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Abstract

This dissertation consists of three essays on empirical finance. In the first essay (job market paper) entitled "Why do analysts differ in forecast provision? A signaling explanation", I study financial analysts' forecast reporting behaviors. In the second essay entitled "Capacity overhang, investment, and accruals" (co-authored with Professor Peter Pope at Bocconi University), we study the dynamics of firms' investment and accruals. In the third essay entitled "How do asset pricing models capture leverage effects?" (also co-authored with Professor Peter Pope at Bocconi University), we study how empirical asset pricing models capture leverage effects in the cross section of expected stock returns.

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Introduction

"Why do analysts differ in forecast provision? A signaling explanation" (Job Market Paper)

Analysts differ strikingly in the number of forecast types they provide to I/B/E/S for the firms they follow. I hypothesize that analysts provide more forecast types to signal their superior ability and effort to forecast firm fundamentals. Consistent with my hypothesis, I document positive associations of the number of forecast types provided by analysts with 1) earnings forecast accuracy, 2) price target accuracy, 3) stock recommendation profitability, 4) market reactions to stock recommendation revisions and, 5) analyst career outcomes. The findings are robust to controlling for firm and analyst characteristics, brokerage fixed effects, analysts' issuance of specific forecast types, and even firm-analyst fixed effects. The number of forecast types provided by analysts is a parsimonious ex-ante measure of analyst forecasting performance and is particularly useful for identifying high-quality new analysts with a limited track record.

"Capacity overhang, investment, and accruals" (co-authored with Professor Peter Pope at Bocconi University)

Capacity overhang is the difference between a firm's installed production capacity and its optimal capacity. When investment is costly to reverse, firms can ex post have capacity overhang due to negative demand shocks. Based on real options theory, we empirically show that future investment and investment-cash flow sensitivity are negatively related to capacity overhang after controlling for existing investment determinants. Given the role played by accruals in reflecting firms' growth in the scale of business operations, we also find a negative accruals-capacity overhang relationship. Finally, we augment optimal investment models, the Performance-adjusted Modified Jones Model, and an investment-based accruals model, with capacity overhang. We find that investment efficiency and accruals management estimates may be biased if capacity overhang is ignored.

"How do asset pricing models capture leverage effects?" (co-authored with Professor Peter Pope at Bocconi University)

This paper investigates how empirical asset pricing models capture leverage effects. Generally, empirical asset pricing models do not directly model leverage in their theoretical frameworks and/or empirical constructs. Nevertheless, prominent asset pricing models can explain expected stock returns satisfactorily well. To shed light on this issue, first, we use an illustrative conceptual framework to show that differentiating between unlevered factors related to firms' operating risks and a leverage multiplier is crucial to understanding expected stock returns. We then empirically show that popular asset pricing factors like value, investment, or profitability, can only absorb leverage effects to a limited degree. Finally, we empirically demonstrate that abnormal leverage—the component of leverage unexplained by asset pricing factors, is positively priced in the cross section—Failure to handle leverage properly in asset pricing models may lead to pricing errors.

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Chapter 1

Job Market Paper

Why do analysts differ in forecast provision? A signaling explanation

Tong Wang*†

Abstract

Analysts differ strikingly in the number of forecast types they provide to I/B/E/S for the firms they follow. I hypothesize that analysts provide more forecast types to signal their superior ability and effort to forecast firm fundamentals. Consistent with my hypothesis, I document positive associations of the number of forecast types provided by analysts with 1) earnings forecast accuracy, 2) price target accuracy, 3) stock recommendation profitability, 4) market reactions to stock recommendation revisions and, 5) analyst career outcomes. The findings are robust to controlling for firm and analyst characteristics, brokerage fixed effects, analysts' issuance of specific forecast types, and even firm-analyst fixed effects. The number of forecast types provided by analysts is a parsimonious ex-ante measure of analyst forecasting performance and is particularly useful for identifying high-quality new analysts with a limited track record.

JEL Classification: G24; M41

Keywords: analysts; earnings forecasts; forecasting ability; I/B/E/S; price target forecasts; stock recommendations; capital market reactions; analyst career outcomes

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1.1 Introduction

Since the 2000s, the Institutional Brokers' Estimate System (I/B/E/S) has increased its effort to collect non-earnings per share (EPS) forecasts from financial analysts, while analysts can choose whether and what forecast types to provide.[1] Interestingly, analysts differ strikingly in the number of forecast types they provide despite controlling for firm, brokerage, and analyst characteristics (Beyer et al., 2010). This study provides an explanation for this phenomenon at the analyst level. I hypothesize that analysts provide more forecast types to signal their superior ability and effort to forecast fundamentals of the firms they follow. The results I find are consistent with this hypothesis and cannot be explained by firm and analyst characteristics, brokerage fixed effects, or analysts' issuance of specific forecast types.

My work is related to the literature of analysts' non-EPS forecasts. One strand of the prior literature focuses on the consequences of analysts issuing non-EPS forecasts.[2] For example, Call et al. (2009) document that analysts' earnings forecasts are more accurate when accompanied by cash flow forecasts; Hashim and Strong (2018) document that analysts' price target forecasts are more accurate when accompanied by cash flow forecasts. These studies stop short of investigating why not all analysts provide those non-EPS forecasts, given the benefits of doing so. Another strand of literature speaks to the motives for analysts' non-EPS forecast provision. For example, Keung (2010) argues that analysts are more likely to issue earnings forecasts and sales forecasts simultaneously when they are more informed; Ertimur et al. (2011) provide evidence that analysts issue sales forecasts as a means of establishing reputation; Jung et al. (2012) argue that long-term earnings growth forecasts signal analysts' high ability and effort to analyze firms' long-term prospects.

However, the prior literature is incomplete for the following reasons. First, the number of forecast types available in I/B/E/S has soared in recent years, while the prior

[1] As of 2020, I/B/E/S collects 23 types of 1-year ahead forecasts. For example, cash flow, sales, gross margin, pre-tax income, .etc. Please see Section 1.2.1 for details.

[2] It is impossible to distinguish between analysts' "forecasting" and "reporting" activities because the disclosure from sell-side financial analysts is voluntary. As a result, an analyst can always selectively report forecast types unless her brokerage has specific disclosure policies, which are unobservable to outsiders. In other words, although an analyst can privately forecast an item, she can choose not to report it to I/B/E/S. To avoid overgeneralizing the conclusion of this paper, I do not disentangle "forecasting" from "reporting" or vice versa—An analyst provides an item if and only if 1) she forecasts the item and, 2) she chooses to report the item to I/B/E/S.

literature only focuses on a small subset of non-EPS forecasts. As a result, the motives for and the consequences of analysts' provision of other non-EPS forecast types is still an open empirical question. Second, except for Jung et al. (2012), which focuses on long-term earnings growth forecast, previous studies neglect analysts' provision of longer-term forecasts. Finally, each of these previous studies only focuses on one or two metrics of analyst forecasting performance or proxies for analyst ability. For example, although issuing cash flow forecasts is positively related to earnings forecast accuracy and price target forecast accuracy, Jung et al. (2012) find issuing cash flow forecasts negatively related to analysts' ability to generate stock market reactions, inconsistent with the notion that these analysts have higher forecasting ability.[3] In addition, although Jung et al. (2012) document a positive association between issuing long-term earnings growth forecasts and stock market reactions to analysts' stock recommendation revisions, I find issuing long-term earnings growth forecasts negatively linked to price target forecast accuracy and the profitability of stock recommendations, contradicting the proposition that these analysts have higher ability and effort to analyze firms' long-term prospects.

