THREE ESSAYS IN CORPORATE FINANCE

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Abstract

In the first chapter of my dissertation, I study firm innovation as a transmission channel for monetary policy. Analyzing the impact of unanticipated changes to monetary policy on the cross-section of U.S. equity returns, I show that the sensitivity of firms' equity prices to changes in monetary policy may depend on firms' innovation characteristics. I find that the more the firm employs an exploratory search in its innovation strategy, the higher the sensitivity of its stock price to monetary policy. Further, I present evidence suggesting that variables capturing exploratory and exploitative innovation characteristics of firms may explain the relative sensitivity of firms' future earnings, capital expenditures, and R&D spending to monetary shocks.

In the second chapter of my dissertation, I define a novel measure to capture the timing of the future cash flow generated by the firm's investment in innovation. I call this measure "the duration of firm innovation". I show evidence suggesting that my measure of the duration of firm innovation is a significant channel for the transmission of monetary policy to equity prices.

In the third chapter, I study the effect of work-from-home on employee performance and teamwork in the context of the sell-side analyst industry. Using a difference-in-difference setting utilizing the exogenous adoption of work-from-home following the start of the Coronavirus pandemic, I find that the performances of analysts working both individually and in teams are negatively affected following the adoption of work-from-home. Moreover, I find that following the adoption of pandemic-induced work-from-home, team size becomes negatively related to team performance, supporting the higher coordination costs hypothesis in work-from-home settings. I also find a negative impact of working from home on teams led by female analysts. These findings are in line with the findings of the prior literature which document an unequal impact of work-from-home on female employees due to the unequal burden of household responsibilities.

I extend my profound appreciation to my supervisors, Kee-Hong Bae and Ambrus Kecskes, whose expert guidance and support have been pivotal in shaping my academic journey and scholarly growth.

I proudly dedicate this work to my parents, whose unwavering support and unconditional love have been the bedrock of my accomplishments.

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1 Firm Innovation and The Transmission of Monetary Policy

1.1 Introduction

The Federal Reserve utilizes monetary policy instruments to regulate inflation and unemployment, and to promote economic growth. However, the most direct and immediate effects of policy decisions are observed in financial markets. As highlighted by Bernanke and Kuttner (2005), the Federal Reserve's policy decisions influence asset prices and returns, inducing economic behavior modifications that align with policy objectives.

The literature on transmission of monetary policy scrutinizes how policy decisions propagate through various segments of financial markets, impacting asset returns and economic behavior. A significant body of this literature, with its roots stretching at least back to Tobin (1969) and Modigliani (1971), is dedicated to understanding the transmission channels of monetary policy through the equity markets. Bernanke and Kuttner (2005) find a significant effect of changes in monetary policy on equity prices. They attribute the observed effects to changes in expected future cash flows and changes in the expected excess returns. To investigate the channels linking policy decisions with equity prices and other firm outcomes, previous studies have examined financial constraints (Chava and Hsu (2020)), leverage (Ottonello and Winberry (2019)), liquidity (Gao, Whited, and Zhang (2021)), profitability (Ozdagli and Weber (2017)), and firm age (Cloyne et al (2023)) among other variables.

In this paper, we propose a monetary policy transmission channel that has not been previously examined in the literature, namely, firm innovation. Our empirical strategy proceeds from the notion that the net present value of innovation, much like investments, depends on present value of costs and benefits of innovation, and insofar as monetary policy can change this net present value, there will be a channel for transmission of monetary policy through firms. Understanding the relationship between monetary policy and firm innovation is important to policy makers, investors, and practitioners. Technological innovation is a substantial contributor to economic growth (Schumpeter(1911), Solow(1957), Romer(1986)). Furthermore, Innovation is also vital to a firm's short and long-term competitive advantage (Porter(1992)).

Our analysis is underpinned by Manso's (2011) theoretical framework and the empirical works that have highlighted two distinct key innovation search strategies that firms may choose to adopt: exploration of new capabilities and exploitation of established competencies. Exploratory innovation involves departing from the firm's existing knowledge base and venturing into areas of technology that are new to the firm, while exploitative innovation involves building upon the firm's extant knowledge and refining previously developed technologies. Previous literature associates exploratory innovation with higher levels of uncertainty and risk, and potentially more significant payoff which require a longer-term commitment and higher tolerance for failure. Conversely, exploitative innovation is associated with incremental and process-oriented improvements in familiar practices, a shorter time to realization of payoffs, and lower uncertainty and likelihood of failure (March (1991), Benner and Tushman (2002), Manso (2011), Balsmeier et al. (2017), Gao et al (2018), Fitzgerald et al (2020), and Almeida et al (2021) among others).

Motivated by the above literature, here, we ask whether investors' reactions to monetary policy news are informed by firms' innovation characteristics. Patents are widely used to measure firm innovation characteristics (Hirshleifer, Hsu, Li (2018)); therefore, to answer our research question, we characterize firms based on exploratory or exploitative characteristics of their recent patents. We then analyze the differential impact of unanticipated changes to the monetary policy instrument on equity returns of firms emphasizing exploratory or exploitative innovation. Due to speculative nature of exploratory innovation, we hypothesize that firms who engage more in explorative innovation are more sensitive to interest rate shocks compared to their counterparts who emphasize exploitative search strategy.

The main policy instrument used by the Fed is the target fed funds rate. However, Fed's policy decisions, investors' expectations and underlying economic conditions driving Fed's decisions are endogenous, making casual inferences about the effects of monetary policy challenging. To address this concern, we use monetary shocks, i.e., the unexpected component of the changes to monetary policy, constructed as changes in the price of Fed funds futures contracts in a narrow window around Federal Reserve's Federal Open Market Committee (FOMC) meetings announcements. This approach was pioneered by Cook and Hahn (1989), Kuttner (2001), and Cochrane and Piazzesi (2002) and is henceforth widely used in the literature.

To test our hypothesis, we perform a portfolio-level event study and a firm-level event study. For our portfolio analysis, at each policy FOMC event date, we sort firms into terciles based on their exploratory or exploitative innovation characteristics. We then, over windows of various lengths following the policy announcement, model the *High*, *Mid* and *Low* exploratory or exploitative equal-weighted portfolio returns on the monetary shocks. As expected, all portfolios exhibit negative (positive) reactions to contractionary (expansionary) shocks. However, two clear patterns emerge: First, for each portfolio, the significance and magnitude of returns increase with the length of the post-event window, indicating a drift in market reaction to monetary policy. This result is consistent with Chava and Hsu (2020) who find a drift in the response of financially constrained firms to monetary shocks. Second, we observe negative (positive) and significant returns for the *High* exploratory (exploitative) portfolio relative to the *Low* exploratory (exploitative) portfolio in the days following a contractionary shock. The differential return between the portfolios is significant and increases as the length of the post-event window increases.

To further test our hypothesis, we perform a firm-level event study by regressing firm-level cumulative abnormal returns on the interaction of monetary shocks and firm exploratory or exploitative characteristics. We include a battery of control variables and fixed effects. Our most demanding setting includes firm-quarter fixed effects which difference away all firm characteristics within the same quarter as the monetary shocks. We find consistent results across all settings, confirming our portfolio-level findings. Following a contractionary shock to monetary policy, on a relative basis, explorative (exploitative) firms earn significantly lower (higher) cumulative abnormal returns. Total innovation or R&D expenditure do not explain the observed effects. When we interact number of patents and other control variables with the monetary shocks, the transmission effects for exploratory or exploitative innovation characteristics become even stronger. Additionally, we find suggestive evidence that more innovative firms, i.e., firms with more patents in their innovation portfolio, are more sensitive to monetary policy.

Overall, our event-study analyses put forth evidence of an innovation channel for transmission of monetary policy to equity prices. Our results support the hypothesis that the market incorporates information about firm innovation characteristics when reacting to changes in monetary policy; the more the firm deviates from its existing knowledge base and adopts an explorative innovation search strategy, the more sensitive the firm stock price will be to interest rate fluctuations. As a result, following a contractionary (an expansionary) change in monetary policy, the equity price of exploration-inclined firms will be more negatively (positively) affected.

Next, we investigate the economic channels underlying the innovation-driven heterogeneity in sensitivity of equity prices to monetary policy. Specifically, we study the mediatory effect of firm innovation characteristics on the real impact of monetary policy on firm fundamentals. To this end, following Daniel, Garlappi and Xiao (2021) and Ottonello and Winberry (2020) and other recent empirical work, we use the local projection method developed by Jorda (2005) in a quarterly panel data setting and examine impulse responses of firm fundamentals to interaction of firm innovation characteristics and monetary policy shocks.

We begin by investigating the degree of variations in passthrough of monetary shocks to firm earnings based on firm innovation characteristics. This inquiry proceeds from the understanding that equity prices reflect discounted future cash flows. Moreover, the literature, including Bernanke and Kuttner (2005) and Chava and Hsu (2020), has established a link between the cash flow channel and the transmission of monetary policy. Our findings are consistent with the results from our event study; future earnings of firms emphasizing exploratory innovation are more sensitive to monetary shock. Put another way, a contractionary shock to monetary policy leads to significant relative decline in future earnings of firms emphasizing exploratory innovation, and a significant relative increase in future earnings of firms emphasizing exploitative innovation. Similar results are observed for firm investments: Firms emphasizing exploratory innovation experience a relative negative effect on their capital stock several quarters after a contractionary shock. These findings suggest that as the firm deviates from its existing knowledge base, its earnings and investments become more sensitive to changes in interest rates. For such a firm, as the interest rates increase, its ability to extract value from its innovation portfolio is negatively affected and the firm reduces its future capital expenditures.

Next, we examine the effect of monetary shocks on firms' R&D spending based on their innovation characteristics. Moran and Queralto (2017) find that R&D responds positively to expansionary monetary policy. Our baseline results confirm their findings. We, however, find that after a contractionary shock to interest rates, firms emphasizing exploratory innovation do not decrease their R&D spending as much as their counterparts.

Overall, our impulse-response analyses suggest a significant innovation-based passthrough of monetary shocks to firm outcomes. Following an expansionary shock to monetary policy, a firm whose innovation portfolio emphasizes exploratory search strategy experiences a relative increase in earnings and investments and a relative decline in R&D.

To the best of our knowledge, ours is the first paper exploring firm innovation as a transmission channel for monetary policy by studying interaction of macro-level shocks and cross-firm heterogeneity in innovation characteristics. In doing so, this paper contributes to various strands of literature. We contribute to the literature studying the impact of monetary policy on firms. Bernanke and Kuttner (2005) find that a hypothetical unanticipated 25-bp cut in the Federal funds rate target is associated with about a 1% increase in broad stock indexes. They attribute their findings to the effect of monetary policy on excess returns and on expected cash flows. Cieslak et al (2019) note a biweekly pattern in average excess stock returns over the FOMC cycle. Ozdagli (2018) and Chava and Hsu (2020) examine financial constraints as possible channel for transmission of monetary policy to equity prices. In contrast to Ozdagli (2018), Chava and Hsu (2020) suggest that financially constrained firms are more sensitive to monetary shocks.

We also build on and contribute to the literature on firm innovation. We lean on the literature that recognizes a tension within a firm when strategizing innovation between exploration and exploitation. As March (1991) notes, "the search for new ideas… has less certain outcomes, longer time horizons, and more diffuse effects than does further development of existing ones". Exploratory and exploitative innovations have been examined in various contexts in empirical corporate finance. Balsmier et al (2017) find that firms that transition to independent boards focus more on exploitative innovation. Gao et al (2018) compare innovation strategies of private and public firms and find that private firms' patents are more explorative. Almeida et al (2021) suggest that firms who experience sudden influx of cash flows, especially the ones with weaker governance, are more likely to employ an exploratory search strategy in their innovation. Byun et al (2021) show that technology spillovers promote exploitative innovation.

Moreover, we extend the literature examining the relationship between firm innovation characteristics and stock returns. Kogan et al (2017) examine stock market response to news about patents to generate estimates for economic value of patents. Fitzgerald et al (2020) find that innovative firms focusing on exploitation rather than exploration tend to generate superior subsequent short-term operating performance and are more likely to be undervalued. Similarly, Hirshleifer et al (2018) find that firms' innovative originality strongly predicts higher abnormal stock returns.

Overall, our paper presents evidence that is consistent with the findings of the innovation literature which attributes higher uncertainty and longer horizon to exploratory innovation. Our findings suggest that the value implications of monetary policy are larger for firms with higher share of exploratory patents in their innovation portfolio. However, there is a drift in manifestation of the return differential.

1.2 Data and Variables

Our dataset is defined at the intersection of United States Patents Office (USPTO) citation dataset, Kogan, Papanikolaou, Seru and Stoffman (2017) (KPSS) patent dataset, and the monetary shocks time series data from Acosta (2022) and Gorodnichenko and Weber (2016). For this sample of US firms, we use CRSP to calculate the stock returns and use Compustat Quarterly to calculate accounting panel variables such as earnings and capital expenditures. We drop firms belonging to financial industry identified with 4-digit SIC codes between 6000 and 6999. Moreover, from the sample, we drop observations with negative quarterly assets, sales, cash, and long-term debt. Further, firms with market capitalization less than $10 million, or return on equity less than −100% are dropped from our sample.

1.2.1. Innovation Variables

To measure the innovation output of firms, we use Kogan, Papanikolaou, Seru and Stoffman (2017) (henceforth KPSS) patent data. This dataset contains information about the application and grant date of patents. KPSS is especially useful in studying corporate innovation because it employs a disambiguation method that matches patents to their owners through PERMNO identifier. As a result, the link between patents and public firms that have developed them is straightforward. The updated KPSS patent data includes information on all the patents filed between 1926 and 2022. We also directly use United States Patents Office (USPTO) citation dataset. This dataset records each citing patent and its corresponding cited patent, thus enabling us to construct variables that are based on citations.

Since our goal is to study how innovation characteristics affect firms' outcomes, following Hirshleifer, Hsu, Li (2018) and others, we look at firms' innovative activities during five-year windows prior to each FOMC meeting at time t. Thus, our analyses exclude non-innovative firms who have not filed any patents during this five-year period. Based on the databases mentioned above, we develop our innovation variables as follows. First, to proxy for firm innovation characteristics at time t, we look at a five-year-window prior to time t. For each t, we define *Num* as the number of filed patents by firm i. Following Benner and Tushman (2002), for each patent p

filed by firm *i* during the window, *Explore* (*Exploit*) is an indicator variable equal to 1 if more (less) than 80 (20) percent of the patents that the patent *p* cites adhere to these two conditions: First, these cited patents do not belong to the originating firm *i* and second, the originating firm has not cited these patents before. For each t, we aggregate *Explore* and *Exploit* at the firm *i* level by taking their respective means. For our quarterly panel data analysis, we aggregate the innovation variables 5 years prior to each quarter end date.

1.2.2. Firm Characteristics

For our event-study analyses, we follow Chava and Hsu (2020) and include quarterly values for firm log of assets, log of market to book ratio, return on assets and leverage as our control variables. Further, since the effect of financial constraints is documented in the literature (Chava and Hsu (2020), Ozdagli (2018)), we calculate the Whited and Wu (WW) index as our measure of financial constraint and include it as a control variable. Moreover, since we are studying the monetary transmission effects of firm innovation characteristics, we add total recent innovation activity of the firm, proxied by log number of patents within the past 5 years, and firm R&D expenditure over total assets as control variables. We replace missing values of the R&D variable with zero.

Log of assets is defined as log of total assets (Compustat item *atq*). Market to book ratio is defined as stock price (Compustat item *prccq*) multiplied by shares outstanding (Compustat item cshoq) divided by total book value of equity (Compustat item *ceqq*). Return on assets is defined as income before extraordinary items (Compustat item *ibq*) divided by total assets. Leverage is defined as sum of short-term debt (Compustat item *dlcq*) and long-term debt (Compustat item *dlttq*) divided by total assets. WW index is defined following Whited and Wu (2006).

For our dynamic quarterly panel data analyses, we use log earnings, log capital expenditures, and log R&D expenditure as our dependent variables. For earnings, we use EBITDA defined as the sum of net income (Compustat item *niq*), depreciation (Compustat item *dpq*), interests (Compustat item *xintq*), and taxes (Compustat item *txtq*). We also use net income defined as item *niq* over *atq*. For R&D we use Compustat item *xrdq*. We replace missing values of R&D variable from Compustat with zero. To calculate quarterly capital expenditure flows, we use Compustat item *capxy* as follows. For the first fiscal quarter (Compustat item *fqtr*) capital expenditures will be equal to *capxy*. For fiscal quarters 2 to 4, capital expenditures will be the *capxy* value in the fiscal quarter minus the *capxy* value of the previous fiscal quarter.

Table 1.1 presents the summary statistics for innovation as well as firm characteristics. Panel A presents the descriptive statistics at the firm-FOMC level and Panel B presents the same statistics aggregated at the firm-quarter level.

[insert table 1.1 here]

Table 1.2 presents the pairwise correlation among all the regression variables.

[insert table 1.2 here]

As expected, *Explore* and *Exploit* variables are very negatively correlated (correlation = -0.82). Similarly, Log number of patent is positively (negatively) correlated with the *Explore* (*Exploit*) variable. The greater the number of recent patents in the firm's innovation portfolio, the more its innovation portfolio to be exploitation oriented. As the correlation between Explore (Exploit) and firm age shows, as the firm gets older, it's more likely to innovate based on its existing knowledge base.

1.2.3. Monetary Shocks

To capture the effect of interest rates on innovative firms, we use high-frequency monetary shocks measured in a narrow window around each Federal Open Market Committee meeting. To construct the shocks, we follow the literature and use unexpected changes in the price of the same month fed funds futures contract during the 30-minute (-10,+20) window around each FOMC meeting.

Fed funds futures are traded on the Chicago Board of Trade. The contracts are cash settled on the last business day of their expiry months. Fed funds futures contract for month *m* trades at *p* and pays off 100-*r* where *r* is the average realized effective fed funds rate over the month. Each day, the value-weighted average inter-bank rate (the effective fed funds rate) is calculated and announced by the Federal Reserve Bank of New York. At any point in time, the price of same-month expiry fed funds futures contract is arithmetic average of realized (for the portion of the month already passed) and expected (for the portion of the month still left) fed funds rate.

Suppose we are at time *t*, right after the FOMC announcement when *d* days have passed in the month with *m* days and $r_{(0,t)}$ is the average daily effective fed funds rate (*EFFR*) for the first *d* days and $E_t\left[r_{(t,T)}\right]$ is the expected average daily *EFFR* for the remainder of the month. If f_t is the price of the same-month-expiry futures contract at time t, then

$$f_t = \frac{d}{m}\, r_{(0,t)} + \frac{m-d}{m}\; E_t\left[r_{(t,T)}\right]$$

If $t - \Delta t$ indicates the time right before the FOMC announcement, then

$$f_{t-\Delta t} = \frac{d}{m}\, r_{(0,t)} + \frac{m-d}{m} E_{t-\Delta t}\left[r_{(t,T)}\right]$$

Then we can derive the unexpected shock to fed funds rate as

$$\Delta i^u = E_t[r_{(t,T)}] - E_{t-\Delta t}[r_{(t,T)}] = \frac{m}{m-d}(f_t - f_{t-\Delta t}) \quad (1)$$

The expected change in the fed funds rate then can be written as:

$$\Delta i^e = \Delta i - \Delta i^u$$

Where Δi is the total change in the target fed funds rate announced by the FOMC. Krueger and Kuttner (1996) suggest that fed funds futures prices help identify unexpected fed funds rate changes and provide an efficient forecast of future rate changes.

For the period of 1999-2021 we use monetary shocks from Acosta (2022). For the period of 1994-1999, we supplement Acosta's series with the shock series from Gorodnichenko and Weber (2016). The resulting shock time series identify the shocks in a 30-minute-window around each FOMC meeting announcements which are made within a few minutes of 2:15 pm Eastern Time. During this 30-minute window, the only relevant shock (if any) to rates is likely due to changes in monetary policy. The first monetary shock in our sample is on Feb 4th, 1994, and the last shock is on Dec 15th 2021. Before 1994, monetary policy decisions were not announced, and investors had to infer policy actions through the size and type of open market operations in the days following each meeting (Lucca and Moench (2015)). To make sure no overlap exists across event windows and there's sufficient distance between our monetary shocks, we exclude FOMC meetings on 07 Aug 2007, 10 August 2007, 17 August 2007, 22 January 2008, 30 January 2008, 11 March 2008 and 18 March 2008[1]. We also drop the shock from the FOMC meeting on 17 September 2001.

[1] Alternatively, we include these event days but limit the event windows for these events to 2 days post FOMC date. Our results remain robust.

As is the convention in the literature, throughout our analyses, a positive value for Δi^u means an increase in the interest rates and thus a contractionary monetary shock.

[Insert table 1.3 here]

Table 1.3 reports descriptive statistics for the monetary policy shocks. Panel A is the full sample; panel B is negative total rate changes by the Fed; panel C is positive total rate changes; and panel D is the summary for the days on which the policy was left unchanged by the Fed. In total, we have 225 monetary events. FOMC meetings are on average 45 days apart. According to panel A, the average total target rate change is 0.444 bps and the average unexpected rate change is -0.818 bps. The most negative shock is -43.8 bps, about three times as large in absolute value as the most positive shock which is 16.3 bps. Panel B indicates that 40 of FOMC events are positive/contractionary policy announcements. Average positive announcement for this subsample is 28.75 bps, close to the 25 bps standard policy step. For this subsample, the average unexpected policy shock is 2.22 bps. According to panel C, the average target decrease announced by the Fed is -37.5 bps. The surprise component of the announcement for this subsample is -7.01 bps. Lastly, Panel D indicates that there are 157 days on which the fed didn't announce any changes to the target rate. The average rate shock on these days is expectedly at -0.488 bps.

[Insert figure 1.1 here]

Figure 1.1 illustrates the evolution of monetary policy throughout our sample period by showing total rate change, as well as the unexpected and expected components of the policy announcements in panel A, B, and C respectively.

1.3. Empirical Analysis

To examine innovation-based cross-firm heterogeneity in market reaction to monetary shocks, we perform a portfolio-level event study and a firm-level event study. We then, in a quarterly panel data setting, study the underlying economic channels which may drive the effects we observe in our event studies.

1.3.1. Event Study

1.3.1.1. Portfolio-level returns

At each FOMC event date and for each firm, we calculate cumulative abnormal market-adjusted return over windows of various lengths starting at the day of the event. Moreover, we sort firms into *High*, *Mid* and *Low* tercile portfolios based on their exploratory or exploitative innovation characteristics, *Explore* and *Exploit*, calculated prior to each event date. Next, for each event-window, we calculate equal-weighted tercile portfolio returns. We then, regress the *High*, *Mid* and *Low Explore* or *Exploit* equal-weighted portfolio returns on the monetary shocks using the following regression model:

$$r_s^{port} = \alpha + \beta \cdot \Delta i_s^u + \epsilon_s^{port} \tag{2}$$

Where *s* denotes time of the monetary shock. Δi_s^u is the unexpected monetary shock at *s* expressed in percentage points. A positive (negative) value for Δi_s^u means a contractionary (an expansionary) shock to monetary policy. Since there are 225 event dates, each regression will have 225 observations.

Table 3 and 4 present the portfolio performance around FOMC announcement days for *Explore* or *Exploit* innovation characteristics respectively. In both tables, Column 1 indicates equal-weighted portfolio return of all firms in the sample while columns 2, 3, and 4 indicate equal-weighted return of *Low*, *Mid*, and *High* portfolios.

[Insert table 1.4 here]

Reviewing table 1.4, we observe that as expected, all portfolios exhibit negative (positive) reactions to contractionary (expansionary) shocks. However, three clear additional patterns emerge: first, for each portfolio, the significance and magnitude of returns almost invariably increase with the length of the post-event window, indicating a drift in market reaction to monetary policy. This result is consistent with Chava and Hsu (2020) who find a drift in the response of financially constrained firms to monetary shocks. Second, when the length of post-event window is greater than 1 day, which is the case for panels B through E, *High* E*xplore* portfolio return is more negative than *Mid* Explore portfolio return which itself is more negative than the return of *Low Explore* portfolio. Third, the differential return between the portfolios becomes larger as the length of the post-event window increases. Moreover, the differential return between *High* and *Low* portfolios is significant at the 1% level across all panels. Combined, results from table 3 indicate that the higher the ratio of exploratory patents in a firm's innovation portfolio, the more sensitive its stock price to monetary shocks. Moreover, there is a drift in manifestation of the sensitivity.

[insert table 1.5 here]

Table 1.5 confirms the findings of table 1.4, using *Exploit* variable which captures the degree of emphasis the firms put on exploiting the areas of technology familiar to them. Same patterns observed in table 4 are observed in table 5. The *Low Exploit* portfolios earn significantly lower return compared to *High Exploit* portfolios, and the return differential becomes significantly larger as the length of the post-even window increases.

