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DISCUSSION PAPER SERIES

IZA DP No. 17359

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ABSTRACT

Affordable Housing and Individual Labor Market Outcomes*

We investigate the employment effects of living in affordable housing. We develop a unique administrative data set of labor market biographies linked to affordable housing projects in five German cities. This allows us to follow individuals in affordable housing over almost 20 years. The funding scheme is similar to the American LIHTC program, so the results are applicable beyond Germany. We use an event study design to exploit the quasi-random timing and allocation of applicants to units. Our findings show that access to affordable housing increases labor income and job quality while decreasing the likelihood of being unemployed. We explain these results by four mechanisms. These mechanisms work through a higher centrality of affordable units, enabling investment in work-related skills, improved housing stability, and increasing work incentives due to reduced housing benefit payments.

JEL Classification: I31, I38, J13, R23, R38

Keywords: affordable housing, unemployment, urban labor market access, labor supply, housing policy

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1 Introduction

It is a major political and economic challenge in urban areas worldwide to keep housing affordable for low-income households. Affordable housing provision is one of the most important pillars of low-income housing policy. The OECD Affordable Housing Database reveals that public and affordable housing accounted for 7% of the total housing stock in OECD countries in 2020, with over 20% in Austria, Denmark, and the Netherlands, 17% in the UK, 14% in France, 10% in the US, and 3% in Germany. It is clear that expenditure on project-based affordable housing is a significant item in public budgets. For example, the federal government of the US will spend around seven billion USD annually on the Low-Income Housing Tax Credit (LIHTC) program between 2022 and 2026 (Keightley 2023), making it one of the largest federal housing assistance programs in the US. LIHTC-funded projects provided 3.55 million units between 1987 and 2021. This is a significant number compared to the total of 10.8 million privately-owned multifamily units built in the US during that period.[1]

In this paper, we investigate the labor market outcomes of individuals living in affordable housing. We use a unique administrative data set of 465 subsidized rental housing projects in five major cities in Bavaria, Germany. The German funding scheme for affordable housing shares key features with the LIHTC program: Access to affordable units is means-tested, rents in subsidized projects are strictly controlled for a fixed period of typically 25 years, and the rent does not depend on household income. Our findings on why residents have better labor market outcomes after being admitted to affordable housing therefore provide valuable insights on the ramifications of affordable housing policies in the US and other countries.

We link the subsidized projects to a 100%-sample of the Integrated Labor Market Biographies of the Institute for Employment Research (IAB), based on geocoded building-level address information. These administrative data cover the universe of workers in Germany subject to social security contributions, as well as all persons registered as unemployed. We follow these individuals over time and space to investigate the long-run effects of affordable housing provision on individual labor market outcomes.

For identification, we make use of the fact that applicants cannot determine the time of admission to affordable housing. The local housing offices allocate workers to subsidized housing based on the availability of vacant units. This means that timing and allocation arguably cannot be influenced by the applicant. The timing of admission is determined by the waiting period and on a list of admission criteria. In the cities and period under study, there was excess demand for affordable housing. Applicants had to wait several years before being assigned to a housing unit. For example, the waiting list of the largest city in our sample, Munich, comprised more than 30,000 applicants as of January 2024, but only about 3,000 applicants are admitted each year. The processing time for registering applications alone is around four months.[2] Therefore, conditional on applying, the timing of admission ultimately depends on factors arguably exogenous to the applicant's behavior.

[1] Sources: HUD: Characteristics of LIHTC Properties - Properties Placed in Service through 2021, and FRED series COMPU24UNSA and COMPU5MUNSA.

[2] https://stadt.muenchen.de/service/info/soziale-wohnraumversorgung/1073964/, last accessed January 15, 2024.

We exploit this source of exogenous variation by using the event-study difference-in-differences estimator recently developed by Borusyak *et al.* (2024) to compare treated and not-yet treated individuals. This empirical strategy requires that, conditional on observable person characteristics and various fixed effects, the applicant cannot influence the timing of admission. The event study graphs generally support the assumption of timing exogeneity, as there are no visible differential pre-trends between treated and not-yet treated observationally similar individuals prior to admission. The absence of pre-trends is confirmed by joint pre-trend tests.

Two to three years after admission, labor income starts to increase more strongly than the counterfactual. Yearly labor income is about 4,000 EUR higher than the counterfactual 12 to 13 years after admission – a 20% increase relative to the counterfactual of around 20,000 EUR. The fraction of the year spent in unemployment decreases about three years after being admitted to the affordable housing unit, with a total long-run reduction of about ten percentage points after ten to 13 years. This reduction is quantitatively large, relative to the level of the counterfactual outcome of around 25%, suggesting that a large part of the effect on total income is due to formerly unemployed persons re-entering the workforce.

These effects are quantitatively important both from the perspective of the individual and from an aggregate perspective. They suggest that affordable housing can help workers with low incomes to improve their labor market situation considerably in the long run, thereby reducing the need for government assistance overall. In this way, affordable housing may help individuals to grow out of subsidized housing over time, which reduces the overall fiscal cost of housing assistance. They are important from an aggregate perspective because of the large number of low-income households in urban areas that rely on housing assistance.

We discuss four potential mechanisms to explain our results. First, the subsidized housing units in our sample are more centrally located in the local labor market and better connected to local public transport than the previous places of residence prior to admission to affordable housing. Affordable housing thus facilitates access to the local labor market, which likely contributes to better employment opportunities and lower unemployment risk. Consistent with this mechanism, the treatment effects are more pronounced for individuals who moved closer to the city center and to public transport stops. At the same time, commuting distances decreased for workers who moved towards the city center. The commuting distances of female workers decreased particularly strongly, suggesting that women used the improved accessibility to shorten their daily commute. Finally, we demonstrate that better access to the city center and public transport helped workers to find higher-paying employers, as captured by the plant-specific component of the wage (Abowd et al. 1999), and employment in better-paid occupations. Overall, these results suggest that the centrality of affordable housing improved both access to employment and job quality.

Second, affordable housing empowers residents to invest in their human capital. We focus on vocational training, which is well-documented in our data. Vocational training in Germany usually takes three years and consists of on-the-job training and schooling. Trainees earn a wage that is typically much lower than the minimum wage or wages paid to unskilled workers outside of vocational training. A substantial share of the workers in affordable housing who start vocational training for the first time in their career are already more than 30 years old.

Moreover, we find that, conditional on worker characteristics, the propensity to start vocational training one to five years after having moved into affordable housing is higher than in the five years before moving in. This is consistent with an income effect of implicit rent subsidies on investment in human capital, as argued by Pollakowski *et al.* (2022), but it could also result from improved labor market access.

Third, the high level of stability of affordable housing arrangements in Germany arguably increases the planning horizon by shielding residents from being priced out of the local housing market. We show that rates of residential mobility in affordable housing are considerably lower than average mobility rates in the cities studied in this paper. Furthermore, comparable workers who have not-yet been assigned to affordable housing move house much more frequently than workers in affordable housing. All else equal, higher residential stability increases the returns from investment in firm-specific human capital, thereby providing an incentive for both employers and employees to establish a more stable employer-employee relationship. Access to affordable housing may also reduce housing-related stress, making it easier for individuals to concentrate on their labor market success.

Fourth, object-based housing subsidies may mitigate labor supply disincentives of tenant-based housing assistance. The latter have been found to cause strongly negative labor supply effects (Jacob and Ludwig 2012). However, the labor supply disincentive embedded in tenant-based housing assistance typically weakens as rents decrease. This suggests that affordable housing, where rents are below market rates and independent of household income, can reduce negative labor supply effects of tenant-based housing assistance.

In addition, we study another potential mechanism that is unlikely to explain our main results: effects related to neighborhood quality. In our setting, the affordable housing buildings are distributed relatively evenly across the city. We do not observe that, for the average resident, the neighborhood quality changed significantly upon admission to affordable housing. Hence, it is unlikely that improved neighborhood quality can account for the positive effects we find.

The Bavarian case is especially intriguing to study, for three reasons. First, the rent subsidy's dependence on worker income was small until 2006 and completely abandoned afterwards. Therefore, the rent subsidy did not depend at all on worker income – even if incumbent residents had crossed the income eligibility threshold. On the one hand, this may have reduced individuals' mobility out of the subsidized housing units. On the other hand, it removed an incentive for affordable housing residents to work fewer hours, which potentially enabled them to "grow out" of the affordable housing unit deliberately. Such negative labor supply incentives are embedded in housing benefit schemes such as *Section-8 Housing Vouchers* in the US (Jacob and Ludwig 2012), the German *Wohngeld*, and the British *Universal Credit*, among others, where individuals gradually lose the housing subsidy as they approach the income eligibility threshold. In this sense, our results suggest that the benefit-cost ratio of affordable housing may be more advantageous than previously thought, thereby adding to recent evidence for public housing that points in the same direction (Pollakowski *et al.* 2022).

Second, the urban housing markets in Bavaria experienced particularly strong rent increases starting in 2009, making low-income households vulnerable to being priced out of the local market. This includes both, workers formerly living in central locations who had to move outwards to cope with the increasing rents, and workers willing to move closer to the city center, but unable to do so due to a lack of low-cost housing options.

Third, the German affordable housing program is in many ways comparable to LIHTC in the United States, which has been found to revitalize left-behind neighborhoods and to lower neighborhood-level crime rates (Diamond and McQuade 2019). Affordable housing in Germany provides a comparably high level of housing quality and is distributed evenly across poorer and more affluent neighborhoods. Moreover, the developments are smaller in size than the high-rise and high-density public housing programs studied by Chyn (2018), Haltiwanger *et al.* (2020), and Aliprantis and Hartley (2015), among others. This suggests that the housing developments studied in this paper likely offer a relatively secure and amenable housing environment, factors that are potentially important for their residents' labor market outcomes.

Evidence on the labor market outcomes of residents in public, social, and other types of affordable housing is still very scarce. Notable exceptions are van Dijk (2019), Chyn (2018), Haltiwanger *et al.* (2020), and Pollakowski *et al.* (2022).[3]

Van Dijk (2019) investigates labor market effects of admission to affordable housing through a lottery scheme in Amsterdam, finding that the average move into affordable housing negatively affects labor market outcomes one to two years after admission. However, there is substantial heterogeneity, with positive effects for households that move from economically worse to economically better neighborhoods.

There are important differences between our study and van Dijk (2019). First, our data allow us to follow individuals for up to 20 years after gaining access to affordable housing, enabling us to estimate treatment effects fairly precisely up to 13 years after the initial move. Our results suggest that there are substantial frictions in the short-run that are likely related to the change in neighborhoods and the social and work environments. Moreover, we find that the positive accessibility and stability effects emerge more slowly. Second, the housing markets of Germany and the Netherlands differ in important respects, with much lower shares of affordable housing, stricter admission criteria, and a larger private rental market in Germany.[4]

Chyn (2018), Haltiwanger *et al.* (2020) and Pollakowski *et al.* (2022) study the long-run labor market consequences of living in public housing in the U.S. as a teenager. Chyn (2018) and Haltiwanger *et al.* (2020) compare children and adults in the U.S. whose families moved out of public housing in exchange for housing assistance, to other children who stayed in public

[3] Several papers study the role of public housing for education and crime rates, exploiting the demolition of high-density public housing in Chicago. Jacob (2005) documents a zero effect on student achievement, likely because the schools chosen by the displaced former public housing residents were similar in quality to their previous schools. Aliprantis and Hartley (2015) find substantial decreases in local crime rates as well as the city-wide crime rate due to the demolitions, suggesting an overall negative impact of high-density public housing. Other work suggests ambiguous overall effects. Using a different methodology, Bruhn (2018) finds an overall increase in city-wide crime after the public housing units were demolished. New public housing seems to reduce local and aggregate crime rates in poor neighborhoods, suggesting that the effects may depend on the quality of the public housing units (Freedman and Owens 2011).

[4] In Amsterdam, the eligibility threshold is approximately at the median household income (accounting for household size), and it accounts for 46% of the housing stock, see van Dijk (2019). In contrast, the affordable housing stock 2021 in Munich, the largest city in our sample, consisted of only 88 000 units (10.7% of the stock) see https://stadt.muenchen.de/service/info/soziale-wohnraumversorgung/1073964/, last accessed January 2024.

housing. On average, mover families relocated to neighborhoods with lower crime rates and better job opportunities. At age 26, children from the mover group had substantially higher earnings than children from the control group. Moreover, Chyn (2018) documents positive employment effects and Haltiwanger *et al.* (2020) provide evidence that the earnings gains are mostly due to better job accessibility and lower poverty rates at the new residential locations. For adults, the authors do not find statistically significant effects.

Using a different identification strategy that exploits variation in siblings' exposure to public housing and housing vouchers during childhood, Pollakowski *et al.* (2022) find positive earnings effects. For each year spent in affordable housing between 13 and 18, earnings at the age of 26 increase by around six percent, whereas each year with housing voucher assistance between 13 and 18 increases earnings at the age of 26 by around four percent. The impact on earnings is generally larger for households with lower incomes – arguably because housing assistance allows parents to invest in their children's human capital.

Consistent with the evidence from Haltiwanger *et al.* (2020) and Pollakowski *et al.* (2022), we find positive effects of increased job accessibility. In contrast to these two papers, we also find positive effects on labor market outcomes of adults, exploiting a different source of variation. Importantly, workers in our setting cannot choose their residential location when moving into affordable housing. This differs from the setting in Haltiwanger *et al.* (2020), where program participants can choose to stay in the vicinity of their previous address. In this context, our spatially highly granular data on job and public transport accessibility allow us to carve out additional details on the mechanisms that contribute to the labor market effects of affordable housing. Finally, in contrast to the public housing tenants studied by Haltiwanger *et al.* (2020) and Pollakowski *et al.* (2022), tenants in our setting face income-independent affordable rents and have access to other forms of housing assistance.

A related literature investigates the non-housing consequences of housing vouchers. Jacob and Ludwig (2012) and Jacob *et al.* (2015) study housing voucher recipients exploiting exogenous variation created by a housing voucher lottery in Chicago. Jacob and Ludwig (2012) find negative labor supply effects and a higher likelihood to receive government benefits, clearly dominating any potential positive effects due to neighborhood quality or residential stability. Consistent with this result, Jacob *et al.* (2015) document only modest effects on educational attainment, health, and school and neighborhood quality. Using a propensity-score matching difference-in-differences strategy, Carlson *et al.* (2012) report similar negative earnings effects of housing voucher receipt but do not find evidence for negative labor supply effects.

The core contributions of this paper are threefold: First, we provide evidence on the long-run effects of living in affordable housing on key labor market outcomes. The event study design builds on the arguably exogenous timing of admission to affordable housing through the local housing offices. Our data cover the universe of employees and unemployed persons assigned to the buildings in our sample, which strengthens the reliability of the estimates.

Second, we use geo-coded data on neighborhood quality and employment opportunities to investigate the importance for low-income workers, in particular of having access to thick urban labor markets, in conjunction with living in a stable residential arrangement that shields these workers from being priced out of the local labor market. Although a common theme in urban and labor economics, there is surprisingly little causal empirical evidence on the extent to which low-skilled workers benefit from gaining access to the urban labor market. A notable exception is Eckert *et al.* (2022), who study the role of big-city experience for refugees' labor market success in Denmark. The affordable units in our sample are typically situated in more central locations and better connected to the public transport network. Hence, they provide better access to various types of jobs than the average residential locations of similar workers living in private rental housing. This setting also allows us to contribute to the evidence on differences in job search and commuting behavior between women and men (Le Barbanchon *et al.* 2021, Liu and Su 2022).

