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

Jesse Matheson [University of Sheffield] **Brendon McConnell** [City, University of London]
James Rockey [University of Birmingham] **Argyris Sakalis** [University of Sheffield]

Monday 24th June, 2024

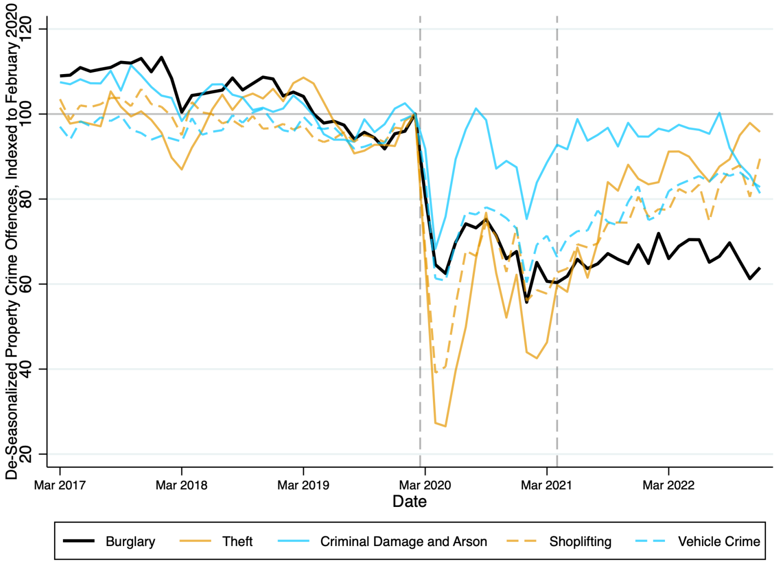
UCL Econ PhD Alumni Conference

Motivation I

- Since the pandemic working from home (WFH) has substantially increased in many countries (Barrero, Bloom and Davis, 2021; Aksoy et al. 2022; Alipour, Flack and Schüller, 2023).
  - In 2023, 24% of employed "normally work from home" vs. $<$ 6% in 2019 (*UK Quarterly Labour Force Survey*).
  - UK workers report employer-planned work from home of about two days per week (*UK Survey of Working Arrangements and Attitudes*).
- The post-pandemic rise in WFH has led to a spatial shift in economic activity.
  - Where work is done (Althoff et al., 2022; De Fraja et al., 2021; Barrerro et al., 2021).
  - Where people spend money (De Fraja et al., 2022; Barrerro et al., 2021, Alipour et al., 2022).
  - Where people want to live (Gupta et al., 2022; Gokan et al., 2022; Gupta et al., 2023).

- This large spatiotemporal shift of workers during the week $\rightarrow$ large changes in residential activity
- **RQ:** How did this impact neighbourhood crime?

Property Crime Time Series



- UK property crimes fell during the pandemic.
- Burglary is the only property crime showing no sign of recovery.
- The 30% decrease in burglaries equates to a £635 million reduction in social cost of crime.

Motivation II

The post-pandemic fall in burglary has important economic and societal consequences.

1. The decrease in burglary is very large (30% drop relative to 2019).
    - Corresponding to 107,000 fewer reported crimes per year.
    - Burglary ranks highest among property crimes according to victim costs (Heeks at al., 2018).
2. Studying this change will shed light on how WFH affects urban economic activity.
3. The decrease in burglary will not be equally realized across all neighborhoods.
   The benefit will likely concentrate in affluent neighborhoods $\rightarrow$ exacerbating urban inequalities.

Literature

This study contributes to two strands of literature.

- **Economic and societal consequences of the rise of WFH**
  - **Spatial distribution of economic activity** (Barrerro, Bloom and Davis, 2021; De Fraja, Matheson and Rockey, 2021; Delventhal and Parkhomenko, 2020; Althoff et al., 2022; Alipour et al., 2022; Duguid et al. 2023)
  - **Labor markets and cities** (Bamieh and Ziegler, 2022; Gokan at al., 2022; Monte, Porcher and Rossi-Hansberg, 2023)
- **Economics of crime and criminal decision making**
  - **Routine activity theory** (Cohen and Felson, 1979) and **spatial models of crime** (Zenou, 2003; Verdier and Zenou, 2004; Kirchmaier, Langella, and Manning, 2021)
  - **Shocks to crime detection probability** (Doleac and Sanders, 2015)
  - **Spatial displacement of crime** (Gonzalez-Navarro 2013; Maheshri and Mastrobuoni, 2021)

Conceptual Model

Conceptual Model

“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).

