The Consequences of Working from Home: Evidence from Sell-Side Analysts

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March 2021

1. Motivation and Significance

The COVID-19 pandemic has resulted in a massive shift in the number of employees working from home (WFH). Bick, Blandin, and Mertens (2020) document that the fraction of the workforce WFH increased from roughly 8% in February 2020 to more than 35% by May of 2020. Further, the shift towards WFH is unlikely to fully revert after the pandemic ends. A recent survey by PWC finds that more than 50% of workers are interested in working from home at least three days a week even after COVID-19 is no longer a concern (PWC, 2021).

While many workers are clearly enthusiastic about WFH, the value implications to corporations is unclear. Proponents of WFH argue that it can enhance firm value by increasing worker productivity (e.g., due to eliminating commuting and minimizing distractions) and/or allowing companies to attract and retain talented employees who value this flexibility. On the other hand, critics argue that WFH can encourage shirking, reduce focus, limit opportunities for valuable collaboration, and potentially attract lower-quality employees. Existing empirical evidence is also mixed. For example, studies of call-center workers find increased productivity (see, e.g., Bloom et al., 2015; Emanuel and Harrington, 2020), and evidence that at least some workers place a significant premium on being able to work from home (Mas and Pallais, 2017). However, there is also evidence that WFH can attract less productive workers (Emanuel and Harrington, 2020) and leads to declines in performance for more cognitively challenging tasks (Kunn, Seel, and Zegners, 2020).

In this paper, we examine the consequences of WFH among sell-side analysts. Sell-side analysts provide an excellent laboratory for studying the consequences of WFH for several reasons. First, there is rich and observable data on sell-side analysts that allow precise measures of output quantity and quality. In particular, comparing analysts issuing forecasts for the same firm-quarter along a variety of dimensions (e.g., forecast frequency, timeliness, accuracy, informativeness, etc.) offers objective measures of performance for workers performing essentially the same task (i.e., forecasting earnings for the same firm-quarter). Second, there is good reason to believe that there will be substantial dispersion in WFH intensity across analysts. Our sample of more than 3,000 analysts span a broad set of brokerage houses, brokerage branches, and geographic locations. This likely results in significant variation in WFH behavior across analysts including brokerage house fixed effects (e.g., the culture of the brokerage house and the preferences of top executives)[1], branch fixed effects (e.g., within a brokerage house certain branches may have different

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[1] For example, Jamie Dimon, the CEO of JP Morgan has been outwardly critical of WFH (see, e.g., https://www.fnlondon.com/articles/how-are-you-going-to-learn-properly-jpmorgan-ceo-jamie-dimon-warns-over-increasing-negatives-of-working-from-home-20201016). On the other hand, many others employers including Deutsche Bank are much more open to letting employees WFH at least two days a week (see: https://www.bloomberg.com/news/articles/2020-11-24/deutsche-bank-considering-40-permanent-work-from-home-policy?sref=VdHMQbm0).

cultures)[2], and time-varying state-wide policies that prohibited or limited analysts from in-person work. Relatedly, Dingel and Neiman (2020) estimate that 88% of jobs in Financial Operations can be done at home, indicating great potential for variation in WFH. Third, sell-side analysts are highly educated employees performing cognitively challenging jobs. Thus, evidence of productivity consequences of WFH on sell-side analysts will provide an important complement to much of the existing literature which has primarily focused on less cognitively demanding tasks (e.g., Bloom et al., 2015).[3] Finally, analysts are important intermediaries in financial markets and their forecasts have implications for asset prices (Kothari et al., 2016). Our setting therefore allows us to study whether WFH behavior has implications for financial markets.

