Covid, Work-from-Home, and Securities Misconduct

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Abstract

We consider whether traders are more likely to commit securities violations when trading at home, a new form of working induced by the Covid pandemic. We examine data pre- and post-Covid, during which some traders were unexpectedly forced to work at home. The data indicate the presence of both a treatment and a selection effect, such that those working at home exhibit fewer misconduct cases. Work at home is associated with fewer cases of trading misconduct, although no difference in communications misconduct. The economic significance of working from home on trading misconduct is large for both the treatment and selection effects.

Keywords: Market Manipulation, Trading, Surveillance, Securities Regulation

JEL Codes: G12, G14, G18, K22

1. Introduction

Financial fraud and securities violations are costly to firms and society. Firms in the U.S. lose on average 22-38% of their equity value upon the revelation of fraud, which is mostly due to the reputation loss (Karpoff, Lee and Martin (2008)). Individuals responsible for financial misrepresentation in the U.S. lose their jobs in 93% of cases, face criminal penalties in 28% of cases, and jail sentences that average 4.3 years (Karpoff, Scott Lee and Martin (2008)). 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in patent citations (Cumming, Ji, Peter and Tarsalewska (2020)) and a 12% greater likelihood that mergers will be withdrawn and a 25% reduction in merger premiums (Cumming, Ji, Johan and Tarsalewska (2020)). More detailed trading rules and computerized surveillance designed to detect and enforce market manipulation are associated with fewer cases of insider trading (Aitken, Cumming and Zhan (2015a)), more new listings on stock markets, larger stock markets (Porta, Lopez-De-Silanes and Shleifer (2006)), (Cumming, Johan and Li (2011)), (Jackson and Roe (2009)) and more active stock markets with higher liquidity (Cumming, Johan and Li (2011)).

Although there is evidence for the increasing use and effectiveness of fraud deterrents (Karpoff (2021)), research in law and finance fundamentally seeks to determine the causes of market misconduct[1]. This work shows that the capability and desire of traders to manipulate markets depends on a variety of factors pertinent to technology, liquidity, information asymmetry, and reputational capital, as well as linkages across markets and products. An increasingly important influence is the shift to working from home, a trend accelerated and

[1] For example, see (Aggarwal and Wu (2006)), (Allen and Gale (1992)), (Allen and Gorton (1992)), (Comerton-Forde and Putniņš (2011)), (Comerton-Forde and Putniņš (2014)), (Hillion and Suominen (2004)), (Merrick Jr, Naik and Yadav (2005)), (Pirrong (1999)), (Pirrong (2004)), (Putniņš (2012)).

probably made permanent by the Covid-19 pandemic (Barrero, Bloom and Davis (2021)). The effects of home working on traders are unclear; we could posit outcomes in either direction. On one hand, market manipulation may be more likely to happen at home, where there is less direct managerial oversight and monitoring of personal calls. Also, with more distraction at home, there is a greater scope for 'fat finger trades', or trades by mistake that might look like misconduct. On the other hand, violations may be more likely to happen in the office because physical proximity offers greater opportunity for collusion and potentially more direct exposure to inside information. Furthermore, at the office there is a greater likelihood of unethical conduct if employees can observe the misconduct of others; that is, there is contagion in unethical conduct (Gino, Ayal and Ariely (2009)), and this contagion in unethical conduct has been widely regarded with well-publicized cases such as doping in professional cycling in the 1990s and early 2000s, for example. Overall, therefore, without examining data, it is hard to conjecture which effect dominates in the impact of working from home on securities fraud.

In this paper, we address the question of whether traders working from home causes more or fewer cases of securities violations. We examine a large and propriety dataset from an investment bank operating in London, England. Unlike prior work that examines which securities were manipulated, and what enabled the security to be manipulated, instead we examine manipulation at the level of the trader using data from the bank's supervisory systems. The data comprise information on 162 employees and 88,441 trader-days spanning January 2019 to March 2021. We observe 138 cases of suspected securities violations in the data. After the onset of Covid-19 crisis, by necessity, some (but not all) traders that previously worked from the office were then forced to work from home, so that the bank was compliant with social distancing requirements on the trading floor and to minimize the risk of virus spreading.

Working from home was a new experience for traders in UK investment banks, facilitated by emergency changes in financial regulation relating to where trading could occur.[2]

Our results indicate both a selection effect, whereby traders selected to work from home were those at less risk of incurring securities violations pre-pandemic, and also a causal effect of working from home on further lowering the risk of securities violations during the pandemic. First, the data examined indicate 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 pre-Covid, a period during which all trades were in fact undertaken from the office. This first piece of evidence is not 'causal' as there is a selection effect associated with which trader is selected to work from home. 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, these data further indicate that, after the onset of Covid restrictions, there is a significant treatment effect. Those traders subject to treatment exhibit substantially fewer securities violations and the economic significance of the treatment effect is large: working from home post Covid results in a 14.7 percentage point reduction 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 post Covid[3].

