A New Spatial Hedonic Equilibrium in the Emerging Work-from-Home Economy?

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February 2021, revised October 2021, January 2022

Abstract

This paper studies the impacts of work-from-home (WFH) in the housing market from both intercity and intracity perspectives. Our results confirm the theoretical prediction that WFH puts downward pressure on housing prices and rents in high-productivity counties, a result of workers starting to relocate to cheaper metro areas during the pandemic without forsaking their desirable jobs. We also show that WFH tends to flatten intracity house-price gradients, weakening the price premium associated with good job access.

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1. Introduction

Cities differ in their abilities to attract workers and firms. San Francisco has an advantage in attracting workers over a city like Detroit because of its desirable attributes, including warmer winters and milder summers, less air pollution, and lower average crime levels. Dispersion in productivity also leads to differences in cities' abilities to attract workers. Some locations have a productive advantage over others because of a dense spatial concentration of jobs, creating agglomeration economies, or a favorable industry mix. Housing costs and wages adjust across space to arbitrage away these advantages. In a spatial hedonic equilibrium, where price signals and city characteristics are linked, high productivity leads to high rents and high wages, whereas high amenities are associated with high rents but lead to low wages.

In this paper, we explore how the spatial hedonic equilibrium is affected by the introduction of a work-from-home (WFH) option. Since a WFH-induced shift in the equilibrium alters the connections between where people live and what they earn and pay for housing, it is of utmost importance to understand the nature of the shift. To this end, we model WFH as an unbundling technology that allows an individual to live in one city and work in another. Breaking the link between workplace and residence allows for spatial arbitrage opportunities that were not available in the past. Workers in expensive, high-productivity places can move to cheaper, low-productivity areas while keeping their original productive jobs through remote work. The media is full of anecdotal evidence of such relocations (see Bindley, 2020; Dillon, 2021), although firm statistical evidence has yet to be presented. Another possibility, less

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anticipated in popular discussions, is that WFH allows workers to move to high-amenity places without changing jobs. Both types of relocations have price effects, leading to a new spatial hedonic equilibrium.

To highlight these new possiblities, we develop a simple Rosen-Roback model with homogeneous workers.[1] When cities differ only in productivities and WFH is introduced, workers move to cheap, low-productivity places while telecommuting to their original jobs, matching the anecdotal evidence. This residential relocation causes housing prices to fall in productive places and rise in the disadvantaged cities that receive the WFH migrants. By contrast, when cities differ only in amenities, workers move to high amenity areas under WFH while keeping their jobs in low-amenity cities. Housing prices then rise in the advantaged, high-amenity places while falling in disadvantaged cities, a pattern opposite to the one in the differential-productivity case. Underlying both outcomes are two key features of the new hedonic equilibrium: wage equalization across cities, which must occur when people can work anywhere; and a disconnect between a city's population and employment levels, which are no longer equal. In the differential-amenity case, wage equalization means that housing prices alone adjust to equalize utilities (yielding stronger capitalization of amenities), whereas in the differential-productivity case, wage equalization leads to equalization of housing prices as well. In both cases, wage variation disappears as a utility-equalizing force, with housing prices doing all the work in ensuring that cities are equally attractive to consumers. The resulting hedonic equilibria are therefore novel, with features not previously seen in Rosen-Roback models.[2]

While these patterns show the possible *intercity* effects of WFH, *intracity* effects may emerge as well. Workers who remain in their original city under WFH are likely to maintain some physical connection to the workplace, commuting to it occasionally rather than completely severing the physical link. For such workers, WFH lowers commuting costs without

[1] See Rosen (1979) and Roback (1982).

[2] Discussion in the media speculates that firms might cut pay if remote workers face a lower cost of living (see Buhayar, 2020), something that does not occur in our model. However, see Coy (2021) and Kamp (2021) as well as an online statement about Zillow's corporate pay policy says that when "you work for Zillow, your long-term earning potential is determined by how you perform, and will not be limited by where you live." See `https://www.zillowgroup.com/news/why-zillow-group-is-de-emphasizing-location-as-a-component-of-compensation-making-it-easier-for-employees-to-move/`.

reducing them to zero, thereby lowering the value of access to the CBD. From the standard urban model, lower-valued access implies a reduction in the city's housing-price gradient, with prices under WFH falling more slowly than before moving away from the CBD (the job-access premium thus falls).

In the empirical section of the paper, we present evidence for both our intercity and intracity hypotheses, relying on the growth of WFH during the pandemic year of 2020. We harmonize information from several sources, using house-price and rent data from Zillow and productivity and amenity measures from Albouy (2016). Using Dingel and Neiman's (2020) industry-level index of job shares in occupations that allow WFH, we create a county-level measure of WFH potential. The measure equals a weighted average of their industry indices, with the weights equal to industry employment shares in the county.

First, consistent with our intercity model, we show that the annual changes in both house prices and rents between 2019 and 2020, when the COVID-19 pandemic spurred WFH, are lower in high-productivity counties with high WFH potential.[3] Second, using address-change data, we show that these same counties experienced higher population outflows, confirming the theoretical link between price changes and WFH-induced household relocation. Third, using monthly data, we show that high productivity and high WFH potential lead to lower levels of county house prices and rents in the months following December 2019. These results, which are based on monthly price and rent *levels*, reinforce the previous results using annual price changes between 2019-2020 at at finer temporal level. In contrast to these supportive results, the main specification does not provide support for the model's prediction of falling prices and rents in low-amenity cities with high WFH potential.

Fourth, to test our intracity hypothesis of a declining house-price gradient under WFH, we combine Zillow data at the zip-code level with data from Lee and Lin (2018a). We compute monthly metro-area price gradients and show that high WFH potential in the metro area's central county is associated with a flattening of the price gradient during 2020, as expected.

Fifth, we also present regressions showing the effect of WFH on population inflows. These

[3] A placebo test shows that these same effects were not present in previous years, when WFH played a smaller role.

regressions include a state tax effect, showing that WFH-induced changes in county inflows were smaller in states with high top marginal income-tax rates.

We recognize the growth of WFH was not the only force affecting house-price behavior in our focal year of 2020: the effects of the pandemic-induced recession were also present. However, the house-price effects of the recession at the national level have been hardly noticeable, presumably because job losses were concentrated among lower-income workers (many of whom were unable to work from home). While prices may have been supported by lower job losses in high-WFH-potential counties, these effects should have been positive, not negative like those that we predict and find empirically. As a result, we believe that our hypothesis tests are credible despite the coincidence of the recession and the growth of WFH.

Our paper relates to a burgeoning literature on the impact of telecommuting and remote work on the US economy. Early research by Rhee (2008) and Safirova (2002) has been complemented by the recent studies of Althoff et al. (2020), Bartik et al. (2020), Brynjolfsson et al. (2020), and Dingel and Neiman (2020). Within this literature, our work is most closely related to Behrens, Kichko and Thisse (2021), Delventhal and Parkhomenko (2020), Delventhal, Kwon, and Parkhomenko (2020), and Larson and Zhao (2017), who build theoretical spatial models to explore the local labor market effects of telecommuting and WFH. Our simpler theoretical model and reduced-form empirical approach adds to the insights from their models. Our work is also connected to Davis, Ghent, and Gregory (2021), who estimate the elasticity of substitution between office and home work, relying on a theoretical model.[4]

The paper proceeds as follows. Section 2 develops our theoretical predictions, while section 3 discusses the empirical model. Section 4 discusses the data, while section 5 presents our empirical results. Section 6 offers perspective on the findings, and section 7 presents conclusions.

[4] After our price-gradient work was complete, we became aware of a contemporaneous paper by Gupta et al. (2021) that carries out a very similar exercise. They investigate changes in intracity price and rent gradients between 2019 and 2020 and use the results to compare expectations about real-estate price growth between suburbs and the central cities, relying on changes in the price-to-rent ratio. While we present similar price-gradient results (though for a larger collection of metro areas), our main focus is on the intercity effects of WFH. Similarly, a contemporaneous paper by Bloom and Ramani (2021) uses the same US Postal Service address-change data we use to study population movements under WFH, finding evidence of relocation from central cities to suburbs. Ouazad (2020) also finds evidence of increased suburbanization during 2020, but he argues that long-run population growth across cities is more strongly associated with local fundamentals, such as local productivity, than short-run shocks, including disasters and pandemics.

2. Theory

2.1. Intercity analysis

2.1.1. Intercity model and equilibrium conditions

The intercity model has two cities, denoted s (San Francisco) and d (Detroit), with equal fixed land areas and hence zero land supply elasticities, that together accommodate a total population of $2\overline{N}$.[5] The wage in city i is given by $w(L_i, \alpha_i)$, $i = s, d$, where L_i is employment and α_i is a shift parameter that raises worker productivity and thus the wage ($w_\alpha > 0$). Since this wage function is just the downward-sloping inverse demand curve for labor, $w_L < 0$. Without WFH, a city's employment level equals its population N_i, so that the wage is given by $w(N_i, \alpha_i)$. Labor productivity is higher in city s than in city d ($\alpha_s \geq \alpha_d$), and the cities also differ in the amenities A_i they offer, with $A_s \geq A_d$. City s is thus the high-productivity, high-amenity city.

Consumers have identical preferences, with utility in city i given by the quasi-linear function $u(e_i, q_i, A_i) = A_i + e_i + v(q_i)$, where q_i is housing (land) consumption and e_i is non-housing consumption, $i = s, d$.[6] With units of measurement for amenities and e being chosen appropriately, their linear utility coefficients are the same and equal to unity. Letting p_i denote the unit housing price in city i, the consumer budget constraint is $e_i = w(N_i, \alpha_i) - p_i q_i$, which assumes that the price of non-housing consumption (set to unity) is the same in both cities. Substituting this expression for e_i allows utility to be rewritten as $A_i + w(N_i, \alpha_i) + v(q_i) - p_i q_i$. The last two terms represent "net housing utility" (v minus housing cost), which can be written as a function $H(N_i)$ of population that decreases with N_i due to the positive effect of population

[5] Replacing fixed land areas with a common upward-sloping housing supply function would have no qualitative effect on the ensuing results. However, if the supply elasticities were to differ across cities (Glaeser and Gyourko, 2005; Saiz, 2010), the sizes of their population changes under WFH would be affected. Note also that rental income from the city's land flows to absentee landowners.

[6] Remote work is assumed to have no effect on housing demand. The empirical study of Stanton and Tiwari (2021) recognizes, however, that the houses of remote workers may need be larger to offer adequate office space. The model of Behrens, Kichko and Thisse (2021) includes such an effect.

on the housing price.[7] Thus,

$$utility_i \;=\; A_i \;+\; w(N_i, \alpha_i) \;+\; H(N_i), \quad i = s, d. \tag{1}$$

Since both the wage and net housing utility decrease with N_i, utility also decreases with population.[8]

In the equilibrium without WFH, the consumer utility expression in (1) is equalized between the two cities via migration, which is costless. The non-WFH equilibrium condition is then

$$A_s \;+\; w(N_s^*, \alpha_s) \;+\; H(N_s^*) \;=\; A_d \;+\; w(N_d^*, \alpha_d) \;+\; H(N_d^*), \qquad \text{(Non-WFH)} \quad (2)$$

where the asterisks denote non-WFH equilibrium values. An immediate implication of this condition is $N_s^* > N_d^*$, so that city s is larger than city d, reflecting its amenity and productivity advantages.[9] With city s larger, its housing price is then higher than in city d ($p_s^* > p_d^*$).

Now suppose that WFH becomes feasible. Since an individual can now work in either city regardless of where he or she lives, equilibrium requires indifference between the two work locations, which in turn implies equalization of wages. As a result, $w(\widetilde{L}_s, \alpha_s) = w(\widetilde{L}_d, \alpha_d)$ must hold, where $\widetilde{L}_s$ and $\widetilde{L}_d$ are the employment levels under WFH in the two cities, which no longer need to be the same as the city populations. With wages the same across cities, they drop out of the equilibrium condition (2), so that regardless of where residents of the two cities

[7] To derive the H function and its properties, city land areas are normalized at unity, yielding $q_i = 1/N_i$. The housing first-order condition ($v'(q_i) = p_i$) then yields $H(N_i) = v(q_i) - p_i q_i = v(1/N_i) - v'(1/N_i)(1/N_i)$, which is decreasing in N_i. This conclusion follows because differentiation yields $H'(N_i) = (1/N_i^3)v''(1/N_i) < 0$, an expression proportional to minus the positive derivative of $p_i = v'(1/N_i)$ with respect to N_i.

[8] While the model assumes a competitive labor market, Kahn and Tracy (2019) argue that, if labor market power exists, it will be capitalized into local real-estate prices. They document that counties featuring more concentrated employment (a higher HHI) indeeed have lower real-estate prices, with landowners thus bearing part of the economic incidence of monopsony power. The rise of remote work would increase competitiveness in such labor markets, as the outside option for local workers expands.

[9] Suppose instead that the two cities had identical populations, both equal to $\overline{N}$. Then, given $A_s > A_d$ and $\alpha_s > \alpha_d$, the LHS of (2) would be larger than the RHS. Since both sides of (2) are decreasing in population, an increase in N_s^* along with a corresponding decrease in N_d^* makes them equal, yielding $N_s^* > N_d^*$.

work, their utilities are equal when

$$A_s \; + \; H(\widetilde{N}_s) \;\; = \;\; A_d \; + \; H(\widetilde{N}_d), \qquad\qquad \text{(WFH)} \quad (3)$$

where the $\widetilde{N}_s$ and $\widetilde{N}_d$ are the city populations under WFH. As in the non-WFH case, city s is larger than d under WFH (with $A_s > A_d$, $\widetilde{N}_s$ must exceed $\widetilde{N}_d$ to equate the two sides of (3)). Since $\widetilde{N}_s > \widetilde{N}_d$, the housing price in city s is again higher than in city d ($\widetilde{p}_s > \widetilde{p}_d$), canceling its amenity advantage.

An implicit assumption under WFH is that a worker's productivity at a given workplace is unaffected by residential relocation to a different city. The popular discussion of WFH sometimes argues otherwise, with work that is physically remote from colleagues viewed as possibly less productive, thus commanding lower pay.[10]

2.1.2. Comparing the WFH and non-WFH equilibria

To compare the WFH and non-WFH equilibria, the first step is to rewrite (2) and (3) as

$$A_s \; - \; A_d \; + \; H(N_s^*) \; - \; H(N_d^*) \;\; = \;\; w(N_d^*, \alpha_d) \; - \; w(N_s^*, \alpha_s) \qquad \text{(Non-WFH)} \; (4)$$

$$A_s \; - \; A_d \; + \; H(\widetilde{N}_s) \; - \; H(\widetilde{N}_d) \;\; = \;\; 0 \qquad\qquad \text{(WFH)} \; (5)$$

From comparison of (4) and (5), the following conclusion emerges:[11]

$$\widetilde{N}_s \;>(<)\; N_s^* \qquad as \qquad w(N_d^*, \alpha_d) \;>(<)\; w(N_s^*, \alpha_s). \qquad (6)$$

In other words, WFH leads to an increase (decrease) in the population of city s when its wage without WFH is lower (higher) than the non-WFH wage in city d.

Unfortunately, the sign of $w(N_d^*, \alpha_d) - w(N_s^*, \alpha_s)$ is ambiguous in general, making it impossible to carry out a general comparison of $\widetilde{N}_s$ and N_s^* using (6). The source of the ambiguity is

[10] See, for example, Buhayar (2020).

[11] To verify (6), note that the LHS of (4) is positive if $w(N_d^*, \alpha_d) > w(N_s^*, \alpha_s)$, and that its magnitude must be reduced to zero to satisfy the WFH condition in (5). Since $H' < 0$, this reduction requires an increase in N_s with N_d falling in step, yielding $\widetilde{N}_s > N_s^*$. Reversing this argument, $w(N_d^*, \alpha_d) < w(N_s^*, \alpha_s)$ implies $\widetilde{N}_s < N_s^*$.

that city s has dual advantages over city d, in both amenities and productivity. However, if city s only has a single advantage, in either productivity or amenities, then definitive conclusions can be reached, as follows.