2. **Measuring Working from Home Activity**

We measure WFH intensity at the brokerage-branch level. Our analysis relies on geospatial data provided by Veraset, a leading provider of anonymized movement across the United States. Veraset partners with smartphone application developers to aggregate GPS data from over 50 million smartphones in the U.S. Unlike other geospatial data providers, Veraset allows us to see the raw geo-location and timestamp of an individual device when it is "pinged."[4] The data not only include the latitude and longitude of the device, but commonly detail the altitude of a device. This allows us to differentiate whether, for example, analysts working at 277 Park Avenue in New York are employed by J.P. Morgan (2nd & 3rd floor) or Ladenburg Thalmann & Co (26th floor). This movement data allow us to estimate the extent to which workers are working from the office (WFO) at any point in time. Combining this dataset with the locations of each brokerage branch provides us a time-series of movement intensities for each branch.

We plan to use 2019 – the first year of available data – as the benchmark period as this is a time when WFH was relatively infrequent. For each quarter (q) in the post-2019 period, and each brokerage branch (b), our key variable is:

$$WFH_{b,q} = 1 - \frac{WFO_{b,q}}{WFO_{b,q2019,}}, \tag{1}$$

where $WFO_{b,q}$ is a measure of the intensity of movement in brokerage branch (b) during quarter (q). To construct this measure, for each device, day, and branch, we calculate the time difference between the first and last ping of a cell phone. For example, if the first ping occurs at 8 am and the last ping occurs at 6 pm, we credit an analyst with working 10 hours from the office. We note this is typically a lower bound since we may be missing hours outside of the range if the phone doesn't ping right when the analysts arrive or

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[2] We define a branch as a specific address. Across the 452 brokerage houses in our sample, the average (median) firm has 2.4 (1) branch, but several large brokerage houses have more than 20 distinct branches.

[3] We also note that the sell-side analyst industry is similar to many other high skill industries, in which the core tasks can likely performed anywhere, but perhaps not without costs. For example, the core skills required to be a good analysts, such as past industry experience (Bradley, Gokkaya, and Liu, 2017), the ability to private talk with management over the phone (Brown, Call, Clement, and Sharpe, 2015), and access to publicly available data like EDGAR Filings (Gibbons, Iliev, and Kalodimos, 2020) are unlikely to critically depend on where the analysts works. On the other hand, analysts benefit from social interactions with other analysts (Chen, Mayew, and Yan, 2018; Hwang, Liberti, and Sturgess, 2019) which are likely less frequent when WFH is more prevalent.

[4] A ping occurs at irregular time intervals, either when a smartphone has an application pulled up or when it is running in the background. A smartphone in the dataset is typically pinged every ten minutes, however there is considerable variation in ping frequency.

depart from the office.[5] We sum this measure across all devices present in the branch on a given day to compute a daily branch-level measure of WFO intensity ($WFOb, d$). We aggregate this a quarterly measure ($WFO_{b,q}$) by averaging *Daily* $WFOb, d$ across all days in the quarter. Thus, higher values of $WFH_{b,q}$ are consistent with a large fraction of workers being absent from the office (or an increase in the number of workers who are presumably working from home). Since our measure of *WFH* is at the branch level, we assign all analysts (*i*) working at the same branch during the same quarter the same value ($WFH_{i,q}$).[6]

3. Proposed Empirical Tests

This section describes the empirical design for our four main proposed tests.

3.1 Work from Home and Analyst Research Quality

Our initial tests focus on the link between WFH intensity and measures of the quantity and quality of analyst research. Specifically, for each analyst (*i*), firm (*j*), and quarter (*q*), we estimate the following baseline panel regression:

$$Y_{\mathrm{i,j,q}} = \beta_1 WFH_{i,q-1} + \beta_2 Analyst\_Controls_{i,q} + \beta_3 COVID\_Controls_{i,q} + \delta_i + \delta_b + \delta_{bh} + \delta_{j,q} + \varepsilon_{\mathrm{i,j,q}}. \quad (2)$$

We estimate this regression for each firm-quarter with analyst coverage greater than or equal to three over the period 2015-2020. We set all values of WFH prior to 2020 equal to 0, consistent with the view that there was limited working from home prior to COVID pandemic. Although the pre-COVID period does not provide any variation in our variable of primary interest, we include several years prior to the pandemic in order to more accurately estimate control variables, particularly the fixed effects (described below). To increase power, we plan to extend the sample beyond 2020 as more data becomes available.