I study analysts' provision of non-EPS forecasts from a new perspective. Instead of studying all the forecast types and forecast periods one by one, I consider all the forecast types and forecast periods simultaneously. I first document substantial within-firm-year heterogeneity in the number of forecast types analysts provide to I/B/E/S. This heterogeneity is beyond analysts' provision of any specific forecast types. I then construct a variable, the number of forecast types an analyst provides for the firm she follows *relative to her peers*, to capture the overall forecast type provision of the analyst. I then examine the association of this variable with proxies for analyst forecasting ability and effort. I hypothesize that analysts provide more forecast types to I/B/E/S as a means for signaling their higher ability and effort to forecast firm fundamentals.[4]

I develop the hypothesis as follows. First, by forecasting more firm fundamentals, analysts can improve their performances in forecasting earnings and picking stocks, which

[3] In an efficient financial market, investors should recognize analysts' superior forecasting ability and put more weight on forecasts issued by more able analysts.

[4] Although analysts' forecasting ability can grow with experience (Clement et al., 2007; Mikhail et al., 1997, 2003), a general view is that forecasting ability is constant or at most slow-moving. Ability is not the single factor affecting analysts' forecasting performance given the substantial variation in the forecasting performance in the time series. Analysts' effort to gain and process information about firm values can also affect their forecasting performance.

are arguably the most important metrics of analyst performance.[5] The rationale is that forecasting a full set of financial statement line items facilitates analysts' understanding of the interdependence between firms' operating, investing, and financing activities (Lundholm and Sloan, 2004). Second, recent empirical evidence shows that a large set of analysts' non-EPS forecasts are value-relevant and demanded by investors.[6] For example, Bilinski (2020) and Hand et al. (2021) document that investors react to a broad set of non-EPS forecast surprises. These non-EPS forecast surprises have incremental explanatory power to EPS forecast surprises in explaining earnings announcement returns. Through providing non-EPS forecasts to meet investors' demand, analysts can establish professional reputation and generate larger capital market reactions.[7]

However, providing more forecast types is costly for all analysts and more so for less able ones. First, forecasting additional items increases analysts' task complexity, negatively affecting analysts' forecasting performance, especially for less able ones. Alternatively, analysts can choose to make more effort (e.g. work more intensively or work more hours) to reduce the negative impact of forecasting additional items. As a result, holding the marginal benefit of forecasting additional items constant, the costs are more likely to outweigh the benefits for less able/diligent analysts. Second, holding the number of predicted items constant, reporting more forecast types to I/B/E/S exposes analysts to more extensive scrutiny from investors. The additional estimates forecasted by less able/diligent analysts are more likely to be relatively inaccurate ex-post, so less able/diligent analysts would be more reluctant to disclose additional estimates to avoid reputation losses. In contrast, more able/diligent analysts would be more willing to disseminate additional forecast types through I/B/E/S to signal the superior credibility of their estimates.[8]

To test my hypothesis, I employ a wide spectrum of metrics to measure analysts'

[5] Stock recommendations are arguably the ultimate products of analysts' research and, analysts' compensation is partially determined by the profitability of their stock recommendations (Brown et al., 2015; Groysberg et al., 2011). Earnings forecast accuracy is associated with analyst turnover (Mikhail et al., 1999) and is a metric used by investor services firms like StarMine to rate analysts.

[6] Managers may also demand analysts' non-EPS forecasts. See Choi et al. (2020) for Capital Expenditure forecasts and Bratten et al. (2017) for Pre-tax Earnings forecasts.

[7] Analysts' compensation partially depends on their ability to generate trading commissions (Brown et al., 2015; Groysberg et al., 2011), so analysts have sufficient incentives to predict and report forecast types in addition to earnings, price target, and stock recommendations to stimulate tradings.

[8] Although analysts can opt to disclose additional forecasted items in their research reports or to other financial data vendors like FactSet, given the important role played by I/B/E/S as an information dissemination channel, not disclosing to I/B/E/S nevertheless hampers the dissemination of signals.

ability or effort to forecast firm fundamentals. These metrics include earnings forecast accuracy, price target forecast accuracy, the profitability of stock recommendations, the stock market's reactions to analysts' stock recommendation revisions, and analyst career outcomes. The five metrics capture analysts' ability and effort from different aspects. Earnings forecasts have received the most attention from capital market researchers and the media and are a key performance metric used by investment professionals. In addition, earnings forecasts are an important input in theoretical accounting-based equity valuation models (Chen and Jiang, 2006; Ohlson, 1995) as well as in buy-side investors' equity valuation models (Bradshaw, 2004). An analyst' earnings forecast accuracy reflects her understanding of the operating, investing, and financing activities of the firms she follows.

However, as pointed out by Bradshaw (2011), earnings forecasts are not the ultimate products of an analyst's research: they are the intermediate products towards the ultimate product—stock recommendations (Ertimur et al., 2007; Loh and Mian, 2006; Schipper, 1991). Stock recommendations are important for all investors and more so for retail investors in that these investors usually do not have the skills or resources to develop valuation models independently. As a complement to stock recommendations, price targets directly reflect an analyst's valuations for the stocks she studies. In addition, price targets are more granular than and contain incremental information to stock recommendations (Asquith et al., 2005; Brav and Lehavy, 2003). For example, two analysts may have different price target forecasts but the same stock recommendation for the same firm. After controlling for earnings forecast accuracy, the profitability of stock recommendations and the accuracy of price target forecasts reflect analysts' ability and effort to predict discount rates and to use appropriate valuation models. Overall, price target forecast accuracy and stock recommendation profitability can reflect analysts' forecasting ability and effort beyond earnings forecast accuracy.

Earnings forecast accuracy, price target forecast accuracy, and stock recommendation profitability are *ex-post* performance measures. To examine whether investors perceive stock recommendations accompanied by more forecast types as more informative *ex-ante*, I test the association between the number of forecast types and the stock market's reactions to analysts' revisions in stock recommendations. If the stock recommendation revisions accompanied by more forecast types have stronger price impacts systematically, these stock recommendations may be more informative ex-ante, implying that the issuing analysts may have higher ability or effort to incorporate value-relevant information into their stock recommendations. Importantly, this superior ability or effort has been recognized by investors.

I finally examine the association between the number of forecast types provided by analysts and analyst career outcomes. If a successful career is what analysts ultimately pursue, more able/diligent analysts should end up with better career outcomes in general. I hypothesize that, if so, analysts who provide more forecast types are less likely to be terminated by their employers, and these analysts are more likely to be promoted from small brokerage houses to big ones.

The empirical results largely support my hypothesis. I find that the number of forecast types provided by analysts is related to several measures of analyst ability or effort developed by the prior literature. The number of forecast types is positively associated with analysts' ability to move consensus earnings forecasts towards the actual earnings, a proxy for innate analyst ability (Chen and Jiang, 2006; Ertimur et al., 2011). The number of forecast types is also positively related to earnings forecasting frequency, a measure of analyst effort (Jacob et al., 1999), and earnings forecasting timeliness, a robust identifier of lead analysts (Cooper et al., 2001; Shroff et al., 2014). In addition, consistent with Bayesian investors learning about analyst ability from analysts' historical performance, less experienced analysts provide more forecast types than their more experienced peers, indicating that the number of forecast types reflects analysts' innate forecasting ability. Firm-analyst fixed effects, a surrogate for innate analyst ability (Clement et al., 2007), can explain 50.1% of the variation in the number of forecast types provided by analysts. The above findings show that the number of forecast types provided by analysts captures both analyst' innate ability *and* effort.

