition affect employment?

Table 3 presents the regression coefficient estimates based on a pooled probit model. The marginal effects show the predicted probability of change in employment when the housing demolition variable goes from zero to one. The first column of Table 3 suggests that individuals with housing demolition experience are much less likely to participate in employment relative to individuals without such experience. The relevant marginal effect of –0.129 is statistically different from zero at the 1 percent level of confidence. The negative change in employment does not change when province fixed effects are included in the specification (column 2). When the individual and household characteristics are included, the predicted change in employment becomes smaller (point estimate –0.059), but still statistically significant at the 1 percent level. These findings are not surprising and are consistent with previous studies documenting the negative impact of housing demolition on labor force participation in China (see, for example, Zhao and Liu (2022)).

5.2 Does housing demolition affect occupational mobility?

Table 4 presents the estimates of the effect of housing demolition on occupational mobility obtained with OLS (columns 1 and 3) and FE (columns 2 and 4) methods. We report estimation results for the short term effect (which we define as the 2-year effect) and the medium term effect (which we define as the 6-year effect) in Panels A and B of Table 4 respectively. The upper panel indicates that the estimated coefficients of interest are small and not significantly different from zero. In other words, housing demolition has no short term effect on either upward or downward occupational mobility of employed individuals. Looking at medium term effects in the lower panel, we find a strictly positive and statistically significant effect of housing demolition on upward occupational mobility. More specifically, we find that housing demolition increases the probability of upward occupational mobility by 7.1 percentage points in the OLS regressions, while it leads to a greater likelihood of upward occupational mobility by 10.8 percentage points according to our preferred FE estimates. Again, we find no evidence that housing demolition causally impacts occupational downgrading.

To address the potential endogeneity concern, we first show in Table 5 that the ratio (the delta) between the unobservable and observable selection that causes the effect of experiencing housing demolition to become zero at an inflated R^2 which is referred to as R^2_{max} in Oster (2019). This ratio is 7.63, which means that the amount of selection on the unobservables has to be 8 times of that on observables to remove completely the causal effect and this is unlikely. Table 6 shows the range of the causal effects when the delta is artificially varied in the interval [0,1]. We can see that zero is never within the range of the causal effects when delta varies from zero to one. Therefore, we are confident that our results are robust to omitted variable bias and can be interpreted as causal.

5.3 Heterogeneity analysis and robustness checks

In the main results, we present an overall effect of housing demolition on the labor market outcomes of working-age individuals. In this section, we explore heterogeneous treatment effects on different groups of workers. Do skilled or less skilled workers drive the upward mobility presented in Table 4? Where does the occupational change happen along the occupational ladder? We answer these questions by splitting our sample based on the relevant characteristics and estimating our main specification on these subsamples separately.

Table 7 presents the results from workers with high and low skills respectively. We define high-skilled workers as those who have at least some college education. Panel A in Table 7 compares the occupational change between 2017 and 2019. Unsurprisingly, within the relatively short time frame, the change is noisy for both low- and high-skilled workers. We again do not see any clear pattern of upward or downward movement. When we examine the change between 2013 and 2019 in Panel B, however, we find that workers with college education have a slightly higher probability of moving to a better occupation (7.8 p.p.) compared to workers without college education (7.0 p.p.) in the OLS specification. After controlling for individual and time-invariant effects, the effect of housing demolition on upward occupational mobility becomes insignificant for high-skilled workers. Similar to the OLS specification, the point estimate for low-skilled workers is highly significant and the size of the effect becomes larger. We conclude that, in our preferred specification, the positive impact on upward occupational mobility is primarily driven by low-skilled workers.

We report in Table 8 the effect of housing demolition on different steps of upward occupational movement. Consistent with the results in Table 7, low-skilled workers are more likely to move up (Panels A and B). Around 72% of the upward movement documented in Table 7 are workers moving up one step on the occupational ladder.[15] The magnitude of coefficients reported in Panel C is small because it is hard for anyone, skilled or not, to move from low-skilled blue-collar jobs to high-skilled white-collar jobs.

In Table A5 we conduct additional heterogeneity analyses by looking at whether there are any differences by gender, age group, and household type. Interestingly, we find that the effect of housing demolition on upward occupational mobility is economically stronger for young males and individuals living in relatively poorer households.

In addition to our main specification, we perform robustness checks by aggregating the occupational categories, excluding individuals who had high-skilled white collar occupations in 2013, using an alternative clustering level, and excluding individuals with previous housing demolition experience. We report the results in Table 9. In Panel A, we use a more aggregated definition, where occupations are divided into two occupational categories: blue-collar occupations and white-collar occupations (ranked 1 and 2, respectively). In Panel B, we exclude all individuals who had high-skilled white collar occupations in 2013, since by definition they cannot move up the occupational ladder between the previous occupation and the 2019 occupation. In Panel C, we cluster the standard errors at the regional level (i.e., East, Central, or West). In Panel D, we exclude all individuals who experienced housing demolition before 2013. Our main findings on the intensive margin – having housing demolition experience increases the probability of upward occupational mobility – remain robust across these specifications.

[15] $0.086 \div 0.119 \approx 0.72$

6 Mechanisms and Discussion

In the previous section, we find that individuals who experienced housing demolition are more likely to switch to better occupations. In this section, we discuss potential mechanisms for our findings. There are several possible explanations for the observed upward occupational mobility. One such explanation is that the individual invested in their education and obtained better skills. Alternatively, if housing demolition encourages workers to move out of their hometown, they may have found better, well-compensated jobs in other locations. In this section, we present an empirical investigation on whether upward occupational mobility can be explained by educational investment or internal migration.