1.3.1.2. Firm-level returns

To further study the innovation-based variation in passthrough of monetary policy to firm values, we perform an event-study using a panel regression of event window returns around FOMC event-days. Compared to portfolio setting, firm-level event study dramatically increases the number of observations and allows us to control for firm-level characteristics and fixed effects. Firm-level cumulative abnormal returns (CARs) are regressed on *Explore* or *Exploit* innovation characteristic and interest rate shocks and their interaction:

$$CAR_{j,s}^{(0,5)} = \beta EXP_{j,s} \Delta i_s^u + \delta\, EXP_{j,s} + \gamma \Delta i_s^u + \eta\, \Gamma_{\mathrm{j,q}} + \zeta_{kq} + \epsilon_{j,s} \qquad (3)$$

s, j, and q denote monetary shock, firm and quarter respectively. $CAR_{j,s}^{(0,5)}$ is the cumulative abnormal return from the day of the FOMC meeting to 5 days afterwards. We use a 5-day post-event window since our portfolio-level analyses, document a drift in the response to monetary news. $EXP_{j,s}$ is our firm-level innovation variable of interest, *Explore* or *Exploit*, defined over a 5-year window prior to the shock *s*, and Δi_s^u is the unexpected change in Fed funds rate at time *s*. $\Gamma_{j,q}$ is a vector of control variables. From Compustat quarterly, we use firm size, market to book ratio, leverage, return-on-assets, and R&D over assets at the end of the quarter prior to the monetary shock. The financial constraints measure by Whited and Wu (2006) is also defined using Compustat variables and added as a control variable. Since we're studying firm innovation characteristics as a transmission channel, we control for total innovation activity of the firm measured by natural log of firm's total number of patents filed over the the 5 years prior to the shock s. All control variables except the Whited and Wu index are winsorized at the 1% level. ζ_{kq} is a set of fixed effects. k can denote firm or industry.

Table 6 presents results when we use *Explore* to characterize firm innovation. An increase in our monetary shock Δi^u means a contractionary shock to the aggregate rate. Standard errors are clustered at the firm and event level.

[Insert table 1.6 here]

In column 1 of table 1.6, no fixed effects are used. In column 2, industry and quarter, and in column 3 interaction of industry and quarter fixed effects are used. In column 4 firm and quarter fixed effects are used. Our most demanding setting is presented in column 5 in which we use interaction of firm and quarter fixed effects. Since firms *Explore* or *Exploit* characteristics could change within the quarter in which treatment is taking place, we are able to isolate the treatment effect by differencing away all firm characteristics which are fixed within the quarter. This will remove the possible endogenous-to-treatment effects of any information conveyed to investors at the end of each fiscal quarter prior to the event. As a result, any remaining observable or unobservable factors which affect investor behavior and could potentially impact the treatment outcome have to have variation within the quarter in which treatment is taking place.

The results presented in table 1.6 confirm the main hypothesis of this paper. Across all settings, the interaction coefficient is significant at the 1% level. The negative sign of the coefficient of the interaction variable between *Explore* and Δi^u indicates that the values of firms emphasizing exploratory innovation are more sensitive to aggregate shocks. Put another way, the more the firm employs exploratory search in its innovation strategy and deviates from its existing knowledge base, the more negative (positive) its stock price will react to contractionary (expansionary) shocks.

If the above results using *Explore* variable are robust, we expect to see an opposite effect when we use *Exploit* variable to measure the degree to which the firm deviates from its knowledge base. From the outset, observing the opposite effects using *Exploit* is not a certainty; since a firm could use both search strategies in its innovation portfolio, *Explore* and *Exploit* are diagonally related but are not exact opposite of each other. Therefore, a-priori it is not clear whether using *Exploit* variable instead of *Explore* would confirm the results we obtain in table 1.6.

Table 1.7 presents the results when we use *Exploit* in model (3) to indicate innovation characteristics of firms. As in table 1.6, an increase in our monetary shock Δi^{u} means a contractionary shock to the aggregate rate. Standard errors are clustered at the firm and event levels. Fixed effects specifications are also similar to table 7.

[Insert table 1.7 here]

The results presented in table 1.7 further confirm our main hypothesis. Across all settings, including column 5 with interaction of firm and quarter fixed effects, the coefficient on the interaction of monetary shock, Δi^{u}, and *Exploit* variable is positive and significant at the 1% level. This means the more the firm relies on its extant knowledge in its innovation search strategy, the less sensitive its stock price will be to changes in the aggregate rates. Such a firm would react less negatively to contractionary shocks and less positively to expansionary shocks.

The effects observed in table 1.6 and 1.7 are also economically significant. As indicated by results in column (5) of table 1.6, a median-sized increase of 0.455 in *Explore* innovation characteristics combined with a standard 25 bp step down in target rate leads to a statistically significant differential cumulative abnormal return of around 0.55% for the firm (4.812 x 0.455 x 25bp). Similarly, based on column (5) of table 1.7, a median-sized increase of 0.278 in *Exploit* innovation characteristics combined with a standard 25 bp step up in target rate leads to a statistically significant differential cumulative abnormal return of around 0.5% for the firm (7.21 x 0. 278 x 25bp). These differential returns are comparable to the findings of Bernanke and Kuttner (2005) who show that a hypothetical unanticipated 25-basis-point cut in the Federal funds rate target is associated with about a 1% increase in broad stock indexes.

Overall, our event-study analyses suggest an innovation channel for transmission of monetary policy to equity prices. Our results support the hypothesis that the market incorporates information about firm innovation characteristics when reacting to changes in monetary policy; the more the firm deviates from its existing knowledge base and adopts an exploratory innovation search strategy, the more sensitive the firm stock price will be to interest rate fluctuations. As a result, following a contractionary (an expansionary) change in monetary policy, the equity price of exploration-inclined firms are more negatively (positively) affected. The opposite effect is observed for exploitation-inclined firms.

1.3.1.3. Event study robustness

In the previous subsection, we measure the innovation-based effect of monetary policy on firm values over a 5-day window after each FOMC event. Our portfolio-level analysis suggests a drift in response to monetary policy. Similarly, Chava and Hsu (2020) note a drift in response to monetary shocks based on financial constraints. To examine firm-level innovation-based drift in the response to monetary policy and to make sure there are no reversals in the observed effects when the lengths of the event windows are modified, we first repeat our firm-level event study over windows of various lengths starting at the day of the FOMC event. The results for both

Explore and *Exploit* variables are presented in table 1.8 which extends the event windows as far as 15 days after the FOMC meeting. All columns use interaction of firm and quarter fixed effects. Standard errors are clustered at the firm and event levels.

[Insert table 1.8 here]

For all event windows in table 1.8, we find robust effects consistent with the result of our firm-level event studies presented in tables 1.6 and 1.7. We don't observe any reversals in the transmission effects documented for either *Exploit* or *Explore* variables. More interestingly, when we extend our event windows up to 10 days after the shock, the magnitude and significance of the coefficients of interest increase.

Lucca and Moench (2015) document a pre-FOMC announcement drift. To make sure our results are not simply a reversion of the pre-announcement drift documented by Lucca and Moench (2015), we repeat our firm-level event study with event windows starting one day prior to the FOMC meeting. If the observed post-announcement effects are simply capturing reversion of the documented pre-announcement drift, the observed effect should disappear if we include the day prior to the FOMC meeting in our event windows. On the contrary, we find that the significance and magnitude of the coefficients of interest remain almost unchanged (results are presented in the appendix table A1.2).

In our firm-level analyses, we use log number of patents and R&D scaled by total assets as control variables. In doing so, we measure the marginal effect of *Explore* or *Exploit* characteristics of firm innovation on transmission of monetary policy to equity prices while keeping total innovation and R&D activity of the firm fixed. It is possible that total innovation and research activity of firms affect transmission of monetary policy shocks to equity prices. If this is the case, it is also possible that the effects we observe using *Explore* or *Exploit* variables are partially captured by the total innovation or research activity of the firm. To address this concern, in our firm-level regressions, we interact log number of patents, R&D over assets and other control variables with the policy shocks. Results for event windows of various lengths are presented in table 1.9.

[insert table 1.9 here]

Comparing the results from table 8 with the results presented in table 1.6 and 1.7, we observe that adding the interactions of *Lnum* and R&D with the monetary shock to the model does not weaken the transmission effect we documented earlier for *Explore* and *Exploit*. In fact, the magnitude and significance of the coefficients on interaction of shocks and *Explore* and *Exploit* variables increase. For example, according to column 5 of tables 1.6 and 1.7, the interaction coefficients on *Explore* and *Exploit* are -4.812 and 7.2 respectively. The coefficients for the same interaction variables presented in table 8 are -7.762 and 9.128 respectively.

Moreover, we observe in table 1.9 that the signs of the interaction terms for both *Lnum* and R&D over assets are negative but the coefficients are insignificant and therefore we cannot make any inference about the transmission effects of firms' innovation and R&D activities to equity prices.

Next in our robustness tests, in addition to exploratory or exploitative characteristics of firm innovation, we take into consideration differential transmission effect for firms with high vs low innovation activity prior to monetary shocks. Since *Explore* and *Exploit* variables are defined as proportion of exploratory or exploitative patents over total number of recent patents in the firm's innovation portfolio, it is possible that the observed transmission effect is mainly driven by the firms with few recent patents prior to the policy shocks. Moreover, it can be argued that when firms have more patents in their innovation portfolio, investors have more information about innovation search strategy recently employed by firm and as a result, investors can characterize firms more accurately prior to monetary shocks. If this is the case, the effect we document would be more pronounced for firms with higher number of recent patents. Therefore, to make sure our results are robust to exclusion of firms with small number of patents, we repeat our firm-level analysis but only include firm-event pairs for which the firm has more than 5 patents prior to the event. Doing so reduces the number of observations from 221,284 to 143,632. Results which are available in appendix table A1.3, show that the magnitude and coefficients of interest increase substantially across all event windows. For example, in column 5 in tables 1.6 and 1.7, the value of coefficients on interaction of *Explore* and *Exploit* and monetary shock are -4.81 and 7.21 respectively. As presented in column 3 of table A1.3, when we drop firms with five or fewer patents prior to each event, the coefficients change to -11.44 and 15.55 respectively and the statistical significance of the coefficients increases. Similar results are observed if we limit the sample to firm-event pairs in which the firm has 10 or more recent patents prior to the event. These findings support our conjecture that when investors have access to a higher number of recent patents for the firm, they are able to characterize firm innovation portfolio more accurately and therefore react more sharply to policy shocks.

Additionally, to make sure our results are not mainly driven by young firms with few patents, we calculate firm age as the distance between the event date and the date of the earliest firm data availability on Compustat. We then, in addition to dropping firms with 5 or fewer number of patents, drop firms younger than 5 years old at the time of the event. Results, presented in appendix table A4, indicate that the magnitude and significance of the coefficients of interest do not change in a meaningful way compared to table A1.3.

Finally, since the Federal Reserve followed a prolonged expansionary policy in response to the financial crisis of 2007-2008, it is possible that the effects we observe are attributed to the low-rate environment and the zero lower bound which was in effect for much of the 2010s. However, as indicated by table A1.5 in the appendix, our results are robust to limiting the sample to monetary events prior to August 2007.

1.3.2. Innovation-based heterogeneity and firm outcomes

In this section, we investigate the economic channels underlying the innovation-driven heterogeneity in sensitivity of equity prices to monetary policy. Specifically, we study the mediatory effect of firm innovation characteristics on the real impact of monetary policy on firm fundamentals. To this end, following Daniel, Garlappi and Xiao (2021) and Ottonello and Winberry (2020) and other recent empirical work, we use the local projection method developed by Jorda (2005) in a quarterly panel data setting to examine dynamic responses of firm fundamentals to the interaction of firm innovation characteristics and monetary policy shocks. Local projection allows us to estimate the impulse responses without specifying the underlying multivariate dynamic system[2]. Using local projection, we can also take advantage of the large cross-sectional dimension of our quarterly panel data (Daniel, Garlappi and Xiao (2021)).

For our quarterly panel setting, we follow Daniel, Garlappi and Xiao (2021) who sum up the monetary shocks at the annual level and Ottonello and Winberry (2020) who sum up the monetary

[2] For comparison between local projection and VAR see Jorda (2005), Montiel Olea and Plagborg-Møller (2021), and Lusompa (2022)

shocks at the quarter level and aggregate FOMC shocks, which on average occur every 45 days, at the quarter level. For each quarter t, we sum up the high-frequency shocks from the end of quarter t-1 to the end of quarter t.

$$\Delta i_t^u = \sum_{t' \in t} \Delta i_{t'}^u$$

Δi_t^u can be thought of as an imperfect quarterly measure of structutal monetary policy shocks which cannot be observed. If $\Delta i_{t'}^u$ shocks are uncorrelated with monetary and other types of structural shocks at other points in time, then their aggregation at the quarter-level, Δi_t^u, will also be independent of these shocks (Jeenas (2019)). Moreover, for each quarter *t*, we calculate innovation-based variables *Explore*, *Exploit* and log number of patents over a five-year window prior to the end of quarter t-1. We implement local projection method using the regression model

$$Log\left(outcome_{i,t+h}\right) = \beta_h \, EXP_{i,t-1} \, \Delta i_t^u + \delta \, EXP_{i,t-1} + \psi \, \Delta i_t^u + \zeta \Gamma_{\mathrm{i,t-1}} + ind_{n,t+h} + \epsilon_{i,t+h}$$

$$with \; h = 0,1, \dots, H \text{ and } X \in \{Explore, Exploit\}$$

As outlined above, we are regressing h-forward values of our outcome variables of interest on lagged values of our quarterly measure of interest rate shocks Δi_t^u and firm innovation characteristics $EXP_{i,t-1}$. $\Gamma_{i,t-1}$ is our vector of firm-level controls. To ensure exogeneity to monetary shocks, we measure control variables with a one-period lag at prior quarter t-1. We use size, market-to-book ratio, leverage, and financial constraints measured by Whited and Wu (2006) index in our local projection regressions. We include financial constraints in our controls since prior literature identifies balance sheet liquidity and financial constraints as determinants of firm outcomes in reaction to monetary policy shocks. $ind_{n,t+h}$ indicates industry-quarter fixed effects at the SIC 3-digit level. To control for outlier observations which might affect the estimates, we winsorize all our control variables (except WW index) at the 1% level. Standard errors are clustered at the firm and quarter level.

In the following subsections, we study firm earnings, capital expenditures, and R&D spending as outcome variables which might be affected by innovation-based heterogeneity in transmission of monetary policy.

1.3.2.1 Firm Earnings

In our event study analysis, we have shown that firms emphasizing exploratory innovation are more sensitive to interest rate fluctuations. Insofar as investors are discounting future free cash flows when reacting to monetary policy, we expect to see corresponding effects on firms' future earnings. Therefore, the first category of firm outcomes we study in this section is firms' earnings. The goal is to estimate how measures of firm *i*'s earnings at horizon $h \geq 0$ respond to monetary shocks aggregated at time *t* conditional on firm *i*'s innovation portfolio characteristics measured by our variables *Explore*, and *Exploit*. We use net income as our first measure of earnings. Figure 2 presents the impulse response function estimates as well as their 95% confidence interval for our coefficient of interest $\beta_h^{net\ income}$.

[insert figure 1.2 here]

Figure 2a shows the estimates for the *Explore* measure of firm innovation. Impulse responses confirm our cash flow hypothesis; future cash flows of firms who emphasize exploratory search strategy are more sensitive to monetary policy. These firms tend to experience relatively lower earnings in the quarters after a contractionary monetary shock. The differences based on the point estimates become negative immediately in the quarter following the shock and stay negative for the next 15 quarters. Furthermore, they become statistically significant four quarters after the shock and remain significant nine quarters after the shock. Four quarters following the shock, a surprise standard 25 bp step up in target rate combined with one standard deviation increase of 0.33 in *Explore* leads to a statistically significant relative decline of 2.13% in earnings (25.82 x 0.33 x 25 bp). If the results observed in figure 2a are robust, we expect to see an opposite effect when we use the *Exploit* variable to characterize firm innovation. Panel 2b shows the net income impulse responses for the *Exploit* variable. As expected, point estimates indicate the opposite effect compared to figure 2a. The differences based on the estimates become positive immediately in the quarter following the shock and stay positive for the next fourteen quarters. Furthermore, they become statistically significant four quarters after the shock and remain significant nine quarters after the shock.

Since monetary policy affects the amount of interest paid on debt, it is possible that the effect we observe in figure 2 is driven by the effect of monetary policy transmitted though the balance sheet channel. To ensure our earlier results are robust to the effects of monetary policy on interest payments and taxes, we use EBITDA as an alternative measure of firm earnings defined as net income plus interest, depreciation, and taxes. Figures 3a and 3b show the EBITDA impulse responses when we characterize firm innovation by *Explore* and *Exploit* respectively. Results from figure 3 further confirm our cash flow hypothesis.

[insert figure 1.3 here]

Overall, our earnings analyses support the result from our event studies. The more the firm deviates from its extant knowledge and ventures into areas of technology not in its core competencies, the higher the sensitivity of its stock price and future cash flows to monetary policy.

1.3.2.2 Capital Expenditures

Our earlier results documenting innovation-based heterogeneity in the response of equity prices and future cash flows to monetary policy motivates analyses of capital expenditures as outcome variable. To the extent that capital expenditures is financed by future free cash flows, there is a channel for monetary policy to impact the firm's future investments. Furthermore, we have shown that innovation-based heterogeneity significantly affects equity prices, which in turn could affect financing of future investments through equity. Therefore, we may expect that future investments of firms who deviate from their existing knowledge base are more sensitive to interest rate fluctuations. Impulse responses shown in figure 4 confirm our hypothesis.

[insert figure 1.4 here]

Impulse responses in figure 4a are generated using *Explore* to characterize firm innovation. The investment differences based on the point estimates become negative immediately in the quarter following the shock and stay negative for the next 20 quarters. Furthermore, they become statistically significant five quarters after the shock and remain significant for several quarters. Four quarters after the shock, a surprise standard 25 bp step up in target rate combined with one standard deviation increase of 0.33 in *Explore* leads to a statistically significant relative decline of 1% in investments (12.49 x 0.33 x 25 bp). As illustrated in figure 4b, the investment responses are robust to using *Exploit* to measure deviation from core competencies; point estimates indicate opposite effect compared to figure 4a. The differences based on the point estimates become positive immediately in the quarter following the shock and stay positive for the next nineteen quarters. Furthermore, they become statistically significant three quarters after the shock and remain significant eight quarters after the shock.

1.3.2.3 R&D

The innovation-based effect of monetary policy on firm R&D spending is not clear from the outset. We have provided evidence that when subjected to a contractionary shock, exploration-inclined firms experience relatively lower equity prices, future earnings, and investments. As a result, these firms might reduce their R&D spending which would have been allocated to development of further exploratory innovation. On the other hand, these firms could also increase their R&D spending to pivot their innovation strategy from exploratory to exploitative. Furthermore, after a contractionary shock, exploration-inclined firms might substitute between intangible assets and tangible assets by increasing their R&D and reducing their capital expenditures. It is also possible that R&D strategy of firms are formulated independently of innovation-based monetary shocks.

[insert figure 1.5 here]

Figure 5a and 5b illustrate the R&D response of firms to monetary shocks based on *Explore* and *Exploit* innovation characteristics, respectively. Based on figure 5a, the firms emphasizing exploratory innovation relatively increase their R&D spending in quarters following a contractionary shock to monetary policy. The R&D differences based on the point estimates become positive immediately in the quarter following the shock and stay positive and significant almost entirely through the next 20 quarters. As shown in figure 5b, the opposite effect is observed when *Exploit* is used to characterize firm innovation. Further analyses are needed to examine the channel through which the R&D is affected by innovation-based heterogeneity in transmission of monetary policy.

1.4. Conclusion

Our paper builds a bridge between the literature on firm innovation characteristics and the literature that studies macroeconomic aggregates as predictors of asset returns. We propose firm innovation as a channel for transmission of monetary policy. We lean on the innovation literature which recognizes a tension within firms when strategizing innovation: to exploit i.e., to stay within the boundaries of the firm's extant knowledge, or to explore i.e., venture into areas previously unexplored to the firm. Both search strategies are necessary for short- and long-term survival and success of the firm. However, the outcome of exploratory innovation, while potentially more substantial, is more uncertain and could take longer to realize. On the other hand, the outcome of exploitative innovation, while possibly more incremental, is likely realized sooner with less uncertainty.

We show that the more the firm emphasizes the exploratory search strategy, the more sensitive it becomes to interest rate fluctuations. The results of our event study indicate that stock price of exploration-inclined firms react more negatively to contractionary changes to monetary policy and more positively to expansionary changes to monetary policy. The sensitivity is manifested with a lag over several days after the policy shock. We explore the underlying economic channels for the observed innovation-based heterogeneity in sensitivity of equity prices to monetary shocks. In line with the findings of our event study, we show that earnings and capital expenditures of firms emphasizing exploratory search strategy are more sensitive to monetary shocks. R&D of exploration-inclined firms, however, are less sensitive to monetary policy.

In conclusion, our paper contributes to the understanding of the relationship between monetary policy and firm innovation. Our findings highlight the importance of firm innovation, particularly exploratory or exploitative characteristics of innovation, when analyzing the transmission of monetary policy. Our results have implications for policymakers, investors, and practitioners. By exploring a new channel through which monetary policy affects equity prices and firm outcomes, our paper provides valuable insights to policymakers seeking to promote economic growth and stability. Furthermore, our results help investors and practitioners make better informed decisions about the potential effects of monetary policy on individual firms. Overall, our paper adds to the literature on the role of innovation in economic growth and highlights the importance of considering firm innovation in monetary policy analysis.

Figure 1.1: Changes in Expected and Unexpected Interest Rates 1994-2021

Figure 1a illustrates changes in the Fed funds rate after each FOMC meeting. Figure 1b shows unexpected changes in Fed funds rate during each FOMC meeting. Panel C illustrates the expected part of changes in Fed funds rate. To find out more about how we construct unexpected changes in Federal Funds rate consult the Data and Variables section of the paper.

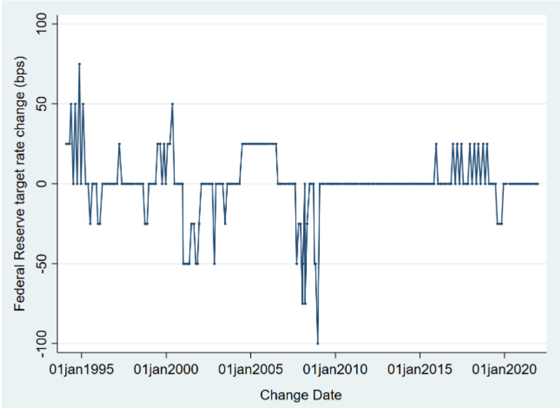


Figure 1.1a. Total change in Federal funds rate

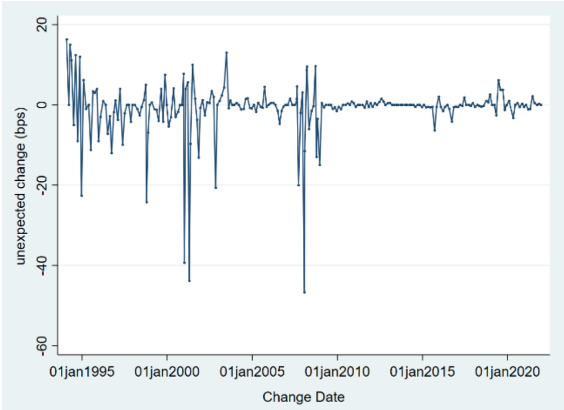


Figure 1.1b. unexpected monetary shocks

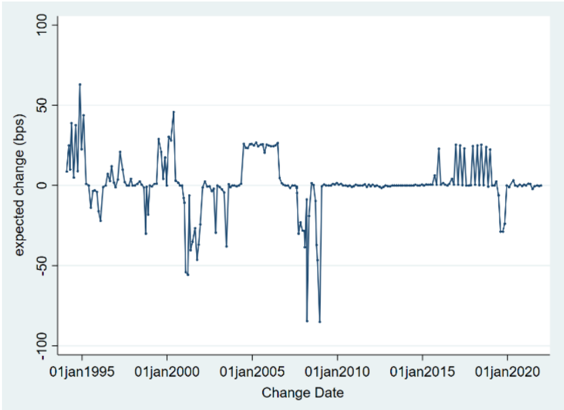


Figure 1.1c. expected change in federal funds rate.

Figure 1.2: Quarterly panel impulse response analysis: innovation-based heterogeneity in dynamic responses of Net Income to monetary shocks

This figure illustrates the dynamic responses of firms' net income to the interaction of firm innovation characteristics, *Explore* and *Exploit*, and monetary policy shocks. Monetary shocks are aggregated at the quarter level. The dependent variable is the log of net income up to 20 quarters ahead. We regress h-forward values of net income on lagged values of our quarterly measure of interest rate shocks and firm innovation characteristics. The gray area illustrates 95% confidence interval. The x-axis measures the number of quarters after aggregated monetary shock. The y-axis represents the coefficient on the interaction term of interest.

