Do Remote Workers Deter Neighborhood Crime? Evidence from the Rise of Working from Home*

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Abstract

In this paper, we provide the first evidence on the effect of working from home (WFH) on crime. We combine monthly, geographically granular crime data with a neighborhood WFH measure to estimate the impact on burglary using a difference-in-differences design. We document four key findings. First, a one standard deviation increase in neighborhood WFH (9.5 percentage points) reduces burglary by 4%, an effect that persists through 2022. Second, WFH is one shock to daytime home occupancy, and our finding extends to the broader occupancy–burglary relationship. Third, our mechanism evidence supports the spatial search model we develop, in which both opportunity and eyes-on-the-street channels deter burglars. Fourth, combining a hedonic house price model with a triple-difference design, we value the aggregate welfare gain at £24.5bn, around 1% of 2022 UK GDP. This places the fall in burglary among the most important consequences of the WFH revolution.

Keywords – Working From Home, Property Crime, Spatial Spillovers, Hedonic House Price Models

JEL Codes – H75, K42, R20.

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1 Introduction

> [T]here must be eyes upon the street, eyes belonging to those we might call the natural proprietors of the street. The buildings on a street equipped to handle strangers and to insure the safety of both residents and strangers, must be oriented to the street. They cannot turn their backs or blank sides on it and leave it blind.
> – Jane Jacobs, *The Death and Life of Great American Cities* (1961)

Economists have long studied the spillover effects of where we choose to work and live. These spillovers depend not just on location, but on the timing of our location choices. The powerful agglomeration effects associated with city centers depend on workers being in the same place at the same time; the congestion externalities of rush hour are a by-product of the same confluence of space and time. These spatiotemporal forces shape crime rates as well – criminals avoid busy areas to evade witnesses, so residents consistently present in a neighborhood should reduce crime. Yet the requirement of standard business hours traditionally left many residential neighborhoods empty during the day.

In this paper, we provide the first evidence on the effect of working from home (WFH) on crime. Our setting is England and Wales, where property crimes fell by over 30% during the nationwide lockdown. Most rebounded once restrictions were lifted; burglary did not, and remains 30% below its pre-lockdown level.[1] This persistence motivates our focus on burglary.[2] The natural explanation is the WFH revolution, which fundamentally changed where large swathes of the working population spent the working week (Barrero et al., 2021; Hansen et al., 2023), and which has persisted well beyond the lockdown period.[3]

We ask four questions. First, how does WFH affect neighborhood burglary? Second, does the effect generalize beyond WFH to home occupancy more broadly? Third, what mechanisms drive the effect, and is it displaced across neighborhoods? Fourth, what are the welfare consequences?

Two features make England and Wales well suited for this study. First, pre-lockdown working from home was low and initial compliance with the national lockdown was high (Ganslmeier et al., 2022), so we can exploit the lockdown as a clean event. Second, police forces across England and Wales record crimes to a common standard and make granular data available through a single platform.

We motivate the empirical analysis with a spatial search model of burglary, developed in Section 2. The model identifies two channels through which residential occupancy affects

[1] Burglary is a serious property crime: it accounts for 6% of all reported crimes in 2019 and ranks highest of all property crimes in terms of victim costs (Heeks et al., 2018).

[2] There are two additional aspects of burglary that are of particular relevance when considering how the WFH-induced spatial reallocation of the working population may impact crime. First, unlike theft, vehicle crime, or robbery, the target location of burglary is fixed and known. Second, the vast majority of burglary is *residential* burglary. That is, the key target of burglary – the home – is the same location most impacted by the rise of remote work.

[3] The Office for National Statistics reports that as of February 2022, 84% of workers who worked from home during the pandemic intended to continue to do so, in hybrid form (`https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/ishybridworkingheretostay/2022-05-23`).

burglary. An opportunity channel: empty homes are easier targets, so burglary falls when fewer homes are empty. An eyes-on-the-street channel: more residents at home means more potential witnesses, raising the chance a burglar is seen. The two channels both scale with daytime home occupancy, h_n.

We estimate the effect of WFH on burglary using a difference-in-differences design at the neighborhood level. We combine a pre-pandemic measure of WFH potential, following Dingel and Neiman (2020) and De Fraja et al. (2021), with monthly crime data for 6,837 neighborhoods across England and Wales. Two aspects of our empirical design – the fixed-effects structure and our interaction terms – protect against a wide range of potential confounders. Police-force-area-by-month-by-year fixed effects absorb every shock common to a local labor market in a given month, including changes in police staffing, tactics, and intensity, regional mobility patterns, and local labor market conditions. We then allow pre-pandemic neighborhood characteristics – homeownership, social housing, welfare claims, and retail floor space – to interact with the lockdown and post-lockdown periods. This avoids conflation bias (Kuminoff and Pope, 2014): without these interactions, the period $\times$ WFH coefficient would absorb differential responses to pandemic-era shocks across observably different neighborhoods, biasing our estimates. We document four key findings.

First, neighborhood WFH potential led to a large and persistent drop in burglaries. A one standard deviation increase in WFH potential (9.5 percentage points) reduces the burglary rate by 3.8% in the lockdown period and 4.0% in the post-lockdown period, relative to pre-pandemic rates. Event study estimates show no pre-trends and an effect that is stable for almost three years after the first lockdown, and the result is robust to the standard battery of pre-trends and continuous-treatment diagnostics. Two further pieces of evidence tie the effect to WFH-induced occupancy change. Using restricted data for London with crime timestamps, we find the burglary effect is concentrated entirely in weekday working hours, with no relationship on evenings or weekends. The effect is also specific to crimes whose target is the home: vehicle crime, which is also residence-based, shows a sustained post-lockdown effect close to that for burglary; theft and robbery, which target people, do not.

Second, the burglary effect generalizes beyond WFH to home occupancy more broadly. The prediction in our model is about h_n, the share of residents at home during the working day – WFH is one channel that raises h_n, but the same logic applies to other compositional changes to the resident population, such as retirement and gentrification. Two exercises support this claim. We use pre-period London Underground commuting – a turnstile-based measure built independently of WFH potential – to identify neighborhoods with greater scope for h_n to rise, and find larger post-lockdown burglary reductions where that scope was largest and WFH potential could realize it. Instrumenting realized 2021 home occupancy with WFH potential delivers a direct estimate: a ten percentage point rise in daytime occupancy reduces the burglary rate by approximately 3.5% of the pre-pandemic mean.

Third, both channels in our model are active in the data. We provide two pieces of evidence on mechanisms. The eyes-on-the-street channel predicts a stronger effect during daylight; using crime timestamps and civil-twilight data for London, we find the early-morning and early-evening burglary reductions are concentrated in light hours. Cross-sectional variation in housing type is also informative: WFH reduces burglary least in apartment-dominated neighborhoods (where both channels are weak), more in house-dominated neighborhoods without driveway parking (where eyes-on-the-street is strong but occupancy is hard to scout), and most in house-dominated neighborhoods with driveway parking (where both cues are strong). Spatial spillovers are weak: we find no displacement out of high-WFH neighborhoods, and some displacement into low-WFH neighborhoods only where their high-WFH neighbors are themselves surrounded by high-WFH areas. The net effect on high-WFH neighborhoods is unchanged, consistent with high travel costs for burglars.[4]

Fourth, the welfare consequences are large. We estimate them with a hedonic house price model in a triple-difference design that uses ex-ante low-burglary neighborhoods as a control: WFH should raise house prices through burglary reduction only where there is burglary to reduce. The third difference is what allows us to isolate the burglary channel from the other ways WFH may affect house prices, such as changes in local amenities or the value of larger properties. Households' willingness to pay to live in higher WFH neighborhoods is monotonically increasing in ex-ante burglary risk, and the gradient is concentrated in houses, with no effect for apartments – a pattern consistent with the mechanism evidence. Scaling these willingness-to-pay estimates by the value of the affected housing transactions delivers an aggregate welfare measure: our most conservative estimate of the welfare gain from the WFH-induced reduction in burglary is £24.5bn, equivalent to 1% of 2022 UK GDP. This figure is many times larger than direct accounting estimates of the cost of burglary, suggesting the reduction in burglary is among the most important consequences of the rise of WFH.

Our work makes significant contributions to three distinct literatures.

First, we provide the first evidence on the crime consequences of working from home, and the first estimate of the welfare gains those consequences imply.[5] The foundational literature on WFH establishes its scale and persistence (Bloom et al., 2015; Barrero et al., 2021; Aksoy et al., 2022; Hansen et al., 2023); a closely related literature documents how the resulting reallocation of daytime activity is reshaping cities (Althoff et al., 2022; Delventhal et al., 2022). Our WFH potential measure builds on the occupation-level index of Dingel and Neiman (2020), adapted to UK occupations by De Fraja et al. (2021). We extend this body of work to a downstream consequence not yet studied: a large, persistent fall in burglary, with welfare gains worth roughly 1% of GDP – among the largest documented consequences of the WFH revolution.

Second, we contribute to the literature on deterrence and informal monitoring. The deterrence tradition has largely focused on formal police presence (Chalfin and McCrary, 2018),[6] with non-police evidence coming from organized substitutes – private security at concentrated targets such as banks (Maheshri and Mastrobuoni, 2021), vehicle anti-theft technology (Gonzalez-Navarro, 2013), Business Improvement Districts (Cook and MacDonald, 2011), and university

[4]The model in Section 2 predicts weak spatial displacement when travel costs are high or burglars are geographically specialized. Kirchmaier et al. (2024) document that most UK burglaries occur within a five-minute car journey of the perpetrator's home.

[5]A separate literature studies the temporary effect of pandemic shelter-in-place orders on crime (Kirchmaier and Villa-Llera, 2020; Abrams, 2021); we focus on the persistent post-lockdown effect.

[6]See Chalfin and McCrary (2017) for a comprehensive survey of deterrence and crime.

campus police forces (Heaton et al., 2016) – or from environmental shocks to detection, most directly the daylight saving experiment of Doleac and Sanders (2015). We provide the first evidence on a different kind of non-police deterrence: incidental, informal monitoring by residents who happen to be at home for unrelated reasons. We also identify the spatial spillovers from this shock and find them weak: criminals deterred from one neighborhood can substitute across many others, across crime types, or to the outside option, unlike in settings with concentrated targets such as banks (Maheshri and Mastrobuoni, 2021) or vehicles (Gonzalez-Navarro, 2013) where deterrence at one location sharply displaces crime to nearby substitutes.

Third, we contribute to the literature using hedonic house price models to value reductions in neighborhood crime risk. Earlier hedonic studies of crime have used cross-sectional variation in crime risk (Gibbons, 2004) or exploited single-channel shocks to it (Linden and Rockoff, 2008); the WFH shock is multi-channel, and we use a triple-difference design across ex-ante burglary risk to isolate the burglary channel from other ways WFH may affect house prices. We further find that the willingness-to-pay gradient by housing type matches our model's mechanism predictions, providing a test of the hedonic estimates that earlier designs cannot deliver. Our magnitudes are closest to those of Gibbons (2004), and confirm that hedonic valuations of crime risk are an order of magnitude larger than accounting-based costs of crime (Heeks et al., 2018). Following Adda et al. (2014), we then aggregate these willingness-to-pay estimates into a population-level welfare measure, delivering the £24.5bn welfare figure (1% of 2022 UK GDP) that anchors our paper's welfare claim.

The paper proceeds as follows. Section 2 presents the spatial search model. Sections 3 and 4 describe the data and the empirical design. Section 5 reports the main DD and event-study results and the analysis of other neighborhood crimes. Section 6 estimates the effect of home occupancy directly. Section 7 presents the mechanism evidence. Section 8 addresses spatial displacement. Section 9 estimates the welfare gains. Section 10 concludes.

2 A Spatial Search Model of Burglary and Occupancy

Here we micro-found the criminal's decision process with a spatial-search model which captures several key features of burglary, as is well documented in previous studies (including Nee and Meenaghan (2006), Bernasco and Nieuwbeerta (2004), Kirchmaier et al. (2024), and Andresen and Shen (2019)). First, burglary is an opportunistic crime, burglars actively search for exposed homes within neighborhoods which they are familiar with. Second, a key feature that criminals look for in finding an "exposed" home to burgle is that the home is unoccupied. Third, burglars will avoid neighborhoods in which they are likely to be seen by neighbors. A document published by the Metropolitan Police states that "*Burglars typically do not want to be seen or heard and if they feel that they would be noticed by a neighbor or passerby then they are more likely to feel exposed and may move on to find somewhere else to burgle*" (Metropolitan Police, 2023). In an interview study with convicted burglars, a home being unoccupied and having sufficient coverage to reduce visibility from neighbors are essential criteria (Nee and Meenaghan, 2006). These will be the key channels through which residential occupancy rates affect burglary; more residents at home decreases opportunities for burglary, as fewer homes are unoccupied, and increases the chances of being seen.

An additional feature of the model is that burglars have heterogeneous specialization in neighborhoods. We model this through the cost of searching for an appropriate target; criminals differ in their cost of searching in different neighborhoods. A driver of this heterogeneity will be distance, consistent with the empirical finding from several studies that burglars tend to commit crimes close to where they live (Bernasco and Nieuwbeerta, 2004; Kirchmaier et al., 2024).

The empirical exercise in this paper will focus on a partial equilibrium response of burglars to an increase in residential occupancy during work hours. Therefore, our conceptual framework should also be thought of as a short-run partial equilibrium response. In the long-run we may expect residential occupancy to influence many neighborhood features including residential sorting. For analytical simplicity, we focus on the case of a two neighborhood city; a generalization to N cities is straightforward.

2.1 Home occupancy and the expected value crime

Consider a city which has two neighborhoods, denoted by $n = \{1, 2\}$. A burglar who searches in neighborhood n will successfully find a vulnerable house to burgle with probability ϕ_n and find no house to burgle with probability $1 - \phi_n$.

Let h_n be the proportion of residents in n which are home during the time of search. As a house being empty is a key criterion for a home being suitable to burgle, ϕ_n is decreasing in h_n. We posit the following relationship:

$$\phi_n = 1 - h_n^{\kappa}.$$

Where $\kappa > 0$. This simple equation has a number of nice properties. If all residents are home, $h_n = 1$, then there are no opportunities for burglary, $\phi_n = 0$. If no residents are home, $h_n = 0$, then any randomly drawn home will provide an opportunity for burglary, $\phi_n = 1$. The parameter $\kappa > 0$ governs how $h_n \in (0, 1)$ affects the proportion of vulnerable homes. A natural way to think about $\kappa > 0$ is that it is the number of random house draws a criminal makes when searching in n; as the criminal draws more homes, this increases the probability of finding a suitable home.

In addition to decreasing the number of unoccupied homes, h_n also increases the (subjective) probability of being seen while searching or actively burgling a house. Consider a neighborhood with R_n homes. When a resident of this neighborhood works from home they informally *monitor* r_n other houses in the neighborhood (i.e. these are the houses they see out their window as they work.) Monitoring is imperfect, if a burglary takes place the resident will see this with a probability given by $0 < \eta < 1$. Therefore, the probability a burglar is unseen by this resident burgling a randomly drawn home is given by $p(unseen) = 1 - \frac{r_n \eta}{R_n}$.

Now consider a residential population of size R_n (i.e. one resident per home) in which proportion h_n are at home with the same monitoring, r_n and η. Now, the probability of the criminal being seen is

$$p_n(seen) = 1 - \left(1 - \frac{r_n\eta}{R_n}\right)^{h_n R_n}.$$

We write the probability of being seen while engaging in criminal activities as $\pi(h_n)$:

$$\pi(h_n) = \pi_{n0} + \left(1 - \left(1 - \frac{r_n\eta}{R_n}\right)^{h_n R_n}\right),$$

where π_{n0} is a neighborhood specific base level of burglary arising from police, private security, or other non-residential neighborhood monitoring. The probability of being seen is an increasing function of the household occupancy rate:

$$\frac{d\pi(h_n)}{dh_n} = -R_n \left(1 - \frac{r_n\eta}{R_n}\right)^{h_n R_n} \ln\left(1 - \frac{r_n\eta}{R_n}\right) \geq 0.$$

This specification leads to some sharp predictions. For small values of $r_n\eta$, the cross-derivative $d^2\pi(h_n)/dh_n dr_n$ is positive[7]; neighborhood features which increase visibility between homes (i.e. larger r_n) increase the effect of h_n on $\pi(h_n)$. Notice that visibility operates through $\pi(h_n)$ but not through $\phi(h_n)$.

2.2 Expected utility of criminal search

Finally, we write the burglar's expected utility-value of three different outcomes as μ^P if a successful burglary is committed, μ^F if seen while burgling a home, and $\tilde{\mu}^F$ if not actively burgling a home but still seen. Therefore, the expected utility of searching for burglary opportunities in neighborhood n, denoted v_n, is given by

$$v_n = \phi_n(1 - \pi_n)\mu_n^P + \phi_n\pi_n\mu^F + \pi_n\tilde{\mu}^F. \quad (1)$$

We assume that this expected value is common to all criminals in n and that $\mu_n^P > \mu^F > \tilde{\mu}^F$ in both neighborhoods.

We assume that there is a homogeneous outside option, determined exogenously (with respect to i's decision) in the local labor market, available to all potential criminals. Denote this outside option by $\bar{\omega}$.

2.3 Search costs and the outside option

We denote i's total cost of searching in neighborhood n by λ_{in}, which is written as a linear function of three components. The first is the distance a burglar needs to travel to search in neighborhood n which we denote by $D_{in} \in \{0, 1\}$, where distance depends on in which of the two neighborhoods i lives. The distance D_{in} is normalized to 0 for all i who live in n and 1 for all i who do not live in n. We denote by θ_1 the fraction of all i who live in 1 and by θ_2 the fraction of i who live in 2, such that $\theta_1 + \theta_2 = 1$. In addition to the cost of actual travel distance, this variable could reflect a knowledge of streets and getaways within the neighborhood that come

[7]This requires that $h_n R_n \ln(1 - \frac{r_n\eta}{R_n}) + 1 > 0$, which holds for small values of $r_n\eta$.

from having a close geographic proximity. We write the contribution to search costs associated with D_{in} as ξD_{in}.

The second cost component is based on the structure of the neighborhood and is common to all criminals. It reflects invariant (over the period considered) attributes of the environment such as the type of housing, and is written as Πx_n, where x_n is a vector of observable neighborhood characteristics which affect search and Π is a vector of associated costs.

The final component of search cost is ξ_{in} which reflects idiosyncratic influences on the cost of search in n. An example of such an idiosyncratic cost is an information tip that i receives about a house in n. We assume that ξ_{in} is distributed iid type 1 extreme value.

So the total cost of search for a potential criminal i is

$$\lambda_{in} \quad = \quad \xi D_{in} + \Pi x_n + \xi_{in}. \tag{2}$$

2.4 Criminal choice and equilibrium burglary

Potential burglars must decide whether or not to burgle, and if so, in which neighborhood. Individual i considers the common value to searching in each neighborhood, v_n, the value of value of the outside option ω, and the cost of search in each neighborhood, $(\lambda_{1i}, \lambda_{2i})$. Given this, i chooses according to:

$$v^\star = \max\{v_1 - \lambda_{1i},\, v_2 - \lambda_{2i},\, \bar{\omega}\}. \tag{3}$$

Given our assumption on the type 1 extreme value distribution of ξ, the probability that i searches in neighborhood n can be written as:

$$s_{in} = \frac{\exp(v_n - \xi D_{in} - \Pi x_n - \bar{\omega})}{1 + \exp(v_1 - \xi D_{i1} - \Pi x_1 - \bar{\omega}) + \exp(v_2 - \xi D_{i2} - \Pi x_2 - \bar{\omega})}. \tag{4}$$

Based on this, and the residential distribution of each i, we can write the share of total criminal search which we expect to take place in neighborhoods 1 and 2 as:

$$\begin{aligned} s_1 = & \frac{\exp(v_1 - \Pi x_1 - \bar{\omega})}{1 + \exp(v_1 - \Pi x_1 - \bar{\omega}) + \exp(v_2 - \xi - \Pi x_2 - \bar{\omega})}\theta_1 \\ & \qquad + \frac{\exp(v_1 - \xi - \Pi x_1 - \bar{\omega})}{1 + \exp(v_1 - \xi - \Pi x_1 - \bar{\omega}) + \exp(v_2 - \Pi x_2 - \bar{\omega})}\theta_2, \\ s_2 = & \frac{\exp(v_2 - \xi - \Pi x_2 - \bar{\omega})}{1 + \exp(v_1 - \Pi x_1 - \bar{\omega}) + \exp(v_2 - \xi - \Pi x_2 - \bar{\omega})}\theta_1 \\ & \qquad + \frac{\exp(v_2 - \Pi x_2 - \bar{\omega})}{1 + \exp(v_1 - \xi - \Pi x_1 - \bar{\omega}) + \exp(v_2 - \Pi x_2 - \bar{\omega})}\theta_2. \end{aligned}$$

The total number of criminals searching in neighborhood n will be $C_n = M s_n$ where M is the population of potential criminals in the city; those who make the choice between crime and the outside option. Given that burglaries are only observed in n if search is successful, which happens fraction ϕ_n of the time, we write the observed number of burglaries in each neighborhood as:

$$B_1 = \phi_1 M \left(s_1^{D=0}\theta_1 + s_1^{D=1}\theta_2 \right), \qquad B_2 = \phi_2 M \left(s_2^{D=1}\theta_1 + s_2^{D=0}\theta_2 \right). \tag{5}$$

where $s_n^{D=d}$ is the value of s_{in} for an individuals i for whom $D_{in} = d \in \{0, 1\}$.

The effect of residential occupancy on burglary

Consider first what we expect to happen to burglary in each neighborhood when h_1 increases. First in neighborhood 1:

$$\frac{dB_1}{dh_1} = \underbrace{\frac{d\phi_1}{dh_1} C_1 + \Delta C_1 \frac{d\phi_1}{dh_1}((1-\pi_1)\mu_1^P + \pi_1 \mu^F)}_{\text{Opportunity}} - \underbrace{\Delta C_1 \frac{d\pi_1}{dh_1} \left(\phi_1(\mu_1^P - \mu^F) - \tilde{\mu}^F \right)}_{\text{Eyes on the street}} < 0, \tag{6}$$

where $C_1 = M \left(s_{i1}^{D=0}\theta_1 + s_{i1}^{D=1}\theta_2 \right)$ and $\Delta C_1 = \phi_1 M \left(s_1^{D=0}(1 - s_1^{D=0})\theta_1 + s_1^{D=1}(1 - s_1^{D=1})\theta_2 \right)$.