City s has higher productivity. Suppose that $A_s = A_d$ while $\alpha_s > \alpha_d$, so that the only advantage of city s is higher productivity. Then, it is easily seen using (4) that $w(N_d^*, \alpha_d) < w(N_s^*, \alpha_s)$ holds, so that the wage is higher is city s than in city d, in parallel with the price of housing.[12] From (6), this inequality in turn implies $\widetilde{N}_s < N_s^*$, so that the population of city s drops under WFH, with city d's population rising.[13] Since $H(\widetilde{N}_s) = H(\widetilde{N}_d)$ must hold by (5) when amenities are equal, these population changes end up equating the populations of the two cities, so that $\widetilde{N}_s = \widetilde{N}_d = \overline{N}$. Equal populations in turn imply equality of housing prices, with $\widetilde{p}_s = \widetilde{p}_d$, so that prices drop in city s and rise in city d ($\widetilde{p}_s < p_s^*$, $\widetilde{p}_d > p_d^*$). Residents of both cities thus earn equal wages and pay equal prices, ensuring equal utilities.

WFH breaks the link between employment and population levels, with employment exceeding population in city s (as outward-migrants keep their jobs) and falling short of population in city d.[14] Correspondingly, $\widetilde{L}_s > N_s^*$ and $\widetilde{L}_d < N_d^*$ hold, so that employment rises above its pre-WFH level of N_s^* in city s even though its population is falling, while employment falls in city d even though its population is rising (see the online appendix for a proof). This drop in employment means that some original residents of city d then work remotely in city s, explaining its employment gain.

Summarizing yields

Proposition 1. *When city s has only a productivity advantage, some of its residents move to city d under WFH while keeping their original jobs. Population and the price of housing then fall in city s, while city d's population and housing price rise. Despite*

[12] When $A_s = A_d$, (4) becomes

$$H(N_s^*) \; - \; H(N_d^*) \;\; = \;\; w(N_d^*, \alpha_d) \; - \; w(N_s^*, \alpha_s). \tag{$f1$}$$

Since $N_s^* > N_d^*$ holds from above, the LHS of ($f1$) is negative given $H' < 0$, implying negativity of the RHS and thus $w(N_d^*, \alpha_d) < w(N_s^*, \alpha_s)$.

[13] Howard (2020) shows that migration into a city creates a beneficial construction boom. While fixed land areas in our model rule out such an effect, a more detailed framework could capture this positive effect of WFH.

[14] These conclusions follow because the WFH employment levels $\widetilde{L}_s$ and $\widetilde{L}_d$ lead to equal wages ($w(\widetilde{L}_s, \alpha_s) = w(\widetilde{L}_d, \alpha_d)$), implying $\widetilde{L}_s > \widetilde{L}_d$ given $w_N < 0, w_\alpha > 0$ and thus $\widetilde{L}_s > \widetilde{N}_s = \overline{N} = \widetilde{N}_d > \widetilde{L}_d$.

its lower population, employment rises in city s, exceeding the population, while employment decreases in city d, falling short of its larger population. Along with the new arrivals, some original residents of city d then work remotely in city s.

In generating these changes, WFH leads to a new hedonic equilibrium in the economy. Prior to WFH, both the wage and the price of housing were higher in city s than in city d, signaling the productivity difference between the cities. With WFH breaking the employment-population link, wages and prices are then equated between the cities, so that market signals no longer reveal the intercity productivity differential.

City s has higher amenities. Suppose instead that $A_s > A_d$ holds while $\alpha_s = \alpha_d = \overline{\alpha}$, so that the only advantage of city s is better amenities. Since $N_s^* > N_d^*$ from above and $w_N < 0$, $w(N_d^*, \overline{\alpha}) > w(N_s^*, \overline{\alpha})$ is satisfied, so that the higher housing price in city s is now accompanied by a lower wage. Since (6) then implies $\widetilde{N}_s > N_s^*$, the population of city s expands under WFH, with residents relocating from city d. This population shift raises the housing price in city s and lowers it in city d, so that $\widetilde{p}_s > p_s^*$ and $\widetilde{p}_d < p_d^*$. Since city d's outward migrants keep their jobs, city d's employment under WFH exceeds its population, while employment falls short of population in city s.[15] Correspondingly, the online appendix shows $\widetilde{L}_s < N_s^*$ and $\widetilde{L}_d > N_d^*$, so that employment falls in city s even though its population is rising, while employment rises in city d even though its population is falling. The drop in employment in city s means that some of its original residents then work remotely in city d, explaining its employment gain.

Summarizing yields

Proposition 2. *When city s has only an amenity advantage, some of city d's residents move to city s under WFH while keeping their original jobs. Population and the price of housing then fall in city d, while population and the housing price rise in city s. Despite its larger population, employment decreases in city s, falling short of its population, while employment rises in city d, exceeding its smaller population. Along with the new arrivals, some original residents of city s work remotely in city d.*

In generating these changes, WFH again leads to a new hedonic equilibrium in the economy.

[15] These conclusions follow because, when city s has only an amenity advantage, the wage equalization condition $w(\widetilde{L}_s, \overline{\alpha}) = w(\widetilde{L}_d, \overline{\alpha})$ implies equalization of employment, or $\widetilde{L}_s = \widetilde{L}_d = \overline{N}$. Since $\widetilde{N}_s > \widetilde{N}_d$, it follows that $\widetilde{N}_s > \widetilde{L}_s = \overline{N} = \widetilde{L}_d > \widetilde{N}_d$.

Prior to WFH, city s had a higher housing price and a lower wage than city d, reflecting the standard outcome in the Rosen-Roback model when cities differ only in amenities. Together, these differences served to offset the amenity advantage of city s. With wages being equalized under WFH, housing prices must then do all the work in equalizing utilities, requiring a larger price differential than before. Therefore, in the new hedonic equilibrium, the role of wages disappears while that of housing prices is accentuated.

Given the preceding results, the intuition underlying the effects of WFH is clear. When city s has only a productivity advantage, workers can escape its high housing price by moving to city d while keeping their productive city-s jobs, a movement that causes the population in city s to fall short of employment. By equalizing populations, this shift eliminates the housing price differential between the cities, mirroring the equalization of wages. When city s has only an amenity advantage, wage equalization under WFH means that city-d workers can move to enjoy the higher amenity level without the previous wage sacrifice, keeping their city-d jobs. This movement causes population in city s to exceed employment and pushes up the housing price enough to exactly cancel the utility benefit from the amenity differential. As these adjustments unfold, population and employment move in opposite directions within each city. In the productivity differential case, employment rises in city s as its population falls, while in the amenity-differential case, employment falls in city s as its population rises (with opposite changes in city d).

Note that the population changes in Proposition 1 match up with media anecdotes about migration out of high-productivity cities. But the effects in Proposition 2, which are exactly the opposite of those in Proposition 1, have been less anticipated in the popular discussion of WFH. Observe also the opposing outcomes in the two propositions show why unambiguous results cannot be derived when city s has both productivity and amenity advantages.

2.1.3. Wage effects of WFH

A final question concerns the wage changes experienced by the residents of the two cities under WFH. To explain the outcome, let $\widetilde{w}_\alpha$ denote the uniform WFH wage when the cities have different productivities (different α values) and let $\widetilde{w}_A$ denote the uniform WFH wage when the cities have different amenities.[16] Analysis in the online appendix shows that, in the differential-productivity case, $w(N_s^*, \alpha_s) > \widetilde{w}_\alpha > w(N_d^*, \alpha_d)$ holds, while in the differential-amenity case, $w(N_s^*, \overline{\alpha}) < \widetilde{w}_A < w(N_d^*, \overline{\alpha})$ holds. Thus, the WFH wage lies between the pre-WFH city-s and city-d wages in both cases. Stated in terms of wage changes, this conclusion implies

Proposition 3.

(i) *When city s has only a productivity advantage, its original residents earn a lower wage under WFH, with the original residents of city d earning a higher wage.*

(ii) *When city s has only an amenity advantage, its original residents earn a higher wage under WFH, with the original residents of city d earning a lower wage.*

Drawing on Propositions 1 and 2, Proposition 3 yields a simple rule for telling whether a city's wage will rise or fall under WFH. The wage in a city falls (rises) when WFH causes its employment level to exceed (fall short of) its population.

Finally, the welfare effects of WFH remain to be considered. With housing prices moving in the same direction as wages in both cities in the differential-productivity case (Proposition 1 plus part (i) of Proposition 3), the welfare effects of WFH are ambiguous in this case. For the same reason, the same conclusion applies in the differential-amenity case (Proposition 2 plus part (ii) of Proposition 3).[17]

2.1.4. Two comparative-static predictions

This section states two comparative-static results that are useful in the subsequent empirical work. The results, which make intuitive sense, focus on the size of the housing-price declines in the cities that lose population under WFH (city s in the differential-productivity case and city d in the differential-amenity case). The results are proved in the online appendix and are stated as follows:

[16] Thus, $\widetilde{w}_\alpha = w(\widetilde{L}_s, \alpha_s) = w(\widetilde{L}_d, \alpha_d)$ and $\widetilde{w}_A = w(\widetilde{L}_s, \overline{\alpha}) = w(\widetilde{L}_d, \overline{\alpha})$, where the $\widetilde{L}_s$ and $\widetilde{L}_d$ values in the first (second) set of equalities pertain to the case where city s has a productivity (amenity) advantage.

[17] Sayantani (2021) adds a class of nonremote workers, who must work where they live, to the current model, with little effect on the main results.

Proposition 4.

(*i*) *In the differential-productivity case, the WFH-induced housing-price decline in city* s *is larger the higher is the city's productivity level.*

(*ii*) *In the differential-amenity case, the WFH-induced housing-price decline in city* d *tends to be smaller the higher is the city's amenity level.*

2.3. Intracity analysis

As we have seen, some workers under WFH live in a different city from their jobs and thus never physically visit the workplace. This same freedom should also apply to workers whose jobs and residences are in the same city, who could also work entirely from home, thus incurring zero commuting costs. The upshot is that, in a WFH model that incorporates space, commuting costs would equal zero for *all* workers in a city, regardless of whether or not their jobs are local.

This outcome has implications for a spatial pattern of housing prices in such a model, an issue that has not arisen in the nonspatial setting analyzed above. In the standard monocentric-city model, the parameter t gives commuting cost per mile to the city center, which contains all jobs (commuting cost per period from distance x is then tx). In the model, the housing price p per square foot declines with distance x to compensate for longer commutes, and Wheaton (1974) showed that this price gradient flattens as commuting cost t falls, with the required compensating differential shrinking (see also Brueckner (1987)). Since WFH as portrayed in our nonspatial model eliminates commuting costs, it would thus imply a zero price gradient within cities. However, residents have other reasons (entertainment, dining) to visit the city center (at cost per period of T per mile), which would maintain a negative but smaller price gradient under WFH. Note also that a different hybrid WFH scheme, where workers visit the worksite a few days per week, would help to maintain a negative (but smaller) price gradient under WFH, although hybrid WFH would eliminate the possibility of intercity relocation. Empirically, this discussion implies that estimated housing-price gradients in individual cities should flatten under WFH, with the negative distance coefficient in the price regression becoming smaller in absolute value.

These elements can be incorporated in the previous nonspatial model under certain assumptions, as follows. First, with their (now circular) land areas being fixed, cities do not have flexible boundaries, in contrast to the monocentric model. Second, housing developers impose uniform lot sizes, so that land consumption q_i is uniform across space in each city i. Third, the housing (land) price is set to satisfy the first-order condition for the consumer living at the city center (with $x = 0$). Then (following (2) and using the definition of H), the utility of the consumer living at distance x from the city i's center equals amenities plus the wage plus $v(q_i) - p_i(x)q_i - (t + T)x$, where $p_i(x)$ is the housing price at distance x in city i, t is commuting cost, and T is the cost of traveling to the city center for other reasons. For utility to be spatially invariant, $p_i(x)q_i + (t + T)x$ must equal a constant, which requires $p_i(x) = p_i^0 - (t+T)x/q_i$, where p_i^0 is the housing price at the center. The housing-price gradient is thus equal to $-(t+T)/q_i$, and it decreases in absolute value to $-T/q_i$ when WFH eliminates commuting cost (holding q_i fixed).[18] Adding space to the model in this fashion leaves all the previous results (Propositions 1-4) unaffected, while generating the prediction that WFH tends to reduce the housing-price gradient in both cities.[19]

3. Empirical frameworks

3.1. House-price-change regression

As explained in the introduction, our empirical work mostly explores the effects of WFH on housing prices, building on both the intercity and intracity theoretical analysis. This section explains the structure of the first of two empirical frameworks motivated by the intercity analysis, which consists of a regression explaining the change in house prices between 2019 and 2020. In developing this framework, it is helpful to distinguish between "sending" and "receiving" cities. Sending cities lose population under WFH, which is then "sent" to receiving cities, whose populations increase. In the theoretical model, the sending city (city s in the

[18] In this setup, p_i^0 would replace p_i as the price variable in the model. Observe also that the third assumption above, which says that the first-order condition for housing consumption is $v'(q_i) = p_i^0$, means that $v'(q_i)$ does not equal the price $p_i(x)$ at locations away from the center, where prices are lower. This outcome is unpalatable, but it is needed to put space into our nonspatial model without compromising its structure. A richer and more detailed approach designed to properly allow both intercity and intracity analysis, as in some of the studies cited in the introduction, could avoid this kind of shortcut.

[19] With land areas fixed, the cities' q levels (which appear in the gradient denominator) change with their populations under WFH, possibly altering this conclusion. However, if the commuting-cost changes are large relative to population changes, the conclusion will be accurate.

differential-productivity case and city d in the differential-amenity case) sends population to a single receiving city. In reality, however, the population leaving sending cities under WFH will relocate to a multitude of receiving cities, with the housing-price impacts in any particular receiving city likely being too small to measure. For this reason, our empirical analysis focuses on price impacts in sending cities, which (according to the model) have either high productivity or low amenities.

While all jobs in the model are homogeneous and can be done remotely, WFH in reality is possible for some jobs and not for others, as documented by Dingell and Neiman (2020), whose data we use (see below). As a result, the ability of workers to relocate and work remotely in a different city depends on the WFH potential of the origin city's jobs, which we measure in a fashion described below. WFH potential thus partly determines a city's potential role as a sending city, but the city must also have features that will lead workers to relocate once WFH is introduced (high productivity or low amenities). Guided by the theory, our empirical exercise focuses on potential sending cities, which have both high WFH potential and, alternatively, high productivity or low amenities.

The variables designed to capture the house-price effects of WFH in sending cities are generated as follows. First, as explained in more detail below, our variables are measured at the county, not the city, level. The variable PROD denotes the county-level job-productivity measure, while QOL denotes the amenity (or quality-of-life) measure. The work-from-home potential of the county's jobs is denoted by WFHPOT. Construction of these variables is explained below.

Our first set of regressions captures the determinants of the change in county-level house prices between the pre-pandemic (pre-WFH) year of 2019 and the pandemic year of 2020, which saw the widespread introduction of WFH. A variable that can gauge the impact of productivity on the WFH-induced house-price change is the interaction variable PROD$\times$WFHPOT. This variable will be large in sending counties, which have high productivity and high WFH potential. To appraise the variable's marginal effect on price changes in such counties, recall from Proposition 4 that an increase in PROD, which increases the magnitude of the interaction variable, leads to a larger decline in housing prices, holding WFHPOT fixed. In addition, a higher WFHPOT means that more workers can move under WFH, thus raising the price decline at a given PROD level. With an increase in either element of the interaction variable thus leading to a larger price decline, the variable's effect on house-price changes in sending counties should be negative.

While this discussion shows how house-price changes respond to the level of the interaction variable in sending counties, where its magnitude is large, what can be said for other counties? If PROD is low, then the county is not a sending county, which means that marginal increases in either PROD or WFHPOT should have no house-price effect. As a result, the coefficient of PROD×WFHPOT should be zero when PROD is low.

If PROD×WFHPOT appeared in a price-change regression run on a sample of all counties, both sending and receiving, then its estimated coefficient would be a blend of the negative and zero values expected in the former and latter counties. While this blending may yield a negative coefficient, a superior approach is to allow the interaction coefficient to be different across sending and receiving counties. This flexibility can be achieved by defining two dummy variables, high_PROD and low_PROD, which take the value 1 in counties where PROD lies, respectively, above and below the median value among MSAs, equaling zero otherwise.[20] Then, the triple-interaction variables high_PROD×PROD×WFHPOT and low_PROD×PROD×WFHPOT can be created, and their regression coefficients are expected to be negative and zero, respectively. These variables allow the coefficient of PROD×WFHPOT to differ between sending and receiving counties, where PROD is above or below the median.