Dependent Variable Definitions:

$Y_{\mathrm{i,j,q}}$ = various dimensions of analyst performance – all measured using analyst forecast data from IBES – described in greater detail below.

- *Proportional Mean Absolute Forecast Error (PMAFE)* = a measure of sell side accuracy. Following Clement (1999) we measure *PMAFE* as: $\frac{AFE_{i,j,q}-\overline{AFE_{J,q}}}{\overline{AFE_{J,q}}}$, where $AFE_{i,j,q}$ is the absolute forecast error of analyst *i,* following firm *j*, in quarter *t* and $\overline{AFE_{J,q}}$ is the average absolute forecast error across all analysts covering firm *j* in quarter *t*.
- *Relative Pessimism* = a measure of forecast bias. Following Bradley, Jame, and Williams (2020), we compute *Relative Pessimism* as: [(*Rank* -1)/(*Number of Analysts* -1)], where *Rank* is the rank of

[5] On the other hand, if an analyst arrive in in the morning, leaves for a large chunk of time in the middle of the day, and then returns in the evening, we will overstate the number of hours he worked from the office. An alternative approach would be to calculate the number of unique hours that the analyst's phone is pinged. However, analyst phones can be pinged at irregular intervals which raises concerns about the accuracy of these more granular measures.
[6] Ideally, we would also be able to develop an analyst-specific measure of working from home (e.g., by tracking an analyst movement from his home address to his branch office). Unfortunately, this approach would violate the terms of use by Veraset, which promises anonymity at the individual level.

the analyst's forecasted earnings estimate, where the highest estimate is given a rank of 1, the second highest estimate is a given a rank of 2, etc., and *Number of Analysts* is the number of analysts issuing a forecast for the firm-quarter. Thus, higher values of *Relative Pessimism* indicate greater pessimism (a common proxy for catering to firms' preferences to meet or beat short-term earnings forecasts).

- *Forecast Frequency* = a measure of output quantity. The total number of forecasts issued by analyst (*i*), for firm (*j*), in quarter (*t*).
- *Forecast Timeliness* = a measure of effort. Following Merkley, Michaely, and Pacelli (2017) we measure *Forecast Timeliness* as the number of days between the earnings announcement for firm (*j*) in quarter (*t-1*) and the first earning forecast made by analyst (*i*) for firm (*j*) for quarter (*t*) following the previous earnings announcement.
- *Forecast Informativeness* = a measure of the private information contained in the analyst's forecasts. We measure informativeness as the two-day (0,1) absolute return following the earning revision. For this analysis, we exclude earnings forecasts that coincide with other major information events that could also impact absolute returns including earnings announcements, earnings guidance, or earnings forecast revisions by other analysts.
- *Forecast Boldness* = a measure of how much the analysts deviates from the consensus when issuing a forecast. High levels of boldness are associated with more accurate and informative forecasts (Clement and Tse, 2005). Following Hong, Kubik, and Solomon (2000) we measure a forecast's boldness as the forecast's percentage absolute deviation from the consensus: $\frac{Forecast_{i,j,q} - \overline{Forecast_{j,q}}}{\overline{Forecast_{j,q}}}$.

Independent Variable Definitions:

$WFH_{i,q-1}$ = The intensity with which analyst *i* worked from home in the previous quarter (as defined in Section 2).

$Analyst\_Controls_{i,q}$ = A set of controls that the prior literature has shown will impact the outcome variable (*Y*) of interest. For example, when the outcome variable is analyst forecast accuracy, we will follow Clement (1999) and include controls for: *Broker Size*, *Number of Firms Covered*, *Number of Industries Covered*, *Forecast Horizon*, and *Forecast Frequency*.

