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

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Abstract

We examine the impact of the working from home (WFH) shift on neighborhood-level burglary rates, employing detailed street-level crime data and a neighborhood WFH measure. We find a one standard deviation increase in WFH (9.5pp) leads to a persistent 4% drop in burglaries. A spatial search model identifies two deterrence channels: occupancy, as burglars avoid occupied houses, and "eyes on the street". We provide evidence supporting both channels. Despite crime displacement to low WFH areas offseting 30% of the burglary reduction, a hedonic pricing model reveals significant willingness to pay for high WFH areas, especially those with high ex-ante burglary risk.

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, . . . to insure the safety of both residents and strangers,—Jane Jacobs, *The Death and Life of Great American Cities* (1961)

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

In this paper, we study the effect on burglary of the working from home (WFH) revolution, which fundamentally changed the location of large swathes of the working population during the working week (Barrero et al., 2021; Hansen et al., 2023). Our work provides the first evidence quantifying the relationship between working from home and crime. The setting for our study is in England and Wales. In 2020, property crimes in England and Wales fell by over 30% during the nationwide lockdown. After lockdown restrictions were lifted, most crimes returned to pre-pandemic levels, except for burglary, which remains 30% lower compared to pre-lockdown levels. For this reason, our core focus will be on burglary.[1] A likely explanation for this shift is the concomitant change in where workers were located during the early days of the pandemic, a shift that has persisted due to the rise of remote work.[2]

Why should remote work change burglary rates? Our conceptual framework to answer this question is that (i) the rise of remote working led to a large spatial reallocation of workers to residential areas, which (ii) led to a substantive increase in informal crime deterrence, which (iii) caused a large drop in burglary rates. The persistence of the drop in burglary rates is based at least in part due to the persistence of WFH. This increase in informal deterrence has happened along two margins. First, many homes are no longer empty during the daytime (an *occupancy effect*). Second, more workers at home during the day increases "eyes on the street" as highlighted by Jacobs (1961). The ensuing reduction in burglary, which accounted for 6% of all reported crimes in 2019, is quantitatively important—a 30% decrease corresponds to 107,000 fewer reported crimes per year and a £635 million reduction in total costs (Heeks et al., 2018). This increase in deterrence due to WFH has the important feature that it affected the population as a whole, but unequally. In some neighborhoods relatively few workers are able to WFH, in others many more. We make use of this heterogeneity to identify the effect of WFH on the rate and distribution of burglaries. We then go on to provide evidence consistent with

[1] 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 selfsame location most impacted by the rise of remote work.

[2] 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`).

the occupancy and eyes on the street effects, study spatial spillovers, and use a hedonic analysis to identify the impact on overall wellbeing.

In order to guide our empirical analysis, we begin the paper by developing a simple spatial search model which captures key elements of the relationship between criminal activity and changes in the spatial distribution of work. In the model criminals allocate their time to searching for suitable homes to burgle across different neighborhoods. Using this model we identify three mechanisms by which WFH can impact burglary crime rates: (i) decreasing the number of empty houses; (ii) increasing the number of eyes on the street; and (iii) reallocating criminal search efforts away from high WFH neighborhoods to neighborhoods where WFH is relatively low. The model also suggests a non-linear relationship between crime and WFH—as WFH increases, spillovers from eyes on the street lead to a greater decrease in crime.

We start our empirical analysis by documenting the effect of working from home on property crime rates for all of England and Wales for both the lockdown period (March 2020 to May 2021) and the post-lockdown period (June 2021 to December 2022) separately, using both a difference-in-differences (DD) estimation strategy and an event study approach. Our data combines a neighborhood-level measure of the local residents' ability to work from home, following the approach of Dingel and Neiman (2020) and De Fraja et al. (2021), with detailed monthly crime data, as well as a large set of additional information on the characteristics of the neighborhood. We account for neighborhood fixed effects and *police-force-by-year-by-month* fixed effects to account for local area differences in crime as well as temporal shocks, such as changes in police force strategy, that occur within local policing areas over time.

We present a range of evidence to provide support for the parallel trend assumption: an event study analysis, a formal test of pre-trends, and an implementation of the worst-case bounding approach suggested by Rambachan and Roth (2023). Each piece of evidence provides support for the parallel trends assumption. This evidence is consistent with the observation that the WFH potential of an area was essentially a latent characteristic of a neighborhood that suddenly became relevant once the lockdown started.

Next, we conduct a set of additional analyses to explore the mechanisms at play behind the impact of WFH on crime in the lockdown and post-lockdown periods. First, we obtain restricted access data for London which is richer than our main data along two key dimensions: (i) the data allows us to distinguish between residential and commercial burglary at the local level and (ii) the data is offense-level data that contains time and date of offense. With this data, we can repeat our core analysis, splitting the timing of offenses to coincide with three distinct periods: the working hours in the week, non-working hours in the week, and the weekend. This analysis serves as a test of the mechanisms proposed in our model. If they are truly what drives the aggregate WFH–crime relationship, then we should see the most pronounced effects during working hours, when the distribution of the population is substantially different from the pre-Covid distribution. If it is changes in crime rates outside working hours that drive our main results, this suggests other factors may be at play.

We then proceed to disentangle the two main effects we suspect are at play behind the impact of WFH on crime: the occupancy effect, whereby workers in their properties during the day acts as a deterrent to burglars, and the eyes on the street effect. We do this in two ways. First, we return to our national-level data, and use non-parametric estimation methods to document the shape of the crime–WFH relationship across the WFH distribution. If only the occupancy effect is at play, we would expect the shape of the crime–WFH relationship to be linear across the WFH distribution, with every additional occupied property essentially one fewer property to burgle. If the eyes on the street mechanism also plays a role in driving our main effects, then we expect a non-linearity in the crime–WFH relationship: once a certain threshold of additional eyes on the street[3] are present, it becomes increasingly likely that a potential burglar will be spotted, and identified, by local residents.

Second, we note that, for a given neighborhood and at a particular time of day, the eyes on the street effect should be more pronounced when it is light outside, but the occupancy effect will be unaffected. Such a "veil of darkness" approach has been used in other literatures (Grogger and Ridgeway, 2006). Using our data for London, we estimate a triple difference (DDD) model allowing the effect of WFH on crime across our three, core periods to vary by whether it is daylight or not. The test of the eyes on the street mechanism is not whether crime rates drop when it is light outside, but rather whether our DD term is different when it is dark or light out.

We then turn to consider the consequences of an uneven spatial distribution of WFH potential for burglary. Our spatial model of crime indicates that burglars will account for the proportion of people at home in their properties while choosing where to burgle. Thus, neighborhoods with high WFH potential may no longer experience falls in burglary in the post-lockdown periods if these areas are surrounded by neighbors with even larger WFH potential. It is precisely this idea that we investigate with our spatial analysis. We extend our DD strategy by including a third difference: a dummy variable indicating for each of our neighborhoods if the area's contiguous neighbors have relatively higher WFH potential than the reference area. This gives rise to a DDD estimation strategy. Given that the spatial scale of our neighborhoods is fairly small, such a consideration of crime displacement effects due to the new WFH environment is an important aspect of the broader question we study in this paper, and will be of particular interest to police and other local government policymakers.

We complete the paper with a hedonic-house-price-model-based analysis. More specifically, we use a very rich DDD specification, where we allow the house price impact of our main DD term to differ by the ex-ante burglary risk of the neighborhood, measured by pre-pandemic quartiles of burglary. Key aspects of our specification are the inclusion of very low level spatial fixed effects (the spatial unit is an Output Area, which had an average population of 309 as of the 2011 Census. These are akin to a US Census Block.), *housing-market-by-month-by-year* fixed effects, and the flexibility to allow the housing characteristics to vary by housing market and period in order to avoid conflation bias (Kuminoff and Pope, 2014; Banzhaf, 2021). The purpose of this analysis is to quantify the welfare impact of the changing benefit of WFH potential experienced from the national lockdown of 2020 onward. By allowing the welfare impact to differ by the ex-ante burglary risk of the neighborhood, we align our welfare analysis with the key findings of our work. Using hedonic house price models to understand local residents' willingness to pay for non-market local amenities has a long history going back to Rosen (1974), and the validity of using hedonic models in conjunction with a DD specification was recently clarified by Banzhaf (2021).

Our first main finding is that neighborhoods' WFH potential led to a large and persistent drop in burglaries.

[3]Eyes on the street may be inferred by burglars by windows being open, cars in the drive or on the street, or lights being on.

In our preferred specification, a one standard deviation increase in neighborhood WFH potential (9.5 percentage points) led to a 3.8% drop in the burglary rate in the lockdown period and a 4.0% drop in the post-lockdown period, relative to pre-pandemic rates. These results are very stable, as we show in our event study analysis: almost three years after the first lockdown, the WFH potential of the neighborhood still has a large and statistically significant impact on burglary crime rates. This is consistent with the evidence on sustained rates of WFH since the pandemic De Fraja et al. (2023).

We then move to our London Met data, first repeating our core analysis to document similar patterns for London only, as we do for the country as a whole. Further analysis of the London data highlights that the changes we document for residential burglary are driven by large and significant declines in burglaries during the working week, particularly weekday mornings. Such a finding buttresses the notion that we are indeed capturing the impact of a reallocation of where the working population is during the working week, and suggests that our empirical specification is apt in accounting for other neighborhood unobservables that are correlated with WFH potential.

Returning to our national data and using non-parametric estimation methods, we document important non-linearities in the crime–WFH relationship in both the lockdown and post-lockdown period. Specifically, we find that while WFH leads to a steady, linear decline in crime for the levels of WFH below the mean, there is an inflection point just above the mean where WFH has a disproportionately stronger effect on crime. Such a pattern suggests that both the occupancy effect, and the eyes-on-the-street effect are both important mechanisms underpinning our key findings: the former for generating a steady negative decline in crime, and the latter mechanism for generating the inflection point. It is notable that we find this inflection point at almost the identical point of the (residualized) WFH distribution in both the lockdown and post-lockdown periods respectively. The veil of darkness analysis confirms the importance of the eyes-on-the-street effect.

Our spatial analysis highlights that the impact of WFH will depend not just on the WFH potential of a given neighborhood, but also on the relative differences between a neighborhood and the surrounding areas. Our spatial–empirical approach takes the form of a DDD specification, where in the interest of ease of interpretation we binarize our WFH measure, and include as a third difference a dummy for whether adjacent neighborhoods have higher WFH potential than one's own area. Within this framework we document large and meaningful spatial spillovers. While a neighborhood with high WFH potential that is surrounded by neighbors with, on average, lower WFH potential experiences a 3.9% drop in burglary in the post-lockdown period, a similar high WFH potential neighborhood that is surrounded by neighbors with higher average WFH potential experiences as good as no change in burglary rates (a 0.4% drop). This analysis thus provides evidence for the displacement effects of WFH on burglary suggested by the model. Overall, this displacement effect is large enough to reduce the overall effect of WFH on burglary by 30% in the post-lockdown period. We interpret this as evidence that burglars face large costs to searching further afield.

Our final set of analyses aims to quantify the total welfare changes experienced by neighborhoods with greater or lesser WFH potential in our period of study. The evidence we provide is consistent with households having a large willingness to pay to live in higher WFH potential areas in the post-pandemic period. The richness of our DDD specification, where we allow our main DD term to vary by the ex-ante burglary risk of a neighborhood, informs us of the welfare gains from the potential to WFH in areas with different risks of burglary. The first point to note from our welfare analysis is that households have an unambiguous positive willingness to pay for living in higher WFH potential areas in the post-pandemic period. The second point, which aligns with our main finding on crime, to note is that the willingness to pay for WFH potential is monotonically *increasing* in the ex-ante burglary risk of the neighborhood: areas with higher ex-ante risk have more to gain from the shift to remote working, and this is borne out in the higher willingness to pay we document for these areas. A one standard deviation increase in WFH potential leads to a 3.9% increase in house prices in the lowest ex-ante risk quartile, and a 7.7% increase for those in the highest quartile. Interestingly, the housing-type specific estimates show that while our core findings extend to all houses, there is little change in the willingness to pay for apartments in neighborhoods with higher WFH potential. This may reflect several channels, including that, as we show, the WFH-induced crime drop is larger in less urban areas (apartments are more common in urban areas) and the possibility that the eyes on the street mechanism plays less of a role for apartment blocks as compared to a house-lined street.

Our work makes significant contributions to three distinct literatures. First, by providing the first evidence on the crime consequences of the shift to remote and hybrid work, we make a key contribution to the literature studying the economic and societal consequences of the rise of WFH (Bloom et al., 2015; Barrero et al., 2021; Hansen et al., 2023), and in particular work on the implications of the consequent change in the spatial distribution of economic activity (De Fraja et al., 2021; Delventhal and Parkhomenko, 2020; Delventhal et al., 2022; De Fraja et al., 2022b). Existing work has shown the consequences of this change for inequality (Althoff et al., 2022; De Fraja et al., 2023), and the labor market (Bamieh and Ziegler, 2022) which we build on to consider the effects on crime.[4] Indeed, our hedonic analysis suggests that the welfare gains from reductions in burglary due to WFH are large, and thus an important component of the overall welfare effects of WFH.