This logic is illustrated in Figure 1, which shows the relation between $\Delta \log \mathrm{P}$ and WFHPOT for different values of PROD. When PROD takes a low value (PROD_1, PROD_2, or PROD_3), housing prices are low and workers have no incentive to move to another city. As a result, prices are unaffected by the level of WFHPOT as well as by the level of PROD, as shown in the horizontal line in the figure. However, when PROD takes a higher value ($\mathrm{PROD}_4 < \mathrm{PROD}_5 < \mathrm{PROD}_6$), then an incentive to move exists, and the magnitude of the

[20] Recall that PROD (and QOL) are MSA-level values assigned to component MSA counties. The variable high_PROD takes the value 1 if the PROD value for the county's MSA is above the MSA median and zero otherwise. With this assignment method, 575 out of 792 counties have high_PROD = 1. By contrast, the analogous variable high_QOL described in the next paragraph takes the value 1 in a minority (352 out of 792) of counties.

price decline is larger the higher is WFHPOT (since more workers can then move). While the curves relating $\Delta \log \mathrm{P}$ to WFHPOT are therefore downward sloping for these PROD values, a higher PROD value also yields a lower curve by Proposition 4(i). The regression specification should therefore allow the relationship between $\Delta \log \mathrm{P}$ and WFHPOT to be flat for low levels of PROD while allowing it to be decreasing for high levels and for the slope in this range to depend on the magnitude of PROD. The triple interaction specification achieves these goals.

A related logic applies to the interaction variable QOL×WFHPOT. Since high-QOL counties are not sending counties, the house-price change should be unaffected by marginal changes in the county's QOL and WFHPOT levels, suggesting a zero value for the interaction coefficient. In sending counties, where QOL is low, Proposition 4 indicates that an increase in QOL reduces the size of the price decline under WFH. However, by allowing more people to move to high amenity cities, a larger WFHPOT makes the price decline larger for a given QOL. As a result, the effects of QOL and WFHPOT go in opposite directions, yielding an ambiguous effect for the QOL×WFHPOT interaction variable in low-QOL counties. Use of the triple-interaction variables high_QOL×QOL×WFHPOT and low_QOL×QOL×WFHPOT then allows a zero effect to emerge in high-QOL counties and either a positive or negative coefficient to emerge low QOL counties depending on the relative strengths of the QOL and WFHPOT effects.

Therefore, letting c be the county index, the preferred house-price change regression takes the form

$$\begin{aligned}\Delta \log \mathrm{P}_c \;&= \qquad\qquad (7)\\ \beta_0 \;+\; \beta_1\, \mathrm{high\_PROD}_c \times \mathrm{PROD}_c \times \mathrm{WFHPOT}_c \;&+\; \beta_2\, \mathrm{low\_PROD}_c \times \mathrm{PROD}_c \times \mathrm{WFHPOT}_c \\ +\; \beta_3\, \mathrm{high\_QOL}_c \times \mathrm{QOL}_c \times \mathrm{WFPOT}_c \;&+\; \beta_4\, \mathrm{low\_QOL}_c \times \mathrm{QOL}_c \times \mathrm{WFHPOT}_c \;+\; Z_c\gamma \;+\; \epsilon_c,\end{aligned}$$

where Z_c is a vector of control variables, which includes PROD_c, QOL_c, WFHPOT_c, $\mathrm{high\_PROD}_c \times \mathrm{PROD}_c$, and $\mathrm{high\_QOL}_c \times \mathrm{QOL}_c$, and ϵ_c is the error term. The remaining controls are discussed below. In addition to using the change in house prices as the dependent variable, this regression is also estimated using the 2019-2020 change in rents.

A less-preferred version of (7) uses as covariates the original double-interaction variables, whose coefficients reflect the blending effect discussed above. The relevant portion of the RHS of this regression is $\alpha_0 + \alpha_1 \, \mathrm{PROD}_c \times \mathrm{WFHPOT}_c + \alpha_2 \, \mathrm{QOL}_c \times \mathrm{WFHPOT}_c$. A nonparametric approach to the regression in (7) is also possible, but discussion of this approach is deferred until presentation of the empirical results.

Figure 2 provides a schematic representation of the population flows predicted by the model, which generate the predicted changes in house prices. The black vertical arrows illustrate the model's prediction that, when QOL is identical across cities (either high or low), WFH causes a population flow from high-productivity to low-productivity cities. Conversely, the grey horizontal arrows illustrate the prediction that, when PROD is identical across cities (either high or low), WFH causes a population flow from low-QOL to high-QOL cities. The premise of identical QOL or PROD across cities is, of course, fictitious, and actual population flows may look like those indicated by the thin dotted arrows, with population moving, say, from a low-QOL/high-PROD city to a high-QOL/low-PROD city (grey arrow) or from a high-QOL/high-PROD city to a low-QOL/low-PROD city (black arrow). However, because the regression coefficients have a ceteris-paribus interpretation, they allow us to test the predictions embodied in the thick vertical or horizontal arrows based on movements that may be neither horizontal nor vertical.[21]

A final point is that, while the model predicts an *absolute drop* in house prices in sending counties, the empirical expectation is only that price changes are *smaller* in such counties than elsewhere. Other forces, such as the recession and a nationwide housing supply reduction in 2020 due to COVID fears among potential sellers, played a role in determining the overall level of prices.

3.2. Population outflow regressions

The predicted housing prices changes that (7) captures are the consequence of population

[21] This discussion suggests an idealized experiment that would allow a direct test of our predictions. Suppose workers in one high-productivity city (A) are free to relocate under WFH, while workers in a second high-productivity city (B) are not, possibly due to a city requirement that all work must be done in the office. Then, we would expect house prices to drop in city A under WFH but to be unchanged in city B, a prediction that could be tested by a direct comparison. This experiment is, of course, fanciful, requiring us to rely instead on regression analysis.

outlows in high-productivity counties (or low-QOL counties) with high WFH potential, as seen in the theoretical model. With these outflows being the mirror image of the predicted price declines, running the same regression as in (7) using outflows as the dependent variable can give further credence to our story. To measure outflows, we use address-change data from the US Postal Service, which has also been used by Bloom and Ramani (2021) and Kolko, Badger and Bui (2021) for a similar purpose. The signs of the key coefficients should be the reverse of those in (7), with high_PROD×PROD×WFHPOT having a positive coefficient and low_QOL×QOL×WFHPOT having a negative coefficient.

3.3. Monthly house-price level regression

While the regression in (7) focuses on the annual 2019-2020 house-price change as well as the change in rents, a different month-based regression shows the effect of WFH potential and productivity on the *levels* of house prices and rents in each month of a 48-month window around December 2019.

The monthly price-level regression, which uses the simpler double-interaction approach, takes the following form:

$$\begin{aligned}\log \mathrm{P}_{ct} \;&=\; \alpha_c \;+\; \sum_t \Big[\delta_t(\mathrm{PROD}_c \times \mathrm{WFHPOT}_c \times g_t) \;+\; \mu_t(\mathrm{QOL}_c \times \mathrm{WFHPOT}_c \times g_t) \\ &\quad +\; (\mathrm{Z}_c \times g_t)\gamma_t\Big] \;+\; \epsilon_{ct}, \end{aligned} \tag{8}$$

where α_c is a county fixed effect, t denotes months, the g_t's are month dummies, and Z_c again consists of control variables. Note that the right-hand variables in (8) are constant over time but that the specification allows their price effects to vary by month. We expect high productivity or low amenities to depress monthly house prices and rents after December 2019, which in the productivity case implies a declining pattern of PROD×WFH coefficients over the period. This same regression is also run using rent as the dependent variable.

3.4. Intracity empirical model

To investigate the intracity effects of WFH, we again use monthly house price data, now measured at the zip-code level, and first regress prices on distance to the metro-area CBD, generating a price gradient for each MSA in each month of the same 48-month window.[22] The estimated gradients are then used in a second-stage regression that relates their monthly magnitudes to the WFH potential of the metro area's central county. We expect the monthly coefficients relating the price gradients to WFH potential to increase over the months following December 2019, indicating less-negative values. This exercise borrows data from Lee and Lin (2018b).

The first stage estimates MSA-specific price gradients, one for each month (using the same 48-month window as the price-level regressions in (8)). Thus, for each metro area m and month t, we separately estimate the following equation:

$$\log \mathrm{P}_{mzt} \;\; = \;\; \mu_{mt} \; + \; \rho_{mt} \log \mathrm{DISTANCE}_{mz} \; + \; \mathrm{X}_{mz}\theta_{mt} \; + \; \nu_{mzt}, \tag{9}$$

where m denotes the metro area (MSA), z is the zip code, and t is the month. DISTANCE denotes the distance from the zip-code centroid to the metro CBD, and X is a set of controls. Note that all coefficients in (9) vary with the metro area and month.

In the second stage, the estimated distance coefficient $\widehat{\rho}_{mt}$ from (9) is regressed on the WFH potential of the metro area's principal-city county, allowing for month-specific coefficients:

$$\widehat{\rho}_{mt} \;\; = \;\; \sum_t \xi_t \left(\mathrm{WFHPOT}_m \times g_t\right) \; + \; \kappa_m \; + \; \eta_{r(m)t} \; + \; \upsilon_{mt}, \tag{10}$$

where κ_m is a metro-area fixed effect and $\eta_{r(m)t}$ is a Census-division $\times$ month-year fixed effect ($r(m)$ is the division containing metro area m).[23] We expect the ξ_t coefficient to rise across months, indicating flattening of the price gradient in metro areas with high-WFH-potential principal-city counties as time progresses.

[22] By focusing on a single CBD, these regressions ignore the polycentricity of some cities. But since our goal is to isolate a single price gradient, polycentricity cannot be taken into account, with our sole focus being on distance to the city's main employment center.

[23] When there are multiple principal-city counties in a metro area, we use the population-weighted average of the gradients from these counties.

3.5. Identification issues

As usual, correlation between the focal regression covariates and the regression error term, which contains unobservables affecting housing prices or the metro price gradients, could be a source of bias. However, the monthly price-level regressions in (8) use county fixed effects, and the monthly gradient regressions in (13) use metro-area fixed effects, with both regressions covering a short time interval where most unobservables are fairly constant. As a result, omitted variable bias is unlikely to be a serious issue in either of these regressions. County fixed effects in the price-difference regression in (9) are differenced out, and while one could argue that time-varying unobserved factors affecting county price changes might still lead to bias, the possibility that our triple-interaction variables are correlated with the error term seems slight, limiting any bias concerns.[24]

4. Data

4.1. Data on WFH potential

We measure WFH potential by combining 2018 data from County Business Patterns (the most recent data available) with the industry-level remote work index constructed by Dingel and Neiman (2020). For each NAICS3 industry, they measure the share of employment in occupations that can be done from home based on occupational characteristics from the US Department of Labor's Occupation Information Network (O*NET). Intuitively, an industry has a higher WFH potential if much of its employment is in occupations that require low levels of face-to-face interaction, if work involves low levels of physical effort, and if it relies more on information and communication technologies, such as e-mail. The WFH potential of county c is the employment-weighted average of WFH potentials for the county's industries (denoted by WFHPOT^j for industry j):

$$\text{WFHPOT}_c \quad = \quad \sum_{j \in J} s_{jc} \text{WFHPOT}^j, \tag{11}$$

[24] Inclusion of 2000 county COVID cases, implicitly a time-varying covariate since 2019 cases were zero, had no effect on the main results (in addition, its coefficient was counterintuitively positive.)

where s_{jc} is the employment share of industry j in county c. Table 1 shows the counties with the highest and lowest WFH potentials among the 100 largest counties. High-WFHPOT counties are concentrated in the finance and insurance hubs of the Northeast corridor as well as in the tech hubs of California. Low-WFHPOT counties are relatively less populous and more likely to be located in the South and the West.

4.2. Housing price and rent data

Our source of county-level house price and rent data is Zillow (2020). House prices are measured using the Zillow Home Value Index, which gives selling prices for typical for houses and condominiums in a geographic area, and rents are measured by the Zillow Observed Rent Index, which captures asking rents for representative units, but whose coverage of the country is less extensive than that of the price index. These Zillow datasets are monthly time series, which we aggregate to the yearly level for the price- and rent-change regressions. In addition, the rent data, which are available at the zip-code level, are weighted by zip-code population and aggregated to the county level using population data supplied by Manson et al. (2021) and a geographic crosswalk supplied by US Department of Housing and Urban Development (2020).

4.3. Amenity and productivity data

In addition to housing prices, critical to our analysis are measures of local amenities and productivity. We source these key variables from Albouy (2015), who builds a Rosen-Roback model to generate hedonic estimates of QOL and productivity at the metropolitan statistical area (MSA) level. We assign these MSA-level estimates to counties based on 1999 metro area standards, relying on the assumption that cross-county differences in amenities and productivity are small enough within MSAs that MSA values can be used.[25] It is interesting to note that a more-recent QOL measure developed by Carlino and Saiz (2019), based on the volume of online photo postings of metro-area scenes, is strongly correlated with Albouy's QOL measure (see their Figure 3). This outcome is not surprising given evidence that productivity and

[25] We use the term MSA to refer to metro areas whose designation is either MSA or CMSA (the latter are the largest MSAs).

quality-of-life in US metro areas are fairly stable over time.[26]

4.5. Other data

As mentioned above, a county's 2020 gross population outflow was captured using US Postal Service (2020) address-change data. These data show outflows by the origin Zip codes and were aggregated to the county level.[27] For our control variables, we supplement the main datasets with information on the share of the population with a college degree,[28] the Wharton Residential Land-Use Regulatory Index (WRLURI), measured for the county's MSA (Gyourko, Saiz and Summers, 2008), and a measure of terrain ruggedness, equal to the percent of the MSA land area with slope greater than 15 degrees (both measures are taken from Albouy, 2016). In addition, to capture the impacts of changing employment on house prices, the price-change regression includes a variable known as the Bartik "instrument," which equals the weighted average of 2019-2020 sectoral employment changes at the national level, with the weights equal to county-level sectoral job shares.[29] Census-division fixed effects are also included.

The metro-area county sample includes 792 counties. However, Zillow rents are available for only 269 counties, yielding a smaller sample for the rent regressions. Summary statistics for the regression variables over the larger sample are shown in Table 2, and Figure 3 shows a point scatter of WFH potentials and productivity for major MSAs, with the values expressed as deviations from medians.[30] The figure shows that WFH potential and productivity are positively correlated (at the county level, the correlation equals 0.33).

[26] One piece of evidence comes from Glaeser, Scheinman and Shliefer (1995), who show that a metro area's baseline characteristics (including QOL) determine its population growth over subsequent decades, which suggests that characteristics evolve slowly from their baseline.

[27] To separate household from business moves, the variable was set equal to the total Zip code outflow minus the business outflow.

[28] This share is the average county share of the college educated over the period 2014-2018 from the American Community Survey (US Census Bureau (2018)).

[29] National employment changes are between the second quarters of 2019 and 2020 (the latest available quarter in the Quarterly Census of Employment and Wages). Local shares are from County Business Patterns 2018. The Bartik instrument is omitted from the controls in (8).

[30] MSA WFH values are found by averaging across component counties. Note that Detroit is shown as a high-productivity city, in contrast to its status in the model of Section 2.

5. Empirical results

5.1. Regressions using price and rent changes

Table 3 shows the estimation results for the 2019-2020 price-change regressions (columns 1-4) and for the regressions using the change in the change in rents as dependent variable (columns 5-8). Column 1 of Table 3 shows that the high_PROD×PROD× WFHPOT coefficient is significantly negative in the price-change regression based on the specification in (9). This result confirms the prediction that 2019-2020 house-price changes were smaller in high-productivity counties with high WFH potential. Moreover, as predicted, the low_PROD×PROD×WFHPOT coefficient is not significantly different from zero. While the high_QOL×QOL×WFH coefficient is insignificant, matching predictions, the low_QOL×QOL×WFH is also insignificant, an outcome consistent with the prediction of an ambiguous sign for this interaction variable.

Dropping the insignificant triple QOL interactions leaves the coefficient pattern for triple PROD interactions unchanged, as seen in column 2 of Table 3. Column 3 replaces the triple interaction terms in column 1 with the double interactions PROD×WFHPOT and QOL×WFHPOT, whose coefficients are likely to be a blend of the corresponding triple-interaction coefficients. This expectation is confirmed by the significantly negative PROD× WFHPOT coefficient and the insignificant QOL×WFHPOT coefficient. Column 4 follows column 2 by dropping the insignificant interaction variable in column 3, with the remaining PROD×WFHPOT coefficient again significantly negative.