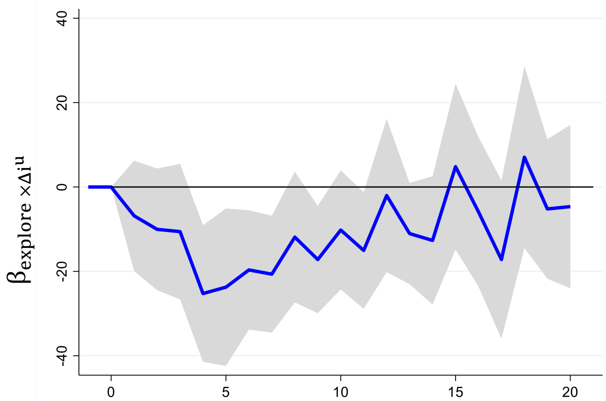


Figure a. Heterogenous response of Net Income using *Explore*

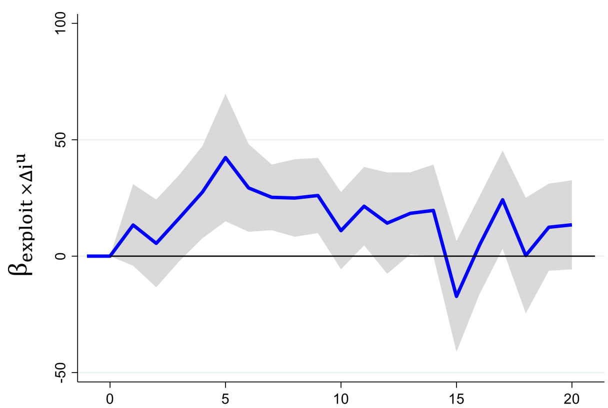


Figure b. Heterogenous response of Net Income using *Exploit*

Figure 1.3: Quarterly panel impulse response analysis: innovation-based heterogeneity in dynamic responses of EBITDA to monetary shocks

This figure illustrates the dynamic responses of firms EBITDA to interaction of firm innovation characteristics, *Explore* and *Exploit*, and monetary policy shocks. Monetary shocks are aggregated at the quarter level. The dependent variable is log of EBITDA up to 20 quarters ahead. We regress h-forward values of EBITDA on lagged values of our quarterly measure of interest rate shocks and firm innovation characteristics. The gray area illustrates 95% confidence interval. The x-axis measures the number of quarters after aggregated monetary shock. The y-axis represents the coefficient on the interaction term of interest.

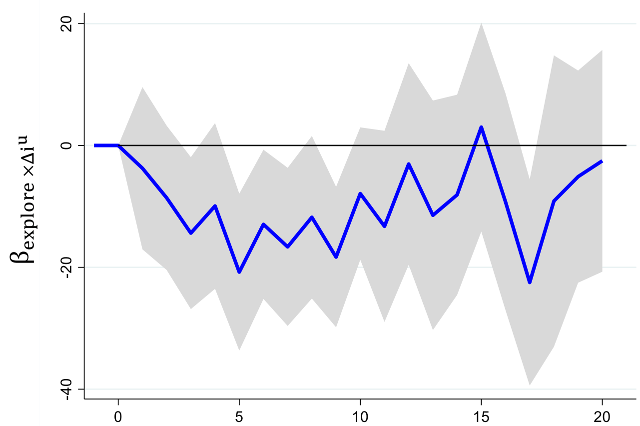


Figure a. Heterogenous response of EBITDA using *Explore*

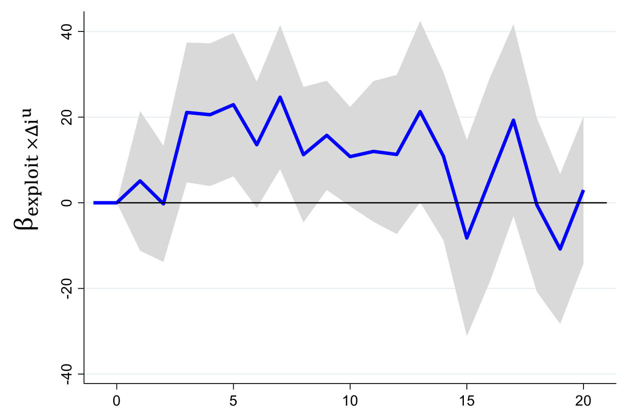


Figure b. Heterogenous response of EBITDA using *Exploit*

Figure 1.4: Quarterly panel impulse response analysis: innovation-based heterogeneity in dynamic responses of CapEx to monetary shocks

This figure illustrates the dynamic responses of firms CapEx to interaction of firm innovation characteristics, *Explore* and *Exploit*, and monetary policy shocks. Monetary shocks are aggregated at the quarter level. The dependent variable is the log of capital expenditures up to 20 quarters ahead. We regress h-forward values of log of CapEx on lagged values of our quarterly measure of interest rate shocks and firm innovation characteristics. The gray area illustrates 95% confidence interval. The x-axis measures the number of quarters after aggregated monetary shock. The y-axis represents the coefficient on the interaction term of interest.

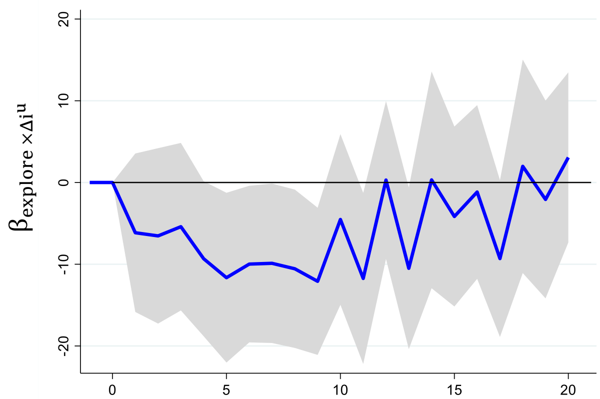


Figure a. Heterogenous response of CapEx using *Explore*

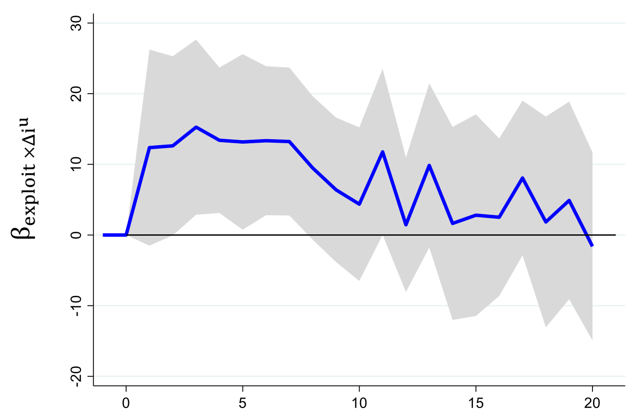


Figure b. Heterogenous response of CapEx using *Exploit*

Figure 1.5: Quarterly panel impulse response analysis: innovation-based heterogeneity in dynamic responses of R&D to monetary shocks

This figure illustrates the dynamic responses of firms R&D to interaction of firm innovation characteristics, *Explore* and *Exploit*, and monetary policy shocks. Monetary shocks are aggregated at the quarter level. The dependent variable is log of R&D up to 20 quarters ahead. We regress h-forward values of log of R&D on lagged values of our quarterly measure of interest rate shocks and firm innovation characteristics. The gray area illustrates 95% confidence interval. The x-axis measures the number of quarters after aggregated monetary shock. The y-axis represents the coefficient on the interaction term of interest.

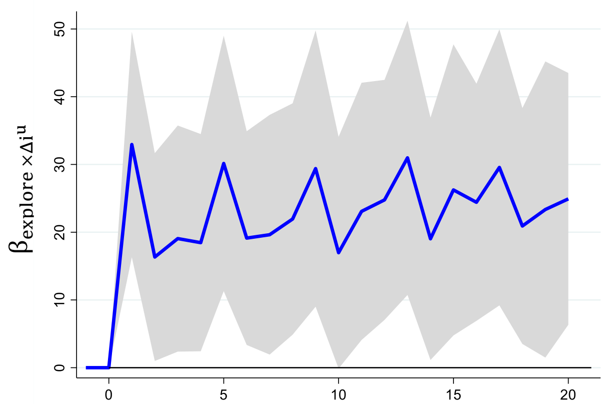


Figure a. Heterogenous response of R&D using *Explore*

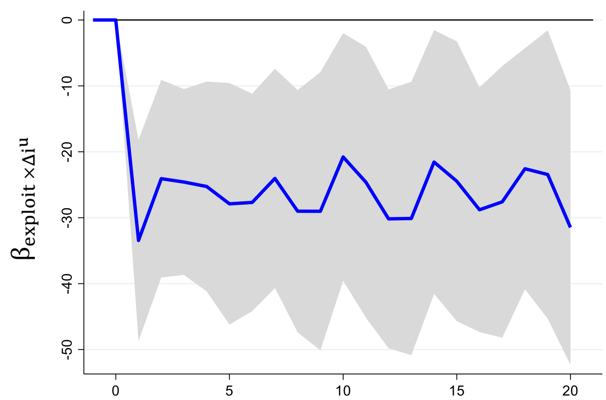


Figure b. Heterogenous response of R&D using *Exploit*

Table 1.1: Summary Statistics

This table reports the summary statistics for variables used in our regression analyses. Panel-A reports the summary statistics for FOCM level event-study return analyses. Panel-B reports summary statistics for variables used in our quarterly panel regressions. Lnum is log number of patents. WW is the financial constraints measure by Whited and Wu.

Variable	N	Mean	SD	Min	P25	Median	P75	Max
<u>*panel A. Firm characteristics sample statistics at the firm-FOMC level*</u>								
Explore	284711	0.506	0.332	0.000	0.238	0.472	0.800	1.000
Exploit	284711	0.300	0.275	0.000	0.000	0.260	0.500	1.000
Lnum	297202	2.904	1.891	0.693	1.386	2.485	4.043	7.992
Assets	367373	6.501	2.291	0.169	4.711	6.402	8.127	13.649
Market/Book	341800	0.926	0.834	-0.978	0.374	0.842	1.382	3.611
ROA	366938	-0.009	0.069	-0.478	-0.007	0.009	0.020	0.097
Leverage	351118	0.252	0.193	0.000	0.101	0.228	0.358	0.957
R&D/Assets	367373	0.018	0.034	0.000	0.000	0.003	0.022	0.232
Cash/Assets	366272	0.181	0.217	0.000	0.027	0.091	0.249	0.954
Age	375766	19.814	13.748	0.334	8.468	16.378	29.504	58.570
WW	360994	-0.316	0.130	-0.602	-0.412	-0.315	-0.221	0.050
<u>*panel B. Firm characteristics sample statistics at the firm-quarter level*</u>								
Variable	N	Mean	SD	Min	P25	Median	P75	Max
Explore	128400	0.489	0.332	0.000	0.222	0.444	0.750	1.000
Exploit	128400	0.306	0.279	0.000	0.000	0.271	0.500	1.000
Lnum	134041	2.887	1.910	0.693	1.386	2.485	4.043	8.195
Assets	130876	6.613	2.316	0.123	4.807	6.517	8.256	13.649
Market/Book	121870	0.956	0.831	-0.933	0.405	0.875	1.404	3.685
ROA	130717	-0.010	0.069	-0.470	-0.008	0.009	0.020	0.095
Leverage	124770	0.247	0.192	0.000	0.100	0.222	0.349	1.002
R&D/Assets	130431	0.191	0.221	0.001	0.030	0.102	0.270	0.952
Age	134041	19.599	13.240	0.000	8.759	16.011	29.019	56.786
Cash	130431	0.191	0.221	0.001	0.030	0.102	0.270	0.952
WW	130352	-0.319	0.132	-0.607	-0.417	-0.319	-0.224	0.066
EBITDA	102216	0.014	0.152	-26.758	0.011	0.029	0.045	10.063
Net Income	104541	3.033	2.238	-6.908	1.305	2.924	4.621	11.753
CapEx	144328	2.350	2.074	0.000	0.512	1.904	3.696	10.403
R&D	144394	1.541	1.884	0.000	0.000	0.772	2.639	9.802

Table 1.2: Pairwise Correlations

This table reports the pairwise correlation between independent variables and control variables of the regressions. Lnum is log number of patents. WW is the financial constraints measure by Whited and Wu.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Δi^u	1.000										
(2) Explore	-0.017	1.000									
(3) Exploit	0.021	-0.819	1.000								
(4) Lnum	0.013	-0.443	0.315	1.000							
(5) Size	0.018	-0.099	0.056	0.524	1.000						
(6) M/B	0.019	-0.131	0.147	0.121	-0.057	1.000					
(7) ROA	0.013	0.037	-0.084	0.124	0.364	-0.137	1.000				
(8) Leverage	0.004	-0.018	0.043	-0.013	0.198	0.069	-0.069	1.000			
(9) R&D / Assets	-0.006	-0.110	0.151	0.023	-0.370	0.306	-0.614	-0.093	1.000		
(10) WW	-0.019	0.076	-0.033	-0.462	-0.913	0.017	-0.428	-0.134	0.390	1.000	
(11) Cash / Assets	-0.002	-0.117	0.163	0.003	-0.341	0.294	-0.371	-0.246	0.562	0.346	1.000
(12) Age	0.033	-0.193	0.143	0.271	0.519	-0.089	0.226	0.111	-0.275	-0.493	-0.337

Table 1.3: Monetary policy sample statistics

This table reports the summary statistics of total, expected and unexpected changes in monetary policy during the sample period from 1994 to 2021. All values are in basis points. Excluding 6 FOMC meeting in 2007 and 2008 which occur very close to each other and the meeting after 11 September 2001, the period contains 225 FOMC meetings. Panel A reports the mean, standard deviation, maximum, and minimum of raw monetary policy changes, as well as monetary policy shocks measured in a tight 30-minute window around the FOMC announcement. FOMC announcement shocks are computed using prices of Fed funds futures contracts. Panel B reports the same statistics for the contractionary or positive rate changes. Panel C reports the statistics for expansionary or negative rate changes. Finally, panel D reports the statistics when the Federal Reserve leaves the target rate unchanged.

	Counts	Mean (bps)	SD(bps)	Min(bps)	Max(bps)
A. Full sample					
Raw policy change	225	0.444	19.475	-100.000	75.000
Policy shock (FFShock)	225	-0.818	6.222	-43.800	16.300
B. Contractionary rate change					
Raw policy change	40	28.750	10.667	25.000	75.000
Policy shock (FFShock)	40	2.220	4.970	-5.370	16.300
C. Expansionary rate change					
Raw policy change	28	-37.500	17.347	-100.000	-25.000
Policy shock (FFShock)	28	-7.009	13.430	-43.800	13.000
D. No rate change					
Raw policy change	157	0.000	0.000	0.000	0.000
Policy shock (FFShock)	157	-0.488	2.974	-22.600	9.643

Table 1.4: Equal-weighted *Explore* portfolio performance following FOMC event days

The table shows the cumulative abnormal return for the three *High Explore*, *Mid Explore* and *Low Explore* portfolios of firms. During a 5-year window prior to each monetary shock, we assign *Explore* values to firms based on exploratory characteristics of their patent portfolios. Then, at each FOMC event date, we sort innovative firms into terciles based on their exploratory innovation characteristics. We then, over windows of various lengths following the policy announcement, regress the *High*, *Mid* and *Low Explore* equal-weighted portfolio returns on the monetary shocks.

$$r_s^{port} = \alpha + \beta \cdot \Delta i_s^u + \epsilon_s^{port}$$

s indicates the time of the FOMC meeting. Δi_s^u is the unexpected monetary shock at s. Δi_s^u is the unexpected monetary shock. Robust standard errors are used in reporting the t-statistics in parentheses.

	(1)	(2)	(3)	(4)
	Full Sample	*High*	*Mid*	*Low*
A. (0,1) post-FOMC cum. return				
Δi^u	-1.936***	-3.046***	-2.977***	-1.046*
	(0.725)	(0.883)	(0.917)	(0.613)
adjR2	0.030	0.057	0.064	0.004
B. (0,2) post-FOMC cum. return				
Δi^u	-3.394***	-5.123***	-4.082***	-2.291***
	(0.891)	(0.932)	(1.148)	(0.775)
adjR2	0.057	0.096	0.070	0.020
C. (0,3) post-FOMC cum. return				
Δi^u	-3.706***	-5.062***	-4.295***	-2.469***
	(0.927)	(0.924)	(1.012)	(0.905)
adjR2	0.053	0.078	0.062	0.016
D. (0,4) post-FOMC cum. return				
Δi^u	-4.486***	-6.288***	-5.499***	-2.970***
	(1.076)	(1.068)	(1.293)	(1.068)
adjR2	0.062	0.095	0.075	0.020
E. (0,5) post-FOMC cum. return				
Δi^u	-4.939***	-6.973***	-5.881***	-3.268***
	(1.224)	(1.279)	(1.492)	(1.138)
adjR2	0.058	0.093	0.065	0.019
N	225	225	225	225

Table 1.5: Equal-weighted *Exploit* portfolio performance following FOMC event days

The table shows the cumulative abnormal return for the three *High Exploit*, *Mid Exploit* and *Low Exploit* portfolios of firms. During a 5-year window prior to each monetary shock, we assign *Exploit* values to firms based on exploitative characteristics of their patent portfolios. Then, at each FOMC event date, we sort innovative firms into terciles based on their exploitative innovation characteristics. We then, over windows of various lengths following the policy announcement, regress the *High*, *Mid* and *Low Exploit* equal-weighted portfolio returns on the monetary shocks.

$$r_s^{port} = \alpha + \beta \cdot \Delta i_s^u + \epsilon_s^{port}$$

Δi_s^u is the unexpected monetary shock. Robust standard errors are used in reporting the t-statistics in parentheses.

	(1)	(2)	(3)	(4)
	Full Sample	*High*	*Mid*	*Low*
A. (0,1) post-FOMC cum. return				
Δi^u	-1.936***	-0.684	-3.363***	-2.858***
	(0.725)	(0.706)	(0.813)	(0.922)
adjR2	0.030	-0.001	0.083	0.048
B. (0,2) post-FOMC cum. return				
Δi^u	-3.394***	-2.223**	-4.192***	-4.853***
	(0.891)	(0.908)	(1.041)	(1.019)
adjR2	0.057	0.017	0.076	0.083
C. (0,3) post-FOMC cum. return				
Δi^u	-3.706***	-2.742***	-4.056***	-4.840***
	(0.927)	(1.018)	(1.006)	(0.980)
adjR2	0.053	0.019	0.058	0.068
D. (0,4) post-FOMC cum. return				
Δi^u	-4.486***	-3.031**	-5.482***	-5.975***
	(1.076)	(1.214)	(1.273)	(1.139)
adjR2	0.062	0.019	0.075	0.082
E. (0,5) post-FOMC cum. return				
Δi^u	-4.939***	-3.091***	-6.132***	-6.557***
	(1.410)	(1.227)	(1.745)	(1.746)
adjR2	0.058	0.015	0.071	0.079
N	225	225	225	225

Table 1.6: Firm-level event study around FOMC meetings. Exploratory innovation-based heterogeneity in transmission of monetary policy to equity prices

The table presents the findings of firm-level event study analysis over a five-day-window starting at the day of the FOMC event. *Explore* indicates exploratory characteristics of firm innovation portfolio prior to the shock. We use cumulative abnormal return of firms in a five-day window after each FOMC meeting as the dependent variable. Δi^u is the unexpected monetary shock.

$$CAR_{j,s}^{(0,5)} = \beta\ Explore_{j,s}\Delta i_s^u + \delta Explore_{j,s} + \ \gamma\Delta i_s^u + \eta\ \Gamma_{j,q} + \zeta_{k,q} + \epsilon_{j,s}$$

s, *j*, and *q* denote monetary shock, firm and quarter respectively. $\zeta_{k,q}$ is a set of fixed effects. *k* can denote firm or industry. In column 1, we use no fixed effects. In column (2) SIC3 industry and quarter fixed effects are used. In column (3) the interaction of industry and quarter fixed effects are used. In column (4) firm and quarter fixed effects are used. In column (5) we use the interaction of firm and quarter fixed effects. Standard errors are clustered at the firm and event levels. To find detailed variable specification consult table Appendix A1.

	(1)	(2)	(3)	(4)	(5)
Explore x Δi^u	-4.951***	-5.083***	-5.096***	-5.369***	-4.812***
	(1.114)	(1.094)	(1.086)	(1.175)	(1.522)
Explore	-0.001	-0.000	0.000	-0.000	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.009)
Δi^u	-2.531**	-2.251*	-2.510*	-2.043	-1.575
	(1.263)	(1.314)	(1.427)	(1.307)	(1.547)
Size	-0.000	-0.001*	-0.001*	-0.009***	
	(0.000)	(0.000)	(0.000)	(0.002)	
M/B	-0.003***	-0.003**	-0.003***	-0.009***	
	(0.001)	(0.001)	(0.001)	(0.002)	
Leverage	0.003	0.005	0.005*	0.016***	
	(0.004)	(0.004)	(0.003)	(0.005)	
ROA	0.042***	0.045***	0.044***	0.039***	
	(0.012)	(0.011)	(0.010)	(0.009)	
R&D/Assets	0.077***	0.079***	0.076***	0.087***	
	(0.022)	(0.020)	(0.019)	(0.024)	
Lnum	0.000	0.000	0.000	0.000	-0.003
	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)
WW	-0.003**	-0.003**	-0.003**	-0.005***	
	(0.001)	(0.001)	(0.001)	(0.001)	
N	221445	221284	221284	221284	221284
adjR2	0.004	0.010	0.004	0.021	-0.022
Industry FE		x			
Quarter FE		x		x	
Industry x Quarter FEs			x		
Firm FE				x	
Firm x Quarter FEs					x

Table 1.7: Firm-level event study around FOMC meetings. Exploitative innovation-based heterogeneity in transmission of monetary policy to equity prices

The table presents the findings of firm-level event study analysis over a five-day-window starting at the day of the FOMC event. *Exploit* indicates exploitative characteristics of firm innovation portfolio prior to the shock. We use cumulative abnormal return of firms in a five-day window after each FOMC meeting as the dependent variable. Δi^u is the unexpected monetary shock.

$$CAR_{j,s}^{(0,5)} = \beta\ Exploit_{j,s}\ \Delta i_s^u + \delta\ Exploit_{j,s} +\ \gamma\ \Delta i_s^u + \eta\ \Gamma_{j,q} + \zeta_{k,q} + \epsilon_{j,s}$$

s, *j*, and *q* denote monetary shock, firm and quarter respectively. $\zeta_{k,q}$ is a set of fixed effects. *k* can denote firm or industry. In column 1 we use no fixed effects. In column 2, SIC3 industry and quarter fixed effects are used. In column 3, the interaction of industry and quarter fixed effects are used. In column 4, firm and quarter fixed effects are used. In column 5, we use the interaction of firm and quarter fixed effects. Standard errors are clustered at the firm and event levels. To find detailed variable specification consult table Appendix A1.

	(1)	(2)	(3)	(4)	(5)
Exploit x Δi^u	6.468***	6.752***	6.545***	7.135***	7.210***
	(1.781)	(1.764)	(1.581)	(1.866)	(2.067)
Exploit	0.001	0.001	0.000	0.003**	0.024**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.010)
Δi^u	-6.891***	-6.756***	-6.962***	-6.803***	-6.046***
	(1.570)	(1.607)	(1.685)	(1.598)	(1.520)
Size	-0.000	-0.001*	-0.001*	-0.009***	
	(0.000)	(0.000)	(0.000)	(0.002)	
M/B	-0.003***	-0.003**	-0.003***	-0.009***	
	(0.001)	(0.001)	(0.001)	(0.002)	
Leverage	0.003	0.005	0.005*	0.016***	
	(0.004)	(0.004)	(0.003)	(0.005)	
ROA	0.042***	0.045***	0.044***	0.039***	
	(0.012)	(0.011)	(0.010)	(0.009)	
Lnum	0.000	0.000	0.000	0.000	-0.004
	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)
R&D/Assets	0.077***	0.080***	0.077***	0.087***	
	(0.022)	(0.020)	(0.019)	(0.024)	
WW	-0.003**	-0.003**	-0.003**	-0.005***	
	(0.001)	(0.001)	(0.001)	(0.001)	
N	221445	221284	221284	221284	221284
adjR2	0.004	0.010	0.004	0.021	-0.022
Industry FE		x			
Quarter FE		x		x	
Industry x Quarter FE			x		
Firm FE				x	
Firm x Quarter FE					x

Table 1.8: Firm-level event study around FOMC meetings. Drift in the innovation-based heterogeneity in transmission of monetary policy

The table presents the findings of firm-level event study over windows of various lengths starting at the day of the FOMC event. *Explore* and *Exploit* respectively indicate exploratory and exploitative characteristics of firm innovation portfolio prior to the shock. We use cumulative abnormal returns as the dependent variable. Δi^u is the unexpected monetary shock.

$$CAR_{j,s}^{(0,T)} = \beta\ EXP_{j,s}\Delta i_s^u + \delta EXP_{j,s} + \gamma \Delta i_s^u + \zeta_{jq} + \epsilon_{j,s} \quad T\ \in \{1,3,5,7,10,15\}$$

s, *j*, and *q* denote monetary shock, firm, and quarter respectively. ζ_{jq} denotes interaction of firm and quarter fixed effects which are used in all columns. In panels A and B, *Explore* and *Exploit* are used respectively to characterize firm innovation. Standard errors are clustered at the firm and event levels. To find detailed variable specification consult table Appendix table A1.