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[2] https://www.fca.org.uk/coronavirus/information-firms; see also https://www.ft.com/content/8066154d-83c4-49a6-97d4-4c3c65684136

[3] This gap is computed on the aggregate data. Equivalent gaps by alert type may be visualized in Figure 1, which shows probabilities separately for the two types.

The evidence in this paper has important implications for designing securities regulation surveillance and enforcement. Also, there are useful implication for the design of trading environments to ensure greater compliance with securities laws. The UK regulator (Financial Conduct Authority) provided emergency provision for home working across the financial industry (including trading) and 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.[4]

Our findings also relate to the literature on working from home and productivity, including studies of the effects of the Covid pandemic of work from home. Bloom, Liang, Roberts and Ying (2015) conduct a randomized control trial of home working at a Chinese travel agency and find that home working leads to a 13% increase in productivity, and also that allowing self-selection into working from home increased the productivity gain to 22%. This is consistent with our finding that work from home might improve worker performance through both selection and treatment effects. The Covid pandemic has led to a surge of studies on the feasibility and effects of home working in a variety of contexts (see, for examples, (Adams-Prassl, Boneva, Golin and Rauh (2020)), (Barrero, Bloom and Davis (2021)), (Dingel and Neiman (2020)).

This paper is organized as follows. Section 2 discusses the institutional context of market manipulation and surveillance. Section 3 introduces the data and provides summary statistics and comparison tests. Multivariate analyses are presented in section 4. The last section summarizes

[4] 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#market-trading-reporting

the findings, discusses limitations and extensions in future research, and offers concluding remarks and policy implications.

2. Institutional Context and Related Literature

2.1. Trading Rules, Surveillance, and "Alerts"

Securities laws for trading conduct comprise a number of rules regarding insider trading (trading on material non-public 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, Johan and Li (2011) provide a full list and explanation of each of the different forms of trading misconduct). These rules are found on the stock exchange webpages in most countries around the world. In some countries they are also codified in securities laws, such as the China Securities Regulatory Commission. In other countries they are codified in self-regulatory organizations, such as the Investment Institute Regulatory Organization in Canada. And in European countries, they 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 (Cumming and Johan (2019)). Specifically, the trading rules are in MAD (July 2007[5]), and the enforcement provisions are in MiFID (November 2007).[6]

[5] http://ec.europa.eu/internal_market/finances/docs/committees/071120_final_report_en.pdf.

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

Of key importance for our analysis, we do not observe differences in rules or enforcement over time. Given the sudden imposition of the requirement to work from home the bank used the same enforcement algorithms and software with the same settings throughout.

Trading rules are ineffective or even meaningless without enforcement. Enforcement of trading rules means that there are computerized algorithms that detect unusual trading patterns. Algorithms are needed because millions of trades can now take place in seconds or even fractions of seconds. The only way regulators can realistically detect unusual activity is to have computerized algorithms, alongside information sharing agreements across exchanges to detect cross-market and cross-product manipulations (Cumming and Johan (2008)). When there is a securities violation, the computerized algorithm sends a message known in practice as an “alert” to the surveillance staff to investigate. The triggering of an alert means there has been a potential securities violation. The violation could be due to intentional misconduct, or an unintentional mistake, or a false alarm. Here, in our empirical analyses, we do not distinguish between intentional or unintentional misconduct. We only measure suspected cases. Whether violations are enforced and result in some form of sanction or other punishment for the trader can take many years and depends on numerous factors that are beyond the scope of this paper.[7]

2.2. Alerts and Work from Home

The straightforward question in this paper is whether a trader is more likely to generate alerts (engage in securities violations, as discussed in subsection 2.1 above) when working from

[7] For example, in popular media it is often discussed that top investment banks hire former SEC staff in order to benefit from inside connections to get securities violation investigations quashed. https://www.rollingstone.com/politics/politics-news/is-the-sec-covering-up-wall-street-crimes-242741/

home compared to working in the office. In this subsection, we summarize reasons why traders might be more or less likely to engage in securities violations when they work from home.

2.2.1. 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 (Hong, Kubik and Stein (2005)), (Ahern (2017)). Working from home would therefore generate fewer opportunities to benefit from illegal tips and hence could result in fewer securities violations.