6.1 Mechanism 1: Education expenditures

We use propensity score matching to select a control group of individuals who are sufficiently similar to the group of individuals who have experienced housing demolition (the treated group). We then compare the educational expenditures between the treated and control groups. To ensure that individuals in the treated group have time to invest in education if they choose to do so, we make the treatment variable an indicator for whether the individual experienced demolition before 2012. We dropped all individuals who experienced demolition from 2012 to 2019 to prevent them from showing up in the control group. We use the same set of covariates as our main specification to calculate the propensity scores.

Table 10 presents the sample characteristics of the matched and unmatched samples. It is crucial for the matched samples to be "balanced"; that is, the treated and control groups share similar observable characteristics. The mean and variance of all covariates are fairly close between the treated and control groups, suggesting that the control group is sufficiently similar to the treated group in all observed aspects other than if they have experienced housing demolition or not.

Table 11 presents the average treatment effects on the treated (ATET) of the natural logarithm of education expenditures. We do not find evidence for further educational investment from the treated group. If anything, they seem to spend less on education than the control group with similar household income, geographic location, and rural/urban status. In our benchmark results in the first row, we use the nearest neighbor method with replacement. We can see that the average treatment effect on the treated is –0.347, which means that the expected expenditure on education for the group that experienced demolition is 70.7% of what it would be had they not experienced demolition.[16] This result is robust under different matching methods and is statistically significant. Our results are consistent with the findings by Li and Xiao (2020), who also document that recipients of demolition compensation invest less in education.

One potential concern with the propensity score methods is whether the result is robust to different sets of matching characteristics. If we select a large set of characteristics, we are also worried about whether we can successfully find a set of controls that are sufficiently similar to the treatment group. To address this concern, we use the "leave-one-covariate-out" (LOCO) method to perform a sensitivity analysis (Cerulli, 2018). In our baseline model, we have 42 covariates. This approach starts with a subset of size $S < 42$ and randomly draws 10 subsets of size S without replacement from our original set of covariates. We then run 10 matching models with S characteristics to obtain 10 ATET and standard error estimates and calculate the average of the estimates. We perform the steps above for $S = 1, \ldots, 41$, and report the results in Figure A1 in the Appendix. The ATET in the simulations consistently approaches our baseline ATET after we include over 10 covariates. We find it reassuring that most of the simulated ATETs are negative and significantly different from 0 as long as we include more than a handful of covariates. The sensitivity analysis confirms that individuals who experienced demolition likely did not invest more in education. This conclusion is robust to different sets of characteristics we use to perform propensity score matching.

6.2 Mechanism 2: Internal migration

Another mechanism worth exploring is internal migration in the process of urbanization. If housing demolition leads to outward migration and the workers find better jobs in the new city, this can potentially explain the upward mobility observed previously. We examine this hypothesis by identifying migrants who have experienced housing demolition

[16] Denote the education expenditure for individual i as x_{i1} if the individual experienced demolition (treated), and x_{i0} if the individual is not treated. Denote the treatment status for individual i as T_i. The average treatment effect on the treated is: $E[\ln(x_{i1})|T_i = 1] - E[\ln(x_{i0}|T_i = 1] = E[\ln(x_{i1}) - \ln(x_{i0})|T_i = 1] = E[\ln(\frac{x_{i1}}{x_{i0}}|T_i = 1] = -0.347$. $e^{-0.347} \approx 0.707$.

and re-estimate our main specification by excluding migrants from our estimation sample. We find that housing demolition primarily affects local households.

The upper panel in Table A6 reports the effect of housing demolition on occupational mobility among non-migrants. Compared to our benchmark results in the lower panel, the magnitude of parameters is almost identical and the effect on occupational upward mobility is even slightly large. While internal migration is a possible explanation for upward mobility, in our sample, the main results are not driven by migrants.

Although our data indicate that the fraction of migrants directly affected by housing demolition is small, demolition can still indirectly affect the labor market if it draws migrants from other parts of the country through, for example, the growth potential of real estate. Since housing demolition is a phenomenon in urbanization, we need to separate housing demolition and the job opportunities available in expanding cities by controlling for a set of labor market characteristics.

We test this channel by estimating the following equation:

$$M_{ct} = \beta_0 + \beta_1 D_{ct} + X_{ct}^{'}\gamma + \delta_t + \eta_c + \epsilon_{ct} \tag{6.1}$$

where c represents a city, M_{ct} is the migrant ratio in city c in year t, D_{ct} is the demolition rate in city c in year t, δ_t indicates year fixed effects, η_c denotes city fixed effects, and X_{ct} is a collection of city-year specific characteristics. The characteristics include imputed population, unemployment rate, labor force participation rate, average annual job income, the ratio of residents with rural *hukou*, average household income, the ratio of Han ethnic group, the ratio of males, the ratio of high-skilled workers, the ratio of low-skilled workers, average resident age, average resident education (years), and a rural area indicator. We also include city fixed effects to account for all time-invariant city characteristics. We construct the city-year level demolition ratio by calculating the ratio of individuals sampled in the city who have experienced demolition and are also not migrants. The city population is measured with their sample representation in our dataset.

The first three columns in Table A7 report the estimates from equation 6.1. After controlling for city level characteristics that capture the local labor market conditions, the correlation between internal migration and housing demolition is weak (–0.041) and not statistically significant. This suggests that when workers are making migration decisions, it is unlikely that they factor housing demolition in the destination cities into their decisions.

