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Abstract

In this paper, we provide the first evidence of the effect of the shift to remote work on crime. We examine the impact of the rise of working from home (WFH) on neighborhood-level burglary rates, exploiting geographically granular crime data and a neighborhood WFH measure. We document three key findings. First, a one standard deviation increase in neighborhood WFH (9.5pp) leads to a persistent 4% drop in burglaries. This effect is large, explaining more than half of the 30% decrease in burglaries across England and Wales since 2019. Second, this treatment effect exhibits heterogeneity according to the remote work capacity of contiguous neighborhoods. Specifically, being surrounded by relatively high WFH neighborhoods can entirely offset the crime-reducing benefit of a given neighborhood's WFH potential. This is consistent with the predictions of a spatial search model of criminal activity that we develop in the paper. Finally, we document large welfare gains to the decrease in burglary. We estimate welfare gains using a hedonic house price model. Our most conservative estimates show the welfare gains are £24.5billion (1% of 2022 UK GDP), but the true gains are likely much higher. These estimates suggest the reduction in burglaries are among the most important consequences of the rise in WFH.

JEL-Codes: H750, K420, R200.

Keywords: working from home, property crime, spatial spillovers, hedonic house price models.

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1 Introduction

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

Economists have long studied the spillover effects 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 England and Wales, where property crimes 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% below its pre-lockdown level. For this reason, our core focus will be on burglary.[1] A likely explanation for the persistent fall in burglary is the concomitant change in where many workers were located during the early days of the pandemic, a shift that has persisted due to the rise of remote work.[2] We address three specific question: What is the average treatment effect of a neighborhood's WFH potential on burglaries?; Does this treatment effect exhibit heterogeneity arising from spatial displacement of burglary across neighborhoods?; and What are the welfare consequence of these changes?

The post-pandemic fall in burglary has important economic and societal consequences. First, the decrease in burglaries is very large; a 30% drop relative to 2019 rates, corresponding to 107,000 fewer reported crimes per year. The welfare consequences of this are also large; our most conservative welfare estimates, based on property price increases associated with declines in burglary due to WFH, put the aggregate welfare gains at 1% of 2022 GDP. This is many times larger than the direct costs of burglary. This reflects the fact that burglary imposes large, difficult to measure, costs on society including physical and emotional harm, lost output and health costs. Burglaries account for 6% of all reported crimes in 2019, and rank the highest of all property crimes in terms of victim costs (Heeks et al., 2018). Such a large welfare gain suggests that the reduction in

[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`).

crime may be one of the most important consequences of the WFH revolution.

Just as the rise in remote working is not unique to our setting in England and Wales (Barrero et al., 2021; Hansen et al., 2023), neither are the mechanisms through which WFH will affect crime. In Appendix B.2 we document aggregate burglary rates for major US cities. Although more volatile than the English data, burglaries in the US since 2020 exhibit a similar pattern, falling by as much as 20% relative to 2019 rates. Our focus on England and Wales is motivated by two key features that make it uniquely suited for this study. First, as pre-lockdown working from home was low and initial compliance with the national lockdown was high (Ganslmeier et al., 2022), we can exploit the nation-wide lockdown as a clean "event". Second, police forces across England and Wales have a standardized approach to recording crimes, and make granular data available through a common platform.

To guide our empirical analysis, we begin by developing a spatial search model of criminal activity which incorporates three key features: i) empty houses are more suitable for burglary than occupied houses; ii) burglars will avoid neighborhoods in which they are likely to be seen; iii) burglars impose a congestion externality upon one another, as the same house cannot be burgled multiple times in a given period. Within this conceptual framework, an increase in WFH affects neighborhood burglary by decreasing the number of empty houses and increasing the number of "eyes on the street" (and therefore the probability of being seen). When WFH rates increase in one neighborhood, but not another, we find that the number of observed burglaries will decrease in the neighborhood experiencing the WFH increase and burglars shift their search into the neighborhood which did not experience an increase in WFH.

Our empirical analysis is centered around a difference-in-differences (DD) estimation strategy and an event study approach to document the effect of WFH on burglary rates for 6,837 neighborhoods across England and Wales during both the lockdown period (March 2020 to May 2021) and the post-lockdown period (June 2021 to December 2022). Our data combines a neighborhood-level measure of the local residents' ability to work from home (WFH potential), 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 document three key findings corresponding to our research questions.

Our first key finding is that neighborhood WFH potential led to a large and persistent drop in burglaries. 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. A back-of-the-envelope calculation shows that these estimates explain more than half of the 30% decline in burglaries.[3] These results are very stable, an event study analysis shows that the WFH potential of the neighborhood still has a large and statistically significant impact on burglary crime rates almost three years after the first lockdown. This is consistent with the evidence on sustained rates

[3]This is based on post-lockdown estimates for our preferred specification (column 4, Table 1), evaluated at the mean pre-lockdown burglary rate and WFH potential: $(-2.475/5.919) \times 0.365 = 0.153$.

of WFH since the pandemic De Fraja et al. (2023). We provide a range of evidence to support the identify parallel trends assumption including event study analysis, a formal test of pre-trends, an implementation of the worst-case bounding approach suggested by Rambachan and Roth (2023). We further address identification concerns regarding the use of continuous treatment in a difference in differences framework (Callaway et al., 2021). Each piece of evidence provides support for our identifying 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. This main result is highly robust to different specifications and relaxation of the identifying assumptions.

We present evidence that this result reflects the effect of increased WFH and not alternative channels. For example, using restricted access data for London, which provides time and date of each offense, we find that the negative relationship between London burglaries and WFH is entirely found during weekday working hours. We do not observe a significant relationship on weekends or evenings. This buttresses the notion that we are indeed capturing the impact of a reallocation of where the working population is during the working week. We also rule out alternative explanations such as neighborhood-specific changes in policing effort or effectiveness.

We also show evidence of the different mechanisms—housing occupancy versus eyes on the street—at play behind the impact of WFH on burglary. Specifically, non-parametric analysis shows that the crime-WFH relationship exhibits a backwards S relationship across the WFH distribution. This shape is consistent with externalities arising from a critical mass of eyes on the street. We further note that the effect of having more eyes on the street will be more pronounced when it is light outside, and employ a 'veil of darkness" approach as used in other literatures (Grogger and Ridgeway, 2006). Using precise information on the time of crimes for London, we exploit daylight variation in early mornings and early evenings, allowing the effect of WFH on crime to vary by whether it is daylight or not. Consistent with the importance of the eyes-on-the-street effect, we find that the fall in crime during these early hours is greatest when it is light outside.

Our second key finding is that the relationship between WFH potential and burglaries is heterogeneous, consistent with the spatial displacement of burglaries predicted by our theoretical model. Specifically, we allow a neighborhood's treatment effect to vary as a function of its relative standing in WFH potential among its contiguous neighbors. We do this by extending our baseline model to a triple difference (DDD) specification in which we allow the burglary–WFH potential relationship to vary by a dummy variable which captures if an area's contiguous neighbors have on average higher WFH potential than it does. Within this framework we document meaningful spatial displacement, but concentrated only among high-WFH neighborhoods. A high WFH potential neighborhood experiences a 3.9% drop in burglary in the post-lockdown period if it is surrounded by neighbors with a lower WFH potential. A similar high WFH potential neighborhood that is surrounded by neighbors with higher WFH potential realizes a change in burglary rates not significantly different that zero (a 0.4% drop). Absent this displacement effect, our main estimates of the effect of WFH on burglary would be 30% higher in the post-lockdown period. Interestingly, we do not find evidence of spatial displacement into low-WFH potential neighborhoods.

Our third key finding is that the effect of the post-lockdown rise in WFH on burglary had large welfare consequences. Our welfare estimates are based on a hedonic-house-price-model, using a very rich DDD specification. We allow the effect of neighborhood WFH potential on house prices to vary with neighborhood ex-ante burglary risk, measured by pre-pandemic quartiles of burglary. The intuition for this specification is that the effect of WFH on housing prices through the burglary channel will be low if the risk of burglary was low to begin with; we therefore look at changes in housing prices with WFH in higher ex ante burglary neighborhoods relative to the lowest-risk quartile neighborhoods. Our specification also includes 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 results of this analysis are consistent with significant welfare gains from WFH potential in areas with different risks of burglary. First, we find that households have an unambiguous positive willingness to pay for living in higher WFH potential areas in the post-pandemic period. Second, the post-pandemic change in willingness to pay for WFH potential is monotonically *increasing* in the ex-ante burglary risk of the neighborhood. A one standard deviation increase in WFH potential leads to a 3.5% increase for those in the highest quartile. Third, these results vary by housing-type, with the greatest effect for detached houses but little to no effect for apartments. We interpret this as consistent with the absence of an eyes-on-the-street effect for apartments, as this plays less of a role for apartment blocks compared to a house-lined street. We use these estimates to compute the aggregate welfare gains associated with the fall in burglary due to WFH, and find they are extremely large. Our most conservative estimates are equivalent to 1% of UK GDP, but they could be as large as two-thirds of GDP. These estimates are many times larger than the direct costs of burglary.

Our work makes significant contributions to three distinct literatures. First, by providing the first evidence on the crime consequences of the WFH, 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). This is important as we provide new evidence on the effects of widespread non-police deterrence. In this respect,

[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.

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, has 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 risk but displaces crime to banks without guards. We build on this literature by identifying spillovers at the neighborhood level for routine crimes.

Third, 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, informal, 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. Section 5.1 presents our baseline difference and difference and event study results. This is followed by the spatial displacement results in Section 6. Finally, we provide an analysis of the effects on welfare based on an hedonic house pricing model in Section 7 and conclude in Section 8.

2 A Spatial Search Model of Burglary and WFH

Here we present a simple spatial-search model of crime which incorporates working from home and captures a key feature of property crime, and burglary in particular. Specifically, burglary is an opportunistic crime, burglars actively look for exposed homes. A document published by the Metropolitan Police states that "*Burglars typically do not want to be seen or heard and if they feel that they would be noticed by a neighbor or passerby then they are more likely to feel exposed and may move on to find somewhere else to burgle*" (Metropolitan Police, 2023). With this in mind, we want to distinguish between two ways in which an increase in WFH will affect burglaries. First, the number of unoccupied—and therefore suitable to burgle—homes will decrease (the occupancy effect). Second, the probability of being caught while committing a burglary 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 Model Set Up

Potential criminals must decide whether to pursue burglary and, if so, 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—the probability of getting caught multiplied by the punishment. Those who choose to search for a house to burgle, indexed by i, each have one unit of time to allocate to searching for suitable houses to burgle. There are two neighborhoods, denoted by $n = \{1, 2\}$, with an identical number of residential properties, in which criminals search for for suitable homes to burgle. Each criminal allocates proportion $\lambda_i \in [0, 1]$ of their time to searching in neighborhood 1 and $1 - \lambda_i$ of their time to searching in neighborhood 2.

A suitable target for burglary is a house which is both empty and not previously burgled. In neighborhood n the probability of finding a suitable house to burgle is described by the function $\phi_n = \phi(\rho_n, C_n)$, where ϕ_n is a decreasing function of two variables. The first variable, ρ_n, is the proportion of residents in neighborhood n who work from home. As burglars prefer empty houses, a higher value of ρ_n means that more homes are occupied and therefore not suitable to burgle. The second variable, C_n, is the total number of burglars operating in neighborhood n. This can be thought of as reflecting a congestion externality that criminals impose on one another; more criminals in a neighborhood means more houses already burgled by others. We assume ϕ is a strictly decreasing and differentiable function of its arguments (for relevant values of ρ_n and C_n), with the following limiting properties:

$$\phi(1, C_n) = 0 \quad \text{and} \quad 0 < \phi(0, C_n) < 1 \text{ for all } C_n \in (0, \infty), \text{ and}$$

$$\lim_{C_n \to \infty} \phi(\rho_n, C_n) = 0 \quad \text{and} \quad 0 < \phi(\rho_n, 0) < 1 \text{ for all } \rho_n \in (0, 1).$$

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. 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 weakly decreasing in 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 attempting a burglary. We further assume that π is differentiable and $0 < \pi(\rho_n) < 1$ for all values of $\rho_n \in [0, 1]$.