The full regression results, including the coefficients on the control variables involving separate elements of the interactions (PROD, QOL, WFHPOT, high_PROD×PROD and high_QOL×PROD) are reported in the online appendix (Table A1), as are full results for the regressions in Tables 4 and 5 below.

The interaction coefficients in columns 1–4 of Table 3 thus confirm the theory's prediction of downward pressure on house prices under WFH in counties with high productivity and high WFH potential. House-price changes are also affected by some of the control variables. The WRLURI coefficients are significantly positive in each of the columns 1–4, naturally indicating larger price changes in counties with greater land-use regulation. The college-education coefficient is significantly negative in columns 1–4, showing that 2019-2020 price changes were lower in highly educated counties, a result that is not transparent and may reflect other factors correlated with education. Unexpectedly, the Bartik coefficient is insignificant in each of these columns, and the terrain-slope coefficients are insignificant as well.

Columns 5–8 of Table 3 show the rent-change regression results, with the specifications matching those in columns 1–4. While the triple QOL interaction coefficients in column 5 are insignificant, as in column 1, both of the PROD triple interactions are significantly negative. Even though the negative high_PROD×PROD×WFHPOT matches expectations, the significance of the low_PROD×PROD×WFHPOT coefficient is unexpected, showing that house-price changes were affected by the levels of PROD and WFHPOT in receiving counties, when zero effects are anticipated. One possible explanation is that, among low-productivity counties, the highest productivity ones were actually sending (not receiving) counties for renters, so that the above-median/below-median productivity split does not separate sending and receiving counties as well as it does for homeowners.

As for the control-variable coefficients in columns 5–8, changes relative to columns 1–4 are that the Bartik coefficients become significantly positive, showing that a favorable employment change has a positive effect on the 2019-2020 rent change, while WRLURI coefficients become insignificant.

5.2. Outflow regressions

The downward pressure on prices and rents in counties with high-productivity and high WFH potential are generated in the model by population outflows. To check whether outflows match up with the pattern of house-price changes seen in Table 3, Table 4 presents the same regressions as in Table 3 but with the 2019-2020 change in the county population outflow, normalized by total population, as the dependent variable (recall that the variable comes from Postal Service data). As can be seen in the table, the main coefficient pattern is the mirror image of the pattern in columns 1–4 of Table 3, with significantly positive triple interaction coefficients wherever the coefficients in Table 3 are negative, and with insignificant triple interaction coefficients wherever the Table 3 coefficients are insignificant. The double interaction coefficients are also the mirror image of those in Table 3. This correspondence provides strong support for the theoretical prediction that house-price changes under WFH are inversely associated with changes in household outflows.

As for the control variables, the significantly positive education coefficients in Table 4 are the mirror image of the negative coefficients in Table 3, and the negative WRLURI coefficients are the mirror image of the positive coefficients in columns 1–4 of Table 3 (indicating smaller outflows in highly regulated counties). However, most of the other control-variable coefficients are insignificant.

5.3. Nonparametric approach

A nonparametric approach to the regressions in Tables 3 and 4 is possible. Under this approach, the high_PROD×PROD×WFHPOT and low_PROD×PROD×WFHPOT variables are replaced by the variables PROD_Quartile_i ×WFHPOT, $i = 1, 2, 3, 4$. The PROD_Quartile_i component of this interaction variable is a dummy equal to 1 if the county's PROD value lies in the i^{th} quartile and equal to zero otherwise, and it replaces the high_PROD×PROD and low_PROD×PROD components of the previous variables, doing so with a finer quartile breakdown.[31] Since WFHPOT should have no effect on the house-price change in low-PROD-quartile (non-sending) counties, the quartile interaction coefficients should be zero in these counties. But since a higher WFHPOT should lead to a larger price decline in high-PROD-quartile counties, the interaction coefficient should be negative in these counties. Looking across PROD quartiles holding WFHPOT fixed, the house-price change is then smaller in high- than in low-PROD-quartile counties, as in Proposition 4(i).[32]

The results are shown in Table 5. Column 1, which shows the house-price regression, reveals much of the anticipated pattern for the PROD quartile interactions, with the quartile_1 coefficient insignificant and the quartile_4 coefficient significantly negative (the second quartile coefficient, however, is significantly positive). In the rent regression in column 2, the quartile_1

[31] In order to create roughly equal-size cells, the PROD and QOL quartiles are based on county, not MSA counts, in contrast to the construction of the high_PROD and high_QOL dummies. In other words, to generate quartiles, PROD is listed by county from highest to lowest, recognizing that county values within a given MSA are repeated (similarly for QOL). If this county-level approach were taken in defining the high_PROD and high_QOL dummies, similar results to those Tables 3 and 4 would emerge.

[32] The logic of this approach is similar to that illustrated in Figure 1. For low PROD quartiles, the relationship between $\Delta \log \mathrm{P}$ and WFHPOT is flat, while it is downward-sloping for higher quartiles. Since the quartile dummy captures both the high-low position of PROD as well as its magnitude, the nonparametric specification captures both elements that the triple-interaction approach is designed to capture.

coefficient is insignificant while the higher-quartile coefficients are all significantly negative and ascending in absolute value. This pattern shows the anticipated insignificant rent effect in the lowest productivity counties that was missing in Table 3. The outflow regression in column 3 also shows the anticipated PROD effects, with the quartile_1 coefficient insignificant and the higher-quartile coefficients positive and ascending in value.

The interaction variables involving QOL are similarly altered under the nonparametric approach. Since an increase in WFHPOT in low-QOL-quartile (sending) counties should lead to a larger house-price decline, the interaction coefficients should be negative in lower quartiles while being zero (insignificant) for higher QOL quartiles. Looking across QOL quartiles holding WFHPOT fixed, the house-price change is then smaller (zero rather than negative) in high- than in low-PROD-quartile counties, as in Proposition 4(*ii*). As can be seen in columns 1 and 2 of Table 5, these predictions are not met, with the quartile_1 coefficient positive, not negative, and larger than the coefficients for the other quartiles (quartile 4 is omitted to prevent collinearity). Therefore, while QOL results under the triple interaction approach are consistent with the theory, the nonparametric QOL results are not. Since the main focus of the paper is on productivity effects under WFH, where the triple-interaction and nonparametric approaches agree, this outcome seems acceptable.

5.4. Further robustness checks

Table 6 presents further robustness checks for the price-change regressions in the main specification of Table 3, focusing for simplicity only on the specification containing the single PROD × WFH interaction, as in columns 3 and 7 of the table. Column 1 shows the results of a price-change regression when metro-area counties other than the county containing the area's prinicipal city are dropped, reducing the sample size by about half, to 378. As can be seen, the interaction coefficient remains significantly negative. This modification addresses a potential concern that suburban MSA counties, where jobs may be less concentrated than in the central county, are dispreferred for gauging the effects of WFH. While our results are qualitatively unaffected by the modification, the concern may misplaced in any case given job-decentralization trends in US cities.

Column 2 shows the effect of aggregating to the MSA level, which reduces the number of observations by almost three quarters, to 236. Nevertheless, the PROD $\times$ WFH coefficient remains negative and significant.

Column 3 provides a placebo test by replacing the 2019-2020 house-price change by the 2018-2019 price change. Since WFH took off only in 2020, we would expect to see no WFH effect on house-price changes between 2018 and 2019, and this expectation is confirmed by the insignificant coefficient of PROD $\times$ WFHPOT in column 3. A regression using the 2017-2018 price change also yields an insignificant interaction coefficient. Therefore, our placebo tests are successful, showing no WFH effects where they should not be present.[33]

Columns 4–6 of Table 6 show robustness checks when the rent change is the dependent variable, and the results are similar to those in columns 1–3. The interaction coefficient remains significantly negative when non-principal-city counties are excluded (column 4) and when counties are aggregated to the MSA level (column 5). The placebo test is again successful, with a regression using the 2018-2019 change in rents yielding an insignificant interaction coefficient (column 6). Table 6 thus shows that the price- and rent-change effects of the PROD$\times$WFHPOT variable are highly robust.[34] As for the controls, the sign and significance pattern of the coefficients closely matches that of Table 3.

5.5. Monthly price-level regressions

The results of estimating the monthly price-level and rent-level regressions in (11) are shown in Figure 4. The figure graphs the monthly magnitude of the PROD $\times$ WFH interaction coefficients relative to the coefficient for December 2019, which is normalized to zero. As shown, the regressions cover the period from 35 months prior to December 2019 through the end of 2020. The solid curve shows the estimated PROD $\times$ WFH coefficients, while the dotted lines show the 95% confidence bounds. As can be seen, the magnitude of a county's PROD $\times$ WFH interaction variable has no effect on the monthly level of either housing prices or rents prior to December 2019, with the confidence bands covering the horizontal axis. But after December

[33] Note, however, that the PROD$\times$WFH coefficient's confidence interval from column 4 of Table 3 covers the placebo point estimate in Table 5. Nevertheless, the first coefficient is significantly different from zero while the second is not.

[34] Additional regressions using the change in the price-to-rent ratio (a measure of future price growth) as dependent variable show no WFH effect. Thus, prices and rents appeared to decline in step under WFH, leaving their ratio unchanged.

2019, house prices and rents in counties with a large interaction value dropped significantly relative to their levels in this benchmark month, as predicted by the theory. This conclusion follows since the confidence bounds lie below the horizontal axis after the benchmark month.[35]

The results in Figure 4 reinforce the conclusions of the price- and rent-change change regressions from Table 3 at a more disaggregated level. The finding that monthly prices and rents fell following the benchmark month in counties with high productivity and high WFH potential matches the finding that average 2020 prices were lower than average 2019 prices in such counties.

5.6. Monthly price-gradient regressions

The first step in exploring the effect of WFH potential on house-price gradients is estimation of monthly price gradients at the MSA level. Zillow house-price data at the zip-code level in the sample MSAs are used rather than county-level data, so as to provide more spatial variation in prices, and the regressions include a variety of controls.[36] The resulting regressions yield a large number of price gradients across metro areas (of which there are 120) and months, and the mean value is negative (equal to -0.108), as predicted by the urban model.[37]

Table 7 shows price-gradient regressions for the New York-Newark-Bridgeport CMSA for the months of December 2019 and 2020. We find that zip-code-level home prices in the New York metro area have a strong negative association with distance to the CBD in both periods. Furthermore, the table shows a flattening of the intracity price gradient over the year between these two months, as predicted.

The second-stage regression relates the estimated gradients to the WFH potential of the

[35] Figure A1 in the online appendix, which uses bootstrapped standard errors, is very similar to Figure 4. Figure A2 in the appendix also is a bootstrapped version of Figure 5 below.

[36] The controls are zip-code-level measures of (log) distance to nearest river, distance to nearest lake, distance to nearest coastline, average annual precipitation between 1971 and 2000, minimum temperature in January, maximum temperature in July, average slope, log population density, and log average household income, all drawn from Lee and Lin (2018b). Their data are measured at the census tract level, and we use a crosswalk supplied by US Department of Housing and Urban Development (2020) to map tracts to zip codes. Note that while house size should ideally be a control in such a regression (so that it has price-per-square-foot interpretation), this variable is not available. However, inclusion of income helps offset this omission since it is generally a strong determinant of house size.

[37] Table A4 in the online appendix shows a regression that pools the data from all MSAs. Like that in Table 6, the pooled gradient also declines across the two months.

principal county of the metro area. The theory predicts that price gradients should have flattened (becoming less negative) in metro areas with high WFH potential, implying a positive coefficient for the WFHPOT variable. Note that the metro area's productivity or amenities play no role in this prediction.

Following the structure of Figure 4, the results are shown in Figure 5, which graphs the magnitude of the estimated monthly WFH coefficients over the same monthly window. The coefficients are again normalized, with the December 2019 value set at zero, and confidence bounds are again shown as dotted curves. As can be seen in the figure, WFH potential has no effect on a metro area's price gradient in the months prior to December 2019. This conclusion, which is relative to the gradient in the benchmark month, follows because the confidence bands cover the horizontal axis prior to that month. After the benchmark month, however, the WFH coefficient becomes significantly larger than its benchmark value, as predicted, with the confidence bands no longer covering the horizontal axis. Therefore, price gradients in counties with high WFH potential flattened (becoming less negative) relative to their benchmark value in the months following December 2019. This conclusion complements our evidence on the intercity effects of WFH by showing that the value of CBD access fell in metro areas with high WFH potential, leading to a smaller price premium for central locations.

5.7. Gauging the effect of WFH on population inflows

The results so far have focused on the price effects of predicted WFH-induced intercity population outflows and household relocation within MSAs, with Table 4 also showing WFH impacts on outflows themselves. Gauging the effect of population inflows is much less straightforward since inflows of remote workers into receiving counties will not depend on the WFH potentials of jobs in those counties but rather on WFHPOT values for the various origin counties. The approach we adopt, which disconnects somewhat from the theory, argues that WFH should have amplified *previous* population flows between counties. Accordingly, we use the American Community Survey matrix of migration flows over the period 2015-2019 between pairs of the 3000+ US counties (US Census Bureau, 2019), and we weight the flow F_{ji} from county j into county i by WFHPOT_j, the WFH potential of the origin county. These weighted values are then summed across j, with the result divided by county i's 2015 population, P_i.

The result is a WFHPOT-weighted ACS inflow measure for 2015-2019 (per capita), equal to $\equiv (\sum_j \text{WFHPOT}_j \text{F}_{ji})/\text{P}_i$.

The expectation is that this new variable will help explain the change in population inflows between 2019 and 2020 as measured by US Postal Service data.[38] The USPS inflow variable is USPS_inflow, and the dependent variable for the regression is the 2020-2019 difference in the logs of USPS_inflow, which equals the percentage change in the flow between those years. This variable is regressed on the log of WFHPOT-weighted ACS inflow, 2015-2019 (per capita) and several controls, including the receiving county's PROD and QOL values as well as the county's state tax rate, which should have a negative effect (see Kleven, Landais, Muñoz and Stantchevar, 2020, for evidence on taxes and migration).[39] The results are shown in Table 8. Column 1 uses the state's 2021 top marginal tax rate as the tax variable (Tax Foundation, 2021), while column 2 uses the 2018 marginal tax rate for a household with an adjusted gross income of $75,000 (Feenberg, 2018). As can be seen, the coefficient of the WFHPOT-weighted ACS inflow variable is significantly positive in both regressions, showing that when pre-WFH migration inflows came from counties with high WFH potentials, the onset of WFH raised USPS-measured inflows, confirming expectations. In addition, a higher county QOL raises migration inflows. The results in column 1 also show that, when the tax variable is the state's top marginal tax rate, a higher rate deters population inflows, as expected. However, when the marginal tax rate of a middle-income household is used instead (column 2), the tax effect is insignificant, suggesting that middle-income households may be insensitive to tax rates in their migration decisions.

We also explored tax effects in unreported outflow regressions similar to those in Table 4, finding only marginally significant tax coefficients. However, since these regressions were based on outflows from a single sending county, whereas the regressions in Table 8 capture inflows to a receiving county from *all* sending counties, tax effects are more likely to be measurable (in this case via the receiving county's state tax rate, not that of the sending county).

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[38] We prefer to create the dependent variable using a different data source than that used to create the WFHPOT-weighted ACS inflow measure.

[39] Note that, while the scaling of the WFHPOT-weighted ACS inflow measure is somewhat arbitrary, rescaling would just alter the magnitude of the coefficient with no effect on its sign or significance.

6. A new spatial hedonic equilibrium?

In the initial hedonic equilibrium, the high-productivity city in the theoretical model started out with high wages and high housing prices, while the disadvantaged, low-productivity city had low wages and prices. These differences served to equate utilities between the two cities. In the model, the onset of WFH initiated a movement to a new hedonic equilibrium, with housing prices falling in the high-productivity city as residents relocated to its low-price counterpart (raising prices there) while keeping their original jobs. By documenting price and rent decreases in high-productivity cities with high WFH potential, our empirical results appear to show the beginnings of such an equilibrium shift.[40] But with WFH being a recent phenomenon, it appears that the economy still has a long way to go before reaching the new predicted equilibrium, where wages within high-WFH-potential occupations are equalized across locations and the house-price premium in high-productivity cities wanes or disappears. Our empirical results suggest, though, that we may headed in this direction, with market signals of intercity productivity differences becoming muted or vanishing entirely, in stark contrast to predictions of models in the Rosen-Roback tradition.[41]

Another possibility is that the WFH phenomenon is just temporary, simply being a response to the COVID pandemic, and that the economy will eventually return to the pre-COVID spatial equilibrium. While some media stories take this viewpoint, others argue that WFH (including remote work from different cities) is here to stay. See, for example, Bindley (2021), who describes how Silicon Valley firms are hiring nationally with no requirement that recruits move to California. An intermediate possibility is that a potential threat of pay reductions for remote workers moving to other cities (Buhayar, 2020) will constrain such relocations in the long run. However, there seems little doubt that hybrid WFH arrangements (with workdays

[40] In reality, WFH-induced relocations are sometimes between high-amenity, high productivity cities like San Francisco and low-productivity cities that also have high amenities, such as frequently-mentioned destination cities like Boise, Idaho, or Bozeman, Montana.