Consistent with the number of forecast types reflecting analysts' ability and effort to forecast earnings (price targets), the earnings (price target) forecasts accompanied by the most forecast types is 1.8% (1.3%) more accurate than the consensus relative to those accompanied by the fewest forecast types. Consistent with the higher ability and effort of analysts who provide more forecast types to valuate stocks, investors who follow stock recommendations accompanied by the most forecast types for at most 180 (30) days can earn 2.3% (9.3%) higher annualized size-adjusted returns than those who follow the recommendations accompanied by the fewest forecast types. Consistent with the hypothesis that analysts who provide more forecast types are more able/diligent to incorporate information into stock recommendations, the absolute value of 3-day market-adjusted cumulative abnormal returns is 0.41% higher per unit of revision around stock recommendation revisions accompanied by the most forecast types than around those accompanied by the fewest forecast types. Consistent with the high ability and effort of analysts who provide more forecast types, analysts who provide more forecast types than their peers are less likely to be fired by their employers (average marginal effect = -0.112, Z-score = -6.16) and are more likely to be promoted from small brokerage houses to large ones (average marginal effect = 0.246, Z-score = 2.16). The above findings are robust to a comprehensive set of control variables and brokerage fixed effects. The results are still valid after controlling for firm-analyst fixed effects, suggesting that analysts strategically provide more forecast types when they have exerted higher effort to analyze the firms they follow.[9]

I make several contributions to the literature. First, my study extends our understanding of what shapes analysts' voluntary forecast provision. Beyer et al. (2010) comment that "it is puzzling for analysts only to forecast a subset of firm fundamentals given that they rely on some of these measures to forecast others" and call for more insights into this. My study reveals that analysts exploit a broad set of forecast types to signal their ability and effort to forecast firm fundamentals rather than sticking to a small subset of forecast types. My research design is insensitive to firm characteristics and the data-collecting exercises of I/B/E/S, which may affect analysts' provision of a specific forecast type. Using this research design, I document a negative relationship between the number of forecast types and analysts' firm-specific forecasting experience. This finding generalizes Ertimur et al. (2011)'s conclusion that issuing sales forecasts is a means for high-ability lesser-known analysts to establish reputation.

Second, I propose a new ex-ante measure of analysts' forecasting performance—the number of forecast types provided by analysts to I/B/E/S. This measure is parsimonious and applies to the following analysts of most firms in the I/B/E/S universe.[10] This measure does not require a long time series of data to estimate as opposed to historical

[9] Alternatively, the statement can be re-written as "...when they are better informed". I assume that analysts' temporary information advantage comes from higher effort, although alternative explanations are possible too.

[10] For example, if using the issuance of cash flow forecasts to identify superior analysts, the following analysts of firms without cash flow forecast coverage would be ignored.

forecast accuracy, forecasting frequency, and forecasting timeliness, so it is particularly useful for discerning high-quality new analysts without a long track record. Using this measure, investors can identify and put more weights on potentially more accurate forecasts to reap higher investment returns. In addition, academics should anticipate this when using analysts' earnings forecasts as a proxy for the capital market's expectation of earnings (Clement, 1999). Moreover, brokerages can use this measure to make hiring and dismissing decisions. As this measure can identify more profitable stock recommendations ex-ante, it is potentially of greater interest for retail investors who do not have the skills and resources to conduct independent equity research.

Third, my findings also contribute to our understanding of the determinants of stock recommendation profitability and price target accuracy—a relatively under-researched area (Bradshaw et al., 2013), and investors' differential reactions to analysts' stock recommendation revisions.[11] Finally, my study improves our understanding of the labor market of sell-side financial analysts.

This paper is related to Keung (2010) and Ertimur et al. (2011), who study the motives and implications of analysts' provision of sales forecasts, and Jung et al. (2012), who focus on analysts' provision of long-term earnings growth forecasts. However, these studies only focus on a small subset of forecast types while ignoring the majority of forecast types available in I/B/E/S.[12] Recent studies show that a wide spectrum of non-EPS forecasts are useful to investors (Bilinski, 2020; Bilinski and Bradshaw, 2015; Bratten et al., 2017; Givoly et al., 2019; Hand et al., 2021; Mauler, 2019). Given that investors pay attention to and demand various forecast types, it is plausible that analysts use many of them if not all to signal higher ability and effort to forecast firm fundamentals. Supporting this hypothesis, the effects of the number of forecast types provided by analysts cannot be subsumed by analysts' provision of specific forecast types. This paper further distinguishes from Keung (2010), Ertimur et al. (2011), and Jung et al. (2012) by examining the associations of analysts' forecast provision with a comprehensive set of

[11] In prior literature, for example, Stickel (1995) documents that investors' reactions to recommendation revisions are a function of the reputation of the analyst, the size of the brokerage house, the size of the focal firm, and accompanied earnings forecast revisions. Loh and Stulz (2011) document that recommendation revisions are more likely to be influential if they are from leader, star, previously influential analysts, issued away from consensus, and accompanied by earnings forecasts.

[12] It is necessary to control for analysts' provision of other forecast types when studying one specific forecast type. This is because analysts' provision of different forecast types may be interdependent. However, given the large number of forecast types, controlling for all forecast types is unrealistic.

metrics of analysts' ability or effort, including price target forecast accuracy and stock recommendation profitability, which are not investigated in their studies.

The remainder of the paper is arranged as follows. Section 2.4 introduces regression models for main tests; Section 1.3 describes the sample and descriptive statistics for the variable of interest—the number of forecast types; Section 1.4 investigates the correlations between the number of forecast types and analyst characteristics; Section 1.5 reports and discusses main empirical results; Section 1.6 provides supplementary analyses; Section 2.7 concludes the paper.

1.2 Models

To test the hypothesis that the number of forecast types provided by analysts signals analyst ability and effort to forecast firm fundamentals, I respectively examine the associations of the number of forecast types an analyst provides for the firm she follows with her 1) earnings forecast accuracy, 2) price target forecast accuracy, 3) stock recommendation profitability, 4) ability to generate market reactions, and 5) career outcomes.

I use "NFT" to denote "the number of forecast types" for brevity purposes.

1.2.1 How to measure NFT?

NFT is based on a count of the number of financial statement line items an analyst provides to I/B/E/S.[13] Besides financial statement line items, analysts also provide stock recommendations or price targets. I do not include stock recommendations and price targets in the calculation of NFT because they are arguably the ultimate products of an analyst's research (Schipper, 1991). In addition, price target accuracy and the profitability of stock recommendations are two metrics of analyst forecasting performance to be tested in this paper. To capture the time-varying and slow-moving properties of NFT, I calculate NFT on a 90-day rolling window and on a day-to-day basis.[14] Specifically, I define the NFT of analyst j for firm i on day d as the total number of forecast types the analyst has provided to I/B/E/S for firm i during the past 3 months prior to the month

[13] I/B/E/S also collects key performance indicator (KPI) forecasts and forecasts at geographic, product, and segment levels from analysts. Taking other forecasts into account can be an opportunity for future research.

[14] NFT is defined differently in the tests of earnings forecast accuracy and analyst career outcomes. Please see the respective sections for detailed definitions.

of day d.[15] Note that NFT does not count forecasts of the same type repeatedly. For example, multiple sales forecasts issued during the 90-day rolling window are counted as one forecast type. I choose a 90-day calculation window because analysts usually do not release all forecast types on the same day.[16] I do not consider the forecasts provided in the month of day d for the following reasons. First, excluding contemporaneous forecasts mitigates the concern that the effects of NFT on analyst forecasting performance are purely driven by the information conveyed by the additional forecasts per se.[17] Second, this variable construction only uses past information, so it allows investors to use NFT in real decision makings. I construct NFT on a firm-specific basis because analysts may strategically allocate more effort to firms that are more important to their careers (Harford et al., 2019).