Second, by documenting the deterrent role that remote workers can play, and the subsequent reductions in burglary crime, we contribute to the literature on criminal decision-making and deterrence.[5] Our results on the deterrent effects of WFH provide a new source of variation to the literature on the effects of deterrence on crime which has previously focused on police numbers (Evans and Owens, 2007; Chalfin and McCrary, 2018; Blesse and Diegmann, 2022; Chalfin et al., 2022) or exploited natural experiments in the intensity of policing of different areas due to terrorism (Di Tella and Schargrodsky, 2004; Klick and Tabarrok, 2005; Draca et al., 2011). Due to our focus on non-police deterrence, our paper is perhaps closest to Doleac and Sanders (2015), who use the introduction of Daylight Saving Time as quasi-random source of variation in darkness, finding that robbery falls by 7% in the weeks following DST. Our focus on the deterrent effect that remote workers play, and our subsequent findings of spatial spillovers, shares commonalities with the work of both Gonzalez-Navarro (2013), who studies the introduction of LoJack on car theft and subsequent geographical externalities of an area-based treatment, and Maheshri and Mastrobuoni (2021) who study the deterrent effect of private security guards on bank robberies. The authors document that by hiring an armed guard, a bank reduces its own crime

[4]There have been a number of studies, for example Kirchmaier and Villa-Llera (2020) and Abrams (2021), which look at how public health policies during the 2020 pandemic affected crime, but this literature is fundamentally different to our paper as that literature focuses on the temporary effects of shelter-in-place orders.

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

risk but displaces crime to banks without guards.

By documenting the self-policing roles that remote workers play in their local communities—directly deterring crime via the occupancy effect, implicitly deterring crime and acting as potential witnesses to any realized crimes via the eyes on the street mechanism—our third contribution is to the literature documenting the role of private policing on crime. This small but growing literature includes work on the consequences for crime of both Business Improvement Districts (Brooks, 2008; Cook and MacDonald, 2011; Faggio, 2022) and private, university campus-based police forces (Heaton et al., 2016; MacDonald et al., 2016).

The remainder of the paper proceeds as follows. In Section 2 we provide a spatial search model of burglary and WFH. Section 3 discusses the data and Section 4 discusses the main empirical strategy. This is followed by our main results in Section 5 and spatial displacement results in Section 6. Finally, we provide an analysis of the welfare effects through housing prices in Section 7 and conclude in Section 8.

2 Model

Here we present a simple spatial-search model of crime which captures a key feature of property crime, and burglary in particular. Specifically, burglary is an opportunistic crime, burglars actively look for exposed homes. A fact sheet 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). With this in mind, we want to distinguish between two ways in which an increase in WFH will affect burglaries (the occupancy effect). First, the number of unoccupied—and therefore suitable—homes will decrease. Second, the probability of being caught while burgling increases, as there are more eyes on the street (the eyes on the street effect).

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 occupancy 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.

2.1 A Spatial Search Model of Crime

Potential criminals must decide whether to commit burglaries, and if they choose to burgle, how to allocate the time they spend searching for appropriate targets. These decisions are made based on the expected benefit of committing a burglary, the chance of success multiplied by the reward, and the expected cost given by the probability of getting caught multiplied by the expected punishment. Each criminal has one unit of time to allocate to searching for suitable houses to burgle. There are two neighborhoods, denoted by $n = \{1, 2\}$, between which the unit of time can be allocated. The criminal allocates $\lambda \in [0, 1]$ of their time to search in neighborhood 1 and $1 - \lambda$ of their time to search in neighborhood 2. Optimal behavior by each criminal implies their time is allocated such that the marginal value of searching in each neighborhood is equalized.

In neighborhood n the probability of finding a suitable house to burgle is described by the function $\phi_n = \phi(\rho_n, C_n)$. Here ϕ_n is a decreasing function of two variables. The first, ρ_n, is the proportion of residents in neighborhood n who work from home. This reflects the preference that burglars have for empty houses. A higher value of ρ_n means that more homes are occupied during working hours. The second is the total number of criminals operating in neighborhood n, C_n, reflecting that the same house cannot be profitably burgled multiple times. We assume that $\phi(1, C_n) = 0$ for all C_n and $0 < \phi(0, C_n) < 1$ for all values of C_n under consideration.

If a suitable house is found, the criminal burgles the house and, with probability $\pi_n = \pi(\rho_n)$, the burglar receives a payoff P_n. We assume that $P_1 > P_2$, meaning the payoff from a successful burglary is higher in neighborhood 1 than in neighborhood 2, perhaps as a result of 1 being more affluent than 2. With probability $(1-\pi_n)$ the burglar is caught by the police and faces a penalty F, common to all criminals and all neighborhoods. The probability of a successful burglary, π_n, is a decreasing function of ρ_n, reflecting that more residents are working from home means more eyes on the street, and thus a greater chance of being seen while engaging in a burglary. We assume that $0 < \pi(\rho) < 1$ for all values of $\rho \in [0, 1]$.

The expected value to an individual criminal spending a unit of time in each neighborhood is:

$$E(VC_1) = \phi_1(\pi_1 P_1 - (1 - \pi_1)F) \qquad \text{and} \qquad E(VC_2) = \phi_2(\pi_2 P_2 - (1 - \pi_2)F).$$

Consider how a change in ρ_n affects the expected value to burglary in neighborhood n.

$$\frac{\partial E(VC_1)}{\partial \rho_n} = \underbrace{\frac{\partial \phi_n}{\partial \rho_n}(\pi_n P_n - (1 - \pi_n)F)}_{\text{Occupancy effect}} + \underbrace{\frac{\partial \pi_n}{\partial \rho_n}(P_1 + F)\phi_n}_{\text{Eyes on the street effect}} .$$

ρ_n, affects the expected value of burglary in neighborhood n in two ways. By reducing the availability of suitable houses (the occupation effect) and by increasing the chance of being caught if a suitable house is found and is burgled (the eyes on the street effect). As ϕ_n and π_n are both decreasing in ρ_n, the expected value to burglary in neighborhood n is strictly decreasing in ρ_n.

The number of criminals searching in each neighborhood is determined by the total amount of criminals, C, and how their time is allocated between neighborhoods 1 and 2. Given C burglars, the total burglars in each neighborhood, C_1 and C_2, will be determined by how much time each allocates to each neighborhood. Let λ_i be the proportion of time burglar i allocates to neighborhood 1, then:

$$C_1 = \sum_{i=1}^{C} \lambda_i \quad \text{and} \quad C_2 = \sum_{i=1}^{C} (1 - \lambda_i).$$

2.1.1 The Criminal's Decision

A potential burglar makes two choices. The first is whether to seek to commit a burglary. The participation decision is made based on the value of the criminal's outside options, denoted by ω, which is common to all criminals. A criminal only participates if the expected value of crime is higher than the value of the outside option:

$$\max_{\lambda_i \in [0,1]} \{\lambda_i \phi_1(\pi_1 P_1 - (1-\pi_1)F) + (1-\lambda_i)\phi_2(\pi_2 PV_2 - (1-\pi_2)F)\} \geq \omega. \tag{1}$$

The second choice is, conditional on participating, how to allocate search between the two neighborhoods. This is determined by the value of λ_i which maximizes the left-hand side of (1):

$$\begin{aligned}\arg\max_{\lambda_i} \Big\{ & \lambda_i \phi(\rho_1, \lambda_i + \sum_{j \neq i} \lambda_j) \left[\pi(\rho_1, e_1) P_1 - (1 - \pi(\rho_1, e_1))F\right] \\ & + (1-\lambda_i)\phi(\rho_2, C - \lambda_i - \sum_{j \neq i} \lambda_j) \left[\pi(\rho_2, e_2) P_2 - (1 - \pi(\rho_2, e_2))F\right] \Big\}.\end{aligned} \tag{2}$$

2.1.2 Equilibrium

Equilibrium is defined by the total number of criminals committing burglaries, C, and the number of criminals in each neighborhood, C_1 and C_2.

Equilibrium requires that two conditions are satisfied. First, that there is no one who chooses to commit burglary that would prefer not to, and vice-versa. That is, the criminal on the margin of committing burglary is indifferent. The second is that no burglar wishes to change their search allocation between neighborhoods 1 and 2. This is reflected by writing the equilibrium versions of (1) and (2):

$$\phi(\rho_2, (1-\lambda)C) \left[\pi(\rho_2) P_2 - (1 - \pi(\rho_2))F\right] = \omega, \tag{3}$$

$$\phi(\rho_1, \lambda C) \left[\pi(\rho_1) P_1 - (1 - \pi(\rho_1))F\right] = \phi(\rho_2, (1-\lambda)C) \left[\pi(\rho_2) P_2 - (1 - \pi(\rho_2))F\right], \tag{4}$$

where $C_1 = \lambda C$ and $C_2 = (1-\lambda)C$. Notice that the equilibrium value, λ reflects the aggregate behavior of the criminals, not the individual values λ_i. There are many possible combinations of λ_i which can be an equilibrium, including $\lambda_n = \lambda$ for all i, but they must satisfy (3) and (4). As we are only interested in aggregate criminal behavior, not individual, for our purposes we will focus only on the aggregate allocation λ.

The condition expressed in Equation (3) reflects a participation constraint while (4) reflects a spatial equilibrium. The spatial equilibrium states that the expected return to investing a unit of search effort must be the same in each neighborhood. If this does not hold, then criminals can improve their expected payout by allocating more search effort to the neighborhood with the higher expected payout. Notice that (3) follows from (1) when the spatial equilibrium holds.

2.1.3 Comparative Statics

We consider here an asymmetric increase in ρ across neighborhoods; there is an increase in ρ_1, but not ρ_2. This will decrease the expected return to searching in neighborhood 1 through two channels. First, the number of suitable (empty) houses in 1 decreases (ϕ_1 decreases), the occupation effect. Second, the probability of getting caught increases (π_1 decreases), the eyes on the street effect. Therefore, the left-hand-side of (4) decreases, so criminals reallocate their time from 1 to 2 (λ decreases), the displacement effect. The decrease in λ means that the left-hand-side of (3) decreases, so it must be the case that the total number of criminals is decreasing also

(C decreases.)

Formally, the effect of changing ρ_1 on C and λ can be written as:

$$\frac{dC}{d\rho_1} = -\left[\frac{\frac{\partial\phi_1}{\partial\rho_1}}{\frac{\partial\phi_1}{\partial C_1}} + \frac{\phi_1[P_1+F]\frac{\partial\pi_1}{\partial\rho_1}}{E(VC_1|s)\frac{\partial\phi_1}{\partial C_1}}\right] < 0, \tag{5}$$

$$\frac{d\lambda}{d\rho_1} = -\frac{1-\lambda}{C}\left[\frac{\frac{\partial\phi_1}{\partial\rho_1}}{\frac{\partial\phi_1}{\partial C_1}} + \frac{\phi_1[P_1+F]\frac{\partial\pi_1}{\partial\rho_1}}{E(VC_1|s)\frac{\partial\phi_1}{\partial C_1}}\right] < 0, \tag{6}$$

where $E(VC_1|s) = \pi_1 P_1 - (1-\pi_1)F$ is the expected value of burglary in neighborhood 1, conditional on finding a suitable house. Notice that both the channels discussed above are captured in these comparative statics. When having more *eyes on the street* is important, implying a non-zero value of $\partial\pi_1/\partial\rho_1$, both the total crime reduction and the reallocation of crime is larger than implied by that effect alone.

The above comparative statics tell us how the allocation of criminals will change. We can also look at how the expected amount of observed burglary changes in each neighborhood, given by $\phi_1\lambda C$ and $\phi_2(1-\lambda)C$. For neighborhood 2, we will not see a change in crime overall. This follows from equation (1) in which $(1-\lambda)C$ and therefore ϕ_2 are invariant to changes in ρ_1. For neighborhood 1, we can write the relevant comparative static as:

$$\frac{d\phi_1 C_1}{d\rho_1} = -\frac{1}{E(VC_1|s)}\left[\underbrace{\frac{\phi_1}{\frac{\partial\phi_1}{\partial C_1}}\frac{\partial\phi_1}{\partial\rho_1}E(VC_1|s)}_{\text{Occupancy effect}} - \left(C_1 - \frac{\phi_1}{\frac{\partial\phi_1}{\partial C_1}}\right)\underbrace{\frac{\partial\pi_1}{\partial\rho_1}(P_1+F)\phi_1}_{\text{Eyes on the street effect}}\right] < 0, \tag{7}$$

Equation (7) reflects the channels through which remote working affects the overall change in crime for neighborhood 1. The first term on the right-hand-side is determined by the occupancy effect: the direct effect of remote working as a result of having fewer empty houses. The second term is the effect of eyes on the street on the number of criminals in neighborhood 1. The second term reflects the increase in the importance of the eyes-on- the-street effect to the change in chance of finding somewhere to burgle as aggregate search effort increases. Notice that both of these effects are larger if the reduction in crime doesn't make suitable, un-burgled, properties too easier to find (i.e. $\partial\phi_1/\partial C_i$ is small in magnitude).