We propose a spatial model of criminal search:

- Two neighborhoods which experience an (asymmetric) increase in WFH.
- Each (potential) criminal must decide a) whether to engage in burglary, b) how to allocate time searching for targets in each neighborhood.
- Key model features:
  1. empty houses are more suitable targets for burglary
  2. burglars will avoid neighborhoods in which they are likely to be seen;
  3. burglars impose a congestion externality upon one another – the same house cannot be burgled multiple times in a given period.

Conceptual Model

"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).

We propose a spatial model of criminal search:

- Two neighborhoods which experience an (asymmetric) increase in WFH.
- Each (potential) criminal must decide a) whether to engage in burglary, b) how to allocate time searching for targets in each neighborhood.
- Key model features:
    1. empty houses are more suitable targets for burglary
    2. burglars will avoid neighborhoods in which they are likely to be seen;
    3. burglars impose a congestion externality upon one another – the same house cannot be burgled multiple times in a given period.

Conceptual Model

- WFH affects a criminal's decision through two channels:
  1. **Occupancy Effect:** WFH $\downarrow$ the number of empty houses (fewer suitable targets).
  2. **Eyes on the Street Effect:** WFH $\uparrow$ the number of "eyes on the street" (higher chances of being caught).
- An increase in WFH will:
  - $\downarrow$ the total number of burglars
  - $\downarrow$ number of burglaries, with a greater $\downarrow$ in higher WFH neighborhoods;
  - moves criminal search from high WFH areas to relatively low WFH areas.

Data and Empirical Specification

Data 1 – WFH Measure

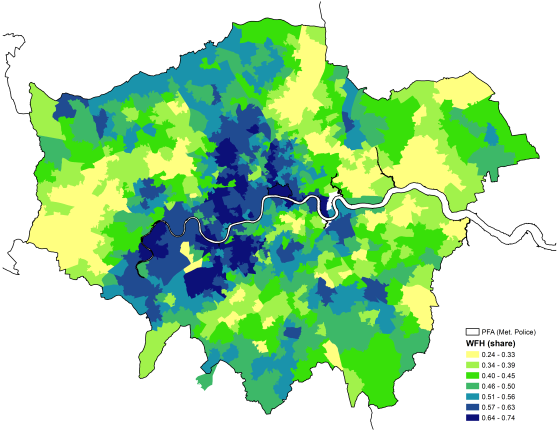
WFH Estimate vs Actual

- WFH measure calculated following the methodology proposed by Dingel and Neiman (2020), adapted to UK by De Fraja, Matheson and Rockey (2021):

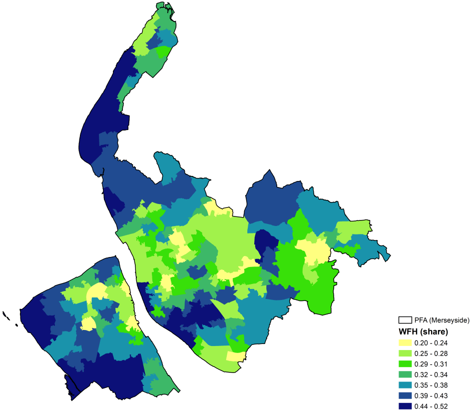
$$WFH_n = \frac{\sum_o E_{o,n} \times h_o}{E_n}$$

  - $E_{o,n}$ is the count of neighborhood n residents employed in occupation o
  - E_n is the total number of employed residents in neighborhood n
  - h_o is an occupation specific work from home index (Dingel and Neiman, 2020)
- $E_{o,n}$ and E_n are based on information from the 2011 UK Population Census. Occupation reflects four-digit UK SOC codes.
- 6,855 neighborhoods (*middle super output areas*) each reflecting approximately 3,500 residential properties (similar in size to US Census Tracts).

Spatial Distribution of Working from Home



(a) Metropolitan Police Force Area (*London*)



(b) Merseyside Police Force Area (*Liverpool*)

Data 2

- Core crime data from police.uk – offense type-by-street-by-month level data
- Supplement this with restricted access data from London Met – offense level data with time and date of offense
- Neighborhood covariates from Census 2011, Office of National Statistics and Valuation Office Agency
- House price data from Land Registry – near universe of house sales in England and Wales

Empirical Specification

Key empirical specification is a DD:

$$crime_{nt} = \alpha_1 (LD_t \times WFH_n) + \alpha_2 (PLD_t \times WFH_n) + (LD_t \times X_n^{'} \beta_1) + (PLD_t \times X_n^{'} \beta_2) + \gamma_n + \theta_{A \times t} + \varepsilon_{nt} \, , \quad (1)$$