Third, we examine several further mechanisms that explain the positive impact on labor market outcomes we observe when workers gain access to affordable housing. The rich information on the individuals' full employment and welfare benefit receipt biographies allows us to shed light on the presence of labor supply incentives and the role of residential stability as well as investments into human capital.

Section 2 of the paper briefly presents the institutional framework. In Section 3, we discuss potential mechanisms that suggest an impact of affordable housing tenure on the success of low-income individuals on the labor market In Section 4, we discuss the data, the empirical approach, and the empirical results. We offer conclusions in Section 5.

2 Institutional Framework

This paper uses data on 465 subsidized affordable rental housing projects completed between 1997 and 2007 in the five largest Bavarian cities. All five cities experienced strong rent increases and under-supply of affordable housing during the housing boom 2009-2020, with under-supply of housing being a pre-requisite for the public funding of affordable housing in Germany. Figure 1 shows the locations of the affordable housing projects in each city.

The provision of affordable housing in Germany works through subsidies to developers. In exchange for the subsidy, the developers have to rent out the units at a reduced rate during a pre-determined period, typically 25 years. Most developers are private building cooperatives[5] or municipal housing companies, but the subsidy is also open to private investors with profit-maximization goals. Restricting rent stabilization to 25 years implies that the affordable housing stock consists of relatively modern buildings, as older buildings eventually fall out of the affordable housing stock.

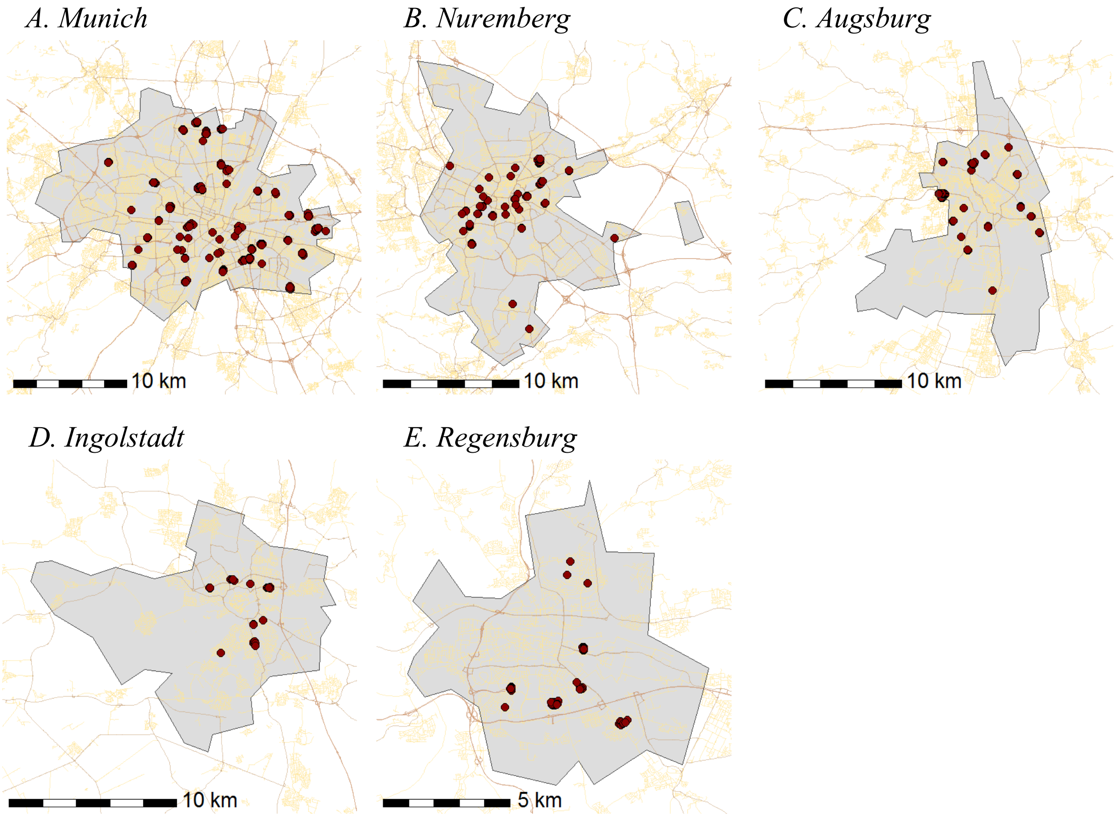
The funding regime is federal-state-specific. In projects granted before 2002, all rental units in subsidized housing projects in Bavaria had to be rented to tenants that met an income threshold in terms of household-level income, subject to a number of blanket deductions. We describe in detail the calculation of the eligibility thresholds and how these thresholds compare to the yearly gross labor income observed in our data in the year prior to admission in Appendix A. All renters under this regime, the so-called "first funding route" [*1. Förderweg*] are selected by the local housing offices.[6]

[5] Cooperatives are owned by their members, who are typically residents of the cooperative's housing stock.

[6] In 2001, a new regime was established, the so-called "income-oriented funding" [*Einkommensorientierte Förderung*]. New projects were allowed with four additional income thresholds. Up to two-thirds of the units in

Figure 1

Distribution of affordable housing objects in sample within and across municipalities



Notes: The maps show the extent of the municipalities of Munich, Nuremberg, Augsburg, Ingolstadt, and Regensburg as grey-shaded areas, the street network based on Open Street Map data as light orange lines, and the approximate locations of the affordable housing objects in the data as red dots.
Sources: Open Street Map 2023, GeoBasis-DE/BKG 2023, own representation.

Eligible applicants are admitted by the local housing offices based on a neediness score[7] and waiting time. Among similar eligible applicants, the local housing office makes a random selection. In practice, when an applicant reaches the top of the waiting list, the housing office presents the applicant together with two to four other applicants to the landlord. The landlord may then choose one of these applicants.

One important aspect of this design is that the applicants cannot determine the timing of this process, nor can they choose the location of residence. However, from a labor supply perspective, negative shocks to the worker can lead to quicker admission due to the neediness score. This may bias our event study estimates downwards, to the extent that these negative

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the housing development could be designated to these higher income classes. The investment subsidy for these units was lower, and the rent ceiling was higher. We do not consider these units in our analysis because we cannot identify the income group to which a worker belongs to. Housing units subject to the higher income thresholds are offered privately by the landlords who screen among eligible applicants without further restrictions.

[7] The City of Munich gives the highest priority to individuals facing homelessness or the termination of a rental contract, having serious health issues, and having experienced domestic violence. There are a number of other cases with lower priority, see this table, https://stadt.muenchen.de/dam/jcr:ac217207-8afd-4a45-9507-9df75c8d3c1a/LHM%20Punktetabelle%20zur%20Registrierung%20und%20Vergabe%20von%20gef%c3%b6rderten%20Wohnungen.pdf, and Online Appendix B for further details.

shocks have persistent effects on labor supply or human capital of the worker.[8] We investigate this possibility in robustness checks.

3 Theoretical Mechanisms

3.1 Access to the urban labor market

One potential mechanism is improved access to the urban labor market. To the extent that low-skilled individuals have a spatially narrow job search radius, they do not benefit from the thick urban labor market unless they live close enough to the urban core. As we show below, the affordable housing units in our sample are located in more central, better-connected neighborhoods with a higher density of employment, indicative of overall better access to the local labor markets of the cities in our sample. Hence, they facilitate access to better employment opportunities especially for workers with a narrow job search radius.

From the perspective of the individual worker, access to a thick urban labor market helps to realize better matches, which results in better employment outcomes (Dauth *et al.* 2022). Workers also benefit from the possibility to accumulate labor market skills more easily and quickly when working for more productive firms (De la Roca and Puga 2017, Eckert *et al.* 2022).

In contrast to recipients of housing benefits, affordable housing residents are not in a position to trade off housing quality, neighborhood quality, and labor market accessibility when entering affordable housing. Instead, they faced a unit with a predetermined bundle of attributes. Depending on its location, affordable housing may thus provide better access to employment than the location the household would have chosen with other types of housing assistance.

3.2 Investment in human capital

Rents in affordable housing are lower than market rents. This implicit rent subsidy may allow affordable housing residents to invest more time and resources into their human capital development. Pollakowski *et al.* (2022) emphasize this channel as the main explanation for the positive earnings effects due to participation in public housing during childhood.

Moreover, to the extent that affordable housing provides more stability than other forms of rental housing, both the employee and the employer have a longer joint planning horizon and thus benefit more strongly from investment in firm-specific human capital. Employers learn about the affordable housing applications of their employees because the employer has to report an income projection to the local housing office at the time of application.[9]

[8] We do not observe the items of the neediness score. However, we observe health incidences lasting more than six weeks for male workers. For female workers, these health incidences also include birth events, but we cannot distinguish between births and illness. Online Appendix Figure B2 shows that these incidences are indeed more common for women shortly before and at admission to affordable housing, but we do not see a comparable pattern for men.

[9] This enables the affordable housing office to screen applicants that expect substantial pay rises in the near future.

3.3 Residential stability and security

Affordable housing residents are particularly well protected from eviction. In Germany, renter protection in private rental housing is strong but not universal. There are several ways a tenant can be forced to leave: First, the landlord may reclaim the unit when they or a close relative want to self-occupy the unit. Second, landlords may refurbish the building and charge a higher rent in return. Such rent changes may overwhelm low-income tenants financially. Third, tenants in arrears with rent can be evicted eventually.[10]

Affordable housing implicitly protects its tenants from these threats. First, landlords cannot reclaim the unit to self-occupy it. Second, they cannot reclaim investment expenses through higher rents because the rent is controlled by the local housing office. Third, the subsidized rent reduces the likelihood that a tenant is in arrears. In addition, affordable housing landlords may be more willing to provide additional assistance to a tenant suffering financial hardship to prevent a potentially costly and lengthy eviction process.

These aspects suggest that tenants in German affordable housing have a much higher planning horizon with respect to their residential location. The residential planning horizon is linked closely to decisions on the labor market. Workers and unemployed persons with higher residential stability arguably invest less time in housing-related search activities, which frees up time and energy that can be devoted to work-related activities. Moreover, as noted above, greater residential stability increases the expected returns to investments in firm-specific human capital, from both, the perspective of the employer and the employee.

3.4 Labor supply (dis-)incentives and interaction of housing policies

The neoclassical theory of housing subsidies suggests an income effect of subsidized housing on a household's time allocation. According to this theory, recipients use part of the subsidy to work less and enjoy more leisure time instead. This results in a reduction of labor supply, and hence, labor income. This negative effect of rent subsidies on labor supply is stronger if housing and leisure are complements.

In combination with other housing policies, however, rent subsidies do not only have an income effect. According to the affordable housing scheme examined here, rents increased only slightly with rising household income until 2006 and were completely independent of household income from 2007. While this may affect the allocative efficiency of the policy – affordable housing residents can significantly increase their income but do not have to leave subsidized housing – it has the advantage that working more hours remains attractive.[11]

Since the rent in affordable housing is below market rate, the costs of accommodation likely decrease when a recipient moves from private to affordable rental housing. This is the income effect, which per se leads to a decline in labor supply under plausible assumptions. However, in the German welfare system, many individuals that meet the income eligibility criterion of affordable housing have access to other types of housing benefits. One important group are

[10] There is additional protection for long-term tenants, disabled or unhealthy persons, and other vulnerable groups. Because of these additional rules, evictions are regularly decided before court.

[11] This is in contrast to public housing in the US, where rents increase with household income, which likely represents a disincentive to work more hours.

workers on basic income support regulated under the Second Book of the Social Code (SGB II). This means-tested cash transfer is supposed to cover standardized basic living costs including the cost of accommodation and heating.[12] As long as individuals receive these welfare benefits, the net wage of an additional hour of work and thus the incentive to work is low due to the high transfer withdrawal rate. When income exceeds the threshold for receiving basic income support, the net wage and thus the incentive to work increases sharply. This implies that the recipient's reservation wage decreases, which ultimately compensates the pure income effect. The combination of the loss of the basic income support and the provision of affordable housing leads to higher incentives to work. In Online Appendix A, we provide a graphical illustration of this mechanism.

3.5 Neighborhood and peer quality

The literature on housing assistance and neighborhood effects has emphasized the role of neighborhood quality and residential stability as positively affecting labor supply and labor market outcomes (Oreopolus 2003, Chetty *et al.* 2016, Pollakowski *et al.* 2022). While our baseline results may indeed vary with neighborhood quality, this cannot explain the average treatment effect as the average neighborhood quality of the affordable housing projects in our sample is similar to the neighborhood quality at the last address prior to affordable housing, as documented in Online Appendix Table B1. If anything, the quality of the neighborhood decreases on average. This is because the affordable housing units in our sample are not concentrated in particularly poor or affluent neighborhoods, but distributed evenly over the entire cities, as documented in Figure 1.

4 Empirical Analysis

4.1 Data

This project relies on the full sample of the Integrated Labor Market Biographies (IEB, version 15.00.00-201912) of the Institute for Employment Research (IAB). This dataset covers the entire employment biographies of all employees in jobs subject to social security contributions, unemployed individuals, and individuals receiving other labor-related welfare benefits between 1992 and 2019 in Germany.[13] We complement these data by the exact geocodes of the registered addresses of (almost) all individuals and plants from 2000 to 2017.

We link the IEB to data on affordable housing units provided by the municipalities of Munich, Nuremberg, Augsburg, Ingolstadt, and Regensburg, based on the residential address information. The total number of distinct affordable housing addresses is 465. These affordable housing projects represent all newly built affordable housing in the five cities completed between 1997 and 2007 under the "first funding route". We link the two data sets at the building address level, using standard geocoding software.

[12] Accommodation and heating costs are covered up to a threshold specific to the municipality. The costs for accommodation vary substantially between cities and are particularly high in Bavarian cities. In 2022, Munich was the city with the highest payments for accommodation per recipient in all of Germany (Mense 2023).
[13] We do not observe self-employed individuals, civil servants, and retired individuals. While civil servants are typically not eligible for affordable housing due to their salary, we caveat that this does not necessarily hold for self-employed individuals. We exclude retired individuals participating in the labor market by restricting the sample accordingly, since this group is not the focus of our paper.

For each residential address observed between 2000 and 2017, we compute neighborhood characteristics based on all individuals living inside a circle with a radius of 500m around the target address, again using the full IEB sample.[14] We use as neighborhood variables the median daily wage, the share of unemployed persons, and the share of low-skilled individuals (i.e., workers without vocational training or college education).

In addition to the individual and neighborhood characteristics from the IEB, we compute the commuting distance, the distance to the city centers of the five cities[15], rounded to the nearest 500m, as well as the distance to the nearest rail-based public transport stop, rounded to the nearest 250m. These are railway, tramway, and subway stops, as well as high-frequency commuter train stations, the so-called “S-Bahn”. The latter variable is truncated at a maximum distance of 3,000m.

We restrict the sample to individuals observed in the data one period prior to moving into an affordable housing unit, and we drop individuals observed in an affordable housing unit for the first time in 2000, unless the building was constructed in that year. We impose these restrictions to ensure correct assignment of the treatment date, since we do not observe addresses before 2000. Moreover, we drop individuals older than 55 years at the time of admission as they were subject to more generous rules regarding the duration of unemployment benefits. Applying these restrictions, we have 185,479 person-year observations and 9,916 persons in the sample.

Table 1 displays summary statistics for the variables used in the analysis. Panel A shows descriptive statistics for the whole sample. Panel B refers to the period prior to admission to the subsidized unit.[16]

In addition, we make use of novel data from the SGB II welfare benefits payment statistics. It includes different welfare benefit items and the household composition for SGB II welfare recipients, covering the years 2007 to 2018. A particularly important payment category for our purpose are housing benefits. This allows us to investigate the difference in housing benefits before and after admission to affordable housing. We link these data to welfare recipients in the IEB data. In Online Appendix B, we describe these data in greater detail and we show summary statistics for welfare benefit payments in the sample of welfare recipients one year prior to admission to affordable housing in Online Appendix Table B2. We also make use of welfare payment items related to residential moves to validate the timing of admission to affordable housing.