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 final dataset is constructed by aggregating individual crimes to the MSOA level and combining this with information reflecting predictions on the number of workers in occupations which can be done from home.

3.1 Working From Home

WFH has increased dramatically in England and Wales compared to prior to the pandemic, as in other Western countries. Prior to the pandemic 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., 2022a). 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).

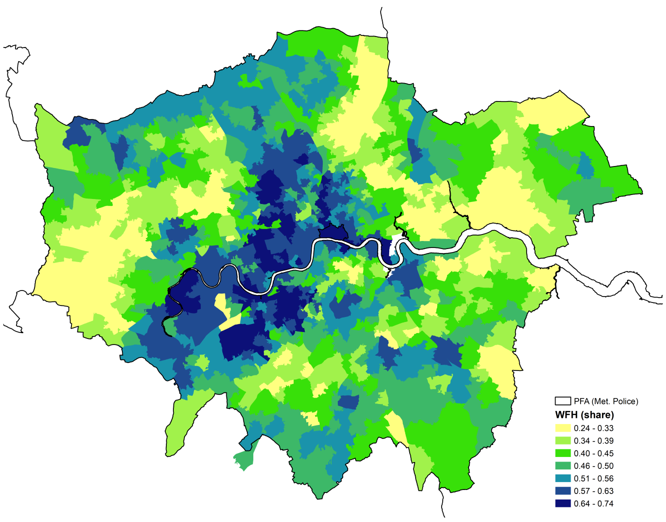
Our measure of WFH is based on work in De Fraja et al. (2021) and is an estimate of the percentage of employed residents in a neighborhood able to work from home. It is obtained by computing an occupation specific WFH index for each occupation, h_o. This reflects the extent to which a particular occupation 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.

The index is then calculated as the average of the index values for employees in the neighborhood. That is:

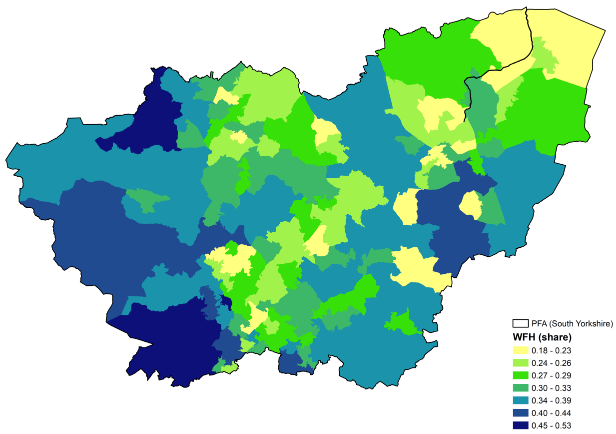
$$WFH_n = \frac{\sum_o E_{o,n} \times h_o}{E_n}, \tag{8}$$

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.

Figure 1: 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.

By using the 2011 Census we avoid concerns about endogenous changes in residential location choice by occupation. Importantly, however, as shown in Figure A9 in the Appendix there is 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.[6]

The maps in Figure 1 show how the (estimated) proportion of people working from home varies across neighborhoods in Greater London and South Yorkshire. 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 6.

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 such as those in the Peak District on the west of the map. This may reflect the larger numbers of commuters into London from other areas.

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* is data from the Metropolitan Police which additionally has precise information on the time at which each offense was committed and more disaggregated information about the offense type, but covers only the (London) Metropolitan Police Force Area.

We collect data on burglary as well as other property crimes such as, theft, (acquisitive) vehicle crime, arson, and shoplifting.[7] 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

[6]In Figure A9 we plot our predicted values for each neighborhood against the proportion of respondents who reported they work from home in the 2021 Census. The UK Census took place March 2021, during the second national lockdown. 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.

[7]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.

are nested within MSOAs allowing us to straightforwardly aggregate and match to the WFH data at the MSOA level.[8] Since we are interested in the period before and after the pandemic, we use data spanning the 30 months before March 2020 to the most recently available period, from September 2017 to December 2022.

Figure 2 shows the time series of each type of crime over the period we study. 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. Perhaps the most notable feature of the graph is that following the end of lockdown in England and Wales there is no recovery in rates of burglary, which remains below two-thirds 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 2022

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.

[8] 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 and mobility data.

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.[9] 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

3.3.1 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. We aggregate this information to the level of our neighborhood (the MSOA). We stratify our main analysis according to urbanicity, which we measure using residential population density.

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 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 provided as 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.

3.3.2 House Price Data

We additionally use house price data from the UK Land Registry. The data cover the near universe of 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.

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

4 Empirical Specification

This section outlines our strategy for estimating the causal effect of working from home on criminal activity. We obtain our baseline estimates using a difference-in-differences estimation strategy, in which our treatment is the neighborhood potential to WFH, as detailed in Section 3:

$$crime_{nt} = \alpha_1(LD_t \times WFH_n) + \alpha_2(PLD_t \times WFH_n) + LD_t \times X_n^{'}\beta_1 + PLD_t \times X_n^{'}\beta_2 + \gamma_n + \theta_{A\times t} + \varepsilon_{nt}\,, \quad (9)$$

where $crime_{nt}$ is the number of crimes per ten-thousand residents in neighborhood n and month t. Given that we are implementing a DD design, we do not log our dependent variable (McConnell, 2023). On the right-hand side we include dummy variables equal to 1 if month t occurs in the national lockdown period, and 0 otherwise (LD_t), and equal to 1 if month t occurs in the post-national lockdown period PLD_t.[10] These time dummies are interacted with the time-invariant variable measuring the proportion of work that can be done from home in neighborhood n, denoted by WFH_n, and a vector of pre-determined characteristics of neighborhood n, denoted by X_n. Unobserved variation in crime is captured by two parameters: γ_n is a neighborhood-level fixed effect, and $\theta_{A\times t}$ is a *month-by-year-by-police force area* fixed effect, where neighborhood n is exclusively within area A. Therefore, $\theta_{A\times t}$ non-parametrically captures police force and area-specific changes over time in the crime rate. There may also other neighborhood characteristics correlated with WFH which determine the behavior of $crime_{nt}$ over the lockdown and post-lockdown periods. We address this problem by also including X_n, a vector of variables describing key neighborhood characteristics, and allowing each of these variables to affect crime differently in the lockdown and post-lockdown periods. Specifically, we include the pre-lockdown rate of public support claims, the proportion of housing that is resident owned, the proportion of housing that is publicly provided (i.e., social housing), and the total amount (in square meters) of retail space in the neighborhood. Finally, ε_{nt} reflects the residual time and neighborhood varying factors that affect reported crime.

The key identifying assumption required for our DD strategy is the parallel trends assumption: we require areas with high and low levels of WFH potential to exhibit similar pre-lockdown trends in crime.[11] The event study that we present in Section 5.2 provides strong support for this assumption: there is no evidence of differential pre-trends.

We provide further evidence for the parallel trends assumption in the Appendix. First, in Table A1, where we report an analogous specification to Equation (9), but where we replace our DD terms with a time trend interacted with WFH potential. This serves as a placebo regression, and directly gets at the notion of parallel trends. Second, in Section A.1.2 we provide the results of the worst-case bounding approach of Rambachan and Roth (2023) which show that even if post-treatment violations of the parallel-trends assumption were three times as large as any pre-period violation, the confidence set for the treatment effect of WFH on burglary would not include zero.

[10] 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 the lockdown restrictions where relaxed in most parts of the UK, 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.

[11] In fact, as our treatment is continuous the necessary assumptions for our DD model to estimate a causal effect may be stronger (Callaway et al., 2021). We discuss these assumptions, and why here they are reasonable, in Appendix A.1.3.

5 Results

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. 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.

We report the DD parameter estimates from Equation (9) in Table 1. As a first step, column 1 reports results from a simplified version of Equation (9) 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. The coefficients imply that a one standard deviation (9.5pp) increase in WFH rates 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 precise. In column 3 we now allow the *month* × *year* fixed effects to vary by government region.[12] Column 4 reports the estimates of our preferred, and most demanding, specification in which we include *police force* × *month* × *year* fixed effects as in Equation (9). 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. In Table A5 we alternatively report results using a binary measure of WFH potential. The results are very similar, 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.

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

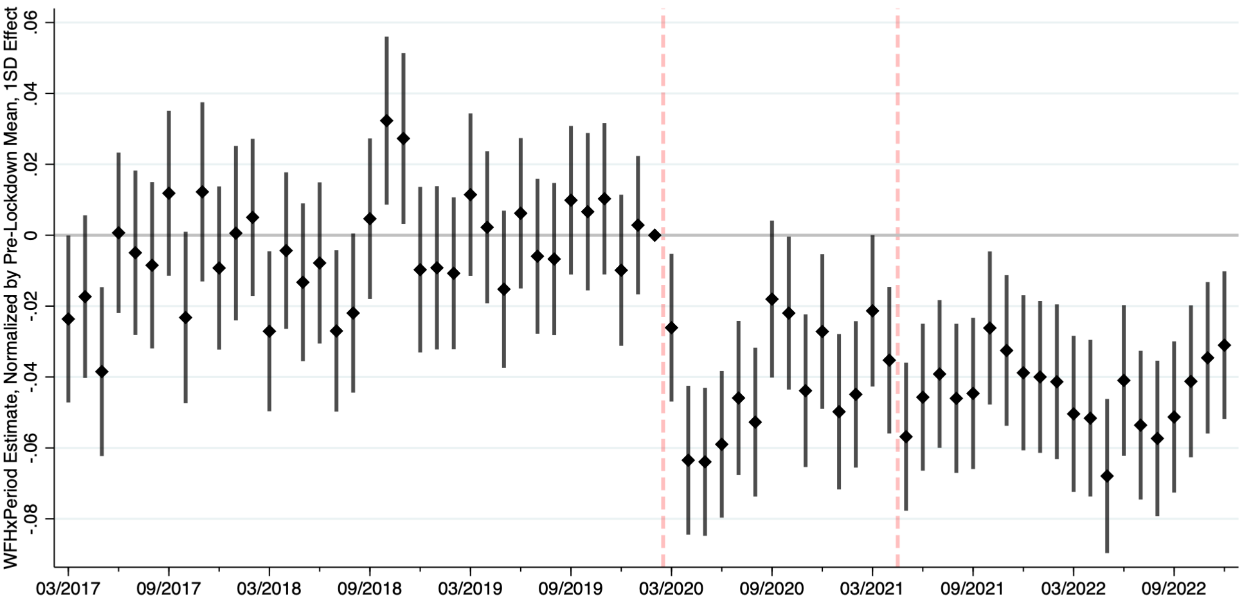
5.2 Dynamic DD Results: Event Study Graphs

In Table 1 we document a highly persistent negative impact of WFH potential on burglary. 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.[13] As above, this analysis also has the important additional benefit of describing visually the any differences 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 Table A1.

The event study estimate is described by Equation (10) in which we modify Equation (9) such that the effects of WFH are allowed to vary by month:

$$\text{crime}_{nt} = \sum_{t} [\alpha_t WFH_n] + (LD_t \times X_n^{'} \beta_1) + (PLD_t \times X_n^{'} \beta_2) + \gamma_n + \theta_{A\times t} + \varepsilon_{nt}. \tag{10}$$

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 (10). 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. See Figure A6 for the unscaled equivalent. 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 Figure 3 we present the event study graph for burglary. 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. 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. To put the coefficient estimates into perspective,

[13] We present the results of the event study approach for other property crimes in Figure A5.

recall from Table 1 that the mean of the burglary rate in the pre-lockdown period is 5.9. Thus, the point estimates ranging from -1 to -4 in levels represent a percentage decline relative to the pre-lockdown mean of 17%–68%.

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 Mechanisms

5.3.1 The Timing of the WFH-Induced Decline In Burglary

Our key explanation for our core findings is that once the British population exited the lockdown period, the nature of work—specifically 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 the number of eyes on the street during the daytime in the week.

For our eyes-on-the-street mechanism to be credible, the large declines in burglary that we document for high WFH neighborhoods in the post-lockdown period 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 estimate Equation (9) separately for residential and commercial burglary crime using the Met data, splitting the data by the day of the week and the time of day crimes were committed. We present the results of this exercise for domestic burglary in Table 2. For residential burglaries the results are quite striking. The 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. This is the case in both the lockdown and post-lockdown periods. We do not observe statistically significant, nor economically large, changes during weekdays outside these hours or on weekends. To put this into context, a neighborhood with a 30% WFH rate experienced an average decrease of 0.38 working hour burglaries, or a 41% decrease relative to pre-pandemic rates.

Interestingly, and unlike in the national data, the decline in burglary in working hours did not lead to an overall decline in burglary in WFH areas during the lockdown period. Instead, there was a countervailing increase in burglary outside working hours. This did not persist post-lockdown, our interpretation of this is that it reflects experimentation as burglars learn the new expected payoffs in high-WFH neighborhoods.