- Outcome in levels, not logs, as this is a DD (McConnell, 2024)
- Coefficients of interest are the DD terms: α_1 and α_2
- γ_n controls for neighbourhood fixed effects, $\theta_{A \times t}$ controls for police force $\times$ month $\times$ year effects.
- X_n includes (pre-lockdown) rates of public support claims, % of owned and % of socially provided housing, retail floor space (m^2).
- **Identification** – evidence in support of PTA [No Pre-trends] [Non-Parametric Placebo] [Honest DD]

Results

DD Estimates

Binary Treatment

Table 1: DD Estimates for Burglary

	(1)	(2)	(3)	(4)
LD $\times$ WFH	–1.987***	–3.042***	–3.473***	–2.357***
	(0.356)	(0.344)	(0.333)	(0.367)
PLD $\times$ 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 $\times$Year	Month $\times$Year	Region $\times$Month $\times$Year	PFA $\times$Month $\times$Year
Control Variables		$X_0 \times$Period	$X_0 \times$Period	$X_0 \times$Period
$\overline{Y}_{PRE}$	5.919	5.919	5.919	5.919
$1\sigma_{WFH} \times$(LD $\times$ WFH)/ $\overline{Y}_{PRE}$	–0.032***	–0.049***	–0.056***	–0.038***
	(0.006)	(0.006)	(0.005)	(0.006)
$1\sigma_{WFH} \times$(PLD $\times$ 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

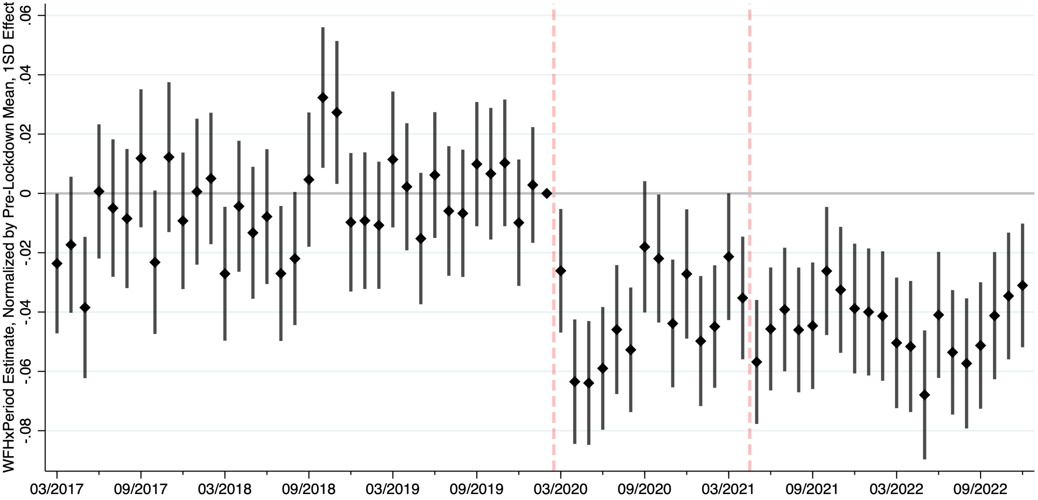
Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level, and standard errors are clustered by neighborhood. The dependent variable is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census.

Event Study Estimates – Burglary

▸ ES Burglary – Unscaled

▸ ES Other Property Crimes

▸ ES Vehicle Crime



Estimating Equation: $crime_{nt} = \sum_t \alpha_t WFH_n + (LD_t \times X_n' \beta_1) + (PLD_t \times X_n' \beta_2) + \gamma_n + \theta_{A \times t} + \varepsilon_{nt}$

The Timing of the WFH-Induced Decline In Burglary (London)

DOW

	(1)	(2)	(3)	(4)
		Working Hours	**Non-Working Hours**	
	All	Weekdays, 8:00am-5:59pm	Weekdays, Outside of 8:00am-5:59pm	Weekend
LD × WFH	0.304	–0.745***	0.448*	0.600***
	(0.529)	(0.234)	(0.253)	(0.186)
PLD × WFH	–1.606***	–1.269***	–0.280	–0.058
	(0.523)	(0.245)	(0.235)	(0.159)
$\overline{Y}_{PRE}$	5.710	2.192	2.123	1.395
Adjusted R^2	0.307	0.214	0.154	0.128
Observations	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. Data used: Met Police recorded crime data, 03/2017-12/2022

Relationship between burglary and WFH only present during working hours.