	(1)	(2)	(3)	(4)	(5)	(6)
	CAR(0,1)	CAR(0,3)	CAR(0,5)	CAR(0,7)	CAR(0,10)	CAR(0,15)
A. Explore						
Explore x Δi^u	-1.459	-3.048**	-4.606***	-6.575***	-7.677***	-6.107*
	(0.899)	(1.264)	(1.567)	(2.046)	(2.915)	(3.356)
Explore	-0.006	-0.005	-0.004	-0.007	-0.004	-0.006
	(0.005)	(0.007)	(0.008)	(0.011)	(0.013)	(0.016)
Δi^u	-1.215	-0.747	-1.723	-3.912*	-6.327***	-10.168***
	(0.738)	(1.225)	(1.564)	(2.198)	(2.123)	(2.667)
Lnum	-0.003	0.003	-0.003	-0.010	-0.015*	-0.013
	(0.003)	(0.004)	(0.005)	(0.007)	(0.008)	(0.009)
Age	0.005	0.007	0.000	-0.002	0.004	0.026
	(0.004)	(0.006)	(0.008)	(0.012)	(0.016)	(0.021)
N	221284	221284	221284	221284	221284	221284
adjR2	-0.028	-0.012	-0.022	-0.046	-0.070	-0.064
B. Exploit						
Exploit x Δi^u	2.884**	3.001*	6.681***	9.556***	10.703***	8.293*
	(1.191)	(1.792)	(2.158)	(2.794)	(4.041)	(4.559)
Exploit	0.014**	0.016*	0.023**	0.031***	0.030**	0.045**
	(0.006)	(0.008)	(0.010)	(0.012)	(0.014)	(0.018)
Δi^u	-2.740***	-3.189***	-5.943***	-9.942***	-13.255***	-15.623***
	(0.712)	(1.023)	(1.508)	(2.598)	(3.528)	(3.869)
Lnum	-0.003	0.002	-0.004	-0.011	-0.017**	-0.015
	(0.003)	(0.004)	(0.005)	(0.007)	(0.008)	(0.009)
Age	0.005	0.007	0.000	-0.002	0.004	0.025
	(0.004)	(0.006)	(0.008)	(0.012)	(0.016)	(0.021)
N	221284	221284	221284	221284	221284	221284
adjR2	-0.028	-0.012	-0.022	-0.046	-0.070	-0.064
Firm x Quarter FEs	x	x	x	x	x	x

Table 1.9: Firm-level event study around FOMC meetings. Interacting log number of patents, R&D over assets and other control variables with monetary policy shocks

The table presents the findings of firm-level event study over a five-day-window starting at the day of the FOMC event. *Explore* and *Exploit* indicates exploratory and exploitative characteristics of firm innovation portfolio prior to the shock. We use cumulative abnormal returns during the five-day-window after the shock. Δi_s^u is the unexpected monetary shock.

$$CAR_{j,s}^{(0,5)} = \beta\ EXP_{j,s}\Delta i_s^u + \delta EXP_{j,s} + \gamma\Delta i_s^u + \eta\ \Gamma_{k,q} + \theta\ \Gamma_{k,q}\Delta i_s^u + \zeta_{k,q} + \epsilon_{j,s}$$

s, *j*, and *q* denote monetary shock, firm and quarter respectively. $\zeta_{k,q}$ is a set of fixed effects. *k* can denote firm or industry. To save space, coefficients for control variables other than log number of patents and R&D over assets are not shown in the table. In panels A and B, *Explore* and *Exploit* are used respectively to characterize firm innovation. In column 1 we use no fixed effects. In column 2, SIC3 industry and quarter fixed effects are used. In column 3, the interaction of industry and quarter fixed effects are used. In column 4, firm and quarter fixed effects are used. In column 5, we use the interaction of firm and quarter fixed effects. Standard errors are clustered at the firm and event levels.

	(1)	(2)	(3)	(4)	(5)
A. Explore					
Explore x Δi^u	-6.066***	-6.344***	-5.889***	-6.764***	-6.762***
	(1.733)	(1.674)	(1.525)	(1.851)	(2.010)
Δi^u	-9.076**	-9.156***	-9.411***	-9.069***	-6.923*
	(3.489)	(3.466)	(3.440)	(3.466)	(4.072)
Lnum x Δi^u	-0.660	-0.712	-0.631	-0.765	-1.130*
	(0.725)	(0.692)	(0.661)	(0.704)	(0.598)
R&D/Assets x Δi^u	-18.680	-20.723	-21.431	-20.787	-27.400
	(25.569)	(24.610)	(19.673)	(25.335)	(26.469)
N	221445	221284	221284	221284	221284
adjR2	0.005	0.012	0.005	0.023	-0.020
B. Exploit					
Exploit x Δi^u	7.649***	8.122***	7.416***	8.649***	9.128***
	(2.248)	(2.215)	(2.033)	(2.345)	(2.545)
Δi^u	-14.527***	-14.875***	-14.715***	-15.157***	-13.131***
	(4.274)	(4.174)	(4.023)	(4.248)	(4.531)
Lnum x Δi^u	-0.453	-0.500	-0.427	-0.538	-0.931*
	(0.683)	(0.655)	(0.628)	(0.654)	(0.558)
R&D/Assets x Δi^u	-20.872	-23.151	-23.361	-23.379	-29.851
	(25.674)	(24.723)	(19.833)	(25.434)	(26.588)
N	221445	221284	221284	221284	221284
adjR2	0.005	0.012	0.005	0.023	-0.020
Controls	x	x	x	x	
Controls x Δi^u	x	x	x	x	x
Industry FE		x			
Quarter FE		x		x	
Industry x Quarter FEs			x		
Firm FE				x	
Firm x Quarter FEs					x

2. Duration of Firm Innovation

2.1 Introduction

In the first chapter, I studied firm-level innovation as an intermediary channel for the transmission of monetary policy. The study rested upon the innovation literature which recognizes a tension within firms as they formulate their innovation search strategies: When innovating, firms have a choice between exploitation and exploration. As delineated in the literature, exploratory innovation entails a deliberate departure from the firm's pre-existing knowledge base and technologies. In contrast, exploitative innovation entails the enhancement and refinement of previously developed technologies. Previous literature associates exploratory innovation with longer horizon to payoff which are potentially more significant and higher levels of uncertainty and risk. Conversely, exploitative innovation aligns with stepwise, process-oriented enhancements in familiar practices, yielding quicker realization of gains, and a lower likelihood of failure (March (1991), Benner and Tushman (2002), Manso (2011), Balsmeier et al. (2017), Gao et al (2018), Fitzgerald et al (2020), Almeida et al (2021), among others).

My analysis in this chapter proceeds from the notion that the net present value of innovation, much like investments, depends on present value of costs and benefits of innovation. As discussed in the firm innovation literature which delineates between explorative and exploitative innovation, the future costs and benefits of innovation can happen over different horizons, depending on the characteristics of the innovation. For example, exploratory innovation's payoffs are likely realized over a longer horizon compared to exploitative innovation. The goal of this chapter is to propose a novel measure to capture the horizon over which the investment of firm in innovation is realized. I call this measure "duration of firm innovation". Similar to the concept of duration for fixed rate bonds (Vernoesi (2010)), at the patent level, duration of a patent can be thought of as weighted average time difference between filing of the patent and the future cash flows generated by the investment of the firm in the patent.

Weber (2018) proposes an estimate of cash flow duration at the firm level using balance sheet data. However, it's not clear what portion of the cash flow generated by the firm at a specific future time is generated from the firm's prior investment in a specific patent. Kogan et al (2017) use stock market reactions to patent grants to calculate private value of patents. However, from their study, it's not clear over what horizon this net present value is to be generated. As is clear from the literature delineating between explorative and exploitative innovation, the time to realization of payoff is an important characteristic of firm innovation. However, to the extent of my knowledge, there's no study in the innovation literature which captures the timing of future cash flows generated from innoavtion. The aim of this study is to fill this gap by proposing several measures for the duration of firm innovation.

This chapter contributes to the body of literature which uses patent data to characterize innovation at the firm level. Some of the notable examples from this body of literature include Seru (2014) which proposes a measure to calculate patent novelty; Hirshleifer, Hsu, Li (2018) which suggests a measure for innovative originality, and Balsmeier, Fleming, and Manso (2017) which uses a similar measure as the one I used in chapter 1 to capture explorative nature of firm innovation.

2.2 Data

To measure the innovation output of firms, I use Kogan, Papanikolaou, Seru and Stoffman (2017) (henceforth KPSS) patent data. This dataset contains information about the application and grant date of patents. KPSS is especially useful in studying corporate innovation because it employs a disambiguation method that matches patents to their owners through PERMNO identifier. As a result, the link between patents and public firms that have developed them is straightforward. The updated KPSS patent data includes dollar value and other information on all the patents filed between 1926 and 2022. I also directly use United States Patents Office (USPTO) citation dataset. This dataset records each citing patent and its corresponding cited patent. The combination of KPSS and USPTO datasets enables me to construct my duration measures based on citations and dollar value of patents. I use Compustat annual and quarterly to calculate accounting panel variables such as market to book ratio. I use CRSP to calculate the stock returns.

2.3 Duration Variables

I start this section by an illustrative example of a patent shown in figure 2.1. The patent is filed in 2005 and receives three citations in 2007, 2012, and 2016.

[insert figure 1 here]

Derrien, Kecskes, and Nguyen (2022) (hereafter DKN) use patent citations to capture the longevity of the firm's innovation activities. To measure patent longevity, they use the time difference between filing of a patent and the patent's last forward citation. The idea is that longer lived inventions should continue to be cited for many years. According to DKN The length of time over which a firm's patent portfolio is cited provides an estimate of the horizon of the firm's innovation activities. It can be argued that the DKN measure of longevity could, on average, capture the length of time over which the cash flows of the patent is generated. Therefore, as the first measure of duration of firm innovation, I used DKN measure of longevity. I call this measure Dur_{max} since it's simply the maximum time between filing of a patent and its forward citation. The

Dur_{max} value for the hypothetical patent shown in figure 1 is around 11 years since the last forward citation of the patent happens in 2016.

DKN use only one forward citation to formulate their longevity measure. As the first alternative to the DKN measure, instead of using just the farthest forward citation, I use mean time difference between a patent and all its forward citation. I call this measure Dur_{mean}. Unlike Dur_{max}, the Dur_{mean} variable uses the time difference for all of the forward citation of the patent. Therefore, Dur_{mean} variable is more likely to reflect duration of a patent if a patent is cited more intensely during a certain future period which is different from the patent's farthest forward citation. The Dur_{mean} value for the hypothetical patent shown in figure 1 is around 6.67 years which reflects the average time difference between the patent and its three forward citations.

The Dur_{max} and Dur_{mean} variables need to be adjusted for cohort effect. Since patents filed earlier will on average have longer time to generate forward citations, they will on average have larger values of *Dur* compared to patents filed later. Therefore, for newer patents, the *Dur* variables will be underestimated. Moreover, average number of citations are systematically different across different patents technology classes. To address these concerns, I follow DKN and scale the Dur_{max} and Dur_{mean} and the other duration measures developed henceforth by the mean of the same *Dur* variable calculated using all patents in the same grant year cohort and technology class and citation decile.

As mentioned earlier, similar to the concept of duration for fixed rate bonds, duration of a patent can be thought of as weighted average time difference between filing of the patent and the future cash flows generated by the investment of the firm in the patent. For a fixed rate bond, the time differences are weighed by the cash flows, i.e. coupons and the face value, of the bond. However, the cash flows generated by a patent cannot be observed. To address this problem, I use citation data and other variables from the innovation literature to proxy for the unobserved future cash flows generated by the patent.

First, I use the number of citations the citing patents itself receives as the proxy for the cash flow the cited patent is generating at the time it's being cited. The idea is that if the citing patent itself receives relatively high number of citations, it's likely that the cited patent has high relevance at the time that it's being cited. If a patent is cited by a patent which itself is not cited at all, the time difference between the citing and cited patent will receive the weight of zero and therefore will not affect the citation-weighted duration measure. I call this measure of duration of a patent $Dur_{citation\text{-}weighted\ mean}$. To illustrate further, figure 2.2 updates figure 1 by denoting the number of forward citations the citing patents each receive.

[Insert figure 2.2 here]

Using figure 2.2 as an example, the cohort-unadjusted value for $Dur_{citation\text{-}weighted\ mean}$ of patent *X* in figure 2.2 will be 5.46 years.

Next, I use the dollar values of citing patents as proxy for the cash flow generated by the cited patent at the time it is being cited. The idea is that if a patent is cited by a high-value patent, the cited patent is also likely to generate relatively high cash flow at the time it's being cited. I call this measure $Dur_{value\text{-}weighted\ mean}$. Since the KPSS value weights are based on market reactions and are therefore forward-looking, no cohort adjustments are needed at the weight level. The resulting value-weighted duration measure however will be adjusted to reflect citation cohort effects. To illustrate further, figure 2.3 updates figure 1 by denoting the dollar value of citing patents.

[Insert figure 2.3 here]

Using figure 2.3 as an example, the cohort-unadjusted value for $Dur_{value\text{-}weighted\ mean}$ of patent X in figure 2.3 will be 3.46 years.

Finally, I combine the last two measures of duration by multiplying the number of citations of the citing patent and its dollar value and using the result as the weight for the time difference between the citing and the cited patent. I call this measure of duration $Dur_{citation\ \&\ value\ weighted\ mean}$. Using the illustrative examples in figures 2.2 and 2.3, cohort-unadjusted value for $Dur_{citation\ \&\ value\ weighted\ mean}$ of patent X will be 3.62 years.

For each patent, the above measures of durations are calculated. Then, for each firm and for each quarter in the period of 1994 to 2021, I calculate the duration of innovation at the firm-level by taking means of patent-level duration across all the patents filed by the firm during the five-year window prior to the end of the quarter. Table 2.1 reports the correlation between the various measures of duration of firm innovation.

[Insert table 2.1 here]

2.4 Empirical Analysis

In this section, I first explore the relationship between my measures of duration and firms' market to book ratio which is the measure frequently used to reflect duration of firms' cash flows. Then, I test my measures of duration in the context of chapter 1, i.e. I test whether firms with higher duration of innovation are more sensitive to monetary shocks.

2.4.1. Duration of firm innovation and market-to-book-ratio

Traditionally, the finance literature uses market-to-book ratio as a measure to capture duration of cash flows. Since stock prices are forward looking, the higher the mark-to-book ratio, the higher the proportion of the firm's cash flow are to be realized further into the future. To the extent that some portion of the future cash flows of the firm is generated by its investment in innovation, it's expected that duration of firm innovation and market-to-book ratio are positively related. Therefore, in a univariate setting, I regress market to book ratio on the various measures of duration of firm innovation which I defined in the earlier section. Table 2.2 reports the results.

[Insert table 2.2 here]

As shown in table 2.2, of all the duration measures defined and discussed above, the citation-adjusted mean duration is the one that is significantly and positively related to market-to-book ratio across all settings.

2.4.2. Duration of firm innovation as a transmission channel for monetary policy

In this section, I test my duration variables in the context of chapter 1. Since higher duration means later realization of cash flows, I expect the firms with higher duration of innovation to be more sensitive to changes in monetary policy. Table 2.3 reports the results when Dur_{mean} is used to measure duration of firm innovation.

[Insert table 2.3 here]

As shown in table 2.3, when Dur_{mean} is used to measure duration of firm innovation, the interaction term between monetary shocks and Dur_{mean} is positive and insignificant. As shown in table 2.4 below, when Dur_{max} is used, the interaction term between monetary shocks and Dur_{max} is negative but insignificant.

[Insert table 2.4 here]

Finally, as shown in table 2.5, when $Dur_{citation\ weighted\ mean}$ is used to measure duration of firm innovation, the interaction term between monetary shocks and $Dur_{citation\ weighted\ mean}$ is negative and significant across all fixed effects specifications. Therefore, the monetary shock sensitivity results support the results shown earlier in table 2.2 that $Dur_{citation\ weighted}$ is more likely to capture duration of firm innovation.

[Insert table 2.5 here]

There's a discussion to be had about studying firm-level duration-based heterogeneity in transmission of monetary policy. *Explore* and *Exploit* measures used in chapter 1 are backward looking measures. Therefore, even if markets are not fully efficient, to the extent that the *Explore* and *Exploit* variables capture the true explorative and exploitative characteristics of firm innovation portfolio, investors have complete information to characterize firms at the time of the monetary shocks. However, as is the case with the measures I defined and used in my analyses, duration is a forward-looking concept. In order to use duration in a firm-study setting, it must be argued that the markets are fully efficient in discerning the true duration of firms' patents and their patent portfolios.

2.5 Conclusion

The aim of this chapter was to develop possible measures to proxy for duration of firm innovation. Based on the measures used for longevity and dollar value of patents, I developed several measures and tested them against traditional measure of duration of cash flow, namely, market-to-book ratio. My univariate results gave support to using citation-weighted mean of time difference between a patent and its forward citations as a possible measure of duration of firm innovation.

Figures

Figure 2.1 Illustrative example of a patent with three forward citations

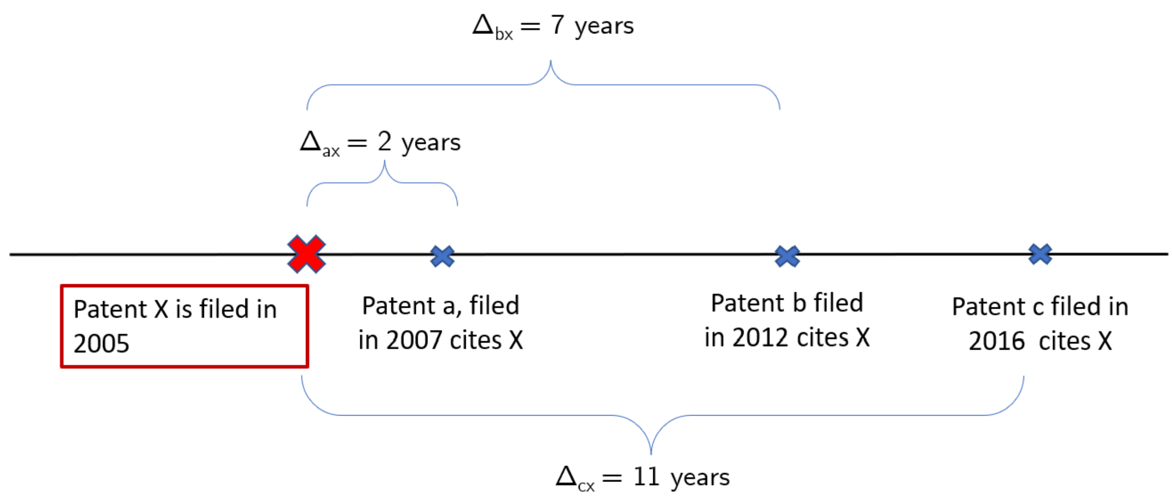


Figure 2.2 Illustrative example of a patent with three forward citations. The figure denotes the number of citations the citing patents each receive

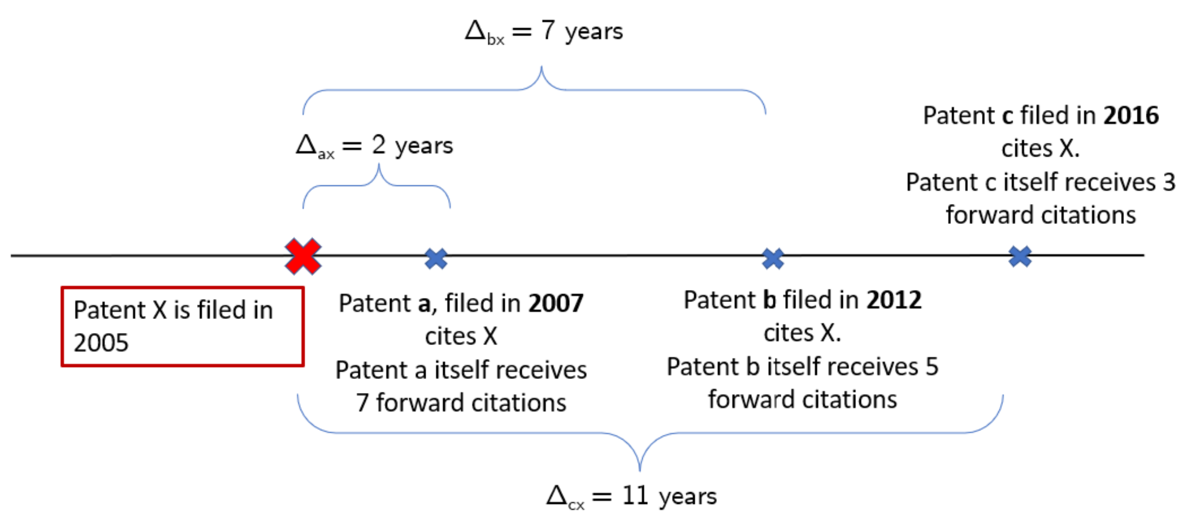
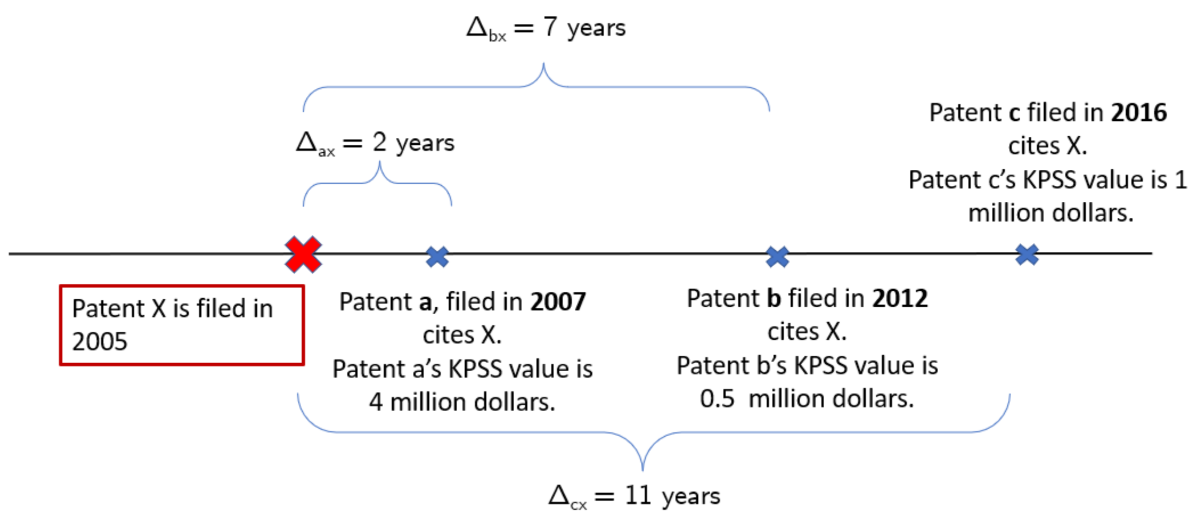


Figure 2.3 Illustrative example of a patent with three forward citations. The figure denotes the dollar value of the citing patents.