We further test if demolition affects the occupational mobility of migrants within a city. We use the occupational mobility indicator from our main specification and interact it with the migration indicator to create a migrant mobility indicator. We then use it as the outcome variable to re-estimate equation 6.1 and report the results in the last two columns of Table A7. If migrant workers live in a city with a higher housing demolition rate, they are more likely to move into an inferior occupation. This is the opposite of our main findings, indicating that the pattern of results revealed in Table 4 is primarily driven by local workers instead of migrant workers.

Our mechanism discussion thus rules out educational investment and internal migration as the explanations for upward occupational mobility. While our investigation did not find evidence supporting the two mechanisms discussed, it suggests that other channels (e.g., better job-skill match) may be driving our main results.

Our results present novel evidence on how relocated residents react to the incidence of experiencing housing demolition along the intensive margin of their labor supply. This dimension of reactions has not been documented despite its obvious importance and implications on welfare considerations from the urbanization policy design point of view. Our paper shows that in the urbanization process in China, housing demolitions have generated opposite impacts on labor market outcomes: a negative one on employment, and a positive one on occupational mobility for relatively low-skilled workers. Policy makers are generally interested in the cost-benefit evaluations of any potential large-scale implementation of public policy. Realizing the opposing forces of these labor supply responses from the relocated residents presents a more complete picture of the welfare consequences to the policy makers. Quantifying the cost of losing on the extensive margin and the benefit of gaining on the intensive margin requires further empirical research and certainly warrants attention from policy designers in the future. One potential direction that the government could think more about housing demolition is to make the compensation packages vary with potential labor market activities to decrease the disincentive employment participation effect and to increase the incentive of those who are already closely attached to the labor market.

7 Conclusion

We evaluate the causal impact of housing demolition on employment and occupational mobility in the Chinese labor market. We contribute to the literature by providing causal evidence on both the extensive and intensive margin. Our identification strategy takes advantage of the exogenous nature of the incidence of housing demolition with detailed individual, household, and province characteristics and is robust towards the selection on unobservable characteristics.

We show that there are positive medium-term causal effects from experiencing housing demolition on upward occupational mobility (by 10.8 percentage points) and this effect is primarily driven by disadvantaged workers who have relatively lower skill levels (the effect is 11.9 percentage points). Moreover, the effect on upward mobility is concentrated on small-step advancement rather than large-step jumps along the occupation scales.

To understand the mechanism of the impact of housing demolition on skill formation and utilization, we carry out a complimentary analysis of educational expenditure that captures mainly the effects on investment in formal schooling at the household level. We find that housing demolition causally decreases the educational expenditure for the affected households. This is consistent with the previous findings in the literature (Li and Xiao, 2020). Our results seem to suggest that the career motivated individuals benefit from the wealth shock offered by the housing demolition and move up on the occupational ladder.

Our paper contributes to the literature by highlighting the intensive margin labor supply channel through which the process of fast urbanization could affect the relocated residents. This dimension of the skill utilization of relocated residents in urban areas has never been studied empirically in China. Our study complements the research on how relocated residents fare in the labor market after being "shocked" by urbanization. Along the same line, Wang et al. (2020) utilizes the incidence of expropriation as an exogenous shock to *hukou* status in China to study the impact of expropriation with *hukou* changes on household heads' employment decisions and wages. They find positive effects on wages and type of employment for the relocated residents and, more importantly, they focus on rural people as land expropriation with *hukou* changes were mostly experienced by rural households who live close to the cities. In this paper, we instead focus on urban residents as 76% of our sample who have experienced housing demolition are urban residents with local urban *hukous*. The comparison of the empirical results reveals differences in the nature of the urbanization shocks as well as different targeted households. Therefore, our paper helps to enrich the literature on the consequences of fast urbanization in China and helps to present a complete picture of how different relocation shocks influence individual labor market outcomes.

Our findings provide important empirical evidence on skill utilization and labor market mobility in reaction to housing demolition to the policy makers in China. We show that on one hand, housing demolition generates skill waste on the extensive margin (some people may choose to leave the labor force due to income effects). On the other hand, we also show that housing demolition can help people who are more motivated and closely attached to the labor market to move up the occupational ladder. Policy makers should bear in mind these potential responses and act accordingly to minimize skill waste and promote labor market efficiency. For example, the compensation scheme following the housing demolition can be designed to vary with labor market activities to reduce the disincentive effect of the housing compensation and to decrease the cost of working. Policy makers should also consider the trade-offs between the extensive and intensive margin when evaluating the cost and benefit of housing demolition to the welfare of the local society.

Unfortunately, our results shall be taken with caution and are subject to data limitations. For example, we notice that there is substantial missing information on the amount and form of compensation following housing demolition in our sample (about 40%), which precludes us from disentangling wealth effects from the current cash incentive and the expected future property value incentive. Moreover, we do not have information for the relocated households from before their housing demolition. This prevents us from estimating the within-individual causal effects that are more accurate. We place these topics on our future research agenda.

Conflicts of Interests

All authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

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Table 1: Descriptive statistics on key variables.