Mechanisms and Extensions

Mechanisms – Suggestive Evidence

- **occupancy + eyes on the street mechanism**: non-linearities in crime-WFH relationship [Non-Parametric]
- **eyes on the street mechanism**: "veil of darkness" approach [Veil of Darkness]
- rule out **differential police effort** in response to WFH potential [Clearance Rates]
- no change in **within-neighborhood distribution of crime** – WFH doesnt lead to within neighborhood crime changes [Concentration]

Additional analysis

- results robust to alternative WFH measures [Rescaled WFH] [IV-DD]
- results are stronger in more rural neighborhoods [Urbanicity]
- evidence of spatial spillovers between neighborhoods [Spatial DDD]
- the increase in housing prices with WFH potential is strongest in high *ex ante* crime rates neighborhoods [House Prices]

Conclusions

- WFH potential led to large and persistent drop in burglaries.
  - A one s.d. $\uparrow$ in WFH potential $\rightarrow$ a 3.8% drop in the burglary rate in the lockdown period and a 4.0% drop in the post-lockdown period.
- Event study analysis shows that this relationship is persistent over time.
- This relationship is driven entirely by a drop in burglaries during the weekday (based on London analysis).
- Both our two proposed mechanisms – occupancy effect and eyes-on-the-street effect – appear to be important here
- Hedonic house price model evidence:
  - large $\uparrow$ in WTP for living in a higher WFH area
  - welfare effects sizeable, even based on conservative estimate

Thank-you

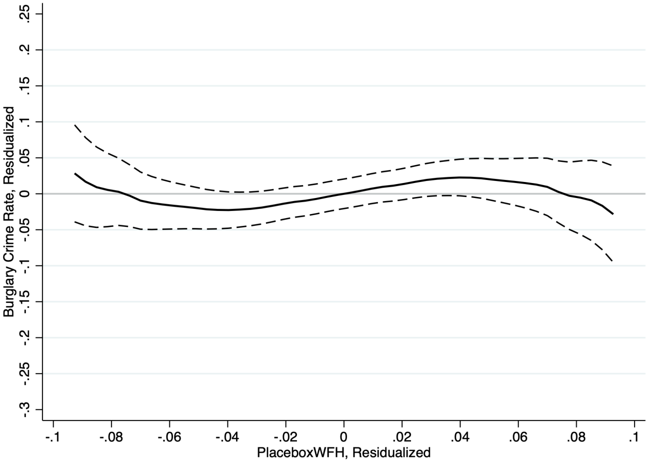
Additional Results

Work from Home Predictions

Data

Non-Parametric Placebo Regression

▸ Empirical Specification



- Local polynomial regression of burglary (residualized) on WFH$\times$Placebo-Post(residualized).
- No evidence of pre-trend across entire (residualized) distribution.

Pre-Lockdown Trends

▸ Empirical Specification

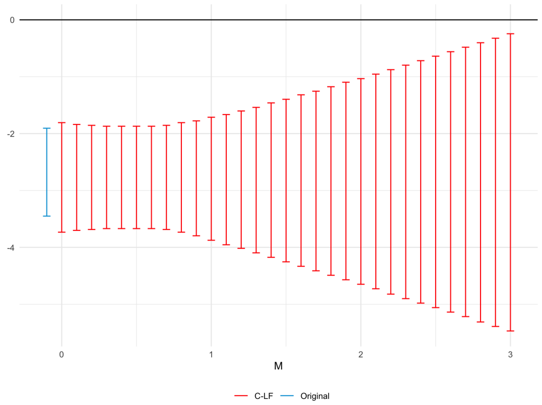
Table 2: Pre-Lockdown Trends

	(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

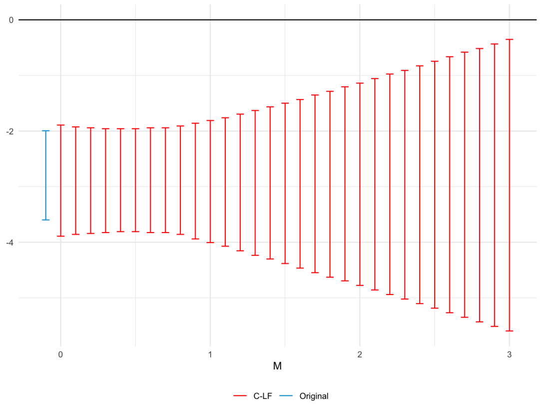
Notes: *** denotes significance at 1%, ** at 5%, and * at 10%. The data is at the neighbourhood-by-month level. The dependent variable is the crime rate per 10,000 inhabitants. Data is weighted by the population count at the 2011 Census. Neighbourhood fixed effects are included in all regressions, as 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