Tables

Table 2.1 Pairwise Correlation between different measures of duration of firm innovation

Variables	Dur_{mean}	Dur_{max}	$Dur_{citation-w}$	$Dur_{value-w}$
Dur_{mean}				
Dur_{max}	0.779			
$Dur_{citation-w}$	0.265	0.161		
$Dur_{value-w}$	0.495	0.309	0.235	
$Dur_{citation-\,\&\,value-w}$	0.213	0.134	0.654	0.376

Table 2.2 Univariate regression of market-to-book ratio on various measure of duration of firm innovation. All standard errors are clustered at the firm and quarter levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dur_{mean}	-0.066	-0.012	-0.038	-0.012	-0.012	-0.012	-0.038
	(0.041)	(0.034)	(0.034)	(0.036)	(0.035)	(0.034)	(0.034)
N	182172	182172	182172	182172	182172	182172	182172
adjR2	0.000	0.520	0.556	0.130	0.167	0.519	0.556
Dur_{max}	0.078	0.042	0.013	0.095**	0.094**	0.042	0.013
	(0.049)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
N	182172	182172	182172	182172	182172	182172	182172
adjR2	0.000	0.520	0.556	0.130	0.167	0.519	0.556
$Dur_{citation\ weight}$	0.088***	0.100***	0.037**	0.073***	0.076***	0.100***	0.037**
	(0.017)	(0.019)	(0.015)	(0.015)	(0.014)	(0.019)	(0.015)
N	164691	164691	164691	164691	164691	164691	164691
adjR2	0.003	0.521	0.559	0.129	0.168	0.521	0.559
Dur_{value}	-0.071*	-0.037	-0.046	-0.028	-0.007	-0.037	-0.046
	(0.038)	(0.031)	(0.030)	(0.032)	(0.032)	(0.031)	(0.030)
N	162220	162220	162220	162220	162220	162220	162220
adjR2	0.000	0.514	0.554	0.125	0.165	0.514	0.553
$Dur_{citation\ \&\ value\ wright}$	0.026**	0.042***	0.004	0.030**	0.032***	0.042***	0.004
	(0.013)	(0.013)	(0.011)	(0.012)	(0.012)	(0.013)	(0.011)
N	151389	151389	151389	151389	151389	151389	151389
adjR2	0.000	0.514	0.554	0.124	0.164	0.513	0.553
Firm FEs		x	x			x	x
Industry FEs				x	x	x	x
Quarter FEs			x		x		x

Table 2.3: Firm-level event study around FOMC meetings. Duration-based heterogeneity in transmission of monetary policy to equity prices using Dur_{mean}

The table presents the findings of firm-level event study analysis over a five-day-window starting at the day of the FOMC event. Dur_{mean} indicates duration of firm innovation portfolio prior to the shock. We use cumulative abnormal return of firms in a five-day window after each FOMC meeting as the dependent variable. Δi^u is the unexpected monetary shock.

$$CAR_{j,s}^{(0,5)} = \beta\ Dur_{mean_{j,s}} \Delta i_s^u + \delta Dur_{mean\,j,s} + \gamma \Delta i_s^u + \eta\ \Gamma_{j,q} + \zeta_{k,q} + \epsilon_{j,s}$$

s, *j*, and *q* denote monetary shock, firm and quarter respectively. $\zeta_{k,q}$ is a set of fixed effects. *k* can denote firm or industry. Standard errors are clustered at the firm and event levels.

	(1)	(2)	(3)	(4)	(5)
Dur_{mean} x Δi^u	3.686	3.323	2.952	3.359	2.922
	(2.823)	(2.842)	(2.996)	(2.814)	(2.751)
Dur_{mean}	0.001	0.001	0.001	-0.001	-0.013
	(0.001)	(0.001)	(0.001)	(0.001)	(0.010)
Δi^u	-8.953***	-8.425***	-8.257***	-8.399***	-7.193**
	(3.132)	(2.817)	(2.849)	(2.833)	(2.912)
Size	-0.000	-0.001*	-0.001	-0.009***	
	(0.000)	(0.000)	(0.000)	(0.001)	
M/B	-0.003***	-0.003**	-0.003***	-0.008***	
	(0.001)	(0.001)	(0.001)	(0.002)	
Leverage	0.003	0.004	0.005**	0.015***	
	(0.003)	(0.003)	(0.002)	(0.005)	
ROA	0.041***	0.043***	0.041***	0.040***	
	(0.011)	(0.011)	(0.010)	(0.009)	
Lnum	0.000	0.000	0.000	0.000	-0.004
	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)
WW	-0.003**	-0.003***	-0.003**	-0.005***	
	(0.001)	(0.001)	(0.001)	(0.001)	
R&D/Assets	0.077***	0.080***	0.076***	0.080***	
	(0.022)	(0.020)	(0.018)	(0.024)	
Age	-0.000	-0.000	-0.000	-0.000	0.002
	(0.000)	(0.000)	(0.000)	(0.007)	(0.009)
Cash	-0.001	-0.002	-0.002	0.000	
	(0.003)	(0.003)	(0.003)	(0.003)	
N	234652	234483	234483	234483	234483
adjR2	0.003	0.010	0.024	0.002	-0.030
Industry FE		x			
Quarter FE		x		x	
Industry x Quarter FEs			x		
Firm FE				x	
Firm x Quarter FEs					x

Table 2.4: Firm-level event study around FOMC meetings. Duration-based heterogeneity in transmission of monetary policy to equity prices using Dur_{max}

The table presents the findings of firm-level event study analysis over a five-day-window starting at the day of the FOMC event. Dur_{max} indicates duration characteristics of firm innovation portfolio prior to the shock. We use cumulative abnormal return of firms in a five-day window after each FOMC meeting as the dependent variable. Δi^u is the unexpected monetary shock.

$$CAR_{j,s}^{(0,5)} = \beta\, Dur_{max_{j,s}} \Delta i_s^u + \delta Dur_{max\,j,s} + \gamma \Delta i_s^u + \eta\, \Gamma_{j,q} + \zeta_{k,q} + \epsilon_{j,s}$$

s, *j*, and *q* denote monetary shock, firm and quarter respectively. $\zeta_{k,q}$ is a set of fixed effects. *k* can denote firm or industry. Standard errors are clustered at the firm and event levels.

	(1)	(2)	(3)	(4)	(5)
Dur_{max} x Δi^u	-4.191	-4.494	-4.580	-4.706	-5.525*
	(4.329)	(4.278)	(4.380)	(3.819)	(3.165)
Dur_{max}	0.001	0.000	0.000	-0.002	-0.013
	(0.001)	(0.001)	(0.001)	(0.001)	(0.011)
Δi^u	-1.128	-0.669	-0.791	-0.399	1.163
	(4.293)	(4.031)	(4.148)	(3.640)	(2.970)
Size	-0.000	-0.001*	-0.001	-0.009***	
	(0.000)	(0.000)	(0.000)	(0.001)	
M/B	-0.003***	-0.003**	-0.003***	-0.008***	
	(0.001)	(0.001)	(0.001)	(0.002)	
Leverage	0.003	0.004	0.005**	0.015***	
	(0.003)	(0.003)	(0.002)	(0.005)	
ROA	0.041***	0.043***	0.041***	0.040***	
	(0.011)	(0.011)	(0.010)	(0.009)	
Lnum	0.000	0.000	0.000	0.000	-0.004
	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)
WW	-0.003**	-0.003**	-0.003**	-0.005***	
	(0.001)	(0.001)	(0.001)	(0.001)	
R&D/Assets	0.077***	0.080***	0.076***	0.080***	
	(0.022)	(0.020)	(0.018)	(0.024)	
Age	-0.000	-0.000	-0.000	-0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.007)	(0.009)
Cash	-0.001	-0.002	-0.002	0.000	
	(0.004)	(0.003)	(0.003)	(0.003)	
N	234652	234483	234483	234483	234483
adjR2	0.003	0.010	0.024	0.002	-0.030
Industry FE		x			
Quarter FE		x		x	
Industry x Quarter FEs			x		
Firm FE				x	
Firm x Quarter FEs					x

Table 2.5: Firm-level event study around FOMC meetings. Duration-based heterogeneity in transmission of monetary policy to equity prices using $Dur_{weighted\ mean}$

The table presents the findings of firm-level event study analysis over a five-day-window starting at the day of the FOMC event. $Dur_{weighted\ mean}$ indicates duration characteristics of firm innovation portfolio prior to the shock. We use cumulative abnormal return of firms in a five-day window after each FOMC meeting as the dependent variable. Δi^u is the unexpected monetary shock.

$$CAR_{j,s}^{(0,5)} = \beta\ Dur_{weighted\ mean_{j,s}} \Delta i_s^u + \delta Dur_{weighted\ mean_{j,s}} + \gamma \Delta i_s^u + \eta\ \Gamma_{j,q} + \zeta_{k,q} + \epsilon_{j,s}$$

s, *j*, and *q* denote monetary shock, firm and quarter respectively. $\zeta_{k,q}$ is a set of fixed effects. *k* can denote firm or industry. Standard errors are clustered at the firm and event levels.

	(1)	(2)	(3)	(4)	(5)
$Dur_{weighted\ mean}$ x Δi^u	-2.212***	-2.214***	-2.042**	-2.465***	-2.006**
	(0.832)	(0.833)	(0.857)	(0.843)	(0.779)
$Dur_{weighted\ mean}$	-0.000	-0.000	-0.000	-0.002*	-0.010*
	(0.001)	(0.000)	(0.000)	(0.001)	(0.005)
Δi^u	-3.433**	-3.308**	-3.652**	-3.000**	-2.588*
	(1.321)	(1.352)	(1.459)	(1.325)	(1.332)
Size	-0.000	-0.001*	-0.000	-0.009***	
	(0.000)	(0.000)	(0.000)	(0.002)	
M/B	-0.003***	-0.003**	-0.003***	-0.009***	
	(0.001)	(0.001)	(0.001)	(0.002)	
Leverage	0.003	0.004	0.005**	0.015***	
	(0.003)	(0.003)	(0.002)	(0.005)	
ROA	0.041***	0.044***	0.041***	0.038***	
	(0.012)	(0.011)	(0.010)	(0.010)	
Lnum	0.000**	0.000	0.000	0.001	-0.003
	(0.000)	(0.000)	(0.000)	(0.001)	(0.006)
WW	-0.003**	-0.003***	-0.003***	-0.005***	
	(0.001)	(0.001)	(0.001)	(0.001)	
R&D/Assets	0.079***	0.082***	0.078***	0.074***	
	(0.023)	(0.021)	(0.019)	(0.026)	
Age	-0.000	-0.000	-0.000	-0.001	
	(0.000)	(0.000)	(0.000)	(0.007)	(0.009)
Cash	-0.001	-0.003	-0.002	-0.001	
	(0.004)	(0.003)	(0.003)	(0.003)	
N	214096	213935	213935	213935	213935
adjR2	0.004	0.010	0.002	0.024	-0.028
Industry FE		x			
Quarter FE		x		x	
Industry x Quarter FEs			x		
Firm FE				x	
Firm x Quarter FEs					x

3. Work-from-Home, Employee and Team Performance: Evidence from Analyst Teams

3.1. Introduction

Coronavirus pandemic has affected global economy in profound and arguably irreversible ways one of which has been how, when, and where future work is done. After the start of the pandemic, in much of the country, non-essential workers were ordered to stay at and work from home. While before the pandemic, at most 5% of Americans worked from home for more than 3 days a week, in a matter of a few weeks, the pandemic caused as many as 37% of Americans to work from home full-time (Brynjolfsson et al, 2020). More than 60% of full workdays were supplied from home in June 2020, compared to only 5% pre-pandemic (Barrero, Bloom and Davis (2022)). As a result, a significant portion of American workforce went through a major shift in their workplace settings. This exogenous shock forced many corporations to quickly transition and adapt to the new work-from-home reality.

Following the forced shift to work-from-home (WFH), some companies, especially in tech industry announced that they were going to embrace and integrate the WFH model on a long-term and in some cases permanent basis into their businesses, giving at least some of their employees flexibility in choosing their preferred mode of work even after the pandemic would have ended. There are indications that WFH will be integrated into workplace after the pandemic is over. Dingel and Nieman (2020) classify the feasibility of working from home for all occupations and find that 37 percent of jobs in the United States can be performed entirely at home. Moreover, Barrero, Bloom and Davis (2022) estimate that 27 percent of full workdays will be supplied from home after the pandemic ends. However, some firms have not been so keen on offering their employees flexibility in their workplace settings. For example, senior managers of big firms in banking and finance such as JP Morgan, Goldman Sachs, and Morgan Stanley have taken hardline stances on bringing employees back to the office[3] as they emphasize benefits of in-person teamwork, insisting that "clients should be catered to in-person, and that banking is an apprenticeship business where juniors learn the ropes by observing their seniors"[4].

Diverging views and approaches to work-from-home (WFH) policies are not limited only to firms or industries; Recent surveys across firms note that the lower the employee level and the younger the employee is, the more likely they are to question the need to return to the traditional workspace[5]. For example, Microsoft's 2022 work trend index reports that 50% of company leaders and upper management worldwide want a full, physical return to the office, while middle managers are having a hard time aligning workers with policies set out by upper management[6]. The survey also indicates that 85% of corporate leaders believe the shift to hybrid work has made it hard to be confident about employees' productivity, even if employee performance studies indicate otherwise. In fact, only 12% of leasers have full confidence in their team productivity in hybrid settings. On the other hand, 87% of workers report their productivity is not affected by WFH and 60% of remote-capable employees want long-term hybrid arrangements in their work settings. This is while 52% of gen Z and millennials are likely to consider changing employers in the near future. Due to these dynamics in the labor markets, despite upper management's insistence on bringing employee back to offices[7], employees are able to push back and demand more flexible

[3] https://finance.yahoo.com/news/goldman-sachs-ceo-demanded-employees-210608499.html
[4] https://www.nytimes.com/2021/11/24/business/wall-street-remote-work-banks.html
[5] https://www.conference-board.org/press/Return-to-Work-Survey-June2021
[6] Apple Return to Office Policy Faces Discontent From Employees (AAPL) - Bloomberg
[7] https://www.cnn.com/2022/06/01/tech/elon-musk-tesla-ends-work-from-home/index.html

work settings[8], forcing employers (at the time of working this paper) to scrap dictates around how often workers need to be at their desks.[9,10]

The long-term viability of WFH in a post-pandemic world, the optimal workplace settings and appropriate degree of flexibility are critical questions answers to which are eagerly sought by every corporate decision maker in modern economies as they weigh the costs and benefits of incorporating work-from-home into their operations. In designing the optimal work setting, managers must consider employee productivity and efficiency and other performance measures while making sure their firm stays competitive in talent acquisition and retention within their industries. [11]

A primary concern frequently cited in relation to WFH is its potential detrimental impact on team building and coordination. Consequently, any policy deliberation must be thoroughly informed about the influence of WFH on teamwork. Furthermore, top executives and management within the banking and finance sector consistently underscore the significance of teamwork within their organizations. Hence, examining how remote work affects team performance within the banking and finance industry could yield invaluable insights for policymakers, extending beyond the confines of this particular sector. The aim of this paper is to make such a contribution.

This paper studies the impact of work-from-home on the performance of individual analysts and analyst teams. More specifically, in a quasi-experimental difference-in-difference setting, I compare the performance of individual analysts and analyst teams before and after the beginning

[8] https://www.businessinsider.com/google-alphabet-employees-push-back-remote-hybrid-work-policy-rules-2022-3
[9] Bloomberg - Return-To-Office Plans Unravel as Workers Rebel in Tight Job Market
[10] https://finance.yahoo.com/news/goldman-sachs-pushed-staff-return-063730538.html
[11] https://fortune.com/2022/06/04/elon-musk-tesla-remote-work-productivity/

of the exogenous shock of pandemic-induced work-from-home. Previous literature indicates that analyst teams outperform individual analysts on various dimensions (Fang, Hope (2021)). Using analyst estimate forecast error as measure of performance, I show that following the start of pandemic-induced work-from-home, the performances of both individual analysts and analyst teams are negatively impacted. These results are consistent when using alternative measures of analyst performance and when applying firm, earning release, or bank fixed effects.

Moreover, I investigate the effect of team size on performance. Consistent with prior literature, I find that before start of pandemic-WFH, team size had positive effect on analyst teams' performance, but the effect becomes negative during WFH, consistent with the view that following the start of WFH, coordination among team members become more difficult as team size increases.

Next, I study lead analysts' prior-to-the-pandemic experience with managing remote teams as a possible channel for the above observed effect. I find that among analyst teams, the ones led by an analyst with no prior experience managing a remote team member underperform teams led by analyst with prior experience managing a remote team member. However, This difference in performance is transitory and only observed in early stages of WFH adoption, giving support to the hypothesis that prior experience with or exposure to remote work settings helped team leaders absorb the initial shock of WFH.

Next, motivated by prior literature which documents the asymmetric effect of lockdowns on performance between male and female analysts (Du, 2021), I test whether performance of teams led by female analysts are affected differently by WFH compared to performance of teams led by male analysts. I find that while prior to the pandemic, female-led teams outperform their male counterparts, among analyst teams, the ones led by female analysts underperform the ones led by males. This evidence supports the hypothesis documented in the literature that household responsibilities such as parenting needs asymmetrically affect female employees.

Financial analysts are considered one of the most important information intermediaries in financial markets (Grossman and Stiglitz (1980), Womack (1996)) and their roles, contributions, various characteristics, and interactions with other players in financial markets are extensively studied in prior literature. However, barring a few exceptions, almost all prior literature assumes analysts work on their reports individually, ignoring the fact documented in this and few prior studies that analyst reports are predominantly issued by analyst teams. The reason for prior literature's ignoring analyst teams likely has to do with lack of data as standard databases such as I/B/E/S assign each report to an individual analyst and do not provide any data on analyst teams. This research fills this gap in the literature by using a hand-collected data on analyst teams and their characteristics.

Besides the literature on financial analysts, this study also makes contributions to other strands of literature. First and foremost, this research contributes to the emerging and quickly expanding literature on the effect of work-from-home on employee and firm outcomes. The purported negative effects on employee and team performance are one of the most cited arguments against working from home. There have been a limited number of studies examining the effect of work from home on employee productivity and coordination. However, to the best of my knowledge, these studies are either qualitative surveys which lack quantitative and objective performance measures or are performed within the context of a specific firm with limited outside sample validity. Further, this study is the first to explicitly examine the effect of WFH on team outputs. The case of analyst teams is especially appealing for studying the impact of WFH because analyst teams and individual analysts operate in the same information environment and can use the same set of inputs from the capital markets. Moreover, unlike data used in other papers studying the effect of WFH on firm outcomes, individual and group analysts' outputs are standardized, similarly structured and publicly available and are not private unique-to-firm variables access to and evaluation of which are limited to firm management. This setting allows a direct comparison between the performances of individual analysts and analyst teams in forecasting earning of the same companies within the same timeframe, alleviating endogeneity concerns.

This research is also related to the cross-disciplinary body of literature on teamwork and performance of teams compared to individuals. Teamwork and division of labor has a rich history in management, organization, and economics literature. Becker and Murphy (1992) discuss a tradeoff between returns to specialization and costs of coordination in teams. Dass, Nanda, and Wang (2013) test the coordination-specialization tradeoff in sole and team-managed mutual funds. Hypothetically, this tradeoff could also apply to analyst teams where analysts with different specializations and skillsets can complement each other's inputs in a team setting; however, as analysts team size grows, coordination costs potentially increase.

In the post-covid19-pandemic settings, the effect of work from home on coordination among employees and more specifically among team members is of special interest. My findings support the specialization-coordination tradeoff hypothesis as I find that prior to the pandemic, team size has a positive effect on team performance. However, following the start of post-pandemic work from home, the smaller teams outperform the larger teams. These findings support the hypotheses that in WFH setting, team coordination has a first-order negative effect on team performance.

This study also contributes to research on teamwork in the corporate finance literature. As noted earlier, analyst teams are rarely studied in the prior literature; A notable exception is Fang, Hope (2021) who study analyst teams and their performance compared to individual analysts and show that analyst teams produce more accurate earning reports, cover more firms, issue forecast more frequently and generate fewer stale forecasts. Another setting in which teamwork has been studied in corporate finance literature is mutual funds industry. Patel and Sarkissian (2017) note a trend in the mutual fund industry toward team management of funds. They show that mutual funds managed by teams outperform the ones managed by individuals. In their more recent work, Patel and Sarkissian (2021) show that compared to mutual funds managed by individuals, the ones managed by teams are less likely to engage in illegal activity of portfolio pumping.

Finally, this paper is related to the literature on gender inequality in the labor markets and factors affecting performance heterogeneity across genders. The most directly related paper is by Du (2021) who shows that during covid19 mandated school-closures, female analysts are less likely to issue timely forecasts and to participate in earning calls compared to male analysts. She attributes her findings to household and childcare responsibilities unevenly placed on female analysts. While Du (2021) does not find a significant difference between performance of male and female analysts during school closures, I show that following the start of work-from-home, female-led analyst teams issue forecast that are less accurate compared to male-led analyst teams. Combined, these results hew closely to the literature in labor economics studying gender pay gap and the literature which attributes gender pay gap in the labor markets to unequal allocation of household and child-bearing responsibilities across male and female workforce.

The rest of this paper is organized as follows. Section 2 discusses relevant literature. Section 3 develops hypotheses; Section 4 describes the data and provides descriptive statistics; Sections 5 reports empirical results; and section 6 concludes.

3.2. Prior Literature

3.2.1 Teamwork

Koslowski and Ilgen (2006) define teamwork as

> (a) two or more individuals who (b) socially interact (face-to-face or, increasingly, virtually); (c) possess one or more common goals; (d) are brought together to perform organizationally relevant tasks; (e) exhibit interdependencies with respect to workflow, goals, and outcomes; (f) have different roles and responsibilities; and (g) are together embedded in an encompassing organizational system, with boundaries and linkages to the broader system context and task environment.

Teamwork allows combination of inputs from individuals with complementary skillsets. In organizations, establishing teams or adding team members allows for division of labor which can increase productivity through higher return to specialization and transfer of idiosyncratic information among team members (Lazar, 1998). As breadth of knowledge grows, skillsets become increasingly narrow and specialized; as a result, teamwork has become indispensable feature and building block of present-day organizational design and vital link between individuals and organizations (Mathieu et al, 2017 and Mathieu et al, 2019) as companies maximize value of their human capital by designing their organizational structures around "network of teams in which companies build and empower teams to work on specific business projects and challenges" (Deloitte, 2016). In the same vein, Aktas et al (2021) document increasing importance of internal teams in mergers and acquisitions and find that internal M&A teams create value, especially relative to external M&A advisors, by directing transaction rationales, screening targets, and employing performance metrics to assess post-merger success.

Teamwork has also been widely adopted in various other settings. For example, Wuchty, Jones, and Uzzi (2007) show increasing dominance of teams in knowledge production and Jaravel, Petkova, and Bell (2018) note increasing importance of teams and team-specific capital in innovation; It's no surprise that scholars across various disciplines including management, organizational and behavioral sciences and psychology have paid considerable attention to various aspects of teamwork. Mathieu et al (2019) provides a good review of the literature in management and organizational science on teamwork and the effects of various team characteristics on productivity, output quality and efficiency.

In addition to the benefits of teamwork, scholars have also noted and studied potential costs and inefficiencies arising in team settings. One example of such costs is moral hazard problem theorized and formulated in seminal papers by Alcian, Demsetz (1972) and Homlstrom (1982). Moral hazard problem in teams arises when monitoring each team member's input is limited and the only observable measure of team performance is the joint output by the team; consequently, each team member has an incentive to shirk, creating free-rider problem and negatively affecting team performance. Free-rider and moral hazard signify potential costs and inefficiencies arising in team settings. As noted by Alcian, Demsetz (1972), team production will only be used instead of individual production if teamwork yields an output that is enough larger than the sum of separable production by individuals. This happens only when using teamwork will more than cover the costs of organizing, monitoring, and disciplining team members. Put another way by Becker and Murphy (1992), in teamwork, there's a tradeoff between marginal returns to specialization and marginal coordination costs among team members and adoption of team settings is justified only when the realized benefits to specialization outweigh the coordination costs. Hence, from the outset, it's not evident whether adoption of teamwork will create or destroy value in a specific setting.

Despite increasing prevalence of teams in organizations, the empirical evidence documenting gains from adoption of teams has been mostly based on experimental studies that employ games (e.g. Almaatouq et al (2021), Laughlin et al (2006), Cooper and Kagel (2004)) or small sample sizes from limited number of firms (e.g. Hamilton, Nickerson, and Owan (2003)). However, mutual funds industry and, more recently, sell-side analysts industry have provided researchers in corporate finance with appropriate settings to directly compare performance of teams and individuals. Patel and Sarkissian (2017) note an overwhelming trend in recent decades toward team management in the mutual funds industry. Comparing the performance of sole- and group-managed funds, they find that team-managed funds outperform sole-managed funds across various performance metrics including risk-adjusted returns. In their more recent work, Patel and Sarkissian (2021) find that illegal trading activity of portfolio pumping is more pronounced in sole-managed funds compared to team-managed funds. They attribute this avoidance of deceptive practices to peer effect within teams. Specialization-coordination tradeoff in teams has also been studied in the context of mutual funds industry.

Dass, Nanda, and Wang (2013) study balanced mutual funds which can hold assets across stocks and bonds. Noting that group managed funds are usually run by team of managers who individually specialize in a particular asset class, they test the coordination versus specialization trade-off hypothesis by studying market timing and security selection performance between sole- and group-managed balanced funds. They show that in sole-managed funds, centralized decision making facilitates market timing which requires timely reallocation across different asset classes. In contrast, they observe no market-timing in group-managed funds. However, team-managed funds exhibit greater returns from specialization in the form of better security selection. Combined, these results provide evidence for positive effects of teamwork on performance and confirm teamwork coordination-specialization tradeoff discussed in Becker and Murphy (1992).