[14] Data protection rules require us to have at least 25 individuals inside the 500m circle. In case there are less than 25 individuals inside the circle, we increase the radius step-wise by 100m, up to a maximum of 1,500m.

[15] As city centers, we use central places in each city: Marienplatz in Munich, Hauptmarkt in Nürnberg, Rathausplatz in Augsburg, Franziskanerplatz in Ingolstadt, and Neupfarrplatz in Regensburg. These places are close to the geographical and historical centers of these cities.

[16] Since people without German citizenship and, to a lesser extent, younger people are overrepresented among recipients of social benefits, this also applies to the residents of affordable housing and our sample.

Table 1
Summary statistics

A. All years	Mean	Median	SD	Min	Max
Age	35.17	34	10.83	13	73
Female	0.43	0	0.50	0	1
Non-German nationality	0.56	1	0.50	0	1
Skilled (voc. training or higher)	0.65	1	0.48	0	1
Real labor income in 1k EUR	18.22	15.12	16.31	0	134.2 [e)]
Real daily wage in EUR [a)]	60.79	57.06	39.98	0.01	971.2 [e)]
Fraction of year in unemployment	0.19	0	0.35	0	1
Year of observation	2007	2008	7.12	1992	2019
First year in affordable housing	2006	2005	4.46	2000	2017
Person-year observations:	185,479				

B. One year before moving into affordable housing	Mean	Median	SD	Min	Max
Age	31.8	31	9.64	14	55
Female	0.45	0	0.50	0	1
Non-German nationality	0.57	1	0.50	0	1
Skilled (voc. training or higher)	0.57	1	0.49	0	1
Real labor income in 1k EUR	14.65	9.98	14.60	0	134.2 [e)]
Real daily wage in EUR [a)]	52.23	46.92	36.58	0.01	202.3 [e)]
Fraction of year in unemployment	0.22	0	0.37	0	1
Distance to CBD [c)]	24.22	5	72.28	0.5	601
Dist. to rail-based public transit [c), d)]	0.94	0.50	0.86	0.25	3.00
Median daily wage in n'hood [b)]	84.57	84.23	14.96	8.62	179.8
Share unemployed in nbh. [b)]	0.08	0.07	0.06	0	1
Share low-skilled in nbh. [b)]	0,24	0,23	0,08	0	1
Persons:	9,916				

Notes: The table refers to the final sample, excluding university and college students at the time of admission to affordable housing, but includes persons in vocational training at the time of admission. Real EUR values were using the CPI with base year 2015. [a)]: Variable set to missing if person is not employed. [b)]: In 500m radius; radius increases up to 1,500m if less than 25 other cases within radius to fulfill data privacy protection requirements. [c)]: Distance rounded up to the nearest 0.5km to fulfill data privacy protection requirements. [d)] Distance truncated at 3km and rounded to the nearest 0.25km to fulfill data privacy protection requirements. [e)] In individual cases, income spells can be one-day spells that may be due to one-time payments or corrections. These spells can lead to very high values for the daily wage and income variables. In total, there are six (three) person-year observations with a daily wage above 250 EUR (500 EUR).

4.2 Empirical strategy

For our empirical strategy, we exploit the plausibly exogenous variation in the timing of admission to affordable housing. To this end, our analysis is based exclusively on people who ultimately gain access to affordable housing and we use the nonparametric event study difference-in-differences estimator of Borusyak *et al.* (2024), henceforth BJS. This estimator does not suffer from overly restrictive assumptions on effect heterogeneity, and it requires weaker assumptions regarding the estimation of long-run effects, as compared to the two-way fixed effects (TWFE) approach using event period dummies.

The estimator proceeds in two steps. In the first step, we estimate a model for the non-treated outcome, $Y_{it}(0)$ of individual i in year t. This model is estimated from the pre-treatment sample, consisting of individual-year observations up to two periods prior to the admission to the subsidized unit. We exclude observations one year prior to the treatment from the first-stage regression, since individuals may know several months ahead of time when they move into affordable housing. We denote the treatment period of individual i by t_i^* and estimate a flexible fixed-effects specification

$$Y_{it}(0) = \phi_i + \psi_t^c + \psi_t^n + \psi_t^s + \kappa_{\alpha(i,t)}^n + \kappa_{\alpha(i,t)}^s + \varepsilon_{it}. \quad (1)$$

Here, ϕ_i is an individual fixed effect. We allow the year fixed effect to be specific to the city (ψ_t^c), the nationality (German/non-German, ψ_t^n), and sex (ψ_t^s). Moreover, we control for nationality- and sex-specific age fixed effects $\kappa_{\alpha(i,t)}^n$, and $\kappa_{\alpha(i,t)}^s$. Equivalently, we control for cohort- and worker-type-specific year fixed effects.

The estimator rests on the assumptions that there are no pre-trends or anticipation effects. These assumptions are necessary for regression equation (1) to predict consistently the counterfactual outcome of the non-treated prior to the treatment. This justifies using $\hat{Y}_{it}(0)$ as a valid estimate for $E[Y_{it}(0)]$ for $t \geq t_i^*$, the counterfactual non-treated outcome in the post-event periods.

Letting $t_{e,i} = t - t_i^*$ denote the "event time" for individual i, the second step of the estimator thus recovers the average treatment effect t_e periods after the treatment as

$$\hat{\tau}_{t_e} = \frac{1}{N_{t_e}} \sum_{i:\, t_{e,i}=t_e} \left(Y_{it} - \hat{Y}_{it}(0) \right). \quad (2)$$

Here, N_{t_e} denotes the number of individuals t_e periods after treatment, and Y_{it} is the observed outcome. (2) can be computed for all t, not just $t \geq t_i^*$, which we use to visualize the treatment effects prior to the admission to the subsidized unit. An analogue of (2) can also be used to calculate treatment effects for subgroups.

Our first baseline outcome is the total yearly labor income in 1,000 EUR deflated by the consumer price index (2015 EUR). This captures the overall effect of affordable housing on a person's labor market success. Our second baseline outcome is the fraction of the year the worker was registered as unemployed, to capture the extensive-margin labor supply effect of affordable housing.

3.7% of the individuals in our sample appear at more than one of the affordable housing projects in our sample, likely because individuals are sometimes allowed to switch to other subsidized housing units when requiring a smaller or larger unit. We therefore consider only the first move into a subsidized unit and do not treat subsequent moves as new "events", as these moves are likely endogenous.[17]

4.3 Main results: Total real labor income and unemployment

4.3.1 Baseline estimates

Panel A1 of Figure 2 displays the actual and counterfactual evolution of our first main outcome, the total yearly real labor income in 1,000 EUR. The counterfactual is estimated from person-

[17] Since we do not observe the universe of affordable housing addresses in the five cities, we cannot rule out that a small number of movers coming from residential addresses other than the affordable housing addresses in our data were in fact affordable housing renters at their previous address. This would bias our estimates towards zero.

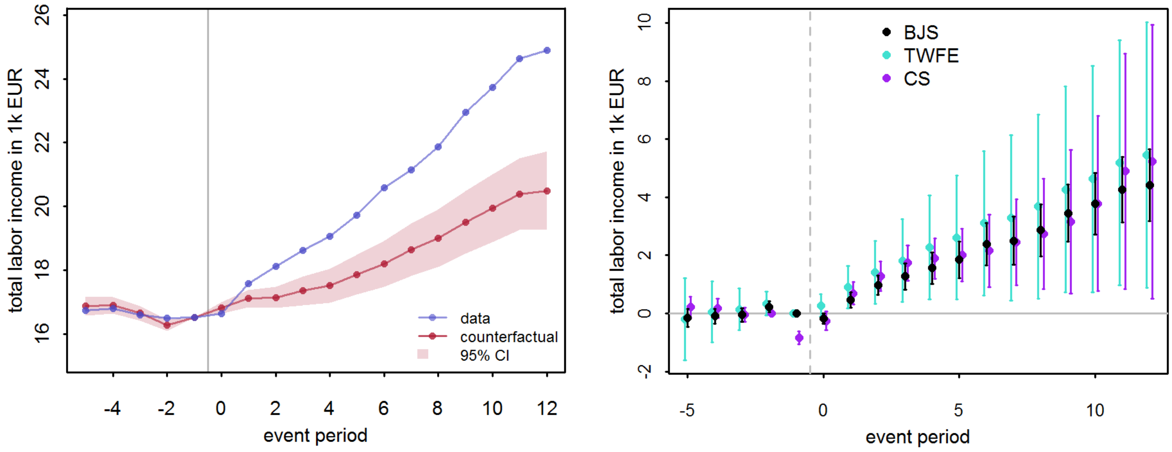
year observations up to two years prior to admission to affordable housing. When computing the counterfactual outcome for equation (2), we exclude all persons in vocational training, college, or university at the time of admission to affordable housing, because of the positive long-run income expectation in this group after graduation. The shaded area is a bootstrapped 95% confidence interval. The difference between the red and blue lines represents the event period-specific treatment effects as defined in equation (2).

Figure 2

Baseline results: Total real labor income and unemployment

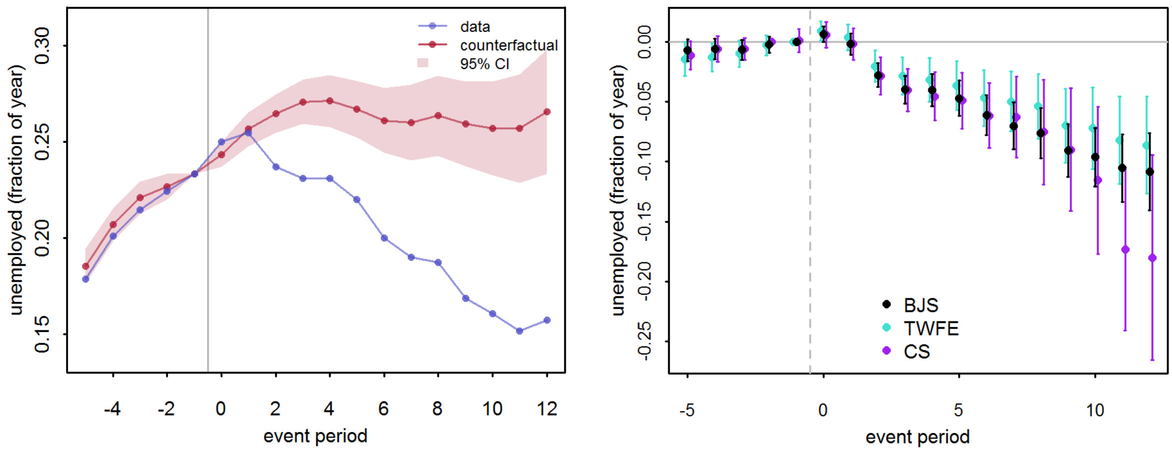
A. Total real labor income

A1. Counterfactual and actual development *A2. Treatment effects*



B. Fraction of year in unemployment

B1. Counterfactual and actual development *B2. Treatment effects*



Notes: In Panels A and C, the blue lines show the mean outcome variable as observed in the data. The red counterfactual lines are constructed using the BJS estimator. The vertical grey lines denote the event date. In period 0, the person was observed at a affordable housing address for the first time. Persons in vocational training or in university or college at the time of admission to affordable housing excluded. The shaded area is a 95% confidence region obtained from 500 block-bootstrap draws at the affordable housing address level. Panels B and D show the treatment effects with 95% confidence bands for the BJS estimator, which amounts to the difference between the blue and red lines in Panels A and C, respectively. They also show estimates from a TWFE regression using event period dummies, and estimates using the CS estimator. The TWFE and CS models were estimated using only person and year fixed effects, and a sex-specific quadratic in age, for computational tractability. Unemployed persons work less than 15 hours per week.

The graph shows a slightly negative trend prior to admission for both the observed and the counterfactual outcome. This likely reflects the fact that admission becomes more likely if the household experienced negative shocks, e.g., health shocks or domestic violence. Importantly, the counterfactual captures very well these dynamics. Consistent with this observation, the formal test of the common trends assumption developed in Borusyak *et al.* (2024) does not allow to reject the null hypothesis of differential pre-trends.[18]

After the treatment date, both lines trend upwards. Among other variables, the dynamics of the counterfactual line depend on year and age effects, which can explain the steady upward trend. However, the yearly labor income observed in the data exhibits an even steeper increase post-treatment, starting one year after admission to affordable housing. The difference – the period-by-period BJS treatment effects as defined in equation (2) – is statistically and economically significant, reaching around 4,000 EUR ten years after admission to the subsidized unit. Relative to the counterfactual, this is a 20% increase in total yearly labor income.

In Panel A2 of Figure 2, we show the BJS treatment effects directly, together with treatment effects from the traditional TWFE estimator, and from the estimator of Callaway and Sant'Anna (2021), henceforth CS. The three estimators produce very similar treatment effects. Although the CS and TWFE effects are slightly larger, they usually fall inside the 95% confidence band of the BJS estimator. This is despite the fact that the bootstrapped BJS confidence band is considerably smaller than the CS and TWFE confidence bands.

In the period of admission, the treatment effects from the BJS and CS estimators are slightly negative, consistent with a temporal disruption effect, arguably due to the change in residential environment. Disruption effects for unskilled workers may explain why this group is particularly reluctant to move to better residential locations within the local labor market, as suggested by low take-up rates in the MTO experiment (Katz *et al.*, 2001).

Panels B1 and B2 of Figure 2 show the results for the second baseline outcome, the fraction of the year in unemployment. Again, there are no differential pre-trends visible in the graphs, and the formal Borusyak *et al.* (2024) test does not allow to reject the null hypothesis of common trends.[19] The treatment effect derived from the BJS estimator is significantly positive in the period of admission, consistent with a short-run disruption effect. Starting two years after admission, however, the treatment effects are significantly negative, suggesting a reduction of unemployment due to affordable housing. Ten years after admission, treated individuals are unemployed for about 16% of the year on average, which compares to a counterfactual outcome of around 26%. Again, the different estimators lead to similar results, with the differences generally being statistically insignificant.

Overall, Figure 2 suggests that residents in affordable housing significantly increase their labor income, mostly because workers are less likely to be unemployed.

[18] Specifically, as suggested by Borusyak *et al.* (2024), we run the first-stage regression on pre-event observations with additional dummies for pre-event periods $1, \dots, k-1$, using event period k as the reference category. The p-value is the p-value of the cluster-robust Wald test for joint significance of the $k-1$ dummies. For $k = 5, 6, 7$, the p-values are 0.334, 0.422, and 0.482, respectively.

[19] For pre-event horizons $k = 5, 6, 7$, the p-values are 0.623, 0.728, and 0.417, respectively.

4.3.2 Identification and robustness

Our empirical strategy hinges on the assumption that individuals do not selectively move into affordable housing in order to shorten their commutes. If this were the case, part of the estimated effect could be attributed to individuals with favorable employment biographies improving their combination of place of residence and workplace. In the first part of Online Appendix C, we test the plausibility of this assumption by comparing the move into affordable housing with earlier moves by the same group of individuals. We find that while the commuting distance does indeed decrease on average after other moves, moves into affordable housing are actually associated with an increase in distance. This suggests that affordable housing is so attractive that applicants accept the housing offered to them, even if it is associated with a disadvantage in the form of longer commuting distances.