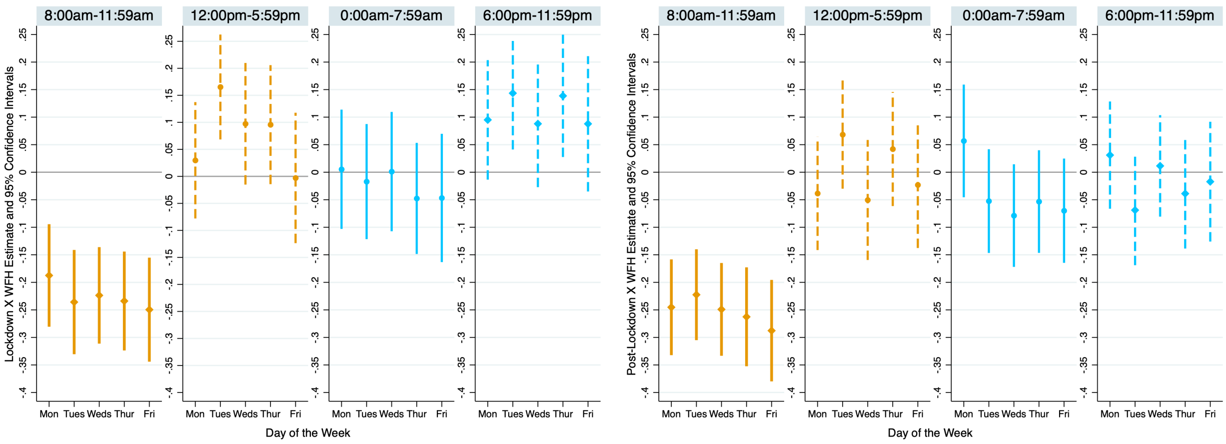
Results for commercial burglary, reported in Table A8 in the Appendix, are also consistent with an eyes on the street effect. WFH led to reductions in commercial burglary at all times of day during lockdown, and in both neighborhoods with large and small amounts of commercial floor space. Post lockdown, 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.

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

Figure 4: Stability of Timing Results by Day of Week



(a) Lockdown

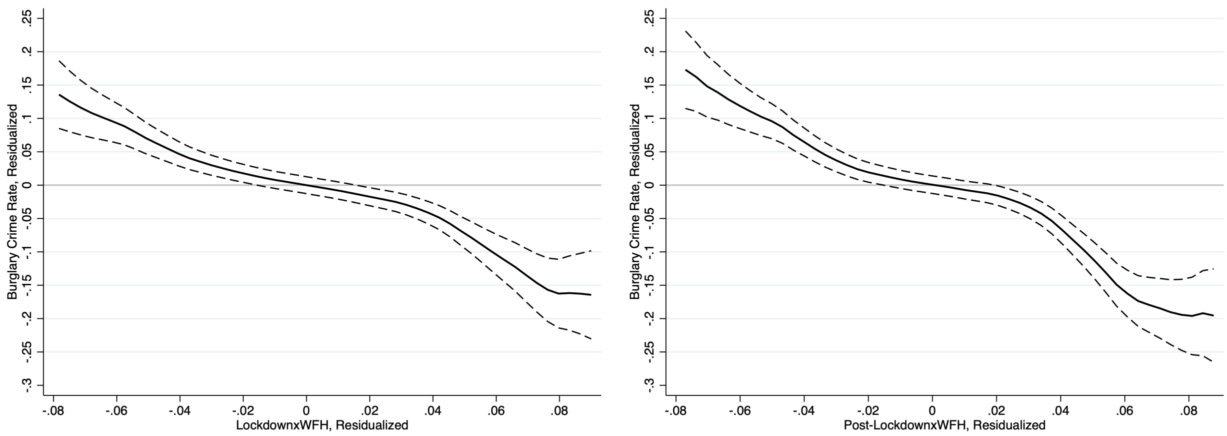
(b) Post-Lockdown

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

5.3.2 Teasing Apart the Occupancy and Eyes-on-the-Street Effects I

The model makes clear that there are two effects of an increase in WFH on crime in a neighborhood. First, the occupancy effect, and second, the eyes-on-the-street effect. The occupancy effect may be expected to be linear, but this occupancy creates "protective" spillovers within a neighborhood. For example, if we assume that each eye on the street observes multiple houses, even with low probability, then we should expect that as the number of eyes passes a threshold value the chance of detection will grow rapidly leading to a corresponding reduction in the number of burglaries. Moreover, once the number of eyes reaches a certain level then the street will be saturated such that the chance of detection is very high, and we should see only small, if any, further reduction in crime due to WFH. Thus, we expect there will be a non-linear relationship between the extent of WFH and

Figure 5: Non-Linearities in the Relationship Between Burglary and 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* × *month* × *year* fixed effects, and 2019 neighborhood characteristics controls as in Equation (9). 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.

crime.

To test this prediction, in Figure 5 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* × *month* × *year* fixed effects, and 2019 neighborhood characteristics controls as in Equation (9). As with previous estimates, there is a clear negative relationship. The relationship also appears to be non-linear. In particular, the decrease in crime is almost perfectly linear at low levels of remote working. This is consistent with a decline in burglaries due to fewer unoccupied homes, but little eyes on the street effect. When remote working becomes sufficiently high (residualized value of approximately 0.02) we reach an inflection point: the gradient of the regression increases, until we reach high values of remote working (residualized value of approximately 0.06) after which the relationship appears to flatten. The pattern is very similar in both the lockdown and post-lockdown period.[14] This pattern is consistent with there being a non-linear relationship between remote working and crime, where once a critical value is reached the eyes-on-the-street spillovers become important, and beyond which there is little further change in eyes on the street.

5.3.3 Teasing Apart the Occupancy and Eyes-on-the-Street Effects II

To further understand the separate roles of the occupancy and eyes on the street hypotheses we exploit the fact that the eyes on the street effect should be expected to be less powerful when it is dark as residents will not be easily able to see what is happening "on the street". Noting that the time at which it gets light and dark each

[14] In Figure A4 we report the results of repeating the same procedure for a placebo period, and show we find no relationship between WFH and crime.

Table 3: 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

day varies over a year provides within neighborhood variation in the expected eyes on the street effect and thus the reduction in crime due to WFH. To test this we use the precise time and date information in the Met data and estimate a DDD model in which we extend Equation (9) to allow the effect of WFH to vary by whether it is light at a given time. Whether it is light or not is defined in terms of the official Civil Twilight time for each day. 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.

The results in Table 3 provide evidence that the eyes on the street effect is important. In particular, we find that the effect of WFH on crime in the early weekday mornings, and Sunday evenings, is significantly larger when it is light outside. This effect is larger and more precisely estimated in the post-lockdown period, but while the coefficient is similar in the evenings in both periods it is not statistically significant.

6 Displacement of Crime Across Space

6.1 Spatial Econometric Estimator

In Section 2 we outline a theoretical framework in which remote working changes burglary patterns in two ways. First, it leads to an overall reduction in crime which we have established above. Second, it suggests that criminals may shift from high-WFH areas to low-WFH areas. In the case of only two neighborhoods, as considered in the model, this means that the overall impact on crime in the low-WFH neighborhood will be the sum of the negative effect of the overall reduction in crime, and the positive effect of the relocation of crime from the high-WFH. In the model in Section 2 these two effects are equal and cancel each other out.

More generally, the change in crime in a given neighborhood will depend on the aggregate change in crime, and the extent to which crime relocates to, or away from it. Thus, two otherwise identical neighborhoods, one with a lower rate of WFH than its neighbors and the other a higher rate, will experience different changes in their crime rates.

In this section we take the possibility of such spatial spillovers to the data. 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. (2021) find that the costs of "commuting" for criminals are very high in the UK, with most burglaries happening within a five-minute car drive of the criminal's home. This suggests our assumption is not, in practice, a strong one.

Furthermore, to facilitate inference, we now work with binary measures of WFH. We define WFH_n^H to be a binary variable equal to one if neighborhood n has a high work from home rate. $NWFH_n^H$ is a binary variable equal to one if the remote working rate in the neighborhoods contiguous to n's is greater than n's remote working rate.

We estimate the following equation:

$$
\begin{aligned}
\text{crime}_{nt} = & \alpha_1(LD_t \times WFH_n^H) + \alpha_2(LD_t \times NWFH_n^H) + \alpha_3(LD_t \times WFH_i^H \times NWFH_n^H) \\
& + \beta_1(PLD_t \times WFH_n^H) + \beta_2(PLD_t \times NWFH_n^H) + \beta_3(PLD_t \times WFH_i^H \times NWFH_n^H) \\
& + \delta_1(LD_t \times X_n) + \delta_2(PLD_t \times X_n) + \gamma_n + \theta_{A\times t} + \varepsilon_{nt}.
\end{aligned}
\tag{11}
$$

We define $NWFH_n^H$ using four different specifications: (1) remote working in n is strictly less than average remote working in n's contiguous neighborhoods; (2) remote working in n is strictly less than the 67th percentile work from home rate in n's contiguous neighborhoods; (3) remote working in n is strictly less than the median work from home rate in n's contiguous neighborhoods; and (4) remote working in n is strictly less than the 33rd percentile work from home rate in n's contiguous neighborhoods. The aim of specifications outlined in points 2–4 is to incrementally increase the threshold by which we define WFH_n^H. Once we arrive at specification (4), where the 33rd percentile of neighboring WFH potential exceeds that of neighborhood n, there is a pronounced disparity.

Based on Section 2, we *a priori* expect that neighborhood n with a WFH rate low relative to n's neighbors will experience an increase in neighborhood crime. We further may expect this effect to be larger when the disparity is larger.

Under the specification in Equation (11) 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 relatively 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, and below that of immediate neighbors. While, α_3 and β_3, describe the effect of being a neighborhood with high remote working relative to the national average, but low relative to its neighbors.

6.2 Results

Table 4 reports estimates for the key post-lockdown terms from Equation (11) for each of the four definitions of $NWFH_n^H$.[15] We first consider column 1, which defines $NWFH^H$ to be places where the mean WFH of n's contiguous neighbors exceeds that of n. Given the specification we implement here is a DDD specification, in addition to the first three rows of estimates, we also provide the total DDD effect for the triple interaction of (i) post-lockdown times, (ii) WFH^H times, and (iii) $NWFH^H$. This is calculated as the sum of the two DD coefficients β_1 and β_2 and the DDD coefficient β_3.

We focus on three key findings from this regression specification. First, areas with high WFH that are surrounded by neighbors with low average WFH enjoy a large and significant drop in burglary incidence in the post-lockdown period. This is the $PLD \times WFH^H$ term. Next, in low-WFH areas that are surrounded by high-WFH neighbors, we do not find any significant spatial spillovers ($PLD \times NWFH^H$).

Finally, for areas with high-WFH potential that are surrounded by neighbors with even higher-WFH potential, the DDD effect we estimate is positive and significant. The overall effect of WFH on burglary in these neighborhoods is given by the total DDD effect, which incorporates all requisite DD and DDD terms. What we find is for high-WFH neighborhoods that are surrounded by neighbors with even higher average WFH, the benefit of high WFH is entirely offset by having neighbors with high-WFH potential. The total effect is $-.024$, and this effect is not statistically different from zero. The remaining three columns change the threshold by which we define $NWFH^H$, but the results are substantively the same.

Of neighborhoods with high-WFH potential, 30% have neighbors with even higher WFH potential. Given, that in these neighborhoods there is no aggregate effect of WFH on crime, 30% of the reduction in crime in high-WFH neighborhoods is offset by spillover effects. This implies that a one-standard deviation higher rate of WFH leads to an overall reduction in burglary of around 2.8% in high-WFH areas post-lockdown, on average, rather than the 4% implied by the DD coefficient in Table 1.

We gain from this analysis a more nuanced understanding of how the impact of WFH on burglary crime in a given city will be determined by how exactly high-WFH areas are distributed amongst other neighborhoods. The fact that we do not document significant spatial spillover effects for low-WFH neighborhoods that are surrounded by neighbors with higher WFH potential is notable. Particularly, given that we do find spillovers for-high WFH neighborhoods surrounded by neighbors with higher WFH potential. There may be several reasons for this. One interpretation consistent with our model is that within a given locality high-WFH areas will be more affluent than low-WFH, so the low-WFH area has an insufficiently low pay-off to induce criminals previously focused on a high-WFH neighborhood to search in it.[16] Furthermore, that spillovers are limited also

[15] We present the extended results for both the lockdown and post-lockdown period in Table A6.

[16] An alternative explanation, not captured by our (linear) model, is consistent with the non-linear relationship between WFH and Burglary documented in Figure 5. There, we interpret this as evidence for the eyes-on-the-street hypothesis and these results further suggest that criminals might be more sensitive to the eyes-on-the-street effect than the occupancy effect when determining when deciding which areas to target.

implies that burglars face a high-cost of search. This is consistent with previous evidence that criminals are in general unwilling to travel far to commit crimes (Kirchmaier et al., 2021).