2.2.2. Contagion

Studies in psychology frequently document the presence of contagion in unethical conduct (Gino, Ayal and Ariely (2009)), (Quispe-Torreblanca and Stewart (2019)). Individuals feel less guilty or see less of a problem with unethical conduct, or at least rationalize unethical conduct when the see other people doing it.[8] 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.[9] 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 small chance of contagion in unethical conduct.

2.2.3. Rumors

[8] It is possible that contagion is transmitted through online social networking, but evidence (Gino et al., 2009) highlights the role of physical proximity in transmitting unethical conduct.
[9] https://tenorfilms.com/collared/

Financial market rumors are more likely to form in geographically proximate (Yu, Li, Lim and Tan (2019)). Rumors often give rise to negative financial market outcomes and at time securities violations (Van Bommel (2003)), (Alperovych, Cumming, Czellar and Groh (2021)). We might therefore conjecture that more securities violations will happen due to work at the office through the channel of rumors.

2.2.4. The Quality of Public Information

Post-Covid, there has been a worsening of publicly disseminated information in terms of the average quality of research reports (Du (2020)), (Li and Wang (2021)). A worsening of public information due to Covid increases information asymmetry in the market and opens the scope for more insider trading (Wu (2019)). Hence, working from home due to Covid could be associated with more securities violations.

2.2.5. Distraction and Mistake

Sometimes securities violations are a result of a mistake. At home, those working in the securities industry are more likely to be distracted (Du (2020)), (Li and Wang (2021)) which might increase the chance of alerts being triggered from home.

2.2.6. Proximity and Oversight

There is evidence that geographic proximity to the securities commission reduces the likelihood of engaging in securities violations (Hu, Wang and Xin (2017)). In a similar way, we might conjecture that geographic proximity to the ethics and compliance department 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.

2.2.7. Summary

In net, we have three factors that would lead us to predict that securities violations are more likely when there is an assignment forcing some traders to work from home, including the worsening in quality of public information and increase in information asymmetry, an increase in distraction and likelihood of mistake, and reduction in proximity and oversight or at least the perception of oversight. However, we have three factors that would lead us to predict that securities violations are less likely when there is an assignment forcing some traders to work from home, including the reduced flow of inside information, reduction in the probability of rumors forming and spreading, and the reduction in the likelihood of contagion in unethical conduct. A simple counting of factors might lead us to predict that the net effect of an assignment of forcing some traders to work from home is zero and that it is neither more nor less likely to cause an increase in securities violations; however, we have no theoretical rationale for equally weighting these factors, and there may be additional factors we have not considered. Which effect dominates is therefore an empirical question that we address below in the remainder of the paper. In the empirics below, we distinguish between selection effects and treatment effects in assessing the impact of working from home on securities violations.

3. Data

We use proprietary data from an investment banking arm of a financial group headquartered in London, England. The data comprise daily information from 1 January 2019 to 18 March 2021 on 162 traders. The pre-lockdown period is 1 Jan 2019 to 18 March 2020 and the lockdown period is 19 March 2020 to 31 March 2021[10]. The 162 employees whose behavior is

[10] Friday 19 March 2020 is the date on which the bank implemented its 'lockdown' plan. The bank chose a Friday

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 on the market and exchange, during UK working hours (typically 7 am to 7pm). Each trader is individually licensed and regulated by the FCA.

We have 88,441 employee-day observations in our sample (restricting to working days only – removing weekends and other non-working days due to bank holidays, sickness or vacation). The traders generated 142 alerts (securities violations) over the sample. One employee generated an alert on a non-working 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 issue and avoid the appearance of multiple counting. After applying these filters, we observe 138 alerts over the period.[11]

Table 1 defines the variables used in our empirical analyses. An alert is a potential securities violation triggered by the surveillance software used by the bank. There was no difference in surveillance software parameters which would trigger an alert over the course of the sample period, with the bank using the same software parameters for workings in the office and those at home. We observe two types of alerts. First, *trading alerts* encompasses many types of trading misconduct, including insider trading, price manipulation, volume manipulation, and spoofing (section 2). Second, *communication alerts* are generated from the bank's monitoring of phone, email, and online chat.

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so that the transition to work from home (for those who would subsequently work from home) could be achieved over the weekend period prior to market opening on Monday 22nd March.

[11] Not applying filters did not materially affect the results.

[Insert Table 1 Here]

Prior to the Covid pandemic, no trading activity took place away from the office and working from home on non-trading related work was rare. Occasionally an employee might work from home due to personal reasons such as a temporary illness or family matter; we do not classify those employees as work-from-home employees.