We carry out a series of further robustness checks, which we describe in detail in the remainder of Online Appendix C. First, we reduce the sample to a balanced panel of individuals observed in each event period from -5 to 12. Second, we exclude individuals in vocational training during the five years prior to admission since they might be on exceptionally steep income paths. Third, we estimate a more parsimonious model where city-specific year fixed effects are not additionally interacted with both sex and age. Fourth, we replace the year fixed effects with a city-specific quadratic polynomial in the year of observations, which allows us the use the final four years to compute the counterfactual. Fifth, we exclude the five years (instead of one year) prior to admission from the first-stage estimation to ensure that our results are not driven by transitory shocks. Finally, we use a more general matching approach to compare the outcomes of individuals after admission with those of other not-yet-treated persons observed between nine and two years before treatment. All of those checks yield qualitatively very similar results both for the significant treatment effects and the absence of pre-trends.

4.4 Further results: Daily wage and job quality

In addition to the extensive-margin labor supply effect documented in Panel B of Figure 2, the effect on the total labor income may also be due to intensive-margin labor supply effects and improved job quality. To shed light on this, we consider as additional outcomes the log daily wage and two proxies for job quality, conditional on currently being employed. First, employer quality, measured by the plant-specific AKM effect (from a two-way fixed effects model following Abowd et al. (1999)) and second, occupational quality, measured by the national median wage of a worker's current occupation. The plant effects allow us to decompose the wage effect into person-specific and employer-specific components, while the occupational quality represents a substantial fraction of the person-specific component.[20]

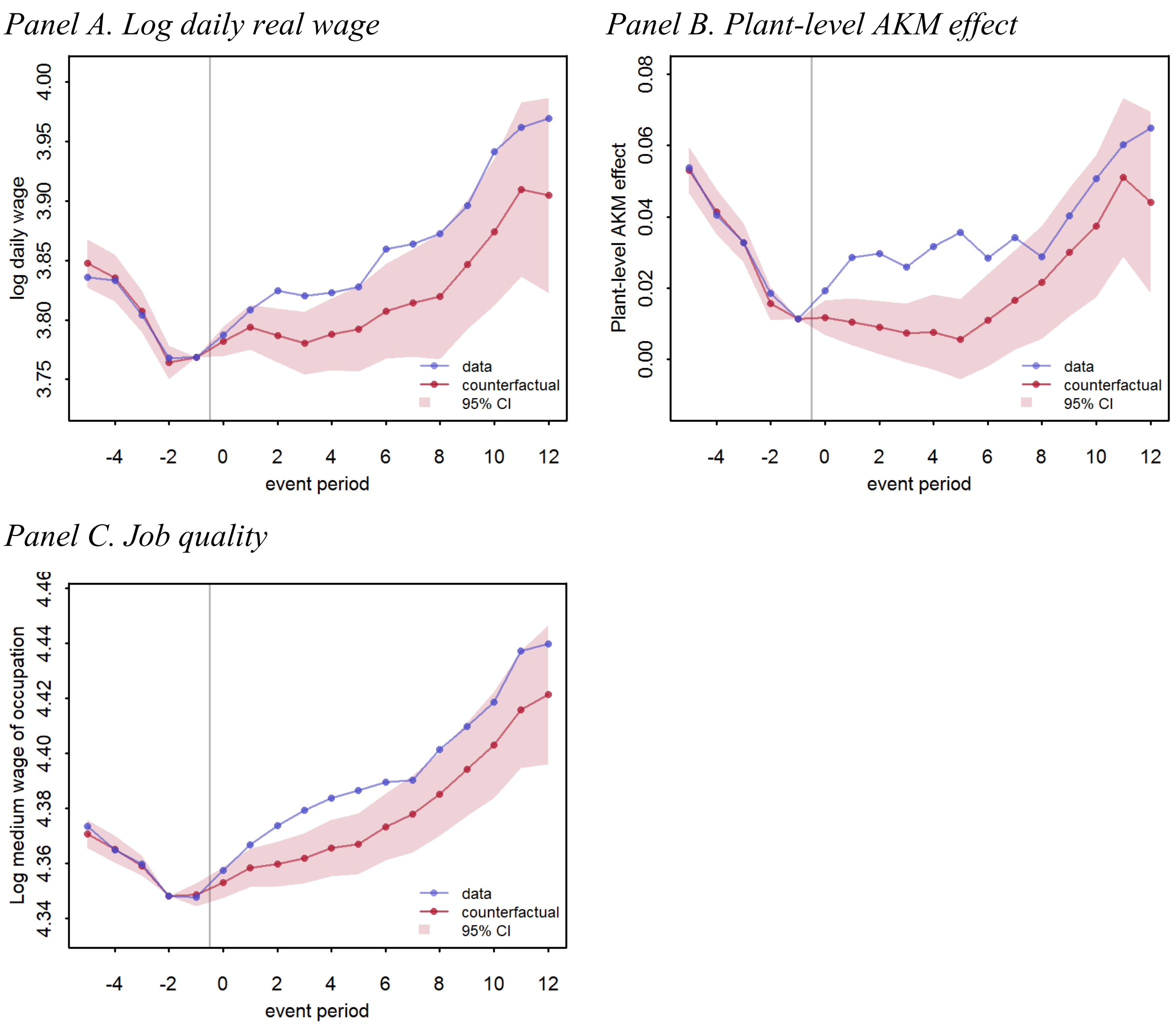
Panel A of Figure 3 displays results for the log real daily wage as the outcome. Consistent with the baseline results, the average employed person in our sample is on a negative trend prior to admission that hits the trough two years prior to admission, as indicated by the blue line. Yet, the counterfactual captures this evolution very tightly. Both the counterfactual and actual evolution is slightly positive during the first year in affordable housing, but the latter then

[20] The daily wage is a product of daily working hours and the hourly wage. Since we do not observe working hours, we unfortunately cannot distinguish intensive-margin labor supply and job quality.

grows more steeply. The difference is significant three years after admission, with the actual outcome hovering around the upper bound of the 95% confidence band of the counterfactual. The difference converges to around +0.05, suggesting that the overall effect on the yearly labor income is partly due to workers finding better paying jobs and/or working more hours.

Figure 3

Actual and counterfactual evolution of log daily real wages and plant-level AKM effects



Notes: The blue lines show the mean outcome variable as observed in the data. The red counterfactual lines are constructed using the estimator of BJS. The difference between the blue and red lines represents the by-period estimate from equation (2). The vertical grey line denotes the event date. In period 0, the person was observed at a affordable housing address for the first time. Persons in vocational training or in university or college at the time of admission to affordable housing excluded. The shaded area is a 95% confidence region obtained from 500 block-bootstrap draws at the affordable housing address level. The outcomes are the log daily real wage in Panel A, the plant-level AKM effect of the worker's current employer in Panel B, and the median wage of full-time workers in the same occupation in Germany (KldB 1988, 3-digit codes).

In Panel B of Figure 3, we consider the plant-level AKM effects as a potential driver behind the effect on daily wages. Again, the pre-treatment trend is negative, but tightly captured by the counterfactual. Especially in the first eight years in affordable housing, the actual plant-level AKM effects are significantly larger than the counterfactual ones, with a difference of around +0.02, suggesting that about 40% of the wage effect can be explained by working for higher-paying employers. In the long run, this difference becomes insignificant and somewhat smaller, owing to a steep increase in the counterfactual.

This counterfactual pattern could result from a regression-to-the-mean effect: Suppose that workers outside of affordable housing tend to stay with low-quality employers for extended periods of time, and move on to better-paying employers only eventually. Potential reasons could be social ties at the place of residence and psychological switching costs that prevent the worker from starting a new job. Arguably, the affordable housing-induced move forces these workers to make the move to a better employer earlier.

Finally, Panel C of Figure 3 shows results for job quality. We measure job quality via the median wage of full-time workers in Germany working in the same occupation, using the KldB-1988 3-digit classification of occupations. The results show that, upon admission to affordable housing, workers tend to work in better-paying occupations, suggesting that job quality increased as well.

In conjunction, the qualities of firms and occupations explain well the overall impact on wages. The positive wage effect therefore stems mostly from workers in affordable housing being able to find better jobs in better firms compared to similar workers in other residences. In the next subsection we explore the mechanisms that might explain how affordable housing facilitates this upgrading of employment quality.

4.5 Mechanisms

In this section, we investigate to what extent the theoretical mechanisms described in Section 3 can explain why workers benefit from living in affordable housing. If considered in isolation, the estimated treatment effects documented in Sections 4.3 and 4.4 are inconsistent with a reduction of labor supply due to an income effect of leisure consumption. We therefore focus on the mechanisms that suggest a positive effect of affordable housing on employment outcomes, namely improved access to the urban labor market, investment in human capital, greater residential stability, and labor supply (dis-)incentives of the interaction of housing and welfare policies.

4.5.1 Access to the urban labor market

Affordable housing-induced change in accessibility. The affordable housing units are located more centrally and with better access to jobs and public transport than the previous residences of the affordable housing residents. The precise geocoded employer-employee data allows us to link these data to the locations of the city center and to Open Street Map data on the rail-based public transport network (railway, tramway, and subway stops, as well as high-frequency train stations, the so-called “S-Bahn”). Table 2 displays the mean change in the log distance to the city center and the distance to the nearest rail-based public transit stop, when moving into affordable housing, together with cluster-robust standard errors. Columns (1) to (3) show the results for the baseline sample. On average, the affordable housing buildings are considerably closer to the city center than the last address prior to admission, and the distance to rail-based public transport decreases, as compared to the workers’ previous addresses.

Table 2
Average change in access to the city center, jobs, and rail-based public transport stops

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline sample			Workers observed in post-treatment period 5 or later		
Variable:	Log distance to city center	Distance to public transport	Distance to public transport < 3 km	Log distance to city center	Truncated distance to public transport	Distance to public transport < 3 km
Mean difference	-0.241*** (0.015)	-0.079*** (0.011)	0.088*** (0.004)	-0.192*** (0.018)	-0.059*** (0.014)	0.083*** (0.005)
Obs.	7,577	7,577	7,577	4,897	4,897	4,897

Notes: Standard errors clustered by person, ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Treatment effect heterogeneity related to accessibility. To investigate whether these variables can also explain heterogeneity in treatment effects, we compute the average long-run treatment effect $\bar{\tau}_i^{LR}$ of worker i in periods 5 to 12 after treatment.[21] We then regress $\bar{\tau}_i^{LR}$ for each baseline outcome (yearly real labor income and fraction of year in unemployment) on the change in labor market accessibility. This approach exploits the fact that affordable housing units are distributed quite evenly across the city (see Figure 1) and allocated by the social housing offices. In addition, we control for the age of the worker at the event date using fixed effects, for the sex of the worker, and for whether the worker is a foreign national or has a vocational degree or higher prior to admission. The regression also includes year-of-admission and city fixed effects, as well as fixed effects for the number of periods the worker was observed between event periods 5 and 12.

To capture the role of affordable housing for job accessibility, we use the change in the log distance to the city center and the change in the log distance to the nearest rail-based public transit stop due to the move into affordable housing. The average changes in accessibility for all workers in the regression sample observed in period 5 after treatment and later are shown in columns (4) to (6) of Table 2.

Panel A of Table 3 displays the results for the yearly real labor income. In column (1), we consider the full sample including the five local labor markets Munich, Nuremberg, Augsburg, Ingolstadt, and Regensburg. The coefficient of the log distance to the city center is negative and highly significant, suggesting that the average long-run effect on yearly real labor income was larger for moves that reduced the distance to the CBD. When comparing workers with a change in distance at the first quartile of the regression sample, to workers at the third quartile, the difference in the treatment effect amounts to approximately 364 EUR per year. The individual characteristics do not have much explanatory power, and all coefficients are insignificant at conventional levels.

[21] In additional regressions, we use the average short-run treatment effect $\bar{\tau}_i^{SR}$ in periods 0 to 4 after the treatment as the outcome. These regressions produce qualitatively similar results, with somewhat weaker relationships in most cases. Results are available on request.

Table 3

Treatment effect heterogeneity: Access to the city center and rail-based public transport stops

A. Yearly real labor income					
Dependent variable:	Person-level average treatment effect total real labor income 5 to 12 years after treatment				
	Full sample	Cities with rail-based public transport (Munich, Nuremberg, Augsburg)			
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
Δ Log distance to city center	-0.3653*** (0.1326)	-0.3674** (0.1450)	-0.2397 (0.1625)	-0.3004 (0.2463)	-0.2399 (0.2207)
Δ Log distance to public transport stop			-0.3066 (0.2118)	-0.5829** (0.2678)	-0.0838 (0.3052)
Female	-0.2315 (0.8653)	-0.0919 (0.8739)	-0.1041 (0.8741)		
Foreign resident	-1.2685 (1.1175)	-1.2638 (1.1227)	-1.2636 (1.1238)	-1.6807 (1.1259)	-0.9487 (1.2312)
Vocational degree or higher	-0.1893 (0.3005)	-0.0552 (0.3203)	-0.0640 (0.3201)	0.0970 (0.4383)	-0.2458 (0.4628)
Age FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Move-In-Year FE	Yes	Yes	Yes	Yes	Yes
#Periods observed FE	Yes	Yes	Yes	Yes	Yes
Adj. R squared	0.061	0.061	0.061	0.069	0.063
Observations	4,897	4,423	4,423	1,907	2,516
Sexes	Both	Both	Both	Female	Male

B. Fraction of year in unemployment					
Dependent variable:	Person-level average treatment effect, fraction of year unemployed 5 to 12 years after treatment				
	Full sample	Cities with rail-based public transport (Munich, Nuremberg, Augsburg)			
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
Δ Log distance to city center	0.0017 (0.0032)	0.0059* (0.0032)	0.0006 (0.0034)	-0.0018 (0.0056)	0.0033 (0.0044)
Δ Log distance to public transport stop			0.0128*** (0.0049)	0.0144* (0.0074)	0.0101 (0.0071)
Female	-0.2315 (0.8653)	-0.0258 (0.0256)	-0.0253 (0.0256)		
Foreign resident	-1.2685 (1.1175)	0.0246 (0.0216)	0.0246 (0.0216)	0.0343 (0.0236)	0.0163 (0.0235)
Vocational degree or higher	-0.1893 (0.3005)	-0.0192** (0.0081)	-0.0188** (0.0081)	-0.0314*** (0.0122)	-0.0074 (0.0112)
Age FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Move-In-Year FE	Yes	Yes	Yes	Yes	Yes
#Periods observed FE	Yes	Yes	Yes	Yes	Yes
Adj. R squared	0.023	0.023	0.024	0.031	0.023
Observations	4,897	4,423	4,423	1,907	2,516
Sexes	Both	Both	Both	Female	Male

Notes: The coordinates of the city centers are based on central places in each city, see the data section for details. Public transit includes train, subway and tramway stations. This variable is truncated at 3,000m and measured with precision 250m. Bootstrapped standard errors clustered at the affordable housing address level in parentheses. ***: p < 0.01, **: p < 0.05, *: p < 0.1.

Ingolstadt and Regensburg do not have a rail-based public transport system, apart from regular railway services. Therefore, in order to study the role of rail-based public transport in our setting, we focus on Munich, Nuremberg, and Augsburg in the remainder of the table. While Munich and Nuremberg have both subway, tramway, and high-frequency commuter train lines, Augsburg has a tramway system. Column (2) replicates column (1) for the three cities, with a very similar result. In column (3), we add the change in the log distance to the nearest public transport stop. In this regression, both distance variables are negative but insignificant at conventional levels.