	Individuals with housing demolition experience (1)	Individuals with housing demolition experience (2)	Difference in means (3)
Employed	0.62	0.76	–0.14***
	(0.49)	(0.43)	(0.01)
Age	47.19	45.74	1.45***
	(11.69)	(11.54)	(0.20)
Age squared	2363.27	2225.02	138.24***
	(1030.34)	(1005.59)	(17.24)
Male	0.50	0.51	–0.01
	(0.50)	(0.50)	(0.01)
Married	0.84	0.87	–0.03***
	(0.37)	(0.34)	(0.01)
Years of education	9.51	8.55	0.96***
	(3.76)	(3.98)	(0.07)
Good health	0.47	0.44	0.03***
	(0.50)	(0.50)	(0.01)
Urban *hukou*	0.45	0.21	0.24***
	(0.50)	(0.41)	(0.01)
Household size	3.65	4.07	–0.41***
	(1.50)	(1.67)	(0.03)
Dependent children<16	0.38	0.48	–0.09***
	(0.49)	(0.50)	(0.01)
Dependent elderly>64	0.22	0.23	–0.00
	(0.42)	(0.42)	(0.01)
# Adults 16-64	2.85	3.06	–0.20***
	(1.04)	(1.12)	(0.02)
Ln(Household income)	10.86	10.42	0.44***
	(1.48)	(1.58)	(0.03)
Ln(Household assets)	13.21	12.46	0.75***
	(1.51)	(1.47)	(0.03)
Get compensation for demolition	0.57	0.00	0.57***
	(0.50)	(0.00)	(0.00)
Amount of compensation (Yuan/10,000)[a]	27.09		
	(53.02)		
Rural area	0.24	0.55	–0.31***
	(0.43)	(0.50)	(0.01)
Observations	3,871	29,394	

Source: CHFS (2013, 2017, 2019).
Notes: The sample comprises individuals aged 16 to 64 in the waves of 2013, 2017, and 2019 across 29 provinces in China. The table displays sample means and standard deviations (in parentheses) of variables of demolished and non-demolished groups in columns (1) and (2). Column (3) presents the results of a *t*-test for whether the difference in means between the two groups is statistically significant and standard errors in parentheses.
[a]Number of observations falls due to missing values. To account for inflation and determine the real compensation values, we use the Consumer Price Index (CPI) to deflate all compensation values to 2010Q1 prices.

Table 2: Descriptive statistics on occupational characteristics.

	Individuals with housing demolition experience (1)	Individuals with housing demolition experience (2)	Difference in means (3)
Panel A: Occupation type			
Low-skilled blue collar	0.25	0.55	–0.30***
	(0.43)	(0.50)	(0.01)
High-skilled blue collar	0.12	0.10	0.02**
	(0.33)	(0.30)	(0.01)
Low-skilled white collar	0.42	0.20	0.22***
	(0.49)	(0.40)	(0.01)
High-skilled white collar	0.21	0.15	0.06***
	(0.41)	(0.36)	(0.01)
Observations	1,776	17,097	
Panel B: Mobility indicators			
Upward mobility (2019 *vs.* 2017)	0.07	0.06	0.02**
	(0.26)	(0.23)	(0.01)
Downward mobility (2019 *vs.* 2017)	0.06	0.05	0.01**
	(0.24)	(0.21)	(0.01)
Observations	1,447	11,287	
Upward mobility (2019 *vs.* 2013)	0.09	0.06	0.04***
	(0.29)	(0.23)	(0.01)
Downward mobility (2019 *vs.* 2013)	0.05	0.03	0.02***
	(0.23)	(0.17)	(0.01)
Observations	1,163	11,482	
Upward mobility (2017 *vs.* 2013)	0.07	0.05	0.02***
	(0.26)	(0.22)	(0.01)
Downward mobility (2017 *vs.* 2013)	0.07	0.03	0.04***
	(0.26)	(0.18)	(0.01)
Observations	942	11,425	

Source: CHFS (2013, 2017, 2019).
Notes: The sample comprises individuals aged 16 to 64 in the waves of 2013, 2017, and 2019 across 29 provinces in China. The table displays sample means and standard deviations (in parentheses) of variables of demolished and non-demolished groups in columns (1) and (2). Column (3) presents the results of a *t*-test for whether the difference in means between the two groups is statistically significant and standard errors in parentheses.

Table 3: Probit estimates of the effect of housing demolition on employment.

Dependent Variable	**Probability of employment**		
	(1)	(2)	(3)
Housing demolition	–0.408***	–0.334***	–0.221***
	(0.032)	(0.032)	(0.044)
Marginal effects (dy/dx)	–0.129***	–0.103***	–0.059***
	(0.010)	(0.010)	(0.012)
Observations	33,265	33,265	33,265
Pseudo-R^2	0.011	0.031	0.166
Individual and household controls	No	No	Yes
Province dummies	No	Yes	Yes
Year dummies	Yes	Yes	Yes

Source: CHFS (2013, 2017, 2019).
Notes: The sample comprises individuals aged 16 to 64 in the waves of 2013, 2017, and 2019 across 29 provinces in China. Pooled probit estimation where dependent variable is the probability of employment as defined in the text. Other controls: age and its squared value, gender, marital status, education years, a dummy for good health, a dummy for whether the individual has urban *hukou*, household size, presence of dependent children, presence of dependent elderly, number of adults, household income, household assets, a dummy for whether the household gets compensation for demolition, and a dummy for whether the household is located in rural areas.
Robust standard errors clustered at the household level are shown in parentheses.
Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 4: Estimates of the effect of housing demolition on occupational mobility.