Equation (6) distinguishes between two key channels that both result in a decline in the number of observed burglaries. The first, is the opportunity effect. This is the result of there being fewer vulnerable homes in the neighborhood, meaning fewer opportunities to burgle (more unsuccessful burglars searching) and a lower expected value to search which discourages criminals from searching in neighborhood 1. The second channel is through eyes on the street. This reflects the fact that more home occupancy means that the chances of being seen while burgling a vulnerable home increases. This externality across homes discourages burglars from searching in 1.

We also may expect to see a displacement of crime into neighborhood 2, given by:

$$\frac{dB_2}{dh_1} = -\phi_2 M (s_{i2}^{D=1} s_{i1}^{D=0}\theta_1 + s_{i2}^{D=0} s_{i1}^{D=1}\theta_2) \frac{dv_1}{dh_1} \geq 0. \tag{7}$$

Notice, the magnitude of this displacement is determined by the importance of the travel component of search costs. If the travel cost, ξ, for criminals is sufficiently high such that few criminals search outside their own neighborhood, then $s_{i2}^{D=1}$ and $s_{i1}^{D=1}$ will both be close to 0. As a result dB_2/dh_1 will also be close to 0, implying very limited spillover.

Consider what happens to the number of criminals who choose the outside option when h_1 increases. The total number choosing the outside option is

$$M - C = M \left((1 - s_{i1}^{D=0} - s_{i2}^{D=1})\theta_1 + (1 - s_{i1}^{D=1} - s_{i2}^{D=0})\theta_2 \right), \text{ so:}$$

$$\frac{d(M-C)}{dh_1} = -M((1 - s_{i1}^{D=0} - s_{i2}^{D=1}) s_{i1}^{D=0}\theta_1 + (1 - s_{i1}^{D=1} - s_{i2}^{D=0}) s_{i1}^{D=1}\theta_2) \frac{dv_1}{dh_1} \geq 0, \tag{8}$$

Notice that when ξ is large, most of the movement out of neighborhood 1 will go to the outside option rather than to neighborhood 2. In the extreme case where $s_{in}^{D=1} = 0$ for both neighborhoods, we end up with $dB_2/dh_1 = 0$ and $d(M-C)/dh_1 = M(1 - s_{i1}^{D=0}) s_{i1}^{D=0}\theta_1 dv_1/dh_1$, meaning all the criminals who leave neighborhood 1 take the outside option.

Change in the outside option

Now consider a change in the outside option available to all criminals, $\bar{\omega}$. We do not believe that $\bar{\omega}$ changes directly from changes in h_n; $\bar{\omega}$ is a variable which is determined within the local labor market. Consider the change in burglaries within each neighborhood when $\bar{\omega}$ changes:

$$\frac{dB_1}{d\bar{\omega}} = -\phi_1 M\left[(1 - s_{i1}^{D=0} - s_{i2}^{D=1})s_{i1}^{D=0}\theta_1 + (1 - s_{i1}^{D=1} - s_{i2}^{D=0})s_{i1}^{D=1}\theta_2\right] \leq 0, \tag{9}$$

$$\frac{dB_2}{d\bar{\omega}} = -\phi_2 M\left[(1 - s_{i1}^{D=0} - s_{i2}^{D=1})s_{i2}^{D=1}\theta_1 + (1 - s_{i1}^{D=1} - s_{i2}^{D=0})s_{i2}^{D=0}\theta_2\right] \leq 0, \tag{10}$$

An increase in the outside option will decrease burglary across both neighborhoods.

2.5 Linking to our empirical strategy

Here we align the model with our primary empirical strategy and in doing so identify some of the key considerations for our analysis. Our empirical strategy will exploit exogenous variation in h_n arising from an instrument z – in our case, an exogenous shift in WFH due to national lockdown policies. Three points are worth keeping in mind: (a) the national lockdown applies to all neighborhoods; (b) the effect of the policy on h_n differs across neighborhoods according to the occupational distribution of residents; and (c) the scale of the change may have had a short-run impact on the outside option available to criminals.

Letting ζ_n be the change in h_n through the shift to WFH resulting from the lockdown policy. In our two neighborhood case, the observed change in burglary in neighborhood 1 resulting from the lockdown policy (ignoring time periods) can be written as:

$$\Delta B_1 = \zeta_1 \frac{\partial B_1}{\partial h_1} + \zeta_2 \frac{\partial B_1}{\partial h_2} + \Delta\bar{\omega}\frac{\partial B_1}{\partial \bar{\omega}}. \tag{11}$$

Where $\Delta\bar{\omega}$ is the change in $\bar{\omega}$ resulting from the aggregate effect of the policy. We are interested in identifying $\partial B_1/\partial h_1$, which we address directly in Section 6. In doing this we have two broad identification concerns which need to be addressed. The first is the spatial displacement of crime. We investigate this in Section 8.

The second is that changes in the outside option may be affecting criminal outcomes. In England and Wales there are two non-criminal sources of income which comprise the outside option. The first is legitimate employment, particularly that in lower-skill occupations such as manufacturing, construction, and hospitality. From aggregate figures for England and Wales, we find that while reported wages in these occupations increased over the time-period of our analysis, employment fell, remaining about 5% below 2019 levels in the post-lockdown period.[8] The second source of outside option is the availability of public support payments (known as "benefits"). This rose considerably over the period of our analysis, male claimants more than doubled in the lockdown period, from 612,450 in December 2019 to 1,448,540 in May 2020. These claims remained high in the post-lockdown period, with 779,900 claims made in December 2022.[9]

[8] Based on data reported in Office for National Statistics (2026b) and Office for National Statistics (2026a).

[9] Based on claimant count data extracted from Office for National Statistics (2025).

Our empirical strategy (Section 4) controls for changes in the outside option in two ways. First we allow for time-varying labor market fixed effects.[10] This absorbs changes in wages or labor market conditions that accompany the shift to remote work. Second, our empirical specification interacts period-dummies with neighborhood characteristics, including the pre-existing uptake of public support payments. This will absorb changes arising from asymmetric neighborhood responses to changes in outside options, such as neighborhoods with a high propensity for benefit uptake being affected by changes to the benefit availability differently than low propensity neighborhoods.

3 Data

Our main analyses are at the neighborhood level, which are defined as Middle Super Output Areas (MSOA). These are census areas with an average population of around 7,800 people, drawn to capture real communities. MSOAs are similar in size to US Census Tracts. Importantly, they are entirely nested within relevant higher-level geographies including English and Welsh Police Force Areas, commuting zones (termed Travel to Work Areas), and towns and cities (Local Government Regions). Our main dataset is based on individual crimes aggregated to the MSOA level. This information is combined with information capturing the expected proportion of workers in each neighborhood in occupations which can be done from home.

3.1 Working From Home

WFH has increased dramatically in England and Wales compared to pre-2020 rates, as it has in other Western countries. Prior to 2020 approximately 5% of workers reported normally working from home, as of the first half of 2022 an estimated 35% of employees report normally working from home (De Fraja et al., 2022). These rates have been stable since national public health restrictions were lifted and are consistent with rates reported in other countries (Barrero et al., 2021; Aksoy et al., 2022; Hansen et al., 2023).

Our measure of WFH is based on work by De Fraja et al. (2021) and is an estimate of the percentage of employed residents in a neighborhood able to work from home. It is obtained by computing an occupation specific WFH index for each occupation, denoted by h_o. This reflects the extent to which a particular occupation can be done remotely and is calculated following the methodology proposed in Dingel and Neiman (2020) and adapted for UK 4-digit standardized occupation classification (SOC) codes by De Fraja et al. (2021). This methodology classifies occupations according to the tasks they involve. For example, jobs which largely involve computer based tasks, such as a programmer or call center worker, will receive an index value of 1, indicating that most or all of the job can be done remotely. Jobs in which face-to-face interactions are important, such as food service or retail sales, will receive a value of 0, indicating that none of the job can be done remotely.

Our index of WFH potential, for a neighborhood n, is calculated as the average of the index

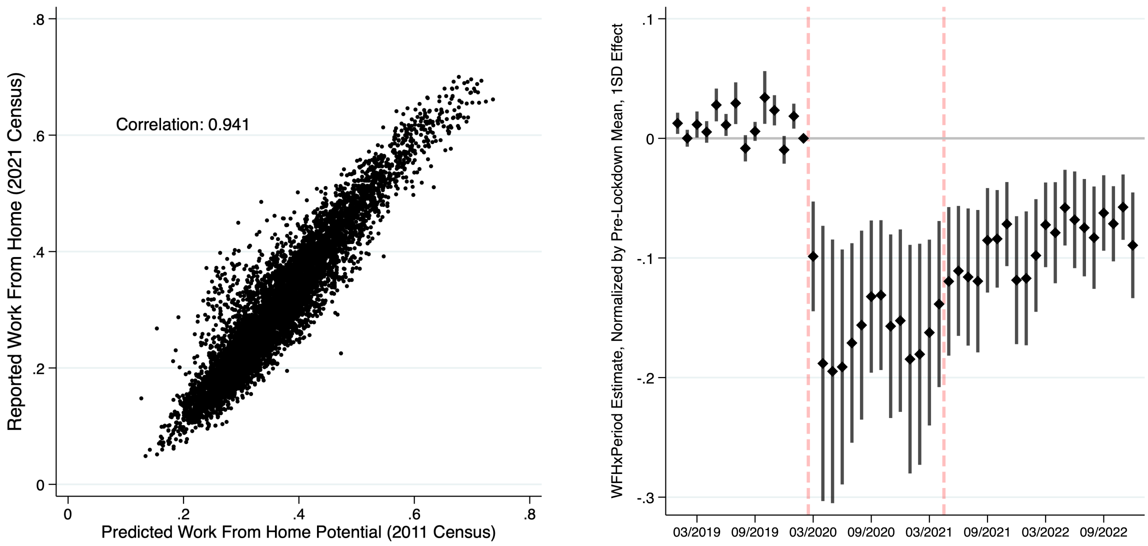
[10] Specifically we include month-by-year-by-police force area fixed effects. A police force area roughly corresponds to a local labor market.

values across all employed residents in the neighborhood. That is:

$$WFH_n = \frac{\sum_o E_{o,n} \times h_o}{E_n}, \tag{12}$$

where $E_{o,n}$ is the count of residents of neighborhood n employed in occupation o, E_n is the total number of employed residents in neighborhood n. The resident counts, $E_{o,n}$ and E_n, are taken from the residential distribution of workers by 4-digit SOC code in the 2011 census. By using

Figure 1: The Relevance of our WFH Potential Measure



(a) Actual WFH (2021) vs WFH Potential (b) Tube Commuting and WFH Potential

Notes: Figure 1a: This figure plots actual WFH rates reported in the 2021 Census against estimated WFH potential for each neighborhood. Figure 1b: Each point presents the (rescaled) event-study coefficient estimates and 95% point wise confidence intervals of an event study regression with neighborhood and month-by-year fixed effects. The outcome variable is the monthly count of London Underground entry tap-ins, representing use of the underground network. The dashed vertical lines denote the introduction of the UK first national lockdown in March 2020, and the start of the post-lockdown period in May 2021. February 2020 is excluded as the reference month. Standard errors are clustered by neighborhood.

the 2011 Census we avoid concerns about endogenous changes in residential location choice by occupation, for which evidence on real estate markets is consistent with having happened during the pandemic (Gupta et al., 2022; Gokan et al., 2022). However, our measure is predictive of behavior both during and after national lockdowns. Figure 1a highlights an extremely close correspondence between the pre-determined predicted WFH rates based on the 2011 Census data and *actual* WFH rates recorded, in the 2021 Census, summarized by a correlation coefficient of 0.94.[11] We also find that our measure is predictive of a sustained drop in neighborhood London Underground service use over the full period of study. Figure 1b highlights this relationship. A standard deviation difference in neighborhood WFH potential is associated with a 9% decrease in underground ridership throughout 2022. We take this as evidence that our measure is a valid measure of the WFH response to the pandemic.

[11]We discuss the 2021 measure in greater detail in Appendix B.10.1. The *actual* WFH rate is calculated based on the Census Question 49, "Where do you mainly work?". It should be noted that no guidance was provided on how the public health restrictions should be factored into answering this question, some respondents may have interpreted it as referring to outside the public health restrictions.

3.2 Crime Data

We work with two datasets recording crime. The first, which we term the *national data* is publicly available, street-level, monthly data for the whole of England and Wales. The second, termed the *Met data* are richer, but only cover the 900 MSOAs in the (London) Metropolitan Police Force Area.

Our core dataset collects data on the number of reported burglaries by month. For our supplementary analyses, we also collect data on other property crimes such as, theft, (acquisitive) vehicle crime, arson, and shoplifting.[12] While crimes that are not reported or detected by the police will not be captured by these data, there is reason to believe that reporting rates will be high for these crimes since a Police Crime Reference Number is necessary for insurance claims. Likewise, shops need to report shoplifting if they wish to pursue prosecution, and even if they do not, reporting crimes serves to attract greater police resources.

National Crime Data

The national crime data come from data.police.uk, a government provided repository of crime and policing data for England and Wales. It provides monthly data recording street-level crime, by type, at the Lower Layer Super Output Area (LSOA) level. LSOAs are small census areas each comprised of around 1,500 people that are nested within MSOAs allowing us to straightforwardly aggregate and match to the WFH data at the MSOA level.[13] Since we are interested in the period before and after the pandemic, we use data spanning the period from September 2017 (30 months before the first national lockdown starts) to December 2024, noting that our core working sample spans September 2017–December 2022.

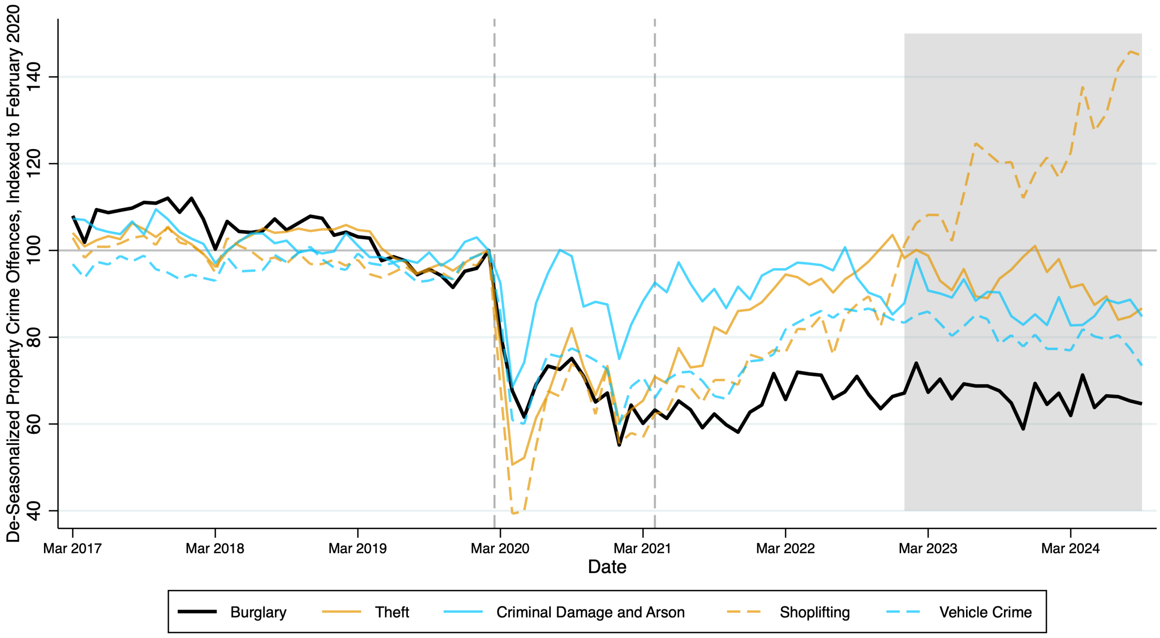
Figure 2 shows the time series for burglaries and other property crimes. Each series is seasonally adjusted using month fixed effects estimated from the pre-March 2019 period only and normalized such that all values are relative to February 2020. The first vertical dashed line denotes the start of the UK national lockdown and the second the end of the third lockdown period. We can see a substantial drop in all property crimes following the start of lockdown with theft falling by around three quarters. Unsurprisingly, we see these rates rebound following the relaxation of the first lockdown, and then a subsequent (smaller) reduction associated with the second lockdown, etc. The key feature of the graph is that following the end of lockdown in England and Wales there is no recovery in rates of burglary, which remain below two-thirds

[12] Burglary, shoplifting, and vehicle crime are all formally sub-categories of theft in English law. However, Home Office guidance is that they are recorded as separate crimes. Broadly speaking, burglary means illegally entering a property in order to steal from it. Theft is a broad term meaning stealing without the use of force, while shoplifting is theft specifically from a shop or store. As such shoplifting is a type of theft but is usually treated differently. Vehicle crime refers to both the theft *of* motor vehicles and theft *from* vehicles.

[13] All LSOA and MSOA boundaries are those of the 2011 Census. Before being published, the national crime data is anonymized in terms of both personal and location characteristics, to limit attempts to identify individual cases. There are some known issues with the data, such as location accuracy, or location changes when more information becomes available. Similarly, the data providers employ location approximation techniques during the anonymization process, resulting in slight variations between the actual point of crime and the published data point. However, such inconsistencies should have a very limited effect in our case, given that we collapse our data from the LSOA to the MSOA, i.e., the same level as our WFH data.

of pre-pandemic levels. This is not true of other property crimes which while still below their pre-pandemic levels, show evidence of an upwards trend.

Figure 2: Property Crime in England and Wales, 2017 to 2024



Notes: This figure reports the number of monthly reported crimes relative to February 2020, for England and Wales. Vertical dashed lines indicate the start of the first national lockdown and the end of the second national lockdown. The gray box denotes the time period lying outside our working sample time period.

Metropolitan Police Force Data

The Met data is provided by the Metropolitan Police Force (the Met). The Met is responsible for policing the Greater London area, the largest police force area in England and Wales which comprises 983 neighborhoods, accounts for 20% of crime in England and Wales, and serves just under 9 million people.[14] These data contain important additional information relative to the national data, notably including the time of day at which each crime was committed. This allows us to distinguish, for example, between crimes committed during or outside, typical working hours. It also contains more precise detail as to the type of crime, separating, e.g., residential versus commercial burglary.

3.3 Auxiliary Data

Neighborhood Characteristics The crime and WFH data are supplemented with information on neighborhood characteristics from a number of additional sources.

Population and land area (in hectares) estimates by neighborhood are provided by the Office for National Statistics LSOA population, and population density estimates respectively. We aggregate this information to the level of our neighborhood (the MSOA).

We use data on the housing tenure from the 2011 Census. Housing tenure data include information on the total number of residential properties, the number of these properties which

[14]The policing responsibility of the Met does not include the City of London proper, which is policed by the City of London Police force.

are owned by the resident, the number of properties which are rented through the private market, and the number of properties which are provided through a social housing scheme (e.g., through local councils). Based on this information we calculate, by neighborhood, the proportion of residential properties occupied by owners and the proportion of residential properties that are publicly provided (i.e. social housing). The proportion of residents receiving income support is calculated as the average number of monthly claimants divided by the neighborhood population.

We also include a measure of the commercial concentration of a neighborhood by including information on the amount of retail floor space (in square meters), from the Valuation Office Agency which captures these data for the purposes of commercial taxation.

Retail, Pubs, and Cafes Data We use Ordnance Survey Point of Interest data to measure the number of brick-and-mortar establishments in a neighborhood. These data provide, for each establishment, details about the type of business and longitude and latitude coordinates, reported quarterly. We use the information to provide counts of the number of pubs, cafes and retail establishments for each neighborhood at different time periods. Data are accessed through Digimap.

Transport for London Underground Data We use data from Transport for London on tube journeys, spanning the period January 2019-December 2022. This allows us to examine the extent to which commuting patterns changed during the pandemic period. The temporal element of this data is at the daily level. For all analysis of this data, we remove weekend days, and then collapse to the monthly level.

House Price Data We additionally use house price data from the UK Land Registry. The data cover the near universe of residential property sales for England and Wales. These data record the sale price, transaction date, and type of house (Apartment, Detached, etc.) for each house sale in England and Wales.

4 Empirical Specification

We estimate the effect of a neighborhood's potential to work from home on burglary using a difference-in-differences design, in which the treatment is the pre-pandemic WFH potential of neighborhood n, WFH_n, constructed as described in Section 3:

$$crime_{nt} = \alpha_1(LD_t \times WFH_n) + \alpha_2(PLD_t \times WFH_n) + LD_t \times X_n^{'}\beta_1 + PLD_t \times X_n^{'}\beta_2 + \gamma_n + \theta_{A\times t} + \varepsilon_{nt}\,. \tag{13}$$

The outcome $crime_{nt}$ is the number of burglaries per ten-thousand residents in neighborhood n and month t.[15] WFH_n is time-invariant and varies at the MSOA level; we aggregate the LSOA-level crime data to MSOAs to match the level of treatment. LD_t equals one in the national lockdown period and zero otherwise; PLD_t equals one in the post-lockdown period and zero otherwise.[16] The parameters of interest are α_1 and α_2, which measure the change

[15] We do not log the dependent variable. McConnell (2024) shows that combining a DD design with a log-transformed outcome estimates not the difference in differences of crime rates but an approximation of the proportional difference in growth rates across neighborhoods.

[16] The UK national lockdown as defined here covers March 2020 to May 2021. This includes the period from July 2020 to November 2020 in which lockdown restrictions were relaxed in most parts of the UK,

in burglary rates associated with an increase in WFH_n in the lockdown and post-lockdown periods, respectively, relative to the pre-lockdown period. The interactions $LD_t \times WFH_n$ and $PLD_t \times WFH_n$ capture the differential change in residential daytime occupancy in high-WFH neighborhoods, which is what the model in Section 2 links to burglary.

X_n is a vector of four pre-lockdown neighborhood characteristics: the rate of public support claims, the proportion of housing that is resident owned, the proportion of social housing, and the total amount (in square meters) of retail space. The motivation for interacting each of these with LD_t and PLD_t follows from the model in Section 2: a labor-market-wide shock to the outside option has heterogeneous effects on burglary across neighborhoods within the same labor market, and the size of that effect varies across neighborhoods. While $\theta_{A\times t}$ absorbs shocks common to the police force area, the period interactions absorb their heterogeneous effect across neighborhoods, by allowing the effect of pandemic-era shocks to differ across neighborhoods with different observable characteristics, period by period.[17] This guards against the WFH coefficient picking up the differential adoption of crime-preventive technology in more affluent neighborhoods, the differential exposure of retail-heavy neighborhoods to pandemic-era changes in footfall, or the differential exposure of low-income neighborhoods to the UK furlough scheme, which raised home occupancy independently of WFH potential.