Job accessibility and the tradeoff between wages and commuting times have been found to be particularly important for women, most likely because they are often the primary caregiver for their children and other relatives (Le Barbanchon *et al.* 2021). This gender commuting gap contributes to the overall gender pay gap. However, Liu and Su (2022) show that this is alleviated for women living close to the city center, which provides them with access to a larger number of good jobs. To investigate whether access to the city center or public transport is more important for women in our setting, we split the sample by gender in columns (4) and (5). The results corroborate this conjecture: For female workers, both distance coefficients are larger in magnitude, and the change in log distance to the public transport system is now statistically significant. Male workers do not seem to benefit much from moving closer to the city center, with both coefficients being smaller in magnitude and insignificant in this regression. This suggests that the access effect of affordable housing is particularly relevant for women.

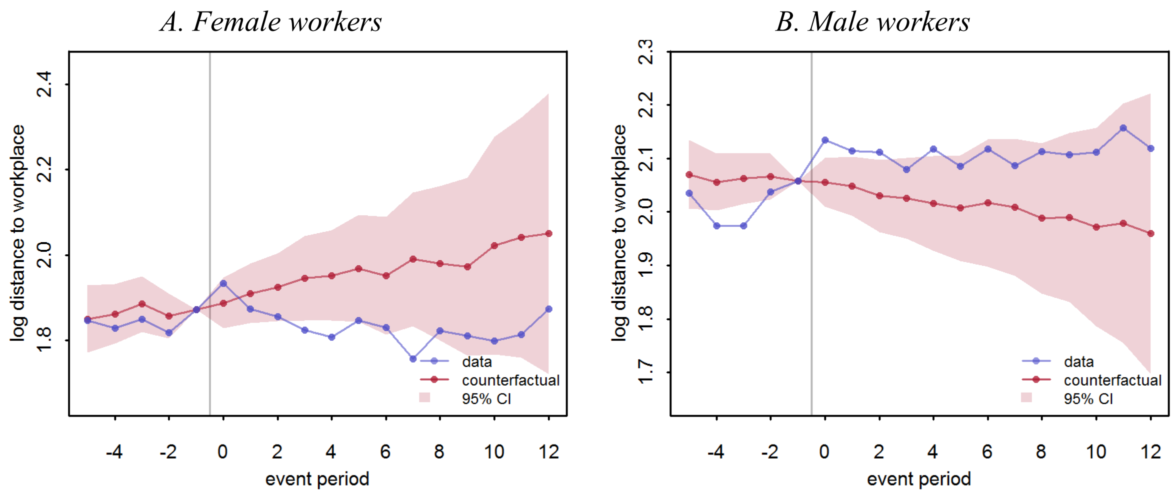
Panel B of Table 3 reproduces these results for the fraction of the year the worker is registered as unemployed as the outcome variable. Consistent with the results for income, moving closer to the city center reduces the likelihood to be unemployed in the larger cities. This effect driven by better access to rail-based public transport, with a significant coefficient in the pooled sample of female and male workers. The coefficient is slightly larger if considering female workers alone, and slightly smaller and no longer significant for the sample of male workers. These results suggest that access to the urban labor market is particularly relevant for female workers at the extensive margin between non-employment and workforce participation.

Commuting distance. To further substantiate the claim that accessibility to employment opportunities is relevant in our setting, we investigate how access to affordable housing accessibility affects the commuting distance of workers in Figure 4. Motivated by the results presented so far, we focus on differences in commuting patterns of female and male workers.

We start by running the baseline event study regression using the log commuting distance as outcome. Panel A of Figure 4 displays the actual and counterfactual log commuting distance by event period for female workers. The two lines move in parallel in the pre-event period. In the year of admission, the commuting distance increases substantially, consistent with moves into affordable housing not being job related. The longer commute in the year of admission likely results from workers initially staying with the same employer and hence facing a longer commute from the new address, on average. One year after admission, the average commuting distance reverts to the pre-event level to then decrease further below the counterfactual line in the subsequent years. Although the actual outcome remains inside the 95% confidence band nine years and more after treatment, the difference to the counterfactual remains relatively stable during this time. This suggests that female workers exploit the improved accessibility of local employment opportunities by selecting jobs with shorter commutes. In contrast, in the post-event period commuting distances of male workers remain above the counterfactual line, although mostly inside the 95% confidence band.

Figure 4

Actual and factual evolution of commuting distances of female and male workers



Notes: The blue line shows the mean outcome variable as observed in the data. The red counterfactual line is constructed using the BJS estimator. The difference between the blue and red lines represents the by-period estimate from equation (2). The vertical grey line denotes the event date. In period 0, the person was observed at a affordable housing address for the first time. Persons in vocational training or in university or college at the time of admission to affordable housing excluded. The shaded area is a 95% confidence region obtained from 500 block-bootstrap draws at the affordable housing address level. The outcome is the log crow-fly distance between the place of residence and the workplace location.

As the next step, we investigate whether better access to the public transport system or the city center translated into shorter commutes. Table 4 displays results for the treatment effect heterogeneity for the same set of regressions as shown in Table 3, but with the log commuting distance as outcome. As expected, workers who moved closer to the center subsequently reduced their commuting distances, see columns (1) and (2) of Table 4. When considering both female and male workers, the coefficient on the distance to the nearest public transport station is negative but insignificant, while the coefficient on the distance to the center retains its significance level.

However, consistent with the results from Table 3, what matters for female workers is access to the public transport system, as documented in column (4) of Table 4. One potential reason could be the limited availability of a car for the secondary earner in the household, making that person especially dependent on the public transport system. To the contrary, the public transport system does not matter as much for male workers in affordable housing, as column (5) shows – again consistent with the results from Table 3. Here, the distance to the center is significant, but the distance to the public transport system is not.

Table 4

Long-run treatment effect heterogeneity for log commuting distance: Access to the city center and rail-based public transport stops

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Person-level average treatment effect log commuting distance 5 to 12 years after treatment				
	Full sample	Cities with rail-based public transport (Munich, Nuremberg, Augsburg)			
	OLS	OLS	OLS	OLS	OLS
Δ Log distance to city center	0.1106***	0.1177***	0.1023***	0.0972**	0.0987***
	(0.0204)	(0.0208)	(0.0235)	(0.0378)	(0.0293)
Δ Log distance to public transport stop			0.0377	0.0688*	0.0133
			(0.0295)	(0.0387)	(0.0431)
Female	-0.3050**	-0.3092**	-0.3078**		
	(0.1329)	(0.1344)	(0.1344)		
Foreign resident	0.0759	0.0624	0.0626	0.0701	0.0764
	(0.1210)	(0.1232)	(0.1233)	(0.1268)	(0.1349)
Vocational degree or higher	0.0298	0.0146	0.0150	0.0207	0.0254
	(0.0424)	(0.0433)	(0.0433)	(0.0789)	(0.0521)
Age FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Move-In-Year FE	Yes	Yes	Yes	Yes	Yes
#Periods observed FE	Yes	Yes	Yes	Yes	Yes
Adj. R squared	0.026	0.022	0.022	0.021	0.011
Observations	3,410	3,116	3,116	1,282	1,834
Sexes	Both	Both	Both	Female	Male

Notes: The coordinates of the city centers are based on central places in each city, see the data section for details. Public transit includes train, subway and tramway stations. This variable is truncated at 3km and measured with precision 250m. Bootstrapped standard errors clustered at the affordable housing address level in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

4.5.2 Investment in human capital

One mechanism proposed but not investigated directly by Pollakowski *et al.* (2022) to explain positive effects of housing assistance on adult labor market outcomes of children is investment in human capital. Our data are well-suited to address directly the question whether residents in affordable housing use the rent subsidy to invest in their labor market skills, since we observe workers in vocational training.

In Germany, a large number of occupations – such as electrician, hairdresser, or office clerk – require certified vocational training with a firm. Apprentices earn a wage, but this wage is typically much lower than wages outside of vocational training – even as compared to jobs that do not require a qualification. This is because apprentices usually spend one to two days per week at a vocational training school. In addition, firms are expected to use own resources to train the apprentices on-the-job. Hence, from the perspective of an unskilled worker, vocational training usually pays off in the long run, but requires an initial investment in the form of forgone income during training.

In Table 5, we analyze the decision of unskilled workers to start vocational training, conditional on whether the worker already lives in affordable housing or not. We restrict the sample to the period up to five years prior to moving into affordable housing, and up to five years after having moved into affordable housing, excluding the year when the worker was first observed in affordable housing. Moreover, we only consider unskilled workers who had never started vocational training before. The model is a linear probability model with controls for worker characteristics through sex- and nationality-specific age fixed effects, and city-fixed effects. Moreover, we control for affordable housing address fixed effects. This means that we compare workers who eventually end up in the same affordable housing building, and we only compare within sex- and nationality-specific cohorts. To ensure overlapping age distributions in both groups, we restrict the sample to workers younger than 40 years.

Table 5

Linear probability model: Unskilled workers' choice to start vocational training

	(1)	(2)
Dependent variable:	Start vocational training	Start vocational training
	OLS	OLS
In affordable housing	0.02152***	0.02147***
	(0.00496)	(0.00723)
Not yet in social housing × time trend		0.00002
		(0.00252)
Individual controls	Yes	Yes
Year x sex FE	Yes	Yes
Year x nationality FE	Yes	Yes
Year x city FE	Yes	Yes
Building FE	Yes	Yes
Baseline probability	0.08451	0.08451
Adj. R squared	0.331	0.331
Observations	12,950	12,950

Notes: The sample consists of unskilled workers who are not in vocational training and are younger than 40 years. For each worker, the sample window is restricted to the five years around the date of admission to affordable housing, excluding the period of admission. The outcome is a binary indicator capturing the start of vocational training in the given year. Standard errors clustered at the affordable housing address in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Column (1) shows that, during the first five years, workers in affordable housing have a 2.15 percentage points higher probability to start vocational training, as compared to workers in the five years prior to moving into affordable housing, conditional on the controls mentioned above. This effect is large relative to the average probability in this sample to start vocational training of 8.45 percent. In column (2), we test whether there is a trend in the probability to start vocational training prior to admission to affordable housing, by including an interaction of the time trend with an indicator for the pre-event period. While this does not affect the coefficient of main interest, the coefficient of the pre-event time trend is virtually zero. Overall, these results support the conjecture that affordable housing allows its residents to invest in their human capital.

4.5.3 Residential stability

The third proposed mechanism that may explain why residents in affordable housing fare better in the labor market than comparable workers living in private rental housing is residential stability. Regarding the institutional rules, affordable housing provides greater protection from eviction, all else equal. The resulting residential stability provides for a longer planning horizon and frees up resources that would otherwise be devoted to residential search activities.

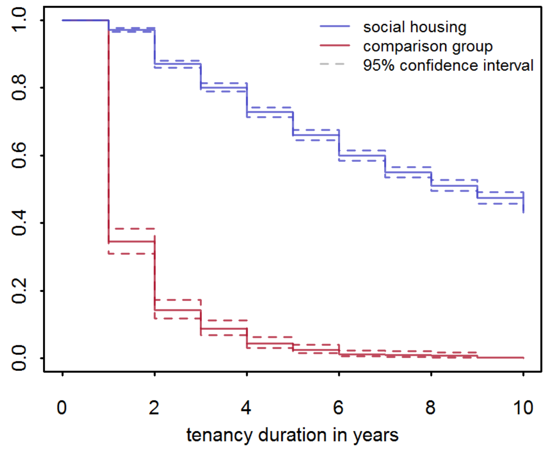
First, the comparatively low mobility of social housing residents can be demonstrated using data from the German Socio-Economic Panel (SOEP). The proportion of tenants who move in a given year in Bavarian cities is 12.3% on average over the years 2000-2017; for affordable housing, this proportion is only 9.5%.[22]

Second, in our sample the average rate of residential mobility in the affordable housing buildings – the share of residents leaving the building in the current year – was as low as 6.4% when averaging over all years. When instead restricting the sample to buildings completed at least ten years ago, the rate drops to 6.0%. This figure is quite low compared to rates of residential mobility among observationally similar workers in our sample before they moved into affordable housing. Specifically, we compare residents in affordable housing who had already moved into affordable housing between 2001 and 2005, to a group of workers who had moved house between 2001 and 2005, but were first observed in affordable housing in 2012 or later. To ensure that the age distributions overlap, we restrict the sample to movers of age 45 or lower. Figure 5 displays the survival probabilities for the two groups following the respective move observed between 2001 and 2005. There is a substantial gap between the two groups, with considerably longer tenancies of affordable housing residents. Whereas more than 50% of the affordable housing residents stay in the subsidized unit for at least ten years, less than 40% of the workers in the comparison group continued to live at the same address in the year following the move. Table 6 displays results from a Cox proportional hazard model, with the affordable housing status as the group identifier. The model controls for age fixed effects, the skill level of the worker, and sex-, nationality, and city-specific year fixed effects. Column (1) shows that the tenure duration of affordable housing residents is much longer than in the comparison group. In column (2), we interact the affordable housing indicator with sex and a dummy capturing age 25 or older. Both groups exhibit longer tenancy durations in affordable housing, as compared to male workers below 26. To conclude, both Figure 5 and Table 6 clearly show that residential stability of eventual affordable housing residents was much lower prior to getting access to the affordable housing, consistent with this group having been particularly vulnerable to housing insecurity.

[22] These shares are based on unweighted values for cities with 20,000 or more inhabitants in Bavaria. Comparable proportions result for values based on cross-sectional weights from the SOEP. The number of cases in the SOEP is too small to allow reliable estimates to be derived from a restriction to larger Bavarian cities.

Figure 5

Survival probabilities for tenancies in affordable housing and in a comparison group



Notes: The blue line displays the survival probability for tenancies in affordable housing, restricted to tenancies starting between 2001 and 2005. The red line shows survival probability for a comparison group with tenancies outside of affordable housing, restricted to tenancies starting between 2001 and 2005. Persons belonging to the comparison group were first observed at an affordable housing address between 2012 and 2017.

Table 6

Cox proportional hazard regression coefficients: Tenancy duration of residents in affordable housing and in the comparison group

	(1)	(2)
Dependent variable:	Tenancy duration	Tenancy duration
Affordable housing	-2.453***	-2.124***
	(0.064)	(0.103)
Affordable housing × female		-0.209*
		(0.112)
Affordable housing × age 26 or older		-0.483***
		(0.113)
Individual controls	Yes	Yes
Year x sex FE	Yes	Yes
Year x nationality FE	Yes	Yes
Year x city FE	Yes	Yes
Persons	4,647	4,647
# of events	2,651	2,651
Log Likelihood	-20,263	-20,248

Notes: The sample consists of workers admitted to affordable housing between 2001 and 2005, and of workers moving house between 2001 and 2005 who were observed in affordable housing 2012 or later. The duration variable is the length of tenancy at the new address following the move between 2001 and 2005. The regression is a Cox proportional hazard model. Robust standard errors in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

4.5.4 Labor supply (dis-)incentives in affordable housing

Finally, the provision of affordable housing changes work incentives. Since 2007, the rent payable under the subsidy program has been independent of household income, including earned income, so the program does not have any direct disincentive effects. Even before that, the direct negative work incentive effects were only slight due to the weak correlation between income and rent levels. Social benefits and special housing allowances, on the other hand, have strongly negative work incentive effects due to high transfer withdrawal rates. The transfer withdrawal rates for Basic Income Support in Germany are 100% or only slightly below 100% in a wide range of incomes. If the recipients of Basic Income Support benefits exceed the income limits that are relevant for receiving these benefits, these negative work incentive effects no longer apply.

However, the rent reduction in the affordable housing program gives rise to a negative income effect that may reduce labor supply. The fact that we find positive treatment effects on average implies, however, that any negative incentives arising from an income effect of the rent subsidy are likely comparatively small.

