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Work-from-home and the risk of securities misconduct

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Abstract

In the wake of the global pandemic, a challenge for CEOs and boards is to set a stakeholder-acceptable organizational balance between remote and traditional office working. However, the risks of work-from-home are not yet fully understood. We describe competing theories that predict the effect on misconduct of a corporate shift to work-from-home. Using internal bank data on securities traders we exploit lockdown variation induced by emergency regulation of the Covid-19 pandemic. Our difference-in-differences analysis reveals that working from home lowers the likelihood of securities misconduct; ultimately those working from home exhibit fewer misconduct alerts. The economic significance of these changes is large.

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Our study makes an important step toward understanding the link between the balance of work locations and the risk that comes with this tradeoff.

KEYWORDS
fraud, risk management, securities misconduct, surveillance, work-from-home

JEL CLASSIFICATION
G12, G14, G18, K22

1 | INTRODUCTION

The global Covid pandemic increased market risk (Ammann & Moerke, 2022; Battauz et al., 2021; Cai et al., 2022; Chiu et al., 2023; Kind et al., 2022), reconfigured how and where employees performed their work (Gregg et al., 2022), and did this at an extreme intensity (Adams-Prassl et al., 2022). Although work-from-home is now seen as a permanent part of business life (Barrero et al., 2021), an online workforce raises issues that do not yet have solutions (Nyberg et al., 2021). Corporate sectors unable to adapt well to remote working are associated with lower expected revenue growth and worse stock market performance (Papanikolaou & Schmidt, 2022). Yet, CEOs and boards have little hard evidence on how to strike an organizational balance between work-from-home and traditional office working. Especially, management needs to create shareholder value without exposing the firm to new, unacceptable risks. Prominent among these hazards, especially for financial institutions, is the (unintended) creation of a work setting that might result in higher chances of financial fraud and regulatory violations. More optimistically, new ways of working may present growth opportunities, improved life balance for employees (Choudhury et al., 2022) and potentially a *reduction* in risk. Understanding these trade-offs is thus a critical concern, not only for corporate executives but also for shareholders, regulators, policymakers and management scholars.

The costs of fraud are well documented. Firms in the US lose on average 22%–38% of their equity value upon the revelation of fraud, which is mostly due to reputation loss (Karpoff et al., 2008a). Individuals responsible for financial misrepresentation in the US lose their jobs in 93% of cases, face criminal penalties in 28% of cases, and jail sentences that average 4.3 years (Karpoff et al., 2008b). Likewise, manipulation of stock market prices has real corporate finance consequences, including a 7% reduction in patents and 25% reduction in patent citations (Cumming, Ji, Peter, et al., 2020) and a 12% greater likelihood that mergers will be withdrawn and a 25% reduction in merger premiums (Cumming, Ji, Johan, et al., 2020). Firms guilty of misconduct have other costs beyond those already mentioned; ongoing corrective actions may also be required to manage the negative effects of earlier misconduct (Hersel et al., 2019). Paruchuri and Misangyi (2015) suggest that misconduct can have vicarious costs too; when one firm reveals wrongdoing others in the sector suffer lower valuations.

Given these significant negatives, the effects of home working on unethical activity are a topic of ongoing research. In this paper, we consider the case of securities trading. This is a highly relevant market for studying the effect of work from home because it is at the same time a market where home working is very feasible technologically, but also a highly regulated activity and one with severe financial consequences of misconduct that might arise from unsupervised interactions. We describe and group the theories that predict three possible directional outcomes (increase, decrease, no change) of rates of misconduct due to work-from-home participation of securities traders. On the one hand, we might argue that market manipulation may be more likely to happen at home, for example, where there is less direct managerial oversight and monitoring of personal calls. On the other hand, we could expect more violations in the office, perhaps because physical proximity offers greater opportunity for collusion and exposure to inside information and misconduct of others. In the middle of these views, we might posit that the virtual world of the 2020s does not distinguish between a physical and digital presence, and thus expect no change in rates of misconduct.

With no empirical scrutiny, we could only speculate on the risk impact of working from home. To this end, we employ data from the internal supervisory systems of a global investment bank, used to monitor the activity of its securities traders. Taking advantage of the lockdown variation induced by emergency regulation of the Covid pandemic (that, for the first time, allowed staff to trade from home), we subject our three hypotheses to empirical tests. We model rare events and account for individual differences in the misconduct rates of traders. Our results indicate a *selection* effect, whereby traders selected to work-from-home were those at less risk of incurring securities violations prepandemic. Differences-in-differences estimates also indicate an induced effect, whereby working from home further lowers the probability of securities violations. Working from home results in an absolute reduction of 14.7 percentage points in the annualized probability of an alert (misconduct report) per trading employee. When securities violations have the potential to draw fines in the region of tens or even hundreds of millions of dollars (or total collapse in the case of Barings Bank), such change in probability is a highly consequential lowering of expected cost.

Our work has general implications for CEOs and boards. We suggest that work-from-home is not just a concession to employee work-life balance or a reconfiguration of office real estate; our evidence points to the possibility that work-from-home can (beneficially) change the risk profile of a firm. Our analysis also has implications for designing securities regulation surveillance and enforcement: our findings suggest that financial regulators should not fear work-from-home even in highly regulated sectors such as securities trading.

2 | BACKGROUND, THEORY AND HYPOTHESES

2.1 | Review

Misconduct in business has such high costs that a vast body of research exists in the domains of management science, law, economics, psychology and finance (among other fields). This literature shows that the capability and desire of individuals to conduct unethical behaviour depends on a variety of factors including: laws and regulations; monitoring and detection technology; enforcement levels; corporate culture and training; information asymmetry; reputational capital; linkages across markets and products and market liquidity. For example, Comerton-Forde and Putniņš (2014) find that larger government regulatory budgets increase the rate of prosecution and deter manipulation. Liu (2016) finds that firms with high corruption culture are more likely to engage in corporate misconduct. Kowaleski et al. (2020) find that those with ethics education are less likely to commit misconduct. Ali and Hirshleifer (2017) show that opportunism is associated with firm misconduct. MacLean and Behnam (2010) demonstrate that separating organizational compliance programs from core business activities can lead to institutionalized misconduct. Cumming et al. (2015) suggest that gender diversity is a factor that changes the frequency and severity of fraud, while Bai and Yu (2022) point to the role of rookie directors.