With the onset of the Covid pandemic, the bank was required to move workers to work from home wherever possible and physical restrictions on distance between seated employees prevented the bank from keeping all trades in the office (including rules of at least two metres distance, with additional maximum limits on number of individuals per room). In practical terms, due to the “2-meter rule” employees could no longer be seated next to one another in the open plan office, and this necessitated a large share of employees moving so as to work elsewhere.

Decisions as to who worked from home were as follows. Business critical functions teams were split up and some critical staff would have to remain in the office during the lockdown and ensure the virus could not affect entire functions (e.g., information services). It was decided that it would be too risky to have certain roles (e.g., book watchers) work from home as they were deemed business-critical functions, and hence they agreed to remain in the office throughout the lockdown. Apart from covering business critical functions that had to be done from the office, there was some flexibility in who work from home based on individual needs (such as personal family matters), decided more on a more ad-hoc basis. The company did not indicate that there was any policy or decision to allow work from home in a way that was correlated with, or averted to any risk of, securities fraud being more or less likely to work from home. Instead, it was based on business-critical functions that needed to be carried out at the office, followed by personal safety and family matters. The decision to have certain roles such as book watchers as business-critical roles at the office would lead any bias in the data towards observing fewer securities violations in the office post covid (and the data actually indicate the opposite, as we explain below).

To set up our analysis, we therefore classify employees as work from home or work from office using data on their location in the Covid period (beginning 19 March 2020). We obtain data on the working location of each employee on each day of the Covid period using scanner data at the entry barriers to the bank's premises. We then classify employees as in the work-from-home group if they worked from home on at least 90% of days from 19 March 2020 onwards.[12] Using this approach we therefore create a work-from-home group of employees that were selected to work at home after Covid, and examine differences in that group's securities violations in the pre- and post-Covid period, compared with those working in the office throughout the period.

Table 2 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, Cumming and Zhan (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.

[12] 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 85% or 95%.

[Insert Table 2 Here]

4. Results

4.1. Univariate Analyses

Figure 1 shows the annualized probability that an employee will have at least one alert before and after lockdown. 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 plotted in separate panels. Prior to 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.

[Insert Figure 1 here]

The mean daily probability of an alert for an employee is shown 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 pre-lockdown divided by the number of employee-days worked in that period by that group. Continuing in 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 an alert increased for those working in the office but decreased for those working from home. These differences, and the difference in the differences of 0.001007, are significant at the 1% level. The increase in the differences 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.

Panel B repeats the analysis for communications alerts and shows a slightly 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.

[Insert Table 4 here]

As a prelude to a multivariate analysis, Table 5 presents a correlation matrix for the full sample in Panel, and the subsamples for the post-covid and pre-Covid lockdown periods in Panels B and C, respectively. The full sample data indicate that work from home is significantly negatively correlated (-0.0117) with all types of alerts (-0.0117, significant at the 1% level) and trade alerts (-0.0128, significant at the 1% level), while the correlation with communication alerts (-0.0008) is not statistically significant. The work-from-home group of employees is negatively correlated with the full sample alerts (-0.0200, significant at the 1% level) as well as communication (-0.0072, significant at the 5% level) and trade alerts (-0.0189, significant at the 1% level).

[Insert Table 5 Here]

The economic and statistical significance of the negative correlations between alerts and work from home is stronger in the post-Covid lockdown period than the pre-lockdown period. For example, work from home and all alerts are negatively correlated at -0.0317 for the lockdown period (significant at the 1% level) and at -0.0149 for the pre-lockdown period (significant at the 1% level). Trade alerts are negatively correlated with the work-from-home group in the post-lockdown period (-0.0259, significant at the 1% level), and negatively correlated in the pre-lockdown period (-0.0136, significant at the 1% level). Communication alerts are negatively correlated with the work-from-home group in the post-lockdown period (-0.0084, significant at the 10% level), and negatively correlated in the pre-lockdown period (-0.0061, not statistically significant).

Overall, the correlation evidence in Table 5 is consistent with the comparison tests in Tables 3 and 4, and Figures 1 and 2. Work from home is negatively correlated with alerts, and this negative relation is stronger post-Covid lockdown, and stronger for trade alerts than communication alerts.