In a paper related to this research, Fang and Hope (2021) study analyst teams and compare their performance with individual analysts. Since databases often used in sell-side analyst research such as I/B/E/S associate each report to a single analyst, prior research had almost completely ignored the teamwork aspect of sell-side analyst industry. Fang and Hope extend I/B/E/S data by matching earning reports to analyst teams or individual analysts and find that analyst teams issue more than 70% of annual earnings forecasts. Further, they document that analyst teams outperform individual analysts across various performance metrics including forecast accuracy, number of firms covered, and forecast frequency and timeliness.

3.2.2 Teamwork and virtuality

Morrison-Smith and Ruiz (2020) define virtual teams as geographically distributed collaborations that rely on technology to communicate and cooperate. Although Covid19 pandemic forced a sharp acceleration in adoption of virtual teamwork, prior to the pandemic, organizations were increasingly using information and telecommunication technologies to facilitate teamwork among individuals who didn't share the same location (Scott and Wildman, 2015). Since virtuality, i.e. not sharing the same location with other team members, is an important feature of working from home, it's worthwhile to briefly go over important findings of the interdisciplinary literature studying the benefits and challenges of virtual team settings.

By bridging geographical and temporal boundaries through use of communication and information technologies, virtual teams can access skillsets that are otherwise not accessible, achieve higher return to specialization, connect dispersed information, reduce costs, increase opportunities for employees and improve productivity (Perry et al, 2013). Moreover, due to reduced social and status cues, virtual teams have more social and status equalization and as a result, the decision-making process gets spread more equally among team members. Lack of status cues also makes it easier for virtual team leaders to be unbiased in their assessment of effectiveness of team members (Hedlund et al, 1998). However, as Mile and Hollenbeck (2014) note, when information is exchanged over a medium that doesn't have the richness of face-to-face communication, team members might not communicate local context to others, fail to distribute the same information to all team members, have difficulty understanding and communicating the salience of information, and access information at different speeds. Additionally, lack of face-to-face communication and monitoring could increase coordination costs, exacerbate free rider problem, and impact the performance of virtual teams negatively.

Overall, previous literature notes a contextual impact of team virtuality on team performance. For example, Blaskovich (2008) finds a positive relationship between social loafing and degree of virtuality in teams while Chidambaram & Tung (2005) suggest that virtuality can decrease loafing, particularly for highly autonomous professionals whose individual contributions are emphasized and who work in teams with high-priority tasks.

3.2.3 Pandemic-induced work from home and employee performance

The literature on post-pandemic effects of work-from-home on firm and employee outcomes is still evolving but most findings are concerned with individual employee productivity at specific companies. For example, Gibbs, Mengel and Siemroth (2021) study employee productivity at a large Asian IT service company and find that hours worked by employees increased, including by 18% outside of normal business hours. They also find that average output declined slightly, and employee productivity fell by 8-19%. They attribute the decrease in productivity to higher communication costs. Higher coordination costs were evidenced by increased time spent on meetings and coordination activities and reduced hours of uninterrupted work. Similarly, Yang et al (2020) use communication data of more than 61,000 Microsoft employees over the first 6 months of 2020 to estimate the causal effect of firm-wide remote work on collaboration and communication. Their results indicate that firm-wide remote work caused the collaboration network of workers to become more static and siloed, with fewer connections made across distant parts of the firm. Furthermore, they document a decrease in synchronous communication and an increase in asynchronous communication. They argue that together, these effects may make it harder for employees to acquire and share new information across the network.

On the other hand, Bloom, Han, and Liang (2022) study a randomized control trial adoption of hybrid WFH and working from office using a sample of more than 1600 engineers from a technology firm. They find that WFH reduced attrition rates by 35%, improved self-reported work satisfaction scores, reduced hours worked on home days but increased it on other workdays and the weekend, increased individual messaging and group video call communication, even when in the office, and had a small positive impact on some performance measures.

Some researchers in corporate finance have also studied the impact of WFH on employee performance. Cao, Simin, Xiao (2021) study performance of actively managed equity mutual funds using staggered state-level stay-at-home orders in the US. They document that after implementation of WFH, fund daily returns over market returns decrease by 90 basis points per day. Finally, Ng, Yu and Yu (2021) study the emotional effect of WFH on managers. They note that WFH dampens managerial sentiment and increases managers' precautionary motives. As a result, managers accumulate excess cash which in turn hurts shareholder value.

3.2.4 Female analysts and WFH

Prior to the pandemic, scholars in socioeconomics and gender studies have documented gender discrepancies in the effect of household responsibilities, flexible working schedules and remote work on career outcomes. Sullivan and Lewis (2001) note that teleworking can simultaneously enhance work–life balance and perpetuate traditional work and family roles which assume a higher share of household responsibilities for women. Lott and Chung (2016) provide evidence that flexible schedule has the potential to traditionalize gender roles and increase the gender pay gap. This is due to men being more likely than women to use flexible working hours for performance enhancing purposes. In contrast, as per the traditional gender roles, women are expected to increase their household responsibilities when they have more flexible working hours. Similarly, Hilbrecht et al (2008) find that women working from home experienced a traditional gendered division of household labor and viewed telework as a helpful tool for combining their dual roles. Chung and Lippe (2020) provide a good review of the multidisciplinary literature on flexible working and gender equality prior to the Covid19 pandemic.

The above-mentioned heterogenous effect of telework and flexible schedule between genders were amplified by the Covid19 pandemic when significant portion of the labor force worked from home while schools and childcare centers were closed. Dunatchik et al (2021) note that closing of schools and childcare centers in many circumstances reinforced an unequal division of labor as mothers take on greater share of facilitating learning for children and taking care of household responsibilities. In the same vein, a McKinsey (2021) study finds that after the start of the pandemic, compared to fathers, mothers are more than three times as likely to meet the household and caregiving responsibilities. They also note that women are more likely to consider leaving the workforce or downshifting their careers because of the pandemic. Finally, Collins et al (2020) reports that following the start of the pandemic, mothers with young children have reduced their work hours four to five times more than fathers.

Most of the above literature reporting heterogenous effects of pandemic and WFH on women are surveys and one-on-one interviews. In this paper, I use a large sample of sell-side analysts estimates to study the effect of WFH on female analysts' performance as individuals and as lead-analysts coordinating teams. The most directly related paper is by Du (2021) who shows that during Covid19 mandated school-closures, female analysts are less likely to issue timely forecasts and to participate in earning calls compared to male analysts. She attributes her findings to household and childcare responsibilities unevenly placed on female analysts. While she doesn't find any effect on accuracy of forecasts issued by female analysts, her data does not distinguish between female analysts working individually and the ones leading teams.

3.3. Hypothesis development

From the outset, it's not clear how WFH would affect the performance of analyst teams. Since the pace of developments following the start of the pandemic was extraordinarily fast, most corporations were caught by surprise and didn't have enough time to adjust quickly enough to work-from-home setting and set up the proper infrastructure. This, at least in the early months, must have created restrictions and frictions in the work and information flow within and across firms and market players. To the extent that work from home created and exacerbated inefficiencies, frictions, and distractions due to limited face-to-face interactions and lack of in-person monitoring, work-from-home might have increased coordination costs and negatively affected analysts team performance. On the other hand, to the extent that work-from-home has broadened the access to the talent pool and created and facilitated new communication possibilities and increased information processing speed and capacities due to new information technology infrastructure and more flexible working hours, one could conjecture that WFH facilitated in-time communication and sharing of information among team members. Therefore, broadly stated, my first hypothesis in the null form is stated as follows:

H1: Work from home doesn't impact performance of individual analysts and analyst teams.

My second hypothesis is concerned with the lead analyst's prior-to-the-pandemic experience with virtual team settings. I hypothesize that lead analysts with prior experience leading a team where at least one member is not located in the same state or country as the lead analyst need less time to adjust to WFH. This could be due to the lead analyst having gained prior experience managing a virtual team or due to the necessary virtual communication systems having been already in place prior to the pandemic. Therefore, broadly stated, my second hypothesis in the null form is stated as follows:

> *H2: lead-analysts prior-to-the-pandemic experience with virtual teams doesn't influence the performance of analyst teams in the WFH settings.*

My third hypothesis concerns team size. Fang and Hope (2021) find a positive relationship between team size and analyst team performance. However, as team size grows, more resources must be spent on coordination among and monitoring of team members. Patel and Sarkissian (2017) note a positive relationship between fund management team size and mutual fund performance. Since WFH removes in-person monitoring and feedback, it could magnify the coordination costs. On the other hand, increased information processing speed and capacities and access to broader pool of talent could lead to increased return to specialization and division of labor. Testing the effect of WFH on the relationship between team size and team performance could help us examine whether the increase in coordination costs in the WFH setting negatively affects performance. Therefore, hypothesis three in the null form is stated as follows:

> *H3: work from home does not affect the relationship between team size and team performance*

My fourth hypothesis is related to the literature on gender inequality in the labor force. If household responsibilities asymmetrically affect female workforce, I expect performance of teams led by female analysts to be negatively affected compared to male-led analyst teams. This is in line with findings of Du (2021). Therefore, my fourth hypothesis in the null form is stated as follows:

H4: the work from home setting doesn't affect the performance of female-led analyst teams.

3.4. Data

23,860 sell-side analyst reports from top brokerage houses including Barclays, HSBC, Credit Suisse, UBS, DBS, RBC, TD, Buckingham Research, and JP Morgan, covering U.S. firms are collected from Investex. To capture the periods before and after the start of post-pandemic WFH, I include the estimates announced between 17 April 2017 and 18 May 2021 corresponding to firm fiscal periods endings from 31 Oct 2017 to 31 Dec 2023. Each report is parsed to extract report date, title, analysts' names, analyst telephone numbers, and broker name. Analyst telephone numbers are used to geolocate each analyst. Then the Investex reports, and the I/B/E/S U.S. database are matched by brokerage firm names, analyst names, and the underlying company identifiers that include trading symbols and company names. In the final database, around 19% of the estimates were issued by individual analysts and 81% by analyst teams. I limit my analysis to earning releases for which at least one analyst team and one individual analyst estimates exist.

The number of analyst teams, percentage of female individual analysts and female-lead teams, and team size before and during the WFH period is shown in figure 3.1.

[Insert figure 3.1 here]

As indicated by figure 3.1, around quarter of the reports were issued after March 15, 2020, which is the date after which WFH is considered in effect in my main analysis[12]. In the sample, prior to (after) March 15, 2020, 79.8% (75.5%) of the reports were issued by teams.

[12] In my robustness tests, I confirm my results using March 1, 2020 or April 1, 2020 as my treatment dates.

In the full sample, around 13% of reports were issued by female individual analysts or female-lead teams while in the WFH period 15.5% of reports were issued by female individual analysts or female-lead teams. Of the individual reports issued prior to (during the) WFH period, 13.4% (11.9%) percent were issued by female individual analysts. Of the reports issued by teams prior to (during the) WFH period, 11.3% (16.9%) percent were issued by female-lead teams.

In the full sample (during the WFH period), 24.6% (21.9%) of reports were issued by teams with 2 analysts, 28.9% (27.44%) were issued by teams with 3 analysts, 20.72% (20.71%) were issued by teams of 4 analysts and 7% (5.35%) were issued by teams of more than 4 analysts. Average team size for female-led (male-lead) teams is 3.16 (3.32).

Lastly, in the full sample, 59.20% of reports were issued by an analysts with no prior virtual work from office experience and 81% of the analysts in the sample have no prior experience managing a virtual team.

3.5 Empirical analysis:

3.5.1 Analyst performance measures and descriptive statistics

Report absolute forecast error is defined as follows:

$$AFE_{i,f,t} = |\ EPS_{ift}^{forecast} - EPS_{f,t}^{actual}\ |$$

In order to make the forecast error measure comparable across analysts and firms, the absolute forecast error needs to be adjusted. I use two main measures of forecast error from the literature.

My main measure of forecast error is constructed following Bradley, Gokkaya, Liu (2017). For each analyst forecast, at the earning-release level and excluding the analyst forecast itself, I calculate the mean forecast error MAFE; I then subtract the mean from the AFE and scale the result by mean AFE:

$$PMAFE_{ift} = \frac{AFE_{ift} - MAFE_{f,t}}{MAFE_{f,t}}$$

To make this measure easier and more intuitive to interpret and consistent with other measures, I add one and multiply by -1. Therefore:

$$PMAFE_{ift} = -1 - \frac{AFE_{ift} - MAFE_{f,t}}{MAFE_{f,t}} = -\frac{AFE_{ift}}{MAFE_{ft}}$$

The most accurate estimate will have the $PMAFE_{ift}$ value of zero and the more negative the value of $PMAFE_{ift}$, the less accurate the forecast is. $PMAFE_{ift}$ can be interpreted as analyst i's fractional forecast error relative to the average of the analysts' forecast error. Alternatively, $MAFE_{ft}$ can be interpreted as the level of difficulty of the forecast; The higher level of $MAFE_{ft}$ across all analysts estimating the firm's earning could indicate the higher level of uncertainty and difficulty of forecast. Dividing by $MAFE_{ft}$ scales up the more predictable estimates and scales down the more difficult and uncertain estimates.

Summary statistics for analyst forecast accuracy measures are presented in table 3.1. To curb outlier effects, all measures are winsorized at the 1% level.

[insert table 3.1 about here]

3.5.2 Analyst teams versus individual analysts

I start my empirical analysis by examining the first hypothesis concerning the performance of analyst teams in the WFH setting. To test the hypothesis, I formulate a difference-in-

(1)

difference model to capture the difference between performance of analyst teams and individual analysts before and after the start of post-pandemic WFH.

$$Performance_{i,f,t} = \beta_0 + \beta_1\, POST_t + \beta_2\, TEAM_{i,f,t} + \beta_3\, POST_t \times TEAM_{i,f,t}$$

$$+ \gamma\, Controls + FE + u_{i,f,t}$$

Where $Performance_{i,f,t}$ is the previously defined performance measure for analyst team or individual analyst *i* in estimating earnings of firm f at time t. the coefficient on *POST,* β_1 captures performance of individual analyst after the start of WFH. β_2 captures the performance of analyst teams before adoption of WFH. β_3 captures the difference in difference between individual analysts and analyst teams.

$POST_t$ is an indicator variable capturing the period after the start of post pandemic WFH. It switches to 1 if the estimate is issued after the adoption of WFH. The state governments' stay-at-home orders were issued in second half of March 2020, but by that time many firms had already asked their employees to work from home. My results are robust to $POST_t$ indicating the period starting March 1, 2022 or March 15, 2020 or March 30 2020. As noted by Bloom et al (2021), it can be safely assumed that for much of the period past March 2020, most of work was performed at home.

Controls is a vector of firm, analyst, and report characteristics. Some of the firm-level control variables I use are log of market value, market-to-book ratio, growth of income before extraordinary items, beta, intangible assets ratio, and standard deviation of return over twelve preceding months. Following Clement (1999), I control for forecast age defined as the number of days from earnings forecast to the announcement of actual earnings. I also include analyst controls such as analyst general and firm-specific experience as well as number of firms and industries the analyst covers in a given earning release year. FE indicates the vector of fixed effects. I perform all my regressions using firm, bank and earning release fixed effects. I also limit the sample to include only the earnings for which both individual and team estimates exist. All my standard errors are clustered at the analyst state level. Table 3.2 presents the difference-in-difference results of model (1) for previously defined PMAFE measure of analyst performance.

[insert table 3.2 about here]

In column 1 no fixed effects are used. In column 2 firm fixed effects are used while in columns 3 and 4 earnings release, and investment bank fixed effects are used respectively. My most-demanding setting is presented in column 3 with earning release fixed effects. Consistent with prior literature who study effect of WFH on individual employees (Gibbs, Mengel and Siemroth, 2021 and Yang et al, 2020) I find that performance of individual analysts is negatively affected after the start of post-pandemic WFH. The coefficients on performance of individual analyst in WFH settings are all significant at 1% level. Columns 1, 2 and 4 indicate a performance decline equal to around half of one standard deviation in analyst forecast error. When using more demanding earning-release fixed effects, the performance decline is equal to around 27% of one standard deviation of PMAFE. The difference-in-difference coefficient is positive but mostly not significant. Combined these results indicate that WFH settings is associated with a decline in performance of individuals and teams.

Since it likely took both firms and employees some time to adjust to the pandemic shock and WFH reality, it's possible that the effect observed is due to the initial shock of WFH setting as the period right after start of the post pandemic WFH was more challenging to both individuals

(2)

and teams. To test if the observed effects are transitory, I divide the Post period in model (1) to two periods: One including March and April 2020 and the next after end of April 2020. I use the following model to test this hypothesis.

$$Performance_{i,f,t} = \beta_0 + \beta_1 \, POST_{1t} + \beta_2 \, POST_{2t} + \beta_3 \, TEAM_{i,f,t} + \beta_4 \, POST_{1t} \times TEAM_{i,f,t} + \beta_5 \, POST_{2t} \times TEAM_{i,f,t} + \gamma \, Controls + FE + u_{i,f,t}$$

Where $Post_1$ indicates the period from start of March 2020 to end of April 2020 and $Post_2$ indicates the period afterwards. Results are presented in table 3.3.

[insert table 3.3 about here]

The results confirm the findings of model (1) with one post period. Interestingly, in the early months of WFH adoption, the negative effect of WFH on individual analysts are insignificant. However, the negative effect on individual analysts in later months becomes larger compared to model (1).

So far, the results suggest a negative and significant impact of WFH on the performance of individual and team analysts. Next section examines the effect of WFH on the relationship between team size and team performance.

3.5.3. Work from home and team size

As noted by Alcian, Demsetz (1972) and Becker and Murphy (1992) team performance and team size can have a positive or negative relationship with performance. On the one hand larger teams can benefit from increased return to specialization and division of labor. On the other hand, coordination costs increase as the team size grows. Fang and Hope (2021) document a positive relationship between analyst team size and team performance. Patel and Sarkissian (2017) also document a positive relationship between mutual funds management team size and mutual funds performance. However, it’s not clear how WFH settings interact with team coordination costs or returns to specialization. To test the effect of WFH on the relationship between team size and team performance, I limit the sample to analyst teams and formulate the following models linear and quadratic in team size.

$$\begin{aligned} Performance_{i,f,t} &= \beta_0 + \beta_2\, TEAMSIZE_{i,f,t} + \beta_3\, TEAMSIZE_{i,f,t}^2 + \beta_3\, POST_t \times TEAMSIZE_{i,f,t} \\ &\quad + \beta_4\, POST_t \times TEAMSIZE_{i,f,t}^2 + \gamma\, Control\ vars + FE + u_{i,f,t} \end{aligned}$$

The results are presented in table 4 below.

[insert table 3.4 about here]

The results of linear model regressions are presented in columns 1 to 4 of table 3.4, while columns 5 to 8 of table 3.4 pertain to quadratic model. Prior to the pandemic, the results confirm the findings of prior literature on the positive relationship between team size and team performance. After the start of the pandemic, however, the relationship changes as analyst team size and team performance become negatively and significantly related.

3.5.4 Analysts’ prior virtual teams experience and team performance

It’s likely that most analysts worked from their offices prior to the pandemic. However, data indicates that some lead-analysts worked with team members which were located outside of their lead analysts’ states. I refer to these teams with members geolocated in states different from that of the lead-analyst “virtual-work-from-office” (VWFO) teams. As discussed in the literature review, while externalities imposed on teams by WFH and VWFO are not the same, they share some aspects. In both WFH and VWFO settings at least some team members do not share a physical location. Therefore, a lead analyst working with a remote team member must develop skills in coordinating, monitoring, and leading virtually. Also, it’s likely that lead analysts with VWFO experience have a lead on adoption of virtual communication technologies compared to lead analysts with no such experience. These lead analysts could benefit from their VWFO experience even when working individually in WFH settings.

In this section, I study whether having prior experience with VWFO has a meaningful impact on individual and team performance in WFH settings. To do so, I define a variable called NVT (number of virtual teams) which captures number of earnings estimates for which the lead analysts worked with a team in which at least one member doesn’t share the same location as that of the lead analyst. I measure NVT starting from 2017 to the beginning of the pandemic. First, I use the following model to compare the performance of lead analysts with and without VWFO experience.

$$Performance_{i,f,t} = \beta_0 + \beta_1 POST_{1t} + \beta_2 POST_{2t} + \beta_3 TEAM_{i,f,t} +$$

$$\beta_4 POST_{1t} \times TEAM_{i,f,t} + \beta_5 POST_{2t} \times TEAM_{i,f,t} +$$

$$\theta_1 NVT + \theta_2 NVT \times POST_{1t} + \theta_3 NVT \times POST_{2t} +$$

$$\theta_4 NVT \times TEAM_{i,f,t} \times POST_{1t} + \theta_5 NVT \times TEAM_{i,f,t} \times POST_{2t} +$$

$$\gamma\, Controls + FE + u_{i,f,t}$$

$POST_1$ captures the period from beginning of March 2020 to end of April 2020. $POST_2$ captures the period after April 31st 2020. Coefficient θ_1 on NVT indicates the performance of a lead analyst with prior to the pandemic experience of managing NVT number of VWFO teams, working individually on estimating earnings of firm f to be released in the future. θ_2 captures the performance of an analyst with prior virtual experience working individually during the early couple of months of WFH adoption. θ_4 captures the performance of a lead analyst with prior to the pandemic experience of managing NVT number of VWFO teams, working with a team on estimating earnings of firm f at time t during the early months of the pandemic WFH. Results are presented in table 3.5 below.

[insert table 3.5 about here]

As illustrated in table 3.5, we do not observe any effect of prior VWFO experience on performance of teams. However, there's some indication that performance of lead analysts with prior VWFO experience working individually was positively affected. For example the coefficients for interaction of NVT and Mar_Apr indicator variable modestly positive and significant at the 5% level when using no fixed effects, earning release fixed effects or bank fixed effects.

The above observed effects support the hypothesis that lead-analysts with more VWFO experience had gained experience coordinating and managing their teams virtually and this skills carried over to early periods of WFH adoption. However, after the initial shock of WFH was absorbed by analysts with less VWFO experience, they benefitted from temporal stability of having all their team members in the same state while working from home. Implied assumption is that VWFO analyst teams are more likely to work with analysts from different states after adoption of WFH.

3.5.5 Female analysts' performance in Work-from-Home settings

As discussed in the literature review, due to heterogenous impact of WFH across genders, it's expected that WFH would affect the performance of analyst teams led by female analysts. To test this hypothesis, I formulate the following model for a subsample of all reports issued by analyst teams.

$$Performance_{i,f,t} = \beta_0 + \beta_1\, POST_t + \beta_2\, FEMALE_{i,f,t} + \beta_3\, FEMALE_{i,f,t} \times TEAM_{i,f,t}$$

$$+ \gamma\, Controls + FE + u_{i,f,t}$$

Coefficient β_3 captures the difference-in-difference between performance of teams led by male and female lead-analysts before and after the start of WFH. β_2 captures the performance of female-led teams prior to the adoption of WFH and β_1 captures the performance of male-led teams after adoption of WFH. The results are presented in table 3.6.

[insert table 3.6 about here]

Across all specifications, the coefficient on Female indicates that prior to pandemic and adoption of WFH, female-led teams significantly outperformed their male counterparts. However, after adoption of WFH, teams led by female analysts significantly underperform team led by male analysts which themselves underperform compared to the period before the adoption of WFH. These results confirm the hypothesis indicating that after adoption of WFH, female analysts underperform their male counterparts possibly due to unequal burden of household and caregiving responsibilities on women.

To further investigate the effect of WFH on teams led by female analysts, I study the interaction of gender and team size. Since bigger teams require higher coordination effort by the team leader, and based on the results from table 3.6, I expect a negative relationship between interaction of female and team size variables in the following model:

$$Performance_{i,f,t} = \beta_0 + \beta_1 \, TEAMSIZE_{i,f,t} + \beta_2 \, POST_t \times TEAMSIZE_{i,f,t} + \beta_3 \, FEMALE \times TEAMSIZE_{i,f,t} + \beta_4 \, POST_t \times FEMALE \times TEAMSIZE_{i,f,t} + \ldots + \gamma \, Control\ vars + FE + u_{i,f,t}$$

The coefficient of interest is β_4 which captures the effect of gender on interaction of post indicator variable and team size. Results are presented in table 8 below.

[insert table 3.7 about here]

Overall, results indicate that in WFH settings the negative effect of team size on team performance is stronger for female-led teams. This is while some results indicate that prior to the pandemic, the positive effect of team size on performance is stronger for female-led teams. These results further support the hypothesis that in WFH settings, performance of female analysts is negatively affected due to unequal burden of household and caregiving responsibilities being placed on them.

3.6. Robustness tests

In my robustness tests, I use an alternative analyst performance measure. I follow Clement, Tse (2003), and construct proportional Range Absolute Forecast Error (PRAFE) as follows:

$$PRAFE_{i,f,t} = \frac{AFE_{f,t}^{max} - AFE_{i,f,t}}{AFE_{f,t}^{max} - AFE_{f,t}^{min}}$$

In calculating the PRAFE measure, I deduct the analyst absolute forecast error from the max absolute forecast error at firm earning release level and then divide by the range of absolute forecast error at firm earning release level.