Our study also relates to the literature on remote working. Despite earlier concerns that teleworking was a poor career choice (Golden et al., 2017) and doubts over what tasks can be done remotely (Adams-Prassl et al., 2022), there is evidence that remote work is about to transition to the mainstream. For example, Barrero et al. (2021) suggest that 20% of full workdays will be undertaken at home after the pandemic, a jump from 5%; Dingel and Neiman (2020) find that 37% of US jobs can be performed entirely at home; and Bick et al. (2020) saw a higher likelihood of highly educated, high-income and white individuals working remotely in the pandemic. Consequently, recent research has started to scrutinize the pros and cons to employees and firms under these new arrangements.

A particular focus is employee satisfaction (Peretz, 2022) and work-family balance (Tabassum et al., 2022). For example, there can be benefits of job flexibility (Mas & Pallais, 2017) but disadvantages of anxiety, stress (Zhou & Flinchbaugh, 2022) and fatigue (Verma & Uy, 2021). There are also efforts to investigate productivity gains from remote work. For example, Bloom et al. (2015) find higher productivity, including by allowing self-selection, Barrero et al. (2021) predict a 5% productivity boost in the postpandemic economy due to reoptimized working arrangements, although Gibbs et al. (2021) find employee productivity falls due in part to lower uninterrupted work hours.

On the other hand, there is very little research attention to the potential changes of risks to firms (and employees) under work-from-home arrangements. Raghuram et al. (2022) advocate a need to relook at orthodox approaches and theories for understanding boundary management in remote work. In analogous fashion, we see an imperative for researchers to better understand approaches and theories of (mis-)conduct risk in the new world of work from home. This issue is not simply of academic interest: indeed, the data in this study were obtained as part of an audit exercise by the bank, where senior management were sufficiently concerned about changing risks due to work-from-home. The economic importance of such risks (discussed later in the paper) cannot be over-stated, as attested by well-known corporate casualties.

2.2 | Trading rules and detection

In this section, we summarize concepts relevant to misconduct in trading of securities in capital markets. Securities laws for trading comprise a number of rules—detailed statements of what is allowed—that cover area such as insider trading (trading on material nonpublic information, including frontrunning client orders), price manipulation (such as end-of-day manipulation, and matched orders), volume manipulation (such as churning and wash trades), spoofing (entering orders and deleting them just before they are about to execute), and broker-agency misconduct (improper communications and related forms of misconduct). Cumming et al. (2011) provide a full list and explanation of the different forms of trading misconduct.

In some countries, rules are codified in securities laws, or via guidelines of bodies such as the China Securities Regulatory Commission. Elsewhere, they are codified by self-regulatory organizations, such as the Investment Institute Regulatory Organization in Canada. In

Europe, rules were codified in a series of pan-European directives known as the "Lamfalussy Directives"—the Market in Financial Instruments Directive (MiFID), the Prospectus Directive, the Market Abuse Directive (MAD), and the Transparency Directive (Aghanya et al., 2020). Specifically, the trading rules are in MAD, and the enforcement provisions are in MiFID (November 2007; see Cumming & Johan, 2019).[1] Exchanges undertake computerized surveillance (external to the bank) and banks undertake computerized surveillance (internal to the bank) to ensure compliance to the same (or a superset) of rules. Banks are motivated to avoid external scrutiny, to nip in the bud bad behaviour of their traders. For this reason, internal surveillance systems may monitor a wider range of behaviours.

Rules and their enforcement appear to be effective. Detailed trading rules and computerized surveillance designed to detect and enforce market manipulation are associated with fewer cases of insider trading (Aitken et al., 2015a), more new listings on stock markets, larger stock markets (Cumming et al., 2011; Jackson & Roe, 2009; La Porta et al., 2006) and more active stock markets with higher liquidity (Cumming et al., 2011). There is evidence for the increasing use and effectiveness of fraud deterrents (Karpoff, 2021).

2.3 | Theories of misconduct

2.3.1 | The flow of inside information

Many forms of securities violations stem from the flow of inside information. Inside information is more likely to flow across traders that are proximate to one another in the same office, and share coffee and lunch breaks (Ahern, 2017; Hong et al., 2005). Working from home would therefore generate fewer opportunities to benefit from illegal tips and hence could result in fewer securities violations.

2.3.2 | Contagion

Studies in psychology frequently document the presence of contagion in unethical conduct (Gino et al., 2009; Quispe-Torreblanca & Stewart, 2019). Individuals feel less guilty or see less of a problem with unethical conduct, or at least rationalize unethical conduct when they see other people doing it. For example, in a well-publicized case of insider trading through sharing information from Toronto to New York, a convicted individual explained that he started insider trading because he saw his colleagues at the office doing it, and it seemed to be part of the culture of the securities trading (https://tenorfilms.com/collared/). Working at home could therefore decrease the likelihood of contagion in securities violations through the reduced visibility of the actions of others engaged in illegal activity and smaller chances of contagion in unethical conduct. On the other hand, ethical peers are an effective control against misconduct (Trevino & Victor, 1992).

[1]The European Commission provided enforcement guidance of MAD rules in July 2007 http://www.cesr-eu.org/data/document/06_562b.pdf.

2.3.3 | Rumours

Rumours often give rise to negative financial market outcomes and at time securities violations (Alperovych et al., 2021; Van Bommel, 2003). We might therefore conjecture that more securities violations will happen due to work at the office through the channel of rumours.

2.3.4 | Information asymmetry

In lockdown there has been a worsening of publicly disseminated information in terms of the average quality of research reports (Du, 2020; Li & Wang, 2021). This increases information asymmetry and opens the scope for more insider trading (Wu, 2019). Hence, working from home in times of crisis could be associated with more securities violations.

2.3.5 | Distraction and mistakes

Sometimes securities violations are a result of a mistake. We could argue home working—with spouses, children or flat mates—is likely to present a distracting environment (Du, 2020; Li & Wang, 2021) which would increase the chances of violations. Similarly, we could make a case for busy market days (with large daily returns) leading to more mistakes.

2.3.6 | Proximity and oversight

There is evidence that geographic proximity to the securities commission reduces the likelihood of engaging in securities violations (Hu et al., 2017). Likewise, financial market rumours are more likely to form in geographically proximate settings (Yu et al., 2019). We might conjecture that physical proximity to the ethics and compliance department (or direct supervisors) at the office would reduce the likelihood of engaging in securities violations. If so, we would expect that working from home would increase the frequency of securities violations.