The neighborhood fixed effect γ_n captures all time-invariant differences across neighborhoods, including baseline burglary risk, the local housing stock, and the average level of WFH_n itself. The fixed effect $\theta_{A\times t}$ is a police-force-area by month-by-year interaction, where each neighborhood n lies entirely within one police force area A. In the model in Section 2, the outside option is determined within the local labor market; we use the police force area as the local labor market, so $\theta_{A\times t}$ absorbs variation in the outside option, including the wage and minimum-wage changes that occurred over our sample period.[18] The same fixed effect non-parametrically absorbs every other shock common to a police force area in a given month, including region-wide changes in mobility of the kind captured by indices such as Google mobility, region-wide changes in policing intensity and resourcing, and any region-wide variation in the timing or severity of lockdown restrictions. Conditional on $\theta_{A\times t}$, α_1 and α_2 are identified from variation in burglary across neighborhoods within the same police force area in the same month. We cluster standard errors at the neighborhood level, the level at which WFH_n varies, following Abadie et al. (2023).

Identification. Identification requires conditional parallel trends in burglary rates across neighborhoods with different WFH potential, conditional on γ_n, $\theta_{A\times t}$, and the period interactions of X_n. The event study in Section 5.2 shows no differential pre-trends by WFH potential. In Appendix A we report three further tests: a direct test of pre-trends, the worst-case bounding approach of Rambachan and Roth (2023), and the continuous-treatment DD diagnostic of

although social distancing and remote working measures continued throughout much of the country. The post-lockdown period is defined as any month after May 2021.

[17]Because X_n is time-invariant, the level terms $X_n'\beta$ are absorbed by γ_n and the covariates can only enter through the period interactions.

[18]For example, the minimum wage paid to workers in their early 20s increased 9% between 2020 and 2022, from £8.20 to £9.80.

Callaway et al. (2021). Each of these points to the same conclusion.

5 Results

We now present our baseline results, estimating the reduced-form effect of WFH potential on burglary. We then trace this effect over time in an event study. We investigate the timing of this effect using restricted-access data from London. Finally, we document the impact of WFH on other neighborhood crimes.

5.1 Baseline Difference-in-Differences Results

Table 1: DD Estimates for Burglary

	(1)	(2)	(3)	(4)
LD × WFH	–1.987***	–3.042***	–3.473***	–2.357***
	(0.356)	(0.344)	(0.333)	(0.367)
PLD × WFH	–2.188***	–3.235***	–3.096***	–2.475***
	(0.337)	(0.361)	(0.344)	(0.381)
Spatial FE	NH	NH	NH	NH
Spatiotemporal FE	Month ×Year	Month ×Year	Region ×Month ×Year	PFA ×Month ×Year
Control Variables		X_0×Period	X_0×Period	X_0×Period
$\overline{Y}_{PRE}$	5.919	5.919	5.919	5.919
$1\sigma_{WFH}$×(LD × WFH)/ $\overline{Y}_{PRE}$	–0.032***	–0.049***	–0.056***	–0.038***
	(0.006)	(0.006)	(0.005)	(0.006)
$1\sigma_{WFH}$×(PLD × WFH)/ $\overline{Y}_{PRE}$	–0.035***	–0.052***	–0.050***	–0.040***
	(0.005)	(0.006)	(0.006)	(0.006)
Adjusted R^2	0.465	0.469	0.476	0.485
Observations	479,780	479,780	479,780	479,780

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level, and standard errors are clustered by neighborhood. The dependent variable is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census. Neighbourhood fixed effects are included in all regressions. Baseline control inteeractions are based on interactions between lockdown periods (pre, during, post) and the following neighbourhood-specific variables (all based on pre-lockdown values): proportion of households living in own home, proportion of households living in social housing, proportion of residents welfare benefit claimants in the pre-lockdown period, retail floor space (m^2) in 2019. Data used: Police recorded crime data, 03/2017-12/2022.

We report the DD parameter estimates from Equation (13) in Table 1. The first and second rows report the main coefficients for lockdown and post-lockdown periods (α_1 and α_2 in Equation (13).) In the lower panel of the table we report the pre-lockdown means and the effect of a standard deviation change in work from home potential as a fraction of the pre-pandemic mean.

As a first step, column 1 reports results from a simplified version of Equation (13) in which there are no control variables, and where we only include month × year fixed effects. We can see that in both the lockdown and post-lockdown periods the effect of WFH on crime is negative and substantial. For example, a coefficient of −2.188 (column 1, row 2) implies that a one standard deviation (9.5pp) increase in WFH potential led to a 3.5% drop in burglaries in the post-lockdown period relative to the pre-pandemic mean. In column 2 we also include the interaction of X_n with the lockdown and post-lockdown dummies. The estimated effect is now around 50% larger, and more precisely estimated. In column 3 we allow the month $\times$ year fixed effects to vary by government region.[19] Column 4 reports the estimates of our preferred, and most demanding, specification in which we include police force $\times$ month $\times$ year fixed effects as in Equation (13). The coefficient estimates are now more similar to those in column 1: a one standard deviation increase in WFH potential leads respectively to a 3.8% and 4.0% decline in burglary rates in the lockdown and post-lockdown periods, relative to the pre-pandemic mean. The coefficient estimates are also fairly precise, a 95% confidence interval for the post-lockdown period is between a 2.8% and a 5.2% decrease in burglaries for a one standard deviation change.

In Table B2 we alternatively report results using a binary measure of WFH potential, equal to 1 for neighborhoods with WFH potential above the national average and 0 otherwise. There is a 15.1 percentage point (1.6 standard deviations) difference in average WFH potential between these two groups. The results are very similar to those with a continuous measure, with crime falling by 3.6% and 2.8% in high WFH areas relative to low WFH in the lockdown and post-lockdown periods, respectively.

5.2 Event Study Results

In Table 1 we document a negative impact of WFH potential on burglary which is stable across several specifications. To further understand any variation over time in the extent to which WFH impacts burglary, we use an event study methodology to trace the burglary–WFH relationship over our sample period.[20] The event study estimate is described by Equation (14) in which we modify Equation (13) such that the effects of WFH are allowed to vary by month:

$$\text{crime}_{nt} = \sum_{\substack{t=03/2017,\\ t\neq 02/2020}}^{12/2022} [\alpha_t(Period_t \times WFH_n)] + (LD_t \times X_n^{'}\beta_1) + (PLD_t \times X_n^{'}\beta_2) + \gamma_n + \theta_{A\times t} + \varepsilon_{nt}. \tag{14}$$

where $Period_t$ is a dummy variable equal to 1 in period t and 0 otherwise.

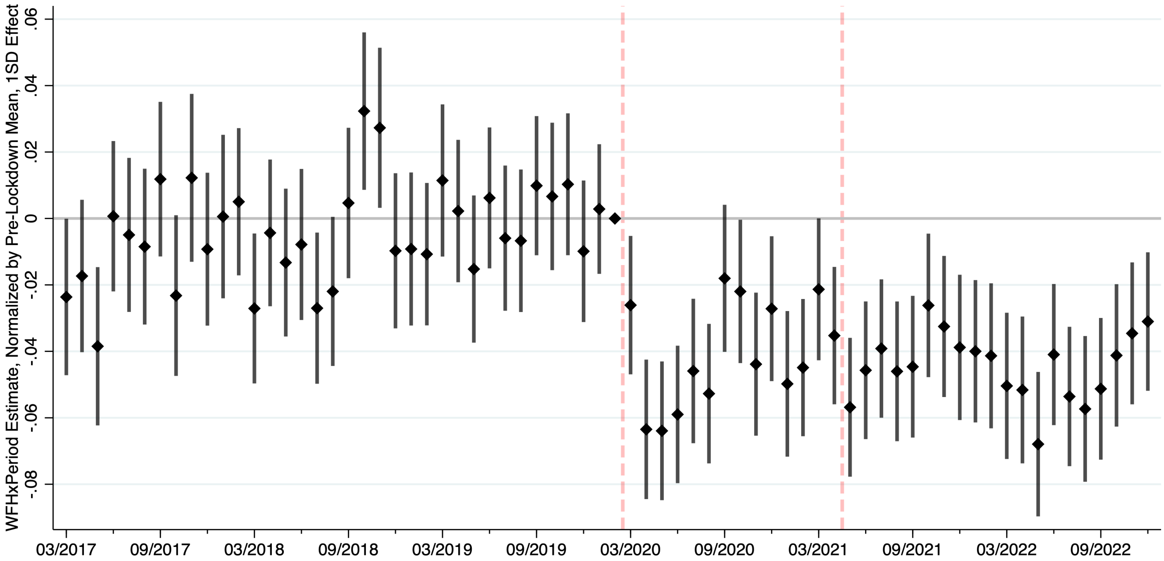
In Figure 3 we present the event study graph; on the y-axis are the coefficients α_t from Equation (14) scaled by the effect of a standard deviation change relative to the pre-pandemic mean (comparable to estimates reported in column 4, row 2 of Table 1). The results are stark. Prior to the first national lockdown we do not observe any systematic correlation between burglaries and remote working. Immediately after the first lockdown, we see a negative and persistent relationship. The point estimates we document indicate that a one standard deviation increase in our WFH measure led to a drop in the post-lockdown burglary rate between 2.6% and 6.8% of the pre-lockdown mean; all of these estimates are statistically different than 0 at the 95% confidence level.

The event study framework has the important benefit of describing visually any differences

[19] These are nine regions in England such as London, or the South-West. Wales is treated as an additional region.

[20] We present the results of the event study approach for other neighborhood crimes in appendix Figure B4.

Figure 3: The Impact of WFH on Burglary



Each point presents the (rescaled) event-study coefficient estimates and 95% point wise confidence intervals of Equation (14). The rescaling factor is $1\sigma_{WFH}/\overline{Y}_{PRE}$, the same rescaling factor we use at the base of Table 1. This enables one to interpret the results as the proportional impact (with respect to baseline crime levels) of a one standard deviation increase in WFH potential. The dashed vertical lines denote the introduction of the UK first national lockdown in March 2020, and the start of the post-lockdown period in May 2021. February 2020 is excluded as the reference month. Standard errors are clustered by neighborhood.

in pre-pandemic trends in burglary crime associated with neighborhood WFH potential. This visual evidence of the absence of any pre-pandemic trend complements the formal statistical tests for pre-trends we present in Appendix A. While there are fluctuations over time in the estimated coefficient these are small relative to the average effect size, and the coefficient is consistently precisely measured and remains significantly different from 0.

A final point to note is the large extent to which our event study estimates mirror the time-series evolution of burglary crime for the country as a whole (burglary is the thick black line in Figure 2). This suggests that WFH plays a first-order effect in driving the aggregate changes we document in burglary crime over time.

5.3 Estimates Across Working and Non-working Hours

Our key explanation for the core findings is that once the British population exited the lockdown period, the nature of work – specifically the persistence of WFH – was markedly different to pre-lockdown patterns. The knock-on effect of this is that residential neighborhoods have fundamentally changed in terms of their levels of activity during working hours, with areas with high WFH potential seeing a large increase in both occupied properties and eyes on the street during the daytime in the week.

For our claim that the decline in burglaries is due to more people working from home to be credible, the post-lockdown period relationship between the large decline in burglary and neighborhood WFH potential, in Table 1 and Figure 3, should be concentrated during working hours (to account for commuting times and the standard British work-day we define working hours as 8:00 a.m.–6:00 p.m.). It is in working hours when the number of people at home has changed (there will have been little if any change at other times) and thus it is in working hours when we expect to observe reductions in crime.

To test this we re-estimate Equation (13) using the restricted Met data. This data allows us to conduct the analysis by the day of the week and the time of day crimes were committed. We are also able to separate residential burglaries from commercial burglaries in these data. We present the results of this exercise for residential burglary in Table 2. The results are quite striking; our main results appear to be driven by a large decrease in residential burglaries taking place early in the day, on weekdays between 8:00 a.m. and 11:59 a.m. A London neighborhood in which WFH potential is one standard-deviation (9.5pp) higher sees a 3.3% and 5.7% decrease in daytime burglaries during lockdown and post-lockdown period, respectively. We do not observe statistically significant, nor economically large, changes during weekdays outside these hours or on weekends.

Table 2: DD Estimates by Time and Day – Residential Burglary (London)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Working Hours			**Non-Working Hours**			
	All	Weekdays, 8:00am-5:59pm	Weekdays, 8:00am-11:59am	Weekdays, 12:00pm-5:59pm	Weekdays, Outside of 8:00am-5:59pm	Weekdays, 0:00am-7:59am	Weekdays, 6:00pm-11:59pm	Weekend
LD × WFH	0.304	–0.745***	–1.130***	0.385**	0.448*	–0.105	0.553***	0.600***
	(0.529)	(0.234)	(0.135)	(0.150)	(0.253)	(0.156)	(0.155)	(0.186)
PLD × WFH	–1.606***	–1.269***	–1.267***	–0.002	–0.280	–0.198	–0.082	–0.058
	(0.523)	(0.245)	(0.131)	(0.155)	(0.235)	(0.144)	(0.140)	(0.159)
$\overline{Y}_{PRE}$	5.710	2.192	0.933	1.259	2.123	1.002	1.121	1.395
Adjusted R^2	0.307	0.214	0.136	0.135	0.154	0.094	0.103	0.128
Observations	68,740	68,740	68,740	68,740	68,740	68,740	68,740	68,740

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level. The dependent variable is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census. Neighbourhood fixed effects are included in all regressions, as are Year-by-Month fixed effects. In addition we control for interactions between lockdown periods (pre, during, post) and the following neighbourhood-specific variables (all based on pre-lockdown values): proportion of households living in own home, proportion of households living in social housing, proportion of residents welfare benefit claimants in the pre-lockdown period, retail floor space (m^2) in 2019. Data used: Met Police recorded crime data, 03/2017-12/2022

Interestingly, during the lockdown period there is evidence of an increase in burglary outside working hours. However, this does not persist in the post-lockdown period. One interpretation of this is that it reflects experimentation as burglars learn the new expected payoffs in high-WFH neighborhoods.[21]

We further stratify our time of day estimates by day of the week, testing for heterogeneity across the working week; the estimated coefficients are reported in Appendix Figure B2. Coefficient estimates are highly stable by time and day of the week, with the effects being entirely

[21] The initial lockdown period, when home occupancy rates were highest, was likely to be difficult for many burglars since the availability of targets was lower but legitimate and criminal outside options were also very limited and many suffer with substance abuse problems (Sanders et al., 2017).

concentrated between 8:00 and 12:00 during the working week. In the post-lockdown period, estimates for all other times of the day are small in magnitude and not statistically different than 0.

Finally, we also use the Met data to look at WFH and commercial burglary, reported in Table B3 in the Appendix. These results are consistent with an eyes-on-the-street effect. WFH led to reductions in commercial burglary at all times of day during lockdown, and in both neighborhoods with large and small amounts of commercial floor space. Post lockdown, the result is only statistically significant in areas with relatively little commercial floor space, perhaps reflecting additional eyes on the street in the kind of mixed-use neighborhoods Jacobs (1961) advocated for.

5.4 Robustness of Main Results

We now present four sets of robustness exercises.

We start by noting that our measure of working from home at the neighborhood level is based only on workers. What about neighborhoods with many non-working households – be these retired couples, or unemployed households? Are we making systematic errors in assigning the WFH potential status of these neighborhoods? We address this point directly, by making several adjustments to our WFH potential measure. We rescale our measure based on (i) the proportion of working age individuals in the neighborhood, (ii) the proportion of prime working age individuals in the neighborhood, (iii) the proportion of employed individuals in the neighborhood, and (iv) the proportion of employed or self-employed individuals in the neighborhood. We present the resulting estimates in Appendix Table B6. The estimates are extremely similar to our baseline DD estimates, and if anything, suggest our baseline specification is conservative in terms of the estimated impact of WFH on burglary rates.

A related concern is whether our WFH potential measure, constructed from 2011 Census occupational data, accurately captures realized post-pandemic WFH. We have already shown in Figure 1a that it does. We return to this question formally in Section 6.2, where we instrument realized 2021 home occupancy with WFH potential and recover a structural estimate of the effect of h_n on burglary that is qualitatively identical to the baseline DD.

Next, we investigate concerns that changes in burglary due to working from home may be highly unevenly distributed within a neighborhood. We use street-level information on crime incidence and construct a variety of time-varying measures to capture the extent to which crime is concentrated in specific street segments within the neighborhood. The concentration measures we use – further detailed in Appendix Section B.11 – are based on the latest methods to estimate crime concentration (Bernasco and Steenbeek, 2017; Chalfin et al., 2021). With these measures in hand, we examine whether there were any systematic changes in the within-neighborhood distribution of burglaries with WFH in the lockdown and post-lockdown periods. As one can see in Table B9, we find no evidence that the shift to remote work led to distributional changes of burglaries within neighborhoods. This suggests that the work from home rates of a neighborhood exert a protective effect on the entire neighborhood, implying a reduction in the crime experienced by all residents. Not only does this imply that our choice of spatial unit is capturing the key variation on crime changes over the period of interest, we can regard the between-neighborhood changes in burglary due to WFH as a sufficient statistic for overall changes in burglary which simplifies the interpretation of our other analyses.

As a final robustness check, we examine the linearity that the DD specification in Equation (13) imposes on the WFH–burglary relationship. We do this with a doubly residualized local polynomial regression in both the lockdown and post-lockdown periods, reported in Appendix Figure B3. The relationship is approximately linear through the lower and middle portions of the WFH distribution, where the bulk of the data lie. There is some steepening in the upper tail, where the data are sparser; if anything, this implies the linear DD is conservative for the highest-WFH neighborhoods. We conclude that the linear specification in Equation (13) is an appropriate approximation.

5.5 Other Neighborhood Crimes

Our focus on burglary throughout the paper has been motivated by a simple observation: the target of a burglary is the home, and homes do not move. The WFH-induced reallocation of the working population to residential neighborhoods during the working day therefore changes the daytime occupancy of the very locations that burglars target, in a way that is not true for crimes whose targets are mobile. We now ask whether the burglary effect documented above is specific to burglary, or whether WFH reduces neighborhood crime more broadly.

We address this by re-estimating Equation (13) for vehicle crime, theft, robbery, and a neighborhood crime aggregate that combines the four. The four outcomes span both property crime (vehicle, theft) and violent crime (robbery), and together comprise the standard components of a neighborhood crime index. Vehicle crime is a particularly natural comparison: cars are mobile, but the overwhelming majority of vehicle crime takes place at the residence (79% in 2018–2019, against just 5% at places of work; ONS 2025), so the same residential daytime occupancy that affects burglary should affect vehicle crime as well. Theft and robbery, by contrast, target people rather than fixed locations, so the relevance of WFH for these crimes depends on how much of the activity takes place in residential neighborhoods, where the WFH-induced increase in eyes on the street is concentrated.

Table 3 reports the DD estimates. All four outcomes show a statistically significant decrease in both the lockdown and post-lockdown periods. Two patterns stand out. First, the lockdown effect is much larger than the post-lockdown effect for theft (3.6 times) and robbery (2.3 times), but not for vehicle crime, which shows a similar magnitude in both periods (-4.5% vs -3.7% per standard deviation of WFH potential). Second, the post-lockdown effect on vehicle crime is close in magnitude to that on burglary (-3.7% vs -4.0%), while the post-lockdown effects on theft and robbery are smaller and reflect the partial recovery of these crimes toward pre-pandemic levels by the end of our sample (see Figure 2).

The dynamic patterns underlying these averages, presented in Appendix Figure B4, are consistent with this reading. Vehicle crime, like burglary, has its target predominantly at the residence, and shows a sustained relationship with WFH throughout the post-lockdown period. Theft and robbery target people rather than locations, so the strength of the measured

Table 3: DD Estimates for Other Neighborhood Crime

	(1)	(2)	(3)	(4)
	Vehicle	Theft	Robbery	Neighborhood Crime
LD × WFH	–3.123***	–17.016***	–1.445***	–23.942***
	(0.547)	(2.195)	(0.259)	(2.710)
PLD × WFH	–2.572***	–4.714***	–0.612***	–10.373***
	(0.510)	(1.308)	(0.201)	(1.648)
$\overline{Y}_{PRE}$	6.564	4.790	1.150	18.427
$1\sigma_{WFH}\times$(LD × WFH)/ $\overline{Y}_{PRE}$	–0.045***	–0.338***	–0.119***	–0.124***
	(0.008)	(0.044)	(0.021)	(0.014)
$1\sigma_{WFH}\times$(PLD × WFH)/ $\overline{Y}_{PRE}$	–0.037***	–0.094***	–0.051***	–0.054***
	(0.007)	(0.026)	(0.017)	(0.009)
Adjusted R^2	0.569	0.793	0.673	0.820
Observations	479,780	479,780	479,780	479,780

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level. The dependent variable is the crime rate per 10,000 inhabitants. Neighborhood crime is an aggregation of those offenses commonly used in neighborhood crime indexes – burglary, vehicle crime, theft, and robbery. Data is weighted by the population count at the 2011 Census. Neighbourhood fixed effects are included in all regressions, as are Police-Force-Area-by-Year-by-Month fixed effects. In addition we control for interactions between lockdown periods (pre, during, post) and the following neighbourhood-specific variables (all based on pre-lockdown values): proportion of households living in own home, proportion of households living in social housing, proportion of residents welfare benefit claimants in the pre-lockdown period, retail floor space (m^2) in 2019. Core Sample: 03/2017-12/2022. Restricted Sample: 01/2019-12/2022.

WFH effect on these crimes depends on where they are taking place. During lockdown, with urban centers largely shuttered, a larger share of theft and robbery took place in residential neighborhoods, where the WFH-induced rise in daytime occupancy had the most scope to deter them. As urban activity recovered, these crimes moved back to the commercial areas where they are usually committed, and the WFH–crime relationship weakened.

6 From WFH to Home Occupancy

Our baseline specification in Equation (13) estimates the reduced-form effect of WFH potential on burglary. However, WFH is one of several shocks to neighborhood daytime population – a central object in recent work on the spatial reorganization of cities under remote work (Ramani et al., 2024) – alongside population aging, retirement, unemployment, gentrification, and changing vacation patterns. The model in Section 2 takes the underlying object, h_n, as its primitive. In this section we present two complementary estimates of the effect of h_n on burglary. Section 6.1 reports a reduced-form exercise using pre-period commuting intensity as an alternative, predetermined measure of the scope for h_n to rise. Section 6.2 reports an IV–DD that instruments realized 2021 home occupancy with WFH potential.