Worst-Case Bounds for our Burglary DD Estimates

Empirical Specification



(a) Lockdown

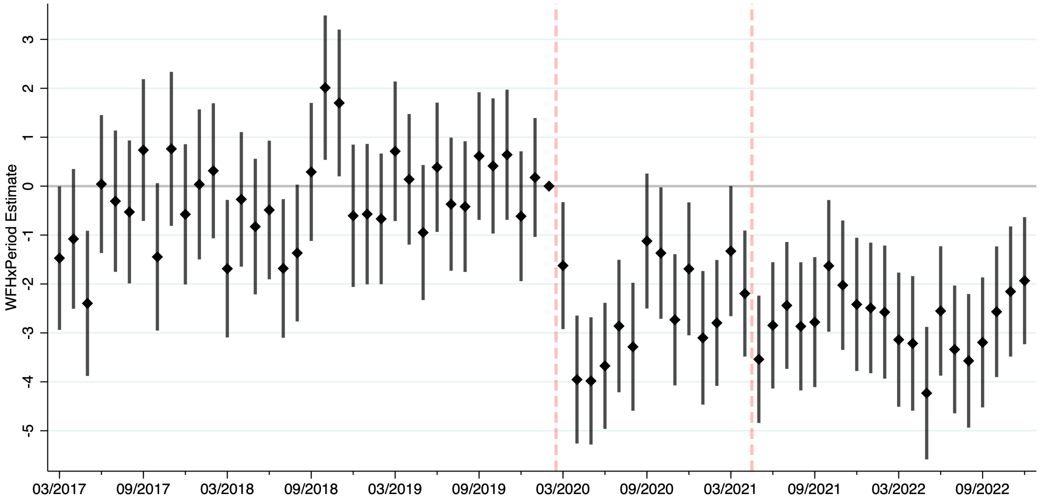


(b) Post-lockdown

Key treatment effect estimates robust to even extreme violation of non-parallel trend assumption

Unscaled Event Study Estimates

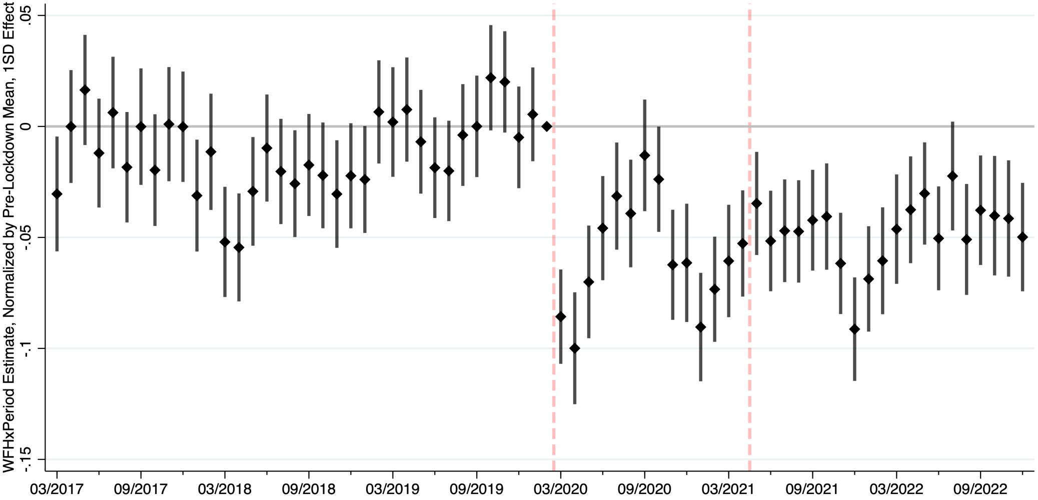
▸ Main Event



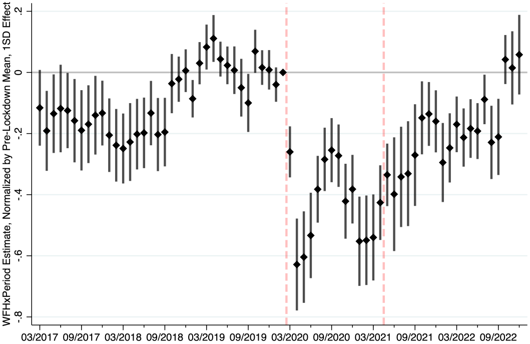
Estimating Equation: $crime_{nt} = \sum_t \left[\alpha_t WFH_n + X_n' \beta_t \right] + \gamma_n + \theta_{A \times t} + \varepsilon_{nt}$