2.3.7 | Priming

Priming is the activation of mental concepts through situational cues (Bargh & Chartrand, 2014). If work-from-home weakens priming of corporate identify, due to a reduced exposure to the work environment, then we might expect an increase in honesty (Cohn et al., 2014) though there is also evidence in the opposite direction (Huber & Huber, 2020; Rahwan et al., 2019).

3 | RESEARCH METHOD

3.1 | Lockdown variation

The UK public were subjected to multiple lockdowns of varying severity and geographic dispersion but the bank in our study went into their particular emergency measures during the week commencing 16th March 2020. In our analysis there are only two measurement periods: prelockdown of before 19 March 2020 and post-lockdown of 19 March 2020 onwards. Henceforth, when we refer to 'lockdown' we mean the bank's tailored version of restrictions.

The bank was triggered to reorganize by an emergency regulation issued by the UK regulator (Financial Conduct Authority). This was for home working across the financial industry, including trading. The FCA has over time supplemented its existing regulatory framework for market trading and reporting to take account of particular arrangements in the home, such as the broader control environment.[2] Before lockdown, no trading activity took place away from the office and even working from home on non-trading related work was rare.

In March 2020, the bank was required to move workers to work-from-home wherever possible. Physical restrictions on distance between seated employees prevented the bank from keeping all trades in the office (including rules of at least 2 m distance spacing between workers in offices, with additional maximum limits on number of individuals per room). This necessitated a large proportion of employees working elsewhere.

The allocation of workers to work from home instead of in the office was decided at the desk level. Apart from some business-critical functions,[3] there was flexibility in around individual needs (such as child in the home, which would make home working less feasible), decided on a more ad hoc basis. Importantly for our identification strategy, the bank indicated there was no policy or decision to allow work-from-home in a way that was correlated with, or averted risk of, securities fraud. For example, the bank did not undertake a risk assessment relating to the likelihood of securities fraud occurring in the home vs the office.

While the allocation to work from home versus work from the office was therefore not random, we have confidence that it was unlikely to be selected upon the propensity to commit securities fraud. Later, we test for parallel trend in securities misconduct between the two groups and find evidence of common trends. In summary, these events—an unanticipated lockdown, emergency regulatory provisions and the nonsystematic selection of which traders worked from home—provide us with a justification for analysis based on differences-in-differences.

3.2 | Key concepts and assumptions

3.2.1 | Alerts

The bank had its own internal surveillance systems to monitor trader compliance to exchange, regulatory and bank rules. When there is a violation of these rules, software highlights the issue for further investigation. Each case of noncompliance is known in practice as an 'alert'. The alerts that we observe in our data set were daily 'L3' alerts, that is, they had already passed through a filter of two preliminary reviews (L1 Initial Review and L2 Further Review). Hence, the alerts we observe in our analysis are already considered serious enough for the surveillance team to seek explanations and rationale from the line businesses.

[2]The Financial Conduct Authority's guidance on supervisory and reporting practices when working from home during the Covid pandemic period is available at: https://www.fca.org.uk/coronavirus/information-firms.

[3]The need to retain a small number of roles, such as book watchers, at the office could lead to bias in the data towards observing fewer securities violations in the office during lockdown (and the data actually indicate the opposite, as we document below).

The alerts come in two flavours. First, *trading alerts* encompasses several types of trading misconduct, including circular trading, wash trades and trading ahead. Second, *communication alerts* are generated from the bank's monitoring of phone, email, and online chat. They include issues relating to scenarios such as deceptive language, front running, and rumours/secrets. Of key importance for our analysis, the bank used the same rules, detection software and management processes throughout the period under study.

Whether any particular alert results in punitive action and sanction by the bank (or, the regulator and courts) depends on numerous factors that are beyond the scope of this paper, and their investigation can take many months or years to finalize. Not all alerts are finally judged as being misconduct. However, a critical assumption is that the rate of alerts is stably correlated with the rate of serious securities misconduct.

3.2.2 | Assignment to treatment

To set up our analysis, we classify employees as work-from-home or work-from-office using data on their location in the lockdown period (beginning 19 March 2020). We obtain data on the working location of each employee on each day using building pass records from entry barriers to the bank's premises. We then classify employees as belonging to the work-from-home group if they worked from home on at least 98% of days from 19 March 2020 onwards.[4] Those in the work-from-home group of employees are assigned to treatment. As stated earlier, group membership is subject to random selection. However, as also discussed earlier, there is *some* selection present. As such, we handle this aspect by our interpretation (below) of the coefficients in our difference-in-difference regressions; we are appropriately cautious with our claims of causality.

3.3 | Data

We use proprietary data from an investment banking arm of a financial group headquartered in London, England. The investment bank is one of the top five UK banks by size, and its range and type of trading operations are, we believe, similar to those of large global investment banks in general. The data comprise daily information from 1 January 2019 to 31 March 2021 on 162 traders. The prelockdown period is 1 January 2019 to 18 March 2020 and the lockdown period is 19 March 2020 to 31 March 2021[5]. The 162 employees whose behaviour is studied are frontline traders of a range of financial instruments in global markets. They are all UK-based and part of trading desks of various sizes that traded, depending in the market and exchange, during UK working hours (typically 7 AM to 7 PM). Each trader is individually licensed and regulated by the FCA.

Table 1 defines the variables used in our empirical analyses. Table 2 shows the number alerts for the all types of alerts (Panel A) and the subset of communication and trade alerts (Panels B and C, respectively).

[4]We do not set this at 100% as many work-from-home employees visited the office on occasion. Our analyses are not materially affected by using a different cutoff such as 90% or 95%.

[5]The bank chose a Friday so that the transition to work from home (for those who would subsequently work from home) could be achieved over the weekend period before market opening on Monday 22nd March.

TABLE 1 Definitions of variables.

This table reports the variables. Variables used in subsequent tables are highlighted in bold font.