To better assess the relevance of the improved labor supply incentives, we examine the rent reduction associated with the program in this subsection. To do so, we exploit administrative data on several financial items at the individual level for welfare benefit recipients in 2006 to 2018, including all payments to the recipients. We use the item "housing costs" to examine whether welfare recipients actually had lower housing costs when they lived in affordable housing. We limit ourselves here to recipients of social benefits, since we cannot observe the rents paid by other individuals in our data

In Online Appendix Table B2, we report summary statistics for the average welfare payment before admission to affordable housing. We deflate all euro values with the CPI (2015 EUR). Between 2006 and 2015, we observe 1,379 individuals of working age receiving benefits in the year prior to admission. Housing benefits per person, excluding heating and utility costs, averaged EUR 193.0, while total social benefits averaged EUR 503.2 per person per month. Thus, housing payments net of heating and utilities accounted for almost 40 percent of total payments.

In Table 7, we examine whether net housing costs changed for benefit recipients after moving to an affordable apartment. We exclude the year of admission from the analysis and focus on the two years following admission to clearly distinguish between housing costs before and after admission.

The simple comparison in column (1) shows that real housing costs decreased by EUR 26.7 per person per month when the recipient moved to an affordable apartment. However, this ignores the fact that local rental prices in major Bavarian cities have risen particularly sharply since 2009. Nevertheless, average rent increases in the local market can result in higher local rent caps for welfare recipients. Higher rent caps may drive up rents for benefit recipients even during a tenancy, as shown in the literature in comparable contexts (Gibbons and Manning 2006, Fack 2006, Eriksen and Ross 2015, Collinson and Ganong 2018). We control for these confounding factors by including year effects in column (2) and city-specific year effects in column (3). Here, housing cost savings amount to €34.6 and €35.2 per person per month, respectively. These regressions suggest that total housing costs for this group decreased by about 20 percent when moving into an affordable apartment.

Table 7

Change in housing benefit for welfare recipients when moving into affordable housing

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Housing benefit amount per person/month in EUR					
	OLS	OLS	OLS	OLS	OLS	OLS
Average costs, period t-1	193.3***					
	(3.9)					
Difference b/w t-1 and t+1	-26.7***	-34.6***	-35.2***	-29.5***	-33.3***	-37.4***
	(3.7)	(5.0)	(5.0)	(4.6)	(5.5)	(5.7)
Employable persons 18 and above in hh.				-43.5***	-48.0***	-48.9***
				(3.6)	(4.5)	(4.5)
Employable persons 15-17 in household				-36.3***	-39.4***	-39.5***
				(1.8)	(2.1)	(2.1)
Persons under under 15 in household				-28.7***	-33.1***	-32.7***
				(4.4)	(6.0)	(6.1)
Elderly persons in household				-25.4	-62.9***	-66.6***
				(31.3)	(14.4)	(14.4)
Other persons in household				-36.0***	-38.7***	-39.0***
				(2.5)	(3.3)	(3.4)
Distance to city center in km						-0.1***
						(0.0)
Year FE	No	Yes	No	No	No	No
Year x City FE	No	No	Yes	Yes	Yes	Yes
Observations	1,912	1,912	1,912	1,912	1,432	1,432
Adj. R squared	0.016	0.023	0.096	0.402	0.412	0.419

Notes: Standard errors clustered by person, ***: p < 0.01, **: p < 0.05, *: p < 0.1. The sample consists of persons observed receiving welfare benefits one year prior to admission to affordable housing, and one year after admission. All persons are observed receiving benefits before and after admission. The sample in columns (5) and (6) is smaller because of missings in the distance to the center variable, which is available only up until 2017 and missing in individual cases.

The benefit payment statistics allocate benefits at the household level, such as housing benefits, to all employable household members, so the per capita amounts depend on the number of children in the household. Therefore, we account for household composition in column (4). This has only a small impact on the estimated effect – most likely because household composition did not change systematically upon admission, as we document in Online Appendix Table B3.

Finally, columns (5) and (6) restrict the sample to individuals for whom we also observe distance to the city center. Distance to the city center is arguably a very important factor for housing costs. When distance is held constant, the reduction in housing costs from entering an affordable apartment slightly increases to €37.4 per person per month.

Overall, these results suggest that, although the subsidized units may be larger and more centrally located than the previous housing units occupied by the benefit recipients, entering affordable housing did indeed reduce the total housing costs for benefit recipients.

5 Conclusions

In this paper, we document substantial positive effects on various labor market outcomes of living in affordable housing. These effects are of quantitative importance at the individual level, and in terms of their aggregate consequences – the latter owing to the fact that affordable housing represents a substantial proportion of the rental housing stock in most OECD countries.

While there are problems associated with the supply of affordable and public housing, and the effects it may have on local communities – such as crowding out other housing investments (Baum-Snow and Marion 2009, Eriksen and Rosenthal 2010) and contributing to the spatial concentration of poverty (Aliprantis and Hartley 2015, Chyn 2018, Haltiwanger *et al.* 2020), we believe that these estimates are highly important for the evaluation of existing housing assistance programs in urban areas around the world.

We offer four explanations for the overall positive effects associated with living in affordable housing. First, affordable housing provides access to the urban labor market for a group that is especially vulnerable to being priced out of the local housing and labor market. Housing available to low-income households on the free market is typically located on the outskirts of major cities and is often not connected to rapid transit. We find that the positive effects of living in affordable housing increase with the locational quality and that especially women benefit from chances offered by the improved access to the urban transit network. Second, the subsidy implicit in affordable housing allows its residents to invest in their human capital. Third, affordable housing creates a stable residential environment, which may contribute to the formation of job- and firm-specific human capital and hence promote long-run success on the labor market. Finally, depending on the design, affordable housing policies interact with other housing policies. In doing so, they effectively complement tenant-based housing policies such as housing benefits or vouchers and can increase the overall efficiency of the housing policy environment. We argue that other housing benefits disincentivize working more hours, whereas the provision of affordable housing does not have any direct negative incentive effects as long as conditions and rent are independent of household income. This is the case in the German setting as well as in LIHTC in the US. The average negative impact of the income effects is comparatively low due to the high proportion of people who received welfare benefits before moving into an apartment included in the support program, and is overcompensated. Through this mechanism, affordable housing development can reduce the net fiscal costs of overall housing policy. This shows that the design of housing policies and their interplay are crucial determinants of successful overall housing policy.

The results indicate that the residential location choice within the local labor market is a significant factor influencing the labor market success of low-income workers. In this sense, a fruitful avenue for future research is to study more deeply the role of networks at the place of residence, how access to urban labor markets shapes the labor market success of low-skilled workers, how access can deteriorate in the face of rising housing costs, and to what extent vulnerable groups can benefit from different types of housing policies.

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Online Appendix – *Not for Publication*

Online Appendix A: Graphical Illustration of Labor Supply Disincentives

In Figure A1, we consider in a stylized fashion the labor supply decision of individuals in affordable housing, as compared to individuals living in non-subsidized rental housing. Panel A shows the standard case of a worker who does not have access to other housing benefits. The horizontal axis measures the labor supply L of the worker, so that the worker's income increases when moving from left to right. When moving along the horizontal line, the worker earns income Y_d from welfare benefits (including housing benefits) and labor. To the left of L', housing costs are fully covered by the state, as is the case in the German welfare system under SGB II. Between L' and L'', labor income is supplemented by a partial coverage of housing costs by the state, as is the case for housing vouchers in the US and for Wohngeld in Germany. To the right of L'', labor income is the only income source.

The vertical axis represents consumption net of rent payments. In private rental housing, the rent is r_0, so that the worker's consumption is $Y_d - r_0$. The corresponding budget constraint is depicted as the blue dashed line, with the kinks reflecting changes in transfer reduction rates. The dashed green curve represents an indifference curve of the worker that touches the dashed blue budget constraint at a point to the right of L''.

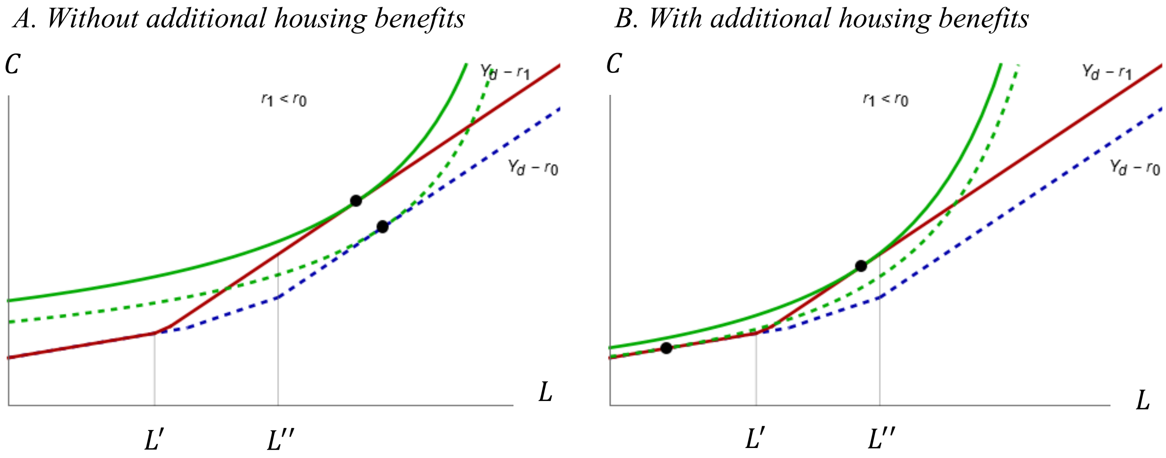
In affordable housing, the rent r_1 is subsidized, i.e., $r_1 < r_0$. This shifts the worker's budget constraint up by $r_0 - r_1$, provided the worker has a labor supply to the right of L''. This allows the worker to reach the green solid indifference curve, which is associated with higher consumption and lower labor supply. In this case, the implicit rent subsidy in affordable housing represents a negative labor supply incentive to the worker – an income effect.

Panel B considers the case of a worker who receives welfare benefits while living in private rental housing. Given this worker's blue dashed budget constraint, the worker can reach at most the green dashed indifference curve and hence prefers to supply an amount of labor less than L'.

However, the lower rent in affordable housing allows the worker to reach the higher, solid indifference curve, which touches the red solid budget constraint at a point to the right of L'. Hence, by moving into affordable housing, the welfare recipient depicted in Panel B escapes the area where high transfer withdrawal rates disincentivize labor supply. In this case, the rent subsidy in affordable housing can be expected to increase labor supply.

Figure A1

Labor supply incentives in affordable housing



Notes: The figures show budget constraints and indifference curves of an individual in a work (L) - consumption (C) diagram with private rental and affordable housing. The dashed lines refer to private rental housing, the solid lines to affordable housing. Y_d denotes the income, r_0 denotes the rent in private rental housing and r_1 the subsidized rent in affordable housing. Panel A represents the situation of a person who does not receive social welfare benefits and Panel B represents the situation of a recipient of social welfare benefits. The housing rent to the left of L' is fully covered by the state. If there is a low supply of work and a corresponding income from work, an individual receives welfare benefits that also cover the rent in full. With a medium income, part of the rent is covered by housing benefit. At higher incomes, the rent must be paid in full by the individual themselves. Due to the high transfer withdrawal rate, the budget constraint is flatter for low incomes than for high incomes. For benefit recipients, the budget constraint in the relevant area becomes steeper when they move into affordable housing, while the slope for non-benefit recipients does not change. The former will increase their labor supply, the latter will generally reduce their labor supply due to a pure income effect. The utility, however, for both individuals increases when they move into affordable housing.

Online Appendix B: Detailed Data Description

This online appendix provides details on the various sources and computation of variables used in our empirical analysis.

The affordable housing data were provided by the local housing offices of Munich, Nuremberg, Augsburg, Ingolstadt, and Regensburg and cover all subsidized housing constructed in the period 1997 to 2007 in these cities. We were able to match the addresses of the buildings with the address-level geocodes in the 100% sample of the linked employer-employee data of IAB Nuremberg.

Income and daily wage. The IEB contains the yearly labor income as reported to the social security insurance. Income is top-coded at the income threshold up to which contributions are mandatory for employees. In rare cases, reported income may be higher due to one-time payments or a change of employer during the year, since firms cannot necessarily top-code earnings at the correct threshold in these cases. The daily wage is computed as the total yearly income divided by the number of days in employment.

Income eligibility thresholds. The income we observe in the data is the total gross labor income. Around 20% of gross income are transferred directly to the social security insurance system and do not appear on the wage bill sent to the employees, with the statutory pension system and the statutory health insurance being the largest components. We observe the remaining 80% of gross income, which we refer to as "employee gross income" below.

Income eligibility is determined in terms of the employee gross income. Employed applicants have to submit a form filled out and signed by the employer stating their current and expected income. The signature on the form must not be older than three months. Moreover, they have to provide the notice of the income tax assessment from the previous year. In case of recent or expected changes in pay, the local housing office uses 12x the monthly pay instead.

Employees pay taxes and an additional 20% of contributions to the social security system out of their employee gross income. The income eligibility rules thus allow for a blanket deduction of 1,000 EUR for work-related expenses, and blanket deductions of 20% for the social security contributions and 10% for income taxes. To this value, other income sources such as received alimony payments are added. Persons having to pay alimony payments may subtract these payments up to thresholds of 4,000 EUR per child and 6,000 EUR per former spouse, respectively. At this point, incomes of all household members are summed up. Moreover, there are deductions of 4,000 EUR for each person in the household with a disability, and of 5,000 EUR for young married couples, which are subtracted in the final stage of the computation. The resulting value is then compared to the threshold value.

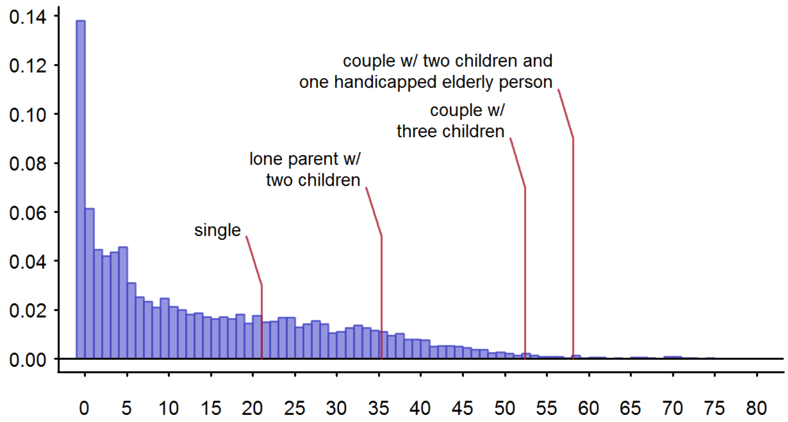
In 2015, the nominal income thresholds were 14,000 EUR for singles, 22,000 EUR for couples, and 4,000 EUR for each additional person in the household. In addition, the threshold increased by 1,000 EUR for each child in the household. In real terms, the income thresholds were more or less constant over time, with adjustments reflecting consumer price inflation in Germany.

Affordable housing admission. We infer admission to affordable housing from worker residential addresses and the street addresses of affordable housing buildings. All affordable housing residents in these buildings are required to fulfill the income eligibility criterion.

We do not observe household-level income and the income eligibility check by the housing offices. To test whether the worker-level incomes observed in our sample in the year prior to admission to affordable housing are consistent with the eligibility rules, we compute income eligibility thresholds for 2015 in terms of the total gross income for example households, assuming that there is a single earner in the household, and plot these thresholds in a histogram of observed real incomes in the year prior to admission to affordable housing in Figure B1.