Table 4: Spatial DDD Model for Burglary

	(1)	(2)	(3)	(4)
	Criterion Used to Define $\mathbf{NWFH^H}$			
	Neighbor WFH Mean $> WFH_i$	Neighbor WFH P67 $> WFH_i$	Neighbor WFH P50 $> WFH_i$	Neighbor WFH P33 $> WFH_i$
$PLD \times WFH^H$	–0.228***	–0.372***	–0.273***	–0.199***
	(0.078)	(0.098)	(0.073)	(0.064)
$PLD \times NWFH^H$	–0.000	–0.081	–0.007	0.084
	(0.073)	(0.093)	(0.071)	(0.066)
$PLD \times WFH^H \times NWFH^H$	0.205**	0.331***	0.311***	0.292***
	(0.103)	(0.113)	(0.094)	(0.100)
Total DDD Effect for:				
$PLD \times WFH^H \times NWFH^H$	–0.024	–0.123	0.031	0.177*
	(0.090)	(0.102)	(0.086)	(0.094)
p-Value: $PLD \times NWFH^H =$ $PLD \times WFH^H \times NWFH^H$	0.758	0.553	0.625	0.314
$\overline{Y}_{PRE}$	5.923	5.923	5.923	5.923
Adjusted R^2	0.485	0.485	0.485	0.485
Observations	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 A6. Data used: Police recorded crime data, 03/2017-12/2022.

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

In this section, we aim to quantify the welfare implications of neighborhoods' differential 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.[17] This approach enables us to estimate the total welfare effects of the ability to work from home at the neighborhood level.

[17]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).

7.1 Empirical Specification

To do this we estimate a DDD house price regression, where the third difference is a measure of ex-ante burglary risk in the neighborhood.[18] The regression model we estimate is:

$$\begin{aligned}
price_{hbnmt} = & \sum_{p=1}^{2}\sum_{q=2}^{4} \alpha_q (Period_t^p \times B_0\, Q_n^q) \\
& + \sum_{p=1}^{2} \beta_{p,1} (Period_t^p \times WFH_n) + \sum_{p=1}^{2}\sum_{q=2}^{4} \beta_{p,q} (Period_t^p \times WFH_n \times B_0\, Q_n^q) \\
& + \sum_{p=1}^{2}\sum_{m=1}^{M}\sum_{q=1}^{4} \delta_{p,mq} (Market_m \times B_0\, Q_n^q \times Period_t^p \times X_h^{'}) \\
& + \sum_{p=1}^{2}\sum_{m=1}^{M}\sum_{q=1}^{4} \lambda_{p,mq} (Market_m \times B_0\, Q_n^q \times Period_t^p \times X_n^{'}) \\
& + \sum_{p=1}^{2}\sum_{q=1}^{4} \kappa_p (Period_t^p \times C_n^{'}) + \gamma_b + \theta_{m \times t} + \epsilon_{hbmnt} \ , \qquad (12)
\end{aligned}$$

where $price_{hbimt}$ is 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.[19] We specify the housing market to be a Travel To Work Area (TTWA) — a statistically constructed spatial unit akin to Commuting Zones in the US. The β parameters are our main focus here. $B_0\, Q_n^q$ denotes the ex-ante burglary risk quartile for neighborhood n.

X_h is a vector of property characteristics including dummies for property type and whether the property is leasehold.[20] X_n is a vector of neighborhood characteristics including the (property-based) proportion of homeownership and social housing, the proportion of welfare benefit claimants and the retail space in m^2. C_n is a vector of additional neighborhood ex-ante crime risk variables, including quartiles of all property crime except burglary, violent crime and drugs crime. 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. The parameter $\theta_{m,r\times t}$ captures month-by-year market-level shocks to house prices, θ_b is an Output Area or block fixed effect. Output Areas (OA) are the smallest census-based geographical unit: there are 181,408 of these in England and Wales, with an average population of 309 at the 2011 Census.[21] This makes OAs most similar to census blocks in the US. The variable γ_b 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

[18]Note, we cannot use WFH as an instrument for burglary crime, and estimate a 2SLS model of prices on crime, instrumenting burglary with WFH, as other factors that homeowners value are likely to change in response to the neighborhood propensity to WFH. By specifying a DDD model where the third difference is ex-ante burglary risk, we are investigating whether the DD coefficient differs systematically for neighborhoods with high initial burglary risk compared to areas with low ex-ante risk.

[19]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 (2023) 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 growth rate across areas with different WFH potential.

[20]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.

[21]`https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/bulletins/2011censuspopulationandhouseholdestimatesforsmallareasinenglandandwales/2012-11-23`

estimations), such as access to good schools or proximity to polluting factories. We cluster the error term ϵ_{hbmit} at the neighborhood level, the area at which WFH varies, following the recent work of Abadie et al. (2023).

We draw the reader's attention to three distinct aspects of our specification above. First, we interact the vector of housing characteristics, X_n, with 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.

Second, we allow the coefficients on all housing characteristics to differ in the three periods, thereby allowing the hedonic price function to shift in the lockdown period, and again post-lockdown. We do so in order to avoid conflation bias (Kuminoff and Pope, 2014; Banzhaf, 2021). Given this flexibility, the regression specification in (12) 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".

Finally, the 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).

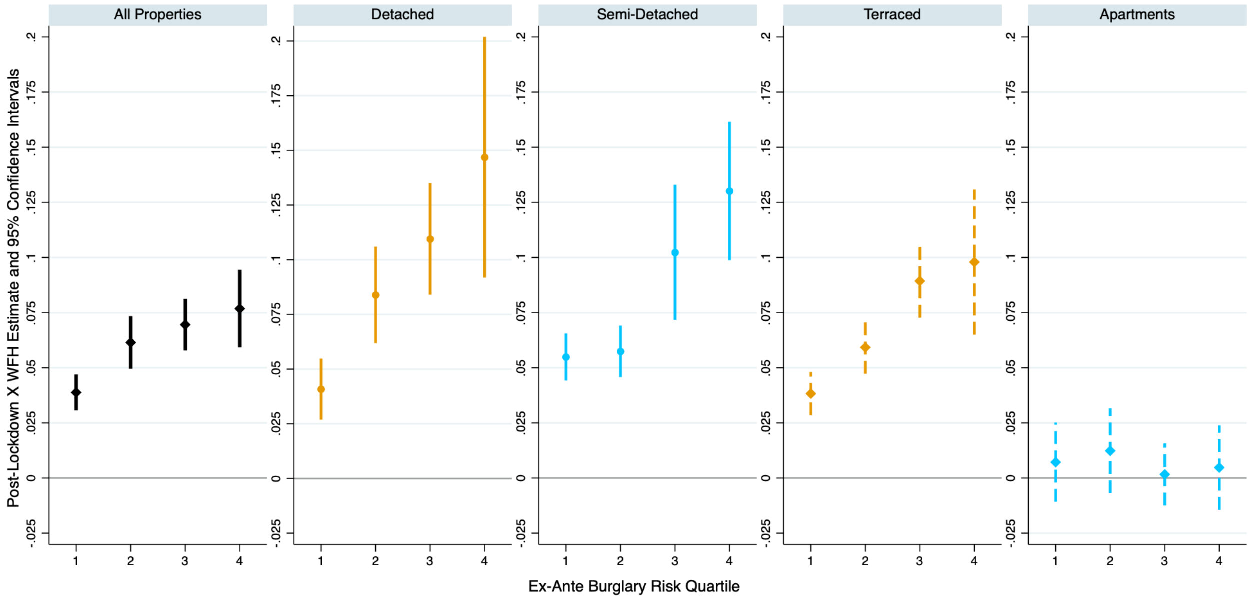
7.2 Results

Figure 6 reports estimates of the post-lockdown DDD coefficients from Equation (12). We focus on the post-lockdown estimates, but the lockdown estimates are broadly similar and are reported in Table A7. 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 two key inferences. First, we can see that all the estimates are positive, implying that homeowners 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.

The right four panels report the results of Equation (12) estimated separately for different property types. Interestingly, we see no increase in the value of flats (apartments): this is consistent with our finding, reported in Appendix A.4.6, that the reductions in crime have been smallest in the most urban neighborhoods. It is also 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. Our interpretation of this is that it reflects the greater willingness to pay for lower burglary risk amongst 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).

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



Notes: The dependent variable is $price_{hbimt}$ — 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 textintpost lockdown-by-WFH effect differs by ex-ante burglary risk of the neighborhood, $\beta_{2,1}$–$\beta_{2,4}$ in Equation (12) 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 (12) 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 homeownership 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 A7.

8 Conclusion

In this paper we provide evidence for the eyes on the street hypothesis, the idea that neighborhoods in which more people are at home during the day will experience fewer burglaries. We show robust evidence that the rise of WFH during and after the UK national lockdown of 2020 led to a substantial decline in the number of burglaries. Specifically, a one standard deviation (9.5pp) increase in neighborhood WFH potential leads to a 3.8% drop in the burglary rate in the lockdown period and a 4.0% drop in the post-lockdown period. Event study estimates show that burglary fell sharply following the introduction of lockdown and, unlike other property crimes such as theft or shoplifting, there is no evidence that this decline is temporary or reflects the continuation of pre-existing trends.

Our conceptual model implies that the increased WFH should have led to both an overall reduction in burglaries, but also a reallocation of burglaries from areas where WFH is more common to areas in which it is relatively less so. We test this hypothesis using a spatial–econometric approach and find evidence that the displacement effects of crime in neighborhoods adjacent to those with the highest rates of WFH are sufficiently large to cancel out the reductions in burglary due to WFH in those neighborhoods.

Finally, we combine a hedonic house price model with a DDD estimation strategy in order to understand the implied welfare gain of the shift to remote work. Our DDD specification allows the effect of WFH to differ by ex-ante burglary risk, which we find to be an important dimension by which to consider the welfare changes across areas. While we document a positive willingness to pay to live in a high-WFH neighborhood for all areas, it is neighborhoods with high ex-ante burglary risk where we document the largest gains.

Our work has important policy implications for the optimal spatial allocation of police resources given post-pandemic WFH. The evidence we document suggests that the shift to working from home, and the consequent change of where a large proportion of the working population are during the working week, has had a profound and persistent effect on the incidence and location of burglary. In Appendix B we extent the conceptual model presented in Section 2 to include police who allocate resources across the two neighborhoods with the objective of minimizing overall burglaries. The implications for resource allocation depend importantly on the interaction between a neighborhood's WFH and its police resources. When complentarities between WFH and police resources are weak, then it is optimal to move police resources away from high WFH areas to lower WFH areas. However, when complentarities between WFH and police resources are sufficiently strong, it is optimal to reallocate resources to the relatively high WFH area. Either way, this means that the optimal spatial allocation of police resources today will look very different to what it did on the eve of the first lockdown.

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Appendix

A Additional Results

A.1 Identification

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.

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 non-parametric DD implementation, 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 A7, we are confident in making the parallel trends assumption in this setting.

A.1.1 Pre-Lockdown Trends

Table A1: Pre-Lockdown Trends

	(1)	(2)	(3)	(4)
a.) WFH: Continuous				
Time Trend × WFH	0.104***	0.101***	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
$\overline{Y}_{PRE}$	6.125	6.125	6.125	6.125
Adjusted R^2	0.466	0.466	0.471	0.475
Observations	287,910	287,910	287,910	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

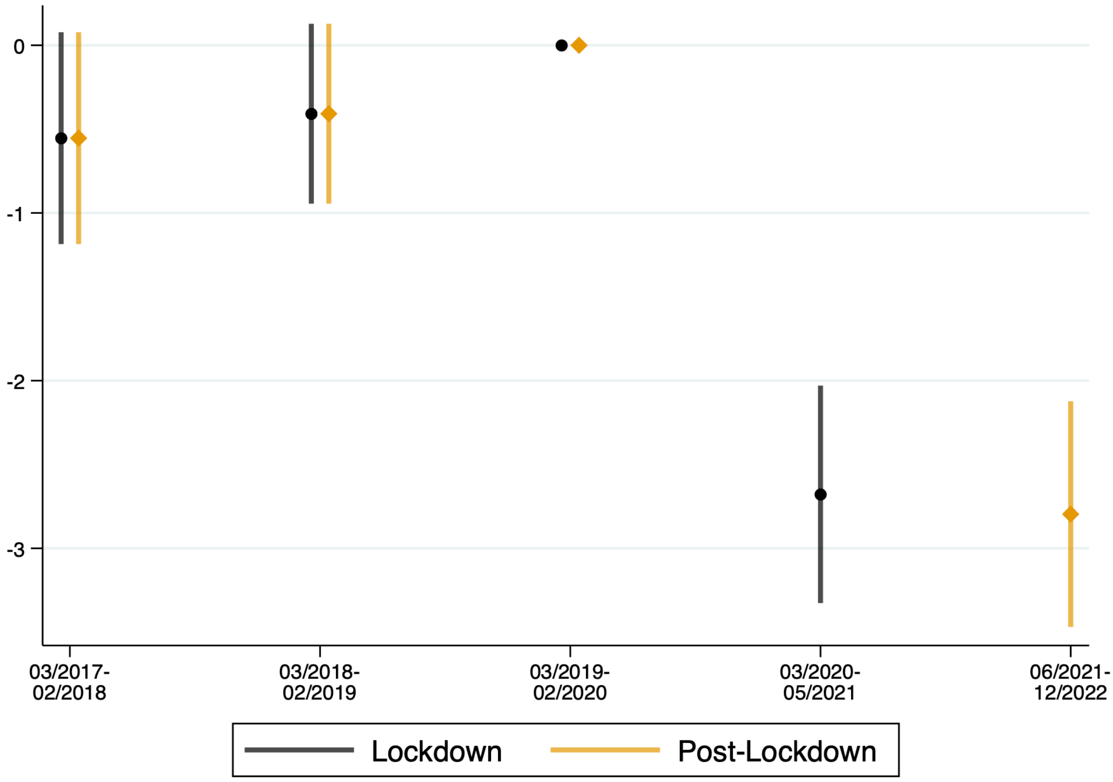
A.1.2 Honest DD à la Rambachan and Roth (2023)

In order to operationalize the approach of Rambachan and Roth (2023), we modify Equation (9), 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:

$$crime_{nt} = \sum_{j=1,\neq 3}^{5} \alpha_j (period_j \times WFH_n) + LD_t \times X_n^{'}\beta_1 + PLD_t \times X_n^{'}\beta_2 + \gamma_n + \theta_{A\times t} + \varepsilon_{nt}\,, \tag{13}$$

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.