Variable	Definition
emp_ID	A unique hash number used to anonymously identify trading employees.
Surveillance	
Alert	A dummy variable equal to one if for a particular *employee-day*, at least one Level 3 (potentially serious) compliance alert was raised. Day means working day, that is, excluding public holidays and employee-level leave. These alerts were bank-defined and were generated by a variety of automated surveillance subsystems, for a range of different trading and communication scenarios, and in consideration of the UK regulatory environment and the bank's risk management.
event.type	A bank-defined categorisation of Alert taking the value 'Comms' or 'Trade'. Comms alerts are through the analysis of communication channels (phone, email, online chat) and obtain when language is inappropriate or indicative of potentially unethical behaviour. Trade alerts are concerned with the nature of the trade, and obtain when the time, execution sequence, amount and circumstances indicate potentially deliberate unethical conduct.
Comms.Alert	A dummy variable equal to one if for a particular *employee-day*, at least one Comms alerts was raised
Trade.Alert	A dummy variable equal to one if for a particular *employee-day*, at least one Trade alerts was raised
Multi.Alert	Takes the following values for a particular *employee-day* (No alert = 0, Comms alert = 1, Trade alert = 2).
Alert.count	The total number of Alerts per employee in a given period.
Work	
wfh	A dummy variable equal to one if for a particular *employee-day*, the employee was work-from-home (wfh), according to entry card scan data records.
intensity	For a given employee it is the fraction of working days spent at home during the full lockdown period. To illustrate, an intensity of 0.9 means that on average during lockdown this employee worked 4.5 days out of 5 at home (and 0.5 day in the office).
wfh.group	A dummy variable equal to one if for an employee the intensity of home working across lockdown was greater or equal to the intensity cut-off (our empirically-derived cut-off unless noted is 0.98).
lockdown	A dummy variable equal to one if the day was on or after 19 March 2020 which is the start of the bank's lockdown regime in response to the pandemic. Note this date is slightly earlier than the start of the first UK national lockdown.

We have 88,441 employee-day observations in our sample (restricting to working days only—removing weekends and other nonworking days due to bank holidays, sickness or vacation). The traders generated 142 alerts over the sample. One employee generated an alert on a nonworking day, which we exclude since we only examine working days. One employee generated three alerts on the same day, but two were subsequently cancelled. One employee generated two alerts on the same day, which we treat as a single alert due to the similarity of the potential violation; we believe this

TABLE 2 Numbers of alerts.

This table reports the number alerts for the all types of alerts in Panel A, and the subset of communication and trade alerts in Panels B and C, respectively.

Prelockdown, employees subsequently classified as work-from-home		Prelockdown, employees subsequently classified as not work-from-home		Lockdown, employees subsequently classified as work-from-home		Lockdown, employees subsequently classified as not work-from-home	
No. alerts	**No. employees**	**No. alerts**	**No. employees**	**No. alerts**	**No. employees**	**No. alerts**	**No. employees**
Panel A. All alerts							
0	68	0	52	0	73	0	50
1	13	1	10	1	13	1	15
2	3	2	9			2	5
3	2	3	2			3	3
		4	1			4	2
		5	1			9	1
		6	1				
Panel B: Communication alerts							
0	82	0	68	0	80	0	66
1	4	1	8	1	6	1	8
						2	2
Panel C: Trade alerts							
0	70	0	55	0	79	0	55
1	12	1	7	1	7	1	13
2	3	2	11			2	3
3	1	3	1			3	3
		4	1			4	1
		5	1			7	1

minor modification greatly simplifies our modelling with no loss of inferential ability. After applying these filters, we observe 138 alerts over the period.[6]

Having a low number of cases or fraud or violations in the data is a common feature of the literature on misconduct [for example, Ahern (2017) analyses 183 insider trading networks in the universe of licensed traders in the United States; Karpoff et al. (2008b) analyze 788 enforcement actions issued by the Securities and Exchange Commission and Department of

[6]Removing these filters does not materially affect the results.

TABLE 3 Descriptive statistics.

This table reports statistics for the sample of employee-day observations in the data.

Variable	Mean
alert	0.00156
comms.alert	0.00034
trade.alert	0.00122
wfh	0.319
wfh.group	0.529
lockdown	0.436

Justice over the period 1978 to 2006]. To address this, we adopted econometric models designed for cases of sparse dependent variables, such as ours.

Table 3 presents the summary statistics for the full sample of employee-days. Alerts are rare insofar as they appear in 0.156% of the employee-days, consistent with other studies that analyze alert frequency using different data, for example (Aitken et al., 2015b). Trading alerts are more common (0.122%) than communication alerts (0.034%). Traders work-from-home in 31.9% of the days covered by the entire sample, and the work-from-home group of employees comprise 52.9% of the sample. The lockdown period post-Covid comprised 43.6% of employee-days in the sample.

3.4 | Econometric models

The average treatment effect on the treated is obtained as the slope coefficient on the interaction term (β_3) using the following:

$$y_{it} = \alpha + \beta_1 \text{wfh.group}_i + \beta_2 \text{lockdown}_t + \beta_3(\text{wfh.group}_i \times \text{lockdown}_t) + \varepsilon_{it}, \tag{1a}$$

where the dependent variable y_{it} is 1 if employee i received one or more alerts at time t, and 0 otherwise. Recognizing the panel nature of our data we are able to include individual effects and also estimate the treatment effect by:

$$y_{it} = \beta_2 \text{lockdown}_t + \beta_3(\text{wfh.group}_i \times \text{lockdown}_t) + \kappa_i + \varepsilon_{it}, \tag{1b}$$

where κ_i is a fixed effect for each trader.

We obtain these difference-in-differences estimators through ordinary linear regression (OLS). The unit of observation for estimating Equations (1a) and (1b) is an employee-day. These models have the advantage of easy interpretability—coefficients can be seen as daily probabilities of an alert for a trader—but are not necessarily the most powerful approach for our sparse data set. Nevertheless, related studies have taken an OLS approach, for example, see Heese et al. (2022) but with different identification strategies and timeframes.

To overcome this issue, we also re-cast our data as counts of alerts for trader i in period p, c_{ip}. The unit of observation in this approach is an employee-period, with prepandemic and postpandemic periods. First, we use a negative binomial mixed model (Fitzmaurice et al., 2012), (Yirga et al., 2020). Hence, we have a negative binomial distribution $c_{ip} \sim \text{NegativeBinomial}(\mu_{ip}, \theta)$ and estimate

$$\log \mu_{ip} = \alpha + \beta_4 \text{wfh.group}_\text{i} + \beta_5 \text{lockdown}_p + \beta_6 (\text{wfh.group}_i \times \text{lockdown}_p) + \gamma_i, \quad \text{(2a)}$$

with $\gamma_i \sim \text{Normal}(0, \sigma)$ and where μ_{ip} is the mean of the negative binomial distribution and parameter θ captures overdispersion, a feature of our data. In the second version of a count model, we assume $c_{ip} \sim \text{QuasiPoisson}(\mu_{ip}, \tau)$ and estimate

$$\log \mu_{ip} = \alpha + \beta_4 \text{wfh.group}_i + \beta_5 \text{lockdown}_p + \beta_6 (\text{wfh.group}_i \times \text{lockdown}_p), \quad \text{(2b)}$$

with μ_{ip} the mean of the quasi-Poisson distribution and parameter τ capturing overdispersion. For (2a) and (2b) the index p indexes periods.