$COVID\_Controls_{i,q}$ = A set of controls that measure the intensity of the COVID crisis in the county where branch b is located. Examples include total number of cases, hospitalizations, and deaths as a percentage of the local population in the county where branch *b* is located, and possibly county × quarter fixed effects. We control for these factors because they are likely correlated with analysts' decision to work from home, and they can also reduce productivity through channels other than WFH (e.g., the analysts may be more likely to have COVID himself or is more likely to be distracted by local news on COVID).

δ_i = analyst fixed effects. This controls for unobservable (time-invariant) measures of analyst quality.

δ_b = branch fixed effects. This controls for unobservable (time-invariant) measures of branch quality.

δ_{bh} = brokerage house fixed effects. This controls for unobservable (time-invariant) measures of brokerage house quality.

$\delta_{j,q}$ = firm × quarter fixed effects. This controls for forecast difficulty (e.g., a large, unexpected earnings surprise) that impacts all analysts covering the same firm in the same quarter.

3.2 Work from Home and Analyst Research Quality - Cross Sectional Patterns

Our second set of tests explore whether costs and benefits of WFH vary systematically across different types of analysts, branches, and brokerage houses by estimating the following panel regression:

$$Y_{\mathrm{i,j,q}} = \beta_1 WFH_{i,q-1} + \beta_2 WFH_{i,q-1} \times CV + \beta_3 Controls_{i,q} + \delta_i + \delta_b + \delta_{bh} + \delta_{j,q} + \varepsilon_{\mathrm{i,j,q.}} \quad (3)$$

All variables are defined as in Equation (2) except that we now include the interaction of *WFH* and *CV*, a conditioning variable. When the conditioning variable is not absorbed by fixed effects, we also include the level of the conditioning variable as a control. We list and motivate below the set of conditioning variables:

- *General Experience* = the number of years the analyst has worked in the industry. We expect that less experienced analysts are more likely to benefit from in-person work since they are likely to learn more from their more experienced colleagues. They also have a smaller network of colleagues to potentially connect with via less formal interactions (e.g., zoom meetings or phone calls).
- *Firm-Specific Experience* = analysts with significant general experience but who are new to covering a specific firm may also suffer relatively more since this is an additional setting where analysts may learn more from colleagues (e.g., a colleague who previously covered the firm).
- *Conglomerate Firms* = Analysts typically specialize by industry. For firms that span multiple industries, learning from colleagues is likely to be particularly important.
- *Valuation Difficulty* = The costs of working from home are likely larger for more cognitively challenging tasks. Thus, we expect any effects are likely to be amplified for harder-to-value firms, such as smaller firms and more volatile firms.

3.3 Work from Home and Analyst Retention and Hiring

3.3.1 WFH and Retention of High-Quality Analysts

One potentially important benefit of permitting analysts to work from home is that it allows the brokerage house (or branch) to retain better talent. To test this possibility, we estimate the following regression:

$$Retain_{\mathrm{i,j,q}} = \beta_1 WFH_{i,q-1} + \beta_2 WFH_{i,q-1} * HQ + \beta_3 Controls_{i,q} + \delta_i + \delta_b + \delta_{bh} + \delta_{j,q} + \varepsilon_{\mathrm{i,j,q.}} \quad (4)$$

All the variables are defined as in Equation (2) except for:

$Retain_{\mathrm{i,j,q}}$ = an indicator equal to one if the analysts (*i*) working for brokerage house (*bh*) in quarter (*q*) continues to work for the same brokerage house in quarter (*q+1*) and zero otherwise.

HQ = an indicator equal to one if the analyst is of high quality. We consider the following proxies:

- *Past Accuracy* = an indicator equal to one if the analysts was in the top quintile of accuracy in the prior year as measured by Clement (1999).
- *Stock Recommendation Performance* = an indicator equal to one if the analyst is in the top quintile of past stock recommendation performance in the prior year as measured in Mikhail, Walther, and Willis (2004)
- *Experience* = An indicator equal to one if the analyst is in the top quintile of past experience. Prior work finds that more experienced analysts issue more accurate earnings forecasts (Clement, 1999).
- *Female* = an indicator equal to one for female analysts. Female analysts have been shown to be more accurate (Kumar, 2010). Plus, existing work suggests that female analysts may place a greater premium on flexible work arrangements (Mas and Pallais, 2017).