[41] In a pre-WFH world with different size households, the high wages in high-productivity cities would be worth more to a two-earner household than to a single-earner household, drawing the former households more strongly to such places. But once WFH equalizes wages across workplaces, this location preference would disappear. Note, however, that a world with variation in the number of earners per household would require a new theoretical analysis. For a demonstration of how locational benefits can vary with the number of earners, see Gyourko and Tracy (1991, Table 4).

split between home and office) will be lasting for many workers, suggesting that the intracity effects of WFH documented in the price-gradient regressions will be permanent.

While the model also predicts that WFH will spur movement out of low-amenity cities toward nicer locations, our empirical results show no evidence of this kind of relocation so far. Unlike in the model, moving between cities may be difficult in the short run without a well-paid, high-productivity job, and since such jobs tend to be located in cities with favorable amenities,[42] there may be little opportunity for low-to-high-amenity relocations in the short time span of our data. However, as the passage of time reduces migration frictions, we may see evidence of migration out of low-amenity areas, provided that they have high WFH potential. Such movements, which drive up housing prices in high-amenity cities, will serve to strengthen the capitalization of amenities in the housing market, as shown in the model.[43]

While we have not empirically explored the wage impacts of WFH (see Proposition 3), it is useful to ask what such an investigation would look like. The crucial equilibrium condition in the model is wage equalization, which occurs for all workers since jobs are homogeneous. But an empirical study would recognize that equalization would obtain only for jobs that can be done remotely. The empirical implication is that, once a WFH equilibrium has been reached, wages for jobs with high WFH potential should be *independent of the place of employment* and thus independent of city characteristics. Empirically, one could test this prediction by regressing the average wage on city characteristics, including amenities and productivity, along with the WFH potential of the city's jobs as well as WFHPOT interaction terms. The prediction would be that the effects of these characteristics on wages (acting both through level and interaction terms) would become weaker as WFH potential rises, disappearing entirely if all the city's jobs can be done remotely. Another related way of testing the wage-equalization hypothesis would be to regress an intercity occupational wage-dispersion measure on the WFH potential of the occupation, with a negative coefficient expected. In other words, occupations with high WFH potential should exhibit low wage dispersion across cities. This kind of empirical work should wait, however, for the effects of the WFH to fully play out across the economy.

[42] The sample correlation between PROD and QOL is 0.35.

[43] Note that this stronger capitalization will hurt retirees who move to high-amenity locations at the end of their working life.

7. Conclusion

This paper has studied, both theoretically and empirically, the impacts of WFH in the housing market, taking both intercity and intracity perspectives. Our results confirm the theoretical prediction that WFH puts downward pressure on housing prices in high-productivity counties, a result of workers starting to relocate to cheaper metro areas during the pandemic without forsaking their desirable jobs. We also present evidence of the population flows that are predicted to drive these price changes. Our results also show that WFH tends to flatten intracity house-price gradients, weakening the price premium associated with good job access.

The WFH effects we identify have important economic incidence implications. Our empirical results suggest that WFH imposes capital losses on real estate owners in high-productivity cities, while renters in such cities tend to gain. The reverse effects are predicted to occur in low-productivity cities. While these impacts are tied by the model to intercity migration, intracity effects (due to relocation within cities and changes in price gradients) will tend to hurt owners and benefit renters in central cities, where prices fall, while having the reverse effects in the suburbs, where prices rise. Also on the intracity level, the reduction in commuting costs due to WFH may also strengthen suburban-flight responses to disamenities such as crime and high central-city taxes (Cullen and Levitt, 1999; Mieszkowski and Mills, 1983).

Possible public-sector impacts of WFH include downward pressure on the property tax revenue of local governments (via lower housing prices) in places disfavored by WFH: central cities and high-productivity metro areas. Another public-sector effect is a possible strengthening of interjurisdictional tax competition (Wilson, 1999) as migration between jurisdictions becomes easier, with remote workers mimicking the footloose star athletes studied by Kleven, Landais and Saez (2013). This same tendency can also limit the market power of local public-sector unions, who may settle for lower pay as WFH limits their ability to extract tax revenue from increasingly footloose residents (Brueckner and Neumark, 2014; Diamond, 2017). Overall, WFH will have a host of effects that researchers should continue to track as time progresses.

Table 1. County Rankings of Work-from-Home Potential

Ranking	County	MSA	WFH potential
1	New York County, NY	New York, NY	0.5147
2	Fairfax County, VA	Washington, DC	0.5118
3	District of Columbia, DC	Washington, DC	0.4942
4	San Francisco County, CA	San Francisco, CA	0.4900
5	Santa Clara County, CA	San Francisco, CA	0.4884
6	Suffolk County, MA	Boston, MA	0.4682
7	Middlesex County, MA	Boston, MA	0.4676
8	Fulton County, GA	Atlanta, GA	0.4500
9	Hennepin County, MN	Minneapolis, MN	0.4366
10	Collin County, TX	Dallas, TX	0.4224
⋮	⋮	⋮	⋮
91	Fresno County, CA	Fresno, CA	0.2900
92	El Paso County, TX	El Paso, TX	0.2864
93	Snohomish County, WA	Seattle, WA	0.2817
94	Hidalgo County, TX	McAllen, TX	0.2788
95	Lee County, FL	Fort Myers, FL	0.2781
96	San Bernardino County, CA	Los Angeles, CA	0.2774
97	Kern County, CA	Bakersfield, CA	0.2717
98	San Joaquin County, CA	Stockton, CA	0.2687
99	Clark County, NV	Las Vegas, NV	0.2679
100	Riverside County, CA	Los Angeles, CA	0.2574

Note: This table reports county rankings in terms of WFH potential for the 100 largest counties.

Table 2. Summary Statistics

	N	Mean	St. Dev.	Min	Max
Home price, 2020	792	244,233.80	147,937.30	58,736	1,427,988
Home price, 2019	792	233,481.90	143,371.20	57,392.08	1,413,393
Home price, 2018	792	224,900.30	143,268.80	55,022.42	1,396,384
Rent, 2020	269	1,631.33	465.23	713.62	4,541.56
Rent, 2019	269	1,580.39	477.56	671.00	4,553.26
Rent, 2018	269	1,527.53	468.75	637.11	4,458.52
Work-from-Home Potential (WFH)	792	0.30	0.06	0.18	0.69
Productivity (PROD)	792	−0.02	0.11	−0.26	0.29
Quality of Life (QOL)	792	−0.01	0.04	−0.10	0.18
Pct. MSA land steeper than 15 degrees	792	0.01	0.01	0.00	0.09
Wharton Residential Land-Use Regulation Index	792	−0.13	0.73	−1.76	4.31
Pct. pop. with a college education	792	0.29	0.11	0.09	0.79

Note: County-level home prices and rents are based on the Zillow Home Value Index (ZHVI) and Zillow Observed Rent Index (ZORI), respectively, for all homes and condos/co-ops. Because county-level ZORI is unavailable, we map zip-code-level ZORI to counties using a HUD crosswalk. Work-from-home potential is based on authors' calculations using 2018 County Business Patterns and the Dingel and Neiman (2020) data. Metro-level productivity, quality of life, land steepness, and Wharton Residential Land-Use Regulation Index come from Albouy (2016). College population shares come from 2014–2018 American Community Survey.

Table 3. Changes in House Prices and Rents, 2019-2020

	Dependent variable: Change in log home price or log rent, 2019–2020							
	Log home price				Log rent			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low_PROD × PROD × WFHPOT	0.178	0.156			-1.434^{***}	-1.554^{***}		
	(0.301)	(0.302)			(0.496)	(0.467)		
High_PROD × PROD × WFHPOT	-0.653^{***}	-0.713^{***}			-0.438^{**}	-0.537^{***}		
	(0.208)	(0.211)			(0.209)	(0.162)		
Low_QOL × QOL × WFHPOT	−0.878				−0.681			
	(0.702)				(0.834)			
High_QOL × QOL × WFHPOT	0.327				−0.239			
	(0.479)				(0.437)			
PROD × WFHPOT			-0.481^{***}	-0.527^{***}			-0.420^{**}	-0.512^{***}
			(0.165)	(0.164)			(0.188)	(0.142)
QOL × WFHPOT			−0.256				−0.393	
			(0.253)				(0.459)	
Pct. pop. with a college education	-0.033^{***}	-0.035^{***}	-0.030^{**}	-0.029^{**}	-0.035^{***}	-0.035^{***}	-0.039^{***}	-0.039^{***}
	(0.011)	(0.011)	(0.012)	(0.012)	(0.010)	(0.010)	(0.010)	(0.010)
Pct. MSA land steeper than 15 degrees	−0.006	−0.025	−0.042	−0.042	−0.096	−0.106	−0.054	−0.065
	(0.092)	(0.092)	(0.094)	(0.094)	(0.170)	(0.173)	(0.171)	(0.175)
Wharton Residential Land-Use Regulation Index	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}	−0.003	−0.003	−0.003	−0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Bartik IV 2019-2020	0.007	0.007	0.017	0.012	0.185^{**}	0.174^{**}	0.180^{**}	0.172^{**}
	(0.053)	(0.055)	(0.058)	(0.057)	(0.077)	(0.075)	(0.075)	(0.074)
Observations	792	792	792	792	269	269	269	269
Adjusted R^2	0.154	0.142	0.127	0.128	0.511	0.514	0.510	0.510
Sample	metro	metro	metro	metro	metro	metro	metro	metro
SE cluster	MSA	MSA	MSA	MSA	MSA	MSA	MSA	MSA

Note: Outcomes are county-level changes in log annual home prices and log rents for all homes and condos/co-ops. Home prices and rents are based on the Zillow Home Value Index and Zillow Observed Rent Index, respectively. Control variables include census division fixed effects, WFH potential, percent of population with a college education, MSA productivity, MSA quality of life, percent of MSA land steeper than 15 degrees, the Wharton Residential Land-Use Regulation Index, and the 2019-2020 Bartik instrument. The metro county sample includes all counties that are part of an MSA. Standard errors are clustered at the MSA level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 4. Change in Population Outflows, 2019-2020

	Dependent variable:			
	Change in log USPS migration outflows, 2019–2020			
	(1)	(2)	(3)	(4)
Low_PROD × PROD × WFHPOT	1.529	1.617		
	(1.139)	(1.149)		
High_PROD × PROD × WFHPOT	1.862^{***}	1.955^{***}		
	(0.483)	(0.485)		
Low_QOL × QOL × WFHPOT	−0.869			
	(1.797)			
High_QOL × QOL × WFHPOT	1.335			
	(1.463)			
PROD × WFHPOT			1.866^{***}	1.998^{***}
			(0.477)	(0.448)
QOL × WFHPOT			0.734	
			(1.064)	
Pct. pop. with a college education	0.138^{***}	0.134^{***}	0.131^{***}	0.129^{***}
	(0.025)	(0.025)	(0.026)	(0.026)
Pct. MSA land steeper than 15 degrees	−0.364	−0.371	−0.318	−0.318
	(0.274)	(0.277)	(0.268)	(0.268)
Wharton Residential Land-Use Regulation Index	-0.011^{*}	-0.011^{*}	-0.011^{*}	-0.011^{*}
	(0.006)	(0.006)	(0.006)	(0.006)
Bartik IV 2019-2020	−0.077	−0.063	−0.089	−0.073
	(0.109)	(0.108)	(0.108)	(0.106)
Observations	792	792	792	792
Adjusted R^2	0.387	0.387	0.387	0.387
Sample	metro	metro	metro	metro
SE cluster	MSA	MSA	MSA	MSA

Note: Outcomes are county-level changes in log USPS migration outflows. USPS migration outflows are estimated using county-to-county U.S. Postal Service address changes. Control variables include census division fixed effects, WFH potential, percent of population with a college education, MSA productivity, MSA quality of life, percent of MSA land steeper than 15 degrees, the Wharton Residential Land-Use Regulation Index, and the 2019-2020 Bartik instrument. The metro county sample includes all counties that are part of an MSA. Standard errors are clustered at the MSA level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 5. Quartile Regressions, 2019-2020

	Dependent variable: Change in log home price, log rent, or log USPS migration outflow, 2019–2020		
	Log home price	Log rent	Log USPS migration outflows
	(1)	(2)	(3)
PROD_Quartile_1 X WFHPOT	0.033	0.0003	0.296
	(0.049)	(0.068)	(0.204)
PROD_Quartile_2 X WFHPOT	0.100**	−0.127**	0.401***
	(0.040)	(0.054)	(0.130)
PROD_Quartile_3 X WFHPOT	0.041	−0.175***	0.467***
	(0.030)	(0.055)	(0.174)
PROD_Quartile_4 X WFHPOT	−0.069**	−0.236***	0.623***
	(0.033)	(0.043)	(0.140)
QOL_Quartile_1 X WFHPOT	0.081**	0.093*	−0.265*
	(0.035)	(0.054)	(0.153)
QOL_Quartile_2 X WFHPOT	−0.003	0.042	−0.418**
	(0.034)	(0.056)	(0.164)
QOL_Quartile_3 X WFHPOT	0.022	0.070	−0.374***
	(0.034)	(0.047)	(0.140)
PROD_Quartile_1	−0.028	−0.066***	0.083*
	(0.018)	(0.020)	(0.046)
PROD_Quartile_2	−0.046***	−0.034*	0.047
	(0.016)	(0.018)	(0.030)
PROD_Quartile_3	−0.028*	−0.016	0.041
	(0.015)	(0.015)	(0.042)
QOL_Quartile_1	−0.018*	−0.021	0.063
	(0.011)	(0.019)	(0.047)
QOL_Quartile_2	0.008	0.001	0.117**
	(0.011)	(0.020)	(0.050)
QOL_Quartile_3	0.002	−0.016	0.106**
	(0.011)	(0.016)	(0.042)
Pct. pop. with a college education	−0.032***	−0.038***	0.161***
	(0.011)	(0.010)	(0.026)
Pct. MSA land steeper than 15 degrees	−0.054	−0.227	−0.418
	(0.088)	(0.182)	(0.286)
Wharton Residential Land-Use Regulation Index	0.006***	−0.003	−0.008
	(0.002)	(0.003)	(0.006)
Bartik IV 2019-2020	0.009	0.172**	−0.142
	(0.055)	(0.082)	(0.112)
Observations	792	269	792
Adjusted R^2	0.151	0.495	0.365
Sample	metro	metro	metro
SE cluster	MSA	MSA	MSA

Note: Outcomes are county-level changes in log annual home prices and log rents for all homes and condos/co-ops and county-level changes in log USPS migration outflows. Home prices and rents are based on the Zillow Home Value Index and Zillow Observed Rent Index, respectively. USPS migration outflows are estimated using county-to-county U.S. Postal Service address changes. Control variables include census division fixed effects, percent of population with a college education, percent of MSA land steeper than 15 degrees, the Wharton Residential Land-Use Regulation Index, and the 2019-2020 Bartik instrument. The metro county sample includes all counties that are part of an MSA. Standard errors are clustered at the MSA level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 6. Robustness Checks

	Change in log home price			*Change in log rent*		
	2019–2020		2018–2019	2019–2020		2018–2019
	(1)	(2)	(3)	(4)	(5)	(6)
PROD × WFHPOT	−0.500**	−0.642**	−0.284	−0.535**	−0.659***	0.067
	(0.198)	(0.289)	(0.180)	(0.238)	(0.241)	(0.119)
Pct. pop. with a college education	−0.050***	−0.045**	−0.049***	−0.037**	−0.033	−0.046***
	(0.017)	(0.022)	(0.013)	(0.015)	(0.042)	(0.010)
Pct. MSA land steeper than 15 degrees	−0.062	0.062	0.180*	−0.152	0.094	−0.097
	(0.115)	(0.095)	(0.099)	(0.137)	(0.106)	(0.154)
Wharton Residential Land-Use Regulation Index	0.006**	0.006*	0.003	−0.003	0.004	−0.002
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Bartik IV 2019-2020	0.157	0.149		0.275***	0.186	
	(0.096)	(0.107)		(0.072)	(0.128)	
Bartik IV 2018-2019			−0.212			−0.239
			(0.241)			(0.309)
Observations	378	236	792	165	83	269
Adjusted R^2	0.140	0.055	0.230	0.491	0.324	0.247
Sample	principal-city	MSA	metro	principal-city	MSA	metro
SE cluster	MSA	State	MSA	MSA	State	MSA