These models also contain a difference-in-difference identification strategy, to estimate the causal coefficient β_6. With these additional models we are able to model rare events, their overdispersion, and individual differences in the propensity of traders to receive alerts. Indeed, such count-based specifications are common in criminology research (see Berk & MacDonald, 2008; MacDonald & Lattimore, 2010) and were used in a recent study investigating gender-diverse boards and bank misconduct (Arnaboldi et al., 2021).

4 | RESULTS

4.1 | Parallel trends assumption

Our econometric approach of differences-in-differences makes a parallel trend assumption, that before lockdown the trends of misconduct rates in the two groups are parallel and that they would have stayed on parallel trends absent the lockdown.

Figure 1 presents the trends of prelockdown alert rates for the two groups; this supports prelockdown parallel trends. With no subsequent (postlockdown) changes to obvious potential determinants of misconduct rates (there were the same traders in the same teams; the same product types traded; an unchanged alert system and its monitoring parameters; an unchanged remuneration structure used by the bank) we reasonably argue that without pandemic-related location changes the parallel trends would have continued.

4.2 | Unconditional means

Figure 2 shows the annualized probability that an employee will have at least one alert, for periods before and after lockdown. Although these calculations are simplifications[7] of the real-world situation, we believe they give highly indicative approximations to the actual change in annual risks faced by the bank.

[7]For example, it is possible that assumptions of independence of alerts over time are not valid—certain traders may be more likely to generate alerts than others.

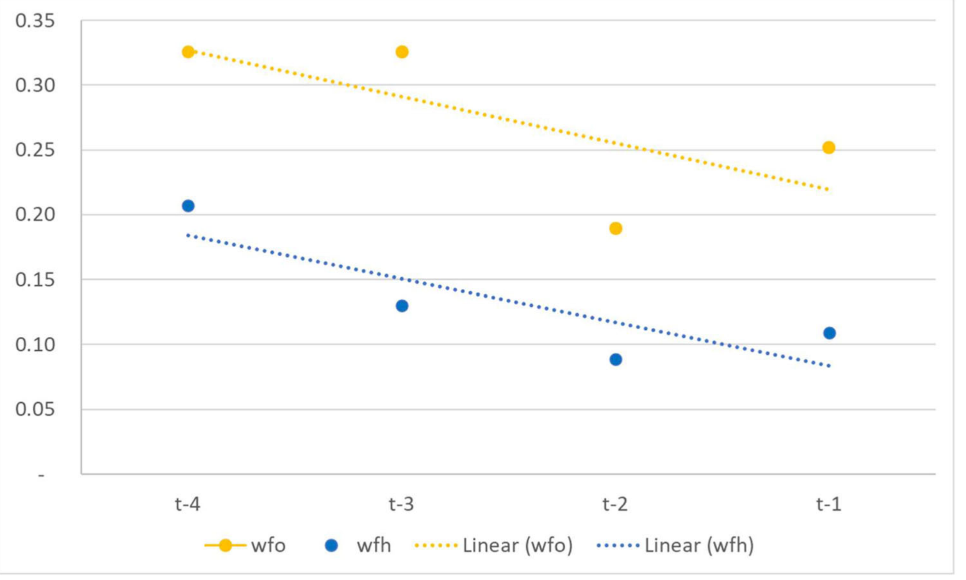

FIGURE 1 Trends of prelockdown alert rates. This shows the prelockdown trends of rate of alerts for the work-from-office (wfo) and work-from-home (wfh) groups. The 440 calendar days of observations before lockdown are divided into four equal periods of 110 days. In the figure, $t-1$ is 1 to 110 days before lockdown, $t-2$ is 220 to 111 days before lockdown and so on. Daily rates are computed by dividing the total number of alerts in a period for that group by the number of employees in the group, divided by 110 days. The *y*-axis shows annualized probabilities of at least one alert per employee computed as $1-(1-p)^{220}$ where p is the computed daily rate for that period. [Color figure can be viewed at wileyonlinelibrary.com]

Alerts are separated for those who would subsequently work-from-home after lockdown and those who would remain in the office. Trading and communications alerts are also plotted in separate panels. Before lockdown, those subsequently in the work-from-home group exhibited a lower probability of both trading and communication alerts than those who remained in the office, consistent with a selection into home or office work after lockdown. After lockdown, trading and communications alerts increased for those working from the office. For those working from home, trading alerts decreased while communications alerts increased. These changes indicate a treatment effect, where assignment to home or office working changes the probability of alerts.

The mean daily probability of an alert for an employee may be seen in Table 4. For example, the figure of 0.002093 in Panel A is the number of alerts (communication *and* trade) for the work-from-office group of traders during prelockdown divided by the number of employee-days worked in that period by that group. We interpret this as: the daily probability of an alert prelockdown for the work-from-office group is 0.2%. To illustrate the method used in Figure 2, we would approximate the annualized (220 working days) probability of there being at least one alert for a work-from-office employee before lockdown by $1-(1-0.002)^{220}$, or around 35.6%.