4.2. Multivariate Analyses

We present the multivariate tests in Tables 6–9. The sample comprises 88,441 observations. Table 6 presents a multivariate OLS analysis most comparable to the simple unconditional difference in difference analysis in Table 4. The coefficients for lockdown × wfh.group, which measures the difference in differences, are extremely similar to the unconditional estimates. While the linear probability model estimates in Table 6 are transparent and relate to the unconditional analysis, we also present alternative specifications to demonstrate robustness. In Table 7 binomial logit regressions are presented for all alert types together as well as communication and trade alert outcomes separately. In Table 8 we present multinomial logit regressions which treat a no employee-alert day as equal to 0, a communication alert as equal to 1, and a trade alert as equal to 2. We also present in Table 9 Poisson regressions. We also considered negative binomial regressions account for the rare likelihood of having alerts, and particularly more than 1 alert, but do not report for reasons of conciseness as the findings were not materially different. Standard errors are clustered by employee identification number in the models.[13]

[Insert Tables 6-9 About Here]

The coefficient on the wfh.group, which estimates the pre-lockdown difference between those who would ultimately work from home and those who would work remain in the office, is robust across specifications. Those working from home has fewer pre-lockdown 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 lockdown × wfh.group is also robust across specifications, showing that the gap in alerts overall opening up, driven by trading alerts not communications alerts. Those who ultimately work from home experienced a reduction in alerts

[13] Alternative ways of clustering by time and employee (Petersen (2009)) did not materially affect the results.

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. The economic significance is large. For example, the gap in the annualized probability of a trading alert for those working from home and those working from the office increases by 14.3 percentage points after lockdown (see Figure 1).

The data offer some additional variables which we can use as control variables in the analysis. We consider control variables for day of week and the FTSE returns. These variables are not significant in any of the models. This suggests that alerts are not sensitive, for example, to a "Friday effect" whereby the likelihood of alert might change due to reduced attention on the part of traders. Nor is there evidence of alerts being sensitive to market returns (notably, here the data offer substantial variation in returns due to high volatility in financial markets during the early stages of the Covid pandemic in particular). We likewise considered other variables, such as month effects, and they were not significant. Other specifications are available on request.

With the OLS models, the goodness of fit is quite low, but the fit improves with the use of logit specifications and Poisson models (pseudo R^2 at 2.6% for trade alerts). With the rare events, the low R^2 values are expected; put differently, it is hard to forecast when employees will commit securities fraud. We have considered additional control variables in alternative specifications which improves the goodness of fit somewhat but does not materially impact the inferences about work from home and securities violations reported above.

5. Limitations, Extensions, and Future Research

We are not able to report information that might lead to some traders being identified personally, or for the bank to be identified. However, notwithstanding this, we have not seen any details that we might have wanted to report that affect the results.

We do not have data on the outcome of these alerts, for example. We report information on the frequency of alerts and not the magnitude of harm, partly due to the sensitive nature of the information (and the scope for outliers to skew the analysis) and also partly due to difficulty in comparability of harm in different contexts; we have not seen information that leads us to believe harm is more pronounced when violations are committed at home or in the office.

But the sensitive nature of the information always opens the door to new studies in the future. For example, others in the future might be permitted to report information on traders' gender, age, ethnicity, religious beliefs, and education. The extent to which these things influence ethical conduct in securities trading would of course be worth examining.

For this study, we do not have sufficient information on the specific forms of misconduct, such as insider trading, price manipulation, volume manipulation, and spoofing. Instead, we know two types of misconduct: trading and communication alerts. And we do not know whether the detected manipulations resulted in enforcement actions against the traders in our sample, or if there has not yet been enforcement, if there might be enforcement actions in the future. Our analysis is based on suspected market manipulation and securities violations.

We do not have measures that control for the presence of different equipment in the office. For example, it is possible that different communication equipment is used at the office, and that higher frequency trading is more common from the office. However, the data indicate no material difference in communication alerts from work at home versus work at the office, which suggests that work activity did not decline when working from home . And extant work shows that higher frequency trading is less often associated with price dislocations (Aitken et al., 2015b), such that work from the office would less like likely correlate with alerts if work from the office is associated with more high-frequency trading.

We only have data from one financial institution; it is hard to get access to information about trading alerts. It is possible that there are differences across other financial institutions due to hiring practices, training policies, and the corporate culture and influence of the ethics and compliance division in the company.

We examine data from London, England. Work from home in different countries has different implications as the societal factors and quality of home living space differs in different parts of the world. It would be worthwhile to replicate these results in other cities and countries around the world to examine comparability due to societal and economic factors.

6. Conclusions

This paper introduced a new yet simple research question: is a trader is working from home more or less likely to commit securities violations? We discussed theoretical reasons either way that might lead affect the frequency of violations, including rumors, contagion in unethical conduct, proximity and monitoring, among other factors, and showed there is no clear prediction one way or the other.