Specifically, $\mathrm{NFT}_{\mathrm{ijd}} = \sum_{\mathrm{h}=1}^{5} \sum_{\mathrm{k}=1}^{23} \mathrm{I\_AF}_{\mathrm{ijd}}^{\mathrm{k,h}} + \mathrm{I\_AF}_{\mathrm{ijd}}^{\mathrm{LTG}}$, where $\mathrm{I\_AF}_{\mathrm{ijd}}^{\mathrm{k,h}}$ is an indicator variable that equals 1 if analyst j provides at least 1 h-year-ahead type k forecast for firm i during the past 3 months prior to the month of day d, and 0 otherwise; the superscript "LTG" denotes long-term earnings growth forecast type. NFT not only reflects the number of 1-year-ahead forecasts but also the number of forecast periods. For example, 1-year-ahead sales forecasts and 2-year-ahead sales forecasts are regarded as two separate forecast types. Except for long-term earnings growth forecasts, I do not consider other forecasts with a forecast period above 5 years because they are scarce in I/B/E/S. To examine the role played by 1-year-ahead forecasts, I define $\mathrm{NFT1}_{\mathrm{ijd}} = \sum_{\mathrm{k}=1}^{23} \mathrm{I\_AF}_{\mathrm{ijd}}^{\mathrm{k,1}} + \mathrm{I\_AF}_{\mathrm{ijd}}^{\mathrm{LTG}}$, the number of 1-year-ahead forecast types analyst j provides for firm i on day d.[18] To explore the different roles played by items belonging to different categories of the financial statement, I construct NFT_BS, NFT_CS, and NFT_IS, the number of forecast types belonging to balance sheet, cash flow statement, and income statement, respectively.[19]

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[15] For example, the NFT on December 13th is determined by the forecasts provided during the period September 1st–November 30th.

[16] I obtain qualitatively similar results when using a 180-day or 1-year calculation window.

[17] To further mitigate this concern, in tests of market reactions, I control for five prevalent contemporary forecast revisions. The main results are qualitatively similar if I calculate NFT using a 90-, 180-, or 365-day window ending on day d. Not including the forecasts in the month of date d is out of conservatism. Even if the effects of NFT on analysts' forecasting performance are solely driven by the information contained in contemporaneous additional forecasts, it is consistent with the hypothesis that more able/diligent analysts provide more forecast types to signal the superior information possessed.

[18] LTG forecasts are categorized as a 1-year-ahead forecast type because unlike other long-term growth forecasts, which are scarce, LTG forecasts are common in I/B/E/S and analysts' research reports.

[19] Please see Appendix for detailed categorization for financial statement line items.

Following Clement and Tse (2003, 2005), I standardize NFT and other continuous control variables using the following range transformation:

$$\text{VARIABLE\_R}_{\text{ijd(t)}} = \frac{\text{VARIABLE}_{\text{ijd(t)}} - \min\{\text{VARIABLE}_{\text{ijd(t)}}\}}{\max\{\text{VARIABLE}_{\text{ijd(t)}}\} - \min\{\text{VARIABLE}_{\text{ijd(t)}}\}}, \tag{1.1}$$

where subscripts i, j, d, and t denote firm, analyst, calendar day, and calendar year, respectively; $\min\{\cdot\}$ ($\max\{\cdot\}$) takes the minimum (maximum) of the raw variable within firm i in year t. After the standardization, VARIABLE_R, the relative measure within each firm-year, falls between 0 and 1. This standardization is essential in that prior studies find that an analyst's forecast provision for the firm she follows is a function of the fundamentals of that firm. The firm fundamentals may be correlated with information users' demand for specific forecast types and the forecasting difficulty, which are assumed to be independent of analysts' ability or effort. (DeFond and Hung, 2003; Givoly et al., 2019; Mauler, 2019). Equation 1.1 eliminates both the firm-level and intertemporal variations, so that I can directly compare the effects of NFT on the dependent variables across firms and years. To correct for endogenous firm-analyst matching and facilitate comparing the marginal effects across all independent variables, I apply Equation 1.1 to all continuous control variables. I obtain qualitatively similar main results when I use demeaned variables, rank-based transformations, or raw variables and firm-year fixed effects.[20]

In the context of signaling ability and effort and predicting analyst forecasting performance, NFT has three main advantages over using analysts' provision of a specific forecast type. First, NFT has desirable within-firm-year granularity. Unlike a dummy variable, NFT_R, the standardized NFT, is usually dispersed between 0 and 1 evenly, within each firm-year. Figure 1.2 shows the average within-firm interquartile range (IQR) for NFT over years. The average within-firm IQR for NFT (NFT1) is around 16 (4.5) in recent years and 6.5 (3) in 2002. Granularity not only allows for ranking analysts more precisely but also alleviates endogeneity problems stemming from variation in firm fundamentals.[21]

[20] One advantage of using Equation 1.1 over using demeaned variables is that range transformation is robust to extreme values and zero denominators; one advantage of using Equation 1.1 over rank-based transformations is that it can reflect an observation's relative position in the distribution of that variable more precisely; one advantage of using Equation 1.1 over using raw variables and firm-year fixed effects is that the estimated coefficients have more meaningful economic interpretations.

[21] Assuming that I want to study the effects of the issuance of cash flow forecasts on analysts' earnings forecast accuracy. As per prior literature does, I restrict my sample to firm-years with cash flow forecast

Second, NFT applies to a larger set of firms than specific forecast types. For example, in 2020, only 56.4% of firms in the I/B/E/S universe had cash flow forecast coverage. The forecasting performance of analysts following the remaining 43.6% of firms cannot be identified ex-ante by their provision of cash flow forecasts.[22]

Finally, the within-firm-year variation in the provision of some forecast types has been decreasing over years. For example, in 2020, for firms with sales forecast coverage, as high as 92.2% of the following analysts provided at least one sales forecast.[23] Ertimur et al. (2011) point out that the decreasing cross-sectional variation of earnings disaggregation "may weaken the potency of disaggregation as a means for establishing reputation". However, even among the analysts who provide sales forecasts, NFT still shows significant within-firm-year variation and is a valid signal for analyst forecasting ability and effort.

1.2.2 Models for tests of NFT and earnings forecast accuracy

If analysts who provide more forecast types have higher ability and exert more effort to forecast earnings, we should observe a negative association between earnings forecast error and NFT. Specifically, I expect a negative β_1 for the following regression equation:

$$\begin{aligned}
&100 \times \mathrm{RAFE}_{\mathrm{ijt(d)}} = \\
&\beta_0 + \beta_1 \mathrm{NFT_R}_{\mathrm{ijt(d)}} + \beta_2 \mathrm{AFE_R}_{\mathrm{ijt-1}} + \beta_3 \mathrm{FEXP_R}_{\mathrm{ijt}} + \beta_4 \mathrm{FREQ_R}_{\mathrm{ijt}} + \beta_5 \mathrm{GEXP_R}_{\mathrm{ijt}} \\
&+ \beta_6 \mathrm{HRZ_R}_{\mathrm{ijt(d)}} + \beta_7 \mathrm{LFR_R}_{\mathrm{ijt}} + \beta_8 \mathrm{NFRM_R}_{\mathrm{ijt}} + \beta_9 \mathrm{NIND_R}_{\mathrm{ijt}} + \beta_{10} \mathrm{SIZE_R}_{\mathrm{ijt}} \\
&+ \beta_{11} \mathrm{WKDN_R}_{\mathrm{ijt}} + \mathrm{Brokerage}\ (+\ \mathrm{Firm\text{-}Analyst}) + \epsilon_{\mathrm{ijt}},
\end{aligned} \tag{1.2}$$

where

coverage. Imagine two firms each with 10 analyst followings in year t. Only one analyst issues cash flow forecasts for firm A, while nine analysts do so for firm B. According to the demand theory by DeFond and Hung (2003), firm B may have larger accruals, more heterogeneous accounting choices, higher earnings volatility, higher capital intensity, and poorer financial health, which make firm B's earnings more difficult to predict holding analyst ability fixed. Firm B's disproportionately high cash flow forecast coverage may distort the results because when calculating the average forecast accuracy for earnings forecasts accompanied by cash flow forecasts, firm B accounts for 9/10 of the observations. Instead, NFT_R is usually dispersed between zero and one evenly, preventing the results from being distorted by overweighting some firms.