Note: Outcomes are county- or MSA-level changes in log annual home prices and log rents for all homes and condos/co-ops. Home prices and rents are based on the Zillow Home Value Index and Zillow Observed Rent Index, respectively. Control variables include WFH potential, percent of population with a college education, MSA productivity, MSA quality of life, percent of MSA land steeper than 15 degrees, and the Wharton Residential Land-Use Regulation Index, and Bartik instruments. Except for the regressions using the MSA sample (Columns 2 and 5), all regression include census division fixed effects. The metro county sample includes all counties that are part of an MSA. The principal-city county sample includes all counties that contain a principal city of an MSA. The MSA sample includes 236 MSAs with non-missing covariates. Standard errors are clustered at the MSA level, except for Columns 2 and 5, which are clustered at the state level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 7. Intracity Zip-Code Home Price Gradients, New York-Newark-Bridgeport, NY-NJ-CT-PA

	Dependent variable: Log home price	
	12/2019	12/2020
	(1)	(2)
Log dist. to CBD	-0.269^{***}	-0.242^{***}
	(0.020)	(0.019)
Log dist. to nearest river	0.050^{***}	0.047^{***}
	(0.012)	(0.012)
Log dist. to nearest lake	-0.033^{***}	-0.033^{***}
	(0.012)	(0.012)
Log dist. to nearest coastline	-0.045^{***}	-0.052^{***}
	(0.010)	(0.009)
Avg. annual precipitation 1971–2000	0.0001	0.0002
	(0.0002)	(0.0002)
Max temperature in July	-0.127^{***}	-0.123^{***}
	(0.014)	(0.014)
Minimum temperature in January	0.099^{***}	0.095^{***}
	(0.012)	(0.012)
Average slope	0.002	-0.001
	(0.003)	(0.003)
Log population density	-0.051^{***}	-0.056^{***}
	(0.012)	(0.012)
Log avg. hhld. income	0.854^{***}	0.814^{***}
	(0.035)	(0.035)
Observations	1,076	1,076
Adjusted R^2	0.673	0.657

Note: The estimation equation is $\log P_{zt} = \alpha_m + \beta_t \log DistCBD_z + \gamma_t X_z + \varepsilon_{zt}$, where P_{zt} is the home price index of zip-code z, α_m are metro area fixed effects, $DistCBD_z$ is distance from zip-code z to the central business district, and X_z are zip-code covariates. Home price indices are based on the the zip-code-level Zillow Home Value Index for all homes and condos/co-ops. Zip-code covariates are based on census tract-level data from Lee and Lin (2018), which we map to zip-codes using a HUD crosswalk.

Table 8: Change in Population Inflows, 2019-2020

	Dependent variable: Change in log USPS migration inflows, 2019–2020	
	(1)	(2)
Log WFHPOT-weighted ACS migration inflows, 2015-2019 (per capita)	0.016^{**}	0.019^{**}
	(0.008)	(0.008)
PROD	-0.007	-0.016
	(0.036)	(0.033)
QOL	0.303^{***}	0.268^{***}
	(0.076)	(0.076)
State's top income tax rate	-0.220^{**}	
	(0.110)	
State's income tax rate, single filer with $75,000 AGI		-0.271
		(0.183)
Observations	792	792
Adjusted R^2	0.078	0.072
Sample	metro	metro
SE cluster	MSA	MSA

Note: Outcomes are county-level changes in log USPS migration inflows. USPS migration inflows are estimated using county-to-county U.S. Postal Service address changes. The main regressor is log county-level WFH potential-weighted ACS inflows per capita. The WFH potential-weighted ACS inflows for destination county i is defined as $\sum_j WFHPOT_j \cdot F_{ji}$, where $WFHPOT_j$ is the WFH potential of origin county j and F_{ji} is the 2015-2019 American Community Survey migration flow from origin county j to destination county i. To express the WFH potential-weighted migration inflows in per-capita terms, we adjust the variable by 2018 destination county population. Control variables include MSA productivity, MSA quality of life, and state-level income tax rates, either as measured by states' tax rate for the top income bracket or states' tax rate for single filers with $75,000 adjusted gross income. State-level top income tax rates come from the the Tax Foundation, and state-level tax rates based on adjusted gross income come from the National Bureau of Economic Research. The metro county sample includes all counties that are part of an MSA. Standard errors are clustered at the MSA level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

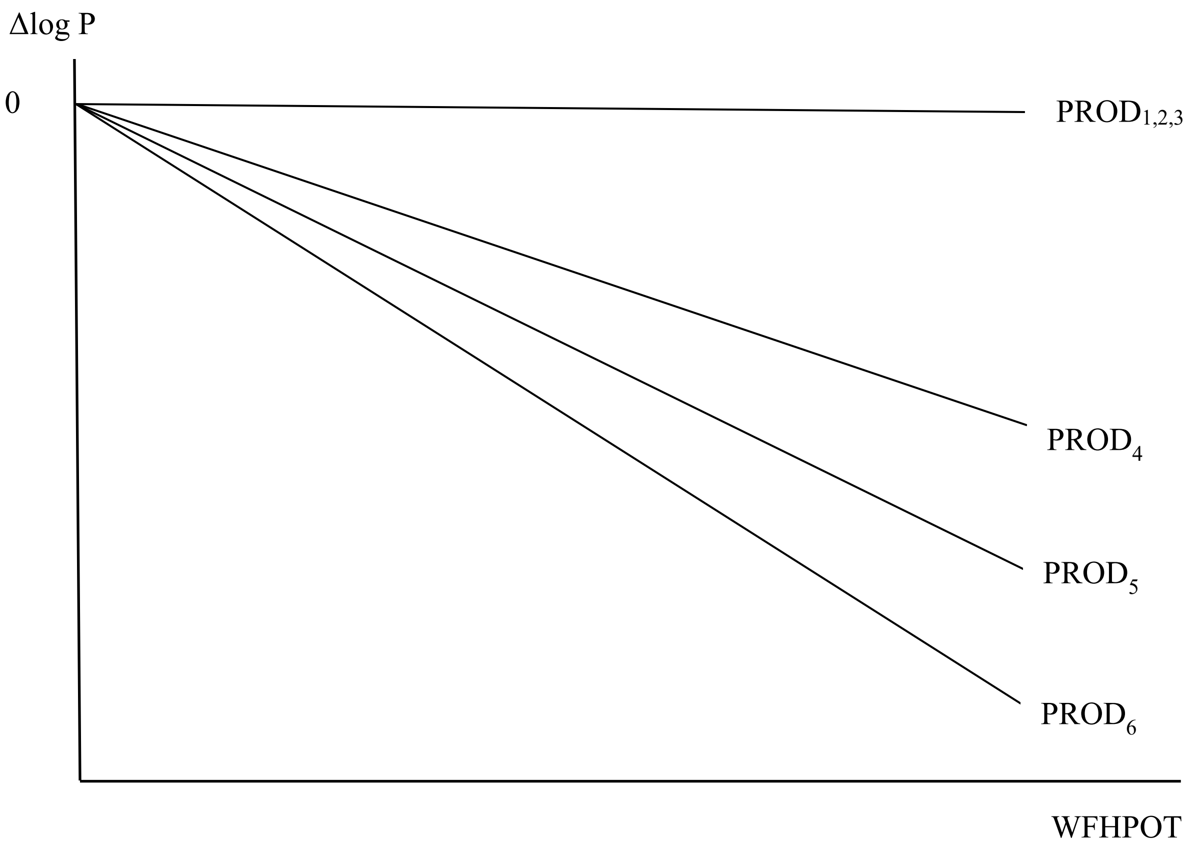


Figure 1: The need for a triple-interaction specification

This figure shows the relation between Δlog P and WFHPOT for different values of PROD. When PROD takes a low value ($PROD_1$, $PROD_2$, or $PROD_3$), housing prices are low and workers have no incentive to move to another city. As a result, prices are unaffected by the level of WFHPOT, as shown by the horizontal line. When PROD takes a higher value ($PROD_4 < PROD_5 < PROD_6$), an incentive to move exists, and the magnitude of the price decline is larger the higher is WFHPOT (since more workers can then move). While the curves relating to Δlog P to WFHPOT are therefore downward sloping for these PROD values, a higher PROD value also yields a lower curve by Proposition 4(*i*). The regression specification should therefore allow the relationship between Δlog P and WFHPOT to be flat for low levels of PROD while allowing it to be decreasing for high levels and for the slope to depend on the magnitude of PROD. The triple interaction specification achieves these goals.

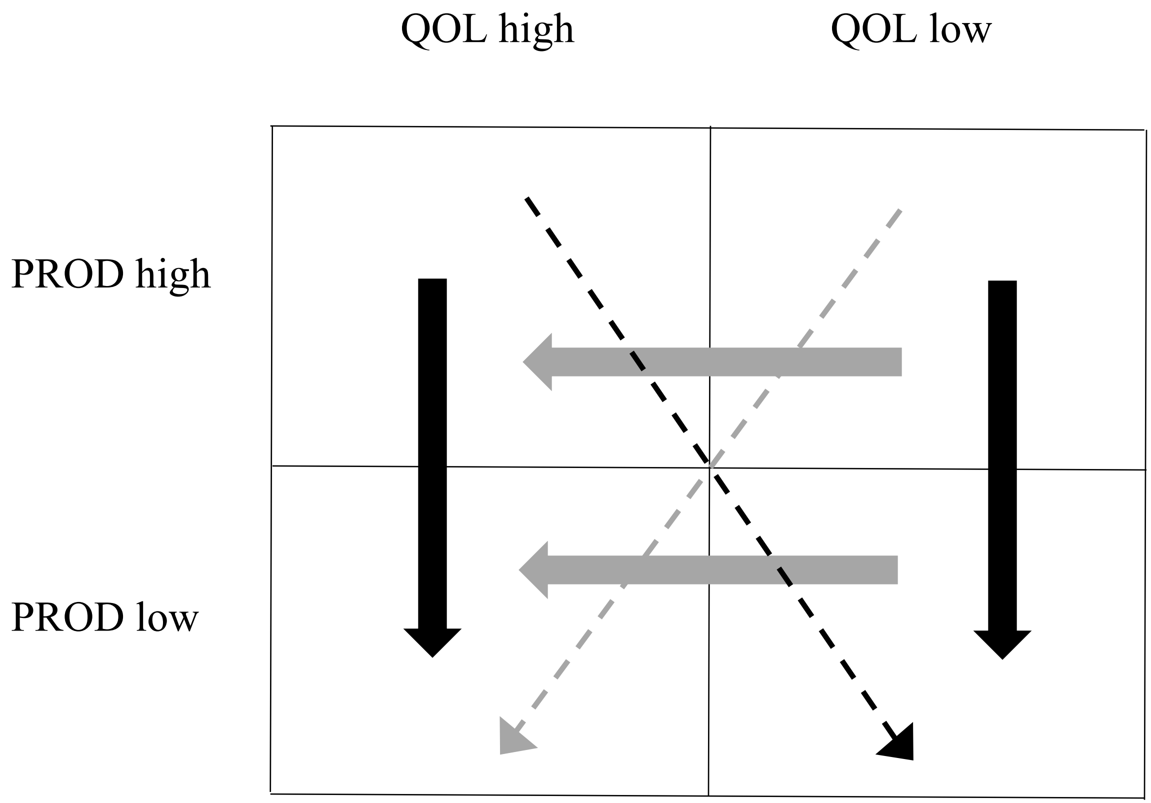
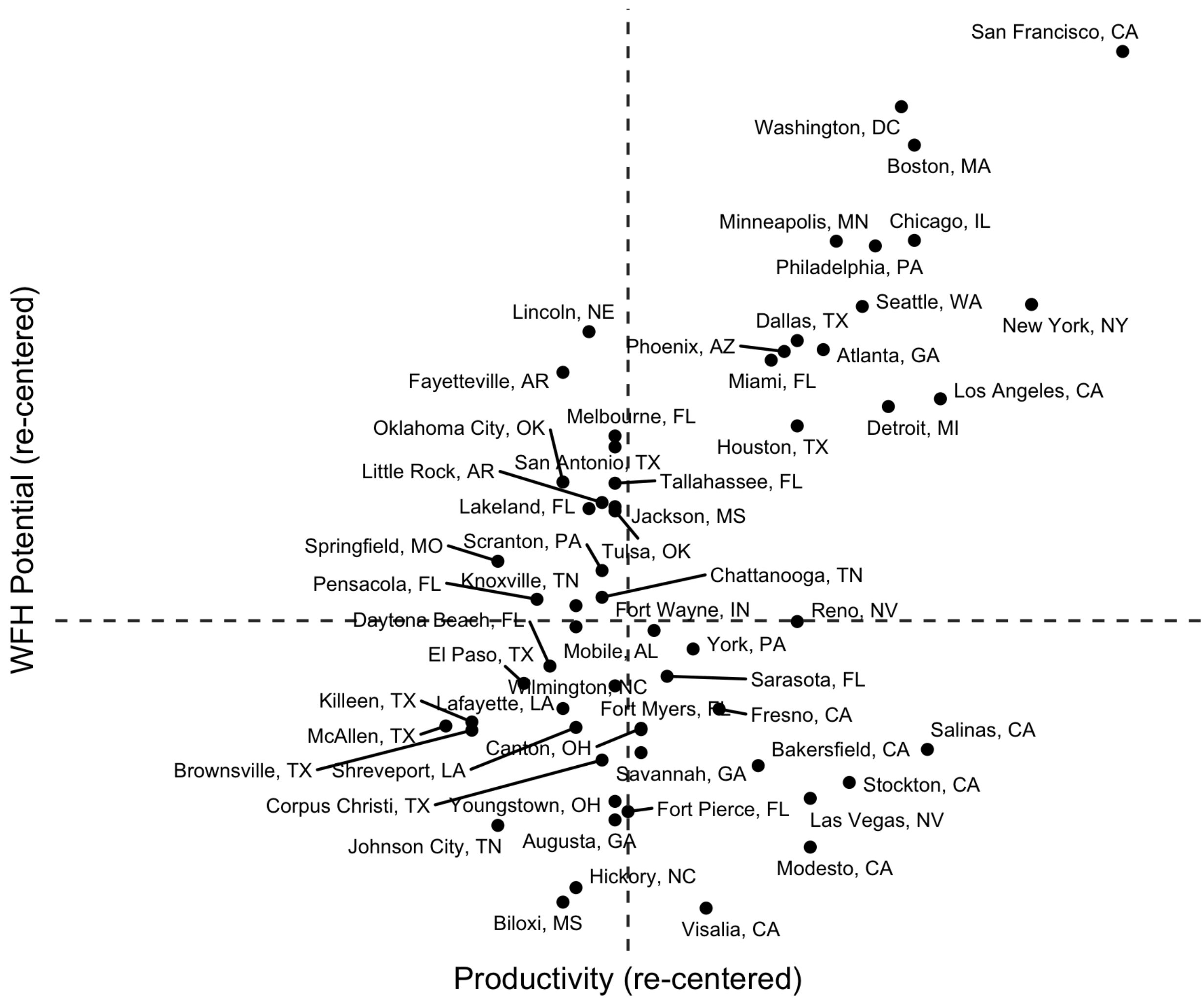


Figure 2: Population flows under WFH

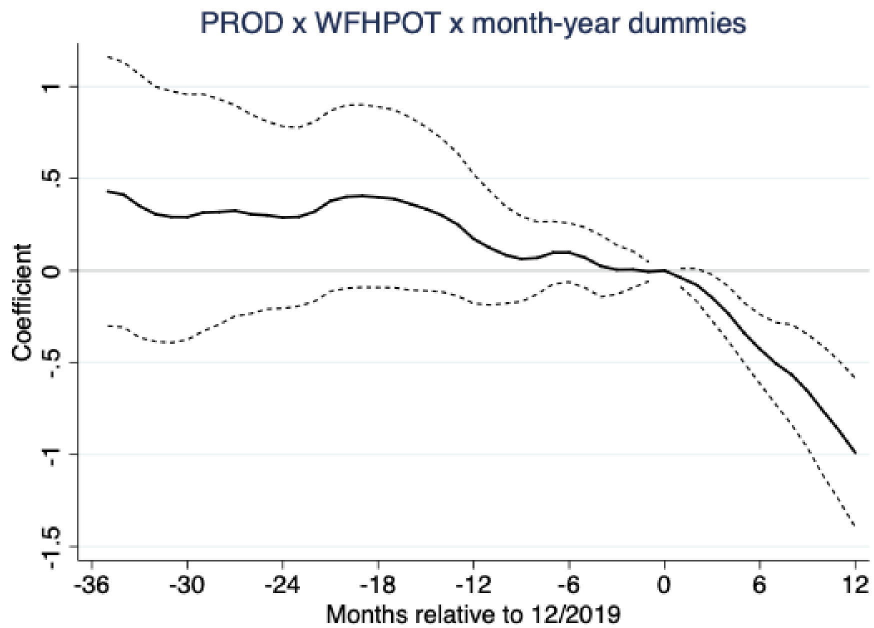
This figure provides a schematic representation of the population flows predicted by the model. The black vertical arrows show that, when QOL is identical across cities (either high or low), WFH causes a population flow from high-productivity to low-productivity cities. The grey horizontal arrows show that, when PROD is identical across cities (either high or low), WFH causes a population flow from low-QOL to high-QOL cities. However, actual population flows may look like those indicated by the thin dotted arrows, with population moving from a low-QOL/high-PROD city to a high-QOL/low-PROD city (grey arrow) or from a high-QOL/high-PROD city to a low-QOL/low-PROD city (black arrow).