We therefore turned to a new dataset on traders in London, England over the 1 January 2019 to 18 March 2021 period. The dataset comprised 162 traders, 138 securities violations, and 88,441 trader-days spanning the pre- and post-Covid lockdown. Pre-lockdown, very few select employees were permitted to work from home. Post-lockdown, many employees were required to work from home.

The summary comparison tests and correlation evidence showed that working from home is more likely to be associated with fewer securities violations, and that this effect is even stronger in the post-Covid lockdown period. This evidence was consistent regardless of comparing the groups in the data by employee pre- and post-covid, or by examining all employee-day observations. The evidence was stronger for trading violations than for communications violations (by phone, email, chat, or online discussion boards).

The multivariate analyses showed consistent evidence with the univariate tests. Working from home exhibits a selection effect pre-covid, and a treatment effect post-covid. The treatment effect showed statistically significant evidence of a reduction in securities violations from forced assignment to working at home, with a reduced probability of a trade violation by 7.2% (annualized). The selection effect observed in the data is slightly larger, where those selected to work at home have a 13.9% less likely chance of generating a securities violation. We do not see any evidence of working from home being related to communications violations. The multivariate analyses were robust to the use of different methods (OLS, logit, multinomial logit, negative binomial, Poisson, etc.).

We discussed many limitations of our dataset and extensions that could be done in future research in section 5 of this paper. We hope future scholars will continue to push this direction of research. Improving the body of knowledge on factors that give rise to securities violations is important to financial market integrity and efficiency, and can help practitioners, policymakers and surveillance staff alike. As more data become available, additional empirical evidence would have great benefits to financial market research, policy, and practice.

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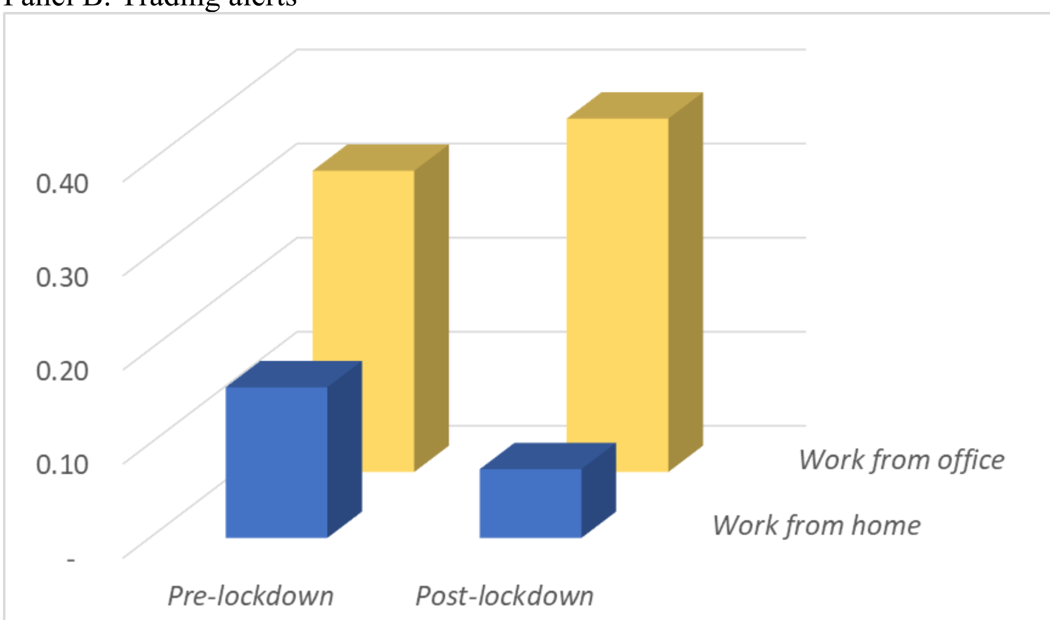
Figure 1. Univariate analyses of annualized probabilities of at least one alert per employee

Panel A. Communication alerts

Panel B. Trading alerts



This figure shows the comparison of actual 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 (that is, not derived from predictions or regression analyses).

Table 1. Definition of Variables

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

Variable	Definition
employee_ID	A unique hash number used to anonymously identify trading employees.
Surveillance Alerts	
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 sub-systems, 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 behavior. 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 Patterns	
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.
Market	
return	The daily return on the FTSE 100 equity index.
Day	Dummy variables equal to one if for a particular day of the week *employee-day* is (**mon**, **tue**, **wed**, **thu**, **fri**).