Based on this, the ex ante expected value to an individual criminal spending a unit of time searching in each neighborhood is:

$$E(VC_1) = \phi(\rho_1, C_1)(\pi(\rho_1)P_1 - (1 - \pi(\rho_1))F) \qquad \text{and} \qquad E(VC_2) = \phi(\rho_2, C_2)(\pi(\rho_1)P_2 - (1 - \pi(\rho_1))F).$$

Consider the two ways in which a change in ρ_n affects the ex ante expected value to searching in neighborhood n:

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

This makes explicit the two channels through which ρ_n operates. First, an increase in ρ_n will decrease the expected value of search in n by the change in the probability of finding a suitable house multiplied by the expected return to burgling a house in n. This is the *occupancy effect* as it reflects the direct effect of fewer unoccupied houses on the expected value of search. Second, an increase in ρ_n will decrease the chance of the payoff, P_n, and increase the chance of the penalty, F, for the criminal when a suitable house is found in n. This decreases the expected value of search through the probability of being caught, $\pi(\rho_n)$. This is the *eyes-on-the-street effect*, as it reflects the indirect effect of more WFH leading to a higher chance of being seen whilst committing a burglary. As ϕ_n and π_n are both decreasing in ρ_n, $E(VC_n)$ is strictly decreasing in ρ_n.

The number of criminals searching in each neighborhood, which we denote with C_1 and C_2, is determined by the total number of criminals, $C = C_1 + C_2$, and how much of their unit of time each criminal allocates between neighborhoods 1 and 2. Denote $\lambda_i \in [0,1]$ be the proportion of time burglar i allocates to neighborhood 1. The number of criminals searching in each neighborhood is:

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

2.1.1 The Criminal's Decision

A potential criminal makes two choices. The first is a participation decision, whether to pursue burglary or not. The participation decision is made based on the value of the potential criminal's outside option, denoted by ω_i, which we assume to vary continuously across potential criminals.[6] A potential criminal only participates if the expected value of crime is higher than the value of the outside option:

$$\begin{aligned} \max_{\lambda_i \in [0,1]} \Big\{ & \lambda_i \phi_1(\rho_1, \lambda_i + \sum_{j \neq i} \lambda_j) \left[\pi_1(\rho_1) P_1 - (1 - \pi_1(\rho_1)) F\right] \\ & + (1 - \lambda_i) \phi_2(\rho_2, C - \lambda_i - \sum_{j \neq i} \lambda_j) \left[\pi_2(\rho_2) PV_2 - (1 - \pi_2(\rho_2)) F\right] \Big\} \geq \omega_i. \end{aligned} \tag{2}$$

All criminals who choose to pursue burglary must decide how to allocate their unit of time to search between the two neighborhoods. This is determined by the value of λ_i which maximizes the left-hand side of (2):

$$\begin{aligned} \arg\max_{\lambda_i} \Big\{ & \lambda_i \phi(\rho_1, \lambda_i + \sum_{j \neq i} \lambda_j) \left[\pi(\rho_1) P_1 - (1 - \pi(\rho_1)) F\right] \\ & + (1 - \lambda_i) \phi(\rho_2, C - \lambda_i - \sum_{j \neq i} \lambda_j) \left[\pi(\rho_2) P_2 - (1 - \pi(\rho_2)) F\right] \Big\}. \end{aligned} \tag{3}$$

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. The first condition is a participation constraint: no criminal who pursues burglary prefers the outside option, and vice versa. As all criminals are identical, the condition requires that everyone is indifferent between being a burglar and the outside option. The second condition requires that search efforts are optimal: no burglar wishes to change their search allocation between

[6] This outside option may be either legitimate labor market activity or alternative types of crime.

neighborhoods 1 and 2. This requires that all λ_i are such that the ex ante expected return to search in each neighborhood is identical. These conditions result in the equilibrium versions of (2) and (3):

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

$$\phi(\rho_1,\lambda C)\left[\pi(\rho_1)P_1-(1-\pi(\rho_1))F\right] = \phi(\rho_2,(1-\lambda)C)\left[\pi(\rho_2)P_2-(1-\pi(\rho_2))F\right]. \tag{5}$$

$\omega(C)$ is a function returning the value of ω_i for the marginal criminal—the criminal for which (2) holds with equality. Clearly, $\partial\omega(C)/\partial C \geq 0$, as the criminals who choose to participate in burglary must have an outside option no greater than those who do choose to participate in burglary.

Equilibrium for this model is defined by the unique values for λ, and C for which (2) and (3) both hold. For example, consider a value $\lambda' > \lambda$. 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 (4) follows from (2) when the spatial equilibrium holds.

There are two important features of this equilibrium. First, the equilibrium is defined in terms of the average of individual search decisions, $\lambda = (\sum_i \lambda_i)/C$. This means that, at the level of an individual criminal multiple equilibria exist—for example $\lambda_i = \lambda$ for all i, or $\lambda_i = 1$ for $i = \{1, ..., \lambda C\}$ and $\lambda_j = 0$ for $j = \{\lambda C+1, ..., C\}$—but they must satisfy (4) and (5). Therefore, the aggregate values λ and C are unique. As our empirical analysis will focus on burglary at the neighborhood level, λ and $C = C_1 + C_2$ are the relevant quantities for us.

Second, there are important differences between the mechanism leading to a non-trivial equilibrium in this model and that of previous spatial crime models (e.g., Zenou (2003), Verdier and Zenou (2004)). In Verdier and Zenou (2004), individuals are heterogeneous in their preferences/distaste for engaging in criminal activity. This individual heterogeneity ensures that equilibria exist in which criminals do not all make identical choices. In our model, where criminals are homogeneous, differences in the behavior of individual criminals comes from the congestion externality created through $\phi(\rho_n, C_n)$; more criminals in a neighborhood decreases the expected return to crime in that neighborhood, decreasing the incentive for future criminals in that neighborhood. This is a mechanism which we believe to be important in the case of burglary, and a mechanism that operates at the same level as the data we use in the empirical section of this paper.

2.1.3 Comparative Statics

We now consider an asymmetric increase in ρ across neighborhoods: that is an increase in ρ_1, but not ρ_2. This will decrease the expected return to searching in neighborhood 1 through both the occupancy and eyes-on-the-street channels, as demonstrated above. This means that the left-hand-side of (5) decreases, and criminals respond by reallocating their search time from 1 to 2 (λ decreases). But in turn, the decrease in λ means that the left-hand-side of (4) decreases, so it must be the case that the total number of criminals, C, is decreasing. Fewer criminals means that the return to search in both neighborhoods increases and the opportunity cost for the marginal criminal, $\omega(C)$, is decreasing. In the new equilibrium, we know that C and λ have both decreased, meaning the total amount of criminals spent searching in neighborhood 1, λC, has decreased. We also know that, although C has increased, $(1-\lambda)C$ has increased overall. This follows from the fact that $\omega(C)$ has fallen, so $\phi(\pi_2, (1-\lambda)C)$ must have also fallen.

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

$$\frac{dC}{d\rho_1} = -\frac{\frac{\partial \phi_2}{\partial C_2}E(VC_2|s)\left(\frac{\partial \phi_1}{\partial \rho_1}E(VC_1|s) + \phi_1\frac{\partial \pi}{\partial \rho_1}(P_1+F)\right)}{\frac{\partial \phi_1}{\partial C_1}\frac{\partial \phi_2}{\partial C_2}E(VC_1|s)E(VC_2|s) - \frac{\partial \omega(C)}{\partial C}\left(\frac{\partial \phi_1}{\partial C_1}E(VC_1|s) + \frac{\partial \phi_2}{\partial C_2}E(VC_2|s)\right)} \leq 0, \tag{6}$$

$$\frac{d\lambda}{d\rho_1} = -\frac{\left((1-\lambda)\frac{\partial \phi_2}{\partial C_2}E(VC_2|s) - \frac{\partial \omega(C)}{\partial C}\right)\left(\frac{\partial \phi_1}{\partial \rho_1}E(VC_1|s) + \phi_1\frac{\partial \pi_1}{\partial \rho_1}(P_1+F)\right)}{C\left(\frac{\partial \phi_1}{\partial C_1}\frac{\partial \phi_2}{\partial C_2}E(VC_1|s)E(VC_2|s) - \frac{\partial \omega(C)}{\partial C}\left(\frac{\partial \phi_1}{\partial C_1}E(VC_1|s) + \frac{\partial \phi_2}{\partial C_2}E(VC_2|s)\right)\right)} \leq 0. \tag{7}$$

where $E(VC_n|s) = \pi_n P_n - (1-\pi_n)F$ is the expected value of burglary in neighborhood n, conditional on finding a suitable house.

Notice that in the numerator of (6) and (7) is the change in the expected value of search in neighborhood 1, $\partial EV(VC_1)/\partial \rho_1$, which reflects both the channels discussed above. When more eyes on the street are 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 the occupancy effect alone.

To map this analysis to empirical observations, we want to consider how the expected number of successful burglaries changes in each neighborhood, given by $\phi_1 \lambda C$ and $\phi_2(1-\lambda)C$. As we saw with (4) and (5) above, we expect successful burglaries in neighborhood 1 to decrease, but it is ambiguous in this analysis what will happen in neighborhood 2 as the number of criminals searching decrease, but the probability of finding a suitable target increases. For each neighborhood, we can write the relevant comparative static as:

$$\frac{d\phi_1 C_1}{d\rho_1} = \frac{\partial \phi_1}{\partial \rho_1}\lambda C + \phi_1 \frac{dC}{d\rho_1}\left(1 - \frac{\partial \omega(C)}{\partial C}\frac{1}{\frac{\partial \phi_2}{\partial C_2}E(VC_2|s)}\right) < 0 \tag{8}$$

$$\frac{d\phi_2 C_2}{d\rho_1} = \phi_2 \frac{dC}{d\rho_1}\frac{\partial \omega(C)}{\partial C}\frac{1}{\frac{\partial \phi_2}{\partial C_2}E(VC_2|s)} \geq 0 \tag{9}$$

A couple of things are worth pointing out with these comparative statics. First, for all $\partial\omega/\partial C > 0$ we can unambiguously say that crime will increase in neighborhood 2 following an increase in ρ_1. Second, the number of successful burglaries in neighborhood 2 will not change if all criminals have the same outside option (i.e. $\partial \omega/\partial C = 0$). This can be seen from Equation (4); if the right-hand-side is constant then $\phi_2(1-\lambda)C$ must also be constant when ρ_1 changes.

3 Data

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

3.1 Working From Home

WFH has increased dramatically in England and Wales compared to pre-2020 rates, as it has in other Western countries. Prior to 2020 approximately 5% of workers reported normally working from home, as of the first half of 2022 an estimated 35% of employees report normally working from home (De Fraja et al., 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 by De Fraja et al. (2021) and is an estimate of the percentage of employed residents in a neighborhood able to work from home. It is obtained by computing an occupation specific WFH index for each occupation, h_o. This reflects the extent to which a particular occupation can be done remotely and is calculated following the methodology proposed in Dingel and Neiman (2020) and adapted for UK 4-digit standardized occupation classification (SOC) codes by De Fraja et al. (2021). This methodology classifies occupations according to the tasks they involve. For example, jobs which largely involve computer based tasks, such as a programmer or call center worker, will receive an index value of 1, indicating that most or all of the job can be done remotely. Jobs in which face-to-face interactions are important, such as food service or retail sales, will receive a value of 0, indicating that none of the job can be done remotely.

Our index of WFH potential, for a neighborhood n, is calculated as the average of the index values across all employed residents in the neighborhood. That is:

$$WFH_n = \frac{\sum_o E_{o,n} \times h_o}{E_n}, \tag{10}$$

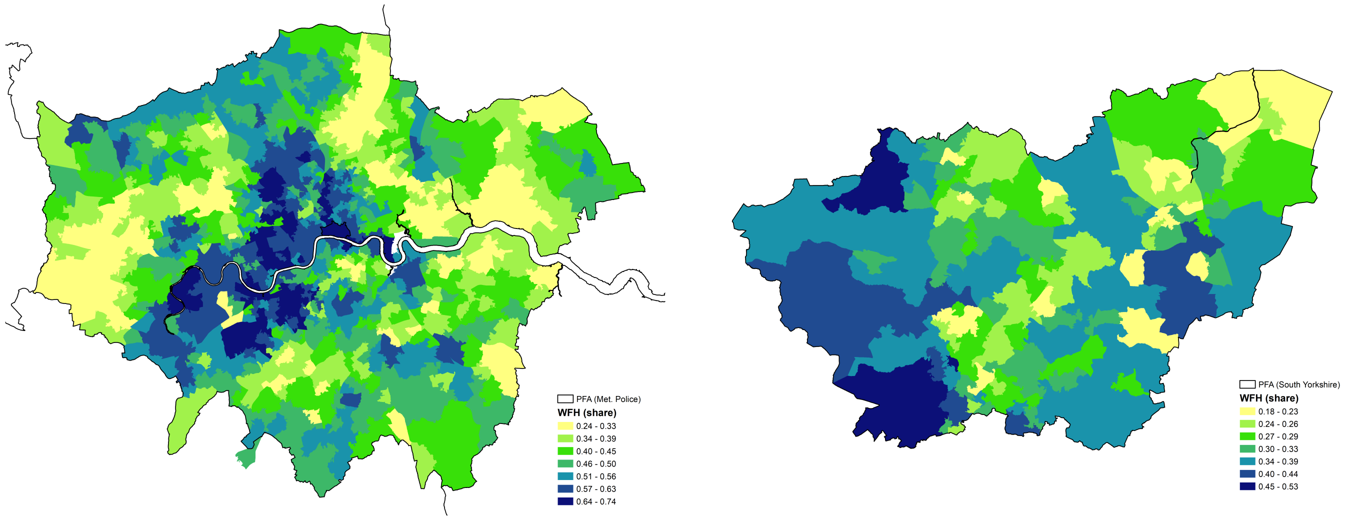
where $E_{o,n}$ is the count of residents of neighborhood n employed in occupation o, E_n is the total number of employed residents in neighborhood n. The resident counts, $E_{o,n}$ and E_n, are taken from the residential distribution of workers by 4-digit SOC code in the 2011 census.