Figure 3. Relationship Between WFH Potential and Productivity, MSA

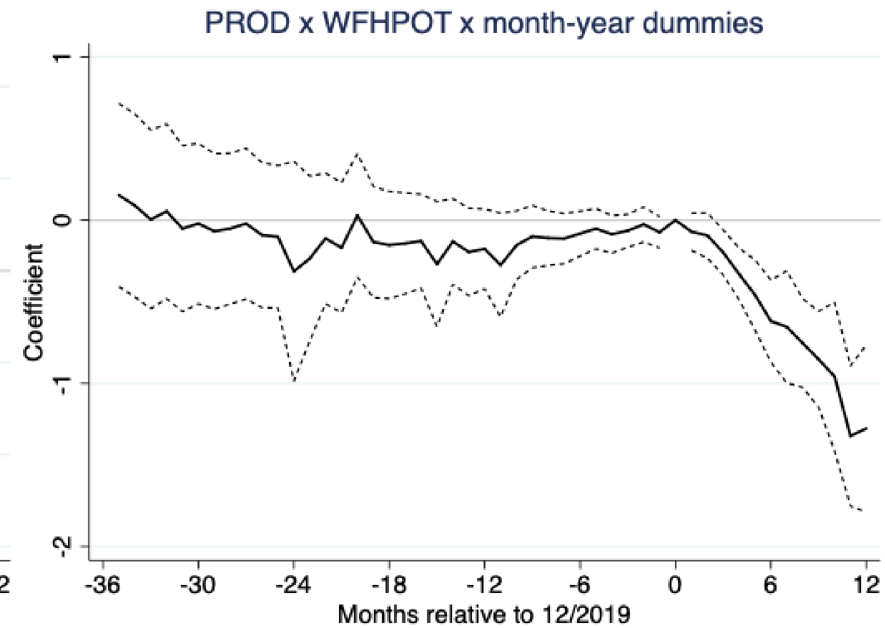


Note: Figure plots the relationship between WFH potential and local productivity for the 15 most populous MSAs (based on 2019 population) in each quadrant.

Figure 4. Home Price and Rental Rate Dynamics, 2017–2020



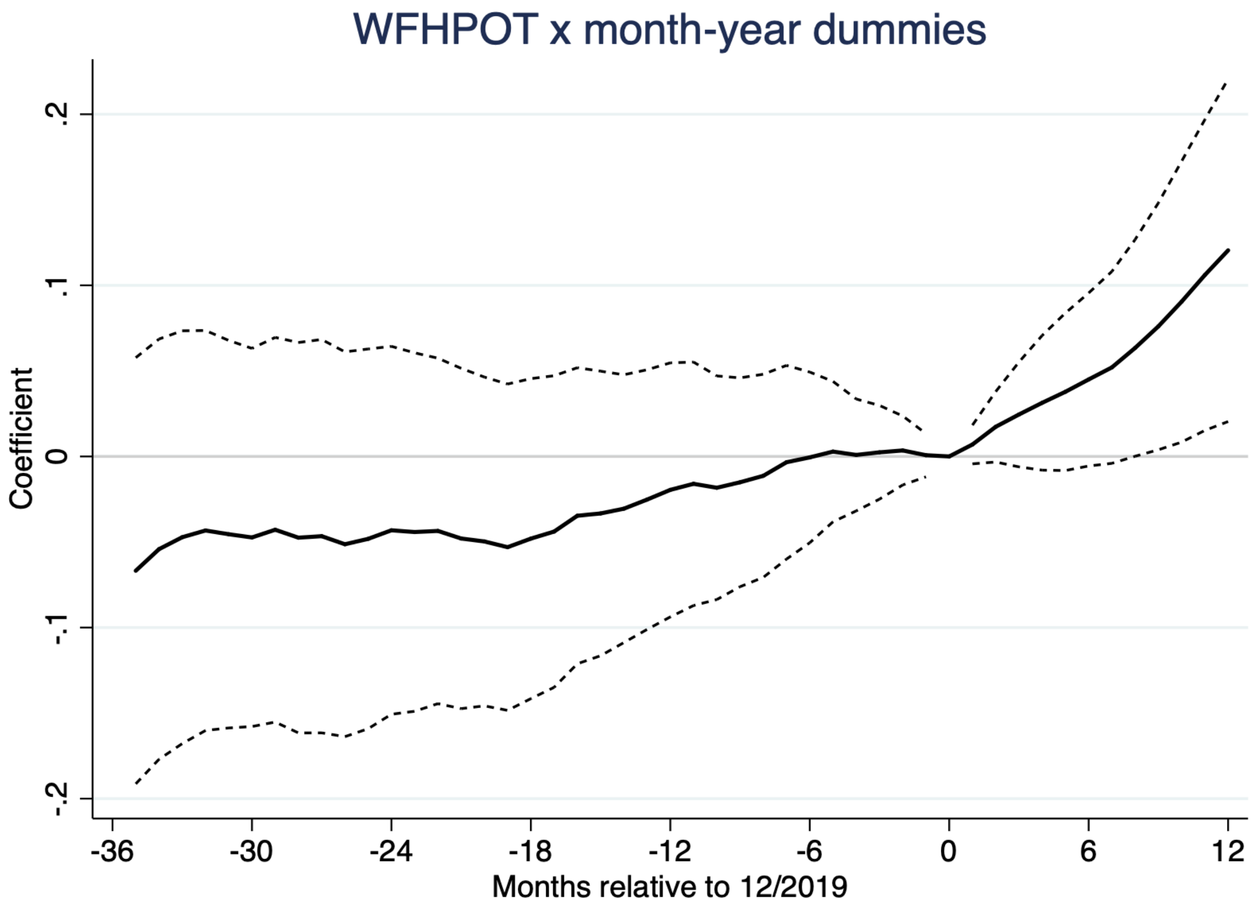
(a) Price



(b) Rent

Note: Figure plots the coefficients and 95 confidence intervals of the event study estimates. Outcomes are the Zillow Home Value Indices and Zillow Observed Rent Indices for all homes and condos/co-ops between January 2017 and December 2020. Control variables include county fixed effects, census division-month-year fixed effects, and the interactions between month-year dummies with a set of county covariates, including WFH potential, percent of population with a college education, MSA productivity, MSA quality of life, percent of MSA land steeper than 15 degrees, and the Wharton Residential Land-Use Regulation Index. Standard errors are clustered at the MSA level.

Figure 5. Intracity Home Price Gradients, 2017–2020



Note: Figure plots the coefficients and 95 confidence intervals of the event study estimates. Outcomes are intracity home price gradients based authors' calculations. In the first stage, we estimate the intracity home price gradient of each MSA with at least 30 zip-codes by separately regressing log zip-code-level Zillow Home Value Index on log distance to the central business district, a set of exogenous amenities (log distances to nearest lake, river, and coastline; the average annual precipitation 1971–2000, January minimum temperature, and July maximum temperature), average slope, and a set of proxies for endogenous amenities (log population density and log average household income). In the second stage, we estimate an event study equation by regressing the estimated intracity home price gradients on the interactions of month-year dummies and principal-city counties' WFH potential, controlling for MSA fixed effects and month-year fixed effects. Standard errors are clustered at the MSA level.

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Online Appendix

A New Spatial Hedonic Equilibrium in the Emerging Work-from-Home Economy?

Jan K. Brueckner, Matthew E. Kahn and Gary C. Lin

A1. Employment comparisons and proof of Proposition 3

Employment relationships $\widetilde{L}_s < N_s^*$ and $\widetilde{L}_d > N_d^*$ stated prior to Proposition 2 follow because $N_s^* > \overline{N} = \widetilde{L}_s$ and $N_d^* < \overline{N} = \widetilde{L}_d$. It then follows that $w(N_s^*, \overline{\alpha}) < w(\widetilde{L}_s, \overline{\alpha})$, with $w(N_d^*, \overline{\alpha}) > w(\widetilde{L}_d, \overline{\alpha})$ holding for city d, establishing Proposition 3 (ii). Therefore, the original residents of city s (city d) earn a higher (lower) wage under WFH.

When the only advantage of city s is higher productivity, the previous results yield $N_s^* > \widetilde{N}_s < \widetilde{L}_s$, which appears to imply that $w(N_s^*, \alpha_s)$ could be larger or smaller than $w(\widetilde{L}_s, \alpha_s)$, and similarly for $w(N_d^*, \alpha_d)$ and $w(\widetilde{L}_d, \alpha_d)$. However, further analysis dispels this ambiguity, as follows.

The first step is to note that the inequalities $N_s^* > \widetilde{L}_s$ and $N_d^* > \widetilde{L}_d$ cannot both hold nor can the reverse of these two inequalities both hold. Either set of inequalities violates the requirements that the city populations before WFH or the employment levels under WFH individually sum to $2\overline{N}$. Therefore, the inequalities

$$N_s^* \ < \ \widetilde{L}_s, \ N_d^* \ > \ \widetilde{L}_d \qquad or \qquad N_s^* \ > \ \widetilde{L}_s, \ N_d^* \ < \ \widetilde{L}_d \tag{$a1$}$$

must be satisfied. The second set of inequalities implies

$$w(N_s^*, \alpha_s) \ < \ w(\widetilde{L}_s, \alpha_s), \quad w(N_d^*, \alpha_d) \ > \ w(\widetilde{L}_d, \alpha_d). \tag{$a2$}$$

Since $w(N_s^*, \alpha_s) > w(N_d^*, \alpha_d)$ holds when city s has only a productivity advantage, the inequalities in ($a2$) can be combined to yield

$$w(\widetilde{L}_s, \alpha_s) \ > \ w(N_s^*, \alpha_s) \ > \ w(N_d^*, \alpha_d) \ > \ w(\widetilde{L}_d, \alpha_d), \tag{$a3$}$$

which violates the condition of wage equality under WFH ($w(\widetilde{L}_s, \alpha_s) = w(\widetilde{L}_d, \alpha_d)$). Therefore, the first set of inequalities in ($a1$) must hold, establishing the claim made prior to Proposition

1, and they imply

$$w(N_s^*, \alpha_s) \ > \ w(\widetilde{L}_s, \alpha_s), \quad w(N_d^*, \alpha_d) \ < \ w(\widetilde{L}_d, \alpha_d), \tag{a2}$$

establishing Proposition 3 (i).

A2. Proof of Proposition 4

Focusing first on the differential-productivity case, after substitution of $N_d^* = 2\overline{N} - N_s^*$ and $A_s = A_d$ in (2), differentiation yields $\partial N_s^*/\partial \alpha_s > 0$, showing that higher productivity in city s raises its population in the absence of WFH. Since the population of city s in the WFH equilibrium ($\widetilde{N}_s$) is independent of α_s, being equal to $\overline{N}$, it follows that the change in the population of city s with the introduction of WFH, equal to $\widetilde{N}_s - N_s^*$ is smaller the larger is α_s. Thus, WFH yields a larger population decline in city s the higher its productivity. This larger population drop in turn implies that the WFH-induced housing-price decline in city s is larger the higher its productivity.

Turning to the differential-amenity case, after substituting $\alpha_s = \alpha_d = \overline{\alpha}$ and $N_s^* = 2\overline{N} - N_d^*$ in (2), differentiation yields $\partial N_d^*/\partial A_d > 0$, so that a higher amenity level in city d raises its population in the absence of WFH. However, in constrast to the differential-productivity case, the population of city d is still affected by A_d under WFH, with $\partial \widetilde{N}_d/\partial A_d > 0$. Although both amenity derivatives are positive, the derivative under WFH tends to be larger, so that $\partial(\widetilde{N}_d - N_d^*)/\partial A_d > 0$.[44] Thus, WFH yields a smaller population decline in city d the higher its amenity level. This smaller population decline in turn implies that the WFH-induced housing-price decline in city d is smaller the higher its amenity level.

[44] Differentiating (2) yields $\partial N_d^*/\partial A_d = -1/(w_s' + H_s' + w_d' + H_d' > 0$, where the subscripts denote evaluation of the function in city s or city d and the prime on the wage functions denotes the population derivative. Differentiation of (3) yields $\partial \widetilde{N}_d/\partial A_d = -1/(\widetilde{H}_s' + \widetilde{H}_d') > 0$, where the tildes on the H functions denote evaluation at the WFH equilibrium. The wage terms tend to make first denominator larger in absolute value than the second, making the amenity's effect on N_d^* smaller than its effect on $\widetilde{N}_d$. However, the fact that the H' functions in the two expressions are evaluated at different equilibria means that this conclusion is likely but not guaranteed to hold (the likelihood grows if H'' is small in absolute value).

Table A1. Changes in House Prices and Rents, 2019-2020

	Dependent variable: Change in log home price or log rent, 2019–2020							
	Log home price				Log rent			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low PROD × PROD × WFHPOT	0.178	0.156			-1.434^{***}	-1.554^{***}		
	(0.301)	(0.302)			(0.496)	(0.467)		
High PROD × PROD × WFHPOT	-0.653^{***}	-0.713^{***}			-0.438^{**}	-0.537^{***}		
	(0.208)	(0.211)			(0.209)	(0.162)		
Low QOL × QOL × WFHPOT	−0.878				−0.681			
	(0.702)				(0.834)			
High QOL × QOL × WFHPOT	0.327				−0.239			
	(0.479)				(0.437)			
PROD × WFHPOT			-0.481^{***}	-0.527^{***}			-0.420^{**}	-0.512^{***}
			(0.165)	(0.164)			(0.188)	(0.142)
QOL × WFHPOT			−0.256				−0.393	
			(0.253)				(0.459)	
High PROD × PROD	0.201^{*}	0.209^{*}			−0.230	−0.235		
	(0.110)	(0.114)			(0.163)	(0.159)		
High QOL × QOL	-0.561^{*}				−0.208			
	(0.302)				(0.383)			
PROD	−0.036	−0.030	0.128^{**}	0.141^{**}	0.365^{**}	0.399^{***}	0.118^{*}	0.145^{***}
	(0.086)	(0.087)	(0.057)	(0.056)	(0.153)	(0.141)	(0.067)	(0.052)
QOL	0.318	−0.034	0.033	−0.046	0.108	-0.152^{***}	−0.012	-0.144^{***}
	(0.207)	(0.031)	(0.095)	(0.030)	(0.342)	(0.044)	(0.183)	(0.045)
WFHPOT	0.045	0.070^{***}	0.040	0.041^{*}	-0.127^{***}	-0.114^{***}	-0.116^{***}	-0.110^{***}
	(0.028)	(0.021)	(0.025)	(0.024)	(0.026)	(0.023)	(0.023)	(0.022)
Pct. pop. with a college education	-0.033^{***}	-0.035^{***}	-0.030^{**}	-0.029^{**}	-0.035^{***}	-0.035^{***}	-0.039^{***}	-0.039^{***}
	(0.011)	(0.011)	(0.012)	(0.012)	(0.010)	(0.010)	(0.010)	(0.010)
Pct. MSA land steeper than 15 degrees	−0.006	−0.025	−0.042	−0.042	−0.096	−0.106	−0.054	−0.065
	(0.092)	(0.092)	(0.094)	(0.094)	(0.170)	(0.173)	(0.171)	(0.175)
Wharton Residential Land-Use Regulation Index	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}	−0.003	−0.003	−0.003	−0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Bartik IV 2019-2020	0.007	0.007	0.017	0.012	0.185^{**}	0.174^{**}	0.180^{**}	0.172^{**}
	(0.053)	(0.055)	(0.058)	(0.057)	(0.077)	(0.075)	(0.075)	(0.074)
Observations	792	792	792	792	269	269	269	269
Adjusted R^2	0.154	0.142	0.127	0.128	0.511	0.514	0.510	0.510
Sample	metro	metro	metro	metro	metro	metro	metro	metro
SE cluster	MSA	MSA	MSA	MSA	MSA	MSA	MSA	MSA