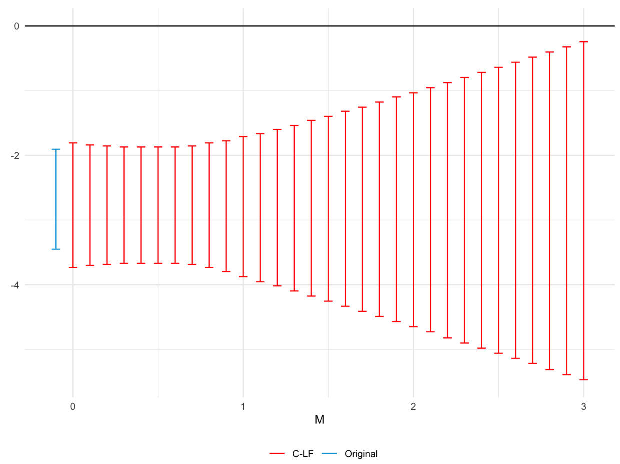
Figure A1: Parameter Estimate Inputs for the Honest DD Routine



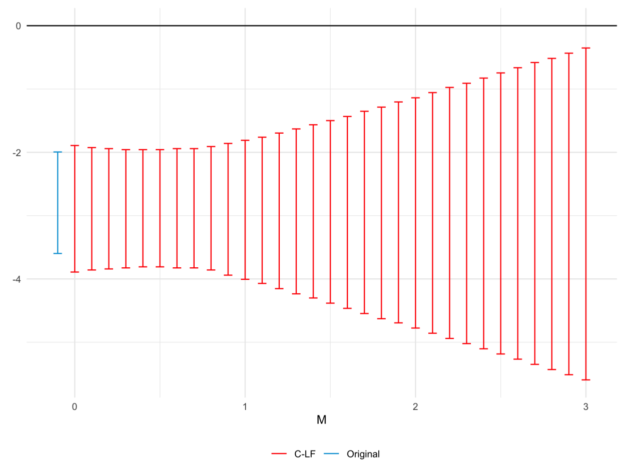
Notes: The data is at the neighborhood-by-month level. The dependent variable is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census. Neighborhood fixed effects are included in all regressions. Baseline control interactions are based on interactions between 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, whilst in panels (c) and (d) we account for the slight positive pre-trend we document in Figure A1.[22] 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.

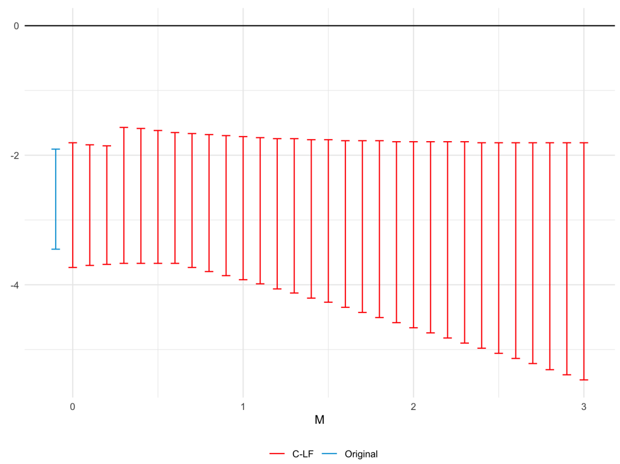
Figure A2: Worst-Case Bounds for our Burglary DD Estimates



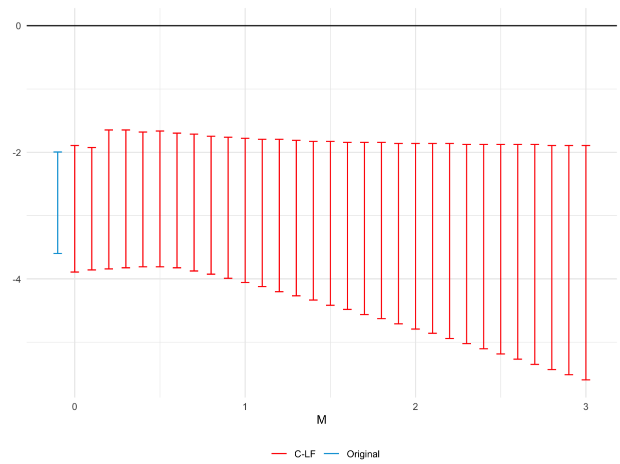
(a) Lockdown



(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). 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.

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

A.1.3 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, that 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 by providing a continuous analogue of a conventional placebo test in Figure A4. This reproduces the non-parametric analysis in Section 5.3.2, but for a placebo policy period of one year from March 2019 onwards compared to the previous year. As such it shows that there is no evidence of differential pre-trends at any point in the WFH distribution, consistent with and, providing further support for the strong parallel trend 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: Non-Linearities in the Relationship Between Burglary and WFH—Placebo

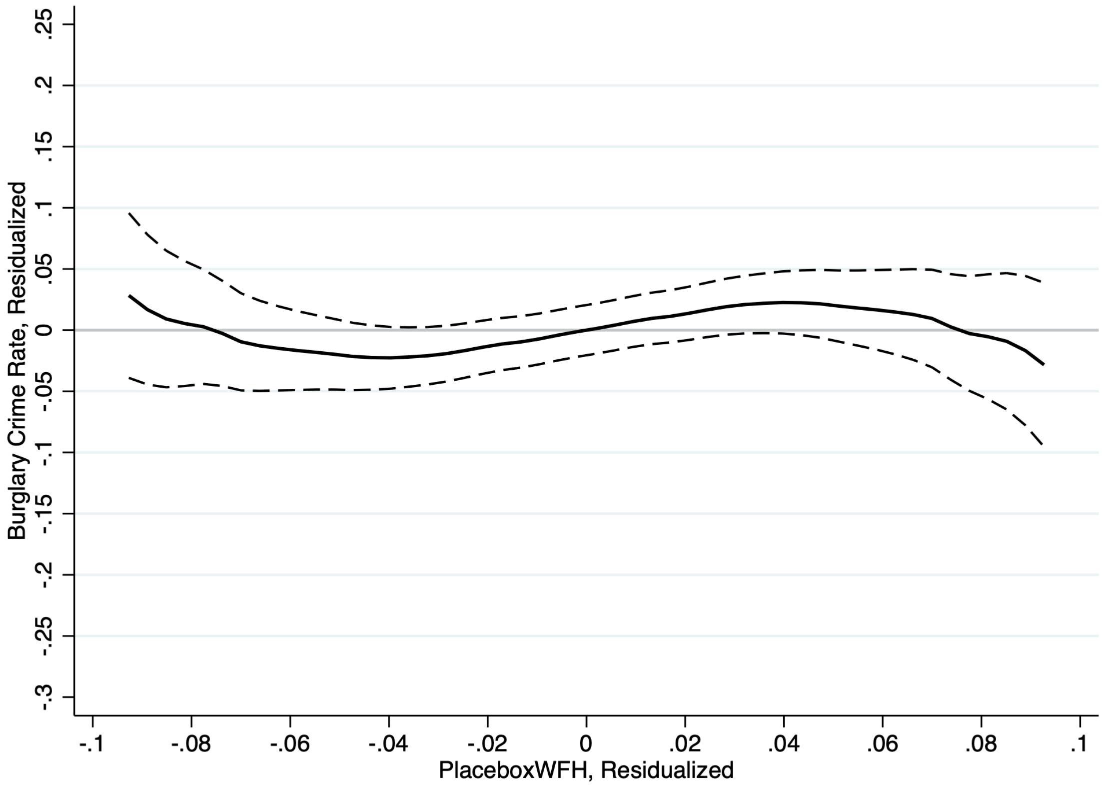


Figure A4: Local polynomial: placebo

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* $\times$ *month* fixed effects, and 2019 neighborhood characteristics controls as in Equation (9). The y-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 (Mar 2018–Feb 2020), define a placebo post term that takes value 1 for time periods from Mar /2019 onwards and zero otherwise, and implement an analogous specification to Equation (9), 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 5.

A.2 Alternative Mechanisms

Here we consider two alternative mechanisms to the occupancy and eyes-on-the-street effects. First, we ask if the decline in burglary in high WFH areas is due to increased police effort in these areas. Second, we study if WFH has led to a change in patterns in crime *within* neighborhoods. In both cases we find no evidence to support these alternative mechanisms.

A.2.1 Policing Effort and WFH

We may be concerned that our DD estimates are capturing not just the negative effect of WFH on crime, but also changes in policing effort. For example, residents of high-WFH neighborhoods may demand more police time when they are at home during the day. To the extent that we should expect more or better policing to translate into more crimes being solved. To test this alternative explanation, we use data on police clearance rates at the neighborhood level to assess the extent to which we may be conflating police effort with our main proposed mechanisms ((i) the occupancy and (ii) the eyes-on-the-street effects). Specifically, we re-estimate Equation (9) but with clearances as the dependent variable. We report the results of this exercise in Table A2. Looking across the table as a whole there is no evidence to support differential police effort in higher WFH areas: there was no statistically or economically significant change in the clearance rate of any type of property crime post-lockdown. This was also true during lockdown, except for theft. We interpret this as evidence against a police-effort explanation we should expect more or better policing to translate into a higher clearance rate.

Table A2: 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.

A.2.2 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.[23,24]

We present the resulting DD estimates from estimating a similar specification to Equation (9) in Table A3. 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.

This is important for several reasons. First, it suggests that in high-WFH neighborhoods where, on average, there has been a reduction in burglary the reduction is shared equally throughout the neighborhood, implying a reduction in the crime experienced by all residents. Assuming that WFH is not uniformly distributed within neighborhoods this in turn might suggest that the effects of additional eyes on the street and greater occupancy are not overly localized, consistent with an effect on criminals search behavior as in the model.

Second, it suggests that 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.

Table A3: 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.