6.1 Pre-Period Commuting and the Occupancy Shock

The WFH shock can only raise h_n in neighborhoods where residents had previously been leaving during the working day. Where pre-period commuting was already low, WFH potential has little scope to shift realized home occupancy; where pre-period commuting was high, the scope is large. A direct test of whether it is the variation in h_n that drives the burglary result therefore compares neighborhoods on the basis of their pre-period distance from the $h_n = 1$ ceiling, using a predetermined measure independent of WFH potential itself.

We estimate four DD specifications on the subsample of London neighborhoods served by a Tube station, reported in Table 4. All specifications use the same fixed-effects structure and $X_n \times$ period controls as Equation (13). The dependent variable is the burglary rate per 10,000 inhabitants, except in Column 1 where it is per-resident Tube journeys.

Table 4: Burglary, Tube Journeys, and WFH

	(1)	(2)	(3)	(4)
	Journeys	Burglary Rate	Burglary Rate	Burglary Rate
LD × WFH	–3.304***	–2.476		
	(1.020)	(1.544)		
PLD × WFH	–1.955***	–3.035**		
	(0.545)	(1.511)		
LD × Journeys_0			–0.500**	0.113
			(0.201)	(0.117)
PLD × Journeys_0			–0.304**	0.220
			(0.145)	(0.143)
LD × Journeys_0 × $\mathbb{1}$[WFH=High]				–0.776***
				(0.223)
PLD × Journeys_0 × $\mathbb{1}$[WFH=High]				–0.661***
				(0.200)
$\overline{Y}_{PRE}$	2.031	10.144	10.144	10.144
Adjusted R^2	0.849	0.624	0.629	0.632
Observations	13,864	13,864	13,864	13,864

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level. The dependent variable in column 1 is per capita tube journeys as measured by entry gate tap-ins, and in columns 2-4 is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census. Neighbourhood fixed effects are included in all regressions, as are Police-Force-Area-by-Year-by-Month fixed effects. In addition we control for interactions between lockdown periods (pre, during, post) and the following neighbourhood-specific variables (all based on pre-lockdown values): proportion of households living in own home, proportion of households living in social housing, proportion of residents welfare benefit claimants in the pre-lockdown period, retail floor space (m^2) in 2019.

Column 1 formalizes the Tube event study from Figure 1b as a DD, and Column 2 reports the baseline burglary DD on the Tube subsample, confirming that the main result of the paper holds in this restricted sample.

Column 3 replaces WFH potential with Journeys_0, defined as per-resident London Underground entry tap-ins in the pre-lockdown period. Journeys_0 is predetermined, is built from turnstile counts rather than occupational composition, and directly measures how many residents were leaving the neighborhood during the working day before the pandemic. It is therefore a direct measure of the pre-period gap between realized home occupancy and the $h_n = 1$ ceiling – that is, of the scope for any shock to raise h_n in neighborhood n. The post-lockdown coefficient on $\text{PLD}_t \times \text{Journeys}_0$ is -0.304 (s.e. 0.145), significant at the 5% level, with a similarly signed and significant estimate for the lockdown period. Neighborhoods with more room for h_n to rise saw larger post-lockdown burglary reductions, using a predetermined measure constructed independently of WFH potential.

Commuting intensity measures the scope for occupancy to rise. WFH potential determines whether it does. Column 4 tests whether the burglary reduction is concentrated where both hold. We interact Journeys_0 with an indicator for above-median WFH potential. The triple interaction $\text{PLD}_t \times \text{Journeys}_0 \times \mathbf{1}[WFH_n = High]$ is -0.661 (s.e. 0.200), while the main $\text{PLD}_t \times$

Journeys$_0$ effect in the low-WFH cell is positive and insignificant, indicating that the Column 3 result is driven entirely by the high-WFH subsample. Pre-period scope for h_n to rise predicts lower post-lockdown burglary only in neighborhoods where the WFH shock could draw on that scope and convert it into realized daytime home occupancy. From this exercise, we conclude that the reduced-form burglary response to WFH potential is a reduced-form response to WFH-induced variation in h_n.

6.2 IV–DD Estimates of the Effect of Home Occupancy

We now turn to recovering the effect of h_n on burglary as a structural parameter. Two issues stand in the way: h_n is not directly observed, and even if it were, it is endogenous with respect to crime – families with young children, stay-at-home parents, or recent retirees may systematically sort into low-crime neighborhoods. We address both with an IV–DD strategy in which we instrument the 2021 Census measure of the proportion of workers who were working from home in the first quarter of 2021 with predetermined WFH potential.[22]

The resulting estimates are reported in Appendix Table B7. The first stage is very strong: the Sanderson–Windmeijer F-Statistic in our preferred specification (column 4) exceeds 19,000, and the first-stage coefficient is 1.146, implying that a one percentage point increase in WFH potential is associated with a 1.146 percentage point increase in realized WFH in the 2021 Census. The second-stage estimates (column 4) are -1.970 for the lockdown period and -2.074 for the post-lockdown period. These estimates have a direct structural interpretation under the model of Section 2: they are the causal effect of a unit change in realized home occupancy on the burglary rate per 10,000 residents, along the margin induced by variation in WFH potential. The post-lockdown estimate implies that a ten percentage point increase in home occupancy leads to a reduction of approximately 3.5% of the pre-pandemic mean burglary rate; the lockdown estimate is of similar magnitude.[23]

Two features of the exercises in this section are worth emphasizing. First, both channels through which h_n affects burglary in the model – the opportunity channel operating through $\phi(h_n)$ and the eyes-on-the-street channel operating through $\pi(h_n)$ – depend on h_n itself, not on the source of the shock that changed it. The qualitative prediction that raising daytime home occupancy reduces burglary therefore applies to any shock that raises h_n, whether through WFH, retirement, or other compositional changes to the resident population. Second, the IV–DD estimate is identified off the working-age remote workers whose home occupancy was shifted by WFH potential, and the magnitude need not carry over to populations whose occupancy rises through other channels, such as retirement or unemployment. What the estimate provides is a benchmark magnitude: the post-lockdown reduction in burglary due to a one percentage point rise in daytime home occupancy, estimated on the population of working-age remote workers.

[22] We provide a full description of this measure in Appendix Section B.10.1.

[23] These 2SLS estimates are highly consistent with the reduced-form DD estimates. The ratio of the reduced-form DD estimate (column 4, Table 1) to the first-stage is, for the post-lockdown period, $-2.475/1.146 = -2.16$, very close to the reported 2SLS coefficient of -2.074.

7 Mechanisms

The preceding section established that the reduced-form WFH effect can be read as an effect of home occupancy, h_n. The model in Section 2 predicts that h_n affects burglary through two channels: an opportunity effect, which operates through the number of vulnerable homes, and an eyes-on-the-street effect, which operates through the probability of being seen. In this section we ask which channel is active in the data. Corresponding figures and tables are in Appendix Section B.6.

We want to distinguish between these two channels through which an increase in WFH will affect burglaries. There is evidence from the criminology literature that both of these effects are important in the criminal decision making process. In studies based on interviews, often including photos of houses as a reference for subjects, with professional burglars, the three most important factors when deciding to burgle a home are the degree of cover available, the occupancy of a home, and the availability of escape routes (Nee and Meenaghan, 2006). Occupancy is often checked by knocking on the door, looking for lights, and checking for cars on the driveway or milk on the doorstep. Surprisingly, security features including alarms and dogs were not seen as deterrents for most of the burglars interviewed. These features highlight the importance of our two channels, burglars actively try to avoid homes that are currently occupied, and burglars actively try to avoid being seen.

These two effects are closely related to, and may be understood in terms of, a key criminological theory of crime, Routine Activity Theory (Cohen and Felson, 1979). This states that for a crime to occur, the coincidence of the following three elements is required: (i) a motivated offender, (ii) a suitable target, and (iii) the absence of a capable guardian. A guardian may be active (a police officer, a security guard) or passive (a local resident looking out the window or walking their dog). What we term the opportunity effect of WFH is a change in the number of suitable targets, while the eyes-on-the-street effect is a change in the number of capable guardians.

As a way of exploring the evidence of the eyes-on-the-street effect, we focus on variation in the data that will affect the magnitude of the eyes-on-the-street effect but not the opportunity effect.

First, we exploit the fact that the eyes-on-the-street effect will be less powerful when it is dark, as residents will not be easily able to see what is happening on the street. We test this by exploiting changes in sunrise and sunset each day over the year. We extend Equation (13) to allow the effect of WFH to vary by whether it is light at a given time. We use the precise time and date information available in the Met data for London combined with daylight information from the official Civil Twilight time for each day of the year. We find that the effect of WFH potential on burglaries during the early morning and late afternoon is only negative and significant during daylight hours (see Table B4). For example, when it's light in the morning a one standard-deviation (9.5pp) greater WFH potential reduces the post-lockdown burglary rate by -0.028 in those hours. Further, as with the analysis in Section 5.3, we do not observe the same pattern during weekends (perhaps with the exception of post-lockdown Sunday evenings). These results provide further evidence that the eyes-on-the-street effect is an important channel through which WFH reduces crime.

As a second strategy, we exploit cross-sectional variation in neighborhood housing structure that affects the scope for each mechanism to operate. Two features of the built environment are relevant. First, houses on a street afford better overlook than apartment blocks, strengthening the eyes-on-the-street channel: a burglar approaching a house-lined street is more exposed to observation than one approaching an apartment block, where common entrances, corridors, and limited sight-lines from upper floors provide cover. Second, driveway parking – driveways, garages, and carports – provides burglars with a visible cue for assessing whether a home is occupied. A car in the driveway signals someone is home; properties without such parking lack this signal, attenuating the *detectability* of occupancy (Nee and Meenaghan, 2006). WFH raises physical occupancy in all property types; what varies across these categories is the extent to which the two channels can influence burglar behavior.

With this in mind, we classify neighborhoods into three groups based on the modal dwelling type and the prevalence of driveway parking: (i) apartment-dominated neighborhoods, where both overlook and parking-based occupancy cues are limited; (ii) house-dominated neighborhoods without prevalent driveway parking, where overlook is strong but occupancy is harder for a burglar to scout; and (iii) house-dominated neighborhoods with prevalent driveway parking, where both overlook and occupancy cues are strong. We classify using administrative data on housing composition and property-listing data on parking availability from the property-listing site Zoopla.[24]

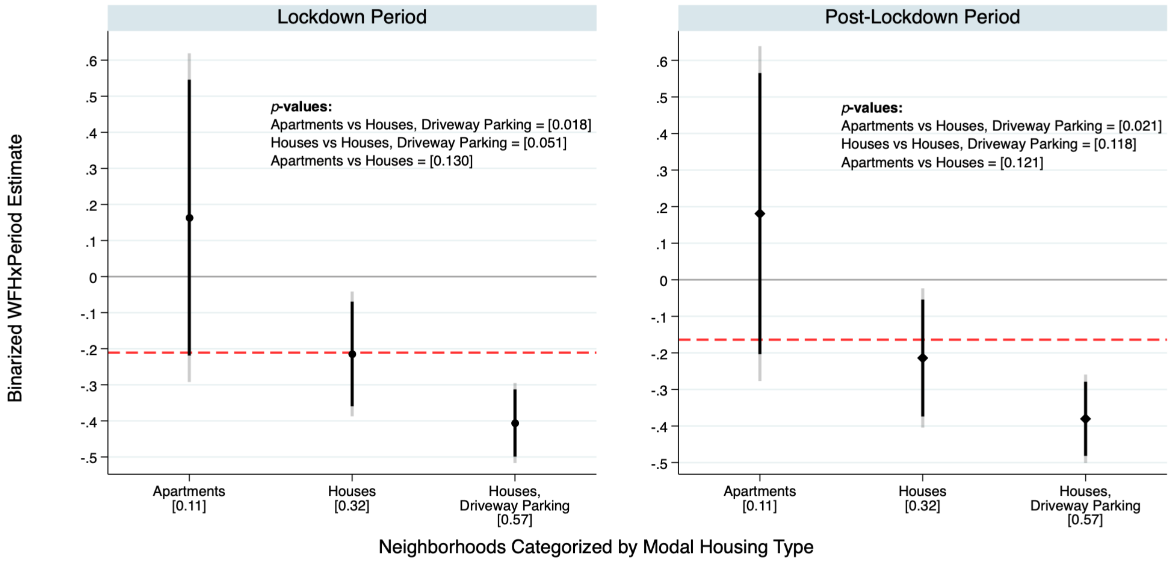
We estimate a triple-difference variant of Equation (13) in which the binarized WFH×period interaction is further interacted with the three housing-type groups, and the control variables are allowed to vary by period×group cell. The resulting estimates are reported in Figure 4. The treatment effect is smallest in apartment-dominated neighborhoods, larger in house-dominated neighborhoods without driveway parking, and largest in house-dominated neighborhoods with driveway parking. The dashed line marks the unconditional binarized DD estimate. This monotonic gradient – strengthening as first overlook and then occupancy cues are present – corroborates the veil-of-darkness evidence that the eyes-on-the-street channel is quantitatively important, while also indicating that the occupancy channel plays an additional role where it is detectable by burglars.

Ruling out Differential Police Effort A final concern is that what we have so far attributed to occupancy and eyes on the street could instead reflect a differential change in police effort in high-WFH neighborhoods. We test this using monthly clearance rates at the neighborhood level. Re-estimating Equation 13 with clearance rates as the dependent variable, we find no economically or statistically significant change in clearance rates for any property crime in the post-lockdown period, and no change during the lockdown period with the exception of theft (Table B5).

In interpreting this null, it is important to be clear about how clearance rates map onto the probability of being seen π_n in the model of Section 2. The model decomposes π_n into two components: a base level π_{n0} arising from police, private security, and other non-residential

[24]We describe the construction of this categorical variable in Appendix Section B.7.

Figure 4: WFH Treatment Effect by Neighborhood Housing Type



Notes: Each point reports the binarized WFH×period coefficient for the indicated neighborhood housing type, from the triple-difference specification described in the text (see Appendix B.7 for the formal specification). *Apartments* denotes apartment-dominated neighborhoods; *Houses* denotes house-dominated neighborhoods with below-median prevalence of driveway parking; *Houses, Driveway Parking* denotes house-dominated neighborhoods with above-median prevalence. The plotted coefficient for apartments is the base WFH×period effect; for the other two groups it is the base effect plus the group-specific increment. The dashed red line marks the unconditional binarized DD estimate. Neighborhood shares in brackets. The regression includes neighborhood fixed effects, PFA×month×year fixed effects, and period×group-specific controls (homeownership rate, social housing share, welfare claimant rate, retail floor space). Standard errors clustered by neighborhood.

monitoring, and a multiplicative term in h_n that captures informal monitoring by residents who are at home. The eyes-on-the-street channel operates entirely through the second component – it is informal, not formal, monitoring that rises with WFH. Clearance rates, by contrast, measure formal police outcomes and therefore map onto π_{n0}. They are not a measurement of the eyes-on-the-street component by construction.

What the clearance-rate null does establish is that π_{n0} – the formal-monitoring component – did not shift differentially across high- and low-WFH neighborhoods. Under the alternative in which our results reflect differential police effort or resourcing, π_{n0} would be higher in high-WFH neighborhoods and realized clearance rates would rise accordingly. We observe no such pattern.[25] We interpret this as evidence against a systematic change in police effort by WFH potential. The null is silent on the eyes-on-the-street component itself, which clearance rates are not designed to capture. That component is identified by the veil-of-darkness and modal-housing evidence above.

Together, the veil-of-darkness estimates identify the eyes-on-the-street channel directly, the modal-housing gradient is consistent with both occupancy and eyes-on-the-street channels operating, and the clearance-rate null rules out differential formal police effort as an alternative explanation.

[25]For the alternative to survive, the rise in police effort would have to be offset by deterrence falling disproportionately on the more clearable burglaries, leaving a residual pool that is harder to clear.

8 Displacement of Crime Across Space

In this section we explore the potential for burglary spillovers between neighborhoods and what this means for the estimates we presented in the previous section. The theoretical framework outlined in Section 2 suggests that the observed change in burglary due to WFH will reflect both an overall reduction in the number of burglaries but also a possible change in the distribution of search activity across neighborhoods. Specifically, the model suggests that criminals may shift their activities away from neighborhoods which experience a large WFH increase. However, the extent to which this happens will depend on how substitutable are different neighborhoods. For example, if distance is an important consideration for burglars, this may result in little or no displacement across neighborhoods.

Here we extend our baseline estimating equation to quantify these spatial spillovers. To do so we assume that the crime rate in a neighborhood n depends on the rate of WFH in neighborhoods contiguous to n, and not others. Of course, in principle, crime in any one neighborhood may be affected by spillovers from any of the other 7,200 neighborhoods. However, in reality most spillovers will be local. Kirchmaier et al. (2024) find that the costs of "commuting" for criminals are very high in the UK, with most burglaries happening within a five-minute car journey of the perpetrator's home. This suggests our assumption is not, in practice, a strong one.

To ease the interpretation of our results, we will focus on a binary measure of WFH. We define WFH_n^H to be a binary variable equal to one if neighborhood n has a WFH potential above the median value for all neighborhoods. Analogously, we also define a binary variable $NWFH_n^H$ which is equal to one if a share τ or more of the neighborhoods contiguous to n – defined as any neighborhood which shares a border with n – have a WFH potential above the median value for all neighborhoods. Our baseline sets $\tau = 0.5$, so $NWFH_n^H$ takes a value of 1 if most of n's neighbors are high WFH areas; we vary τ in the results that follow. With these variables, we estimate the following equation:

$$\begin{aligned}\text{crime}_{nt} =& \alpha_1(LD_t \times WFH_n^H) + \alpha_2(LD_t \times NWFH_n^H) + \alpha_3(LD_t \times WFH_n^H \times NWFH_n^H) \\ &+ \beta_1(PLD_t \times WFH_n^H) + \beta_2(PLD_t \times NWFH_n^H) + \beta_3(PLD_t \times WFH_n^H \times NWFH_n^H) \\ &+ \delta_1(LD_t \times X_n) + \delta_2(PLD_t \times X_n) + \gamma_n + \theta_{A\times t} + \varepsilon_{nt}.\end{aligned} \tag{15}$$

Under the specification in Equation (15) the parameters α_1 and β_1 will have the interpretation of the change in crime for high, versus low, WFH neighborhoods relative to pre-pandemic crime. Our new coefficients of interest capture the impact of having high, as opposed to low, WFH in contiguous neighborhoods. The parameters α_2 and β_2 capture this effect for neighborhoods with levels of WFH below the national average. Finally, α_3 and β_3 describe the effect of being a neighborhood with high remote working relative to the national average, as well as having neighbors with high levels of WFH.

We use five different definitions of $NWFH_n^H$: (1) more than 50% of n's contiguous neighborhoods are above the national median (our baseline measure); (2) 25% or more of n's contiguous neighborhoods are above the national median; (3) 40% or more of n's contiguous neighborhoods are above the national median; (4) 60% or more of n's contiguous neighborhoods are above the national median; and (5) 75% or more of n's contiguous neighborhoods are above the national median. Definitions (2)–(5) progressively require a stricter threshold for the definition of $NWFH_n^H$.

8.1 Spatial Displacement Results

In Table 5 we report estimates for a baseline no-spillovers equation (column 1) and for the key post-lockdown coefficients from Equation (15), using each of the five definitions of $NWFH_n^H$.[26] For each regression, we report three key parameter estimates from Equation (15).

Table 5: Spatial DDD Model for Burglary

	(1)	(2)	(3)	(4)	(5)	(6)
		DDD: Criterion Used to Define NWFH$^{\mathbf{H}}$				
	Baseline DD Estimates	Most Neighbors are High WFH	25%+ of Neighbors are High WFH	40%+ of Neighbors are High WFH	60%+ of Neighbors are High WFH	75%+ of Neighbors are High WFH
$PLD \times WFH^H$	–0.165***	–0.132	–0.116	–0.145	–0.142*	–0.104
	(0.057)	(0.092)	(0.142)	(0.103)	(0.077)	(0.067)
$PLD \times NWFH^H$		0.124*	–0.095	0.023	0.224**	0.168
		(0.073)	(0.066)	(0.067)	(0.089)	(0.126)
$PLD \times WFH^H \times NWFH^H$		–0.117	–0.017	–0.036	–0.191*	–0.261*
		(0.110)	(0.149)	(0.116)	(0.112)	(0.140)
Total DDD Effect for:						
$PLD \times WFH^H \times NWFH^H$		–0.125*	–0.229***	–0.158**	–0.109*	–0.196***
		(0.066)	(0.073)	(0.067)	(0.065)	(0.068)
p-Value: $PLD \times WFH^H =$ $PLD \times WFH^H \times NWFH^H$		0.937	0.418	0.899	0.645	0.166
p-Value: $PLD \times NWFH^H =$ $PLD \times WFH^H \times NWFH^H$		0.001	0.034	0.010	0.000	0.006
$\overline{Y}_{PRE}$	5.923	5.923	5.923	5.923	5.923	5.923
Adjusted R^2	0.485	0.485	0.485	0.485	0.485	0.485
Observations	479,710	479,710	479,710	479,710	479,710	479,710

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level. The dependent variable is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census. Neighbourhood fixed effects are included in all regressions, as are Police-Force-Area-by-Year-by-Month fixed effects. In addition we control for interactions between lockdown periods (pre, during, post) and the following neighbourhood-specific variables (all based on pre-lockdown values): proportion of households living in own home, proportion of households living in social housing, proportion of residents welfare benefit claimants in the pre-lockdown period, retail floor space (m^2) in 2019. The total DDD effect for $PLD \times WFH^H \times NWFH^H$ is calculated as $PLD \times WFH^H + PLD \times NWFH^H + PLD \times WFH^H \times NWFH^H$. When calculating the p-value, we use the total DDD effect when defining $PLD \times WFH^H \times NWFH^H$. We present the extended set of results for both lockdon and post-lockdown coefficients in Table B10. Data used: Police recorded crime data, 03/2017-12/2022.