Event Study Estimates – Vehicle Crime

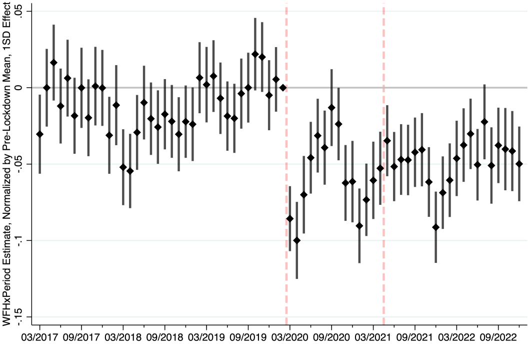
▸ Main Event



Estimating Equation: $crime_{nt} = \sum_t \left[\alpha_t WFH_n + X_n' \beta_t \right] + \gamma_n + \theta_{A\times t} + \varepsilon_{nt}$

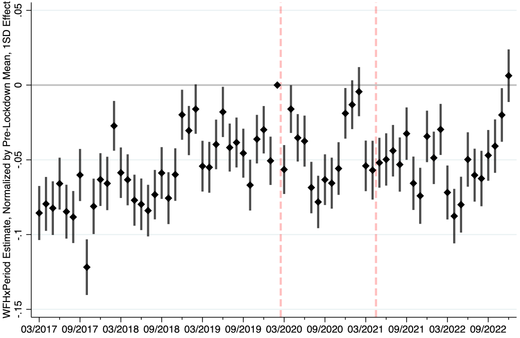


(a) Theft

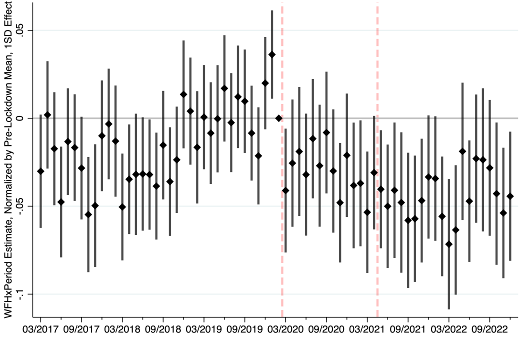


(b) Vehicle

▸ ES Graph – Burglary



(a) Criminal Damage and Arson



(b) Shoplifting

ES Graph – Burglary

DD Estimates – Binary Treatment

Main DD Robustness

Table 3: DD Estimates for Burglary

	(1)	(2)	(3)	(4)
LD $\times$ WFH	–0.248***	–0.412***	–0.422***	–0.211***
	(0.049)	(0.049)	(0.050)	(0.052)
PLD $\times$ 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 $\times$Year	Month $\times$Year	Region $\times$Month $\times$Year	PFA $\times$Month $\times$Year
Control Variables		$X_0 \times$Period	$X_0 \times$Period	$X_0 \times$Period
$\overline{Y}_{PRE}$	5.919	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.

Policing Effort and WFH

▸ Robustness

Table 4: 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.

Within Neighborhood Concentration of Burglaries and WFH

Robustness

Table 5: The Within Neighborhood Concentration of Crime

	(1)	(2)	(3)	(4)	(5)
	MCC 10%	MCC 20%	MCC 25%	MCC 50%	Generalized Gini
LD $\times$ WFH	0.000	–0.001	–0.004	0.007	0.032
	(0.002)	(0.003)	(0.003)	(0.006)	(0.024)
PLD $\times$ 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.

Veil of Darkness Analysis

Robustness

Table 6: 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						
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						
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

Veil of Darkness Analysis Extended

▸ Robustness

Table 7: 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

Spatial DDD – Empirical Specification

Robustness

$$
\begin{aligned}
\text{crime}_{nt} =& \alpha_1(LD_t \times WFH_n^H) + \alpha_2(LD_t \times NWFH_n^H) + \alpha_3(LD_t \times WFH_i^H \times NWFH_n^H) \\
&+ \beta_1(PLD_t \times WFH_n^H) + \beta_2(PLD_t \times NWFH_n^H) + \beta_3(PLD_t \times WFH_i^H \times NWFH_n^H) \\
&+ \delta_1(LD_t \times X_n) + \delta_2(PLD_t \times X_n) + \gamma_i + \theta_{A \times t} + \varepsilon_{nt}.
\end{aligned} \tag{2}
$$

- we binarize our WFH measure into high and low – WFH_n^H is the high indicator
- use data on contiguous neighbors
- define a **relative measure** of neighboring areas ability to WFH – $NWFH_n^H$ indicates neighbors have higher WFH potential

Spatial DDD Estimates

Robustness

Table 8: Spatial DDD Model for Burglary

	(1)	(2)	(3)	(4)	(5)
		DDD: Criterion Used to Define 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. 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 $PLD \times WFH^H \times NWFH^H$. Data used: Police recorded crime data, 03/2017-12/2022.