PRAFE measure is going to be between 0 and 1; Zero will reflect the least accurate forecast while one reflects the most accurate forecast. To make the measure consistent with other measures and make interpretation of coefficients more intuitive, I deduct 1 from the above. Then -1 will represent the least accurate forecast and 0 the most accurate forecast.

$$PRAFE_{i,f,t} = \left(\frac{AFE_{f,t}^{max} - AFE_{i,f,t}}{AFE_{f,t}^{max} - AFE_{f,t}^{min}} - 1\right)$$

Like PMAFE, PRAFE is adjusted using dispersion of forecasts among analysts covering a firm-quarter. As is the case with forecast dispersion among analysts, stock price volatility can also proxy for uncertainty and difficulty of forecast at the firm level. Therefore, I also follow the approach used by Loh and Stulz (2018) and use stock price annualized daily return volatility over 3-, 6- and 12-month windows prior to the estimate as the adjustment factor:

$$AFE_{ift}^{vol} = -\frac{AFE_{i,f,t}}{\sigma_p^2}$$

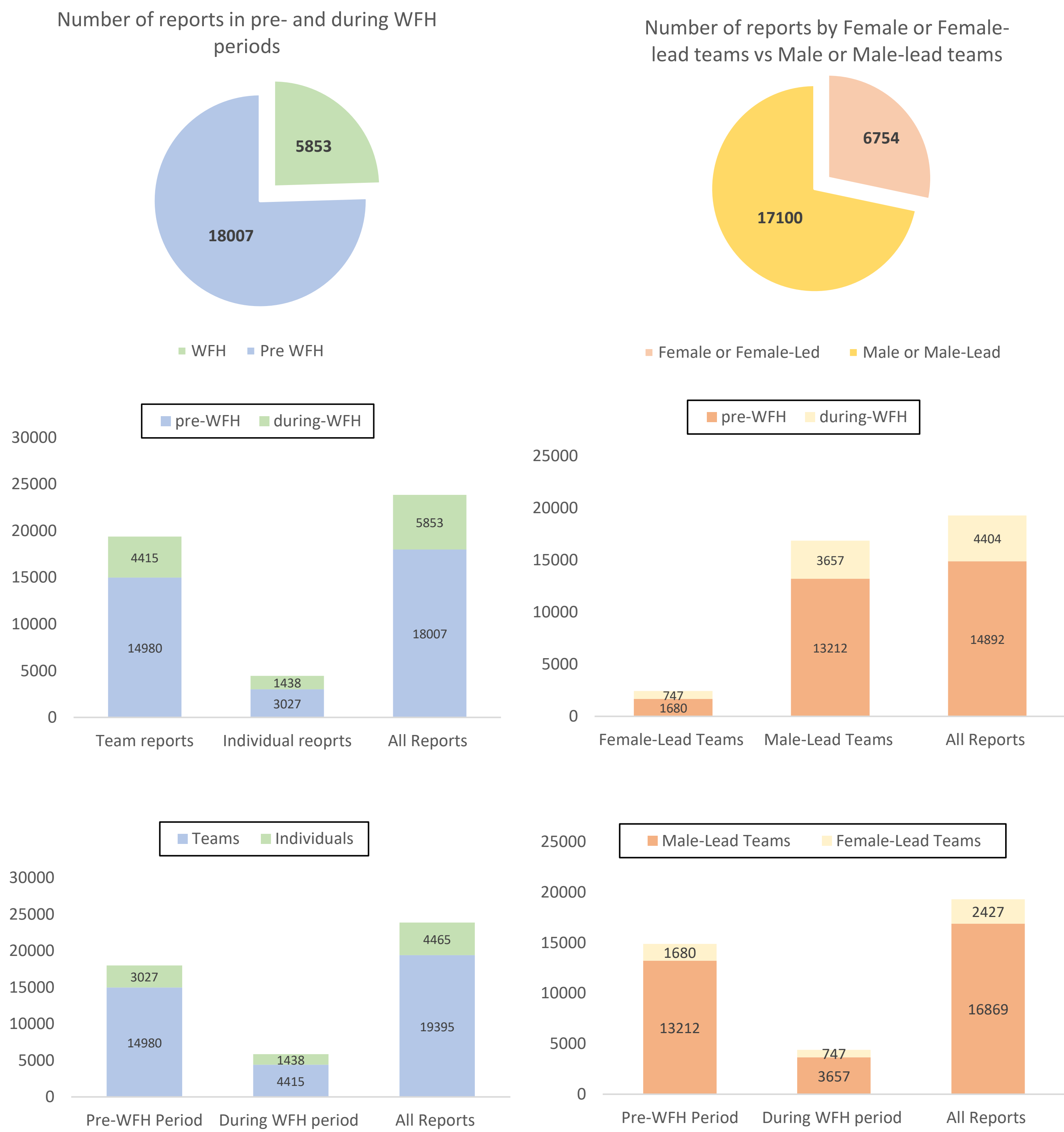
The results for PRAFE measure are presented in appendix in tables A3.1 to A3.9 . All the results observed using PMAFE measure of forecast error are confirmed when using PRAFE.

3.7. Conclusion

This study provides insights into the effect of work-from-home on employee performance. More specifically, I study the effect of work-from-home on the performance of individual analysts and analyst teams. The teamwork aspect of sell-side analyst industry is for the most part ignored in the previous literature. This paper uses a large sample of data on individual analysts and analyst teams to study the impact of work-from-home on their performance. I find that work-from-home affects the performance of individual analysts and analyst teams negatively. Furthermore, I investigate the effects of interaction of team characteristics and work-from-home on team performance. I present evidence suggesting that in work-from-home settings, team size is negatively related to team performance, and prior experience managing virtual teams gave lead analysts a performance edge in the early months of work-from-home. I also find that female analysts' performance is negatively affected in the work-from-home settings.

Figures

Figure1. Number of analyst teams, female-led teams before and during the work-from-home period.



Tables

Table 3.1 Summary statistics for measures of analyst forecast error used in the models. All measures are winsorized at the 1% level. For all measures, the most accurate forecast has forecast error of zero and the more negative forecasts indicate less accuracy.

Analyst Forecast Error Measure	N	Mean	Standard Deviation	Min	P25	Median	P75	Max
$PMAFE$	23737	-1.017	1.125	-6.896	-1.261	-0.720	-0.325	0.000
$PRAFE$	23569	-0.285	0.329	-1.000	-0.461	-0.143	-0.022	0.000
$AFE_{\sigma^2_{3m}}$	23857	-0.141	0.290	-2.004	-0.129	-0.042	-0.014	0.000
$AFE_{\sigma^2_{6m}}$	23857	-0.137	0.281	-1.881	-0.125	-0.041	-0.014	0.000
$AFE_{\sigma^2_{12m}}$	23857	-0.134	0.276	-1.842	-0.122	-0.039	-0.014	0.000
AFE	23860	-0.280	0.621	-4.318	-0.240	-0.080	-0.030	0.000

Table 3.2 Difference-in-difference regression for analyst teams versus individual analysts before and after start of post-pandemic work-from-home using PMAFE as the measure of analyst forecast error . Only earning releases for which both group and individual reports exist are included in the regressions. Post indicates period beginning March 1, 2020. The model in column (1) uses no fixed effects. Models in Column (2), (3) and (4) use firm, earning release and investment bank fixed effects. Standard errors are robust to clustering at the state level. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

$$PMAFE_{ift} = \beta_0 + \beta_1\, POST_t + \beta_2\, TEAM_{i,f,t} + \beta_3\, POST_t \times TEAM_{i,f,t} + \gamma\, Controls + FE + u_{i,f,t}$$

	(1)	(2)	(3)	(4)
Team	0.035	0.015	0.019	0.044
	(0.037)	(0.021)	(0.019)	(0.035)
Post	-0.292***	-0.288***	-0.281***	-0.288***
	(0.038)	(0.032)	(0.050)	(0.036)
Team x *Post*	0.017	0.043*	0.029	0.010
	(0.033)	(0.023)	(0.025)	(0.031)
Size	-0.006	-0.107***	-0.251***	-0.006
	(0.006)	(0.027)	(0.039)	(0.006)
M/B	0.000	-0.004**	-0.006	0.000
	(0.001)	(0.002)	(0.004)	(0.001)
IB growth	-0.003	-0.030	-0.064***	-0.002
	(0.005)	(0.025)	(0.018)	(0.004)
Beta	-0.028	-0.061*	-0.105***	-0.026
	(0.019)	(0.031)	(0.018)	(0.021)
Intangible	0.040	0.797**	1.985***	0.035
	(0.027)	(0.337)	(0.515)	(0.025)
Arpre12	-0.000	-0.001***	0.000	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Loss	0.026	0.083	-0.208	0.026*
	(0.021)	(0.112)	(0.204)	(0.015)
Return Volatility	-0.004	-0.053***	-0.150***	-0.006
	(0.007)	(0.018)	(0.021)	(0.007)
Age	-0.002***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Genex	-0.001	-0.002	-0.003**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Firmex	0.004***	0.008***	0.008***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Ninds	0.003	0.002	0.002	-0.001
	(0.009)	(0.013)	(0.010)	(0.008)
Nfirms	-0.004*	-0.004*	-0.004	-0.008***
	(0.002)	(0.002)	(0.004)	(0.002)
Firm FE		Yes		
Earning release FE			Yes	
Bank FE				Yes
Adjusted R-sq	0.130	0.154	0.165	0.128
N	19487	19477	19487	19487

Table 3.3. Difference-in-difference regression for analyst teams versus individual analysts before and after start of post-pandemic work-from-home with two post periods and using PMAFE as the measure of analyst forecast error. The model in column 1 uses no fixed effects. Models in Column 2,3 and 4 use firm, earning release and investment bank fixed effects. Standard errors are robust to clustering at the analyst state level.

$$PMAFE_{i,f,t} = \beta_0 + \beta_1\, POST_t^1 + \beta_2\, POST_t^2 + \beta_3\, TEAM_{i,f,t} + \beta_4\, POST_t^1 \times TEAM_{i,f,t} + \beta_5\, POST_t^2 \times TEAM_{i,f,t} + \gamma\, Controls + FE + u_{i,f,t}$$

	(1)	(2)	(3)	(4)
Team	0.034	0.015	0.018	0.044
	(0.036)	(0.021)	(0.019)	(0.034)
Mar_Apr	0.004	-0.012	-0.050	0.008
	(0.044)	(0.040)	(0.051)	(0.042)
Post_Apr	-0.370***	-0.396***	-0.404***	-0.366***
	(0.048)	(0.041)	(0.068)	(0.045)
Team x *Mar_Apr*	-0.101	-0.076	-0.091*	-0.105*
	(0.062)	(0.051)	(0.048)	(0.061)
Team x *Post_Apr*	0.029	0.056**	0.048**	0.021
	(0.034)	(0.025)	(0.023)	(0.032)
Size	-0.002	-0.041**	-0.139***	-0.003
	(0.007)	(0.017)	(0.036)	(0.007)
M/B	0.000	-0.003*	-0.004	0.000
	(0.001)	(0.002)	(0.004)	(0.001)
IB growth	-0.002	-0.032	-0.063***	-0.001
	(0.005)	(0.025)	(0.019)	(0.004)
Beta	-0.033*	-0.064**	-0.101***	-0.032
	(0.018)	(0.030)	(0.019)	(0.021)
Intangible	0.043	0.789**	1.829***	0.038
	(0.025)	(0.332)	(0.519)	(0.023)
Arpre12	-0.000	-0.001***	-0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Loss	0.023	0.096	-0.202	0.022
	(0.021)	(0.112)	(0.204)	(0.015)
Return Volatility	0.006	-0.011	-0.091***	0.004
	(0.009)	(0.013)	(0.016)	(0.008)
Age	-0.002***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Genex	-0.001	-0.002	-0.003**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Firmex	0.004***	0.007***	0.008***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Ninds	0.004	0.004	0.003	-0.000
	(0.009)	(0.013)	(0.010)	(0.008)
Nfirms	-0.005**	-0.005*	-0.004	-0.008***
	(0.002)	(0.002)	(0.004)	(0.002)
Firm FE		Yes		
Earning release FE			Yes	
Bank FE				Yes
Adjusted R2	0.133	0.156	0.167	0.131
N	19487	19477	19487	19487

Table 3.4. Analyst team size and team performance using PMAFE as the measure of analyst performance. The model in column 1 and 5 uses no fixed effects. Models in Column 2 & 6, 3 & 7 and 4 & 8 use firm, earning release and investment bank fixed effects respectively. Standard errors are robust to clustering at the analyst state level.

$$PMAFE_{i,f,t} = \beta_0 + \beta_2\, TEAMSIZE_{i,f,t} + \beta_3\, TEAMSIZE_{i,f,t}^2 + \beta_3\, POST_t \times TEAMSIZE_{i,f,t}$$
$$+ \beta_4\, POST_t \times TEAMSIZE_{i,f,t}^2 + \gamma\, Control\ vars + FE + u_{i,f,t}$$

	(1)	(2)	(3)	(4)
Team size	0.034***	0.021***	0.009*	0.050***
	(0.007)	(0.003)	(0.005)	(0.008)
Team Size x *Post*	-0.075***	-0.047***	-0.014**	-0.078***
	(0.003)	(0.004)	(0.006)	(0.003)
Firm controls	Yes	Yes	Yes	Yes
Analyst controls	Yes	Yes	Yes	Yes
Report controls	Yes	Yes	Yes	Yes
Firm FE		Yes		
Earning release FE			Yes	
Bank FE				Yes
Adj. R2	0.127	0.151	0.163	0.125
N	19493	19483	19493	19493

Table 3.5. Analyst performance measured by PMAFE and her prior to the pandemic experience working with virtual teams. The model in column 1 uses no fixed effects. Models in Column 2,3 and 4 use firm, earning release and investment bank fixed effects respectively. Standard errors are robust to clustering at the analyst state level.

$$PMAFE_{ift} = \beta_0 + \beta_1\, POST_{1t} + \beta_2\, POST_{2t} + \beta_3\, TEAM_{i,f,t} + \beta_4\, POST_{1t} \times TEAM_{i,f,t} + \beta_5 POST_{2t} \times TEAM_{i,f,t} + \theta_1 NVT + \theta_2 NVT \times POST_{1t} + \theta_3 NVT \times POST_{2t} + \theta_4 NVT \times TEAM_{i,f,t} \times POST_{1t} + \theta_5 NVT \times TEAM_{i,f,t} \times POST_{2t} + \gamma\, Controls + FE + u_{i,f,t}$$

	(1)	(2)	(3)	(4)
Team	0.023	-0.000	0.001	0.033
	(0.030)	(0.022)	(0.023)	(0.028)
Mar_Apr	-0.035	-0.062	-0.107**	-0.027
	(0.051)	(0.043)	(0.043)	(0.048)
Post_Apr	-0.379***	-0.410***	-0.425***	-0.373***
	(0.029)	(0.028)	(0.040)	(0.029)
Team x *Mar_Apr*	-0.085	-0.047	-0.061*	-0.093*
	(0.057)	(0.042)	(0.032)	(0.054)
Team x *Post_Apr*	0.045**	0.076***	0.069**	0.036*
	(0.020)	(0.025)	(0.031)	(0.020)
NVT	-0.004	-0.005	-0.006	-0.005
	(0.004)	(0.005)	(0.004)	(0.004)
NVT x *Mar_Apr*	0.007**	0.008*	0.008**	0.006**
	(0.003)	(0.004)	(0.004)	(0.003)
NVT x *Post_apr*	0.003	0.003	0.003	0.002
	(0.010)	(0.012)	(0.012)	(0.010)
NVT x *Team*	0.004	0.005	0.005	0.004
	(0.003)	(0.004)	(0.004)	(0.004)
NVT x *Team* x *Mar_Apr*	-0.002	-0.004	-0.005	-0.002
	(0.003)	(0.004)	(0.004)	(0.003)
NVT x *Team* x *Post_Apr*	-0.004	-0.004	-0.004	-0.003
	(0.010)	(0.012)	(0.011)	(0.009)
Firm controls	Yes	Yes	Yes	Yes
Analyst controls	Yes	Yes	Yes	Yes
Report controls	Yes	Yes	Yes	Yes
Firm FE		Yes		
Earning release FE			Yes	
Bank FE				Yes
Adjusted R2	0.133	0.157	0.167	0.131
N	19487	19477	19487	19487

Table 3.6: Difference-in-Difference in performance of female-led and male-led analyst teams measured by PMAFE before and after adoption of WFH. The model in column 1 uses no fixed effects. Models in Column 2,3 and 4 use firm, earning release and investment bank fixed effects respectively. Standard errors are robust to clustering at the analyst state level.

	(1)	(2)	(3)	(4)
Female	0.060***	0.086***	0.085***	0.055***
	(0.021)	(0.011)	(0.011)	(0.009)
Post	-0.269***	-0.231***	-0.221***	-0.271***
	(0.015)	(0.022)	(0.049)	(0.014)
Female x *Post*	-0.076***	-0.145***	-0.147***	-0.077***
	(0.015)	(0.012)	(0.014)	(0.009)
Size	-0.005	-0.111***	-0.248***	-0.005
	(0.006)	(0.026)	(0.036)	(0.006)
M/B	0.000	-0.004	-0.005*	0.000
	(0.001)	(0.002)	(0.003)	(0.001)
Ib growth	-0.004	-0.030	-0.066***	-0.003
	(0.005)	(0.025)	(0.018)	(0.004)
Beta	-0.028	-0.064**	-0.108***	-0.026
	(0.020)	(0.028)	(0.018)	(0.022)
Intangible	0.033	0.736**	1.903***	0.029
	(0.026)	(0.321)	(0.511)	(0.025)
Arpre12	-0.000*	-0.000***	0.000	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Loss	0.027	0.097	-0.193	0.027*
	(0.020)	(0.112)	(0.194)	(0.015)
Return Volatility	-0.004	-0.055***	-0.151***	-0.006
	(0.007)	(0.017)	(0.021)	(0.007)
Age	-0.002***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Genex	-0.000	-0.001	-0.002*	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Firmex	0.004***	0.007***	0.007***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Ninds	0.001	0.001	0.004	-0.002
	(0.010)	(0.013)	(0.009)	(0.008)
Nfirms	-0.005**	-0.005**	-0.006	-0.008***
	(0.002)	(0.003)	(0.004)	(0.003)
Firm FEs		Yes		
Earning release FEs			Yes	
Bank FEs				Yes
Adjusted R2	0.130	0.153	0.164	0.128
N	19394	19384	19394	19394

Table 3.7: The difference across genders between the effect of team size on team performance measured by PMAFE. The model in column 1 uses no fixed effects. Models in Column 2 & 6, 3 & 7 and 4 & 8 use firm, earning release and investment bank fixed effects respectively. Standard errors are robust to clustering at the analyst state level.

	(1)	(2)	(3)	(4)
Teamsize	0.032^{***}	0.019^{***}	0.007	0.049^{***}
	(0.006)	(0.004)	(0.005)	(0.008)
Team size x Post	-0.074^{***}	-0.044^{***}	-0.012^{*}	-0.078^{***}
	(0.004)	(0.005)	(0.007)	(0.003)
Female x Teamsize	0.024^{**}	0.033^{***}	0.032^{***}	0.022^{***}
	(0.009)	(0.006)	(0.005)	(0.004)
Female x Teamsize x Post	-0.014^{*}	-0.027^{***}	-0.028^{***}	-0.014^{***}
	(0.008)	(0.004)	(0.005)	(0.004)
Firm controls	Yes	Yes	Yes	Yes
Analyst controls	Yes	Yes	Yes	Yes
Report controls	Yes	Yes	Yes	Yes
Firm FE		Yes		
Earning release FE			Yes	
Bank FE				Yes
Adj. R2	0.127	0.151	0.163	0.125
N	19493	19483	19493	19493

Appendix

Chapter 1

Table A1.1: Variable Definition

Variable	Description
Δi_t	The change in futures fed funds rate during a [-10,+20] minutes window around each FOMC meeting.
Δi_t^u	The unexpected change in futures fed funds rate during a [-10,+20] minutes window around each FOMC meeting.
$Explore_{it}$	A patent *p* that belongs to originating firm *i* is *Explorative* if more than %80 of patents it cites follow these two conditions: 1- These cited patents do not belong to the originating firm 2- The originating firm has not cited these patents before.
$Exploit_{it}$	A patent *p* that belongs to originating firm *i* is *Exploitative* if less than %20 of patents it cites follow these two conditions: 1- These cited patents do not belong to the originating firm 2- The originating firm has not cited these patents before.
CAR_{it}	Computed by summing up daily abnormal returns over a [0,+t] day window following an interest rate shock. Abnormal returns are returns net of value-weighted market index, obtained from CRSP.
$Net\ Income_{it}$	Natural logarithm of net income.
$EBITDA_{it}$	Natural logarithm of the sum of net income (Compustat item *niq*), depreciation (Compustat item *dpq*), interests (Compustat item *xintq*), and taxes (Compustat item *txtq*).
$Capex_{it}$	Natural logarithm of capital expenditures.
$R\&D_{it}$	Natural logarithm of research and developments.
$Assets_{it}$	Natural logarithm of the book value of assets.
M/B_{it}	Natural logarithm of number of shares outstanding multiplied by the stock price divided by the book value of equity.
$Leverage_{it}$	Long term debt plus the current part of the long term debt, all scaled by the total book value of assets.
ROA_{it}	EBITDA over total book value of assets.
WW_{it}	WW Index is constructed following Whited and Wu (2006) as –0.091 [(ib + dp)/at] – 0.062DIVPOS + 0.021TLTD – 0.044LAT + 0.102ISG – 0.035SG Where DIVPOS is indicator set to one if *dvc + dvp* is positive, and zero otherwise, TLTD is *dltt/at*, LAT is natural log assets, ISG is average three-digit SIC industry sales growth, and SG is firm sales growth. Firms are sorted into terciles based on their index values in the previous year. Firms in the top tercile are coded as constrained and those in the bottom tercile are coded as unconstrained.

Table A1.2: Firm-level event study around FOMC meetings
Drift in the innovation-based heterogeneity in transmission of monetary policy
including pre-announcement trading day in event windows

The table presents the findings of firm-level event study over windows of various lengths starting at the day of the FOMC event. *Explore* and *Exploit* indicate explorative and exploitative characteristics of firm innovation portfolio prior to the shock, respectively. We use cumulative abnormal returns. Δi^u is the unexpected monetary shock.

$$CAR_{j,s}^{(-1,T)} = \beta\ EXP_{j,s}\Delta i_s^u + \delta_x EXP_{j,s} + \gamma \Delta i_s^u + \zeta_{jq} + \epsilon_{j,s} \quad T \in \{1,3,5,7,10,15\}$$

s, *j*, and *q* denote monetary shock, firm, and quarter respectively. ζ_{jq} denotes interaction of firm and quarter fixed effects. In panels A and B, *Explore* and *Exploit* are used respectively to characterize firm innovation. Standard errors are clustered at the firm and event levels. To find detailed variable specification consult table Appendix A1.

	(1) CAR(-1,1)	(2) CAR(-1,3)	(3) CAR(-1,5)	(4) CAR(-1,7)	(5) CAR(-1,10)	(6) CAR(-1,15)
A. Explore						
Explore x Δi^u	-1.374	-3.150**	-4.533***	-6.155***	-7.181**	-5.668
	(0.910)	(1.292)	(1.680)	(2.291)	(3.158)	(3.560)
Explore	-0.000	0.002	0.002	-0.002	0.000	-0.007
	(0.007)	(0.009)	(0.010)	(0.013)	(0.015)	(0.019)
Δi^u	-1.951*	-1.297	-2.567	-5.123**	-7.426***	-10.702***
	(1.165)	(1.516)	(1.818)	(2.519)	(2.357)	(2.754)
N	221284	221284	221284	221290	221290	221290
adjR2	-0.026	-0.011	-0.016	-0.038	-0.059	-0.056
B. Exploit						
Exploit x Δi^u	2.899**	3.418*	6.858***	9.056***	10.171**	7.907*
	(1.338)	(1.850)	(2.223)	(2.988)	(4.144)	(4.609)
Exploit	0.005	0.008	0.013	0.020	0.020	0.041**
	(0.008)	(0.010)	(0.011)	(0.013)	(0.015)	(0.020)
Δi^u	-3.434***	-3.904***	-6.795***	-10.798***	-13.950***	-15.827***
	(1.043)	(1.259)	(1.853)	(3.044)	(3.935)	(4.173)
N	221284	221284	221284	221290	221290	221290
adjR2	-0.026	-0.011	-0.016	-0.038	-0.059	-0.056
Firm x Quarter FEs	x	x	x	x	x	x

Table A1.3: Firm-level event study around FOMC meetings
Drift in the innovation-based heterogeneity in transmission of monetary policy
Sample of firm-events with more than five patents

The table presents the findings of firm-level event study for firms with more than five patents over windows of various lengths starting at the day of the FOMC event. *Explore* and *Exploit* indicate explorative and exploitative characteristics of firm innovation portfolio prior to the shock, respectively. We use cumulative abnormal returns. Δi^u is the unexpected monetary shock.

$$CAR_{j,s}^{(0,T)} = \beta\, EXP_{j,s}\Delta i_s^u + \delta\, EXP_{j,s} + \gamma \Delta i_s^u + \zeta_{jq} + \epsilon_{j,s} \quad T \in \{1,3,5,7,10,15\}$$

s, *j*, and *q* denote monetary shock, firm, and quarter respectively. ζ_{jq} denotes interaction of firm and quarter fixed effects. In all columns the interaction of firm and quarter fixed effects is used. Standard errors are clustered at the firm and event levels. To find detailed variable specification consult table Appendix A1.