We focus on the results using definition (1) reported in column 2. First, β_1, the effect associated with being a high WFH neighborhood and surrounded by neighbors with low WFH ($PLD \times WFH^H$). These neighborhoods enjoy a large drop in burglary incidence in the post-lockdown

[26]Extended results for both the lockdown and post-lockdown period are available in appendix Table B10.

period, -0.132 – a drop qualitatively similar to the baseline DD estimate. Second, β_2, the effect of being low WFH and surrounded by neighbors with high WFH ($PLD \times NWFH^H$). In these neighborhoods we see an increase in burglaries. This is consistent with the presence of spatial spillovers for these neighborhoods. Third, β_3, the effect of being high WFH and surrounded by neighbors who are also high WFH ($PLD \times WFH^H \times NWFH^H$). This effect is negative and effectively offsets the positive coefficient estimate we document for β_2. To gauge the overall effect of WFH on burglary in these neighborhoods, we sum the component effects. For high-WFH neighborhoods that are surrounded by high WFH neighbors, we document a fall in burglaries (-0.125). This effect is almost identical to that of being high WFH but surrounded by low WFH neighbors. Indeed, the p-value of equality of effects for these two neighborhood types is 0.937. The remaining four columns change the threshold by which we define $NWFH^H$, but the results are substantively unchanged.

So, what do we learn from this analysis? First, for high WFH areas, we do not document any spatial spillovers – high WFH potential leads to a fall in burglaries in the post-lockdown period, irrespective of the WFH potential of one's neighbors. Second, we find notable spillover effects in low WFH neighborhoods. If these areas are surrounded by high WFH neighbors, then burglaries rise in the post-lockdown period. We are able to reject the null of equality of effects for low vs high WFH areas surrounded by high WFH neighbors in all 5 of our DDD specifications at the 5% significance level.

9 The Implied Welfare Gain to Living in a High WFH Area

In this section, we quantify the welfare implications of differences in neighborhoods' ability to work from home, with a specific focus on changes across quartiles of ex-ante burglary risk. The idea is that an increase in WFH should have a bigger impact on welfare in a neighborhood where the pre-pandemic risk of burglary was higher. Conversely, in areas with very little crime ex-ante, WFH has not meaningfully altered the risk of burglary, and thus has not altered welfare substantially through its impact on crime *ceteris paribus*. To quantify these welfare changes, we use the insights of Rosen (1974), and specify a hedonic house price model.[27] Using the estimates from this model, we then are able to compute estimates of the total welfare effects of reductions in burglary risk due to the rise of WFH.

9.1 Empirical Specification

We specify a triple-differences (DDD) house price regression design, where the third difference is across a measure of ex-ante burglary risk in the neighborhood. We allow the hedonic equation to be highly flexible over time and across geography. We specify three levels of geography for this exercise: the *housing market* as a Travel To Work Area (TTWA) – a statistically constructed spatial unit akin to Commuting Zones in the US; the *neighborhood* as a middle super output area as specified in our previous analysis; the *block* as an output area (OA) – the smallest

[27] The hedonic house price model is widely used to quantify the social welfare consequences of neighborhood characteristics, including crime (Gibbons, 2004; Linden and Rockoff, 2008; Adda et al., 2014), schools (Black, 1999; Gibbons and Machin, 2003) and pollution (Davis, 2004; Chay and Greenstone, 2005).

census-based geographical unit similar to census blocks in the US.[28] Each of these three units of geography are nested such that the housing market is made up of neighborhoods which is made up of blocks.

The regression model we estimate is:

$$
\begin{aligned}
price_{hbnmt} = & \sum_{p=1}^{2}\sum_{q=2}^{4} \alpha_{p,q}(Period_t^p \times B_0\, Q_n^q) \\
& + \sum_{p=1}^{2} \beta_{p,1}(Period_t^p \times WFH_n) + \sum_{p=1}^{2}\sum_{q=2}^{4} \beta_{p,q}(Period_t^p \times WFH_n \times B_0\, Q_n^q) \\
& + \sum_{p=1}^{2}\sum_{m=1}^{M}\sum_{q=1}^{4} \delta_{p,mq}(Market_m \times B_0\, Q_n^q \times Period_t^p \times X_h^{'}) \\
& + \sum_{p=1}^{2}\sum_{m=1}^{M}\sum_{q=1}^{4} \lambda_{p,mq}(Market_m \times B_0\, Q_n^q \times Period_t^p \times X_n^{'}) \\
& + \sum_{p=1}^{2}\sum_{q=1}^{4} \kappa_{p,q}(Period_t^p \times C_n^{'}) + \gamma_b + \theta_{m\times t} + \epsilon_{hbmnt} \ , \qquad (16)
\end{aligned}
$$

where $price_{hbnmt}$ is the sale price of house h, located in block b, neighborhood n, and housing market m, sold at time t, where time is measured at the month-year level.[29] $Period_t^p$ is an indicator variable where $Period_t^1$ is equal to 1 in the lockdown period and $Period_t^2$ is equal to 1 in the post-lockdown period. $B_0\, Q_n^q$ is an indicator variable for the ex-ante burglary risk quartile for neighborhood n, measured based on burglary in the pre-lockdown period. Neighborhoods with the lowest burglary risk, $B_0\, Q_n^1 = 1$, serve as the base category for the third difference of our identification strategy. The $\beta_{p,q}$ parameters are our main focus in this exercise.

We include a wide array of controls in this flexible regression. X_h is a vector of property characteristics including dummies for property type and whether the property is leasehold.[30] X_n is a vector of neighborhood characteristics including the (property-based) proportion of home ownership and social housing, the proportion of welfare benefit claimants and the retail space in m^2. Both housing characteristics and neighborhood characteristics are interacted with housing market dummies in order to respect the "law of one price function" (Bishop et al., 2020). This allows the valuation of key property characteristics to vary across housing markets. In addition, we allow the coefficients for these characteristics to vary by the burglary risk quartiles and time periods. This accommodates the possibility that WFH itself shifted the valuation of housing

[28]There are 181,408 output areas in England and Wales, with an average population of 309, at the 2011 census `https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/bulletins/2011censuspopulationandhouseholdestimatesforsmallareasinenglandandwales/2012-11-23`.

[29]Unlike many hedonic house price model specifications, we intentionally do not use a logarithmic transformation of house prices as our dependent variable. Rather we use house price in levels. In recent work, McConnell (2024) shows that coupling a DD-based design with a log-dependent variable specification leads one to estimate not a difference in differences of prices but rather an approximation of the proportional difference in growth rate across areas with different WFH potential.

[30]In English law, a leasehold property, most commonly an apartment, is one in which the ownership of the underlying land is separate to the ownership of the building.

characteristics – for example, by raising willingness to pay for larger properties suitable for a home office – and allows that shift to differ across markets and across burglary-risk quartiles.

We also control for correlation between burglaries and other types of crime. C_n is a vector of additional neighborhood ex-ante crime risk variables, including quartiles of violent crime, drugs crime, and all property crime (except burglary). Given that at the neighborhood-level, burglary crime is correlated with these other dimensions of crime, we do not want to conflate our key WFH parameters with changes in the valuation of other types of crime over time.

Finally, γ_b is a block fixed effect and will capture all time-invariant local amenities – green spaces, transport links, shops, proximity to busy roads or motorways, as well as many slow-moving time-varying area characteristics (we are only considering five years of data for these estimations), such as access to good schools or proximity to polluting factories. $\theta_{m\times t}$ captures month-by-year market-level shocks to house prices. As before, we cluster the error term ϵ_{hbmnt} at the neighborhood level.

Given this flexibility, the regression specification in (16) is, in the nomenclature of Kuminoff et al. (2010), a generalized DDD estimator. As Kuminoff et al. (2010) note: "the generalized DID estimator appears to be the best suited to hedonic estimation in panel data. The interactions between time dummies and housing characteristics control for changes in the shape of the equilibrium price function over time; the spatial fixed effects control for omitted variables in each time period". Further, recent work by Banzhaf (2021) shows that we are able to use a difference-in-differences approach with a hedonic house price model in order to study welfare. Our generalized DDD model thereby enables us to estimate a lower bound on WFH-induced changes to (general equilibrium) welfare (Banzhaf, 2021).

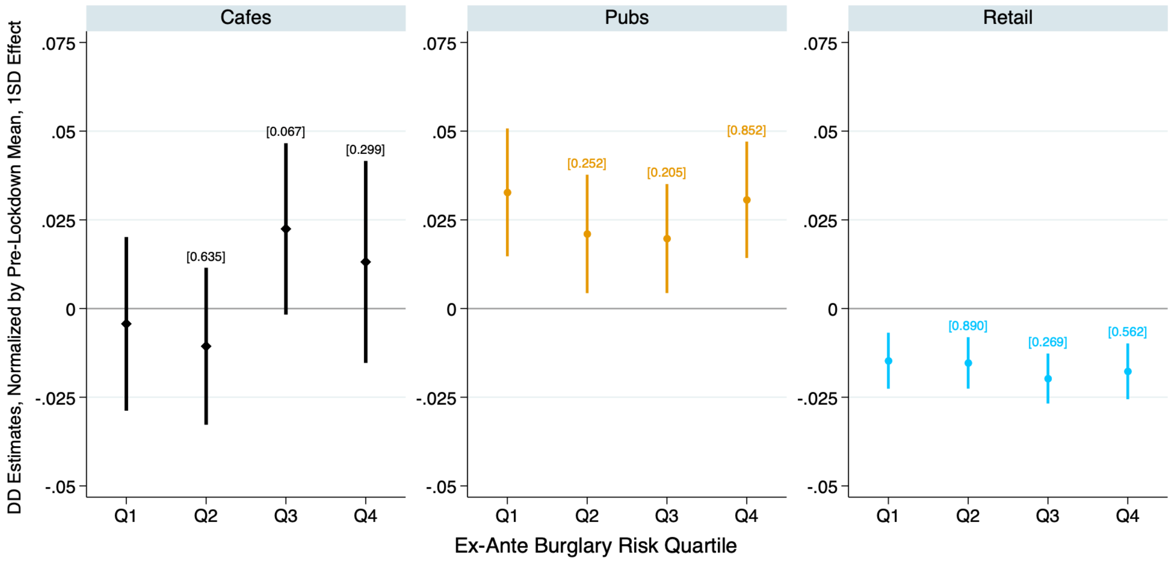
A remaining concern, highlighted by Kuminoff and Pope (2014) and Banzhaf (2021), is conflation bias: the WFH coefficient in Equation (16) may absorb WFH-induced changes in neighborhood valuation that operate through channels other than burglary risk. The leading candidate is the amenity channel – WFH has been shown to reallocate retail and hospitality activity across neighborhoods (De Fraja et al., 2026). The triple difference across ex-ante burglary risk addresses this as long as any such non-crime valuation change is common across burglary-risk quartiles, so that it is differenced out by the contrast between Q1 and Q2–Q4. We test this directly below.

Identification Identification requires that, conditional on the controls in Equation (16), any effect of WFH on house prices operating outside the burglary risk channel is common across ex-ante burglary-risk quartiles. Under this assumption, the contrast between Q1 and Q2–Q4 isolates the burglary risk channel.

To validate our identification strategy, we consider a variety of time-varying, local amenities – cafes, pubs, and retail outlets in the neighborhood – that may plausibly change in response to changing patterns of remote work in our study period. We estimate a DDD variant of Equation (13), where the third difference is across ex-ante burglary risk quartile and the outcome is the number of establishments, and report the post-lockdown estimates in Figure 5. Moving from left to right within each panel, the points depict the total post-lockdown WFH effect in each burglary risk quartile; the p-values above Q2–Q4 are for the DDD increments relative to

Q1. Two points are of note. First, WFH is associated with small, but statistically significant, level changes in some amenities: pubs rise and retail falls across all four quartiles. Second, these effects are uncorrelated with ex-ante burglary risk – the DDD increments are small and statistically indistinguishable from zero in all three panels, so the total effect in each quartile is flat across Q1–Q4. Our hedonic DDD in Equation (16) relies on precisely this pattern: any component of the WFH–price relationship that is common across burglary risk quartiles – including the level shifts in pubs and retail documented here – is netted out by the third difference.

Figure 5: Change in neighborhood amenities, WFH and Ex-Ante Burglary Risk Quartiles



Notes: The figure plots the post-lockdown effect of a one-standard-deviation increase in WFH potential on neighborhood amenity counts, by ex-ante burglary risk quartile, expressed as a fraction of the pre-lockdown mean. Dependent variables are MSOA-quarter counts of cafes, pubs, and retail outlets. Estimates come from a DDD variant of Equation (13), with the inclusion of period interactions with ex-ante quartiles of non-burglary property, violent, and drugs crime. Each point is the total post-lockdown WFH effect in the relevant quartile, computed as the DD coefficient plus the corresponding DDD increment (the Q1 point is the DD coefficient alone). Values in square brackets above Q2–Q4 are p-values on the DDD increments, equivalently tests of whether the post-lockdown WFH effect in that quartile differs from the effect in Q1. Observations are weighted by 2011 MSOA population and standard errors are clustered by MSOA. Vertical bars show 95 percent confidence intervals.

We further test this assumption using London Underground journey data as a proxy for commuting intensity. DDD estimates of the relationship between WFH and Tube journeys by ex-ante burglary risk quartile show no differential reduction in commuting across crime risk quartiles (Appendix Figure B5). Together, these results provide strong support for our identifying assumption: the monotonically increasing relationship between WFH and house prices across burglary risk quartiles that we document in the next section is not driven by differential non-crime benefits of remote work.

Interpretation Our hedonic DDD estimates capture the market premium that buyers pay for a marginal increase in neighborhood WFH potential, over and above what is paid in low-crime neighborhoods. Under our identifying assumption, this premium capitalizes the disutility of burglary risk – not just the expected tangible loss to a burglary victim, but the broader costs of exposure to crime risk, including fear and perceived insecurity. For this reason, hedonic valuations of crime risk are typically much larger than accounting-based cost-of-crime estimates, which capture only the direct costs to actual victims (Gibbons, 2004; Linden and Rockoff, 2008). The estimates we present below are consistent with this pattern.

9.2 Results

In Figure 6 we report estimates of $\beta_{2,q}$ from Equation (16), reflecting the post-lockdown period. Estimates for the lockdown period are broadly similar and are reported in appendix Table B11. The coefficients represent the impact of a standard-deviation increase in WFH as a percentage of the pre-lockdown mean.

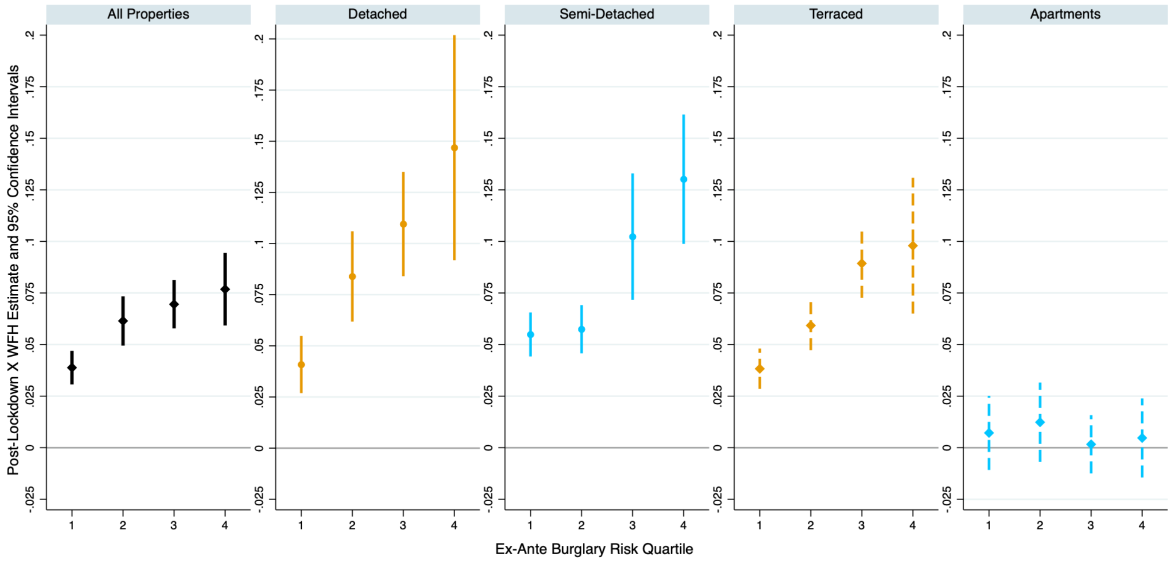
Beginning with the left-most panel, which presents results for all properties, we can make three key inferences. First, we can see that all the estimates are positive, implying that home-owners have a positive willingness to pay to live in a high-WFH potential neighborhood in the post-lockdown period. Second, we document that the willingness to pay to live in a high-WFH potential neighborhood is monotonically increasing in the ex-ante burglary risk of the neighborhood. This is intuitive, given that, *ceteris paribus*, we expect the gains from the shift to working from home to benefit areas with high ex-ante burglary risk. Third, the effects are large: the estimated coefficients imply a 1.3% increase in house prices in the lowest ex-ante burglary risk neighborhoods up to a 4.8% increase in the highest. This implies a causal effect of a one standard deviation higher WFH potential of $\beta_{2,4} - \beta_{2,1} = 4.8\% - 1.3\% = 3.5\%$ in the highest ex-ante burglary risk neighborhoods.

The right four panels report the results of Equation (16) estimated separately for different property types. Interestingly, we see no increase in the value of apartments: this is consistent with the eyes-on-the-street hypothesis. In the case of apartment blocks there is not a street for there to be eyes on in the same way, and burglary is already difficult due to occupancy being hard to assess and a single entrance/exit. A second feature of the estimates is that the difference in coefficient estimates across quartiles is larger for larger properties. The increase in prices, net of the effect for Q1, is from 4.3% in Q2 up to 10.6% in Q4 for detached homes, much larger than the between 2.1% and 5.96% we estimate for terraced houses. Our interpretation of this is that it reflects the greater willingness to pay for lower burglary risk among the purchasers of larger homes, other things being equal. The pattern and magnitude of our findings contribute to the literature documenting the costs of crime, which documents a substantial psychic cost to burglary (Cohen et al., 2004) and a high value that people place on feeling safe in their homes (Manning et al., 2016).

9.3 Aggregate Welfare Effects

To get a sense of the overall change in welfare associated with the reduction in burglary due to WFH, we follow the approach of Adda et al. (2014), using the hedonic house price-derived estimates of the willingness to pay to live in higher WFH areas as inputs into a formula to quantify the welfare change associated with the shift to remote working.

Figure 6: House Prices, WFH and Ex-Ante Burglary Risk Quartiles



Notes: The dependent variable is $price_{hbnmt}$ – the sale price of house h, located in block b, neighborhood n, and housing market m, sold in period t, where periods are measured at the month-year level. Housing markets are defined as Travel To Work Areas. Moving from left to right within each panel, the points depict estimates of how the post-lockdown-by-WFH effect differs by ex-ante burglary risk of the neighborhood, $\beta_{2,1}$–$\beta_{2,4}$ in Equation (16) respectively. The estimates are scaled to represent a one standard deviation increase in WFH as a proportion of the pre-lockdown prices. The vertical lines plot the associated 95% confidence intervals. As in Equation (16) all regression specification include the following as controls: the ex-ante burglary risk quartile for neighborhood; a vector of property characteristics including dummies for property type and whether the property is leasehold; a vector of neighborhood characteristics including the (property-based) proportion of home ownership and social housing; the proportion of welfare benefit claimants and the retail space in m^2; and a vector of additional neighborhood ex-ante crime risk variables, including quartiles of all property crime except burglary, violent crime and drugs crime. The regression model additionally includes month-by-year fixed effects and block fixed effects. Standard errors are clustered by neighborhood. We provide these estimates, and results for the lockdown period, in table format in Table B11.

More specifically, we compute:

$$\text{Welfare}_q = \sum_{p=1}^{2} \sum_{n \in N_q} \sum_{k=1}^{4} \omega_p \, \hat{\beta}_{p,kq} \times \text{WFH}_n \times \overline{\text{Price}}_{0,kn} \times \text{Quantity}_{p,kn} \ , \tag{17}$$

where N_q is the set of neighborhoods in quantile q, $\overline{\text{Price}}_{0,kn}$, is the pre-lockdown average price of property type k in neighborhood n,[31] $\hat{\beta}_{p,kq}$ is the property type-specific DDD parameter estimate from Equation 16,[32] and ω_p is a weighting parameter to combine the estimates from the lockdown and post-lockdown periods in a meaningful way.[33]

There are two ways to compute $Quantity_{p,kn}$. The first, which is extremely conservative, is to base welfare calculations *only* on properties sold post-pandemic period. That is, when scaling up our willingness to pay estimates from individual transactions to a total welfare measure, we only account for the implicit welfare changes of those who bought a property post-pandemic,

[31]In some cases we do not observe a transaction of a particular property type pre-lockdown in a given neighborhood. In this case we, to be as conservative as possible, treat the missing values as 0, thus removing that property-type neighborhood combination from our calculations.

[32]scaled by the pre-pandemic price mean in order to give the parameters a proportional interpretation

[33]$\omega_p \in [0, 1] \ \forall p$ and $\omega_1 + \omega_2 = 1$.

and attribute a zero change to those living in properties that did not change hands in the post-pandemic period. While internally valid, this approach yields very conservative estimates, and can be considered a lower bound on the true welfare gains. The second method, uses the existing stock of private housing in England and Wales as the measure for $\text{Quantity}_{p,kn}$. Implicit in this approach is the assumption that the willingness to pay for WFH of those who buy a property post-pandemic is not systematically different from those who do not.

For the transaction- or flow-based approach to the welfare calculation, we construct the weights ω_p such that the resulting welfare estimates represent the annualized welfare change associated with neighborhood WFH potential. For the stock-based approach, we construct the weights ω_p to account for the different durations of time in the lockdown (15 months) and post-lockdown periods (19 months).[34]

The results are reported in Table 6. As before, we focus on the effects in quartiles 2 to 4 net of the effect in quartile 1. The welfare gains are large. Both measures capitalize the willingness-to-pay estimates into a stock value, while differing in coverage. The transaction-based measure capitalizes the premium only on properties sold in the post-pandemic period. Scaled to the annual rate of post-pandemic transactions, this measure yields a welfare gain of £24.5billion, just over 1% of annual GDP for England and Wales, or £1,000 per household.[35] The stock-based measure applies the same per-property premium to the full housing stock. The resulting £873.9billion is the capitalized welfare gain if households who did not sell their home in the post-pandemic period hold the same willingness-to-pay as those who did.[36] The transaction-based figure is our headline measure. The stock-based figure illustrates the order of magnitude under full coverage.