Continuing in Table 4 Panel A, we see that before lockdown those who would subsequently work-from-home after lockdown had a lower daily probability of an alert—0.001149 lower—than those who ultimately stayed working in the office. This is selection effect where those with a lower probability of incurring an alert selected, or were selected, into working from home after lockdown. After lockdown this difference has grown to 0.002156. The daily probability of

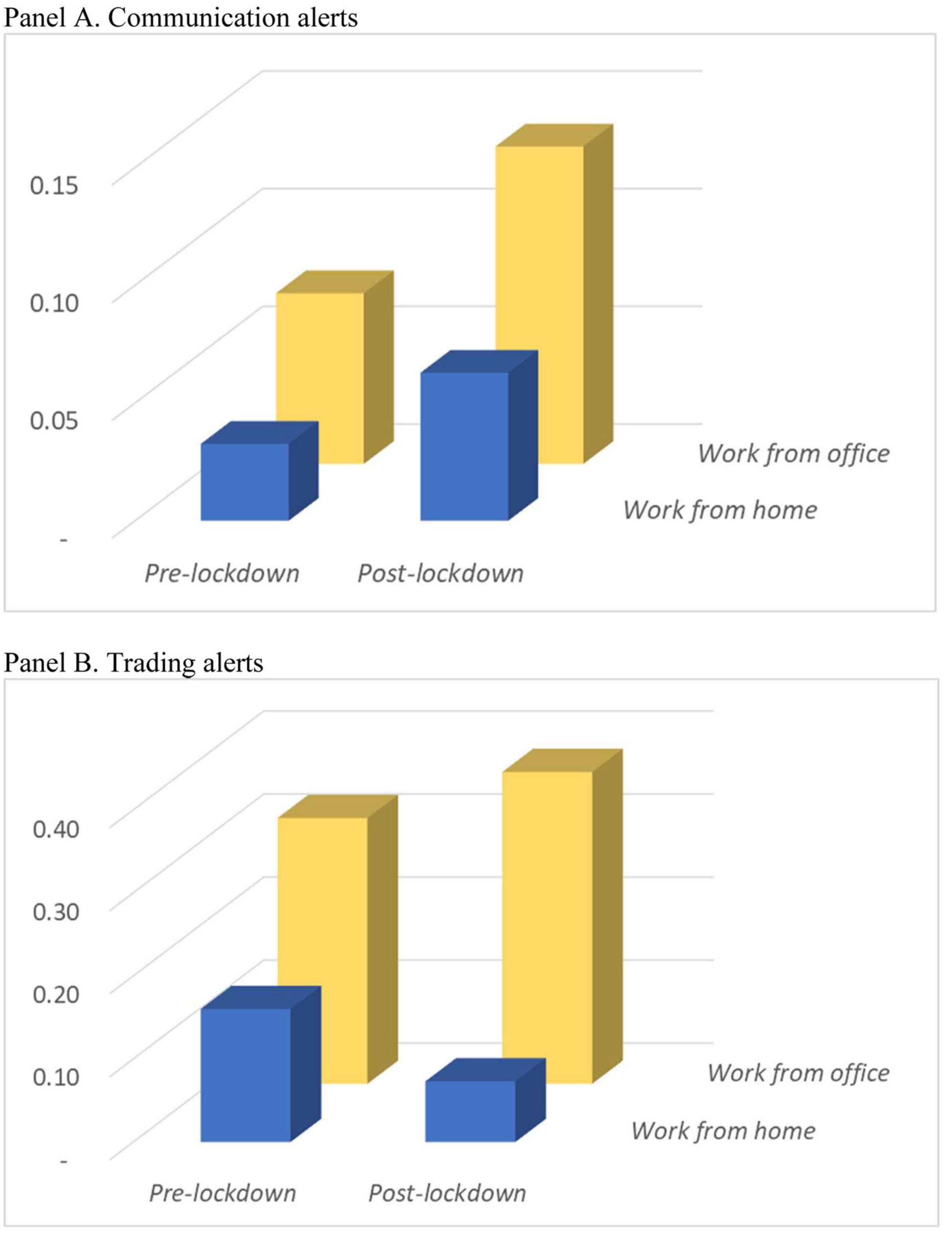

FIGURE 2 Annualized probabilities of at least one alert per employee. (A) Communication alerts. (B) Trading alerts. This figure shows on the *y*-axis the annualized probabilities of at least one alert per employee computed as $1 - (1 - p)^{220}$ where p is the corresponding daily rates in the underlying data (i.e., not derived from predictions or regression analyses) as shown in Table 4. [Color figure can be viewed at wileyonlinelibrary.com]

an alert increased for those working in the office but decreased for those working from home. The increase in the differences, 0.001007, is the treatment effect in which lockdown has a differential effect on those selected to work in the office compared to those selected to work at home.

TABLE 4 Means of alerts.

This table reports means in a difference-in-difference format. Variables as defined in Table 1.

	Work from office (1)	Work from home (2)	Difference [(2)–[1)] (3)	Unconditional DiD (4)	Unconditional DiD % Effect [(4)/ Pre (2)] (5)
Panel A: All alerts					
Prelockdown	0.002093	0.000944	−0.001149		
N	23,408	26,488			
Postlockdown	0.002796	0.000640	−0.002156		
N	18,238	20,307			
Post–Pre	0.000703	−0.000304		−0.001007	−106.7%
Panel B: Comms					
Prelockdown	0.000342	0.000151			
N	23,408	26,488	−0.000191		
Postlockdown	0.000658	0.000295			
N	18,238	20,307	−0.000363		
Post–Pre	0.000316	0.000144		−0.000172	−113.7%
Panel C: Trade					
Prelockdown	0.001752	0.000793	−0.000959		
N	23,408	26,488			
Postlockdown	0.002138	0.000345	−0.001794		
N	18,238	20,307			
Post–Pre	0.000387	−0.000448		−0.000835	−105.3%

Panel B repeats the analysis for communications alerts and shows a different pattern. Both groups show an increase in alerts after lockdown, but those who ultimately remain working from the office start from a higher level (indicating a selection effect) and experience a larger increase (indicating a treatment effect). Panel C repeats the analysis for the trading alerts and shows the same pattern as the overall analysis from Panel A.

4.3 | Multivariate regressions

Table 5 presents a multivariate OLS analysis comparable to the simple unconditional difference in difference presentation in Table 4. As we have said, this analysis has the advantage that the coefficients are comparable to the simple differences in the means, but the analysis does not have the correct model for sparse counts. Standard errors are robust and clustered at individual (trader) level.

TABLE 5 OLS regressions.

This table reports OLS regressions of the determinants of alerts. Variables are as defined in Table 1. The time unit is one workday. Individual fixed effects are at emp_ID level. Standard errors are robust and clustered at emp_ID level. The *, ** and *** are results statistically significant at the 10%, 5% and 1% levels, respectively.