Dependent Variable	**Upward mobility**		**Downward mobility**	
	OLS	*FE*	*OLS*	*FE*
	(1)	(2)	(3)	(4)
Panel A: Short term effect (2019 vs. 2017)				
Housing demolition	0.010	0.025	0.004	0.052
	(0.010)	(0.046)	(0.009)	(0.050)
Observations	12,734	12,734	12,734	12,734
R^2	0.023	0.151	0.014	0.141
Panel B: Medium term effect (2019 vs. 2013)				
Housing demolition	0.071***	0.108***	0.018	0.019
	(0.017)	(0.037)	(0.012)	(0.027)
Observations	12,645	12,645	12,645	12,645
R^2	0.031	0.21	0.028	0.118
Individual and household controls	Yes	Yes	Yes	Yes
Province dummies	Yes	No	Yes	No

Source: CHFS (2013, 2017, 2019).
Notes: The sample comprises individuals aged 16 to 64 in the waves of 2013, 2017, and 2019 across 29 provinces in China. Models are estimated by ordinary least squares and two-way fixed effects specification. Other controls: age and its squared value, gender, marital status, education years, a dummy for good health, a dummy for whether the individual has urban *hukou*, household size, presence of dependent children, presence of dependent elderly, number of adults, household income, household assets, a dummy for whether the household gets compensation for demolition, and a dummy for whether the household is located in rural areas.
Robust standard errors clustered at the household level are shown in parentheses.
Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 5: Oster endogeneity check for medium term effect of housing demolition on upward occupational mobility.

Amount of selection on housing demolition	Amount of selection on unobservables relative to selection on observables	R^2_{max}
	12.78	0.035
	7.63	0.04*
	4.22	0.05
	1.31	0.10

Notes: Methodology based on Oster (2019) and implemented using Stata's command *psacalc*.
*This value of R-squared is calculated following Oster (2019), in particular: $R_{max} = min\{1.3\tilde{R}, 1\}$, $\tilde{R}$ is obtained from the OLS regression of being employed or not on housing demolition and other individual, household and province controls, see the first column of Panel B in Table 4.

Table 6: Oster endogeneity check for medium term effect of housing demolition on upward occupational mobility.

Amount of selection on housing demolition	Estimated coefficient on housing demolition	Delta
$R^2_{max} = 0.04$		
	0.116	1.0
	0.109	0.9
	0.102	0.8
	0.097	0.7
	0.092	0.6
	0.088	0.5
	0.084	0.4
	0.080	0.3
	0.077	0.2
	0.074	0.1
	0.071	0.0

Notes: Methodology based on Oster (2019) and implemented using Stata's command *psacalc*.

Table 7: Heterogeneous effects of housing demolition on upward occupational mobility by skill level.

Dependent Variable	**Upward mobility**		**Upward mobility**	
	Low-skilled		High-skilled	
	OLS	*FE*	*OLS*	*FE*
	(1)	(2)	(3)	(4)
Panel A: Short term effect (2019 vs. 2017)				
Housing demolition	0.015	0.022	–0.004	–0.025
	(0.010)	(0.049)	(0.022)	(0.111)
Observations	10,856	10,856	1,878	1,878
R^2	0.025	0.138	0.034	0.209
Panel B: Medium term effect (2019 vs. 2013)				
Housing demolition	0.070***	0.119***	0.078**	0.055
	(0.020)	(0.041)	(0.034)	(0.089)
Observations	11,086	11,086	1,559	1,559
R^2	0.033	0.22	0.067	0.178
Individual and household controls	Yes	Yes	Yes	Yes
Province dummies	Yes	No	Yes	No

Source: CHFS (2013, 2017, 2019).
Notes: The sample comprises individuals aged 16 to 64 in the waves of 2013, 2017, and 2019 across 29 provinces in China. Models are estimated by ordinary least squares and two-way fixed effects specification. The low-skilled individuals are those who have less than college/vocational education and the high-skilled individuals are those who have college/vocational education and above. Other controls are as described in Table 4.
Robust standard errors clustered at the household level are shown in parentheses.
Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 8: Heterogeneous effects of housing demolition on upward occupational mobility by the extent of mobility in the medium term.

Dependent Variable	**Upward mobility**		**Upward mobility**	
	Low-skilled		High-skilled	
	OLS	*FE*	*OLS*	*FE*
	(1)	(2)	(3)	(4)
Panel A: Moving up the occupational ladder by 1 step				
Housing demolition	0.037***	0.086***	0.053*	0.084
	(0.014)	(0.032)	(0.030)	(0.087)
Observations	11,086	11,086	1,559	1,559
R^2	0.015	0.095	0.06	0.149
Panel B: Moving up the occupational ladder by 2 steps				
Housing demolition	0.019*	0.049*	0.029	–0.008
	(0.011)	(0.028)	(0.018)	(0.021)
Observations	11,086	11,086	1,559	1,559
R^2	0.011	0.084	0.037	0.053
Panel C: Moving up the occupational ladder by 3 steps				
Housing demolition	–0.006	–0.016	–0.004*	–0.021
	(0.004)	(0.012)	(0.002)	(0.014)
Observations	11,086	11,086	1,559	1,559
R^2	0.015	0.051	0.038	0.112
Individual and household controls	Yes	Yes	Yes	Yes
Province dummies	Yes	No	Yes	No

Source: CHFS (2013, 2019).
Notes: The sample comprises individuals aged 16 to 64 in the waves of 2013 and 2019 across 29 provinces in China. Hence, the estimates correspond to the medium term effect of housing demolition on upward occupational mobility. Models are estimated by ordinary least squares and two-way fixed effects specification. The low-skilled individuals are those who have less than college/vocational education and the high-skilled individuals are those who have college/vocational education and above. Other controls are as described in Table 4.
Robust standard errors clustered at the household level are shown in parentheses.
Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 9: Other robustness checks for medium term effect of housing demolition on upward occupational mobility.