	(1) CAR(0,1)	(2) CAR(0,3)	(3) CAR(0,5)	(4) CAR(0,7)	(5) CAR(0,10)	(6) CAR(0,15)
A. Explore						
Explore x Δi^u	-6.775***	-6.628***	-11.443***	-13.812***	-17.634***	-15.784***
	(2.013)	(2.171)	(2.743)	(3.627)	(5.096)	(5.098)
Explore	0.003	0.014	0.005	-0.009	0.008	0.007
	(0.010)	(0.016)	(0.018)	(0.024)	(0.027)	(0.030)
Δi^u	0.712	1.320	1.238	-1.132	-2.765	-6.165**
	(0.923)	(1.399)	(1.774)	(2.261)	(2.206)	(2.885)
N	143632	143632	143632	143632	143632	143632
adjR2	-0.019	-0.011	-0.022	-0.047	-0.073	-0.062
B. Exploit						
Exploit x Δi^u	9.027***	8.792***	15.555***	18.828***	20.668***	17.364***
	(2.063)	(2.586)	(3.731)	(4.533)	(6.570)	(6.653)
Exploit	0.012	0.014	0.027	0.046*	0.032	0.053
	(0.011)	(0.017)	(0.020)	(0.025)	(0.029)	(0.034)
Δi^u	-5.107***	-4.367***	-8.690***	-13.128***	-17.020***	-18.573***
	(0.995)	(1.285)	(1.991)	(3.157)	(4.306)	(4.221)
N	143632	143632	143632	143632	143632	143632
adjR2	-0.019	-0.011	-0.022	-0.047	-0.072	-0.062
Firm x Quarter FEs	x	x	x	x	x	x

Table A1.4: Firm-level event study around FOMC meetings
Drift in the innovation-based heterogeneity in transmission of monetary policy
Sample of firm-events with more than five patents and older than five years

The table presents the findings of firm-level event study over windows of various lengths starting at the day of the FOMC event. *Explore* and *Exploit* indicate explorative and exploitative characteristics of firm innovation portfolio prior to the shock, respectively. The dependent variable is cumulative abnormal returns. Δi^u is the unexpected monetary shock.

$$CAR_{j,s}^{(0,T)} = \beta\ EXP_{j,s}\Delta i_s^u + \delta\ EXP_{j,s} + \gamma\Delta i_s^u + \zeta_{jq} + \epsilon_{j,s} \quad T \in \{1,3,5,7,10,15\}$$

s, j, and q denote monetary shock, firm, and quarter respectively. ζ_{jq} denotes interaction of firm and quarter fixed effects. Standard errors are clustered at the firm and event levels. To find detailed variable specification consult table Appendix A1.

	(1) CAR(0,1)	(2) CAR(0,3)	(3) CAR(0,5)	(4) CAR(0,7)	(5) CAR(0,10)	(6) CAR(0,15)
A. Explore						
Explore x Δi^u	-4.958***	-5.554**	-9.574***	-11.122***	-12.363**	-9.526**
	(1.773)	(2.278)	(3.130)	(3.964)	(5.072)	(4.682)
Explore	0.002	0.005	0.005	-0.007	0.008	0.007
	(0.010)	(0.015)	(0.018)	(0.024)	(0.026)	(0.029)
Δi^u	0.891	1.084	1.065	-0.591	-1.830	-5.186*
	(0.838)	(1.353)	(1.644)	(1.967)	(2.095)	(2.654)
N	129509	129509	129509	129509	129509	129509
adjR2	-0.018	-0.008	-0.015	-0.038	-0.067	-0.058
B. Exploit						
Exploit x Δi^u	7.312***	7.566**	13.099***	15.505***	13.621**	9.487
	(2.087)	(3.182)	(4.734)	(4.778)	(6.403)	(6.104)
Exploit	0.009	0.021	0.025	0.045*	0.036	0.050
	(0.012)	(0.017)	(0.020)	(0.024)	(0.029)	(0.034)
Δi^u	-3.577***	-3.720**	-7.231***	-10.320***	-11.465***	-12.285***
	(0.986)	(1.522)	(2.388)	(2.951)	(3.823)	(3.614)
N	129509	129509	129509	129509	129509	129509
adjR2	-0.018	-0.008	-0.015	-0.038	-0.067	-0.058
Firm x Quarter FEs	x	x	x	x	x	x

Table A1.5a: Firm-level event study around FOMC meetings. Exploratory innovation-based heterogeneity in transmission of monetary policy to equity prices Prior to August 2007

The table presents the findings of firm-level event study analysis around FOMC event days. *Explore* indicates exploratory characteristics of firm innovation portfolio prior to the shock. We use cumulative abnormal return of firms in a five-day window after each FOMC meeting as the dependent variable. Δi^u is the unexpected monetary shock.

$$CAR_{j,s}^{(0,5)} = \beta\ Explore_{j,s}\,\Delta i_s^u + \delta Explore_{j,s} + \gamma \Delta i_s^u + \eta\ \Gamma_{j,q} + \zeta_{k,q} + \epsilon_{j,s}$$

s, *j*, and *q* denote monetary shock, firm and quarter respectively. $\zeta_{k,q}$ is a set of fixed effects. k can denote firm or industry. In column 1, we use no fixed effects. In column 2, SIC3 industry and quarter fixed effects are used. In column 3, interaction of industry and quarter fixed effects is used. In column 4, firm and quarter fixed effects is used. In column 5, the interaction of firm and quarter fixed effects is used. Standard errors are clustered at the firm and event levels. To find detailed variable specification consult table Appendix A1.

	(1)	(2)	(3)	(4)	(5)
Explore x Δi^u	-5.140***	-5.150***	-5.104***	-5.463***	-4.664***
	(1.146)	(1.142)	(1.095)	(1.240)	(1.549)
Explore	0.000	-0.000	0.000	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.002)	(0.010)
Δi^u	-2.591*	-2.501*	-2.841*	-2.241	-1.926
	(1.445)	(1.417)	(1.501)	(1.415)	(1.555)
Size	-0.001	-0.001	-0.000	-0.013***	
	(0.000)	(0.000)	(0.000)	(0.003)	
M/B	-0.003**	-0.003**	-0.003***	-0.010***	
	(0.001)	(0.001)	(0.001)	(0.003)	
Leverage	0.002	0.005	0.005	0.018**	
	(0.005)	(0.004)	(0.003)	(0.007)	
ROA	0.049***	0.051***	0.050***	0.045***	
	(0.014)	(0.013)	(0.011)	(0.011)	
Lnum	0.001*	0.000	0.000	0.002	-0.006
	(0.000)	(0.000)	(0.000)	(0.001)	(0.006)
R&D/Assets	0.084***	0.090***	0.087***	0.090***	
	(0.027)	(0.024)	(0.022)	(0.027)	
WW	-0.004**	-0.004**	-0.003**	-0.006***	
	(0.002)	(0.001)	(0.001)	(0.002)	
N	155983	155850	155850	155850	155850
adjR2	0.004	0.011	0.007	0.022	-0.010
Industry FE		x			
Quarter FE		x		x	
Industry x Quarter FEs			x		
Firm FE				x	
Firm x Quarter FEs					x

Table A1.5b: Firm-level event study around FOMC meetings. Exploitative innovation-based heterogeneity in transmission of monetary policy to equity prices prior to August 2007

The table presents the findings of firm-level event study analysis around FOMC event days. *Explore* indicates exploratory characteristics of firm innovation portfolio prior to the shock. We use cumulative abnormal return of firms in a five-day window after each FOMC meeting as the dependent variable. Δi^u is the unexpected monetary shock.

$$CAR_{j,s}^{(0,5)} = \beta\ Explore_{j,s}\,\Delta i_s^u + \delta Explore_{j,s} + \ \gamma \Delta i_s^u + \eta\ \Gamma_{\mathrm{j,q}} + \zeta_{k,q} + \epsilon_{j,s}$$

s, *j*, and *q* denote monetary shock, firm and quarter respectively. $\zeta_{k,q}$ is a set of fixed effects. *k* can denote firm or industry. In column 1, we use no fixed effects. In column 2, SIC3 industry and quarter fixed effects are used. In column 3, interaction of industry and quarter fixed effects is used. In column 4, firm and quarter fixed effects is used. In column 5, the interaction of firm and quarter fixed effects is used. Standard errors are clustered at the firm and event levels. To find detailed variable specification consult table Appendix A1.

	(1)	(2)	(3)	(4)	(5)
Exploit x Δi^u	6.922***	7.055***	6.673***	7.496***	7.248***
	(1.851)	(1.881)	(1.622)	(1.987)	(2.090)
Exploit	0.000	0.002	0.002	0.005**	0.028**
	(0.002)	(0.001)	(0.001)	(0.002)	(0.012)
Δi^u	-7.163***	-7.113***	-7.328***	-7.136***	-6.321***
	(1.675)	(1.680)	(1.754)	(1.660)	(1.518)
Size	-0.001	-0.001	-0.000	-0.013***	
	(0.000)	(0.000)	(0.000)	(0.003)	
M/B	-0.003**	-0.003**	-0.003***	-0.010***	
	(0.001)	(0.001)	(0.001)	(0.003)	
Leverage	0.002	0.005	0.005	0.018**	
	(0.005)	(0.004)	(0.003)	(0.007)	
ROA	0.048***	0.051***	0.050***	0.045***	
	(0.014)	(0.013)	(0.011)	(0.011)	
Lnum	0.001*	0.000	0.000	0.001	-0.008
	(0.000)	(0.000)	(0.000)	(0.001)	(0.006)
R&D/Assets	0.084***	0.091***	0.088***	0.090***	
	(0.027)	(0.024)	(0.022)	(0.027)	
WW	-0.004**	-0.004**	-0.003**	-0.006***	
	(0.002)	(0.001)	(0.001)	(0.002)	
N	155983	155850	155850	155850	155850
adjR2	0.004	0.011	0.007	0.022	-0.010
Industry FE		x			
Quarter FE		x		x	
Industry x Quarter FE			x		
Firm FE				x	

Chapter 3

Appendix

Table A3.1: difference-in-difference regression for analyst teams versus individual analysts before and after start of post-pandemic work-from-home using PRAFE as the measure of analyst forecast error. Only earning releases for which both group and individual reports exist are included in the regressions. Post indicates period beginning March 1, 2020. The model in column (1) uses no fixed effects. Models in Column (2), (3) and (4) use firm, earning release and investment bank fixed effects. Standard errors are robust to clustering at the state level. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

$$PRAFE_{ift} = \beta_0 + \beta_1 \, POST_t + \beta_2 \, TEAM_{i,f,t} + \beta_3 \, POST_t \times TEAM_{i,f,t} + \gamma \, Controls + FE + u_{i,f,t}$$

	(1)	(2)	(3)	(4)
Team	0.019	0.004	0.005	0.021
	(0.021)	(0.009)	(0.008)	(0.023)
Post	-0.051***	-0.078***	-0.062**	-0.050***
	(0.016)	(0.006)	(0.029)	(0.016)
Team x *Post*	0.006	0.013	0.005	0.005
	(0.020)	(0.011)	(0.012)	(0.020)
Size	0.016***	0.003	-0.050***	0.017***
	(0.003)	(0.009)	(0.010)	(0.003)
M/B	-0.001	-0.002***	-0.001*	-0.001
	(0.000)	(0.000)	(0.001)	(0.000)
IB growth	-0.010***	-0.000	-0.013***	-0.010***
	(0.002)	(0.007)	(0.004)	(0.001)
Beta	0.000	-0.026**	-0.022***	0.001
	(0.013)	(0.011)	(0.004)	(0.014)
Intangible	-0.020	0.199	0.335**	-0.021
	(0.024)	(0.153)	(0.135)	(0.024)
Arpre12	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Loss	0.014	0.087	-0.074	0.014
	(0.011)	(0.052)	(0.057)	(0.010)
Return Volatility	0.004	0.001	-0.029***	0.004
	(0.005)	(0.004)	(0.005)	(0.005)
Age	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Genex	0.001**	0.000	-0.000	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Firmex	0.002***	0.002***	0.001***	0.002***
	(0.001)	(0.000)	(0.000)	(0.001)
Ninds	0.004	0.003	0.004**	0.004
	(0.004)	(0.004)	(0.002)	(0.004)
Nfirms	-0.001	-0.003***	-0.004***	-0.001*
	(0.001)	(0.000)	(0.001)	(0.001)
Firm FE		Yes		
Earning release FE			Yes	
Bank FE				Yes
Adjusted R-sq	0.108	0.111	0.123	0.106
N	19412	19402	19412	19412

Table A3.2: Difference-in-difference regression for analyst teams versus individual analysts before and after start of post-pandemic work-from-home with two post periods and using PRAFE as the measure of analyst forecast error. The model in column 1 uses no fixed effects. Models in Column 2,3 and 4 use firm, earning release and investment bank fixed effects. Standard errors are robust to clustering at the analyst state level.

$$PRAFE_{i,f,t} = \beta_0 + \beta_1\, POST_t^1 + \beta_2\, POST_t^2 + \beta_3\, TEAM_{i,f,t} + \beta_4\, POST_t^1 \times TEAM_{i,f,t} + \beta_5\, POST_t^2 \times TEAM_{i,f,t} + \gamma\, Controls + FE + u_{i,f,t}$$

	(1)	(2)	(3)	(4)
Team	0.018	0.004	0.004	0.022
	(0.020)	(0.009)	(0.008)	(0.023)
Mar_Apr	0.022	-0.014	-0.010	0.024
	(0.036)	(0.023)	(0.034)	(0.037)
Post_Apr	-0.070***	-0.104***	-0.091***	-0.069***
	(0.015)	(0.007)	(0.032)	(0.015)
Team x *Mar_Apr*	-0.030	-0.007	-0.018	-0.031
	(0.049)	(0.035)	(0.024)	(0.050)
Team x *Post_Apr*	0.010	0.014	0.008	0.009
	(0.016)	(0.008)	(0.011)	(0.016)
Size	0.017***	0.020*	-0.023*	0.017***
	(0.003)	(0.011)	(0.012)	(0.003)
M/B	-0.000	-0.002***	-0.001	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)
IB growth	-0.010***	-0.000	-0.012***	-0.010***
	(0.002)	(0.007)	(0.004)	(0.002)
Beta	-0.001	-0.027**	-0.021***	-0.001
	(0.013)	(0.011)	(0.005)	(0.014)
Intangible	-0.019	0.197	0.296**	-0.020
	(0.024)	(0.151)	(0.141)	(0.023)
Arpre12	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Loss	0.013	0.091*	-0.073	0.014
	(0.011)	(0.052)	(0.057)	(0.010)
Return Volatility	0.006	0.012***	-0.014**	0.006
	(0.005)	(0.004)	(0.006)	(0.005)
Age	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Genex	0.001**	0.000	-0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Firmex	0.002***	0.002***	0.001***	0.002***
	(0.001)	(0.000)	(0.000)	(0.001)
Ninds	0.004	0.004	0.004**	0.004
	(0.004)	(0.004)	(0.002)	(0.004)
Nfirms	-0.001*	-0.003***	-0.004***	-0.001*
	(0.001)	(0.000)	(0.001)	(0.001)
Firm FE		Yes		
Earning release FE			Yes	
Bank FE				Yes
Adjusted R2	0.110	0.113	0.124	0.108
N	19412	19402	19412	19412

Table A3.3: Analyst team size and team performance using PRAFE as the measure of analyst performance. The model in column 1 and 5 uses no fixed effects. Models in Column 2 & 6, 3 & 7 and 4 & 8 use firm, earning release and investment bank fixed effects respectively. Standard errors are robust to clustering at the analyst state level.

$$PRAFE_{i,f,t} = \beta_0 + \beta_2\, TEAMSIZE_{i,f,t} + \beta_3\, TEAMSIZE^2_{i,f,t} + \beta_3\, POST_t \times TEAMSIZE_{i,f,t} + \beta_4\, POST_t \times TEAMSIZE^2_{i,f,t} + \gamma\, Control\ vars + FE + u_{i,f,t}$$

	(1)	(2)	(3)	(4)
Team size	0.012**	0.007***	0.004***	0.015**
	(0.005)	(0.002)	(0.001)	(0.006)
Team Size x *Post*	-0.012***	-0.011***	-0.001	-0.013***
	(0.002)	(0.001)	(0.002)	(0.002)
Firm controls	Yes	Yes	Yes	Yes
Analyst controls	Yes	Yes	Yes	Yes
Report controls	Yes	Yes	Yes	Yes
Firm FE		Yes		
Earning release FE			Yes	
Bank FE				Yes
Adj. R2	0.106	0.108	0.121	0.105
N	19418	19408	19418	19418

Table A3.4: Analyst performance measured by PRAFE and her prior to the pandemic experience working with virtual teams. The model in column 1 uses no fixed effects. Models in Column 2,3 and 4 use firm, earning release and investment bank fixed effects respectively. Standard errors are robust to clustering at the analyst state level.

$$PRAFE_{ift} = \beta_0 + \beta_1\, POST_{1t} + \beta_2\, POST_{2t} + \beta_3\, TEAM_{i,f,t} + \beta_4\, POST_{1t} \times TEAM_{i,f,t} + \beta_5 POST_{2t} \times TEAM_{i,f,t} + \theta_1 NVT + \theta_2 NVT \times POST_{1t} + \theta_3 NVT \times POST_{2t} + \theta_4 NVT \times TEAM_{i,f,t} \times POST_{1t} + \theta_5 NVT \times TEAM_{i,f,t} \times POST_{2t} + \gamma\, Controls + FE + u_{i,f,t}$$

	(1)	(2)	(3)	(4)
Team	0.019	0.003	0.002	0.023
	(0.018)	(0.006)	(0.007)	(0.020)
Mar_Apr	0.009	-0.025	-0.021	0.012
	(0.040)	(0.026)	(0.033)	(0.040)
Post_Apr	-0.077***	-0.111***	-0.099***	-0.075***
	(0.011)	(0.006)	(0.027)	(0.010)
Team x *Mar_Apr*	-0.022	-0.000	-0.012	-0.025
	(0.046)	(0.033)	(0.021)	(0.046)
Team x *Post_Apr*	0.017	0.020***	0.015	0.016
	(0.011)	(0.007)	(0.011)	(0.010)
NVT	-0.000	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
NVT x *Mar_Apr*	0.002	0.002*	0.002*	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
NVT x *Post_apr*	0.004	0.003	0.003	0.004
	(0.002)	(0.002)	(0.002)	(0.002)
NVT x *Team*	0.000	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
NVT x *Team* x *Mar_Apr*	-0.000	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
NVT x *Team* x *Post_Apr*	-0.004	-0.003	-0.003	-0.003
	(0.003)	(0.002)	(0.002)	(0.003)
Firm controls	Yes	Yes	Yes	Yes
Analyst controls	Yes	Yes	Yes	Yes
Report controls	Yes	Yes	Yes	Yes
Firm FE		Yes		
Earning release FE			Yes	
Bank FE				Yes
Adjusted R2	0.110	0.114	0.125	0.108
N	19412	19402	19412	19412

Table A3.5: Analysts' prior to the pandemic experience leading a virtual team and the effect of team size on team performance measured by PRAFE. The model in column 1 uses no fixed effects. Models in Column 2,3 and 4 use firm, earning release and investment bank fixed effects respectively. Standard errors are robust to clustering at the analyst state level.

	(1)	(2)	(3)	(4)
NVT x *TEAMSIZE*	0.021^{***}	0.010^{*}	0.016^{**}	0.022^{***}
	(0.003)	(0.005)	(0.006)	(0.003)
NVT x *TEAMSIZE* x *Mar_Apr*	0.089^{***}	0.098^{***}	0.070^{***}	0.088^{***}
	(0.016)	(0.010)	(0.007)	(0.015)
NVT x *TEAMSIZE* x *Post_Apr*	-0.024^{***}	-0.022^{**}	-0.031^{***}	-0.024^{***}
	(0.008)	(0.008)	(0.006)	(0.007)
TEAMSIZE	0.046^{***}	0.052^{***}	0.047^{***}	0.043^{***}
	(0.012)	(0.009)	(0.006)	(0.010)
TEAMSIZE x *Mar_Apr*	-0.020^{*}	-0.039^{***}	-0.034^{***}	-0.016
	(0.011)	(0.010)	(0.004)	(0.011)
TEAMSIZE x *Post_Apr*	-0.063^{***}	-0.090^{***}	-0.076^{***}	-0.060^{***}
	(0.006)	(0.003)	(0.012)	(0.006)
Firm controls	Yes	Yes	Yes	Yes
Analyst controls	Yes	Yes	Yes	Yes
Report controls	Yes	Yes	Yes	Yes
Firm FEs		Yes		
Earning release FEs			Yes	
Bank FEs				Yes
Adjusted R2	0.111	0.115	0.125	0.109
N	19412	19402	19412	19412

Table A3.6: Difference-in-Difference in performance of female-led and male-led analyst teams measured by PRAFE before and after adoption of WFH. The model in column 1 uses no fixed effects. Models in Column 2,3 and 4 use firm, earning release and investment bank fixed effects respectively. Standard errors are robust to clustering at the analyst state level.

	(1)	(2)	(3)	(4)
Female	0.019***	0.021***	0.013***	0.020***
	(0.003)	(0.003)	(0.003)	(0.003)
Post	-0.046***	-0.060***	-0.051**	-0.046***
	(0.005)	(0.003)	(0.023)	(0.005)
Female x *Post*	-0.015**	-0.045***	-0.028***	-0.016*
	(0.006)	(0.007)	(0.004)	(0.008)
Size	0.017***	0.001	-0.051***	0.017***
	(0.003)	(0.009)	(0.009)	(0.003)
M/B	-0.000	-0.002***	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Ib growth	-0.010***	0.000	-0.013***	-0.010***
	(0.002)	(0.007)	(0.004)	(0.002)
Beta	0.000	-0.026**	-0.022***	0.001
	(0.013)	(0.010)	(0.004)	(0.014)
Intangible	-0.021	0.194	0.321**	-0.022
	(0.025)	(0.148)	(0.134)	(0.024)
Arpre12	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Loss	0.016	0.092*	-0.072	0.016
	(0.011)	(0.052)	(0.054)	(0.010)
Return Volatility	0.003	-0.000	-0.029***	0.003
	(0.004)	(0.004)	(0.005)	(0.004)
Age	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Genex	0.001***	0.000	0.000	0.001***
	(0.001)	(0.000)	(0.000)	(0.000)
Firmex	0.002***	0.002***	0.001***	0.002***
	(0.001)	(0.000)	(0.000)	(0.001)
Ninds	0.004	0.003	0.004*	0.003
	(0.005)	(0.004)	(0.002)	(0.005)
Nfirms	-0.001	-0.003***	-0.004***	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Firm FEs		Yes		
Earning release FEs			Yes	
Bank FEs				Yes
Adjusted R2	0.107	0.111	0.122	0.106
N	19319	19309	19319	19319

Table A3.7: the difference across genders between the effect of team size on team performance measured by PRAFE. The models in column 1 and 5 use no fixed effects. Models in Column 2 & 6, 3 & 7 and 4 & 8 use firm, earning release and investment bank fixed effects respectively. Standard errors are robust to clustering at the analyst state level.

	(1)	(2)	(3)	(4)
Teamsize	0.011**	0.007***	0.003***	0.014**
	(0.005)	(0.002)	(0.001)	(0.006)
Team size x Post	-0.012***	-0.009***	-0.001	-0.012***
	(0.002)	(0.001)	(0.002)	(0.003)
Female x Teamsize	0.008***	0.009***	0.005***	0.008***
	(0.002)	(0.001)	(0.001)	(0.001)
Female x Teamsize x Post	-0.006**	-0.013***	-0.006***	-0.006*
	(0.002)	(0.002)	(0.002)	(0.003)
Firm controls	Yes	Yes	Yes	Yes
Analyst controls	Yes	Yes	Yes	Yes
Report controls	Yes	Yes	Yes	Yes
Firm FE		Yes		
Earning release FE			Yes	
Bank FE				Yes
Adj. R2	0.106	0.109	0.121	0.105
N	19418	19408	19418	19418

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