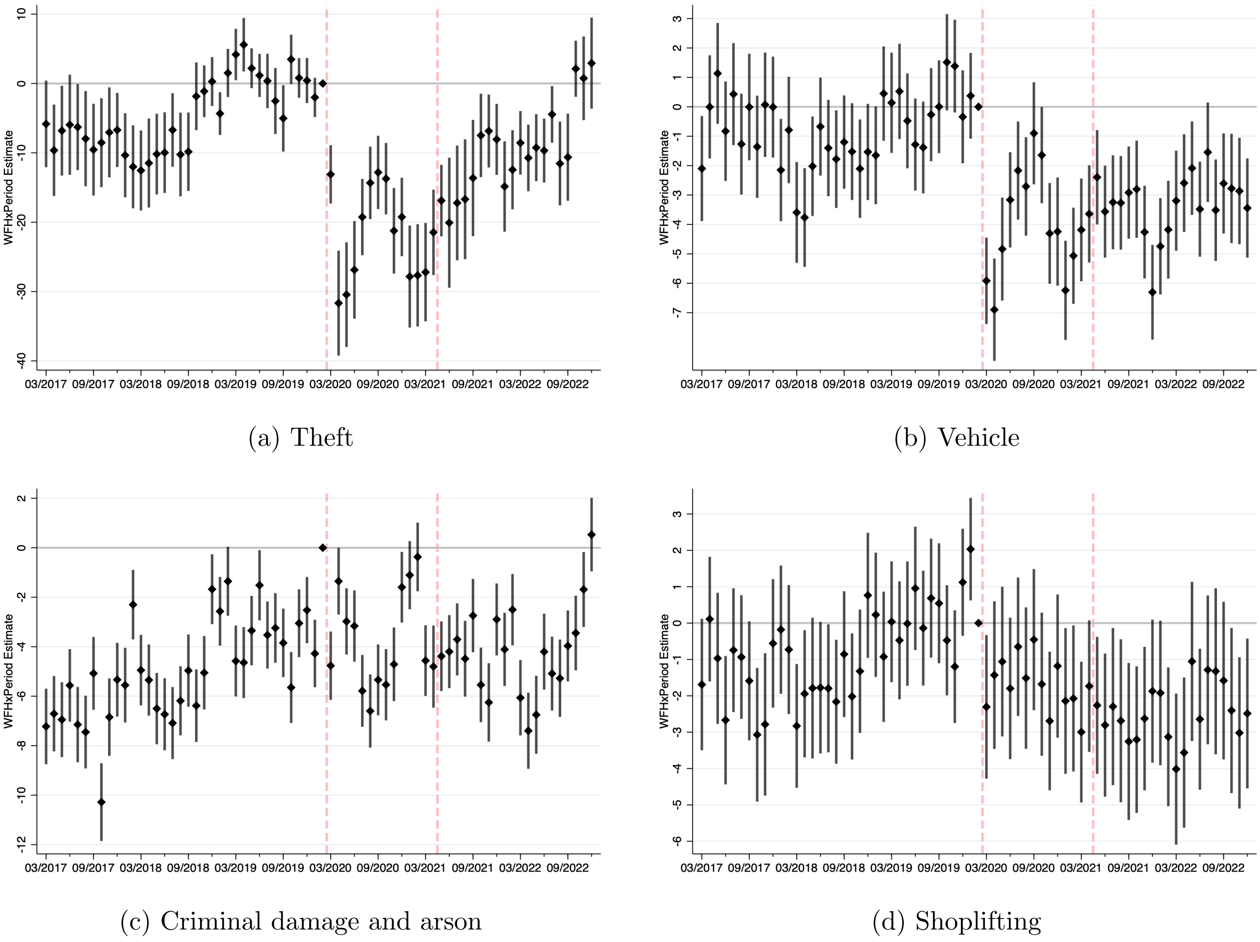
[23] The generalized Gini coefficient is given by $G' = \max\left[\frac{S}{C}, 1\right](G-1)+1$ where G is the conventional Gini coefficient, S the number of street segments in a given MSOA-period, and C the number of crimes in a given MSOA-period. The MCC coefficient is: $MCC_n^k = CC_n^{k,\text{sim}}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

[24] 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. Take the example of a city with 100 homicides and 10,000 streets, and consider the case where homicide is purely randomly located and occurs at 100 different street segments. Without accounting for the disparity between the crime count and street numbers, homicide (artificially) appears to be highly concentrated. Only 1% of streets account for 100% of homicide crime. Using different approaches, the generalized Gini coefficient and the Marginal Crime Concentration coefficient of Bernasco and Steenbeek (2017) and Chalfin et al. (2021) deal with this issue. Both approaches coincide with standard measures when the number of crimes is large relative to the number of streets.

A.3 Other Property Crime Types

In this section we present the results of our event study analysis for all property crime categories except for burglary, which we present in the main body of the text. Given concerns regarding pre-trends for some of these outcomes, including theft as well as criminal damage and arson, we do not devote considerable attention to these crime types. As none of these crime types exhibit negative pre-trends, it is not the immediate drop that concerns us from making a causal interpretation—if there is selection bias here, it is going in the opposite way to the immediate WFH effect, leading us to estimate a *lower bound* of the true WFH effect on these crime types in the period at the start of the first lockdown. Rather it makes it difficult to truly gauge the longer-run effects of higher WFH potential on these crime types.

Figure A5: The Impact of WFH on Other Property Crime Types



(a) Theft

(b) Vehicle

(c) Criminal damage and arson

(d) Shoplifting

Each point presents the (rescaled) event-study coefficient estimates and 95% point wise confidence intervals of Equation (10). 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.

A.4 Ancillary Results

A.4.1 Summary Statistics

Table A4: 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

A.4.2 Core DD Results—Binarized Treatment

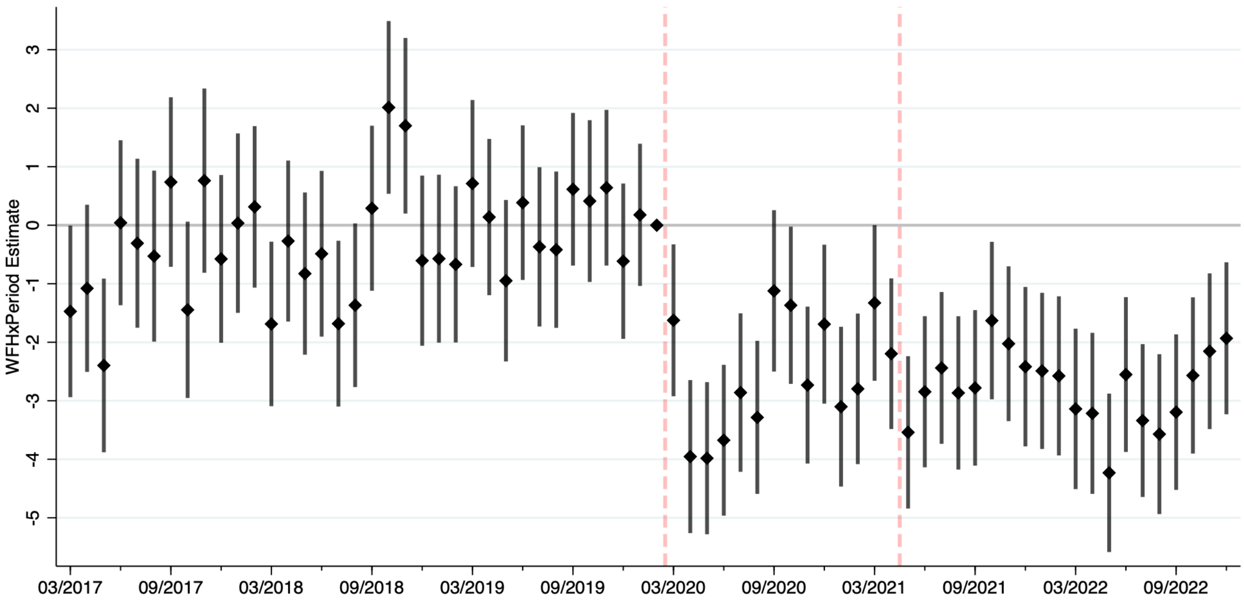
Table A5: DD Estimates for Burglary

	(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. 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.

A.4.3 Unscaled Event Study Graph for Burglary

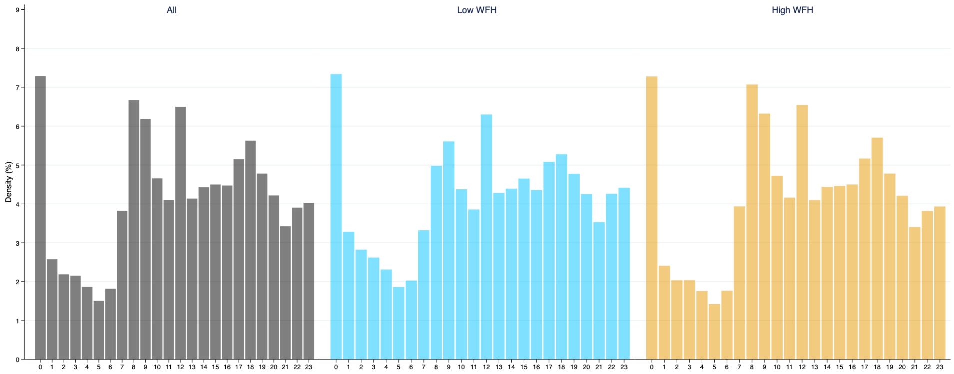
Figure A6: The Impact of WFH on Burglary – Unscaled Estimates



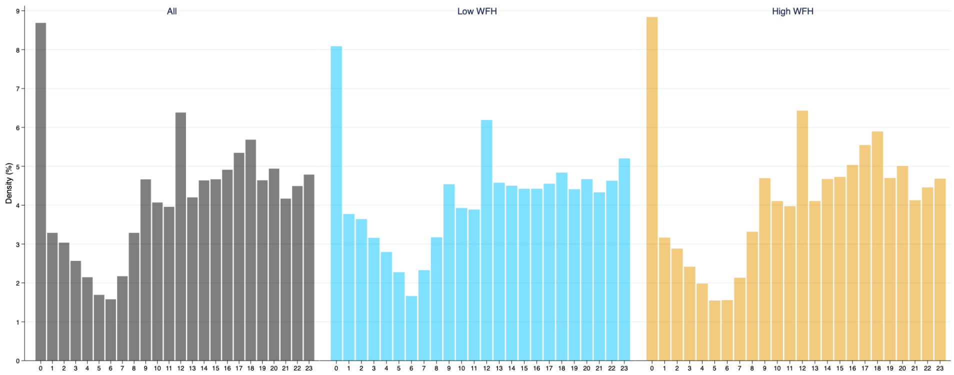
Each point presents the event-study coefficient estimates and 95% point wise confidence intervals of Equation (10). The dashed vertical lines denote the introduction of the UK first national lockdown in March 2020, and the start of the post-lockdown period in May 2021. February 2020 is excluded as the reference month. Standard errors are clustered by neighborhood.

A.4.4 The Timing of Burglaries—Met Data

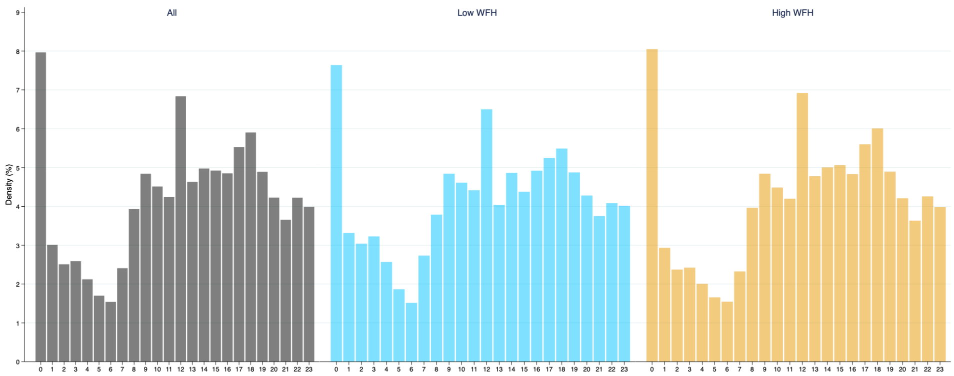
Figure A7: The Timing of Residential Burglaries During the Week



(a) Pre-lockdown



(b) Lockdown



(c) Post-lockdown

Source: Met Data.

A.4.5 Extended Spatial Spillover Results

In Table A6 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.

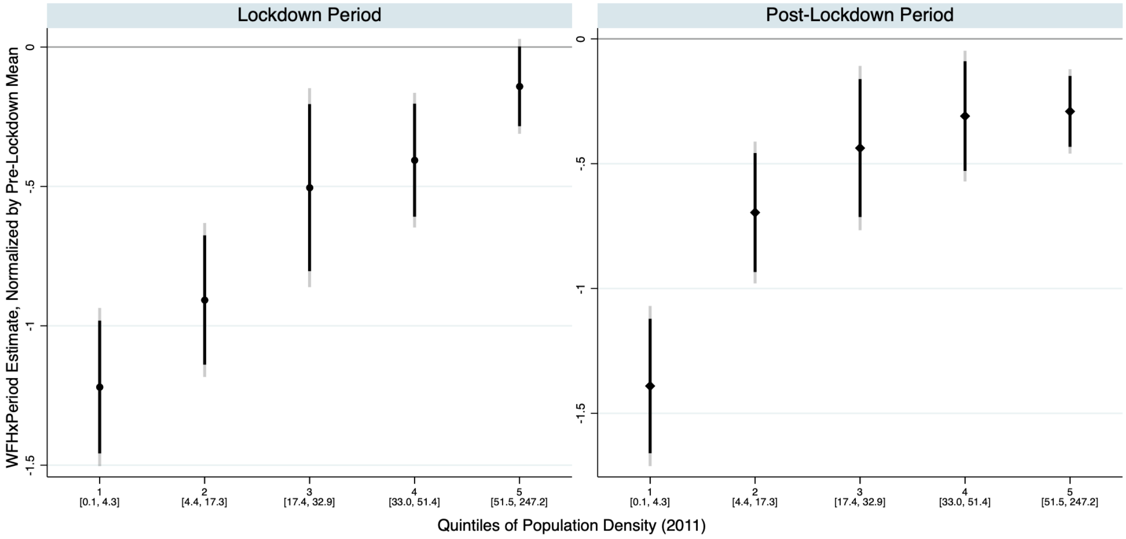
Table A6: Spatial DDD Model for Burglary

	(1)	(2)	(3)	(4)
	Criterion Used to Define $\mathbf{NWFH^H}$			
	Neighbor WFH Mean $> WFH_i$	Neighbor WFH P67 $> WFH_i$	Neighbor WFH P50 $> WFH_i$	Neighbor WFH P33 $> WFH_i$
$LD \times WFH^H$	–0.297***	–0.380***	–0.325***	–0.278***
	(0.070)	(0.085)	(0.068)	(0.060)
$LD \times NWFH^H$	–0.051	–0.072	–0.033	–0.030
	(0.065)	(0.076)	(0.064)	(0.061)
$LD \times WFH^H \times NWFH^H$	0.202**	0.259***	0.291***	0.289***
	(0.099)	(0.100)	(0.091)	(0.105)
Total DDD Effect for:				
$LD \times WFH^H \times NWFH^H$	–0.145*	–0.193**	–0.067	–0.019
	(0.085)	(0.088)	(0.082)	(0.097)
$PLD \times WFH^H$	–0.228***	–0.372***	–0.273***	–0.199***
	(0.078)	(0.098)	(0.073)	(0.064)
$PLD \times NWFH^H$	–0.000	–0.081	–0.007	0.084
	(0.073)	(0.093)	(0.071)	(0.066)
$PLD \times WFH^H \times NWFH^H$	0.205**	0.331***	0.311***	0.292***
	(0.103)	(0.113)	(0.094)	(0.100)
Total DDD Effect for:				
$PLD \times WFH^H \times NWFH^H$	–0.024	–0.123	0.031	0.177*
	(0.090)	(0.102)	(0.086)	(0.094)
p-Value: $LD \times NWFH^H =$ $LD \times WFH^H \times NWFH^H$	0.205	0.059	0.645	0.909
p-Value: $PLD \times NWFH^H =$ $PLD \times WFH^H \times NWFH^H$	0.758	0.553	0.625	0.314
$\overline{Y}_{PRE}$	5.923	5.923	5.923	5.923
Adjusted R^2	0.485	0.485	0.485	0.485
Observations	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.