Table 6: Total Post-Pandemic Welfare Change (Expressed in £Billions)

	(1)	(2)	(3)	(4)
	Ex-Ante Burglary Risk Quartile-Specific Welfare Estimates			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Transactions-Based	5.5	10.1	12.8	18.1
	[3.2, 7.8]	[6.4, 13.9]	[7.0, 18.7]	[8.8, 27.4]
Housing Stock-Based	170.3	310.8	422.0	652.0
	[103.4, 237.3]	[203.1, 418.6]	[247.4, 596.7]	[322.8, 981.1]

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. 95% confidence intervals, based on standard errors clustered at neighborhood level, are in brackets. The transaction-based estimates are annualized, so that the figures represent the annual welfare change in the post-pandemic period. The stock-based estimates cannot be annualized, but the welfare change estimates from the lockdown and post-lockdown periods are weighted proportionally according to the time duration of the two periods (15 and 19 months respectively).

There are two implications of such large estimates. First, they imply that the improvement in welfare associated with reductions in burglary due to WFH is extremely large and as such one

[34] $\omega_1 = 15/34$ and $\omega_2 = 19/34$.
[35] Calculated from Table 6 as $18.1 + 12.8 + 10.1 - (3 \times 5.5) = £24.5$billion.
[36] Calculated from Table 6 as $652.0 + 422.0 + 310.8 - (3 \times 170.3) = £873.9$billion.

of the most important consequences of the rise of WFH. Second, the welfare effects of burglary captured by our hedonic estimates are substantially larger than conventional accounting-based estimates such as Heeks et al. (2018) would suggest, reflecting the different approach taken in Heeks et al. (2018).[37] Notably, our estimates are closest to those of Gibbons (2004) who finds that one standard-deviation reduction in the density of criminal damage is associated with a 10% increase in house prices.

10 Conclusion

The post-pandemic rise of working from home generated plausibly the largest shock to daytime residential occupancy in the post-war labor market. Residential burglary in England and Wales is roughly a third below its pre-pandemic level three years on, a fall that began with the first lockdown and has not reversed. The fall is concentrated where WFH was feasible, occurs during weekday working hours, and runs through residents' daytime presence rather than through any change in formal policing. Capitalized into house prices using a hedonic model, the welfare gain from this reduction in burglary is on the order of one percent of GDP – a magnitude that places the fall in burglary among the most important consequences of the WFH revolution, and one that the literature on the spatial reorganization of cities under remote work has not previously priced.

Two implications follow from our findings. The first is for the economics of deterrence. The literature has identified deterrence with formal monitoring – police, private security, anti-theft technology – or with organized substitutes at concentrated targets. Our results identify a different kind of deterrent: the incidental presence of residents at home for unrelated reasons. What matters is daytime home occupancy, h_n, not the source of the shock that raises it; the same logic applies to population aging, retirement, gentrification, and any persistence of remote work. The second implication follows from the first. A growing literature documents the spatial reorganization of cities under remote work, and prices the resulting changes in commute time, real estate, and consumption agglomeration (Althoff et al., 2022; Delventhal et al., 2022; Ramani et al., 2024). The welfare estimate above is of comparable order to the magnitudes in that literature, and is missed by it. As remote work becomes a permanent feature of the working week, the change in who is in the neighborhood during the day belongs in the amenity calculus alongside the change in who commutes.

The paper closes with an open question: what happened to the burglars? Our results imply that the post-lockdown fall in burglary reflects a fall in the number of burglars, not their

[37] Heeks et al. (2018) categorize crime-related costs as follows: 'In anticipation of crime' costs encompass 'defensive expenditure' and 'insurance'. 'As a direct consequence of crime' costs include property loss or damage, physical and emotional harm, lost output, health services, and victim services. Finally, there are the costs associated with the police and the criminal justice system for a given crime. 'Costs as a consequence of crime' is typically the largest category, within which the modal largest sub-category is 'Physical and emotional harm', a measure based on survey data. The calculation behind this cost is, for each crime type, $L \times RQL \times DUR \times VOLY =$ Average physical and emotional cost, where L is the likelihood of sustaining physical and emotional injuries (estimated from survey data, specifically surveyed victims of the given crime type), RQL the percentage reduction in quality of life, DUR the duration of the injury as a fraction of a total year, and $VOLY$ the value of a year of life at full health (VOLY), using the value of a statistical life year. These numbers are then scaled up by a sample weight.

reallocation across crimes. If burglars had shifted into other property crimes, those crimes would have risen over our sample window to absorb them; Figure 2 shows that none did.[38] Aggregate criminal-justice statistics are consistent with a broader contraction of the offending population of which burglary is one component. The number of defendants proceeded against in England and Wales averaged around 1,350,000 per year in the years before the pandemic, fell to roughly 935,000 in 2020, and remains 20% below pre-pandemic levels across 2020–2022, with similar declines in Crown Prosecution Service charges and in sentencing (Ministry of Justice, 2026). The mechanical disruption of the courts in 2020 explains some of this, but not the persistence. The criminology of burglary points in the same direction. Burglars have been shown to be specialists, with target-selection and entry skills that do not port cleanly to other property crimes (Nee and Meenaghan, 2006); combined with the well-known concentration of burglary careers in young offenders, this means that a sustained collapse in the expected return is more likely to register as fewer new burglars and faster exit by existing ones than as wholesale rotation into other criminal activity. Our reading of the post-lockdown period is therefore that the burglar population adjusted on the extensive margin: fewer would-be burglars entered, and more active burglars exited, in response to the persistent fall in expected returns that the WFH shock produced. Whether the stock of burglars rebounds as both remote work and the labor market more broadly evolve is a question for future work.

[38]Shoplifting does rise above its pre-pandemic level from late 2022 (Figure 2). The rise begins more than two years after the burglary collapse and runs through a period of acute retail price inflation, neither of which a substitution story can easily accommodate.

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Appendix

A Support for the Identifying Assumption

As discussed in Section 4 the key identifying assumption that we make is the parallel trends assumption, which states that absent the pandemic-induced shift to remote work, the time trend for burglary would not depend on the WFH potential of the neighborhood.[39] The clearest way to assess this assumption is to view the event study graph presented in Figure 3. There is no discernible trend evident in this graph.

We provide further evidence in support of the parallel trends assumption holding below. We first present evidence of the absence of pre-trends for both our main, continuous treatment specification, and the binarized treatment. Next, we use the honest DD approach of Rambachan and Roth (2023) to create worst-case bounds for our DD estimates, based on pre-trends-informed violations of the parallel trends assumption. Finally, we relate our empirical strategy to recent work by Callaway et al. (2021), who discuss DD strategies involving continuous treatments. We provide empirical evidence, based on a continuous placebo test using local polynomial regression, which confirms the absence of any pre-trends at any point of the residual distribution of our treatment. Combining the evidence provided here with the event study in Figure 3, we are confident in making the parallel trends assumption in this setting.

A.1 Pre-Lockdown Trends

First, we directly estimate differential pre-trends in burglaries according to WFH potential. To do this we restrict the sample to the pre-lockdown period and repeat the estimates reported in Table 1 in which the lockdown period dummy interactions are replaced with the interaction between WFH and a linear time trend. We report the results of this exercise in Appendix A, Table A1, for both WFH as a continuous variable – see row a) – and a binary variable identifying high WFH neighborhoods – see row b). This strategy serves as a placebo regression, and directly gets at the notion of parallel trends. When controlling for region and police force time variation, the results for both WFH specifications yield estimates that are economically small and statistically indistinguishable from zero.

[39] One way in which this assumption could be violated is if adoption rates of new technologies, such as smart doorbells, varied systematically across neighborhoods. But, this is implausible given we observe such a pronounced and rapid fall in burglary coincident with the beginning of lockdown (see Figure B4).

Table A1: Pre-Lockdown Trends

	(1)	(2)	(3)	(4)
a.) WFH: Continuous				
Time Trend × WFH	0.103***	0.100***	0.002	0.009
	(0.011)	(0.012)	(0.013)	(0.015)
b.) WFH: Binarized				
Time Trend × WFH	0.012***	0.010***	–0.002	–0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Spatial FE	Neighborhood	Neighborhood	Neighborhood	Neighborhood
Spatiotemporal FE	Month×Year	Month×Year	Region× Month×Year	Police Force× Month×Year
Control Variables		X_0×Period	X_0×Period	X_0×Period
$\overline{Y}_{PRE}$	6.121	6.121	6.121	6.121
Adjusted R^2	0.464	0.464	0.469	0.475
Observations	287,868	287,868	287,868	287,868

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level. The dependent variable is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census. Neighbourhood fixed effects are included in all regressions, as are Police-Force-Area-by-Year-by-Month fixed effects. In addition we control for interactions between time trends and the following neighbourhood-specific variables (all based on pre-lockdown values): proportion of households living in own home, proportion of households living in social housing, proportion of residents welfare benefit claimants in the pre-lockdown period, retail floor space (m^2) in 2019. Data used: Police recorded crime data, 09/2016-02/2020

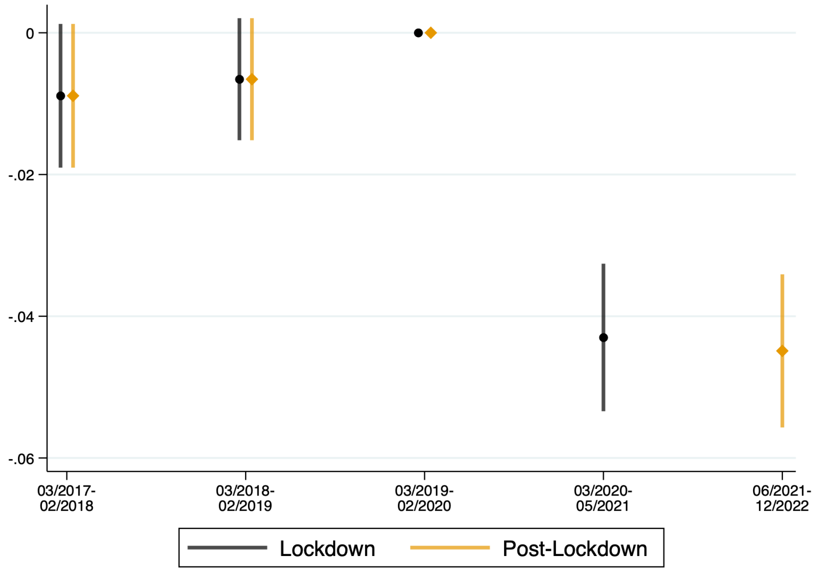
A.2 Honest DD à la Rambachan and Roth (2023)

In order to operationalize the approach of Rambachan and Roth (2023), we modify Equation (13), creating three separate, one-year periods from our three-year pre-period. The lockdown and post-lockdown periods remain the same. We implement this modification in order to create parameter estimates that we will use as inputs for the Rambachan and Roth (2023) routine. This gives rise to a modified equation that is closer to an aggregated event study than a standard DD:

$$crime_{nt} = \sum_{j=1,\neq 3}^{5} \alpha_j (period_j \times WFH_n) + LD_t \times X_n^{'}\beta_1 + PLD_t \times X_n^{'}\beta_2 + \gamma_n + \theta_{A\times t} + \varepsilon_{nt}\,, \quad (18)$$

where period 1 spans Mar 2017–Feb 2018, period 2 spans MAr 2018–Feb 2019, period 3 (the base period) spans Mar 2019–Feb 2020, and periods 4 and 5 are respectively the lockdown and post-lockdown periods, and are as previously defined. Figure A1 presents the resulting parameter estimates, which, along with the accompanying variance-covariance matrices, are the required inputs into the R package (`HonestDiD`) that implements the Rambachan and Roth (2023) approach. With the data aggregated at this level, we notice a slight, but statistically insignificant, positive pre-trend. In the analysis below, we provide worst case bounds that both ignore and incorporate this aspect of the data. In both cases, the results are consistent with the assumption of parallel trends.

Figure A1: Parameter Estimate Inputs for the Honest DD Routine

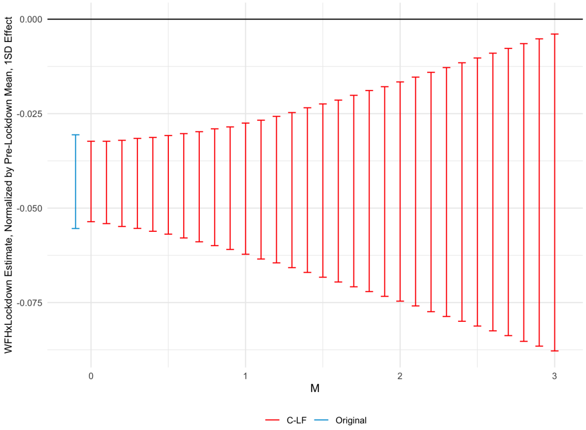


Notes: Estimates are scaled by $\sigma_{WFH}/\overline{Y}_{PRE}$, thus represent an standard deviation increase of WFH, as a proportion of the baseline outcome mean. The data is at the neighborhood-by-month level. The dependent variable is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census. Neighborhood fixed effects are included in all regressions. Baseline control interactions are based on interactions between lockdown periods (pre, during, post) and the following neighborhood-specific variables (all based on pre-lockdown values): proportion of households living in own home, proportion of households living in social housing, proportion of residents welfare benefit claimants in the pre-lockdown period, retail floor space (m^2) in 2019. Data used: Police recorded crime data, Mar 2017–Dec 2022.

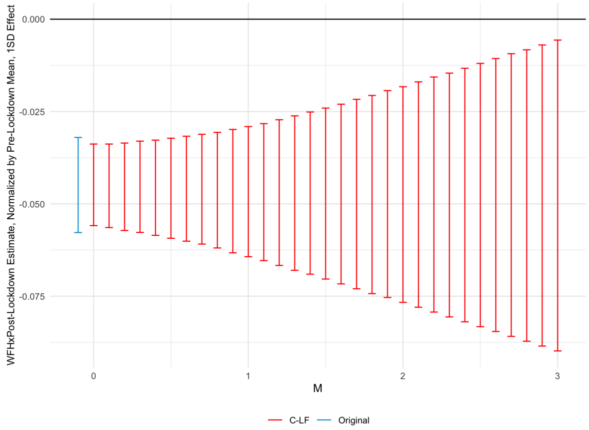
The graphical outputs from the Rambachan and Roth (2023) approach, where we use the Relative Magnitude approach for bounding, are presented in Figure A2. In panels (a) and (b) we provide the standard bounds, while in panels (c) and (d) we account for the slight positive pre-trend we document in Figure A1.[40] For both the lockdown and post-lockdown DD estimates, the "breakdown value" of $\overline{M}$ for the standard setting – the factor of the pre-trends at which the bounds on the estimated treatment effect overlap with zero – exceeds 3. Note that this does not account for the slight but insignificant pre-trend. This means that even if post-pandemic violations of parallel trends were as much as three times as large as any pre-period violations, the confidence set for the treatment effects would not include zero. For the bias-corrected setting, the bounds will not overlap zero for any value of $\overline{M}$. The analysis here corroborates the previous evidence we document in support of the parallel trends assumption.

[40]This uses the `biasDirection = "positive"` option in the HonestDiD R package.

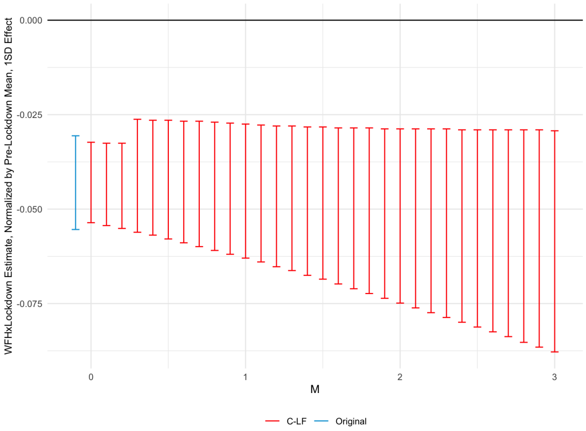
Figure A2: Worst-Case Bounds for our Burglary DD Estimates



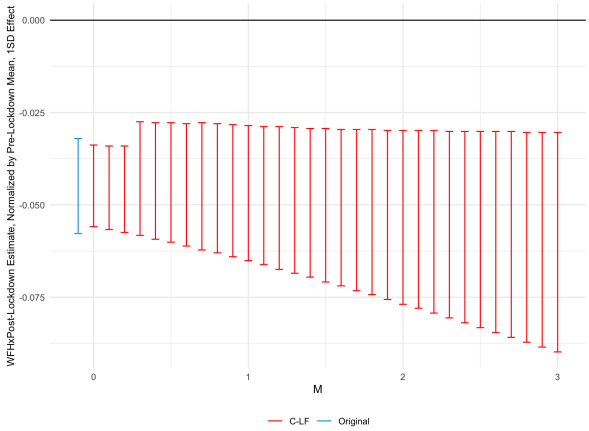
(a) Lockdown



(b) Post-lockdown



(c) Lockdown



(d) Post-lockdown

Notes: The blue band ("Original") is the 90% confidence interval of the DD treatment effect estimates for the lockdown and post-lockdown periods (respectively ($period_4 \times WFH_n$) and ($period_5 \times WFH_n$). These are presented graphically in Figure A1). Estimates are scaled by $\sigma_{WFH}/\overline{Y}_{PRE}$, thus represent an standard deviation increase of WFH, as a proportion of the baseline outcome mean. The red bands ("C-LF") are the robust 90% confidence intervals for the Rambachan and Roth (2023) Relative Magnitude-based bounds. These vary with the x-axis – $\overline{M}$ – which designates factors of the maximum pre-treatment violation of parallel trends. Thus, a confidence interval that does not intersect 0 when $\overline{M} = 3$ informs us that when we allow any parallel trend violations in the post-periods to be three times as large as the maximum pre-treatment violation, the 90% confidence intervals for the bounded treatment effect do not include zero.

A.3 Identification with a Continuous Treatment

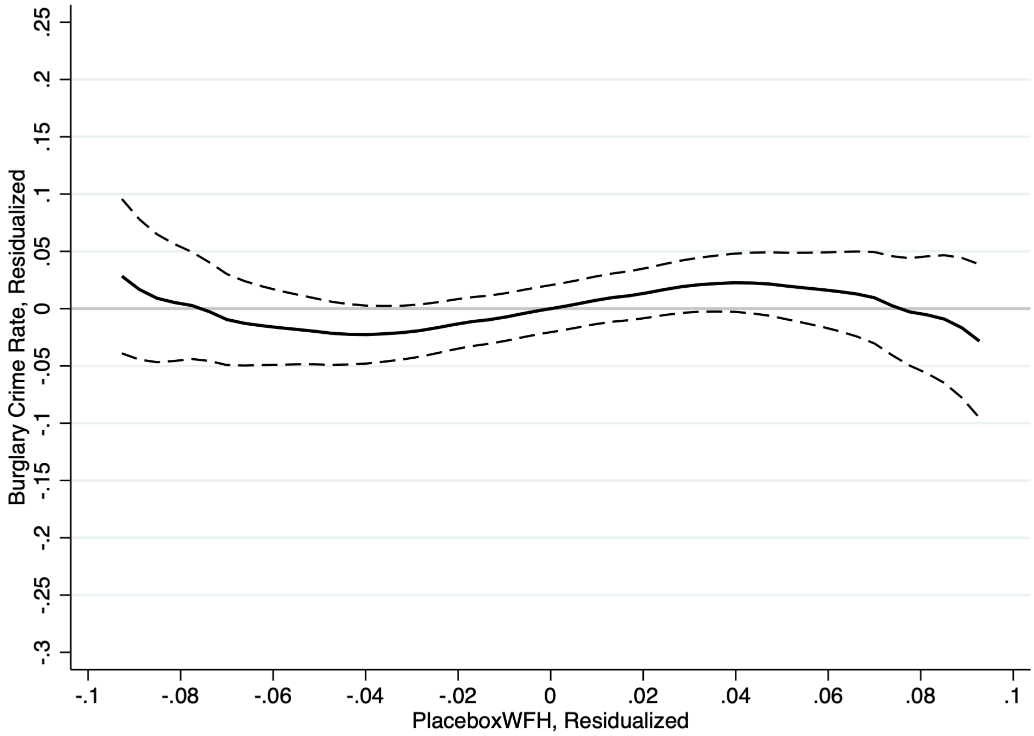
Callaway et al. (2021) show that for continuous treatments, the necessary assumptions for a DD model to estimate a causal effect may be stronger. They show that, for our case where every neighborhood received the treatment simultaneously, we need to make a stronger parallel trend assumption. Instead of the conventional parallel trend assumption (their Assumption 4) in the binary treatment case, we now need to assume that the trend in untreated potential outcomes has to be the same on average as for the treated at all levels of WFH (their Assumption 5). Alternatively, we can instead make the conventional parallel trends assumption and assume that there is no selection effect of neighborhoods into levels of WFH.

This second assumption is very plausible. First, because neighborhoods do not have agency and so any selection effect story is necessarily indirect. Second, because our treatment variable is WFH potential, based on the occupational composition of the neighborhood in 2011. This rules out anticipation effects, etc.

Moreover, the strong parallel trend assumption is also plausible. In our setting it says that two neighborhoods with different WFH potential would have the same outcomes in the absence of the advent of WFH conditional on the rich set of controls we include, and that this is true regardless of the degree of WFH potential. As such it also rules out selection effects, but in a different way. While, like a conventional parallel trend assumption, it cannot be directly tested, we provide support with a continuous analogue of a conventional placebo test in Figure A3. We apply the same local polynomial procedure used in Appendix B.4.2, but for a placebo policy period of one year from March 2019 onward compared to the previous year. The figure shows no evidence of differential pre-trends at any point in the WFH distribution, providing further support for the strong parallel trends assumption.

The literature on DD with heterogeneous treatment effects (de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021) has documented that regression-based approaches to DD amount to a weighted average of period and cohort specific DDs, where these weights may not be such that the two-way fixed effects estimand equals the average treatment effect. In our context, of a simultaneous continuous treatment, Callaway et al. (2021) show that the weights will have a hump-shaped distribution around the mean effect. Given that the distribution of our WFH variable has a similar shape, the two-way fixed effects estimand should be similar to the average causal response.

Figure A3: Continuous Placebo Test for Pre-Trends in the Burglary–WFH Relationship



Notes: The plot reports the results of doubly residualized kernel-weighted local polynomial regression. The solid line depicts the coefficient estimates and the dashed lines the associated point-wise 95% confidence interval. The y-axis values are the (centered) residuals from a regression of burglary rates on the $MSOA$ and police force area × month fixed effects, and 2019 neighborhood characteristics controls as in Equation (13). The x-axis values are the ((centered) residuals from a regression of lockdown or post-lockdown dummy multiplied by neighborhood WFH on the same set of fixed effects and controls. In both cases we specify an Epanechnikov kernel and use the rule of thumb bandwidth. For the placebo regressions, we use the two years prior to the pandemic (March 2018–February 2020), define a placebo post term that takes value 1 for time periods from March 2019 onwards and zero otherwise, and implement an analogous specification to Equation (13), except where the key DD term is $Placebo \times WFH$. We use a common y-scale for the placebo regression as well as our main regressions presented in Figure B3.