By using the 2011 Census we avoid concerns about endogenous changes in residential location choice by occupation, for which evidence on real estate markets is consistent with having happened during the pandemic (Gupta et al., 2022; Gokan et al., 2022). Importantly, however, as shown in Figure B5 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.[7]

The maps in Figure 1 show how the (estimated) proportion of people working from home varies across neighborhoods in Greater London (left) and South Yorkshire (right). Looking first at the map for London we can see that there is substantial variation across neighborhoods in the proportion of people able to WFH. In some neighborhoods it is as high as 74% while in others it is as low as 24%. Broadly speaking, WFH is more common in more central and more prosperous neighborhoods, although notably there is often substantial

[7] In Figure B5 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.

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.

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, particularly those to the west of the map which are adjacent to the Peak District, a major national park. This may also reflect the larger numbers of commuters into London from other areas.

3.2 Burglary Data

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

Our core dataset collects data on the number of reported burglaries by month. For our supplementary analyses, we also collect data on other property crimes such as, theft, (acquisitive) vehicle crime, arson, and shoplifting.[8] 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.

[8]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.

National Crime Data

The national crime data come from data.police.uk, a government provided repository of crime and policing data for England and Wales. It provides monthly data recording street-level crime, by type, at the Lower Layer Super Output Area (LSOA) level. LSOAs are small census areas each comprised of around 1,500 people that are nested within MSOAs allowing us to straightforwardly aggregate and match to the WFH data at the MSOA level.[9] Since we are interested in the period before and after the pandemic, we use data spanning the period from September 2017 (30 months before the first national lockdown starts) to December 2022.

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

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.[10] 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

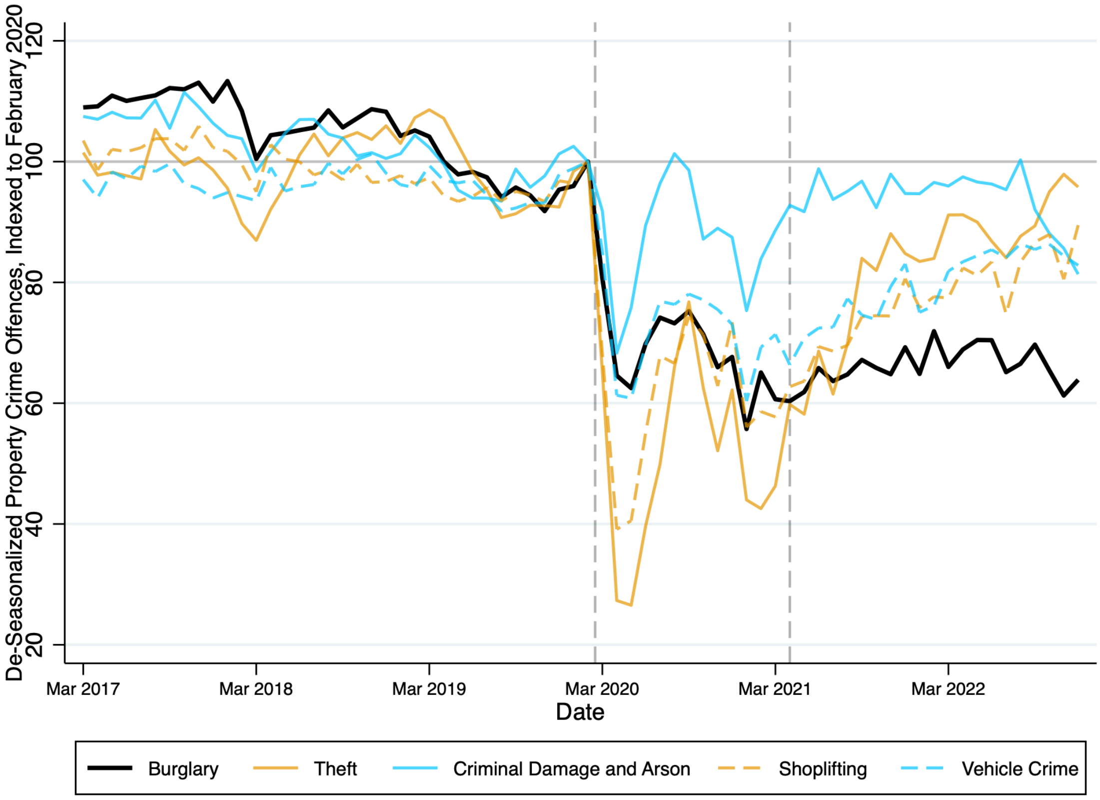
3.3.1 Neighborhood Characteristics

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

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

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

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.

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

We use data on the housing tenure from the 2011 Census. Housing tenure data include information on the total number of residential properties, the number of these properties which are owned by the resident, the number of properties which are rented through the private market, and the number of properties which are provided through a social housing scheme (e.g., through local councils). Based on this information we calculate, by neighborhood, the proportion of residential properties occupied by owners and the proportion of residential properties that are publicly provided (i.e. social housing). The proportion of residents receiving income support is calculated as the average number of monthly claimants divided by the neighborhood population.

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

3.3.2 House Price Data

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

4 Empirical Specification

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:

$$crime_{nt} = \alpha_1(LD_t \times WFH_n) + \alpha_2(PLD_t \times WFH_n) + LD_t \times X_n^{'}\beta_1 + PLD_t \times X_n^{'}\beta_2 + \gamma_n + \theta_{A\times t} + \varepsilon_{nt}\ , \quad (11)$$

where the outcome, $crime_{nt}$, is the number of burglaries per ten-thousand residents in neighborhood n and month t.[11] On the right-hand side we include two dummy variables. The first, LD_t, equals 1 if month t occurs in the national lockdown period, and 0 otherwise. The second, PLD_t, equals 1 if month t occurs in the post-national lockdown period, and 0 otherwise.[12] 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. 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 be 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 social-housing, and the total amount (in square meters) of retail space in the neighborhood. Finally, the residual term ε_{nt} reflects transitory and neighborhood specific variation in crime. These are clustered at the neighborhood level, the area at which WFH varies, following the recent work of Abadie et al. (2023)

The key identifying assumption required for our main DD strategy is the parallel trends assumption: we require there to be no systematic relationship between WFH potential and pre-lockdown trends in crime. We provide several piece of evidence in support of the identifying assumption. First, the event study that we present in Section 5.2 shows that, on average, there is no evidence of differential pre-trends by WFH potential. We further scrutinize this assumption with a number of tests in Appendix A, where we (i) estimate pre-trends directly, (ii) apply the worst-case bounding approach of Rambachan and Roth (2023), and (iii) address identification concerns regarding the use of continuous treatment (Callaway et al., 2021). Each piece of evidence points towards the same conclusion – that the parallel trends assumption is satisfied, thereby enabling us to recover the average treatment effect on the treated (ATT) parameter with our DD estimates.

[11] Given that we are implementing a DD design, we do not log our dependent variable (McConnell, 2023).

[12] 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.

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

We report the DD parameter estimates from Equation (11) in Table 1. The first and second rows report the main coefficients for lockdown and post-lockdown periods (α_1 and α_2 in Equation (11).) In the lower panel of the table we report the pre-lockdown means and the effect of a standard deviation change in work from home potential as a fraction of the pre-pandemic mean.

As a first step, column 1 reports results from a simplified version of Equation (11) in which there are no control variables, and where we only include month × year fixed effects. We can see that in both the lockdown and post-lockdown periods the effect of WFH on crime is negative and substantial. For example, a coefficient of −2.188 (column 1, row 2) implies that a one standard deviation (9.5pp) increase in WFH potential led to a 3.5% drop in burglaries in the post-lockdown period relative to the pre-pandemic mean. In column 2 we also include the interaction of X_n with the lockdown and post-lockdown dummies. The estimated effect is now around 50% larger, and more precisely estimated. In column 3 we allow the month × year fixed effects to vary by government region.[13] 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 (11). 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-

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

pandemic mean. The coefficient estimates are also fairly precise, a 95% confidence interval for the post-lockdown period is between a 2.8% and a 5.2% decrease in burglaries for a one standard deviation change.

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

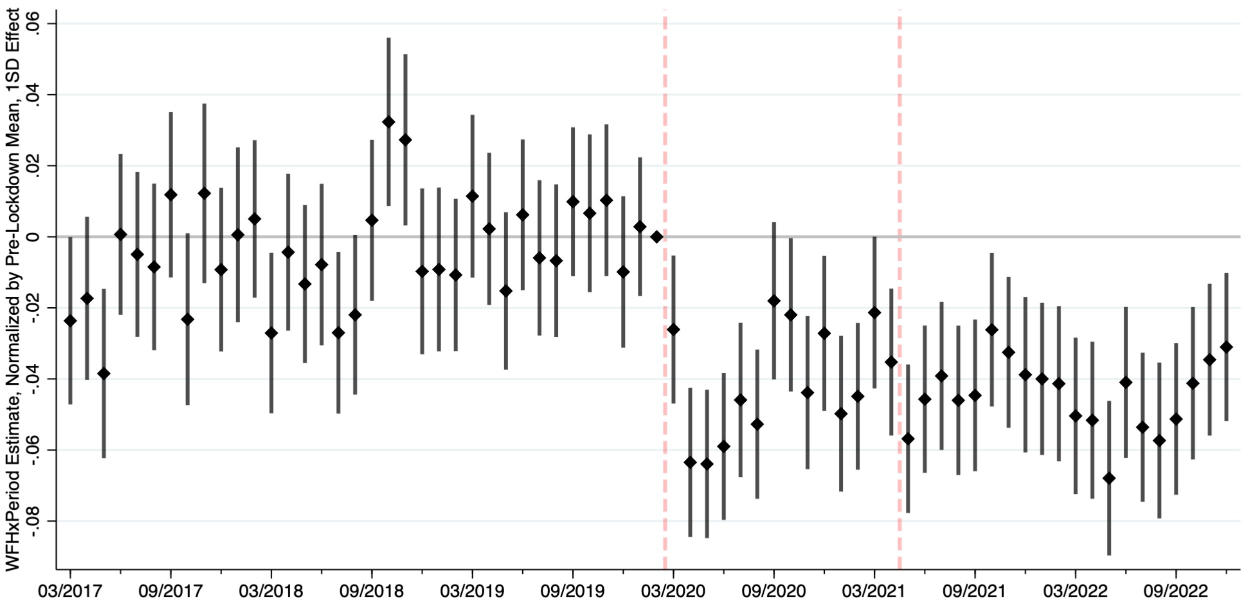
5.2 Event Study Results

In Table 1 we document a negative impact of WFH potential on burglary which is stable across several specifications. To further understand any variation over time in the extent to which WFH impacts burglary, we use an event study methodology to trace the burglary–WFH relationship over our sample period.[14] The event study estimate is described by Equation (12) in which we modify Equation (11) such that the effects of WFH are allowed to vary by month:

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

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

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

[14]We present the results of the event study approach for other property crimes in appendix Figure B6.

In Figure 3 we present the event study graph; on the y-axis are the coefficients α_t from Equation (12) scaled by the effect of a standard deviation change relative to the pre-pandemic mean (comparable to estimates reported in column 4, row 2 of Table 1). The results are stark. Prior to the first national lockdown we do not observe any systematic correlation between burglaries and remote working. Immediately after the first lockdown, we see a negative and persistent relationship. The point estimates we document indicate that a one standard deviation increase in our WFH measure led to a drop in the post-lockdown burglary rate between 2.6% and 6.8% of the pre-lockdown mean; all of these estimates are statistically different than 0 at the 95% confidence level.

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

A final point to note is the large extent to which our event study estimates mirror the time-series evolution of burglary crime for the country as a whole (burglary is the thick black line in Figure 2). This suggests that WFH plays a first-order effect in driving the aggregate changes we document in burglary crime over time. In quantitative terms, the estimates reported in column 4, Table 1, explain over half of the 30% reduction in post-lockdown burglaries.