A.4.6 Heterogeneous Estimates by Urbanicity

Figure A8: The Impact of WFH on Burglary is Most Pronounced in Rural Areas



Notes: Figures depict the impact of WFH on burglary from Equation (9) estimated separately for neighborhoods in each (2011) population density quintile. The coefficients in the left-hand panel are estimates, with associated 95% confidence intervals, of α_1 the impact of WFH during lockdown. The coefficients in the right-hand panel are estimates ofα_2 the effect post-lockdown. Standard errors are clustered by neighborhood.

Does the relationship between remote working and the decrease in burglaries differ in urbanized versus rural areas? An implication of the eyes on the street hypothesis is that, *ceteris paribus*, this will be the case. For example, an empty house in a rural area provides opportunity for a burglary to take place unseen, whereas in a densely populated urban center the more prevalent *eyes on the street* may thwart potential crime. For this reason, working from home may play a larger role in deterring burglaries in rural neighborhoods than in urban neighborhoods.

To answer this question, we repeat the baseline estimates for burglaries, stratifying the neighborhoods according to quintiles of population destiny (measured as the number of residents per square kilometer in 2011.) The resulting point estimates, α_1 and α_2, and 95% confidence intervals, are reported in Figure A8. We observe a monotonically decreasing relationship between WFH and the decrease in burglaries as neighborhood population density increases. During lockdown, a 30% increase in remote working is expected to have decreased burglaries by around 35% in the lowest density neighborhoods, compared to around a 7% decrease in the highest density neighborhoods. The difference is similar, but more marked, when we look at the post-lockdown period, as rural neighborhoods (first quintile) are now (statistically and economically) significantly different from higher-density neighborhoods. Note, however, that even the smaller reduction observed in the densest neighborhoods is substantial. Draca et al. (2011) find an elasticity of crime with respect to hours of policing of between 0.3 and 0.4 suggesting that the observed decline of 7% is equivalent to the reduction expected with a 20% increase in policing. In the most rural areas it is consistent with a doubling of policing, assuming, conservatively, that the elasticity in rural areas is the same as obtained by Draca et al. (2011) for London.

A.4.7 House Price Results

The results that we present below in Table A7 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 A7: 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 £.

A.4.8 Commercial Burglary

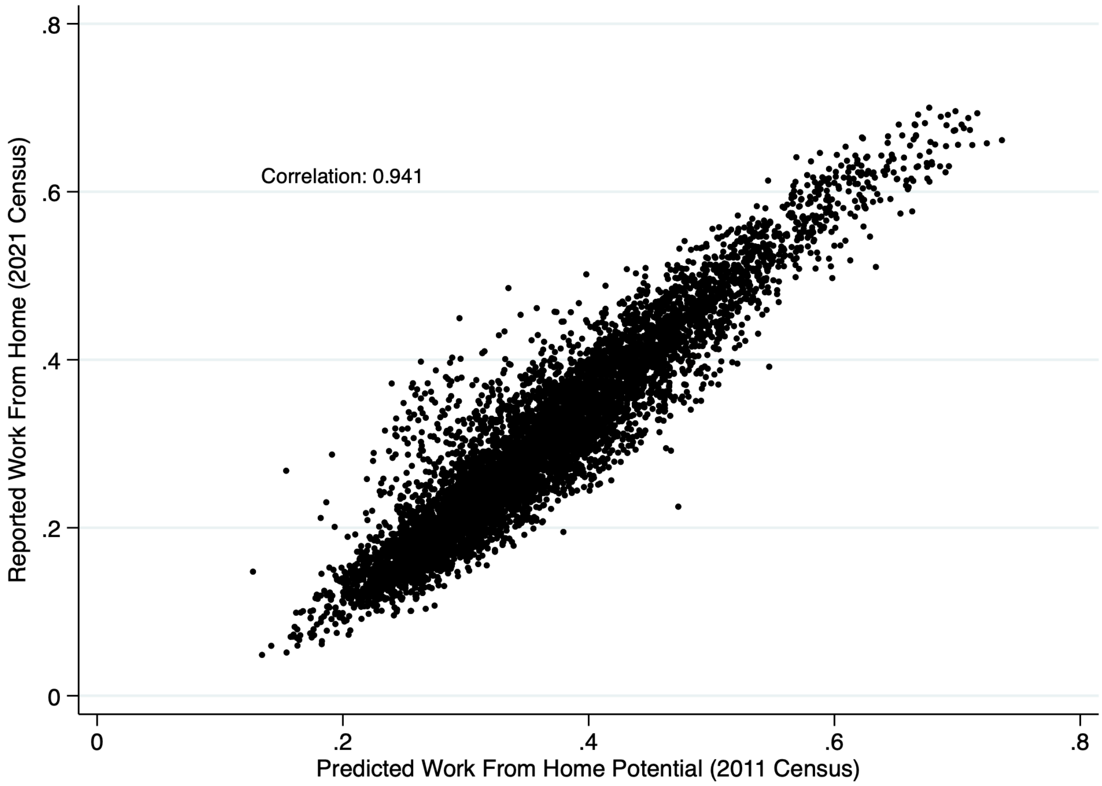
Table A8: DD Estimates by Time and Day – Commercial Burglary – London Metropolitan Police

	(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

A.5 Work from Home Predictions

Figure A9: Estimated Versus Actual WFH by Neighborhood



Notes: This figure plots actual WFH rates reported in the 2021 Census against estimated WFH potential for each neighborhood.

Our primary measure of WFH potential, Equation (8), 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 post-2019 WFH potential. 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".[25] 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.

[25] 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`

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 A9 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.

B Optimal policing

Consider now a police force which is in charge of policing neighborhoods 1 and 2. Police have a resource budget M, earmarked for exclusively for fighting burglary, with which they must allocate across neighborhoods 1 and 2. They allocate $M_1 = \sigma M$ to 1 and $M_2 = (1-\sigma)M$ to 2, where $\sigma \in [0,1]$. The budget allocation can affect crime in each of the neighborhoods by changing the probability that a criminal who finds a suitable house to burgle is successful in their crime. We write this probability, introduced in Section 2, as $\pi_n = \pi(\rho_n, M_n)$, where π_n is decreasing in M_n, and $0 < \pi(\rho_n, 0) \leq 1$ for all ρ_n under consideration.

The police objective is to allocate M as to minimize the total number of burglaries across both neighborhoods,[26] taking into account how burglars will respond in equilibrium. This means that the police solve the following program:

$$
\begin{aligned}
&\min_{\sigma} \left[\phi(\rho_1, \lambda C)\lambda + \phi(\rho_2, (1-\lambda)C)(1-\lambda)\right] C \\
&\qquad \text{subject to} \\
&\phi(\rho_2, (1-\lambda)C) \left[\pi(\rho_2, (1-\sigma)M)P_2 - (1-\pi(\rho_2, (1-\sigma)M))F\right] = \omega, \\
&\phi(\rho_1, \lambda C) \left[\pi(\rho_1, \sigma M)P_1 - (1-\pi(\rho_1, \sigma M))F\right] = \\
&\qquad \phi(\rho_2, (1-\lambda)C) \left[\pi(\rho_2, (1-\sigma)M)P_2 - (1-\pi(\rho_2, (1-\sigma)M))F\right].
\end{aligned}
$$

Notice that the resource allocation only enters the police objective function indirectly, by either deterring criminals all together (reducing C), or reallocating crime across neighborhoods (changing λ). This highlights the instrumental role, rather than the objective role, of arrests, $1 - \pi(\rho_n, M_n)$, in this problem.

B.1 A parametrized model

To make the optimal policing problem more tractable, we propose functional forms for the two probability functions, which allow us to solve for a closed form equilibrium solutions for λ and C. Specifically, we propose

[26] We could easily specify alternative objectives which may also be reasonable. For example, police may wish to maximize their case clearance rate (i.e. minimize a weighted average of π_1 and π_2).

the following:

$$\phi(\rho_n, C_n) = \frac{1-\rho_n}{C_n^{\xi}} \tag{14}$$

$$\pi(\rho_n, M_n) = e^{-(a\rho_n + bM_n + c\rho_n \times M_n)}, \tag{15}$$

where $0 < \xi \leq 1$ and $a \geq 0$, $b \geq 0$ and $c \geq 0$ are parameters. Given these functions, our spatial equilibrium for criminals will be:

$$\lambda^{\star} = \frac{S_1^{\frac{1}{\xi}}}{S_1^{\frac{1}{\xi}} + S_2^{\frac{1}{\xi}}} \quad \text{and} \quad C^{\star} = \frac{S_1(1-\rho_1)^{\frac{1}{\xi}} + S_2(1-\rho_2)^{\frac{1}{\xi}}}{\omega^{\frac{1}{\xi}}}, \tag{16}$$

where:

$$S_n = (1-\rho_n)\left(F + (P_n - F)e^{-(a\rho_n + bM_n + c\rho_n \times M_n)}\right). \tag{17}$$

Given this, it is straightforward to solve for equilibrium burglars and burglaries in each neighborhood as:

$$C_n^{\star} = \left(\frac{S_n}{\omega}\right)^{\frac{1}{\xi}}, \qquad \theta_n^{\star} = \frac{(1-\rho_n)\omega}{S_n}, \qquad \theta_n^{\star}C_n^{\star} = (1-\rho_n)\left(\frac{S_n}{\omega}\right)^{\frac{1}{\xi}-1}. \tag{18}$$

Taking as given a budget of M for burglary, the police force will allocate portion σ of the budget to burglary in neighborhood 1 and portion $(1-\sigma)$ of the budget to burglary in neighborhood 2. This proportion σ is chosen to minimize total observed burglaries across the police force area:

$$\min_{\sigma} \theta_1^{\star}C_1^{\star} + \theta_2^{\star}C_2^{\star}. \tag{19}$$

The optimal budget allocation, $\sigma^{\star}$, solves the first order condition:

$$(bM + cM \times \rho_1)(1-\rho_1)S_1^{\frac{1}{\xi}-1} = (bM + cM \times \rho_2)(1-\rho_2)S_2^{\frac{1}{\xi}-1}. \tag{20}$$

To consider how a change in ρ_1 will affect this allocation, first consider the a simplified version of the model where the parameter $c = 0$, so there is no interaction between M_n and ρ_n in π_n. We can write equation (20) as:

$$(1-\rho_1)S_1^{\frac{1}{\xi}-1} = (1-\rho_2)S_2^{\frac{1}{\xi}-1}. \tag{21}$$

Now consider an increase in ρ_1, but no corresponding increase in ρ_2. For values of $\xi < 1$, an increase in ρ_1 will decrease the left-hand side of (21) relative to the right-hand side (as both $(1-\rho_1)$ and $S_1^{\frac{1}{\xi}-1}$ are decreasing in ρ_1). For (21) to continue to hold, the police will want to reduce σ, reallocating resources from neighborhood 1 to neighborhood 2. In this case, WFH and police are substitutes for one another.

Now consider the case in which $c > 0$, as in condition (20). Now, an increase in ρ_1 decreases $(1-\rho_1)$ and $S_1^{\frac{1}{\xi}-1}$ as above, but there is an offsetting positive effect on the left-hand side through the complementarity of

ρ_1 and $(1-\sigma)M$, reflected by the value of c. If c is sufficiently large, it will be optimal to increase σ, moving resources from neighborhood 2 to neighborhood 1. Otherwise, an increase in ρ_1 will lead to a reallocation of resources from neighborhood 1 to neighborhood 2.