B Additional Results and Analysis

B.1 Summary Statistics

Table B1: Summary Statistics

	(1)	(2)	(3)
		WFH: Binarized	
	All Neighborhoods	**Low**	**High**
Neighborhoods	6,855	3,442	3,413
WFH Potential	0.365	0.289	0.440
	(0.095)	(0.041)	(0.072)
Burglary Crime Rate:			
Pre-Lockdown Period	5.94	5.88	6.00
	(5.19)	(5.08)	(5.30)
Lockdown Period	3.80	3.86	3.75
	(3.83)	(3.82)	(3.83)
Post-Lockdown Period	3.78	3.83	3.74
	(3.93)	(3.91)	(3.96)

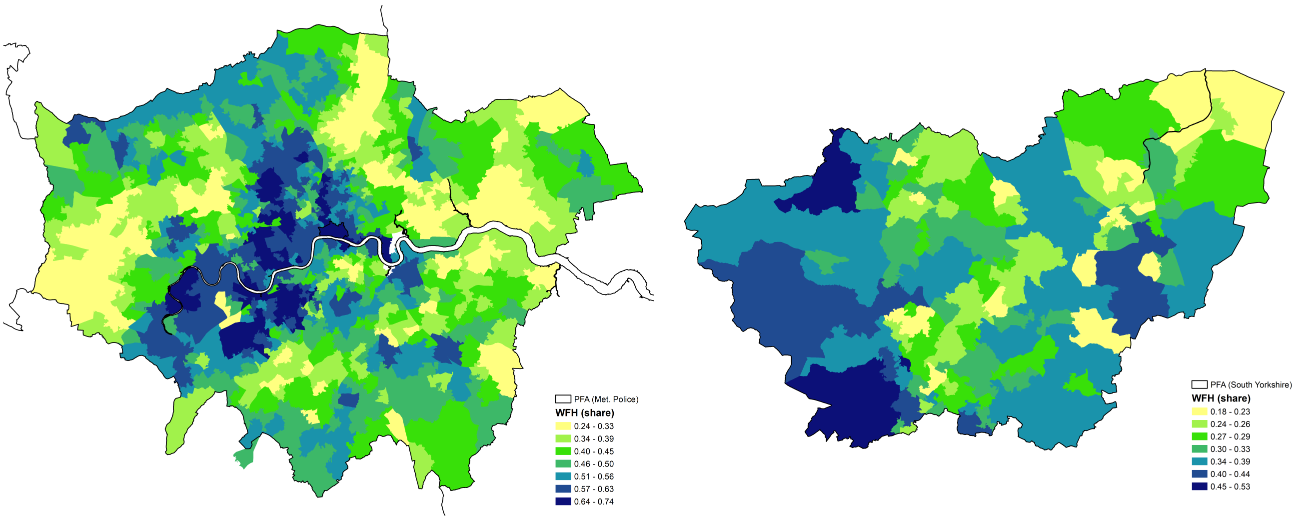
Notes: We report means and, for continuous variables, we report standard deviations in parentheses. Data used: Police recorded crime data, 03/2017-12/2022

B.2 The Spatial Distribution of Working From Home

The maps in Figure B1 show how the (estimated) proportion of people working from home varies across neighborhoods in Greater London (left) and South Yorkshire (right). Looking first at the map for London we can see that there is substantial variation across neighborhoods in the proportion of people able to WFH. In some neighborhoods it is as high as 74% while in others it is as low as 24%. Broadly speaking, WFH is more common in more central and more prosperous neighborhoods, although notably there is often substantial variation between adjacent neighborhoods. This is something we return to when we analyze spillovers in Section 8.

The map for South Yorkshire shows a similar pattern, with substantial variation across even adjacent neighborhoods although the overall level of WFH is lower than in London. An interesting difference is that while in London the areas with the highest rates of WFH include central London, in South Yorkshire there is more evidence of WFH being highest in more rural neighborhoods, particularly those to the west of the map which are adjacent to the Peak District, a major national park. This may also reflect the larger numbers of commuters into London from other areas.

Figure B1: The Spatial Distribution of Working From Home



(a) Metropolitan Police Force Area

(b) South Yorkshire Police Force Area

Notes: The maps plot the proportion of people able to WFH by Police Force Areas for Greater London and South Yorkshire respectively. South Yorkshire Police Force Area contains the city of Sheffield as well as the towns of Barnsley and Doncaster, and the surrounding areas. The total population served is around 1.28 million.

B.3 Core DD Results – Binarized Treatment

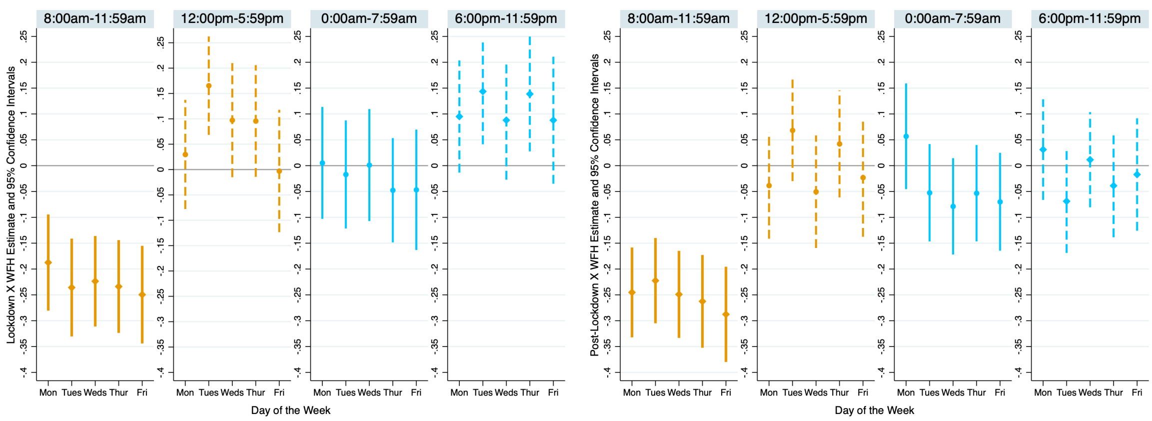
Table B2: DD Estimates for Burglary

	(1)	(2)	(3)	(4)
LD × WFH	–0.248***	–0.412***	–0.422***	–0.211***
	(0.049)	(0.049)	(0.050)	(0.052)
PLD × WFH	–0.236***	–0.377***	–0.319***	–0.164***
	(0.049)	(0.052)	(0.054)	(0.057)
Spatial FE	NH	NH	NH	NH
Spatiotemporal FE	Month ×Year	Month ×Year	Region ×Month ×Year	PFA ×Month ×Year
Control Variables		X_0×Period	X_0×Period	X_0×Period
$\overline{Y}_{PRE}$	5.919	5.919	5.919	5.919
Adjusted R^2	0.465	0.468	0.475	0.485
Observations	479,780	479,780	479,780	479,780

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level, and standard errors are clustered by neighborhood. The dependent variable is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census. Neighbourhood fixed effects are included in all regressions. Baseline control intereactions are based on interactions between lockdown periods (pre, during, post) and the following neighbourhood-specific variables (all based on pre-lockdown values): proportion of households living in own home, proportion of households living in social housing, proportion of residents welfare benefit claimants in the pre-lockdown period, retail floor space (m^2) in 2019. Data used: Police recorded crime data, 03/2017-12/2022.

B.4 The Timing of Burglaries – Met Data

Figure B2: Stability of Timing Results by Day of Week



(a) Lockdown (b) Post-Lockdown

Notes: Results are for the same specification as in Table 2, but estimated separately by weekday in order to generate day-of-week-specific estimates. Data used: Met Police recorded crime data, Mar 2017–Dec 2022

B.4.1 Commercial Burglary

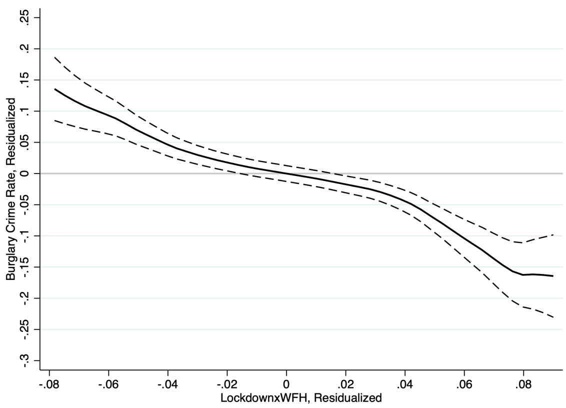
Table B3: DD Estimates by Time and Day – Commercial Burglary – London Metropolitan Police

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Working Hours			**Non-Working Hours**			
	All	Weekdays, 8:00am-5:59pm	Weekdays, 8:00am-11:59am	Weekdays, 12:00pm-5:59pm	Weekdays, Outside of 8:00am-5:59pm	Weekdays, 0:00am-7:59am	Weekdays, 6:00pm-11:59pm	Weekend
A.) All Neighborhoods								
LD × WFH	–1.842***	–0.363***	–0.221***	–0.143*	–0.974***	–0.534***	–0.439***	–0.505***
	(0.390)	(0.109)	(0.054)	(0.079)	(0.231)	(0.116)	(0.137)	(0.122)
PLD × WFH	–1.000**	–0.186*	–0.072	–0.113	–0.515**	–0.268*	–0.246*	–0.300***
	(0.390)	(0.100)	(0.051)	(0.075)	(0.244)	(0.141)	(0.137)	(0.113)
$\overline{Y}_{PRE}$	2.017	0.521	0.149	0.372	0.952	0.450	0.503	0.544
Adjusted R^2	0.688	0.459	0.270	0.359	0.571	0.387	0.493	0.443
Observations	68,740	68,740	68,740	68,740	68,740	68,740	68,740	68,740
B.) Low Commercial Floor Space Neighborhoods								
LD × WFH	–1.146***	–0.237**	–0.134**	–0.104	–0.645***	–0.429***	–0.216**	–0.263**
	(0.288)	(0.108)	(0.056)	(0.080)	(0.168)	(0.100)	(0.103)	(0.104)
PLD × WFH	–0.779***	–0.208**	–0.034	–0.174**	–0.438***	–0.256**	–0.181*	–0.134
	(0.245)	(0.090)	(0.046)	(0.069)	(0.156)	(0.101)	(0.094)	(0.097)
$\overline{Y}_{PRE}$	1.237	0.313	0.080	0.233	0.589	0.288	0.301	0.335
Adjusted R^2	0.241	0.088	0.039	0.063	0.148	0.094	0.081	0.095
Observations	44,940	44,940	44,940	44,940	44,940	44,940	44,940	44,940
C.) High Commercial Floor Space Neighborhoods								
LD × WFH	–2.525***	–0.401*	–0.259**	–0.142	–1.381**	–0.662**	–0.719**	–0.744***
	(0.928)	(0.235)	(0.117)	(0.163)	(0.540)	(0.265)	(0.308)	(0.279)
PLD × WFH	–1.178	–0.120	–0.068	–0.053	–0.571	–0.251	–0.320	–0.487*
	(0.930)	(0.226)	(0.115)	(0.162)	(0.557)	(0.310)	(0.309)	(0.257)
$\overline{Y}_{PRE}$	3.376	0.883	0.269	0.614	1.585	0.732	0.853	0.908
Adjusted R^2	0.738	0.540	0.333	0.446	0.642	0.473	0.577	0.529
Observations	23,800	23,800	23,800	23,800	23,800	23,800	23,800	23,800

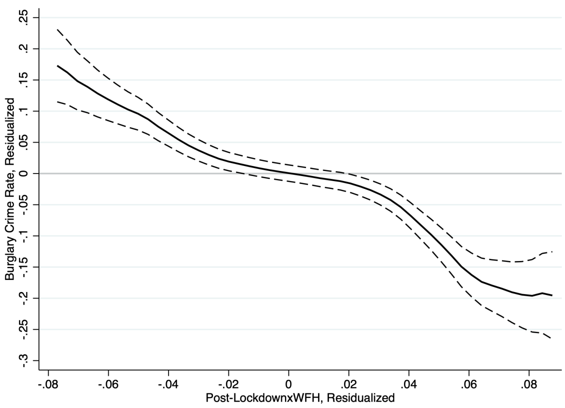
Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level. The dependent variable is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census. Neighbourhood fixed effects are included in all regressions, as are Year-by-Month fixed effects. In addition we control for interactions between lockdown periods (pre, during, post) and the following neighbourhood-specific variables (all based on pre-lockdown values): proportion of households living in own home, proportion of households living in social housing, proportion of residents welfare benefit claimants in the pre-lockdown period, retail floor space (m^2) in 2019. Data used: Met Police recorded crime data, 03/2017-12/2022

B.4.2 Non-parametric Estimation of the Burglary-WFH Relationship

Figure B3: Local Polynomial Fit of Residualized Burglary on Residualized WFH



(a) Lockdown



(b) Post-lockdown

Notes: Each plot reports the results of doubly residualized kernel-weighted local polynomial regression. The solid line depicts the coefficient estimates and the dashed lines the associated point-wise 95% confidence interval. The y-axis values are the residuals from a regression of burglary rates on the MSOA and police force area $\times$ month $\times$ year fixed effects, and 2019 neighborhood characteristics controls as in Equation (13). The x-axis values are the residuals from a regression of lockdown or post-lockdown dummy multiplied by neighborhood WFH on the same set of fixed effects and controls. In both cases we specify an Epanechnikov kernel and use the rule of thumb bandwidth.

We fit the relationship between residualized values of work from home rates and residualized crime rates, using a local polynomial regression, in both the lockdown and post-lockdown period. Both variables are residualized using the same MSOA and police force area $\times$ month $\times$ year fixed effects, and 2019 neighborhood characteristics controls as in Equation (13).

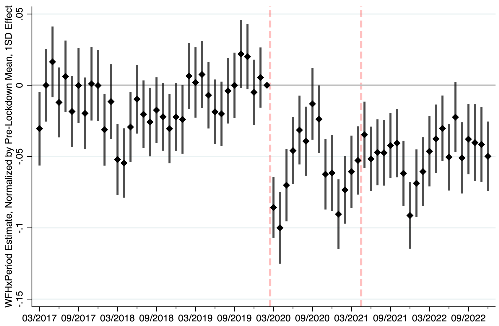
B.5 Event Studies for Other Neighborhood Crimes

Section 5.5 reports DD estimates for vehicle crime, theft, robbery, and the neighborhood crime aggregate. Here we present the corresponding event study figures.

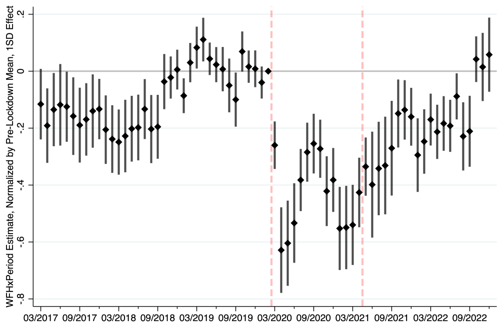
We note first that vehicle crime corresponds to theft from (71% of reported), theft of (10%), or interference with (19%) a vehicle (ONS, 2025). Theft refers to stealing from a person, not including burglary or vehicle theft, and robbery refers to stealing from a person with the use of, or threat of, force. The neighborhood crime aggregate is the sum of burglary, vehicle crime, theft, and robbery.

Figure B4 presents event studies for the four outcomes, analogous to Figure 3 for burglary. Vehicle crime shows a negative WFH–crime relationship throughout the post-lockdown period, noisier than the burglary event study but with point estimates that remain on the negative side and do not show systematic recovery. Theft and robbery show large negative effects during the lockdown period that attenuate steadily as restrictions ease; the late post-lockdown point estimates approach zero, consistent with the time-series evidence in Figure 2 showing that these crimes had largely reverted to pre-pandemic levels by the end of our sample. The neighborhood crime aggregate inherits the dynamics of its components, with a sharp lockdown drop that partially reverses post-lockdown.

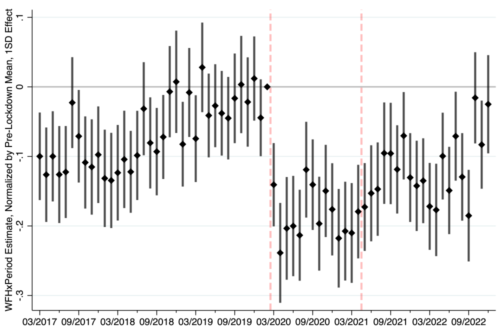
Figure B4: Event Studies for Other Neighborhood Crimes



(a) Vehicle



(b) Theft



(c) Robbery

(d) Neighborhood Crime

Each point presents the (rescaled) event-study coefficient estimates and 95% point wise confidence intervals of Equation (14). The dashed vertical lines denote the introduction of the UK first national lockdown in March 2020, and the start of the post-lockdown period in May 2021. February 2020 is excluded as the reference month. Standard errors are clustered by neighborhood.

B.6 Evidence in Support of our Primary Mechanisms

B.6.1 Veil of Darkness Approach (Eyes-on-the-Street Effect)

Table B4: Burglary, WFH and the Veil of Darkness (London)

	(1)	(2)	(3)	(4)	(5)	(6)
	Weekdays		**Weekend**			
			Saturday		**Sunday**	
	Morning, 3:52am-7:24am	Evening, 4:30pm-10:10pm	Morning, 3:52am-7:24am	Evening, 4:30pm-10:10pm	Morning, 3:52am-7:24am	Evening, 4:30pm-10:10pm
DD Estimates						
LD × WFH	–0.012	0.111***	–0.008	0.029**	–0.001	0.030***
	(0.013)	(0.032)	(0.005)	(0.011)	(0.005)	(0.011)
PLD × WFH	–0.015	–0.003	–0.007	–0.007	0.006	0.015
	(0.013)	(0.029)	(0.005)	(0.011)	(0.005)	(0.009)
DDD Estimates						
LD × WFH	0.004	0.067***	–0.005	0.001	0.001	0.021***
	(0.009)	(0.020)	(0.004)	(0.008)	(0.004)	(0.007)
LD × Light	0.003	0.120***	0.004	0.012*	0.006*	0.027***
	(0.008)	(0.015)	(0.003)	(0.007)	(0.003)	(0.006)
LD × WFH × Light	–0.020*	–0.023	0.002	0.026***	–0.002	–0.012
	(0.011)	(0.023)	(0.005)	(0.010)	(0.005)	(0.009)
PLD × WFH	0.007	0.012	–0.001	–0.000	0.002	0.017***
	(0.009)	(0.019)	(0.004)	(0.007)	(0.004)	(0.006)
PLD × Light	0.013*	0.078***	0.005*	0.009	0.003	0.024***
	(0.007)	(0.014)	(0.003)	(0.006)	(0.003)	(0.005)
PLD × WFH × Light	–0.028***	–0.027	–0.004	–0.007	0.001	–0.019***
	(0.010)	(0.021)	(0.004)	(0.009)	(0.004)	(0.007)
$\overline{Y}_{PRE}$	0.157	0.583	0.028	0.117	0.026	0.087
Observations	137,480	137,480	137,480	137,480	137,480	137,480

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level. The dependent variable is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census. Neighbourhood fixed effects are included in all regressions, as are Year-by-Month fixed effects. In addition we control for interactions between lockdown periods (pre, during, post) and the following neighbourhood-specific variables (all based on pre-lockdown values): proportion of households living in own home, proportion of households living in social housing, proportion of residents welfare benefit claimants in the pre-lockdown period, retail floor space (m^2) in 2019. Data used: Met Police recorded crime data, 03/2017-12/2022

We interact our time and WFH variables with a dummy variable, *Light*, equal to one if daylight is present and zero otherwise. We define a DDD model. Thus, now we are estimating the effect of WFH on the number of burglaries by time and day, allowing the effect at a given time on a given day to vary depending on whether it is light outside. We use the precise time and date information available in the Met data for London combined with daylight information from the official Civil Twilight time for each day of the year.[41]

We report the results of this exercise in Table B4, focusing only on those hours of the day where the amount of daylight varies over a year. The coefficients of interest ($LD \times WFH \times Light$ and $PLD \times WFH \times Light$) are negative and of a similar magnitude for both the morning and evening during the weekdays (although only statistically significant during the morning). For example, when it's light in the morning a one standard-deviation (9.5pp) greater WFH potential

[41] Civil Twilight is the time each morning after which artificial lighting, such as street lights, is no longer necessary.

reduces the post-lockdown burglary rate by -0.028 in those hours. A similar pattern is not observed during weekends (perhaps with the exception of post-lockdown Sunday evenings).

B.7 Characterizing Neighborhoods by Property Type and Parking Availability

We classify neighborhoods into three groups based on housing composition and driveway parking prevalence.

Housing composition. We use Council Tax: Stock of Properties (CTSOP) data for the 2019–2020 tax year, published by the Valuation Office Agency. The data record property counts by type for each MSOA. We group flats and maisonettes as *apartments* and all other dwelling types (bungalows, terraced houses, semi-detached houses, detached houses) as *houses*. Each MSOA is classified by which group accounts for the larger share of properties.

Driveway parking. We measure the prevalence of driveway parking using property listing descriptions from Zoopla, restricting to non-flat dwelling types. For each listing, we code a binary indicator equal to one if the description, short description, or bullet list mentions off-road or off-street parking, a driveway paired with a garage or parking, or a carport. Listings mentioning only allocated (communal) parking or en-bloc garages are coded zero. We collapse to the MSOA level, computing the mean of this indicator across all matched listings. An MSOA is classified as having high driveway parking prevalence if this mean exceeds 0.5. The sample mean of this variable across MSOAs is 0.50, so this threshold corresponds to an above-mean split.

Classification. Combining these two variables yields three groups: (i) apartment-dominated MSOAs; (ii) house-dominated MSOAs with low driveway parking prevalence; and (iii) house-dominated MSOAs with high driveway parking prevalence. Shares of neighborhoods in each group are reported in Figure 4.