	(1) All alerts				(2) Comms alerts				(3) Trade alerts			
	coeff	***t*-stat**	**coeff**	***t*-stat**	**coeff**	***t*-stat**	**coeff**	***t*-stat**	**coeff**	***t*-stat**	**coeff**	***t*-stat**
lockdown	0.000703	0.99	0.000688	0.97	0.000316	1.33	0.000312	1.31	0.000387	0.67	0.000376	0.65
wfh.group	−0.001149	−2.29**			−0.000191	−1.40			−0.000959	−2.23***		
lockdown:wfh.group	−0.001007	−1.36	−0.000991	−1.34	−0.000172	−0.62	−0.000166	−0.60	−0.000835	−1.37	−0.000825	−1.35
constant	0.002093	4.67***			0.000342	2.898***			0.001752	4.15***		
Individual effects?	No		Yes		No		Yes		No		Yes	
Number of observations	88,441		88,441		88,441		88,441		88,441		88,441	
Adjusted R^2	0.000414		0.005009		0.000060		0.000375		0.000359		0.004225	

For the model without fixed effects, the coefficients for wfh.group and the lockdown × wft.group exactly correspond to the difference and difference in differences in Table 4. With fixed effects, the coefficients are very similar. The coefficient on the wfh.group estimates the prelockdown difference between those who would ultimately work-from-home and those who would work remain in the office. Those working from home have fewer prelockdown alerts overall, and this difference is driven by trading alerts but not communications alerts. This is a selection effect, where those with lower propensity for alerts select, or are selected, into ultimately working from home after lockdown. The interaction coefficient on lockdown × wfh.group shows that the gap in alerts overall opening up after lockdown, and this is driven by trading alerts not communications alerts. Those who ultimately work-from-home experienced a reduction in alerts while those who worked from the office experienced an increase in alerts. This is a treatment effect, where lockdown has a differential effect on the two groups of workers, though the effect does not reach significance in this specification. Table 5 include regressions with individual effects, to account for differences across traders. Our estimate of the treatment effect here is within 2% of that from the regression without fixed effects.

Next, we discuss the results using the specifications of Equations (2a) and (2b). We prefer this specification because it is better suited to modelling counts of rare events. We condense our data to 324 counts (162 employees × 2 periods). With such a view of the data, we expect a long tail of high counts and many zero counts; these data points are not considered as outliers. Table 6 presents results with the negative binomial mixed effects model, for all alerts, as well as separate regressions on communication and trade alerts. Random individual effects are included in this model. Table 7 show the results with regressions from the quasi-Poisson model. In both sets of findings, we observe the same pattern of selection and treatment effects as we did for the OLS regressions. That is, we observe a significant selection effect, where those who ultimately work from home experience fewer alerts, and a now significant difference in differences where the gap between the work-from-home group and the others opens up after lockdown, with those working from home experiencing fewer alerts and those working from the office experiencing more alerts. These effects are there overall, and are driven by trade alerts.

TABLE 6 Negative binomial mixed effects regressions.

This table reports negative binomial mixed-effect regressions of the determinants of alert counts. Variables are as defined in Table 1, although the dependent variables here are counts of each alert type organised as a panel of the two sub-periods of the study (prelockdown and postlockdown). Individual random effects are at emp_ID level. The *, ** and *** are results statistically significant at the 10%, 5% and 1% levels, respectively. Pseudo R^2 values were not available for glmer.nb().

	(1) All Alerts		(2) Comms.Alerts		(3) Trade.Alerts	
	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat
lockdown	0.194	0.95	0.565	1.22	0.105	0.47
wfh.group	−0.827	−2.43**	−0.817	−1.32	−0.827	−2.19**
lockdown:wfh.group	−0.686	−1.72*	0.000	0.00	−1.043	−2.12**
constant	−7.211	−28.8***	−8.343	−23.33***	−7.509	−25.40***
Individual effects?	Yes		Yes		Yes	
Number of observations	324		324		324	

TABLE 7 Quasi-Poisson regressions.

This table reports quasi-Poisson regressions of the determinants of alerts. Variables are as defined in Table 1, although the dependent variables here are counts of each alert type organised as a panel of the two subperiods of the study (prelockdown and postlockdown). Standard errors are robust and clustered at emp_ID level. The *, ** and *** are results statistically significant at the 10%, 5% and 1% levels, respectively.

	(1) All Alerts		**(2) Comms.Alerts**		**(3) Trade.Alerts**	
	Coefficient	***t*-stat**	**Coefficient**	***t*-stat**	**Coefficient**	***t*-stat**
lockdown	0.199	0.70	0.565	1.213	0.109	0.377
wfh.group	−0.797	−2.48**	−0.817	−1.376	−0.793	−2.381**
lockdown:wfh.group	−0.694	−1.85*	0.000	0.000	−1.049	−2.305**
constant	−6.530	−30.50***	−8.343	−24.87***	−6.708	−30.87***
Individual effects?	No		No		No	
Number of observations	324		324		324	
Efron pseudo R^2	0.0519		0.0181		0.0533	

4.4 | Inference and robustness

The goodness of fit of our models as measured by R^2 is low, especially for the OLS regressions, but since the key objects of interest are conditional means and because we are looking at rare events, this is to be expected. Put differently, it is extremely hard (if not impossible) to reliably forecast if or when individual employees will commit compliance breaches (or worst case, securities fraud) over daily timeframes. The count models (see Table 7) have better fits, due to their longer timeframes (over 1 year for each observational period), and, arguably, the more appropriate specifications of Equations (2a) and (2b). These tilt us strongly toward favoring the inferences of these models. Both the selection and treatment effects are statistically significant in these estimates, at the 5% and 10% levels, respectively. Importantly, all of our findings are consistent with one other, including the OLS regressions. Moreover, the same patterns reveal themselves in additional analyses we perform to demonstrate robustness. Those results are available in the online appendix.

4.5 | Mechanisms

We have discussed potential mechanisms for why working remotely might affect the probability of misconduct/noncompliance. Ideally, we would also provide evidence as to which mechanisms are at play in the results. We have made some attempts in this direction but are limited by the data available to us. For reasons of confidentiality and UK data protection laws, we are not able to analyze or report information that might lead to some traders being identified personally, or for the bank to be identified.