Note: Outcomes are county-level changes in log annual home prices and log rents for all homes and condos/co-ops. Home prices and rents are based on the Zillow Home Value Index and Zillow Observed Rent Index, respectively. Control variables include census division fixed effects, WFH potential, percent of population with a college education, MSA productivity, MSA quality of life, percent of MSA land steeper than 15 degrees, the Wharton Residential Land-Use Regulation Index, and the 2019-2020 Bartik instrument. The metro county sample includes all counties that are part of an MSA. Standard errors are clustered at the MSA level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A2. Change in Population Outflows, 2019-2020

	Dependent variable: *Change in log USPS outflows, 2019–2020*			
	(1)	(2)	(3)	(4)
Low PROD × PROD × WFHPOT	1.529	1.617		
	(1.139)	(1.149)		
High PROD × PROD × WFHPOT	1.862***	1.955***		
	(0.483)	(0.485)		
Low QOL × QOL × WFHPOT	−0.869			
	(1.797)			
High QOL × QOL × WFHPOT	1.335			
	(1.463)			
PROD × WFHPOT			1.866***	1.998***
			(0.477)	(0.448)
QOL × WFHPOT			0.734	
			(1.064)	
High PROD × PROD	−0.023	−0.028		
	(0.370)	(0.368)		
High QOL × QOL	−0.640	0.052		
	(0.733)	(0.208)		
PROD	−0.390	−0.414	−0.448***	−0.485***
	(0.326)	(0.328)	(0.140)	(0.131)
QOL	0.141**	0.182***	0.198***	0.197***
	(0.067)	(0.049)	(0.060)	(0.059)
WFHPOT	0.138***	0.134***	0.131***	0.129***
	(0.025)	(0.025)	(0.026)	(0.026)
Pct. pop. with a college education	−0.364	−0.371	−0.318	−0.318
	(0.274)	(0.277)	(0.268)	(0.268)
Pct. MSA land steeper than 15 degrees	−0.011*	−0.011*	−0.011*	−0.011*
	(0.006)	(0.006)	(0.006)	(0.006)
Wharton Residential Land-Use Regulation Index	−0.077	−0.063	−0.089	−0.073
	(0.109)	(0.108)	(0.108)	(0.106)
Observations	792	792	792	792
Adjusted R^2	0.387	0.387	0.387	0.387
Sample	metro	metro	metro	metro
SE cluster	MSA	MSA	MSA	MSA

Note: Outcomes are county-level changes in log USPS migration outflows. USPS population outflows are estimated using county-to-county U.S. Postal Service address changes. Control variables include census division fixed effects, WFH potential, percent of population with a college education, MSA productivity, MSA quality of life, percent of MSA land steeper than 15 degrees, the Wharton Residential Land-Use Regulation Index, and the 2019-2020 Bartik instrument. The metro county sample includes all counties that are part of an MSA. Standard errors are clustered at the MSA level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A3. Robustness Checks

	Change in log home price			*Change in log rent*		
	2019–2020		2018–2019	2019–2020		2018–2019
	(1)	(2)	(3)	(4)	(5)	(6)
PROD × WFHPOT	−0.500**	−0.642**	−0.284	−0.535**	−0.659***	0.067
	(0.198)	(0.289)	(0.180)	(0.238)	(0.241)	(0.119)
PROD	0.129*	0.186*	0.086	0.138*	0.163*	−0.023
	(0.072)	(0.097)	(0.059)	(0.082)	(0.083)	(0.048)
QOL	0.049	0.047	−0.021	−0.096***	−0.177*	0.007
	(0.032)	(0.045)	(0.022)	(0.030)	(0.097)	(0.018)
WFHPOT	−0.050***	−0.045**	−0.049***	−0.037**	−0.033	−0.046***
	(0.017)	(0.022)	(0.013)	(0.015)	(0.042)	(0.010)
Pct. pop. with a college education	−0.062	0.062	0.180*	−0.152	0.094	−0.097
	(0.115)	(0.095)	(0.099)	(0.137)	(0.106)	(0.154)
Pct. MSA land steeper than 15 degrees	0.006**	0.006*	0.003	−0.003	0.004	−0.002
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Wharton Residential Land-Use Regulation Index	0.157	0.149		0.275***	0.186	
	(0.096)	(0.107)		(0.072)	(0.128)	
Bartik IV 2019-2020			−0.212			−0.239
			(0.241)			(0.309)
Observations	378	236	792	165	83	269
Adjusted R^2	0.140	0.055	0.230	0.491	0.324	0.247
Sample	principal-city	MSA	metro	principal-city	MSA	metro
SE cluster	MSA	State	MSA	MSA	State	MSA

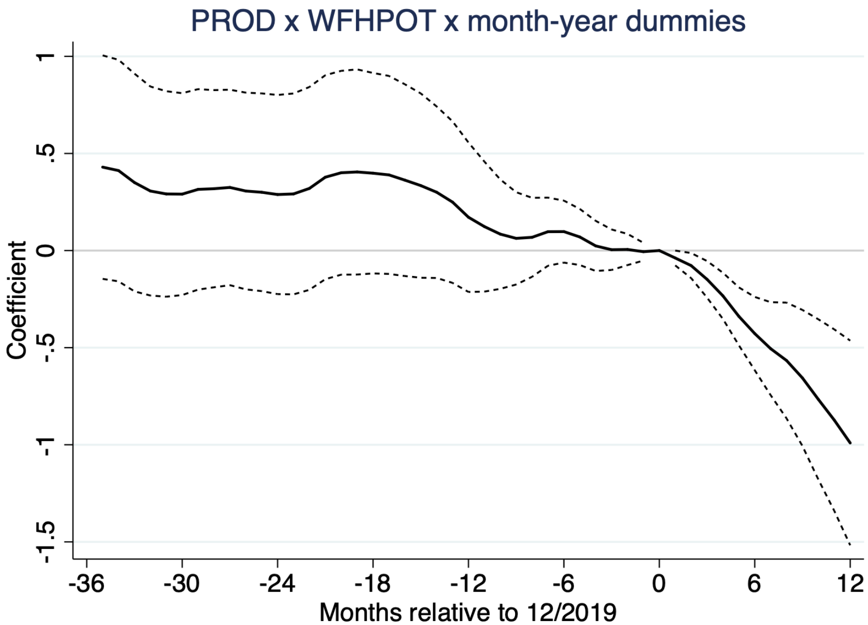
Note: Outcomes are county- or MSA-level changes in log annual home prices and log rents for all homes and condos/co-ops. Home prices and rents are based on the Zillow Home Value Index and Zillow Observed Rent Index, respectively. Control variables include WFH potential, percent of population with a college education, MSA productivity, MSA quality of life, percent of MSA land steeper than 15 degrees, and the Wharton Residential Land-Use Regulation Index, and Bartik instruments. Except for the regressions using the MSA sample (Columns 2 and 5), all regression include census division fixed effects. The metro county sample includes all counties that are part of an MSA. The principal-city county sample includes all counties that contain a principal city of an MSA. The MSA sample includes 236 MSAs with non-missing covariates. Standard errors are clustered at the MSA level, except for Columns 2 and 5, which are clustered at the state level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A4. Intracity Zip-Code Home Price Gradients, All Metro Areas

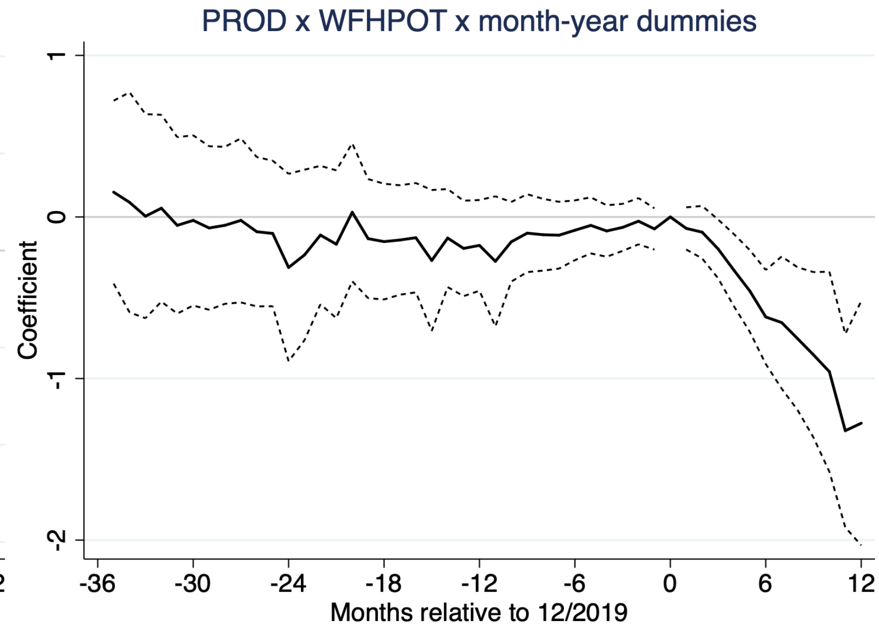
	Dependent variable: Log home price	
	12/2019	12/2020
	(1)	(2)
Log dist. to CBD	-0.090^{***}	-0.087^{***}
	(0.021)	(0.020)
Log dist. to nearest river	0.014	0.014
	(0.017)	(0.016)
Log dist. to nearest lake	-0.010	-0.012
	(0.010)	(0.010)
Log dist. to nearest coastline	-0.018	-0.018
	(0.014)	(0.014)
Avg. annual precipitation 1971–2000	-0.0001	-0.00003
	(0.0001)	(0.0001)
Max temperature in July	-0.035^{***}	-0.033^{***}
	(0.006)	(0.006)
Minimum temperature in January	0.040^{**}	0.036^{**}
	(0.016)	(0.015)
Average slope	0.00005	-0.001
	(0.003)	(0.003)
Log population density	0.008	0.014
	(0.010)	(0.009)
Log avg. hhld. income	1.127^{***}	1.108^{***}
	(0.043)	(0.042)
Observations	12,792	12,792
Adjusted R^2	0.823	0.830

Note: The estimation equation is $\log P_{zt} = \alpha_m + \beta_t \log DistCBD_z + \gamma_t X_z + \varepsilon_{zt}$, where P_{zt} is the home price index of zip-code z, α_m are metro area fixed effects, $DistCBD_z$ is distance from zip-code z to the central business district, and X_z are zip-code covariates. Home price indices are based on the the zip-code-level Zillow Home Value Index for all homes and condos/co-ops. Zip-code covariates are based on census tract-level data from Lee and Lin (2018), which we map to zip-codes using a HUD crosswalk.

Figure A1. Home Price and Rental Rate Dynamics, Bootstrapped Standard Errors, 2017–2020



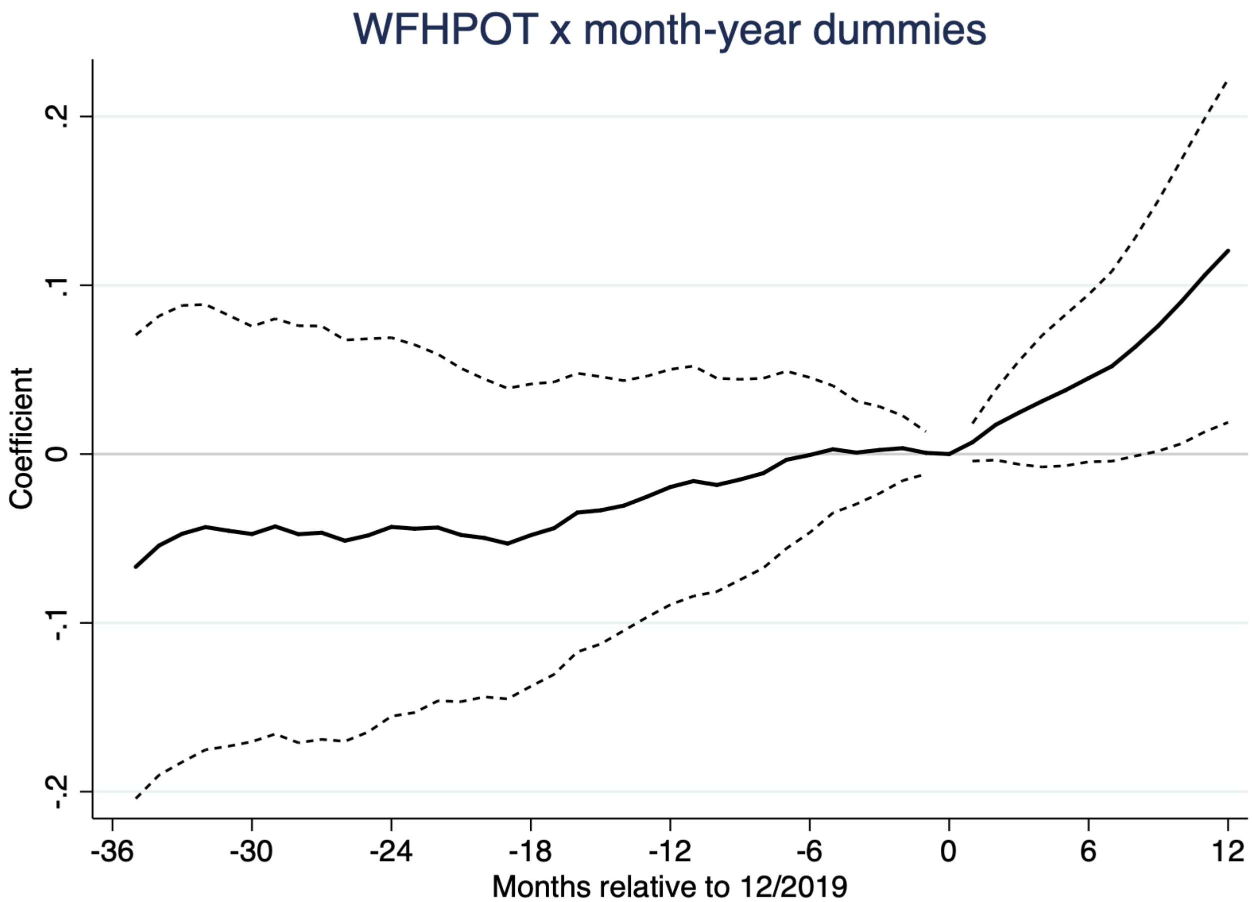
(a) Price



(b) Rent

Note: Figure plots the coefficients and 95 confidence intervals of the event study estimates. Outcomes are the Zillow Home Value Indices and Zillow Observed Rent Indices for all homes and condos/co-ops between January 2017 and December 2020. Control variables include county fixed effects, census division-month-year fixed effects, and the interactions between month-year dummies with a set of county covariates, including WFH potential, percent of population with a college education, MSA productivity, MSA quality of life, percent of MSA land steeper than 15 degrees, and the Wharton Residential Land-Use Regulation Index. Standard errors are estimated using nonparametric boostrap.

Figure A2. Intracity Home Price Gradients, Bootstrapped Standard Errors, 2017–2020



Note: Figure plots the coefficients and 95 confidence intervals of the event study estimates. Outcomes are intracity home price gradients based authors' calculations. In the first stage, we estimate the intracity home price gradient of each MSA with at least 30 zip-codes by separately regressing log zip-code-level Zillow Home Value Index on log distance to the central business district, a set of exogenous amenities (log distances to nearest lake, river, and coastline; the average annual precipitation 1971–2000, January minimum temperature, and July maximum temperature), average slope, and a set of proxies for endogenous amenities (log population density and log average household income). In the second stage, we estimate an event study equation by regressing the estimated intracity home price gradients on the interactions of month-year dummies and principal-city counties' WFH potential, controlling for MSA fixed effects and month-year fixed effects. Standard errors are estimated using nonparametric bootstrap.