5.3 Estimates Across Working and Non-working Hours

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

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

To test this we re-estimate Equation (11) using the restricted Met data. This data allows us to conduct the analysis by the day of the week and the time of day crimes were committed. We are also able to separate residential burglaries from commercial burglaries in these data. We present the results of this exercise for residential burglary in Table 2. The results are quite striking; our main results appear to be driven by a large decrease in residential burglaries taking place early in the day, on weekdays between 8:00 a.m. and 11:59 a.m. A London neighborhood in which WFH potential is one standard-deviation (9.5pp) higher sees a 3.3% and 5.7%

decrease in daytime burglaries during lockdown and post-lockdown period, respectively. We do not observe statistically significant, nor economically large, changes during weekdays outside these hours or on weekends.

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

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

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

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

We further stratify our time of day estimates by day of the week, testing for heterogeneity across the working week; the estimated coefficients are reported in Figure B3. Coefficient estimates are highly stable by time and day of the week, with the effects being entirely concentrated between 8:00 and 12:00 during the working week. In the post-lockdown period, estimates for all other times of the day are are small in magnitude and not statistically different than 0.

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

5.4 Robustness of Main Results

We now present three sets of robustness exercises.

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

A related concern that one may have is the extent to which our WFH potential measure is an accurate measure of the true WFH rates in the post-pandemic period. As we note above, the evidence we provide in Figure B5 highlights an extremely close correspondence between the pre-determined predicted WFH rates based on the 2011 Census data and *actual* WFH rates recorded, in the 2021 Census, summarized by a correlation coefficient of 0.94. This should allay any concerns regarding the relevance of our WFH potential measure. We further address this concern by instrumenting for post-pandemic WFH rates using our pre-pandemic WFH potential measure, in essence implementing an IV-DD estimation. We present the results from this exercise in Table B7. As expected given Figure B5, the magnitude of the first-stage F-Statistics across all specifications suggests there are no concerns about week instruments. As in Table 1, our preferred specification is in Column 4. The estimates we present for our IV-DD specification are qualitatively identical to the DD estimates from our baseline specification using WFH potential.

Finally, we investigate concerns that changes in burglary due to working from home may be highly unevenly distributed within a neighborhood. We use street-level information on crime incidence and construct a variety of time-varying measures to capture the extent to which crime is concentrated in specific street segments within the neighborhood. The concentration measures we use − further detailed in Section B.9 − are based on the latest methods to estimate crime concentration (Bernasco and Steenbeek, 2017; Chalfin et al., 2021). With these measure in hand, we examines whether there were any systematic changes in the within-neighborhood distribution of burglaries with WFH in the lockdown and post-lockdown periods. As one can see in Table B8, we find no evidence that the shift to remote work led to distributional changes of burglaries within neighborhoods. This suggests that the work from home rates of a neighborhood exert a protective effect on the entire neighborhood, implying a reduction in the crime experienced by all residents. Not only does this imply that our choice of spatial unit is capturing the key variation on crime changes over the period of interest, we can regard the between-neighborhood changes in burglary due to WFH as a sufficient statistic for overall changes in burglary which simplifies the interpretation of our other analyses.

5.5 Mechanisms

In Section 2 we model the relationship between working from home and burglary as working through two channels, which we call the occupancy effect and the eyes-on-the-street effect. Here we discuss the evidence regarding these mechanisms, focusing on uncovering the eyes-on-the-street channel; corresponding figures and tables are available in the appendix, Section B.5. We also consider additional dimensions that could change post-pandemic in a manner correlated with WFH potential. The key suspect here is differential policing behavior, of which we find no evidence.

5.5.1 Ruling out Changes in Police Behavior as a Mechanism

One 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, which may translate to more or better policing. Differential police effort in higher WFH areas is an example of a correlated shock, and would prevent us from estimating the direct treatment effect of higher WFH on crime in an unbiased manner. To test this concern, we make use of data on monthly police clearance rates[15] at the neighborhood level for all property crimes. We re-estimate Equation (11) with clearances as the dependent variable (see Table B5). 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 in the post-lockdown period . This was also true during the lockdown period, with the exception of theft. We interpret this as strong evidence against a systematic change in police effort based on WFH potential.

5.5.2 Linking our Spatial Search Model to the Data

In order to provide supportive evidence for the existence of our two proposed channels, we start by estimating the relationship between WFH and burglaries non-parametrically. While we expect that the occupancy effect is approximately linear, an additional occupied house equaling one less suitable target for burglary, the eyes-on-the-street spillovers are likely to be non-linear. If each eye on the street has a chance of spotting someone burgling any of several houses, even with low probability, then past a WFH threshold 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 backward S relationship between the extent of WFH and crime. We test this by using a local polynomial regression in both the lockdown and post-lockdown periods (see appendix Figure B4). 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.[16] 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 large.

[15] Clearance rates reflect the proportion of crimes, by crime type, for which the case is successfully closed.

[16] In Figure A3 we report the results of repeating the same procedure for a placebo period, and show we find no relationship between WFH and crime.

Second, we exploit the fact that the eyes-on-the-street effect will be less powerful when it is dark, as residents will not be easily able to see what is happening on the street. We test this by exploiting changes in sunrise and sunset each day over the year. We extend Equation (11) to allow the effect of WFH to vary by whether it is light at a given time. We use the precise time and date information available in the Met data for London combined with daylight information from the official Civil Twilight time for each day of the year. We find that the effect of WFH potential on burglaries during the early morning and late afternoon is only negative and significant during daylight hours (see Table B4). For example, when it's light in the morning a one standard-deviation (9.5pp) greater WFH potential reduces the post-lockdown burglary rate by -0.027 in those hours. Further, as with the analysis in Section 5.3, we do not observe the same pattern during weekends (perhaps with the exception of post-lockdown Sunday evenings). These results provide further evidence that the eyes-on-the-street effect is an important channel through which WFH reduces crime.

6 Displacement of Crime Across Space

6.1 Spatial Econometric Estimator

In this section we explore the potential for burglary spillovers between neighborhoods and what this means for the estimates we presented in the previous section. The theoretical framework outlined in Section 2 suggests that the observed decline in burglary due to WFH will reflect both an overall reduction in the number of burglaries as well as the changes in the distribution of search activity. Specifically, the model suggests that criminals may shift their activities from high-WFH areas to relatively low-WFH areas. In the case of two neighborhoods, as considered in the model, the overall impact on crime in the low-WFH neighborhood will be the sum of the effect of a reduction in burglary from a change in WFH in that neighborhood, and an increase in burglary from the relocation of crime from the high-WFH neighborhood. In the model in Section 2, neighborhood 2 experiences no change in WFH so the sum of these effects is strictly positive. In general, the sign and magnitude of the total change in crime will depend on the relative magnitude of these two effects.

Here we extend our baseline estimating equation to quantify these spatial spillovers. To do so we assume that the crime rate in a neighborhood n depends on the rate of WFH in neighborhoods contiguous to n, and not others. Of course, in principle, crime in any one neighborhood may be affected by spillovers from any of the other, 7,200, neighborhoods. However, in reality most spillovers will be local. Kirchmaier et al. (2021) find that the costs of "commuting" for criminals are very high in the UK, with most burglaries happening within a five-minute car journey of the perpetrator's home. This suggests our assumption is not, in practice, a strong one.

To ease the interpretation of our results, we will focus on a binary measure of WFH. We define WFH_n^H to be a binary variable equal to one if neighborhood n has a WFH potential above the median value for all neighborhoods.We also define a binary variable $NWFH_n^H$ which is equal to one if the WFH potential in neighborhoods contiguous to n is greater than n's own WFH potential. With these variables, we estimate the following equation:

$$
\begin{aligned}
\text{crime}_{nt} =&\alpha_1(LD_t \times WFH_n^H) + \alpha_2(LD_t \times NWFH_n^H) + \alpha_3(LD_t \times WFH_i^H \times NWFH_n^H) \\
&+\beta_1(PLD_t \times WFH_n^H) + \beta_2(PLD_t \times NWFH_n^H) + \beta_3(PLD_t \times WFH_i^H \times NWFH_n^H) \\
&+\delta_1(LD_t \times X_n) + \delta_2(PLD_t \times X_n) + \gamma_n + \theta_{A\times t} + \varepsilon_{nt}.
\end{aligned} \tag{13}
$$

Under the specification in Equation (13) 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.

We use four different definitions of $NWFH_n^H$: (1) WFH potential in n is strictly less than average WFH potential in n's contiguous neighborhoods; (2) WFH potential in n is strictly less than the 67th percentile WFH potential in n's contiguous neighborhoods; (3) WFH potential in n is strictly less than the median WFH potential in n's contiguous neighborhoods; and (4) WFH potential in n is strictly less than the 33rd percentile WFH potential in n's contiguous neighborhoods. Definitions (2)–(4) progressively restrict spillovers to neighborhoods with larger disparities with their neighbors. In specification (4), where the 33rd percentile of neighboring WFH potential exceeds that of neighborhood n, there is a pronounced disparity.

6.2 Results

In Table 3 we report estimates for a baseline no-spillovers equation (column 1) and for the key post-lockdown coefficients from Equation (13), using each of the four definitions of $NWFH_n^H$.[17] For each regression, we report three key parameter estimates from Equation (13).

We focus on the results using definition (1) reported in column 2. First, β_1, the effect associated with being a high WFH neighborhood and surrounded by neighbors with relatively low WFH ($PLD \times WFH^H$). These neighborhoods enjoy a large and significant drop in burglary incidence in the post-lockdown period, -0.228 or 3.8% of the pre-pandemic mean. Second, β_2, the effect of being low WFH and surrounded by neighbors with relatively high WFH ($PLD \times NWFH^H$). In these neighborhoods we see little to no change; estimate are both small and statistically insignificant. This is consistent with the absence of spatial spillovers for these neighborhoods. Third, β_3, the effect of being high WFH and surrounded by neighbors with relatively high WFH ($PLD \times WFH^H \times NWFH^H$). For these areas we estimate relatively large and statistically significant spillover effects; having comparatively high WFH contiguous neighbors increases burglary by 0.205 per 10,000 residents. We also report the overall effect of WFH on burglary in these neighborhoods; summing the component effects. For high-WFH neighborhoods that are surrounded by neighbors with even higher average WFH, the benefit of high WFH is entirely offset by spatial spillovers. The total effect of -0.024 (column 2) is not statistically

[17] Extended results for both the lockdown and post-lockdown period are available in appendix Table B9.

Table 3: Spatial DDD Model for Burglary

	(1)	(2)	(3)	(4)	(5)
		DDD: Criterion Used to Define $\mathbf{NWFH^H}$			
	Baseline DD Estimates	Neighbor WFH Mean $> WFH_i$	Neighbor WFH P60 $> WFH_i$	Neighbor WFH P50 $> WFH_i$	Neighbor WFH P40 $> WFH_i$
$PLD \times WFH^H$	–0.165***	–0.228***	–0.342***	–0.273***	–0.220***
	(0.057)	(0.078)	(0.085)	(0.073)	(0.067)
$PLD \times NWFH^H$		–0.000	–0.066	–0.007	0.049
		(0.073)	(0.082)	(0.071)	(0.067)
$PLD \times WFH^H \times NWFH^H$		0.205**	0.336***	0.311***	0.273***
		(0.103)	(0.102)	(0.094)	(0.095)
Total DDD Effect for:					
$PLD \times WFH^H \times NWFH^H$		–0.024	–0.073	0.031	0.102
		(0.090)	(0.094)	(0.086)	(0.087)
p-Value: $PLD \times NWFH^H =$ $PLD \times WFH^H \times NWFH^H$		0.758	0.931	0.625	0.529
$\overline{Y}_{PRE}$	5.923	5.923	5.923	5.923	5.923
Adjusted R^2	0.485	0.485	0.485	0.485	0.485
Observations	479,710	479,710	479,710	479,710	479,710

Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level. The dependent variable is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census. Neighbourhood fixed effects are included in all regressions, as are Police-Force-Area-by-Year-by-Month fixed effects. In addition we control for interactions between lockdown periods (pre, during, post) and the following neighbourhood-specific variables (all based on pre-lockdown values): proportion of households living in own home, proportion of households living in social housing, proportion of residents welfare benefit claimants in the pre-lockdown period, retail floor space (m^2) in 2019. The total DDD effect for $PLD \times WFH^H \times NWFH^H$ is calculated as $PLD \times WFH^H + PLD \times NWFH^H + PLD \times WFH^H \times NWFH^H$. When calculating the p-value, we use the total DDD effect when defining $PLD \times WFH^H \times NWFH^H$. We present the extended set of results for both lockdon and post-lockdown coefficients in Table B9. Data used: Police recorded crime data, 03/2017-12/2022.

different from zero. The remaining three columns change the threshold by which we define $NWFH^H$, but the results are substantively unchanged.