[22] For the percentage of firms with a particular forecast type, please see Table A1.

[23] For the within-firm percentage of analysts with a particular forecast type, please see Table A1.

RAFE	analyst j's absolute earnings forecast error for firm i in year t divided by the average absolute forecast error across all forecasts for firm i in year t. Absolute forecast error is defined as the absolute difference between analyst j's 1-year ahead EPS forecast for firm i outstanding on June 30th in year t and the actual.
NFT	number of forecast types analyst j provides for firm i during the 180-day window ending on June 30th in year t.
AFE_{t-1}	analyst j's absolute earnings forecast error for firm i in year t-1.
FEXP	number of years analyst j has provided at least one EPS forecast for firm i through year t.
FREQ	number of EPS forecasts analyst j provides for firm i in year t.
GEXP	number of years analyst j has provided at least one EPS forecast to I/B/E/S through year t.
HRZ	the number of days between analyst j's earnings forecast for firm i outstanding on June 30th in year t and the earnings announcement.
LFR	cumulative number of days by which the preceding two one-year-ahead EPS forecasts lead the focal forecast issued by analyst j for firm i during fiscal year t divided by the cumulative number of days by which the subsequent two forecasts follow that forecast.
NFRM	number of firms for which analyst j provides at least one EPS forecast in year t.
NIND	number of 2-digit SIC industries analyst j covers in year t.
SIZE	number of analysts employed by analyst j's brokerage house in year t.
WKDN	difference between analyst j's first and last one-year-ahead EPS forecast for firm i in year t, divided by absolute value of the actual. The first forecast is no earlier than year t-1's fiscal year-end and no later than 90 days prior to year t's earnings announcement, and the last one is no later than year t's earnings announcement.

Variables with a postfix "_R" are transformed following Equation 1.1 to fall between 0 and 1. Relative absolute earnings forecast error (RAFE) captures analyst j's absolute earnings forecast error (i.e. inverse forecast accuracy) relative to all analysts (including analyst j) following firm i in year t. The construction of RAFE controls for variations in forecasting difficulty across firms and years.[24] I control for lagged earnings forecast error (AFE_{t-1}) as prior literature finds that past earnings forecast accuracy is a determinant of current earnings forecast accuracy (Brown, 2001). I control for analyst j's general (GEXP) and firm-specific forecasting experience (FEPX) because Clement (1999) and Jacob et al. (1999) show that they are positively related to analysts' earnings forecast accuracy.[25] I control for earnings forecasting frequency (FREQ) as Jacob et al. (1999) use FREQ as a measure of analysts' effort and attentiveness to forecast earnings, which is assumed

[24] Using absolute earnings forecast error transformed following Equation 1.1 as the dependent variable leads to qualitatively similar results with even higher statistical significance. However, in this way, the economic interpretation of the estimated coefficient for NFT_R becomes obscure.

[25] I use a sample starting from 1982 to calculate GEXP and FEXP to mitigate potential measurement errors arising from truncation from above. The sample period starts from 1982 because EPS forecasts became prevalent in I/B/E/S Academics (via Wharton's WRDS database) since 1982.

to be positively related to earnings forecast accuracy. I control for earnings forecasting horizon (HRZ) because earnings forecasts are more accurate when they are issued near the earnings announcement. I control for leader-follower ratio (LFR) to capture the timeliness of an analyst's earnings forecasts, which is a robust signal for analyst ability (Cooper et al., 2001; Shroff et al., 2014). According to Clement (1999) and Jacob et al. (1999), I control for the number of firms and the number of industries analyst j covers to capture the potentially negative effect of portfolio complexity on earnings forecast accuracy. I control for analyst j's brokerage size (SIZE) because Stickel (1995), Clement (1999), and Jacob et al. (1999) find that an analyst's forecasting performance is positively associated with the size of her brokerage house. I control for an analyst's walk-down bias (WKDN) because Ke and Yu (2006) empirically show that in pre-Regulation Fair Disclosure (reg FD) period, analysts initially use upward-biased earnings forecasts to please management to gain access to private information and then use pessimistic forecasts to make managers meet and beat the target.

I employ the accuracy of earnings forecasts outstanding on June 30th for the following reasons. First, from an investor's perspective, forecasts issued near a firm's earnings announcement are of little investment value because the return accumulation period is short. In that case, returns are earned only around the earnings announcement window. Second, the accuracy of forecasts issued before a firm's year t-1 earnings announcement may not credibly reflect an analyst's forecasting ability or effort because firm fundamentals of the last period have not become publicly available then and, as a consequence, access to private communication with management, may affect the analyst's forecast accuracy.[26] I obtain qualitatively similar results when I use alternative measures of earnings forecast accuracy. In accordance with the definition of RAFE, I calculate NFT over the half-year window ending on June 30th in the tests of this section.

To mitigate the concern that the effects of NFT are solely driven by factors at the brokerage level, I control for brokerage fixed effects. To examine whether analysts strategically provide more forecast types when they conduct more diligent research to possess better information about the firms they follow, I include firm-analyst fixed effects in some model specifications.

[26] Brown et al. (2015) documents that "...private communication with management is a more useful input to analysts' earnings forecasts..." regardless of reg FD.

1.2.3 Models for tests of NFT and price target forecast accuracy

If analysts who provide more forecast types have higher ability and exert higher effort to forecast firms' price targets, we should observe a negative association between price target forecast error and NFT. Specifically, I expect a negative β_1 for the following regression equation:

$$
\begin{aligned}
&100 \times \mathrm{RPTAFE}_{\mathrm{ijt(d)}} = \\
&\beta_0 + \beta_1 \mathrm{NFT\_R}_{\mathrm{ijt(d)}} + \beta_2 \mathrm{AFE\_R}_{\mathrm{ijt}} + \beta_3 \mathrm{BOLD\_R}_{\mathrm{ijt}} + \beta_4 \mathrm{FEXP\_R}_{\mathrm{ijt}} + \beta_5 \mathrm{FREQ\_R}_{\mathrm{ijt}} \\
&+ \beta_6 \mathrm{FREQ\_PT\_R}_{\mathrm{ijt}} + \beta_7 \mathrm{GEXP\_R}_{\mathrm{ijt}} + \beta_8 \mathrm{LFR\_R}_{\mathrm{ijt}} + \beta_9 \mathrm{NFRM\_R}_{\mathrm{ijt}} + \beta_{10} \mathrm{NIND\_R}_{\mathrm{ijt}} \\
&+ \beta_{11} \mathrm{SIZE\_R}_{\mathrm{ijt}} + \beta_{12} \mathrm{WKDN\_R}_{\mathrm{ijt}} + \mathrm{Brokerage}\ (+\ \mathrm{Firm\text{-}Analyst}) + \epsilon_{\mathrm{ijt(d)}},
\end{aligned} \tag{1.3}
$$

where

RPTAFE	analyst j's absolute price target forecast error for firm i on date d year t divided by the average absolute forecast error across all price target forecasts for firm i in year t. Absolute forecast error is defined as the absolute difference between analyst j's 12-month ahead price target forecast for firm i and firm i's 360-day ahead stock price divided by firm i's stock price on date d year t.
NFT	number of forecast types analyst j provides for firm i during the past 3 months prior to the price target forecast issuance month.
AFE	absolute forecast error of analyst j's one-year-ahead EPS forecast for firm i outstanding on June 30th year t.
BOLD	absolute deviation of analyst j's first one-year-ahead EPS forecasts for firm i immediately after year t-1's fiscal year-end from the average of those issued by all other analysts.
FREQ_PT	number of analyst j's price target forecasts for firm i in year t.