Dependent Variable	**Upward mobility**		**Upward mobility**	
	Low-skilled		High-skilled	
	OLS	*FE*	*OLS*	*FE*
	(1)	(2)	(3)	(4)
Panel A: Aggregating occupational categories				
Housing demolition	0.037**	0.100***	0.046*	0.043
	(0.015)	(0.037)	(0.024)	(0.064)
Observations	11,086	11,086	1,559	1,559
R^2	0.022	0.146	0.042	0.089
Panel B: Excluding high-skilled white collar in 2013				
Housing demolition	0.073***	0.147***	0.074*	–0.065
	(0.021)	(0.047)	(0.042)	(0.155)
Observations	10,320	10,320	869	869
R^2	0.039	0.238	0.138	0.47
Panel C: Clustering at regional level				
Housing demolition	0.070**	0.119	0.078	0.055
	(0.012)	(0.051)	(0.062)	(0.134)
Observations	11,086	11,086	1,559	1,559
R^2	0.033	0.22	0.067	0.178
Panel D: Excluding individuals with previous housing demolition experience				
Housing demolition	0.056**	0.051	0.055	0.105
	(0.027)	(0.049)	(0.042)	(0.131)
Observations	10,553	10,553	1,446	1,446
R^2	0.034	0.219	0.069	0.182
Individual and household controls	Yes	Yes	Yes	Yes
Province dummies	Yes	No	Yes	No

Source: CHFS (2013, 2019).
Notes: The sample comprises individuals aged 16 to 64 in the waves of 2013 and 2019 across 29 provinces in China. Hence, the estimates correspond to the medium term effect of housing demolition on upward occupational mobility. Models are estimated by ordinary least squares and two-way fixed effects specification. The low-skilled individuals are those who have less than college/vocational education and the high-skilled individuals are those who have college/vocational education and above. Other controls are as described in Table 4.
Cluster-robust standard errors are shown in parentheses.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 10: Sample mean and variance of the covariates.

Variable	Unmatched Matched	Mean Treated	Control	% bias	% reduct |bias|	Var(T)/ Var(C)
Age	U	47.83	45.99	15.1		0.97
	M	48.39	48.64	-2.1	86.3	0.98
Age squared	U	2434.10	2265.30	15.9		1.00
	M	2480.00	2507.90	-2.6	83.5	0.97
Male	U	0.49	0.51	-4.5		.
	M	0.48	0.46	3.4	24.6	.
Married	U	0.83	0.86	-9.1		.
	M	0.81	0.82	-1.7	81.3	.
Good health	U	0.45	0.45	0.4		.
	M	0.46	0.47	-3.1	-645.8	.
Urban *hukou*	U	0.51	0.22	63		.
	M	0.40	0.41	-3.4	94.7	.
Household size	U	3.62	4.03	-25.7		0.80*
	M	3.58	3.64	-3.4	86.8	0.77*
Dependent children<16	U	0.36	0.47	-21.9		.
	M	0.39	0.41	-4.4	79.9	.
Dependent elderly>64	U	0.22	0.23	-2.6		.
	M	0.20	0.18	3.3	-25.9	.
# Adults 16-64	U	2.87	3.04	-15.5		0.89*
	M	2.77	2.79	-1.8	88.2	1.00
Ln(Household income)	U	10.68	10.45	13.8	6.01	1.08
	M	11.13	11.06	4	71.2	0.48*
Ln(Household assets)	U	13.38	12.49	60.1		0.95
	M	13.81	13.78	1.8	97	0.94
Rural area	U	0.16	0.53	-83.8	-32.09	.
	M	0.12	0.13	-2.1	97.5	.

Source: CHFS (2013, 2017, 2019).
Notes: This table presents the results of covariates balance testing results. In addition to the covariates listed in the table, the propensity score matching also includes resident province dummies.

Table 11: Average treatment effect on the treated (ATT).

Matching Methods	ln(Educ expenditures)		
	ATT	# treated	# untreated
Nearest Neighbor (w/ replacement)	-0.347 (0.141)	649	597
2 Nearest Neighbors (w/ replacement)	-0.346 (0.130)	649	1135
Caliper (0.0001)	-0.270 (0.135)	600	560
Caliper (0.00005)	-0.242 (0.138)	534	510

Source: CHFS (2013, 2017, 2019).
Notes: Standard errors in parentheses. All standard errors obtained from bootstrap with 50 replications. In all matching methods, ties (observations with the same propensity scores) are also included.

Appendix A Additional Tables and Figures

Table A1: The historic dynamic of Chinese housing demolition.

State	Laws and Regulations	Characteristics
1978-1991		Mandatory directives, very small volume;
1991-2001	Regulations Regarding on the Administration of Urban Housing Removal (1991)	Mandatory directives, no pecuniary compensation, no title to propertyas of 1998, small volume;
2001-2007	Regulations Regarding on the Administration of Urban Housing Removal (2001)	Enforced demolition by property developers, negotiable compensation, title to property, big volume;
2007-2011	Real Rights Law of the People's Republic of China (2007)	Transition from enforced demolition to negotiable compensation, large volume;
2011-2020	Regulations on Expropriation and Compensation of Houses on State Owned Land (2011)	Pecuniary compensation dominant, various modes of compensations, huge private wealth enabled, enormous volume;
2020 onwards	The Law of Land Administration of the People's Republic of China (2020)	Full-fledged rule&law, decreasing compensation, decreasing volume;

Table A2: Full probit estimates of the effect of housing demolition on employment.