Figure B1

Income distribution one year before admission and examples for income eligibility thresholds



Notes: The histogram shows the total yearly gross labor income in 1k EUR in the year before admission. The red lines indicate the eligibility thresholds for different example households, assuming that only one person in the household earns income. The histogram is cut off at 80k, which excludes one observation with a reported income of 134k. This outlier is likely due to a one-time payment.

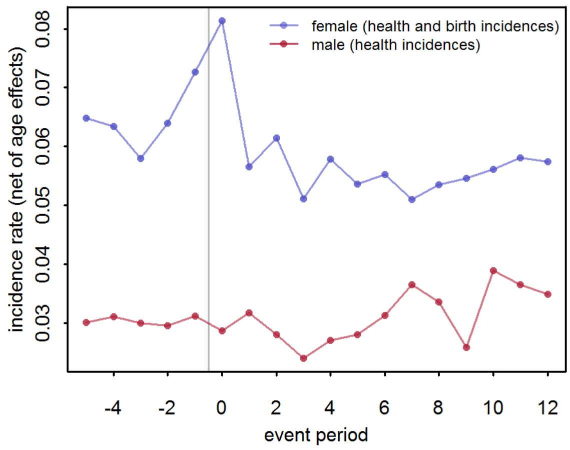
The figure shows that around three quarters of the workers in our sample earn less than the eligibility threshold for singles. There are some workers with relatively high incomes, with the right tail going up to 75,000 EUR. However, these workers may still have met the income eligibility threshold in case they lived in larger households, had to pay alimony, or lived with a disabled person in the household. For example, a couple household with two children and a handicapped (elderly) person had an income threshold of around 58,000 EUR if there was a single earner in the household – as may often be the case when the second adult cares for the handicapped person and the children.

The admission process requires workers to register with the housing office. Workers are then placed on a wait list. There are several criteria that can make a timely admission more likely, whereby the strongest criterion fulfilled by the household counts. These criteria include exposure to domestic violence, homelessness or likely loss of accommodation, severe overcrowding, and health incidences. A (lone-mother) pregnancy can also increase the chances of admission. Conditional on availability of suitable units, the waiting time is used to break ties among equally-needy households.

Figure B2 plots health incidences observed in the data, conditional on year of age, where the event period is the time relative to the date of admission in years. This variable captures long-term sickness events where workers are absent from the labor force for at least 42 days due to health-related reasons. It also includes maternity leave and hence does not allow us to separate health incidences for women from giving birth. Whereas there is no spike around admission for male workers, there are about 1.5 percentage points more health incidences for women one year before and in the year of admission, consistent with the eligibility criteria favoring (lone) parents.

Figure B2

Health incidences around time of admission



Notes: The histogram shows the share of workers with a health incidence, around the time of admission to affordable housing in period 0, separately for female in blue and male workers in red, and holding constant year of age. For female workers, the measure includes birth events. The vertical grey line indicates the time of admission.

Distance variables. We use crow-fly distances throughout. Distances to rail-based public transport stops are computed using Open Street Map data from 2021. The commuting distance is the distance between the establishment and the worker's residential address.

Neighborhood variables. The computation of neighborhood variables is based on the 100% sample of the IEB. For each residential location in our sample, we draw a 500m ring around the location and compute neighborhood statistics based on all observations in this ring, leaving out workers registered at the residential location itself. In cases where less than 25 observations are present, we increment the radius by 100m until the number of valid cases is 25 or higher, up to a maximum of 1,500m. The neighborhood variables are set to missing if less than 25 cases are present in a radius of 1,500m.

For the computation of median daily wages in the neighborhood, we require at least three employed persons. Otherwise, this variable is also set to missing. If exactly one person in the neighborhood is observed to be unemployed or non-German, we change the value to two persons. The same applies reversely if all but one worker are unemployed or if only one worker is German. These changes are necessary to fulfil data protection requirements.

Table B1 shows the average differences in neighborhood quality between the last address prior to entering affordable housing, and at the affordable housing.

Table B1

Average difference in neighborhood quality between affordable housing address and previous residential location

	(1)	(2)	(3)	(4)
	Baseline sample			
Variable:	Median log daily real wage	Share un-employed	Share low-skilled	Share non-German
Mean difference	-0.027***	0.005***	0.003	0.034***
	(0.006)	(0.001)	(0.003)	(0.003)
Obs.	7,524	7,501	7,546	7,501

Notes: The baseline sample consists of observations one year prior to admission and in the year of admission. Neighborhoods are defined as the area in a 500m radius around the residency, excluding the residential building itself. If the number of observations is smaller than 25 in this area, we increment the radius by 100m, up to a limit of 1,500m. Robust standard errors in parentheses. ***: p < 0.01, **: p < 0.05, *: p < 0.1.

SGB II welfare benefits data. We use the "Leistungshistorik Grundsicherung" (LHG, V10.00.00-201904), which contains information on household composition, and the "Leistungsstatistik SGB II" (LST-S, V10.00.00-201904), which provides payment information extracted directly from the payment system of the Federal Employment Agency. We use these data to investigate the fiscal costs of affordable housing, and to measure housing costs of welfare benefit recipients before and after admission to affordable housing.

Panels A and B of Table B2 show summary statistics for monthly welfare benefit payments by category at the person and household level in the year before admission to affordable housing, respectively.

Table B2

Descriptive statistics for SGB2 welfare benefit payments one year before admission to affordable housing, 2006-2015

A. Welfare benefit payments per employable person					
	Mean	Median	SD	Min	Max
Total monthly payment [a), b)]	503.2	495.6	239.3	40.1	2403.3
Non-housing related items [a)]	249.1	301.5	172.7	0.0	675.4
Housing-related items [b)]	254.0	209.5	155.5	14.4	2231.6
Net cost for shelter (rent) [b)]	193.0	159.1	118.9	11.5	852.4
Persons:	1,379				

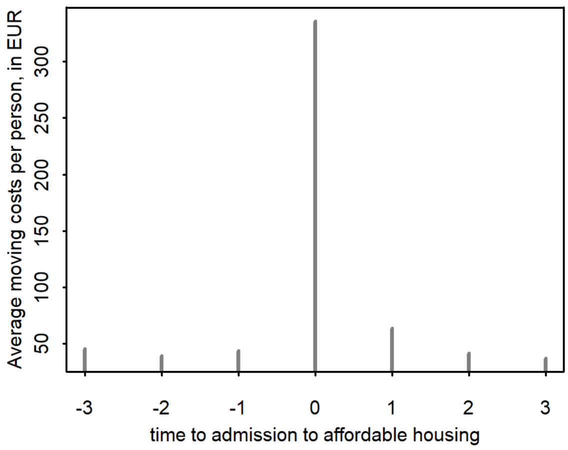
B. Welfare benefit payments per household					
	Mean	Median	SD	Min	Max
Total monthly payment [a), b)]	621.2	617.9	289.9	40.1	2403.3
Non-housing related items [a)]	307.6	358.4	213.7	0.0	1164.6
Housing-related items [b)]	313.6	268.8	182.8	14.4	2231.6
Net cost for shelter (rent) [b)]	238.3	203.8	142.1	11.9	1045.2
Households:	1,117				

Notes: The sample consists of all persons observed in the welfare benefit recipient statistic one year prior to admission to affordable housing. Part A distributes household-level benefits across all employable household members. [a)] Payments are reduced if recipients have own sources of income. [b)] Renters in Germany usually pay a monthly pre-payment for heating and utilities, but actual costs and payments are settled once every year. This may lead to one-time reimbursements when recipients overpaid on heating and utility costs, or to payment of arrears. Both appear in the statistics for net cost for shelter as temporal reductions or increases in the monthly payment, but these events are not flagged in the data.

The payment information system is completely distinct from the information system used to construct the labor market biographies and hence provides an alternative way of assessing the quality of the data. More precisely, welfare recipients can claim support payments for residential moves. Hence, the payment data allow us to test whether the admission to affordable housing – a central piece of information in our empirical approach – was associated with moving costs in the payment data. The admission to affordable housing is based on address information provided to the Federal Employment Agency. Unemployed persons and welfare benefit recipients report their address to the local branches of the Federal Employment Agency. To date, there is little systematic evidence about the quality of these address data. Figure B3 shows the average moving costs in the years shortly before and after admission. The average moving costs are mostly below 50 EUR per person and year both before and after the date of admission, but over 400 EUR per person in the year of admission. This pattern strongly suggests that we assigned correctly the date of admission to the affordable housing address.

Figure B3

Moving costs of welfare benefit recipients around time of admission



Notes: The sample consists of all welfare benefit recipients observed in the respective periods. The figure shows average total yearly moving costs by number of years relative to admission to affordable housing. The most important moving cost item is payments for deposits, which makes up around 80% of moving costs.

Table B3 displays summary statistics for the household composition in the year before admission to affordable housing in Panel A, and one year after admission in Panel B.

Table B3

Descriptive statistics for household composition of SGB2 welfare benefit recipients, 2006-2015

A. One year before admission to affordable housing					
	Mean	Median	SD	Min	Max
Total number of persons [a), b)]	2.578	2.000	1.495	1.000	9.000
Full-aged employable (18+) [a)]	1.455	1.000	0.588	0.000	4.000
Under-aged employable (15-17) [a)]	0.814	0.000	1.048	0.000	5.000
Under-aged (0-15) [a)]	0.123	0.000	0.372	0.000	2.000
Elderly persons [a)]	0.004	0.000	0.060	0.000	1.000
Other persons [b)]	0.184	0.000	0.595	0.000	6.000
Households:	1,116				

B. One year after admission to affordable housing					
	Mean	Median	SD	Min	Max
Total number of persons [a), b)]	2.588	2.000	1.526	1.000	9.000
Full-aged employable (18+) [a)]	1.394	1.000	0.538	0.000	4.000
Under-aged employable (15-17) [a)]	0.954	1.000	1.092	0.000	6.000
Under-aged (0-15) [a)]	0.095	0.000	0.328	0.000	2.000
Elderly persons [a)]	0.003	0.000	0.059	0.000	1.000
Other persons [b)]	0.143	0.000	0.518	0.000	5.500
Households:	869				

Notes: The sample consists of all persons observed in the welfare benefit recipient statistic one year prior to admission to affordable housing. Households in Panel are observed one year prior to admission to affordable housing, and one year after admission. [a)] Persons belonging to the so-called “Bedarfsgemeinschaft” (community of needs), a household concept defined in the SGB II. [b)] Persons who live in the same household, but are not part of the community of needs in the SGB II sense.

Online Appendix C: Robustness of Baseline Results

Moves into affordable housing and commuting distances. Our first check is to challenge the assumption that people do not deliberately move into affordable housing to shorten their commute. In Table C1, we regress the change in the log commuting distance on an indicator for the move into affordable housing, where the sample consists of all moving events up to the point where the worker moved into affordable housing. Column (1) shows that moves into affordable housing are associated with a 6.8% larger increase in commuting distances, as compared to other moves. This holds when controlling for year and city fixed effects in column (2). In column (3), we distinguish between workers employed at the same plant both before and after the move. These workers reduce their commuting distance by 5.3% on average when moving. However, this is not the case when moving into affordable housing. Relative to other moves within this group, commuting distances increase by 8.3%. The result is unchanged when adding fixed effects for the person's age. Overall, these results suggest that moves into affordable housing were not motivated by workplace considerations.

Sample composition. The baseline regression employs the full, but unbalanced panel. This implies that the number of person-year observations used for the computation of the treatment effects differs across event periods. In Figure C1, we provide results for a constant-composition sample which is restricted to individuals observed in each event period from -5 to 12. While this sub-sample exhibits a slightly different evolution of observed and counterfactual total incomes – owing to the change in sample composition –, the pre-treatment fit is exceptionally close for both baseline outcomes. Yet, the differences that begin to emerge two years after admission are very similar to the baseline results. Hence, changes in the sample composition are not responsible for the estimated treatment effects.

Pre-treatment vocational training. Second, while our baseline regressions already exclude persons in vocational training and higher education in event period -1, a related concern may be that workers having finished vocational training only recently are on exceptionally steep income paths. To address this concern, Figure C2 shows results excluding persons observed in vocational training for at least one period between event periods -5 and -1. Again, the pre-treatment fit is very tight, but significant treatment effects emerge one period after admission. The effect sizes and patterns are very similar to the baseline results.

Missing counterfactual predictions for rare covariate combinations. Third, our model featuring sex- and gender-specific age and year fixed effects (in addition to city-specific year fixed effects) may result in a large number of cases where fixed effects of variable combinations are not identified. We therefore estimate a more parsimonious model that uses person and age fixed effects, as well as city-specific year fixed effects instead. The graphs in Figure C3 again exhibit patterns that are very similar to the baseline results.

Missing counterfactual predictions for most recent sample years. Fourth, the year fixed effects in the baseline model are identified up to 2015 only. The reason is that the geocodes are only available up until 2017, which hence marks the latest year with an observed "event" in our data. Moreover, we exclude event period -1 in the first-stage baseline regression to prevent that anticipation effects influence the second-stage estimates. However, the later years are interesting because of the strongly increasing rents in most German cities up until 2020, and in particular in Munich. In order to be able to use the data from 2016 to 2019, we therefore estimate a model that replaces the city-, sex-, and nationality-specific year fixed effects by a city-specific quadratic polynomial in the year of observations. Figure C4 displays the results, with a similar pattern as in the baseline case.

Common trend due to in-sample prediction for pre-event periods. Fifth, we address the potential concern that the negative common trend visible in some graphs prior to admission to the subsidized unit may be transitory, so that the model might inadvertently attribute a "regression to the mean" effect to the fact that the person lives in affordable housing. After all, in our main regression, the estimated treatment effects in the pre-treatment periods are based on in-sample prediction errors.

To address this concern, we exclude the five years prior to admission from the first-stage estimation, where transitory negative trends could allow workers to gain access to affordable housing. In this estimation, the counterfactual evolution is determined only by observations from event periods -6 or earlier. In other words, the counterfactual evolution in periods -5 to -1 is based on an out-of-sample prediction, just like the post-treatment counterfactual evolution. We use the polynomial model to be able to keep a reasonable number of observations in the sample, since otherwise, the year fixed effects for 2010 or later would not be identified. The results in Figure C5 show that the counterfactual and actual outcomes are reasonably close in the pre-event periods for both baseline outcomes, up until one year after admission to affordable housing. From this point onwards, the treatment effects for the labor income variable become significantly positive, whereas the treatment effects for the unemployment outcome are negative and significant. This corroborates our assumption that the pre-event periods are generally suitable for constructing the counterfactual outcome in our setting.

Matching as an alternative approach. The BJS estimator compares predicted outcomes to actual outcomes, using all pre-treatment observations to construct these predictions. One potential concern not addressed so far is that unobserved events that facilitate access to affordable housing – such as a health incidence – are not taken into account in this counterfactual. Therefore, as an alternative approach, we provide evidence from a more direct comparison by using matching techniques. We construct a comparison group from observations of treated individuals long before their actual treatment. This ensures that we draw from a pool of very similar workers that plausibly share unobserved experiences related to their eligibility for affordable housing. To be precise, we match treated individuals in the pre-treatment period to other not-yet-treated persons observed up until nine years before treatment. This allows us to compare outcomes up to seven years into treatment, since at that point, the control observations still have two more years until they eventually get admitted to affordable housing. We ensure exact matching on several important variables, including the city, the year, the health incidence variable, the person's sex, the foreign dummy, and the skilled dummy. We investigate the average difference across matched workers in Figure C6. Although this group of matched workers is much smaller, with 648 matched pairs of individuals, there are again statistically significant effects visible several years after admission to affordable housing, but no differential pre-trends in the pre-treatment periods.