Specification. The regression underlying Figure 4 is:

$$\begin{aligned} crime_{nt} = \sum_{p=1}^{2} \alpha_p \left(Period_t^p \times WFH_n^H\right) + \sum_{p=1}^{2}\sum_{k=2}^{3} \alpha_{pk} \left(Period_t^p \times WFH_n^H \times G_n^k\right) \\ + \sum_{p=1}^{2}\sum_{k=1}^{3} \left(Period_t^p \times G_n^k\right) X_n' \boldsymbol{\delta}_{pk} + \gamma_n + \theta_{A\times t} + \varepsilon_{nt}, \end{aligned} \tag{19}$$

where WFH_n^H is a binary indicator for above-median WFH potential, G_n^k are indicators for the three housing-type groups with $k = 1$ (apartments) as the omitted category, $Period_t^1 = LD_t$, $Period_t^2 = PLD_t$, and X_n is the vector of four pre-lockdown neighborhood controls (homeownership rate, social housing share, welfare claimant rate, retail floor space). The plotted coefficient for apartment-dominated neighborhoods is $\hat{\alpha}_p$; for groups $k \in \{2, 3\}$ it is $\hat{\alpha}_p + \hat{\alpha}_{pk}$.

B.8 Policing Effort as an Alternative Mechanism

Table B5: DD Estimates – Clearance Rate

	(1)	(2)	(3)	(4)	(5)	(6)
	Property	Burglary	Theft	Vehicle	Arson	Shoplifting
LD × WFH	0.015***	–0.009	0.013**	–0.004	–0.007	0.013
	(0.006)	(0.010)	(0.006)	(0.007)	(0.011)	(0.023)
PLD × WFH	0.007	–0.013	0.007	0.006	–0.005	–0.020
	(0.005)	(0.009)	(0.005)	(0.006)	(0.009)	(0.024)
$\overline{Y}_{PRE}$	0.079	0.056	0.045	0.034	0.092	0.227
Adjusted R^2	0.252	0.038	0.056	0.046	0.066	0.163
Observations	488,683	427,196	462,412	425,441	464,781	302,002

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level. The dependent variable is the clearance rate. Data is weighted by the population count at the 2011 Census. Neighbourhood fixed effects are included in all regressions, as are Police-Force-Area-by-Year-by-Month fixed effects. In addition we control for interactions between lockdown periods (pre, during, post) and the following neighbourhood-specific variables (all based on pre-lockdown values): proportion of households living in own home, proportion of households living in social housing, proportion of residents welfare benefit claimants in the pre-lockdown period, retail floor space (m^2) in 2019.

B.9 Adjusting WFH Potential for Differences in Working Population Across Neighborhoods

Table B6: DD Estimates

	(1)	(2)	(3)	(4)	(5)
	WFH Measure Adjusted Based on Local Population Proportion:				
	No Adjustment (Baseline)	Working Age	Prime Working Age	Employed	Employed and Self-Employed
LD × WFH	–2.357***	–3.163***	–2.919***	–2.077***	–2.682***
	(0.367)	(0.554)	(0.632)	(0.773)	(0.753)
PLD × WFH	–2.475***	–3.369***	–3.869***	–3.571***	–4.006***
	(0.381)	(0.553)	(0.640)	(0.755)	(0.736)
$\overline{Y}_{PRE}$	5.923	5.923	5.923	5.923	5.923
$1\sigma_{WFH}\times$(LD × WFH)/ $\overline{Y}_{PRE}$	–0.038***	–0.051***	–0.047***	–0.033***	–0.043***
	(0.006)	(0.009)	(0.010)	(0.012)	(0.012)
$1\sigma_{WFH}\times$(PLD × WFH)/ $\overline{Y}_{PRE}$	–0.040***	–0.054***	–0.062***	–0.057***	–0.064***
	(0.006)	(0.009)	(0.010)	(0.012)	(0.012)
Adjusted R^2	0.485	0.485	0.485	0.485	0.485
Observations	479,780	479,780	479,780	479,780	479,780

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level. The dependent variable is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census. Neighbourhood fixed effects are included in all regressions, as are Police-Force-Area-by-Year-by-Month fixed effects. In addition we control for interactions between lockdown periods (pre, during, post) and the following neighbourhood-specific variables (all based on pre-lockdown values): proportion of households living in own home, proportion of households living in social housing, proportion of residents welfare benefit claimants in the pre-lockdown period, retail floor space (m^2) in 2019. Data used: Police recorded crime data, 03/2017-12/2022.

B.10 Work from Home Predictions and IV Estimates

B.10.1 Realized WFH and WFH Potential

Our primary measure of WFH potential, Equation (12), is calculated using the residential distribution, by occupation, reported in the 2011 Census. One concern with this might be that the geography of where people live has changed significantly enough to make our measure a poor reflection of the realized post-pandemic WFH distribution. Here we provide evidence to address this concern.

To do this we use data from the 2021 UK Census. The Census was conducted during the second national lockdown in March 2021. We use information from the question "How do you usually travel to work?", for which one of the possible answers is "Work mainly at or from home".[42] For each neighborhood we calculate the proportion of census respondents who state they work mainly from home. It should be noted that no guidance was provided in the census questionnaire as to how this question should be answered with respect to the public health measures. Some respondents may have interpreted this question as referring to how they get to work absent the public health restrictions. If this is the case, we may expect it to underestimate the number of respondents that were actually working from home at that time. However, if our WFH potential measure accurately reflects the proportion of employed residents who can WFH, we would still expect this to be reflected in the correlation with this census measure.

In the 2021 Census, the average neighborhood had 30.5% of working residents report that they "Work mainly at or from home". This percent varies substantially, from 4.9% in the lowest WFH neighborhood to 72.1% in the highest WFH neighborhood.

In Figure 1a we plot the reported WFH estimates from the 2021 Census against the predicted WFH potential from the 2011 Census for each neighborhood. The correlation is strong and positive. The correlation coefficient is 0.94. As expected, our measure of WFH potential over-estimates the actual WFH done in 2021. This may reflect how respondents interpret the census question, it may also reflect that some workers in jobs that can be done from home still worked on site. Overall, this suggests that the neighborhood WFH potential measure is a strong predictor of the actual portion of neighborhood residents who could WFH in 2021.

[42] This question is asked only if the respondent has done paid work in the last twelve months. The refers to Question 48 in the individual questionnaire for England, available at `https://www.ons.gov.uk/file?uri=/census/censustransformationprogramme/questiondevelopment/census2021paperquestionnaires/englishindividual.pdf`

B.10.2 IV-DD Estimates: Burglary

Table B7: IV-DD Estimates for Burglary

	(1)	(2)	(3)	(4)
A.) OLS				
LD $\times$ WFH$_{2021}$	–0.933***	–1.958***	–2.335***	–1.778***
	(0.273)	(0.288)	(0.261)	(0.279)
PLD $\times$ WFH$_{2021}$	–1.122***	–2.063***	–1.887***	–1.661***
	(0.266)	(0.304)	(0.271)	(0.289)
B.) 2SLS				
LD $\times$ WFH$_{2021}$	–1.673***	–2.734***	–3.016***	–1.970***
	(0.304)	(0.312)	(0.292)	(0.318)
PLD $\times$ WFH$_{2021}$	–1.859***	–2.935***	–2.684***	–2.074***
	(0.289)	(0.329)	(0.303)	(0.333)
Spatial FE	NH	NH	NH	NH
Spatiotemporal FE	Month $\times$Year	Month $\times$Year	Region $\times$Month $\times$Year	PFA $\times$Month $\times$Year
Control Variables		$X_0\times$Period	$X_0\times$Period	$X_0\times$Period
$\overline{Y}_{PRE}$	5.875	5.875	5.875	5.875
Sanderson–Windmeijer F Statistic	55,679	25,816	22,151	19,891
Observations	471,730	471,730	471,730	471,730

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level. The dependent variable is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census. Neighbourhood fixed effects are included in all regressions. Baseline control intereactions are based on interactions between lockdown periods (pre, during, post) and the following neighbourhood-specific variables (all based on pre-lockdown values): proportion of households living in own home, proportion of households living in social housing, proportion of residents welfare benefit claimants in the pre-lockdown period, retail floor space (m^2) in 2019. First-stage strength is reported as the minimum Sanderson–Windmeijer F statistic across endogenous variables. Data used: Police recorded crime data, 03/2017-12/2022.

B.10.3 IV-DD Estimates: Other Neighborhood Crimes

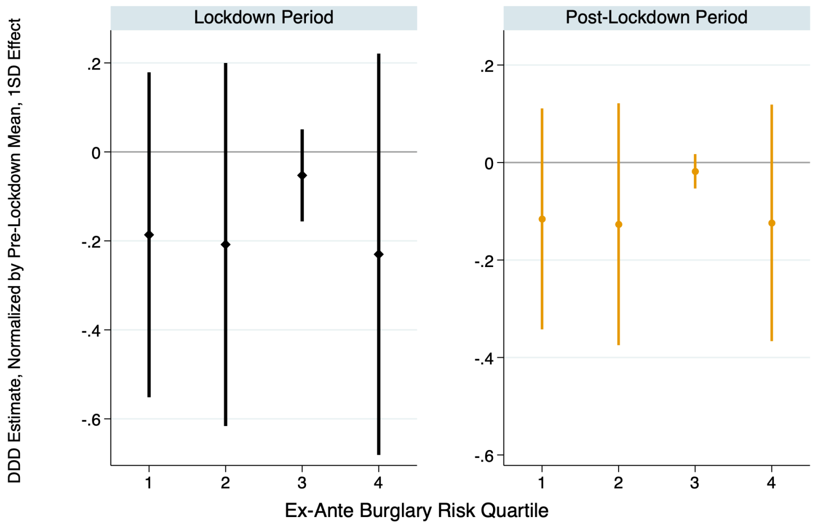
Table B8: IV-DD Estimates for Other Neighborhood Crime

	Burglary	Vehicle	Theft	Robbery	Neighborhood Crime
A.) OLS					
LD × WFH_{2021}	–1.778***	–1.593***	–12.972***	–1.238***	–17.581***
	(0.279)	(0.415)	(1.870)	(0.207)	(2.260)
PLD × WFH_{2021}	–1.661***	–1.163***	–2.037*	–0.343**	–5.204***
	(0.289)	(0.391)	(1.057)	(0.155)	(1.256)
B.) 2SLS					
LD × WFH_{2021}	–1.970***	–2.670***	–14.400***	–1.308***	–20.347***
	(0.318)	(0.479)	(1.892)	(0.225)	(2.331)
PLD × WFH_{2021}	–2.074***	–2.039***	–3.352***	–0.513***	–7.979***
	(0.333)	(0.441)	(1.159)	(0.178)	(1.442)
$\overline{Y}_{PRE}$	5.879	6.503	4.482	1.116	17.980
Sanderson–Windmeijer F Statistic	19,891	19,891	19,891	19,891	19,891
Observations	471,730	471,730	471,730	471,730	471,730

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level. The dependent variable is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census. Neighbourhood fixed effects are included in all regressions. Baseline control intereactions are based on interactions between lockdown periods (pre, during, post) and the following neighbourhood-specific variables (all based on pre-lockdown values): proportion of households living in own home, proportion of households living in social housing, proportion of residents welfare benefit claimants in the pre-lockdown period, retail floor space (m^2) in 2019. First-stage strength is reported as the minimum Sanderson–Windmeijer F statistic across endogenous variables. Data used: Police recorded crime data, 03/2017-12/2022.

B.10.4 London Underground Use, Ex-Ante Burglary Risk, and WFH Potential

Figure B5: Change in London Tube Journeys, WFH and Ex-Ante Burglary Risk Quartiles



Notes: Point estimates and 95% confidence intervals from a DDD regression where the dependent variable is neighborhood-month London Underground journeys. The left panel reports lockdown-by-WFH estimates; the right panel reports post-lockdown-by-WFH estimates. Within each panel, moving from left to right, the points depict how the WFH effect differs by ex-ante burglary risk quartile of the neighborhood. Estimates are normalized by the pre-lockdown mean and scaled to represent a one standard deviation increase in WFH potential. Standard errors are clustered by neighborhood. Sample: neighborhoods served by a London Underground station.

B.11 The Within-Neighborhood Concentration of Crime and WFH

Next we consider the extent to which WFH in the post-lockdown period caused a change in the within-neighborhood distribution of crime. To do so, we use our street-level data to compute the distribution of crime within neighborhoods for each of our three main periods. We do this using concentration indices, measures of spatial inequality in the incidence of crime from the criminology literature. Specifically, we use the modern concentration measures introduced in recent work by Bernasco and Steenbeek (2017),who introduce a generalized Gini coefficient, and Chalfin et al. (2021), who introduce the marginal crime concentration (MCC) coefficient.[43,44] We present the resulting DD estimates from estimating a similar specification to Equation (13) in Table B9. To ease interpretation of these measures, we include the pre-lockdown means at the base of the table and note that both a higher MCC coefficient and a higher generalized Gini means that crime is more concentrated in an area. We document a series of null effects in this exercise: not only are none of the parameter estimates statistically significant, the estimates themselves are also minimal in magnitude. From this exercise, we conclude that the spatial location of crime *within* neighborhoods did not change as a consequence of the shift towards remote work, and the concomitant spatial reallocation of workers during the working week.

Table B9: The Within Neighborhood Concentration of Crime

	(1)	(2)	(3)	(4)	(5)
	MCC 10%	MCC 20%	MCC 25%	MCC 50%	Generalized Gini
LD × WFH	0.000	–0.001	–0.004	0.007	0.032
	(0.002)	(0.003)	(0.003)	(0.006)	(0.024)
PLD × WFH	0.000	–0.001	–0.004	0.005	0.005
	(0.002)	(0.003)	(0.003)	(0.006)	(0.024)
$\overline{Y}_{PRE}$	0.021	0.046	0.060	0.136	0.702
Adjusted R^2	0.710	0.797	0.812	0.838	0.596
Observations	20,558	20,558	20,558	20,558	20,558

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-period level. The column titles denote the dependent variable. Data is weighted by the population count at the 2011 Census. Neighbourhood fixed effects are included in all regressions, as are Police-Force-Area-by-Year-by-Month fixed effects. In addition we control for interactions between lockdown periods (pre, during, post) and the following neighbourhood-specific variables (all based on pre-lockdown values): proportion of households living in own home, proportion of households living in social housing, proportion of residents welfare benefit claimants in the pre-lockdown period, retail floor space (m^2) in 2019. Data used: Police recorded crime data, 03/2017-12/2022.

[43] The generalized Gini coefficient is given by $G' = \max\left[\frac{S}{C}, 1\right](G-1)+1$ where G is the conventional Gini coefficient, S the number of street segments in a given MSOA-period, and C the number of crimes in a given MSOA-period. The MCC coefficient is: $MCC_n^k = CC_n^{k,\text{sim}} - CC_n^{k*}$ where $CC_n^{k,\text{sim}}$ is the simulated concentration rate obtained under uniformity and CC_n^{k*} is the unadjusted concentration index.

[44] These modern crime concentration measures are inequality-indices designed to be robust to a particular feature of crime data in which the number of streets often exceeds the number of crimes. Earlier concentration measures would reflect artificially highly concentration when there were more streets than crimes.

B.11.1 Extended Spatial Spillover Results

In Table B10 we present extended results for our spatial spillover specification, providing key estimates for the lockdown period, and repeating the presentation of the post-lockdown period coefficients.

Table B10: Spatial DDD Model for Burglary

	(1)	(2)	(3)	(4)	(5)	(6)
		DDD: Criterion Used to Define $\mathbf{NWFH^H}$				
	Baseline DD Estimates	Most Neighbors are High WFH	25%+ of Neighbors are High WFH	40%+ of Neighbors are High WFH	60%+ of Neighbors are High WFH	75%+ of Neighbors are High WFH
$LD \times WFH^H$	–0.215***	–0.221***	–0.250	–0.170*	–0.196***	–0.141**
	(0.052)	(0.085)	(0.154)	(0.100)	(0.072)	(0.063)
$LD \times NWFH^H$		0.095	–0.053	0.014	0.160*	0.289**
		(0.072)	(0.061)	(0.065)	(0.089)	(0.126)
$LD \times WFH^H \times NWFH^H$		–0.047	0.058	–0.061	–0.141	–0.381***
		(0.106)	(0.161)	(0.113)	(0.110)	(0.139)
Total DDD Effect for:						
$LD \times WFH^H \times NWFH^H$		–0.173***	–0.246***	–0.217***	–0.176***	–0.234***
		(0.060)	(0.065)	(0.061)	(0.060)	(0.062)
$PLD \times WFH^H$	–0.165***	–0.132	–0.116	–0.145	–0.142*	–0.104
	(0.057)	(0.092)	(0.142)	(0.103)	(0.077)	(0.067)
$PLD \times NWFH^H$		0.124*	–0.095	0.023	0.224**	0.168
		(0.073)	(0.066)	(0.067)	(0.089)	(0.126)
$PLD \times WFH^H \times NWFH^H$		–0.117	–0.017	–0.036	–0.191*	–0.261*
		(0.110)	(0.149)	(0.116)	(0.112)	(0.140)
Total DDD Effect for:						
$PLD \times WFH^H \times NWFH^H$		–0.125*	–0.229***	–0.158**	–0.109*	–0.196***
		(0.066)	(0.073)	(0.067)	(0.065)	(0.068)
p-Value: $LD \times WFH^H =$ $LD \times WFH^H \times NWFH^H$		0.551	0.975	0.627	0.779	0.153
p-Value: $PLD \times WFH^H =$ $PLD \times WFH^H \times NWFH^H$		0.937	0.418	0.899	0.645	0.166
p-Value: $LD \times NWFH^H =$ $LD \times WFH^H \times NWFH^H$		0.000	0.001	0.000	0.000	0.000
p-Value: $PLD \times NWFH^H =$ $PLD \times WFH^H \times NWFH^H$		0.001	0.034	0.010	0.000	0.006
$\overline{Y}_{PRE}$	5.923	5.923	5.923	5.923	5.923	5.923
Adjusted R^2	0.485	0.485	0.485	0.485	0.485	0.485
Observations	479,710	479,710	479,710	479,710	479,710	479,710

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level. The dependent variable is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census. Neighbourhood fixed effects are included in all regressions, as are Police-Force-Area-by-Year-by-Month fixed effects. In addition we control for interactions between lockdown periods (pre, during, post) and the following neighbourhood-specific variables (all based on pre-lockdown values): proportion of households living in own home, proportion of households living in social housing, proportion of residents welfare benefit claimants in the pre-lockdown period, retail floor space (m^2) in 2019. The total DDD effect for $LD \times WFH^H \times NWFH^H$ is calculated as $LD \times WFH^H$ $+LD \times NWFH^H$ $+LD \times WFH^H \times NWFH^H$. The total DDD effect for $PLD \times WFH^H \times NWFH^H$ is calculated as $PLD \times WFH^H$ $+PLD \times NWFH^H$ $+PLD \times WFH^H \times NWFH^H$. When calculating the p-value, we use the total DDD effect when defining $LD \times WFH^H \times NWFH^H$ and $PLD \times WFH^H \times NWFH^H$. Data used: Police recorded crime data, 03/2017-12/2022.

B.11.2 House Price Results

The results that we present below in Table B11 are based on the same regressions that generate the results we present in Figure 6, and serve two purposes. First the table provides, in addition to the DD estimates for a 1 standard deviation increase in WFH, the raw DDD estimates. Second, the table provides the full set of results in table form for the reader who prefers tables to graphs.

Table B11: House Prices and WFH

	(1)	(2)	(3)	(4)	(5)
	All Properties	Detached	Semi-Detached	Terraced	Flats
DDD Point Estimates:					
LD × WFH × BQ_1	41369***	33174	61819***	42559***	3878
	(10606)	(27046)	(9817)	(11275)	(14205)
LD × WFH × BQ_2	76976***	63534**	88662***	61115***	43269
	(13782)	(31372)	(16116)	(13966)	(40327)
LD × WFH × BQ_3	62843***	86014	94549***	73693***	–62999
	(20787)	(64729)	(23587)	(19085)	(57528)
LD × WFH × BQ_4	149158***	283671***	154908***	199372***	17858
	(29596)	(103610)	(48016)	(44667)	(40557)
PLD × WFH × BQ_1	120042***	179982***	148562***	97390***	20521
	(12852)	(31375)	(14716)	(12682)	(26203)
PLD × WFH × BQ_2	190067***	369634***	155386***	150708***	35325
	(18839)	(49570)	(16126)	(15554)	(28037)
PLD × WFH × BQ_3	215046***	482336***	276808***	227220***	4727
	(18456)	(57299)	(42318)	(21553)	(20593)
PLD × WFH × BQ_4	237591***	646790***	352159***	249074***	13549
	(27755)	(123597)	(43276)	(42728)	(27937)
DDD Point Estimate $\times 1\sigma_{WFH}$, Expressed as Proportion of $\overline{Y}_0$:					
$1\sigma_{WFH}$ (LD × WFH × BQ_1)/$\overline{Y}_0$	.0134***	.00753	.0228***	.0167***	.00136
	(.00343)	(.00614)	(.00363)	(.00443)	(.00497)
$1\sigma_{WFH}$ (LD × WFH × BQ_2)/$\overline{Y}_0$	.0249***	.0144**	.0328***	.024***	.0151
	(.00446)	(.00712)	(.00596)	(.00549)	(.0141)
$1\sigma_{WFH}$ (LD × WFH × BQ_3)/$\overline{Y}_0$	.0203***	.0195	.0349***	.029***	-.022
	(.00672)	(.0147)	(.00872)	(.0075)	(.0201)
$1\sigma_{WFH}$ (LD × WFH × BQ_4)/$\overline{Y}_0$	.0482***	.0644***	.0573***	.0784***	.00625
	(.00957)	(.0235)	(.0177)	(.0176)	(.0142)
$1\sigma_{WFH}$ (PLD × WFH × BQ_1)/$\overline{Y}_0$	.0388***	.0409***	.0549***	.0383***	.00718
	(.00416)	(.00712)	(.00544)	(.00499)	(.00917)
$1\sigma_{WFH}$ (PLD × WFH × BQ_2)/$\overline{Y}_0$	.0615***	.0839***	.0574***	.0593***	.0124
	(.00609)	(.0113)	(.00596)	(.00612)	(.00981)
$1\sigma_{WFH}$ (PLD × WFH × BQ_3)/$\overline{Y}_0$	.0695***	.11***	.102***	.0893***	.00165
	(.00597)	(.013)	(.0156)	(.00847)	(.0072)
$1\sigma_{WFH}$ (PLD × WFH × BQ_4)/$\overline{Y}_0$	.0768***	.147***	.13***	.0979***	.00474
	(.00897)	(.0281)	(.016)	(.0168)	(.00977)
$\overline{Y}_0$	292624	416691	255991	240639	270450
σ_{WFH}	.0946	.0946	.0946	.0946	.0946
Adjusted R^2	.646	.656	.858	.809	.525
Observations	3,642,248	891,628	1,063,079	1,055,600	559,309

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The dependent variable in all regressions is the house price in £.