This absence of an overall effect in high-WFH neighborhoods with higher still WFH neighbors implies heterogeneity in the impact of WFH: Otherwise similar neighborhoods will experience different reductions in burglary depending on the composition of their neighbors. But, this is masked by our baseline specification which by design recovers the total effect averaged over all high-WFH neighborhoods. Column 2 makes clear that the estimate of the binarized version of our baseline specification in column 1 is an average of the 30% of neighborhoods with high-WFH potential which have neighbors have $NWFH_n^H = 1$ (as defined in column 2) and in which the average total effect is zero, and other high-WFH neighborhoods in which the average effect is -0.228. To see this, note that we can do a back-of-the-envelope calculation of the DD estimate in column 1 as the weighted average of WFH^H estimates in column 2 ($-0.228 \times 70\% + 0.000 \times 30\% = -0.160$), which is indeed very similar to the estimate in column 1.[18]

The key implication of this analysis is that the overall impact of WFH on burglary in a given city will depend not only on the average WFH potential, but also on how exactly high-WFH areas are distributed among 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

[18]The relationship between α_1 estimated in equation (13) is the weighted average of α_1 and $\alpha_1 + \alpha_2 + \alpha_3$ from (11), where the weight is the probability of having $NWFH^H = 1$, conditional on $WFH^H = 1$.

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.[19] Furthermore, that spillovers are limited also 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).

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

In this section, we quantify the welfare implications of differences in neighborhoods' ability to work from home, with a specific focus on changes across quartiles of ex-ante burglary risk. The idea is that an increase in WFH should have a bigger impact on welfare in a neighborhood where the pre-pandemic risk of burglary was higher. Conversely, in areas with very little crime ex-ante, WFH has not meaningfully altered the risk of burglary, and thus has not altered welfare substantially through its impact on crime *ceteris paribus*. To quantify these welfare changes, we use the insights of Rosen (1974), and specify a hedonic house price model.[20] Using the estimates from this model, we then are able to compute estimates of the total welfare effects of reductions in burglary due to the the rise of WFH.

7.1 Empirical Specification

We estimate a triple-differences (DDD) house price regression, where the third difference is a measure of ex-ante burglary risk in the neighborhood.[21] The regression model we estimate is:

$$\begin{aligned}
price_{hbnmt} = & \sum_{p=1}^{2}\sum_{q=2}^{4}\alpha_q(Period_t^p \times B_0\, Q_n^q) \\
& + \sum_{p=1}^{2}\beta_{p,1}(Period_t^p \times WFH_n) + \sum_{p=1}^{2}\sum_{q=2}^{4}\beta_{p,q}(Period_t^p \times WFH_n \times B_0\, Q_n^q) \\
& + \sum_{p=1}^{2}\sum_{m=1}^{M}\sum_{q=1}^{4}\delta_{p,mq}(Market_m \times B_0\, Q_n^q \times Period_t^p \times X_h^{'}) \\
& + \sum_{p=1}^{2}\sum_{m=1}^{M}\sum_{q=1}^{4}\lambda_{p,mq}(Market_m \times B_0\, Q_n^q \times Period_t^p \times X_n^{'}) \\
& + \sum_{p=1}^{2}\sum_{q=1}^{4}\kappa_p(Period_t^p \times C_n^{'}) + \gamma_b + \theta_{m\times t} + \epsilon_{hbmnt}\ ,
\end{aligned} \tag{14}$$

[19] An alternative explanation, not captured by our (linear) model, is consistent with the non-linear relationship between WFH and Burglary documented in Figure B4. 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.

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

[21] 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.

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.[22] $Period_t^p$ is an indicator variable where $Period_t^1$ is equal to 1 in the lockdown period and $Period_t^2$ is equal to 1 in the post-lockdown period. 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.[23] X_n is a vector of neighborhood characteristics including the (property-based) proportion of home ownership and social housing, the proportion of welfare benefit claimants and the retail space in m^2. 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.[24] 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 estimations), such as access to good schools or proximity to polluting factories. As before, we cluster the error term ϵ_{hbmit} at the neighborhood level.

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 (14) 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, 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

[22] 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 difference in growth rate across areas with different WFH potential.

[23] 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.

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

estimate a lower bound on WFH-induced changes to (general equilibrium) welfare (Banzhaf, 2021).

One potential concern is that these estimates will pick up other changes in neighborhood welfare associated with WFH, beyond its effect on burglary, and beyond those factors we control for such as other types of crime, neighborhood composition in terms of welfare recipients and social-housing, and our various fixed effects. While we expect, given the richness of our model such factors to be small, we focus on the estimated effects for crime-risk quartiles two to four net of the the estimated effect in the first quartile. This means we can be confident of identifying a causal effect on welfare as to the extent that these other possible factors are uncorrelated with ex-ante burglary risk, they will be netted out, and to the extent that they are correlated with other types of crime, they were already accounted for by our controls.

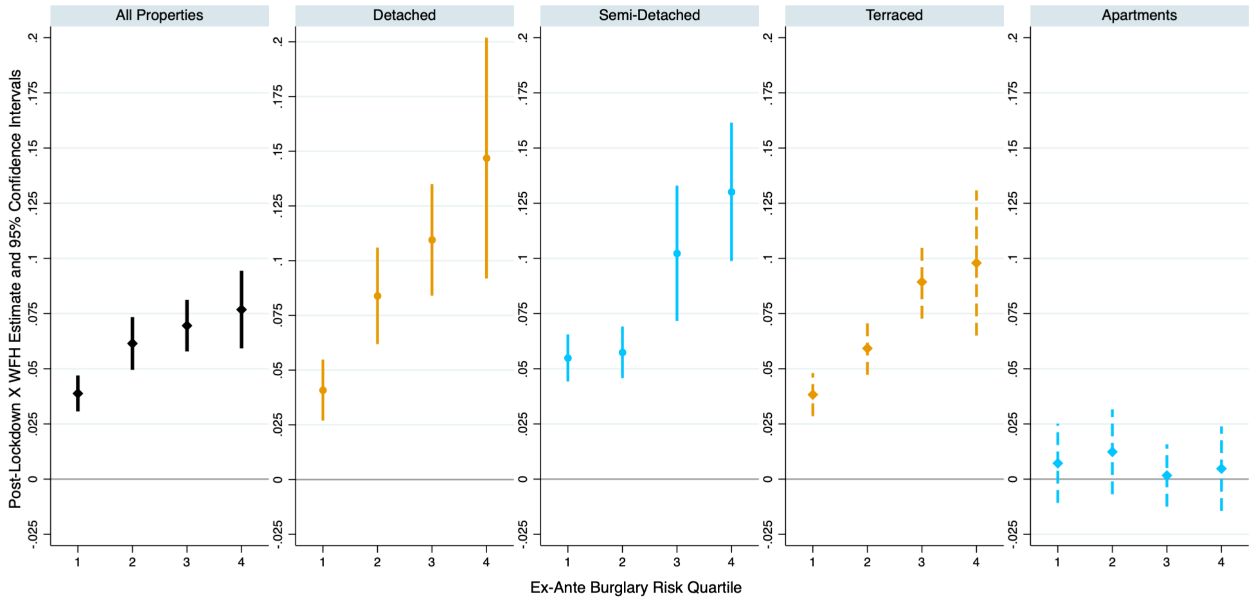
7.2 Results

Figure 4 reports estimates of the post-lockdown DDD coefficients from Equation (14). We focus on the post-lockdown estimates, but the lockdown estimates are broadly similar and are reported in appendix Table B10. The coefficients represent the impact of a standard-deviation increase in WFH as a percentage of the pre-lockdown mean.

Beginning with the left-most panel, which presents results for all properties, we can make three key inferences. First, we can see that all the estimates are positive, implying that 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. Third, the effects are large: the estimated coefficients imply a 1.3% increase in house prices in the lowest ex-ante burglary risk neighborhoods up to a 4.8% increase in the highest. This implies a causal effect of a one standard deviation higher WFH potential of $\beta_{2,4} - \beta_{2,1} = 4.8\% - 1.3\% = 3.5\%$ in the highest ex-ante burglary risk neighborhoods.

The right four panels report the results of Equation (14) estimated separately for different property types. Interestingly, we see no increase in the value of apartments: this is consistent with the eyes-on-the-street hypothesis. In the case of apartment blocks there is not a street for there to be eyes on in the same way, and burglary is already difficult due to occupancy being hard to assess and a single entrance/exit. A second feature of the estimates is that the difference in coefficient estimates across quartiles is larger for larger properties. The increase in prices, net of the effect for Q1, is from 4.3% in Q2 up to 10.6% in Q4 for detached homes, much larger than the between 2.1% and 5.96% we estimate for terraced houses. Our interpretation of this is that it reflects the greater willingness to pay for lower burglary risk among the purchasers of larger homes, other things being equal. The pattern and magnitude of our findings contribute to the literature documenting the costs of crime, which documents a substantial psychic cost to burglary (Cohen et al., 2004) and a high value that people place on feeling safe in their homes (Manning et al., 2016).

Figure 4: 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 post-lockdown-by-WFH effect differs by ex-ante burglary risk of the neighborhood, $\beta_{2,1}$–$\beta_{2,4}$ in Equation (14) 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 (14) all regression specification include the following as controls: the ex-ante burglary risk quartile for neighborhood; a vector of property characteristics including dummies for property type and whether the property is leasehold; a vector of neighborhood characteristics including the (property-based) proportion of home ownership and social housing; the proportion of welfare benefit claimants and the retail space in m^2; and a vector of additional neighborhood ex-ante crime risk variables, including quartiles of all property crime except burglary, violent crime and drugs crime. The regression model additionally includes month-by-year fixed effects and block fixed effects. Standard errors are clustered by neighborhood. We provide these estimates, and results for the lockdown period, in table format in Table B10.

7.3 Aggregate Welfare Effects

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

More specifically, we compute:

$$\text{Welfare}_q = \sum_{p=1}^{2} \sum_{n \in N_q} \sum_{t=1}^{4} \omega_p \, \hat{\beta}_{p,tq} \times \text{WFH}_n \times \overline{\text{Price}}_{0,tn} \times \text{Quantity}_{p,tn} \ , \tag{15}$$

where N_q is the set of neighborhoods in quantile q, $\overline{\text{Price}}_{0,tn}$, is the pre-lockdown average price of property type t in neighbourhood n,[25] $\hat{\beta}_{p,tq}$ is the property type-specific DDD parameter estimate from Equation 14,[26]

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

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

and ω_p is a weighting parameter to combine the estimates from the lockdown and post-lockdown periods in a meaningful way.[27]

There are two ways to compute $Quantity_{p,tn}$. The first, which is extremely conservative, is to base welfare calculations *only* on properties sold post-pandemic period. That is, when scaling up our willingness to pay estimates from individual transactions to a total welfare measure, we only account for the implicit welfare changes of those who bought a property post-pandemic, and attribute a zero change to those living in properties that did not change hands in the post-pandemic period. Whilst internally valid, this approach yields very conservative estimates, and can be considered a lower bound on the true welfare gains. The second method, uses the existing stock of private housing in England and Wales as the measure for $\text{Quantity}_{p,tn}$. Implicit in this approach is the assumption that the willingness to pay for WFH of those who buy a property post-pandemic is not systematically different from those who do not.

For the transaction- or flow-based approach to the welfare calculation, we construct the weights ω_p such that the resulting welfare estimates represent the annualized welfare change associated with neighborhood WFH potential. For the stock-based approach, we construct the weights ω_p to account for the different durations of time in the lockdown (15 months) and post-lockdown periods (19 months).[28]

The results are reported in Table 4. As before, we focus on the effects in quartiles 2 to 4 net of the effect in quartile 1. The welfare gains using both methods are large. The conservative transaction-based measure reflects a £24.5billion welfare increase, while the housing-stock based measure reflects a £873.9billion welfare increase.[29] While the true welfare gain likely lies in-between these two values, we can conclude they are significant: £24.5billion is just over 1% of GDP for England and Wales or £1,000 for every household in both countries.

Table 4: Total Post-Pandemic Welfare Change (Expressed in £Billions)

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

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

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

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

[28] $\omega_1 = 15/34$ and $\omega_2 = 19/34$.

[29] These values are calculated from Table 4 as $18.1 + 12.8 + 10.1 - (3 * 5.5) =$ £24.5billion and $652.0 + 422.0 + 310.8 - (3 * 170.3) =$ £873.9billion.

consequences of the rise of WFH. Second, they suggest that the welfare effects of burglary are several orders of magnitude larger than conventional estimates such as Heeks et al. (2018) suggest. This is not surprising given the different approach taken in Heeks et al. (2018).[30] Notably, our estimates are closest to those of Gibbons (2004b) who finds that one standard-deviation reduction in the density of criminal damage is associated with a 10% increase in house prices.