Table 2. Descriptive Statistics

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

Variable	Mean	Median	Standard Deviation	Min	Max
return	0.00010	0.00070	0.01362	-0.10875	0.09054
alert	0.00156				
comms.alert	0.00034				
trade.alert	0.00122				
wfh	0.319				
wfh.group	0.529				
lockdown	0.436				

Table 3. Number of Alerts

This table shows a histogram of 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.

Pre-lockdown, employees subsequently classified as work-from-home		Pre-lockdown, 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

Table 4. Comparison Tests for Alerts

This table presents a comparison of means in a difference-in-difference format. Figures in bold underwent Welch two sample t-tests using the full panel for subsets as defined from variables in Table 1. The *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively

	Work from office	Work from home	Difference ((2) - (1))	Unconditional DiD	Test (4) Difference from 0	Unconditional DiD % Effect ((4) / Pre (2))
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Alerts						
Pre-lockdown	0.002093	0.000944	**-0.001149*** **			
N	23,408	26,488				
SD	0.045706	0.030708				
Post-lockdown	0.002796	0.000640	**-0.002156*** **			
N	18,238	20,307				
SD	0.052808	0.025294				
Post – Pre	**0.000703**	**-0.000304**		-0.001007	P<0.0001***	-106.7
Panel B: Comms						
Pre-lockdown	0.000342	0.000151				
N	23,408	26,488	**-0.000191**			
SD	0.018484	0.012288				
Post-lockdown	0.000658	0.000295				
N	18,238	20,307	**-0.000363**			
SD	0.025643	0.017187				
Post – Pre	**0.000316**	**0.000144**		-0.000172	P=0.0491**	-113.7
Panel C: Trade						
Pre-lockdown	0.001752	0.000793	**-0.000959*** **			
N	23,408	26,488				
SD	0.041816	0.028146				
Post-lockdown	0.002138	0.000345	**-0.001794*** **			
N	18,238	20,307				
SD	0.046195	0.018564				
Post – Pre	**0.000387**	**-0.000448** **		-0.000835	P<0.0001**	-105.3

Table 5. Correlation Matrix

Panel A presents Pearson correlation coefficients for the full sample of employee-day observations in the data. Panel B is for lockdown and Panel C is for pre-lockdown. The *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively

		alert	comms.alert	trade.alert	wfh	wfh.group	lockdown
Panel A Full Sample	alert	1.0000					
	comms.alert	0.4660***	1.0000				
	trade.alert	0.8845***	-0.0006	1.0000			
	wfh	-0.0117***	-0.0008	-0.0128***	1.0000		
	wfh.group	-0.0200***	-0.0072**	-0.0189***	0.2569***	1.0000	
	lockdown	0.0022	0.0061*	-0.0007	0.7806***	-0.0040	1.0000
Panel B Lockdown Period							
	wfh	-0.0317***	-0.0115**	-0.0302***			
	wfh.group	-0.0264***	-0.0084*	-0.0259***	0.6300***		
Panel C Pre-Lockdown Period							
	wfh.group	-0.0149***	-0.0061	-0.0136***			

Table 6. OLS Regressions

This table presents OLS regressions of the determinants of alerts. Variables are as defined in Table 1. The time unit is one workday. Standard errors are robust and clustered by employee_ID. The *, **, *** 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	1.420	0.000671	1.376	0.000316	1.405	0.000315	1.404	0.000387	0.884	0.000357	0.822
wfh.group	-0.001149	-3.254***	-0.001149	-3.254***	-0.000191	-1.3389	--0.000191	-1.339	-0.000959	-2.964***	-0.000959	-2.964***
lockdown:wfh.group	-0.001007	-1.812*	-0.001009	-1.816*	-0.000172	-0.645	-0.000172	-0.647	-0.000835	-1.710*	-0.000837	-1.714*
return			0.014802	1.305			0.000978	0.260			0.013823	1.291
tuesday			0.000439	1.059			0.000148	0.790			0.000291	0.787
wednesday			0.000099	0.254			0.00097	0.538			0.000003	0.008
thursday			0.000718	1.647			0.000157	0.835			0.000560	1.426
friday			0.000114	0.289			0.000115	0.629			-0.000001	-0.003
constant	0.002093	7.010***	0.001828	4.615***	0.000342	2.829***	0.000238	1.388	0.001752	6.409***	0.001590	4.450***
Number of Observations	88,441		88,418		88,441		88,418		88,441		88,418	
Adjusted R^2, Veall-Zimmermann Pseudo R^2	0.000324		0.000373		0.000760		0.000084		0.000291		0.000340	

Table 7. Binomial Logit Regressions

This table presents binomial logit regressions of the determinants of alerts. Variables are as defined in Table 1. The time unit is one workday. When the FTSE return is included the number of observations drops slightly because some employees worked on a day when the FTSE markets were closed. Standard errors are robust and clustered by employee_ID. Slightly more observations are available when returns is omitted because the traders worked a small number of days when the markets were closed. The *, **, *** are results statistically significant at the 10%, 5%, and 1% levels, respectively.