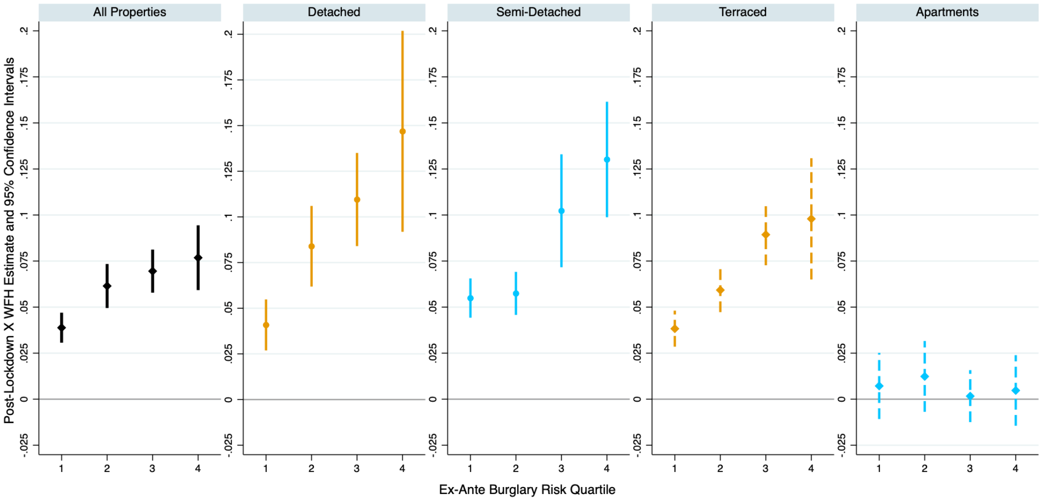
Housing Price Analysis

Robustness

- We estimate a DDD hedonic price equation for local housing markets in which we interact WFH potential, time and a neighborhood's *ex-ante* burglary risk. [DDD equation]
- Key features of DDD model:
  1. Interact housing characteristics, X_i, with district dummies
     - respects **"law of one price function"** (Bishop et al., 2020).
  2. Allow coefficients on all housing characteristics to differ in the pre and post periods
     - Allows the hedonic price function to **shift post-policy**.
     - Avoids **conflation bias** (Kuminoff and Pope, 2014; Banzhaf, 2021].
- Allow coefficients to vary across different property types (detached, semi-detached, terraced and apartment).
- Did housing prices change with WFH potential in the post-pandemic period? Does this change vary with *ex-ante* burglary risk?

House Prices, WFH and Ex-Ante Burglary Risk Quartiles

Robustness



Aggregate Welfare Effects I

▸ Robustness

- To get a sense of welfare implications, follow Adda et al (2014)
- Use DDD estimates as inputs into the following equation:

$$\text{Welfare}_q = \sum_{p=1}^{2} \sum_{n \in N_q} \sum_{t=1}^{4} \omega_p \, \hat{\beta}_{p,tq} \times \text{WFH}_n \times \overline{\text{Price}}_{0,tn} \times \text{Quantity}_{p,tn} \,, \tag{3}$$

  - 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,
  - $\hat{\beta}_{p,tq}$ is the property type-specific DDD parameter estimate from our hedonic HP equation,
  - ω_p is a weighting parameter to combine the estimates from the lockdown and post-lockdown periods

Aggregate Welfare Effects II

Robustness

Table 9: 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).