All other variables have been defined in previous sections. Variables with a postfix "_R" are transformed following Equation 1.1 to fall between 0 and 1. The dependent variable in Equation 1.3 is relative absolute price target forecast error (RPTAFE). RPTAFE is defined along the lines of relative earnings forecast error (RAFE). RPTAFE eliminates the variations in forecasting difficulty across firms and years. Earnings forecasts are an important input in analysts' price target forecasting models (Da et al., 2016; Dechow and You, 2020; Demirakos et al., 2010; Gleason et al., 2013). I control for concurrent earnings forecast error (AFE) to provide evidence that NFT captures analysts' ability and effort to forecast price targets beyond their ability and effort to forecast earnings.[27] I control analysts' price target forecasting frequency (FREQ_PT) to capture analysts' effort and attentiveness to forecast price targets.[28] Although Hashim and Strong (2018) document that price target forecasts accompanied by cash flow forecasts are more accurate, cash flow forecast provision is not significantly correlated with price target forecast accuracy in my research design. As a result, I do not include analysts' cash flow forecasts provision in my regression models to avoid unnecessary complexity.[29]

1.2.4 Models for tests of NFT and the profitability of stock recommendations

If analysts who provide more forecast types have superior ability and exert higher effort to valuate the stocks of the firms they follow, we should observe a positive association between the profitability of stock recommendations and NFT. Specifically, I expect a postive β_1 for the following regression equation:

$$\begin{aligned}
&100 \times \mathrm{REC_RET_\{180, 30\}}_{\mathrm{ijt(d)}} = \\
&\beta_0 + \beta_1\mathrm{NFT_R}_{\mathrm{ijt(d)}} + \beta_2\mathrm{AFE_R}_{\mathrm{ijt}} + \beta_3\mathrm{BOLD_R}_{\mathrm{ijt}} + \beta_4\mathrm{FEXP_R}_{\mathrm{ijt}} + \beta_5\mathrm{FREQ_R}_{\mathrm{ijt}} \\
&+ \beta_6\mathrm{FREQ_REC_R}_{\mathrm{ijt}} + \beta_7\mathrm{GEXP_R}_{\mathrm{ijt}} + \beta_8\mathrm{LFR_R}_{\mathrm{ijt}} + \beta_9\mathrm{NFRM_R}_{\mathrm{ijt}} + \beta_{10}\mathrm{NIND_R}_{\mathrm{ijt}} \\
&+ \beta_{11}\mathrm{SIZE_R}_{\mathrm{ijt}} + \beta_{12}\mathrm{WKDN_R}_{\mathrm{ijt}} + \mathrm{Brokerage}\ (+\ \mathrm{Firm\text{-}Analyst}) + \epsilon_{\mathrm{ijt(d)}},
\end{aligned} \tag{1.4}$$

where

[27] Controlling for lagged earnings forecast error delivers qualitatively similar results, but doing so reduces the sample size aggressively. Controlling for contemporaneous earnings forecast error is a more stringent treatment because Bradshaw et al. (2013) show that analysts lack persistence in providing accurate price targets, while concurrent earnings forecasts directly affect price target forecasting.

[28] I still control for analysts' earnings forecasting frequency (FREQ) because earnings forecasts are an important input in generating the ultimate products of an analyst's research like price targets and stock recommendations. Earnings forecasting frequency reflects an analyst's overall forecasting effort and attentiveness.

[29] The main results are insensitive to the inclusion of analysts' cash flow forecast provision.

REC_RET_{180, 30}	at most 180-day (30-day) size-adjusted buy-and-hold return of the stock recommendation issued by analyst j for firm i on day d year t. I invest \$1 in stocks with a Strong buy or Buy recommendation (coded as 1 and 2 by I/B/E/S), and short \$1 in stocks with a Hold, Sell, or Strong sell recommendations (coded as 3, 4 and 5 by I/B/E/S). The return accumulation period begins the day before the recommendation until the earlier of 180 days (30 days) or two days before the recommendation is revised or reiterated. Size-adjusted returns are calculated by deducting the value-weighted average return for all firms in the same size-matched decile, where size is measured as market capitalization of the equity at the beginning of the return accumulation period.
NFT	number of forecast types analyst j provides for firm i during the past 3 months prior to the recommendation issuance month.
FREQ_REC	number of analyst j's stock recommendations for firm i in year t.

All other variables have been defined in previous sections. Variables with a postfix "_R" are transformed following Equation 1.1 to fall between 0 and 1. Compared to the portfolio approach, multivariate regressions allow for controlling for a broad set of analyst characteristics (Ertimur et al., 2007). I short \$1 in stocks with a Hold recommendation (coded as 3 by I/B/E/S) to correct for the well-documented optimistic bias in analysts' stock recommendations.[30] I choose an at most 180-day return accumulation period in the main analysis because Womack (1996) documents that analysts' stock recommendations have investment value for up to 6 months.[31] I additionally use REC_RET_30, at most 30-day size-adjusted buy-and-hold return, as an alternative measure of recommendation profitability.[32] I control for concurrent earnings forecast error (AFE) as Ertimur et al. (2007) document that earnings forecast accuracy is positively related to analysts' stock recommendation profitability. I control for analysts' stock recommendation frequency (FREQ_REC) to capture analysts' effort and attentiveness to recommend stocks. Other control variables are largely the same as those in Equation 1.2 and Equation 1.3.

[30] The main results are qualitatively similar if I neither buy nor short sell stocks with a Hold recommendation.

[31] If the financial market is efficient, stock prices should reflect the intrinsic values of the stocks in the long run. Stock recommendation profitability over a long period can better capture the analyst's ability and effort to forecast firm fundamentals, which is not the same as the ability to generate market reactions.

[32] I get qualitatively similar results when using market-adjusted REC_RET_180 or REC_RET_30.