Table C1

Change in commuting distance when moving house

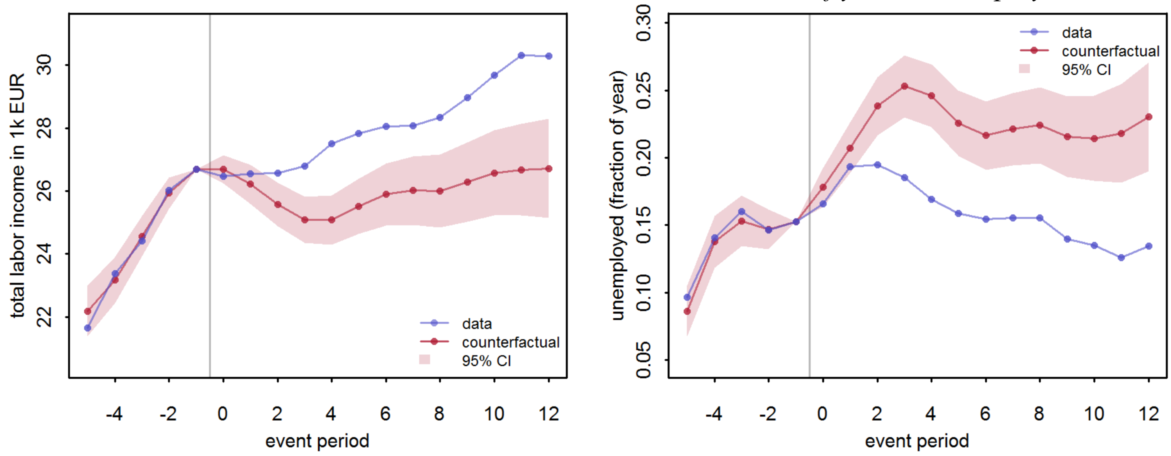
	(1)	(2)	(3)	(4)
Dependent variable:		Δ Log commuting distance		
	OLS	OLS	OLS	OLS
Move into affordable housing	0.068***	0.072**	0.023	0.025
	(0.021)	(0.022)	(0.040)	(0.040)
Same employer			-0.053**	-0.054**
			(0.021)	(0.022)
Move into affordable housing × same employer			0.083*	0.083*
			(0.044)	(0.044)
Year FE	No	Yes	Yes	Yes
City FE	No	Yes	Yes	Yes
Age FE	No	No	No	Yes
Observations	23,371	23,371	23,371	23,371
R squared	0.001	0.002	0.002	0.004
Adj. R squared	0.000	0.001	0.001	0.001

Notes: Standard errors clustered by person, ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. The sample is restricted to years with moves, using up to and including the year when the person moved into affordable housing.

Figure C1

Robustness of baseline results to using a constant-composition sample

A. Total real labor income *B. Fraction of year in unemployment*

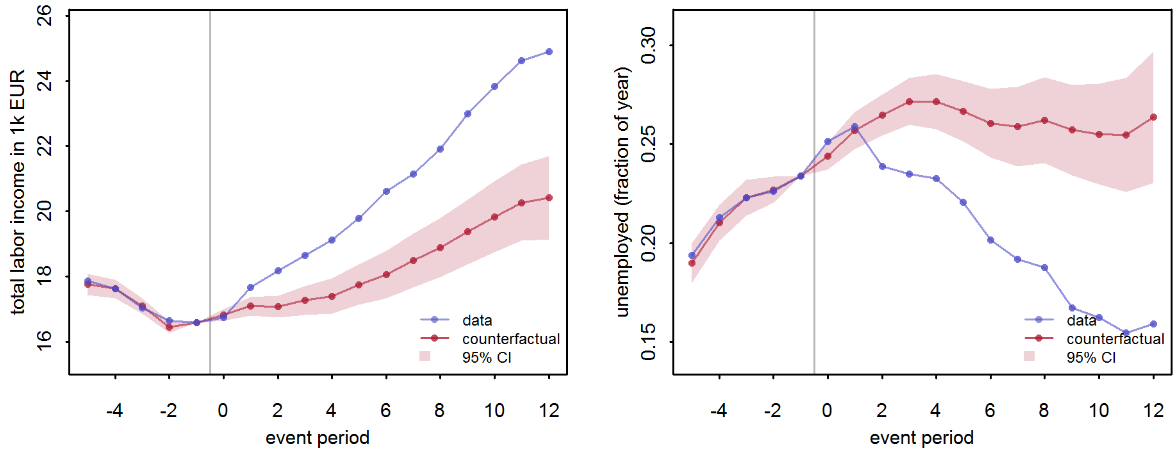


Notes: The blue lines show the mean outcome variables as observed in the data. The red counterfactual lines are constructed using the BJS estimator. The difference between the blue and red lines represents the by-period estimate from equation (2). The vertical grey line denotes the event date. In period 0, the person was observed at an affordable housing address for the first time. The shaded area is a 95% confidence region obtained from 500 block-bootstrap draws at the affordable housing address level. Persons in vocational training or in university or college at the time of admission to affordable housing excluded. The composition of the sample is held constant in all event periods -5 through 12. Persons with missing counterfactual predictions or missing data in at least one event period between -5 and 12 were dropped.

Figure C2

Robustness of baseline results to excluding persons in vocational training in the five years prior to admission to affordable housing

A. Total real labor income *B. Fraction of year in unemployment*

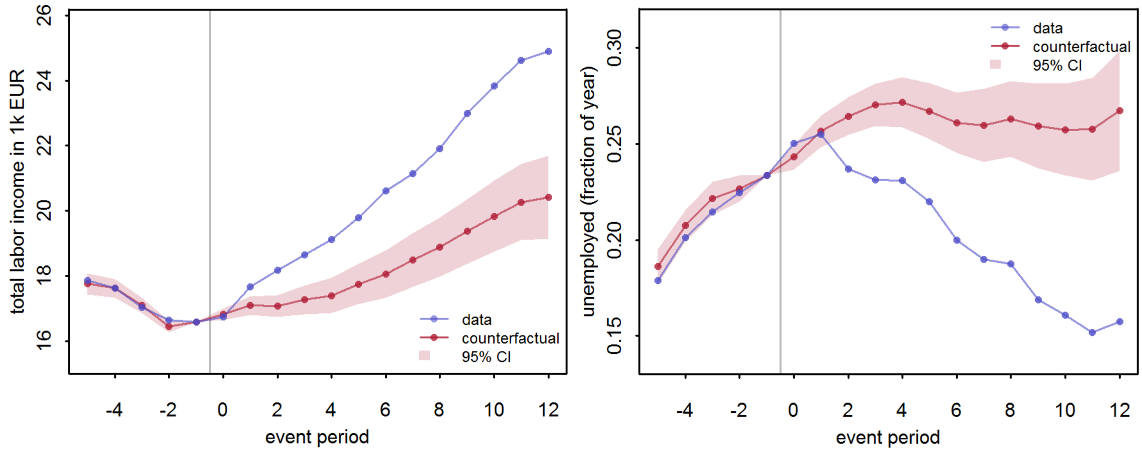


Notes: The blue lines show the mean outcome variables as observed in the data. The red counterfactual lines are constructed using the BJS estimator. The difference between the blue and red lines represents the by-period estimate from equation (2). The vertical grey line denotes the event date. In period 0, the person was observed at an affordable housing address for the first time. The shaded area is a 95% confidence region obtained from 500 block-bootstrap draws at the affordable housing address level. Persons in vocational training or in university or college at the time of admission to affordable housing, and persons in vocational training in the five years prior to admission excluded.

Figure C3

Robustness of baseline results to using common fixed effects for both sexes and all nationalities

A. Total real labor income *B. Fraction of year in unemployment*

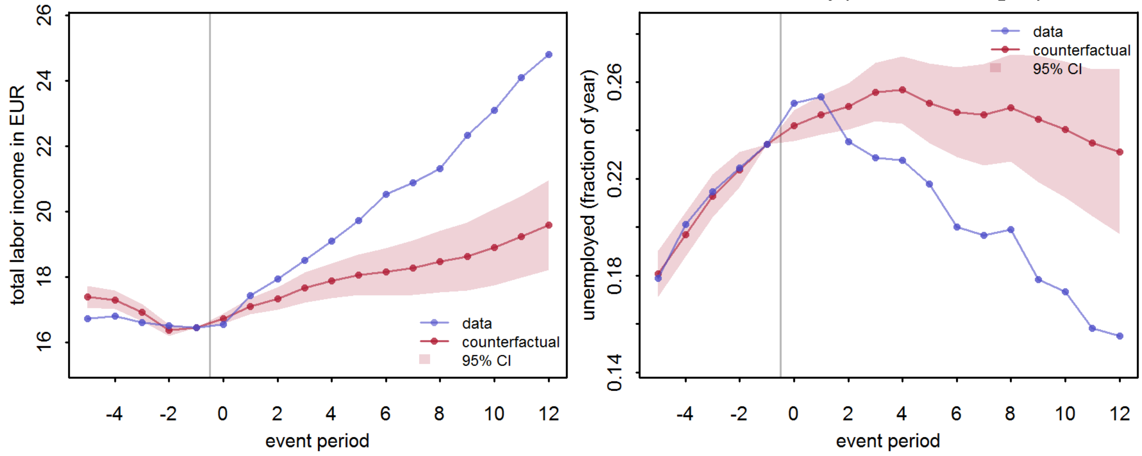


Notes: The blue lines show the mean outcome variable as observed in the data. The red counterfactual lines are constructed using the BJS estimator with person fixed-effects and year-by-city, age fixed-effects that are common for both sexes and for German and non-German persons. The difference between the blue and red lines represents the by-period estimate from equation (2). The vertical grey line denotes the event date. In period 0, the person was observed at an affordable housing address for the first time. Persons The shaded area is a 95% confidence region obtained from 500 block-bootstrap draws at the affordable housing address level. in vocational training or in university or college at the time of admission to affordable housing excluded.

Figure C4

Robustness of baseline results to using alternative regression model

A. Total real labor income *B. Fraction of year in unemployment*

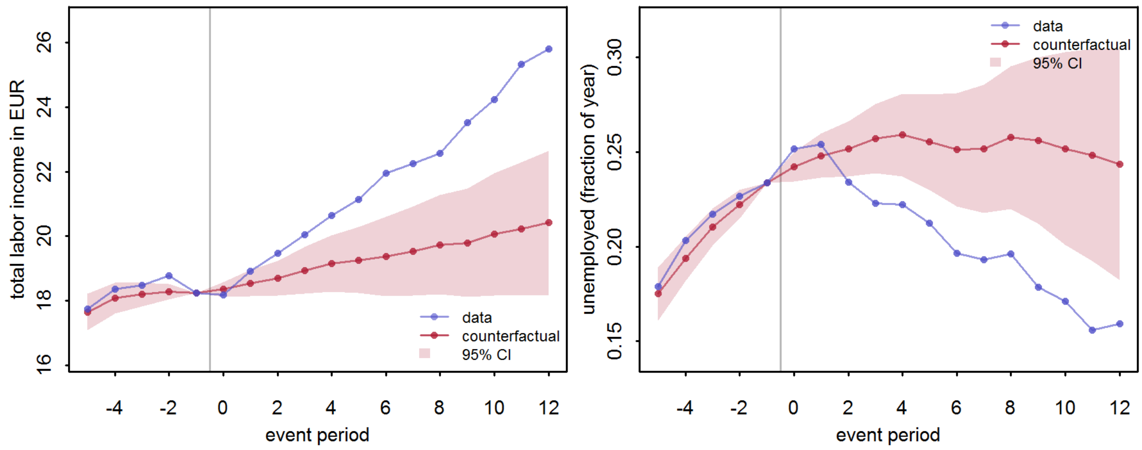


Notes: The blue lines show the mean outcome variable as observed in the data. The red counterfactual lines are constructed using the BJS estimator, with controls for age and person fixed-effects as defined in equation (1), and a city-specific quadratic polynomial in the year of observation instead of city-specific year fixed effects. The pre-event period estimation sample consists of observations from event periods -2 or before. The difference between the blue and red lines represents the by-period estimate from equation (2). The vertical grey line denotes the event date. In period 0, the person was observed at an affordable housing address for the first time. The shaded area is a 95% confidence region obtained from 500 block-bootstrap draws at the affordable housing address level. Persons in vocational training or in university or college at the time of admission to affordable housing excluded.

Figure C5

Robustness of baseline results to using alternative regression model and a restricted pre-event sample period for the first-stage regression

A. Total real labor income *B. Fraction of year in unemployment*

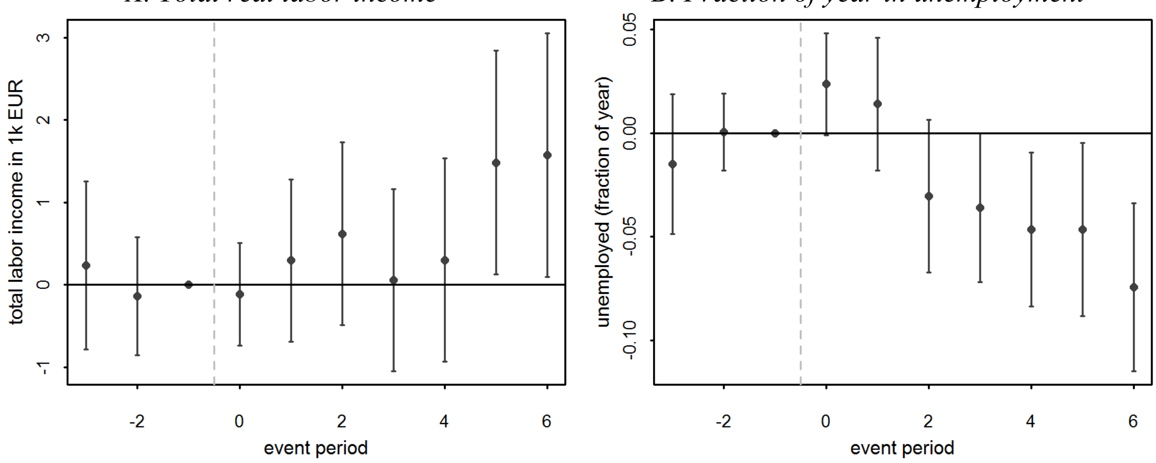


Notes: The blue lines show the mean outcome variable as observed in the data. The red counterfactual lines are constructed using the BJS estimator, with controls for age and person fixed-effects as defined in equation (1), and a city-specific quadratic polynomial in the year of observation instead of city-specific year fixed effects. The pre-event period estimation sample consists of observations from event periods -6 or before. The difference between the blue and red lines represents the by-period estimate from equation (2). The vertical grey line denotes the event date. In period 0, the person was observed at an affordable housing address for the first time. The shaded area is a 95% confidence region obtained from 500 block-bootstrap draws at the affordable housing address level. Persons in vocational training or in university or college at the time of admission to affordable housing excluded.

Figure C6

Robustness of baseline results to using a matching approach

A. Total real labor income *B. Fraction of year in unemployment*



Notes: The dots represent average differences between matched treatment and control observations. The vertical bars denote heteroskedasticity-robust 95% confidence intervals. Matching is exact on city, year, sex, foreign, the sickness indicator at admission and one year prior to admission, and welfare benefit receipt status at admission and one year prior to admission (if observed 2007 or later). Further inexact matching variables are the age, the pre-treatment labor income in the three periods prior to admission, and the unemployment status in the two periods before admission. For these variables, we use a cutoff (caliper) of 0.2 standard deviations. Control observations are drawn from nine periods prior to admission or earlier. In event period 6, these individuals have two more years until they are admitted to affordable housing. There are 648 matched pairs of individuals in total.