Empirical Specification

▸ HP overview ▸ Robustness

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

IV-DD Using WFH_{2021} to Instrument for WFH_{2011}

Robustness

Table 10: 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		$X_0 \times$Period	$X_0 \times$Period	$X_0 \times$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

Adjusting WFH Measure Based on Local Workers

▸ Robustness

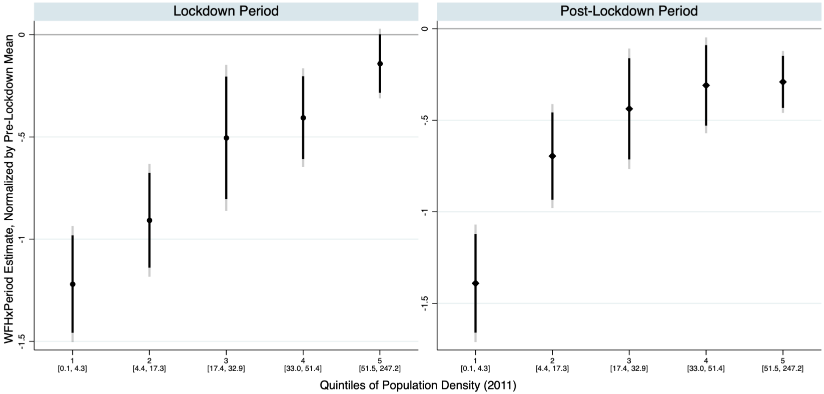
Table 11: DD Estimates

	(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
$1\sigma_{WFH} \times (\text{LD} \times \text{WFH}) / \overline{Y}_{PRE}$	–0.038***	–0.051***	–0.047***	–0.033***	–0.043***
	(0.006)	(0.009)	(0.010)	(0.012)	(0.012)
$1\sigma_{WFH} \times (\text{PLD} \times \text{WFH}) / \overline{Y}_{PRE}$	–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.

Treatment Effect Heterogeneity by Urbanicity

Robustness

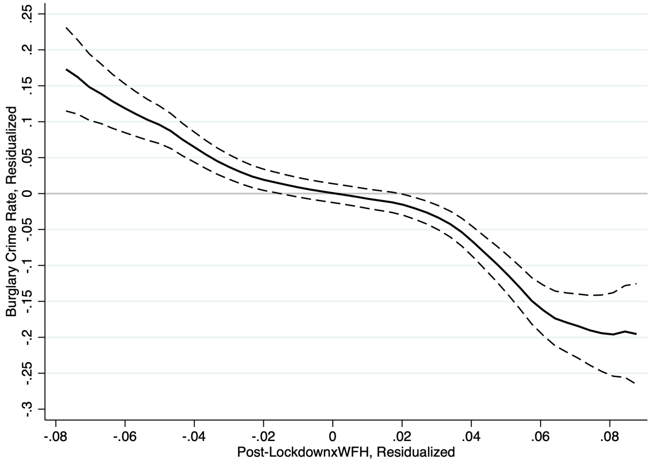


Notes: Figures depict the impact of WFH on burglary estimated separately by neighborhood population density quintile. Bars denote 95% confidence intervals. Robust standard errors are clustered by neighborhood.

The impact of WFH on burglary is most pronounced in rural neighborhoods.

Non-Parametric Estimates

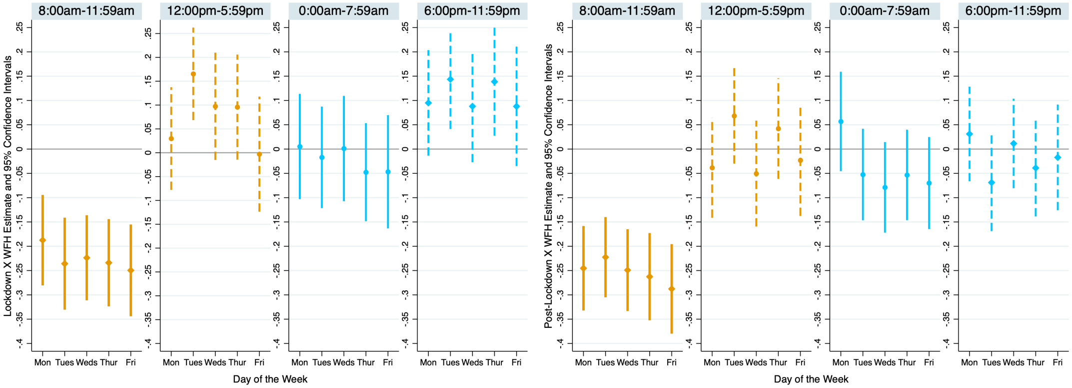
Empirical Specification



- Local polynomial regression of burglary (residualized) on WFH$\times$Post-lockdown (residualized).
- Evidence of non-linearities in the WFH-burglary relationship.
- Consistent with the idea of *eyes on the street* spillovers.

The Timing of the WFH-Induced Decline In Burglary (London)

London



(a) During the lockdown period

(b) Post-lockdown period

Relationship between burglary and WFH during working hours is stable across days of the week.