In additional analysis, we consider two mechanisms which might generate differential rates of alerts. First, differences in alert rates might be explained by selection into days of the week on which workers work in the office versus work from home. A previous study finds that trader inattention varies over the week (Dellavigna & Pollet, 2009). If, for example, traders disproportionally worked in the office on Fridays, then the higher alert rate in the office might be attributable to a weekday effect. In Supporting Information: Table SA5 in the online appendix we add controls for day-of-the-week fixed effects. These fixed effects are not large or statistically significant, and leave the main coefficients unchanged. The data, therefore, do not indicate that a Friday effect explains the differences in alerts between work from home and work from the office.

Second, differences in alert rates might be explained by selection into high- versus low-return days. If workers tend to work in the office more on lower return days, and have a higher temptation on these days to engage in misconduct to increase their returns, then difference between the groups might be explained by differential daily returns. In additional analysis shown in Supporting Information: Table SA5 we control for daily returns (using the daily simply return of the FTSE-100 equity index). Again, we find coefficients on our main variables of interest are unchanged. We therefore suggest that the estimated differences between work from home and work from office most likely arise to differences in the working environment itself, for the reasons we discussed earlier in the paper.

5 | DISCUSSION

5.1 | Interpretation

Our results indicate both a selection effect, whereby traders allocated to work-from-home were those at less risk of incurring securities violations prepandemic, and also an induced effect of working from home on further lowering the risk of securities violations during the pandemic. In allocation, we observe that traders selected to work at home were an absolute 18.2 percentage points less likely (as a difference in an annualized probabilities of alert per employee) to have securities violations prelockdown, a period during which all trades were undertaken from the office. While there was no stated, formal selection of traders based on past conduct, there is the possibility that the bank (informally or unwittingly) selected traders to work-from-home who had fewer previous cases of misconduct.

Second, after the onset of restrictions, the difference-in-differences estimates indicated an induced effect. Those traders subject to work-from-home treatment exhibit substantially fewer securities violations and the economic significance of the treatment effect is large: working from home in lockdown results in an absolute reduction of 14.7 percentage points in the annualized probability of an alert per employee. This figure is a difference-in-difference: the gap between the alert probability for the work-from-home group and the alert probability for the work-from-office group widens when going from pre to postlockdown.[8] Our findings are robust to a variety of controls and econometric approaches, including, but not limited to, models used for rare events.

The economic significance we implicitly observe is large. We argue this as follows. The cost of serious misconduct in dollar terms is huge (fines and/or reputational damage) or even catastrophic for a company. The chances of such an event happening are tiny but, we suggest, correlated with trader behaviour, which in turn is correlated with rates of alerts. Thus, the expected cost of misconduct, which we *do not* measure, is a function of the probability of

[8]This gap is computed on the aggregate data. Equivalent gaps by alert type may be visualized in Figure 2, which shows annual probabilities separately for the two types.

trading alerts per trader, which we *do* observe. When multiplied by a cost in the millions or even billions of dollars, the change in expected cost is highly consequential.

5.2 | Limitations and future research

We caveat our results by noting that we cannot measure the effect of differences arising from technology. It is possible that better computer equipment used at the office (e.g., faster Internet connectivity or more screens) supports higher trading frequency or greater volume. While we cannot completely rule out different trading capabilities, we have corroborating arguments to suggest trading volume was not a driver. First, the data on communication alerts alone indicate no difference in home versus office, which suggests that work activity did not decline at home. Second, traders at home (or in the office) did not change their job objectives, targets or incentives; there was no reason to trade less (or more). Aitken et al. (2015b) show that higher trading frequency is *less* associated with price dislocations, thus a priori there is no reason to expect higher volumes of trades to be associated with misconduct. Further, from the outset of the exercise, the bank itself was aware that activity levels from work-from-home staff could be different to those at the office. Importantly, the bank in its own review accepted that the change of behaviour seen was *not* due to volume.

Our data come from only one financial institution, of traders in one regulatory regime, operating in a predominantly UK corporate culture. It is possible that there are differences in other financial institutions due to hiring practices, training policies, surveillance technology and the influence of ethics and compliance polices. Further, work-from-home in other countries differs on a practical level: societal factors and quality of home living space shape the experience and practicality. It would be worthwhile replicating these results in other jurisdictions. Another phenomenon we have not been able to investigate is persistence. It is possible that the lower misconduct rates of remote workers are transitory, and after the novelty of working at home wears off, individuals revert to their early behaviour and ethical standards.

Our results also arise from a context in which workers were mandated, wherever possible, to switch to working from home. The effect of mandatory working from home (with exceptions) are likely to differ from the effects of the option to work from home. Selection is likely to differ between which types of workers take up the offer to work from home versus which types of workers seek exemption from mandatory work from home. The period we study is of course not a 'typical' period in the trading history of the institution. However, our results provide early insight into the implications of work from home for securities misconduct.

6 | CONCLUSION

To our knowledge, this paper is the first rigorous attempt at using internal company data to investigate changing work patterns and their effect on rates of misconduct. We outline theory that predicts how work-from-home could affect the possibility of securities misconduct. We discussed theory that predicts changes in the frequency of violations, including rumours, contagion in unethical conduct, proximity and monitoring, and noted there is no way to favour one set of predictions over another. We, therefore, turned to a new data set on securities traders at an investment bank in London, England. The data show that working from home is associated with fewer securities violations. The evidence was stronger for trading violations than for communications violations. We acknowledge that we currently lack sufficient data to reveal the causal mechanisms that fully explain trader behaviour; we see this limitation as a spur to future research using richer data sets. Nevertheless, the variation in working locations in our setting goes a long way to overcoming limitations such as unobserved variables. Further, we argue that, with extremely large costs of serious misconduct, even small changes in probabilities of misconduct imply a large economic significance, one that management cannot ignore.

Management must decide how to adapt prudently to the brave new world of an increasingly home-based workforce. Bearing in mind that an element of corporate malfeasance is likely a permanent feature of the business landscape, management needs to understand if reconfiguring how and where employees perform their work will affect the risk profile of their firm, and to what extent. Higher risk lowers corporate valuations. Thus, we believe it will be incumbent on CEOs and boards to have a risk-informed management strategy for rolling out (or rolling back) work-from-home. The dimensions of these risks include (more/less) misconduct, (lower/higher) productivity, (lower/higher) employee loyalty, (loss of/gain in) corporate identity, among many others. Our study, with its focus on securities misconduct, makes an important contribution to management's appreciation and understanding of the link between the organization of work (home vs. office) and the changes in risk that come when making this tradeoff.

DATA AVAILABILITY STATEMENT

The data are confidential and proprietary from an investment bank in London.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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