Dependent Variable	**Probability of employment**		
	(1)	(2)	(3)
Housing demolition	–0.408***	–0.334***	–0.221***
	(0.032)	(0.032)	(0.044)
Age			0.144***
			(0.007)
Age squared			–0.002***
			(0.000)
Male			0.629***
			(0.019)
Married			0.242***
			(0.036)
Years of education			0.019***
			(0.003)
Good health			0.245***
			(0.019)
Urban *hukou*			–0.319***
			(0.027)
Household size			–0.069***
			(0.018)
Dependent children$<$16			0.005
			(0.033)
Dependent elderly$>$64			0.027
			(0.033)
# Adults 16-64			0.026
			(0.021)
Ln(Household income)			0.100***
			(0.007)
Ln(Household assets)			0.024***
			(0.008)
Get compensation for demolition			–0.017
			(0.050)
Rural area			0.471***
			(0.027)
Observations	33,265	33,265	33,265
Pseudo-R^2	0.011	0.031	0.166
Individual and household controls	No	No	Yes
Province dummies	No	Yes	Yes
Year dummies	Yes	Yes	Yes

Source: CHFS (2013, 2017, 2019).
Notes: The sample comprises individuals aged 16 to 64 in the waves of 2013, 2017, and 2019 across 29 provinces in China. Pooled probit estimation where dependent variable is the probability of employment as defined in the text.
Robust standard errors clustered at the household level are shown in parentheses.
Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A3: Full estimates of the short term effect of housing demolition on occupational mobility.

Dependent Variable	**Upward mobility**		**Downward mobility**	
	OLS	*FE*	*OLS*	*FE*
	(1)	(2)	(3)	(4)
Housing demolition	0.010	0.025	0.004	0.052
	(0.010)	(0.046)	(0.009)	(0.050)
Age	0.005***	0.147***	0.004***	0.132***
	(0.001)	(0.019)	(0.001)	(0.015)
Age squared	–0.000***	–0.001***	–0.000***	–0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.026***		0.027***	
	(0.004)		(0.004)	
Married	–0.004	–0.017	–0.009	0.012
	(0.008)	(0.032)	(0.007)	(0.030)
Years of education	0.002***	0.004	0.002***	–0.007**
	(0.001)	(0.003)	(0.001)	(0.003)
Good health	0.003	–0.013	0.000	–0.013
	(0.005)	(0.011)	(0.004)	(0.010)
Urban *hukou*	–0.021***	–0.081***	–0.011*	–0.048*
	(0.007)	(0.029)	(0.006)	(0.026)
Household size	0.001	0.020	0.002	0.001
	(0.004)	(0.014)	(0.004)	(0.011)
Dependent children<16	–0.010	–0.039	–0.003	0.008
	(0.007)	(0.026)	(0.007)	(0.022)
Dependent elderly>64	–0.000	–0.022	0.000	–0.004
	(0.007)	(0.023)	(0.006)	(0.023)
# Adults 16-64	–0.008*	–0.028	–0.002	0.003
	(0.005)	(0.017)	(0.004)	(0.013)
Ln(Household income)	0.015***	0.022***	–0.006**	–0.029***
	(0.002)	(0.004)	(0.002)	(0.005)
Ln(Household assets)	0.003**	0.004	0.004**	0.010**
	(0.002)	(0.006)	(0.002)	(0.005)
Get compensation for demolition	–0.005	0.004	0.013	0.003
	(0.014)	(0.043)	(0.014)	(0.055)
Rural area	0.002	–0.190*	–0.004	–0.059
	(0.006)	(0.111)	(0.005)	(0.121)
Observations	12,734	12,734	12,734	12,734
R^2	0.023	0.151	0.014	0.141
Individual and household controls	Yes	Yes	Yes	Yes
Province dummies	Yes	No	Yes	No

Source: CHFS (2013, 2017, 2019).
Notes: The sample comprises individuals aged 16 to 64 in the waves of 2013, 2017, and 2019 across 29 provinces in China. Models are estimated by ordinary least squares and two-way fixed effects specification.
Robust standard errors clustered at the household level are shown in parentheses.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A4: Full estimates of the medium term effect of housing demolition on occupational mobility.