The key variable of interest is $\beta_2$which tests whether branches where WFH is more prevalent are also better able to retain their most valuable employees.

3.3.2 WFH and Hiring of High-Quality Analysts

We next examine the association between WFH policies and the hiring of higher quality employees. We estimate the following regression:

$$HQ\ Hire_{\mathrm{i,j,q}} = \beta_1 WFH_{i,q-1} + \ \beta_2 Controls_{i,q} + \delta_i + \delta_{bd} + \delta_{bf} + \delta_{j,q} + \varepsilon_{\mathrm{i,j,q.}} \tag{5}$$

In this test, the sample is limited to new hires defined as an analyst (*i*) who works for brokerage house (*bh)* in quarter (*q)* but did not work for the brokerage house (*bh)* in quarter (*q-1*). The dependent variable is an indicator equal to one if the new hire is classified as high quality and zero otherwise. The quality measures are defined as in Section 3.3.1. Note, for all the quality measures except *Female*, the measure is not defined for new hires that do not have previous experience as a sell-side analyst. We will consider tests that include hires with no prior sell-side analyst experience and code them as being of lower quality (consistent with past experience being a measure of high quality), and we will also consider tests that exclude new hires with no prior sell-side analyst experience.

3.4 Financial Market Consequences of WFH Policies

To the extent that WFH policies affect the quality of analyst research, it is possible that WFH has spillover consequences to the firms covered by such analysts. For example, if WFH is associated with lower quality analyst research, then firms who happen to be covered by a large number of analysts who WFH may experience a deterioration in their information environment relative to firms coverage by analysts who primarily work in the office. While this analysis may not have direct implications for the brokerage house, it is a potentially important externality of WFH policies, particularly given the evidence that declines in a firm's information environment can increase a firm's cost of capital (Kelly and Ljungqvist, 2012) and ultimately spillover to the real economy (Derrien and Kesckes, 2013).

For each firm (*j*) and quarter (*q*), we compute a firm-level measure of WFH as the average WFH value across all the analysts covering the firm. We then estimate the following panel regression:

$$Y_{\mathrm{j,q}} = \beta_1 WFH_{j,q-1} + \ \beta_2 Controls_{j,q} + \delta_j + \delta_q + \varepsilon_{\mathrm{j,q.}} \tag{6}$$

Dependent Variable Definitions:

$Y_{\mathrm{j,q}}$ = proxies for the informational environment of the firm. Following Kelly and Ljunqvist (2012) we consider the following as proxies for the firm's informational environment:

- *Bid-ask spread* = (ask – bid)/(ask + bid).
- *Amihud (2002)* illiquidity measure = the natural log of one plus the ratio of the absolute stock returns to the dollar trading volume and scaled by 10^6.
- *Absolute Earnings Surprise* = the difference, in absolute value, between the firm's realized earnings and the IBES mean consensus forecast, scaled by the stock price at the end of the prior quarter.
- *Absolute Earnings Announcement Return* = the three-day absolute market-adjusted return centered around the earnings announcement date.

Independent Variable Definitions:

$WFH_{j,,q-1}$= The average *WFH* value across all analysts covering firm j in quarter *q-1*.

$Controls_{j,q}$= A set of firm characteristics that the prior literature has shown will impact the outcome variable of interest (*Y*) including firm size, firm age, past returns, analyst coverage, media coverage, etc.

δ_j = firm fixed effects.

δ_q = quarter fixed effects.

4. Conclusion

The trend towards working from home is likely to have profound effects on employee performance. In this proposal, we outline a thorough research agenda which will study how the WFH boon influences sell-side analysts and whether there are implications for financial markets. Although our focus is on analyst brokerage houses, our results will likely have general takeaways for any company that is considering a WFH policy for their employees.

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