8 Conclusion

In this paper we provide the first 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 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. Computing the aggregate welfare gain implied by these price changes, we find that the shift to WFH has led to a substantial increase in welfare, with a lower-bound estimate of £24.5 billion, or 1% of GDP. This implies that the reduction in the risk of burglary due to WFH is one of the most important consequences of the shift to remote work.

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 C we extend the conceptual model presented in Section 2 to include police who allocate resources across the two neighborhoods with the

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

objective of minimizing overall burglaries. The implications for resource allocation depend importantly on the interaction between a neighborhood's WFH and its police resources, as studied in Hickey et al. (2021). When complementarities 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 complementarities 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 Support for the Identifying Assumption

As discussed in Section 4 the key identifying assumption that we make is the parallel trends assumption, which states that absent the pandemic-induced shift to remote work, the time trend for burglary would not depend on the WFH potential of the neighborhood. 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 3, we are confident in making the parallel trends assumption in this setting.

A.1 Pre-Lockdown Trends

First, we directly estimate differential pre-trends in burglaries according to WFH potential. To do this we restrict the sample to the pre-lockdown period and repeating the estimates reported in Table 5.1 in which the lockdown period dummy interactions are replaced with the interaction between WFH and a linear time trend. We report the results of this exercises in Appendix A, Table A1, for both WFH as a continuous variable—see row a)— and a binary variable identifying high WFH neighborhoods—see row b). This strategy serves as a placebo regression, and directly gets at the notion of parallel trends. When controlling for region and police force time variation, the results for both WFH specifications yield estimates that are economically small and statistically indistinguishable form zero.

Table A1: Pre-Lockdown Trends

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

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

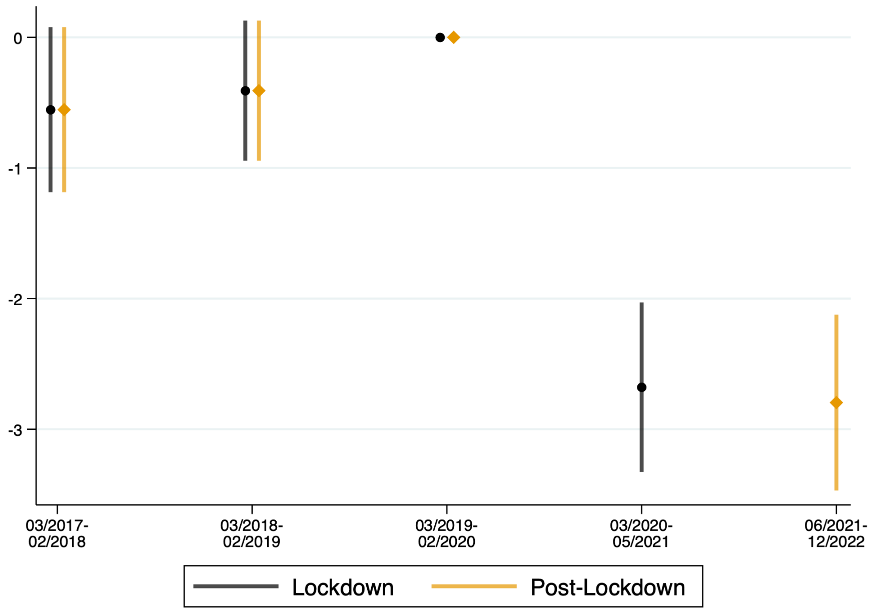
A.2 Honest DD à la Rambachan and Roth (2023)

In order to operationalize the approach of Rambachan and Roth (2023), we modify Equation (11), 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:

$$crime_{nt} = \sum_{j=1,\neq 3}^{5} \alpha_j (period_j \times WFH_n) + LD_t \times X_n^{'}\beta_1 + PLD_t \times X_n^{'}\beta_2 + \gamma_n + \theta_{A\times t} + \varepsilon_{nt}\,, \tag{16}$$

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.

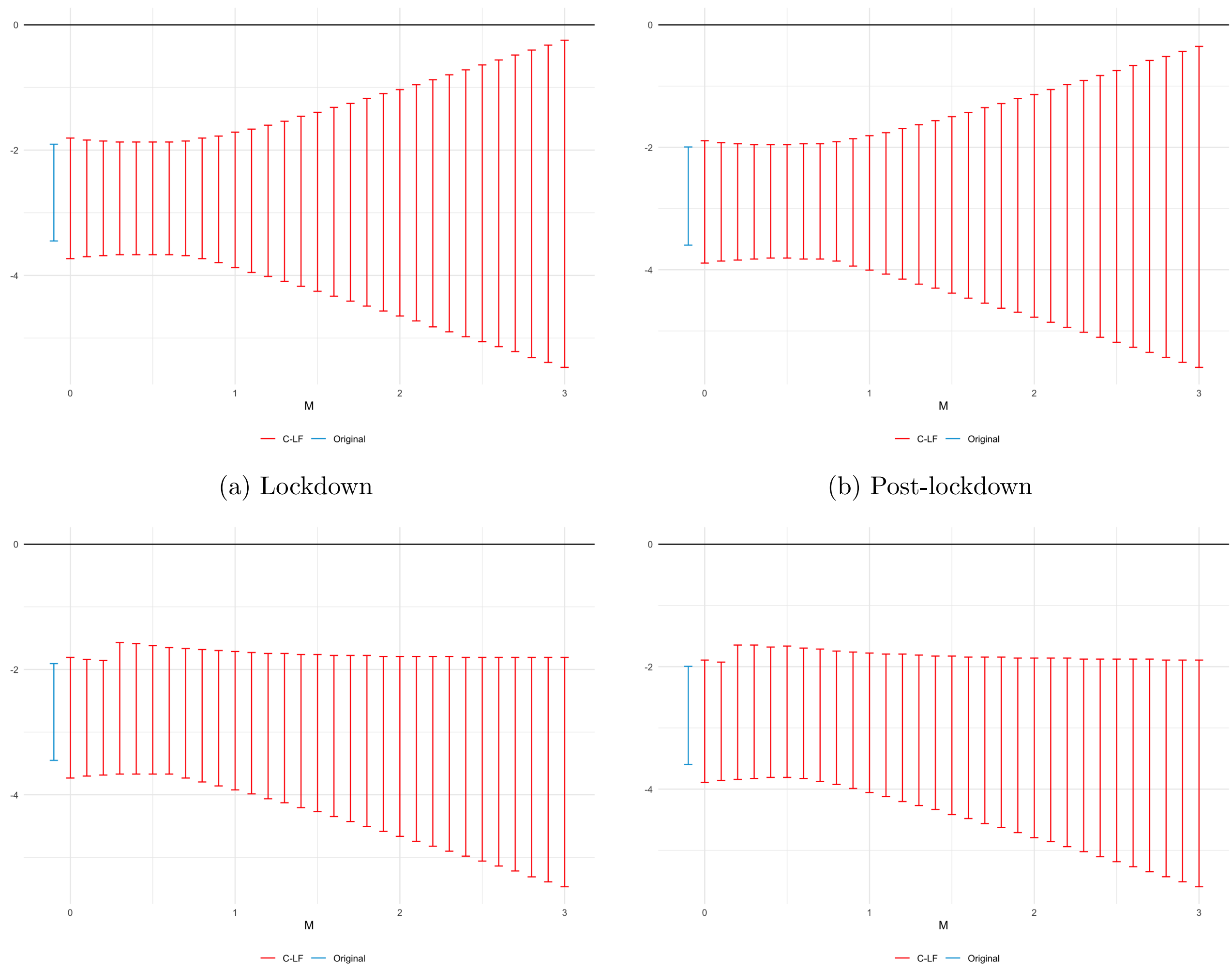
Figure A1: Parameter Estimate Inputs for the Honest DD Routine



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.[31] 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.

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

A.3 Identification with a Continuous Treatment

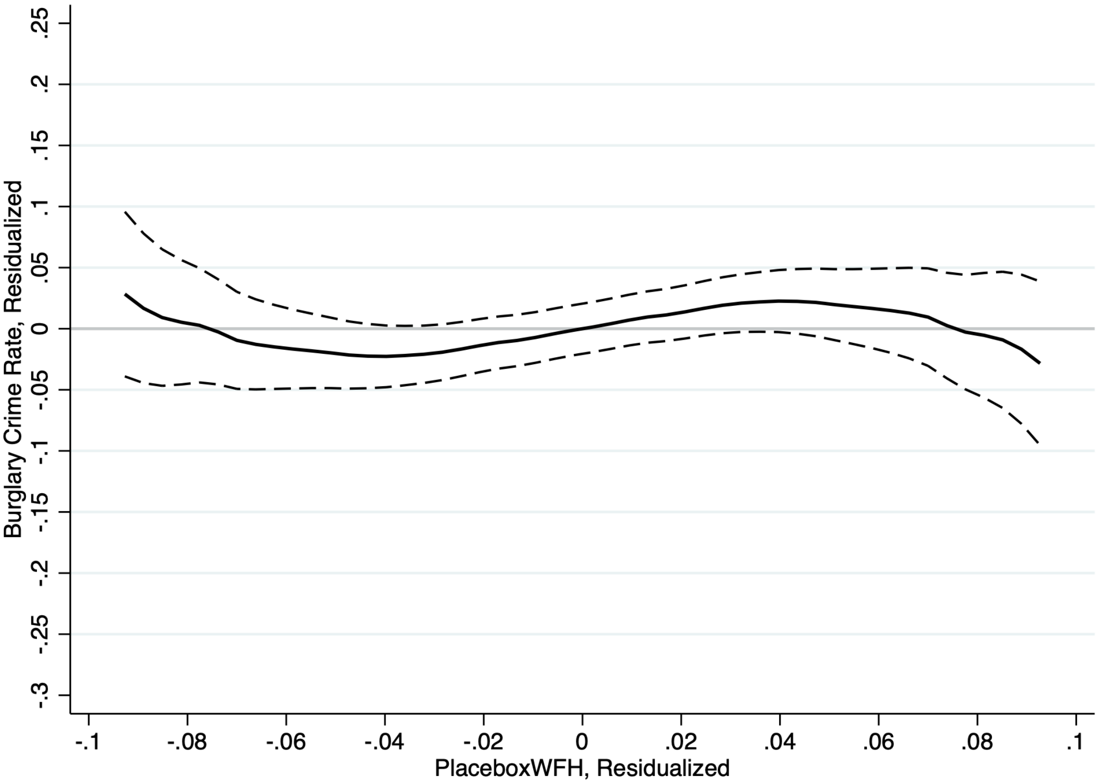
Callaway et al. (2021) show that for continuous treatments, the necessary assumptions for a DD model to estimate a causal effect may be stronger. They show that, for our case where every neighborhood received the treatment simultaneously, that we need to make a stronger parallel trend assumption. Instead 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 A3. This reproduces the non-parametric analysis in Section B.5.1, but for a placebo policy period of one year from March 2019 onward 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-Linear Pretrends in the Relationship Between Burglary and WFH



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 (11). 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 (March 2018–February 2020), define a placebo post term that takes value 1 for time periods from March 2019 onwards and zero otherwise, and implement an analogous specification to Equation (11), 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 B4.

B Additional Results and Analysis

B.1 Summary Statistics

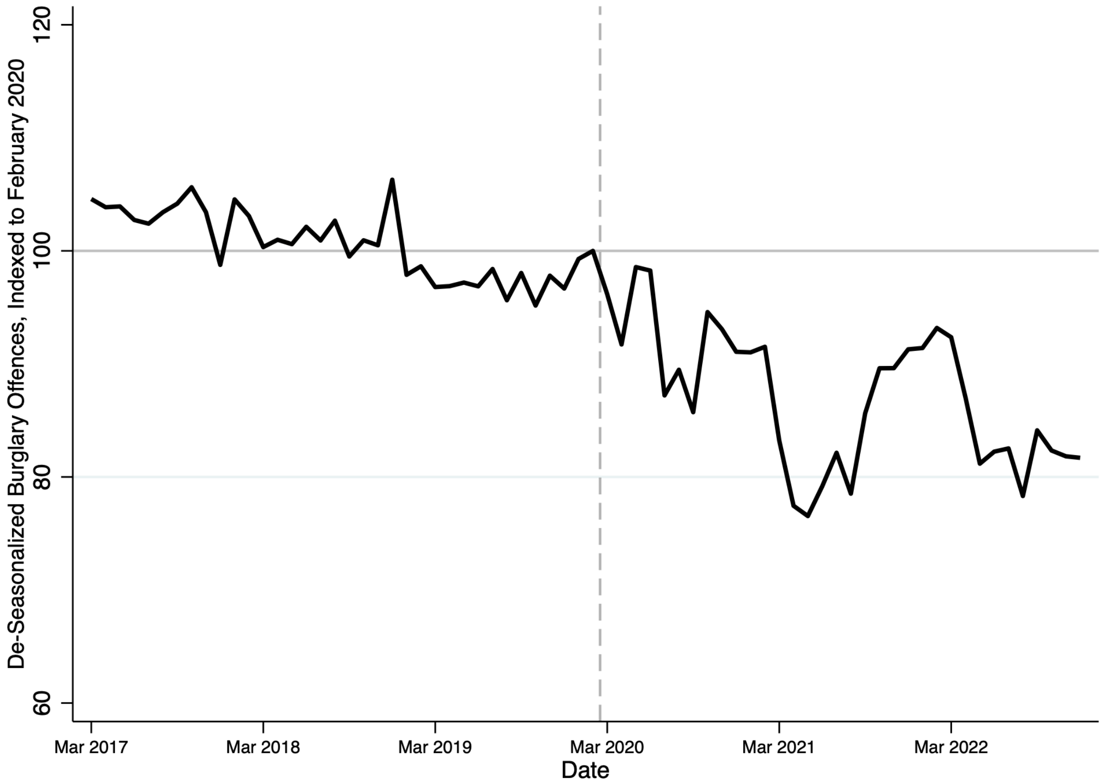
Table B1: Summary Statistics

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

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

B.2 Burglaries in American Cities

Figure B1: De-Seasonalized Burglary Offences, Indexed to February 2020, for US Cities



Notes: This figure reports the number of monthly reported burglaries relative to February 2020, for 20 selected US cities based on Abrams (2021). The included cities are Atlanta, Baltimore, Boston, Chicago, Cincinnati, Dallas, Denver, Detroit, Fort Worth, Houston, Indianapolis, Los Angeles, Milwaukee, Nashville, Philadelphia, Phoenix, Portland, San Francisco, Seattle, and Washington DC. Data are from open source records made available by individual municipal police forces.