1.2.5 Models for tests of NFT and market reactions

If analysts who provide more forecast types are better able to generalize stock market reactions with respect to stock recommendation revisions, we should observe a positive association between the cumulative abnormal returns around the recommendation revision window and NFT. Specifically, I expect a negative β_3 for the following regression equation:[33]

$$
\begin{aligned}
&100 \times \mathrm{CAR3}_{\mathrm{ijt(d)}} = \\
&\beta_0 + \beta_1 \mathrm{RECrev}_{\mathrm{ijt(d)}} + \beta_2 \mathrm{NFT\_R}_{\mathrm{ijt(d)}} + \beta_3 \mathrm{RECrev}_{\mathrm{ijt(d)}} \times \mathrm{NFT\_R}_{\mathrm{ijt(d)}} \\
&+ \sum_{\mathrm{k}=4}^{8} \beta_{\mathrm{k}} \textit{Other Forecast Revision}^{\mathrm{k}-3} + \sum_{\mathrm{k}=9}^{13} \beta_{\mathrm{k}} \mathrm{RECrev} \times \mathrm{I\_}\textit{Other Forecast Revision}^{\mathrm{k}-8} \\
&+ \sum_{\mathrm{k}=14}^{24} \beta_{\mathrm{k}} \textit{Analyst Characteristics}\_\mathrm{R}^{\mathrm{k}-13} + \sum_{\mathrm{k}=25}^{35} \beta_{\mathrm{k}} \mathrm{RECrev} \times \textit{Analyst Characteristics}\_\mathrm{R}^{\mathrm{k}-24} \\
&+ \text{Firm-Year} + \epsilon_{\mathrm{ijt(d)}},
\end{aligned}
\tag{1.5}
$$

where

CAR3 three-day market-adjusted buy-and-hold cumulative abnormal returns around analyst j's stock recommendation revision for firm i on date d year t.

RECrev analyst j's stock recommendation revision for firm i on date d year t. RECrev is defined as the difference between the I/B/E/S recommendation code for the newly-issued recommendation and that for the previous one. For example, RECrev equals 1 if the analyst downgrades the stock by one level, e.g. from Buy (I/B/E/S recommendation code = 2) to Hold (I/B/E/S recommendation code = 3).

NFT number of forecast types analyst j provides for firm i during the past 3 months prior to the month of the day on which the recommendation is revised, d.

Other Forecast Revision = {EPSrev, EBIrev, NETrev, PRErev, SALrev}, where

EPSrev analyst j's one-year-ahead earnings forecast revision for firm i on date d year t. Specifically, EPSrev equals the EPS forecast issued on date d minus the previously outstanding EPS forecast divided by the absolute value of the previously outstanding EPS forecast.

EBIrev, NETrev, PRErev and SALrev are defined analogously.

[33]Recall that a negative RECrev denotes an optimistic (a pessimistic) revision.

I_*Other Forecast Revision* equals 1 if analyst j revises a related forecast type for firm i on date d year t, and 0 otherwise.

Analyst Characteristics = {AFE$_{t-1}$, BOLD, FEXP, FREQ, FREQ_REC, GEXP, LFR, NFRM, NIND, SIZE, WKDN}.

All analyst characteristics have been defined in the previous sections. Variables with a "_R" postfix are transformed following Equation 1.1 to fall between 0 and 1. I control for contemporaneous earnings forecast revisions because Stickel (1995) documents that recommendation revisions have greater price impacts if they are reinforced by a confirming earnings forecast revision. I control for analysts' revisions in sales forecasts and their interactions with RECrev and I_SALrev, the indicator variable that equals 1 if the analyst revises her stock recommendation and sales forecast simultaneously, and 0 otherwise. This treatment is potentially important in that Keung (2010) documents that investors react more strongly to earnings forecast revisions accompanied by sales forecasts even after controlling for the additional information contained in the sales forecast revisions. He attributes this finding to these analysts' better information possessed about the fundamentals of the firms they follow. Although Keung (2010)'s setting is earnings forecast revision, I empirically show that his finding applies to my setting, stock recommendation revisions, too.[34] For the same reason, I control for other common forecast revisions and the interactions between the issuances of these forecast revisions and stock recommendation revisions.

1.2.6 Models for tests of NFT and analyst career outcomes

Assuming that successful career outcomes are what analysts ultimately pursue, analysts who have higher ability or exert higher effort should end up with better career outcomes in general. Specifically, I expect that analysts who provide more forecast types are less likely to be terminated or demoted by their employers and are more likely to be promoted from small brokerage houses to large brokerage houses. I expect a negative (positive) β_1 when TERMINATION or DEMOTION (PROMOTION) is the dependent variable for the following conditional logistic model matched at brokerage house level:[35]

[34] The untabulated results show that investors react more strongly to earnings forecast revisions accompanied by more forecast types too.

[35] Conditional logistic regression models are also known as fixed-effects logit models for panel data. Please see McFadden (1973) for details.

$$
\begin{aligned}
&\{\text{TERMINATION, PROMOTION, DEMOTION}\}_{\text{jt+1}} \\
&= \beta_1 \text{NFT}'_{\text{jt}} + \beta_2 \text{I\_AFLTG}'_{\text{jt}} + \beta_3 \text{I\_AFSAL}'_{\text{jt}} + \beta_4 \text{AFE\_M}_{\text{jt}} + \beta_5 \text{BOLD\_M}_{\text{jt}} \\
&+ \beta_6 \text{COMP\_M}_{\text{jt}} + \beta_7 \text{FREQ\_M}_{\text{jt}} + \beta_8 \text{GEXP\_M}_{\text{jt}} + \beta_9 \text{LFR\_M}_{\text{jt}} + \beta_{10} \text{NFRM\_M}_{\text{jt}} \\
&+ \beta_{11} \text{NIND\_M}_{\text{jt}} + \beta_{12} \text{SIZE\_M}_{\text{jt}} + \beta_{13} \text{WKDN\_M}_{\text{jt}} + \text{Brokerage } + \epsilon_{\text{ijt+1}},
\end{aligned}
\tag{1.6}
$$

where

TERMINATION	= 1 if analyst j disappears from I/B/E/S in year t+1, and zero otherwise.
PROMOTION	= 1 if analyst j worked at a small brokerage house in year t but works at a large brokerage house in year t+1, and zero otherwise. A brokerage house is categorized as a large (small) if its number of employees is above (below) the second (first) tercile.
DEMOTION	= 1 if analyst j worked at a big brokerage house in year t but works at a small brokerage house in year t+1, and zero otherwise.
NFT′	average of analyst j's relative rank of the number of forecast types she provides for all firms followed by her in year t. Specifically, I first apply Equation 1.1 to the number of forecast types provided by analyst j for all firms in her portfolio in year t within each firm she follows in that year. I then take the average of the transformed variable derived in the last step across the firms in analyst j's portfolio in year t.
I_AFLTG′	= 1 if analyst j issued at least one long-term earnings growth forecast in year t, and zero otherwise.
I_AFSAL′	= 1 if analyst j issued at least one one-year-ahead sales forecast in year t, and zero otherwise.
BOLD	absolute deviation of analyst j's first one-year-ahead EPS forecasts for firm i immediately after year t-1's fiscal year-end from the average of those issued by all other analysts, transformed following the average absolute deviation for firm i in year t.
COMP	average number of analysts following the firms covered by analyst j in year t.

All other analyst characteristics have been defined in previous sections. Variables with a postfix "_M" are the average of VARIABLE_R across all firms followed by analyst j in year t, where VARIABLE_R is VARIABLE transformed following Equation 1.1 to fall between 0 and 1. The variable of interest, NFT'_{jt}, is analyst j's cross-firm average of the number of forecast types she provides for all firms in her portfolio in year t transformed with Equation 1.1. This treatment implicitly assumes that all the firms in analyst j's portfolio are equally important to her career. I control for analysts' provision of long-term earnings growth forecasts (I_AFLTG′) as Jung et al. (2012) document that analysts who provide LTG forecasts are less likely to be fired or demoted. I control for analysts' provision of sales forecasts (I_AFSAL′) as Ertimur et al. (2011) find that analysts who provide sales forecasts are more (less) likely to be promoted (demoted or terminated). I control for earnings forecast accuracy (AFE) as prior literature finds that relatively less accurate analysts are more likely to turn over (Mikhail et al., 1999). I control for boldness (BOLD) as Hong et al. (2000) document that inexperienced analysts are more likely to be terminated for bold forecasts. I control for the peer competition facing the analysts (COMP). I control for walk-down bias (WKDN) as Ke and Yu (2006) show empirically that analysts who first provide optimistic earnings forecasts to please the management and then provide pessimistic forecasts to make the manager meet and beat the target are less likely to be terminated.