Dependent Variable	**Upward mobility**		**Downward mobility**	
	OLS	*FE*	*OLS*	*FE*
	(1)	(2)	(3)	(4)
Housing demolition	0.071***	0.108***	0.018	0.019
	(0.017)	(0.037)	(0.012)	(0.027)
Age	0.008***	0.072***	0.004***	0.025***
	(0.002)	(0.007)	(0.001)	(0.004)
Age squared	–0.000***	–0.001***	–0.000***	–0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.024***		0.018***	
	(0.004)		(0.003)	
Married	0.004	–0.014	0.010**	–0.017
	(0.008)	(0.030)	(0.005)	(0.021)
Years of education	0.001**	0.004*	0.002***	–0.001
	(0.001)	(0.003)	(0.000)	(0.002)
Good health	0.008*	0.030***	–0.003	–0.022***
	(0.005)	(0.011)	(0.003)	(0.008)
Urban *hukou*	–0.043***	0.009	0.001	–0.064**
	(0.007)	(0.021)	(0.007)	(0.025)
Household size	–0.001	–0.013	–0.002	–0.003
	(0.004)	(0.009)	(0.002)	(0.006)
Dependent children$<$16	–0.008	0.003	–0.000	–0.001
	(0.007)	(0.017)	(0.005)	(0.013)
Dependent elderly$>$64	–0.005	–0.011	–0.003	–0.003
	(0.007)	(0.017)	(0.005)	(0.014)
# Adults 16-64	–0.013***	–0.002	–0.004	0.018**
	(0.004)	(0.010)	(0.002)	(0.007)
Ln(Household income)	0.023***	0.042***	0.003***	–0.020***
	(0.002)	(0.004)	(0.001)	(0.003)
Ln(Household assets)	–0.001	–0.010*	0.006***	0.015***
	(0.002)	(0.005)	(0.001)	(0.004)
Get compensation for demolition	–0.058***	–0.065**	–0.017	–0.011
	(0.020)	(0.033)	(0.014)	(0.025)
Rural area	0.012**	–0.045	–0.021***	0.018
	(0.006)	(0.048)	(0.004)	(0.032)
Observations	12,645	12,645	12,645	12,645
R^2	0.031	0.21	0.028	0.118
Individual and household controls	Yes	Yes	Yes	Yes
Province dummies	Yes	No	Yes	No

Source: CHFS (2013, 2017, 2019).
Notes: The sample comprises individuals aged 16 to 64 in the waves of 2013, 2017, and 2019 across 29 provinces in China. Models are estimated by ordinary least squares and two-way fixed effects specification.
Robust standard errors clustered at the household level are shown in parentheses.
Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A5: Heterogeneous effects of housing demolition on upward occupational mobility by gender, age and household type in the medium term.

Dependent Variable	**Upward mobility**		**Upward mobility**	
	OLS	*FE*	*OLS*	*FE*
	(1)	(2)	(3)	(4)
	Females		Males	
Housing demolition	0.032	0.065	0.096***	0.134***
	(0.020)	(0.046)	(0.023)	(0.050)
Observations	5,765	5,765	6,880	6,880
R^2	0.032	0.196	0.035	0.238
	Age≤45		Age>45	
Housing demolition	0.067***	0.122*	0.073***	0.065
	(0.023)	(0.071)	(0.024)	(0.049)
Observations	5,540	5,540	7,105	7,105
R^2	0.035	0.303	0.042	0.151
	Low-income HH.		High-income HH.	
Housing demolition	0.067***	0.128**	0.078***	0.002
	(0.022)	(0.050)	(0.027)	(0.101)
Observations	9,937	9,937	2,708	2,708
R^2	0.032	0.213	0.043	0.2
Individual and household controls	Yes	Yes	Yes	Yes
Province dummies	Yes	No	Yes	No

Source: CHFS (2013, 2019).
Notes: The sample comprises individuals aged 16 to 64 in the waves of 2013 and 2019 across 29 provinces in China. Hence, the estimates correspond to the medium term effect of housing demolition on upward occupational mobility. Models are estimated by ordinary least squares and two-way fixed effects specification. The low-income households are defined as households whose annual income is less than double the sample median and the high-income households are those whose annual income is more than double the sample median. Other controls are as described in Table 4.
Robust standard errors clustered at the household level are shown in parentheses.
Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A6: The medium term effect of housing demolition on occupational mobility: Excluding migrants.

Dependent Variable	**Upward mobility**		**Downward mobility**	
	OLS	*FE*	*OLS*	*FE*
	(1)	(2)	(3)	(4)
Panel A: Excluding migrants (2019 vs. 2013)				
Housing demolition	0.074***	0.117***	0.017	0.017
	(0.018)	(0.039)	(0.012)	(0.026)
Observations	12,119	12,119	12,119	12,119
Panel B: Full sample (2019 vs. 2013)				
Housing demolition	0.071***	0.108***	0.018	0.019
	(0.017)	(0.037)	(0.012)	(0.027)
Observations	12,645	12,645	12,645	12,645
Individual and household controls	Yes	Yes	Yes	Yes
Province dummies	Yes	No	Yes	No

Source: CHFS (2013, 2019).
Notes: The sample comprises individuals aged 16 to 64 in the waves of 2013 and 2019 across 29 provinces in China. Hence, the estimates correspond to the medium term effect of housing demolition on occupational mobility. Models are estimated by ordinary least squares and two-way fixed effects specification. Other controls are as described in Table 4.
Robust standard errors clustered at the household level are shown in parentheses.
Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A7: Estimates of the effect of housing demolition on internal migration and migrant mobility.

Dependent Variable	Migration rate			Migrant mobility	
	(1)	(2)	(3)	Upward	Downward
Local demolition rate	–0.032	–0.048**	–0.041	–0.058**	0.011**
	(0.021)	(0.021)	(0.027)	(0.026)	(0.005)
Observations	785	785	684	684	684
R^2	0.003	0.050	0.898	0.869	0.728
City level controls	No	No	Yes	Yes	Yes
Year fixed effects	No	Yes	Yes	Yes	Yes

Source: CHFS (2013, 2017, 2019).
Notes: The sample contains all cities with non-missing names. The city level controls are population measure, unemployment rate, labor force participation rate, average annual job income, ratio of residents with rural *hukou*, average household income, ratio of Han ethnic group, ratio of males, ratio of high-skilled workers, ratio of low-skilled workers, average resident age, average resident education (years), rural area indicator, and resident city fixed effects.
Robust standard errors in parentheses.
Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Figure A1: Sensitivity analysis with simulation methods