	All Alerts				Comms.Alerts				Trade.Alerts			
	(1)		(2)		(3)		(4)		(5)		(6)	
	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat
lockdown	0.290	1.45	0.265	1.33	0.655	1.44	0.650	1.43	0.200	0.893	0.166	0.747
wfh.group	-0.798	-3.24***	-0.798	-3.24***	-0.817	-1.33	-0.817	-1.33	-0.794	-2.956***	-0.794	-2.96***
lockdown:wfh.group	-0.679	-1.73*	-0.680	-1.72*	0.016	0.02	0.015	0.02	-1.033	-2.106***	-1.034	-2.11**
return			9.697	1.32			3.014	0.29			11.826	1.315
tuesday			0.292	1.06			0.488	0.78			0.242	0.43
wednesday			0.078	0.27			0.347	0.65			0.006	0.02
thursday			0.455	1.64			0.517	0.82			0.441	1.42
friday			0.089	0.30			0.404	0.63			0.0003	0.00
constant	-6.167	-43.1***	-6.363	-25.1***	-7.981	-22.6***	-8.350	-13.1***	-6.346	-40.6***	-6.498	-23.6***
Number of Observations	88,441		88,418		88,441		88,418		88,441		88,418	
Veall-Zimmermann Pseudo R^2	0.020		0.023		0.015		0.016		0.023		0.026	

Table 8. Multinomial Regression Analyses

This table presents multinomial logit regressions of the determinants of alerts organised by type. The dependent variable takes the following values (No alert=0, Comms alert=1, Trade alert=2). Variables are as defined in Table 1. The time unit is one workday. When the FTSE return is included the number of observations drops slightly because some employees worked on a day when the FTSE markets were closed. Slightly more observations are available when returns is omitted because the traders worked a small number of days when the markets were closed. The *, **, *** are results statistically significant at the 10%, 5%, and 1% levels, respectively.

	Model (1)				Model (2)			
	Comms Alert		Trade Alert		Comms Alert		Trade Alert	
	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat
lockdown	0.656	1.436	0.200	0.894	0.651	1.422	0.166	0.7636
wfh.group	-0.818	-1.335	-0.794	-2.956***	-0.818	-1.336	-0.796	-2.957***
lockdown:wfh.group	0.015	0.019	-1.033	-2.107**	0.014	0.018	-1.036	-2.108**
return					3.036	0.229	11.827	1.617
tuesday					0.488	0.779	0.242	0.781
wednesday					0.347	0.537	0.006	0.987
thursday					0.517	0.819	0.441	1.448
friday					0.404	0.624	0.004	0.001
constant	-7.979	-22.565***	-6.345	-40.593***	-8.348	-14.253***	-6.498	-24.309***
Number of Observations	88,441		88,441		88,418		88,418	

Table 9. Poisson Regressions

This table presents Poisson regressions of the determinants of alerts. Variables are as defined in Table 1. The time unit is one workday. Standard errors are robust and clustered by employee_ID. Negative binomial and quasi-Poisson regressions produced nearly identical estimates as the Poisson models, and hence are not reported for conciseness. The *, **, *** are results statistically significant at the 10%, 5%, and 1% levels, respectively.

	Poisson Regressions					
	(4) All Alerts		(5) Comm Alerts		(6) Trade Alerts	
	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat
lockdown	0.264	1.332	0.650	1.434	0.165	0.746
wfh.group	-0.797	-3.244**	-0.817	-1.334	-0.792	-2.956***
lockdown:wfh.group	-0.679	-1.715*	0.015	0.020	-1.033	-2.109**
return	9.673	1.323	3.013	0.290	11.801	1.316
tuesday	0.295	1.058	0.488	0.779	0.241	0.784
wednesday	0.078	0.265	0.347	0.537	0.006	0.017
thursday	0.454	1.640	0.516	0.823	0.440	1.425
friday	0.089	0.299	0.404	0.628	0.0002	0.001
constant	-6.364	-24.150***	-8.350	-13.123***	-6.500	-23.603***
Number of Observations	88,418		88,418		88,418	
Adjusted R^2, Veall-Zimmermann Pseudo R^2	0.023		0.016		0.026	