B.3 Core DD Results—Binarized Treatment

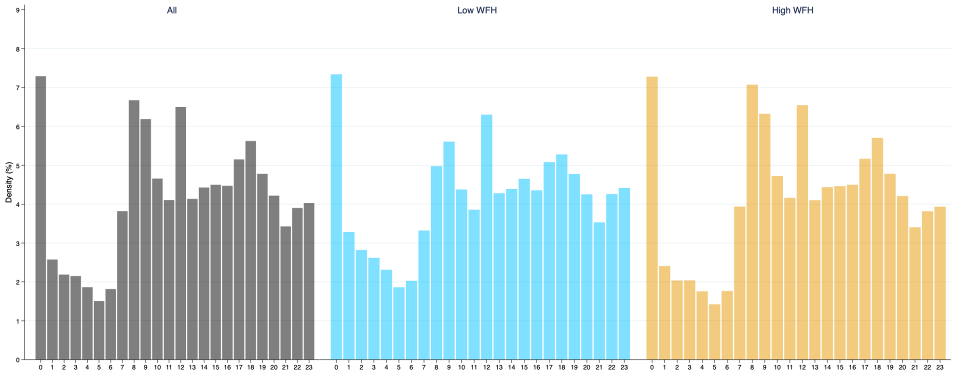
Table B2: DD Estimates for Burglary

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

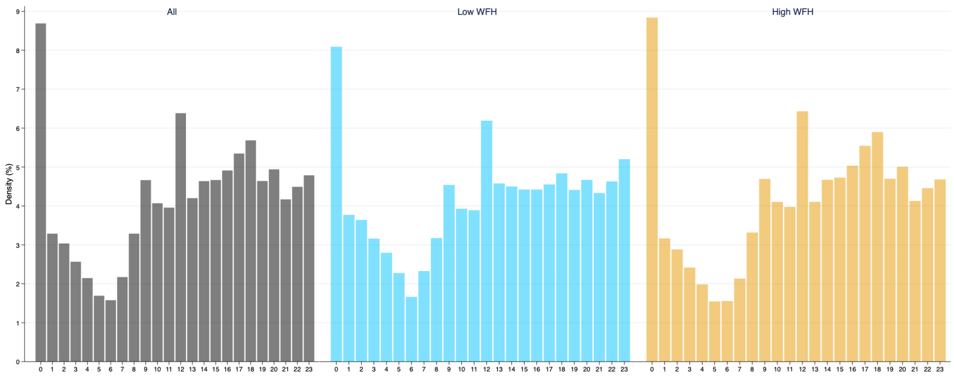
Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level, and standard errors are clustered by neighborhood. The dependent variable is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census. Neighbourhood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

B.4 The Timing of Burglaries—Met Data

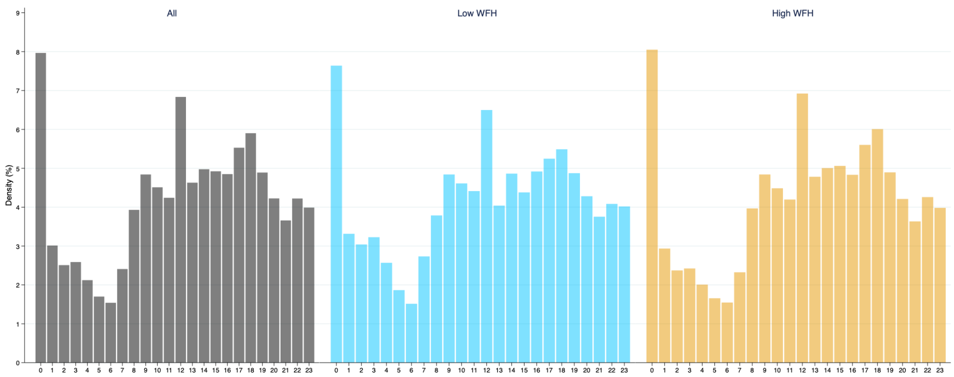
Figure B2: The Timing of Residential Burglaries During the Week



(a) Pre-lockdown



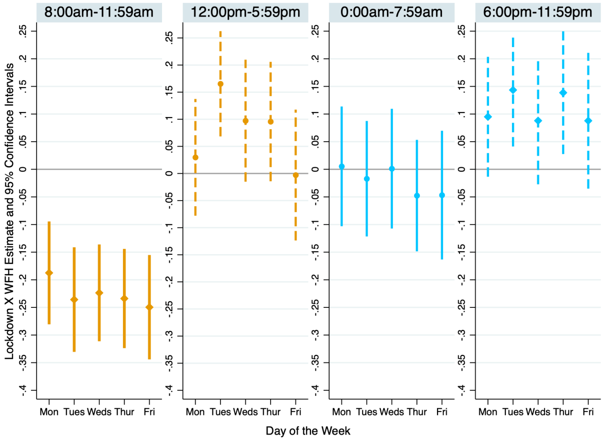
(b) Lockdown



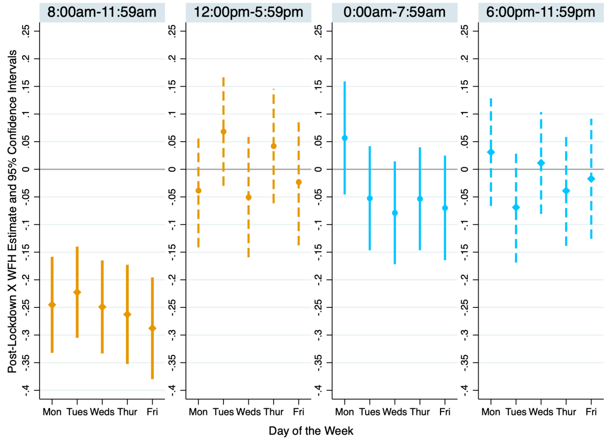
(c) Post-lockdown

Source: Met Data.

Figure B3: Stability of Timing Results by Day of Week



(a) Lockdown



(b) Post-Lockdown

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

B.4.1 Commercial Burglary

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

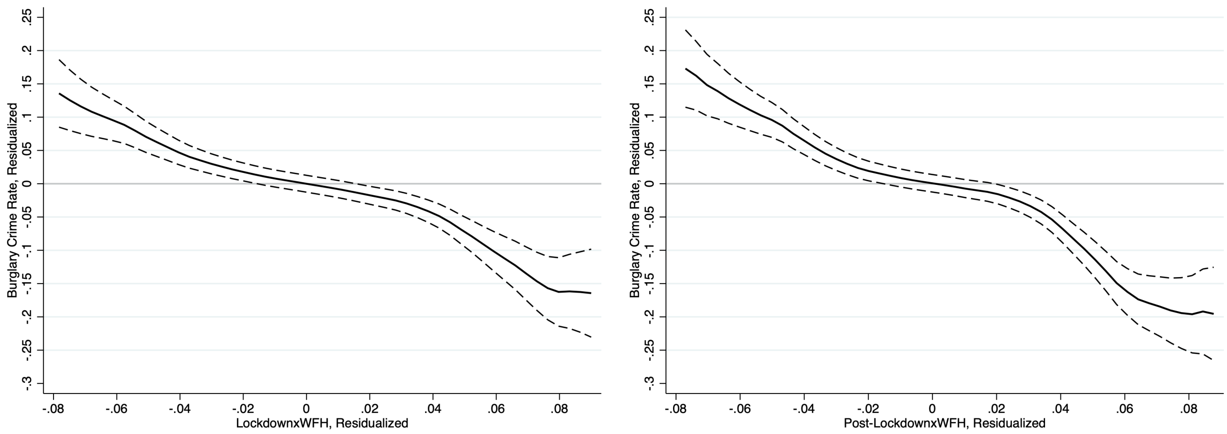
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Working Hours			**Non-Working Hours**			
	All	Weekdays, 8:00am-5:59pm	Weekdays, 8:00am-11:59am	Weekdays, 12:00pm-5:59pm	Weekdays, Outside of 8:00am-5:59pm	Weekdays, 0:00am-7:59am	Weekdays, 6:00pm-11:59pm	Weekend
A.) All Neighborhoods								
LD × WFH	–1.842***	–0.363***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

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

B.5 Evidence in Support of our Primary Mechanisms

B.5.1 Non-parametric Estimation of the Burglary-WFH Relationship

Figure B4: 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 (11). The x-axis values are the residuals from a regression of lockdown or post-lockdown dummy multiplied by neighborhood WFH on the same set of fixed effects and controls. In both cases we specify an Epanechnikov kernel and use the rule of thumb bandwidth.

We fit the relationship between residualized values of work from home rates and residualized crime rates, using a local polynomial regression, in both the lockdown and post-lockdown period. Both variables are residualized using the same MSOA and police force area × month × year fixed effects, and 2019 neighborhood characteristics controls as in Equation (11).

B.5.2 Veil of Darkness Approach (Eyes-on-the-Street Effect)

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

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

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

We interact our time and WFH variables with a dummy variable, *Light*, equal to one if daylight is present and zero otherwise. We define a DDD model. Thus, now we are estimating the effect of WFH on the number of burglaries by time and day, allowing the effect at a given time on a given day to vary depending on whether it is light outside. We use the precise time and date information available in the Met data for London combined with daylight information from the official Civil Twilight time for each day of the year.[32]

We report the results of this exercise in Table B4, focusing only on those hours of the day where the amount of daylight varies over a year. The coefficients of interest ($LD \times WFH \times Light$ and $PLD \times WFH \times Light$) are negative and of a similar magnitude for both the morning and evening during the weekdays (although only statistically significant during the morning). For example, when it's light in the morning a one standard-deviation (9.5pp) greater WFH potential reduces the post-lockdown burglary rate by -0.027 in those hours. A similar pattern is not observed during weekends (perhaps with the exception of post-lockdown Sunday evenings).

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

B.6 Policing Effort as an Alternative Mechanism

Table B5: DD Estimates – Clearance Rate

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

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

B.7 Adjusting WFH Potential for Differences in Working Population Across Neighborhoods

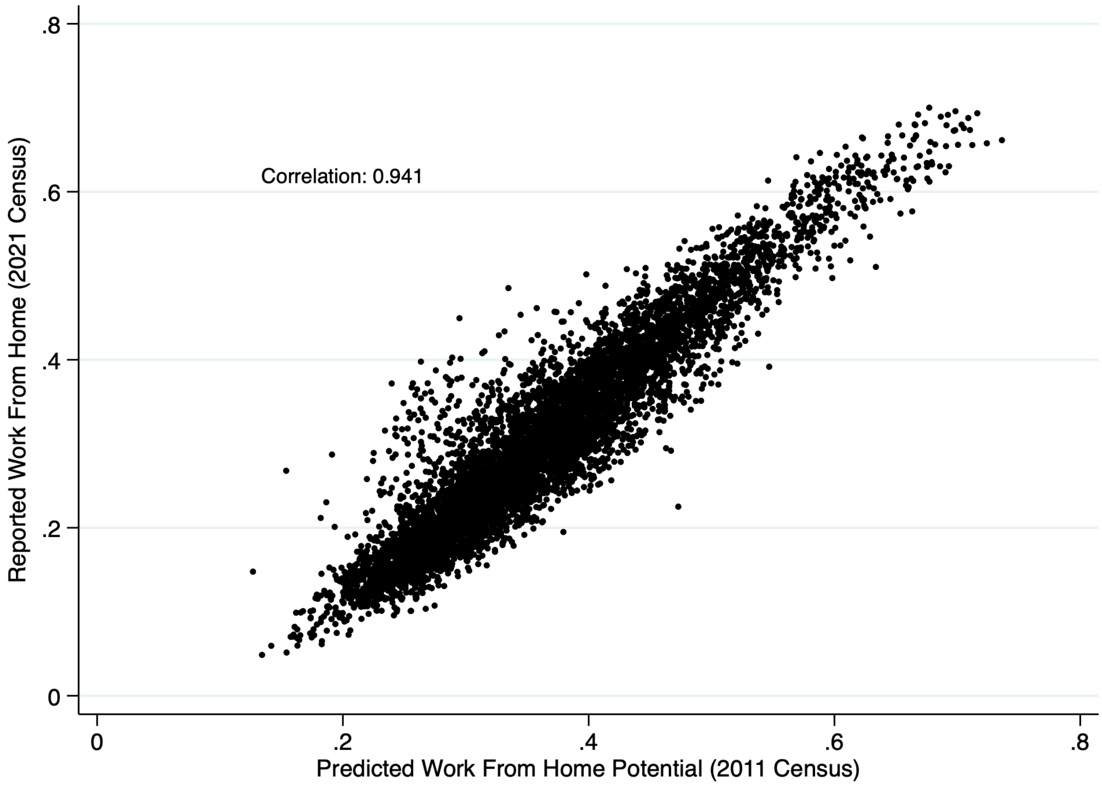
Table B6: DD Estimates

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

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

B.8 Work from Home Predictions and IV Estimates

Figure B5: 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 (10), is calculated using the residential distribution, by occupation, reported in the 2011 Census. One concern with this might be that the geography of where people live has changed significantly enough to make our measure a poor reflection of the realized post-pandemic WFH distribution. Here we provide evidence to address this concern.

To do this we use data from the 2021 UK Census. The Census was conducted during the second national lockdown in March 2021. We use information from the question "How do you usually travel to work?", for which one of the possible answers is "Work mainly at or from home".[33] 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.

[33]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 B5 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.8.1 IV-DD Estimates

Table B7: IV-DD Estimates for Burglary

	(1)	(2)	(3)	(4)
A.) OLS				
LD × WFH_{2021}	–0.933***	–1.959***	–2.338***	–1.780***
	(0.273)	(0.288)	(0.262)	(0.279)
PLD × WFH_{2021}	–1.122***	–2.065***	–1.889***	–1.662***
	(0.266)	(0.305)	(0.272)	(0.291)
B.) 2SLS				
LD × WFH_{2021}	–1.673***	–2.734***	–3.018***	–1.972***
	(0.304)	(0.311)	(0.292)	(0.319)
PLD × WFH_{2021}	–1.859***	–2.936***	–2.686***	–2.076***
	(0.290)	(0.329)	(0.304)	(0.334)
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
$\overline{Y}_{PRE}$	5.875	5.875	5.875	5.875
Kleibergen-Paap F Statistic	27,883.393	12,922.069	11,012.618	9,803.842
Observations	471,730	471,730	471,730	471,730

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

B.9 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.[34][35]

We present the resulting DD estimates from estimating a similar specification to Equation (11) in Table B8. To ease interpretation of these measures, we include the pre-lockdown means at the base of the table and note that both a higher MCC coefficient and a higher generalized Gini means that crime is more concentrated in an area. We document a series of null effects in this exercise: not only are none of the parameter estimates statistically significant, the estimates themselves are also minimal in magnitude. From this exercise, we conclude that the spatial location of crime *within* neighborhoods did not change as a consequence of the shift towards remote work, and the concomitant spatial reallocation of workers during the working week.

Table B8: 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.

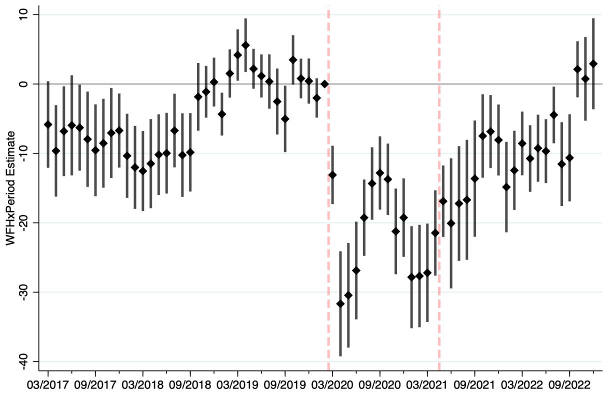
[34] The generalized Gini coefficient is given by $G' = \max\left[\frac{S}{C}, 1\right](G-1)+1$ where G is the conventional Gini coefficient, S the number of street segments in a given MSOA-period, and C the number of crimes in a given MSOA-period. The MCC coefficient is: $MCC_n^k = CC_n^{k,\text{sim}}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

[35] 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.

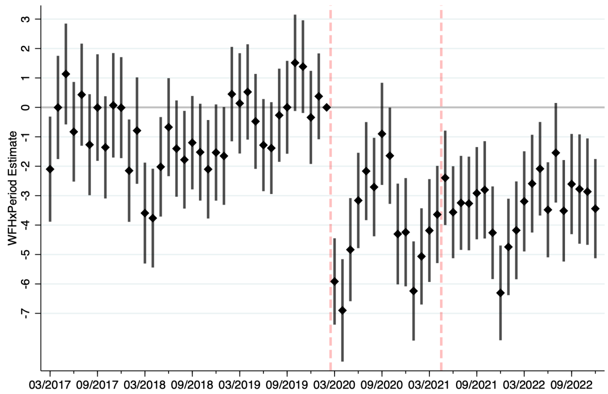
B.10 Other Property Crime Types

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.

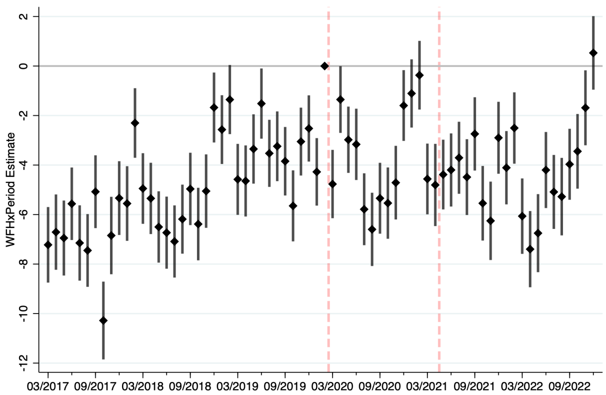
Figure B6: Event Studies for Other Property Crime Types



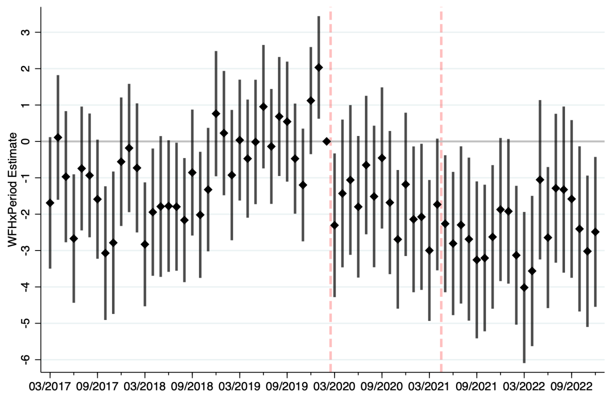
(a) Theft



(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 (12). The dashed vertical lines denote the introduction of the UK first national lockdown in March 2020, and the start of the post-lockdown period in May 2021. February 2020 is excluded as the reference month. Standard errors are clustered by neighborhood.

B.10.1 Extended Spatial Spillover Results

In Table B9 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 B9: Spatial DDD Model for Burglary

	(1)	(2)	(3)	(4)	(5)
		DDD: Criterion Used to Define $\mathbf{NWFH^H}$			
	Baseline DD Estimates	Neighbor WFH Mean $> WFH_i$	Neighbor WFH P60 $> WFH_i$	Neighbor WFH P50 $> WFH_i$	Neighbor WFH P40 $> WFH_i$
$LD \times WFH^H$	–0.215***	–0.297***	–0.351***	–0.325***	–0.312***
	(0.052)	(0.070)	(0.076)	(0.068)	(0.062)
$LD \times NWFH^H$		–0.051	–0.055	–0.033	–0.078
		(0.065)	(0.069)	(0.064)	(0.061)
$LD \times WFH^H \times NWFH^H$		0.202**	0.255***	0.291***	0.301***
		(0.099)	(0.093)	(0.091)	(0.096)
Total DDD Effect for:					
$LD \times WFH^H \times NWFH^H$		–0.145*	–0.150*	–0.067	–0.089
		(0.085)	(0.083)	(0.082)	(0.088)
$PLD \times WFH^H$	–0.165***	–0.228***	–0.342***	–0.273***	–0.220***
	(0.057)	(0.078)	(0.085)	(0.073)	(0.067)
$PLD \times NWFH^H$		–0.000	–0.066	–0.007	0.049
		(0.073)	(0.082)	(0.071)	(0.067)
$PLD \times WFH^H \times NWFH^H$		0.205**	0.336***	0.311***	0.273***
		(0.103)	(0.102)	(0.094)	(0.095)
Total DDD Effect for:					
$PLD \times WFH^H \times NWFH^H$		–0.024	–0.073	0.031	0.102
		(0.090)	(0.094)	(0.086)	(0.087)
p-Value: $LD \times NWFH^H =$ $LD \times WFH^H \times NWFH^H$		0.205	0.152	0.645	0.895
p-Value: $PLD \times NWFH^H =$ $PLD \times WFH^H \times NWFH^H$		0.758	0.931	0.625	0.529
$\overline{Y}_{PRE}$	5.923	5.923	5.923	5.923	5.923
Adjusted R^2	0.485	0.485	0.485	0.485	0.485
Observations	479,710	479,710	479,710	479,710	479,710

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

B.10.2 House Price Results

The results that we present below in Table B10 are based on the same regressions that generate the results we present in Figure 4, 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 B10: 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 £.

C Optimal policing

Here we extend the model of Section 2 to allow for policing. To do this we following a framework inspired by Hickey et al. (2021), which studies complimentary between private and public policing, and Gao and Vásquez (2023), which studies a dynamic model of search and 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,[36] 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.

C.1 A parametrized model

To make the optimal policing problem more tractable, we assume the outside option, ω, is fixed across all criminals, and propose functional forms for the two probability functions, which allow us to solve for closed form equilibrium solutions for λ and C. Specifically, we propose the following:

$$\phi(\rho_n, C_n) = \frac{1-\rho_n}{C_n^{\xi}} \tag{17}$$

$$\pi(\rho_n, M_n) = e^{-(a\rho_n + bM_n + c\rho_n \times M_n)}, \tag{18}$$

[36] 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).

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:

$$\lambda^\star = \frac{S_1^{\frac{1}{\xi}}}{S_1^{\frac{1}{\xi}} + S_2^{\frac{1}{\xi}}} \quad \text{and} \quad C^\star = \frac{S_1(1-\rho_1)^{\frac{1}{\xi}} + S_2(1-\rho_2)^{\frac{1}{\xi}}}{\omega^{\frac{1}{\xi}}}, \tag{19}$$

where:

$$S_n = (1-\rho_n)\left(F + (P_n - F)e^{-(a\rho_n + bM_n + c\rho_n \times M_n)}\right). \tag{20}$$

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

$$C_n^\star = \left(\frac{S_n}{\omega}\right)^{\frac{1}{\xi}}, \qquad \theta_n^\star = \frac{(1-\rho_n)\omega}{S_n}, \qquad \theta_n^\star C_n^\star = (1-\rho_n)\left(\frac{S_n}{\omega}\right)^{\frac{1}{\xi}-1}. \tag{21}$$

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:

$$\min_{\sigma} \theta_1^\star C_1^\star + \theta_2^\star C_2^\star. \tag{22}$$

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

$$(bM + cM \times \rho_1)(1-\rho_1)S_1^{\frac{1}{\xi}-1} = (bM + cM \times \rho_2)(1-\rho_2)S_2^{\frac{1}{\xi}-1}. \tag{23}$$

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 (23) as:

$$(1-\rho_1)S_1^{\frac{1}{\xi}-1} = (1-\rho_2)S_2^{\frac{1}{\xi}-1}. \tag{24}$$

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 (24) relative to the right-hand side (as both $(1-\rho_1)$ and $S_1^{\frac{1}{\xi}-1}$ are decreasing in ρ_1). For (24) 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 (23). 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.