1.3 Sample and descriptive statistics

1.3.1 Sample selection

The initial sample consists of all annual forecasts in the I/B/E/S US file contributed by identifiable individual analysts from the period 2002–2019. Forecasts with a forecast period beyond 5 years are excluded, except for long-term earnings growth forecasts. The sample begins from 2002 since most I/B/E/S forecast types have been available since then.[36] To prevent currency conversion errors, I only consider forecasts and actuals denominated in US dollars. I require a firm-year to have at least 2 analyst followings.[37] I require an analyst to provide at least 2 1-year-ahead EPS forecasts for each firm she follows in year t, the first one being no earlier than year t-1's fiscal year-end and no later than 90 days prior to year t's earnings announcement, the latest one being no later than year t's earnings announcement. This treatment ensures that walk-down bias (WKDN) is well-defined. In each set of tests, the dependent variables are from different data sets. Hence the samples differ across tests. I will introduce the sample used in each set of tests in detail in the respective sections.

[36] Using a post-2002 sample also mitigates the concern that reg FD distorts the results. Using a sample beginning from 2007, when all forecast types had become available, does not change the main results qualitatively.

[37] In portfolio sorting analyses, a firm-year must have at least four analyst followings with unique NFTs.

1.3.2 Descriptive statistics for NFT and NFT_R

In this section, NFT is defined as the number of forecast types analyst j provides for firm i *during year t*. Figure 1.1 shows that in 2002, on average, an analyst provided 3.5 types of 1-year-ahead forecasts for the firm she follows, whereas the number has increased to 8.5 in 2020. The number of longer-term forecast types has increased over years too. In 2002, each 1-year-ahead forecast type has 1 related longer-term forecast on average, whereas this number has increased to 2 in 2020. The increases in both the number of 1-year-ahead forecasts and the forecast horizon lead to a sharp rise in the number of total forecast types, from 7.5 in 2002 to 25 in 2020. Income statement forecast types are much more prevalent than balance sheet forecast types and cash flow statement forecast types. In 2020, the average number of income statement forecast types (NFT_IS) is about 18, compared to 5 for the number of balance sheet forecast types (NFT_BS) and 3 for the number of cash flow statement forecast types (NFT_CS).

Figure 1.2 shows the average within-firm-year interquartile range (IQR) for NFT over years. In 2002, the average within-firm-year IQR for NFT (NFT1) was about 6.5 (3), while the number was 16 (4.5) in 2020. The sizable within-firm-year IQR reveals that analysts following the same firm in the same year differ strikingly in the number of forecast types provided to I/B/E/S.

Table 1.1 reports summary statistics for NFT and analyst characteristics.[38] The sample contains up to 310,534 firm-analyst-year observations. Panel A of Table 1.1 reports summary statistics for the raw variables. The average firm-analyst-year observation has 20.97 (7.88) types of (1-year-ahead) forecasts. The 25th quantile (Q1), median, and the 75th quantile (Q3) for NFT, are 12, 19, and 28, respectively. The Q1, median, and Q3 for NFT1 are 6, 8, and 10, respectively. Most analysts do not provide any balance sheet forecast or cash flow statement forecast, whereas the number of income statement forecast types (NFT_IS), accounts for most of variation in NFT.

Panel B of Table 1.1 shows summary statistics for the transformed variables.[39]

[38] The sample period for the analyses in Section 1.3 and Section 1.4 is 2002–2015. The sample period ends in 2015 since *Institutional Investor* magazine suspended supplying my institute with All-American Research Team nominations since 2014. I use this shorter sample to examine the correlation between NFT and analyst characteristics. In the main tests, I do not include All-star status (STAR) to have a longer sample period. I believe the benefit of including more observations from recent years outweighs the cost of dropping STAR from the regressions because the untabulated results show that the estimated coefficients for STAR are insignificant in all regressions.

[39] I require an observation to have non-missing analyst characteristics and well-defined NFT_R to be

NFT_R spreads evenly between 0 and 1. The mean, Q1, median, and Q3 for NFT_R are 0.44, 0.14, 0.39, and 0.70, respectively. The distribution of NFT_R confirms the substantial within-firm-year variation in analysts' forecast provision.

1.4 What does NFT capture?

1.4.1 Correlations between NFT and other analyst characteristics

Before testing the association of NFT with proxies for analyst ability and effort, I first investigate what kinds of analysts are more likely to provide more forecast types. Specifically, I estimate the following regression equation:

$$\begin{aligned}
&100 \times \text{NFT_R}_{\text{ijt}} = \\
&\beta_0 + \beta_1 \text{ABLT_R}_{\text{ijt}} + \beta_2 \text{BOLD_R}_{\text{ijt}} + \beta_3 \text{CONS_R}_{\text{ijt}} + \beta_4 \text{FEXP_R}_{\text{ijt}} \\
&+ \beta_5 \text{FREQ_R}_{\text{ijt}} + \beta_6 \text{GEXP_R}_{\text{ijt}} + \beta_7 \text{LFR_R}_{\text{ijt}} + \beta_8 \text{NFRM_R}_{\text{ijt}} \\
&+ \beta_9 \text{NIND_R}_{\text{ijt}} + \beta_{10} \text{SIZE_R}_{\text{ijt}} + \beta_{11} \text{STAR}_{\text{ijt}} + \beta_{12} \text{WKDN_R}_{\text{ijt}} + \epsilon_{\text{ijt}},
\end{aligned} \tag{1.7}$$

where

NFT	number of forecast types analyst j provides for firm i in year t.
ABLT	the negative of the average of sign indicators for all forecasts made by analyst j for firm i. The sign indicator equals 1, 0, or -1 if the product of the forecast's error and the error of its corresponding consensus has a positive, zero, or negative sign. Consensus is calculated for each forecast as the average of the latest five outstanding forecasts.
CONS	negative standard deviation of analyst j's quarterly earnings forecasts for firm i throughout the analyst's professional career.
STAR	= 1 if analyst j was nominated as an All-American All-star analyst by *Institutional Investor* magazine in year t-1, and zero otherwise.

All other variables have been defined in previous sections. Variables with a postfix "_R" are transformed following Equation 1.1 to fall between 0 and 1. I define analysts' ability to move the consensus earnings forecasts towards the actuals (ABLT) following Chen and Jiang (2006) and Ertimur et al. (2011), as a proxy for innate analyst ability. I examine the association between NFT and analysts' earnings forecast consistency (CONS) as Hilary and Hsu (2013) show that analysts who forecast earnings more consistently are more able to generate stock market reactions with regard to earnings forecast revisions.

included in the sample. This requirement applies to all samples in this paper.

The association between NFT and All-star status (STAR) is potentially important as prior literature documents a positive association between analysts' reputation and their performance (Stickel, 1992, 1995). The untabulated correlation matrix shows that there is no severe multicollinearity problem.

Panel A of Table 1.2 reports the regression results for Equation 1.7. Except for balance sheet (NFT_BS) and cash flow statement (NFT_CS) forecast types, all other NFT components are statistically positively associated with analyst innate ability (ABLT). The correlation is stronger for income statement components.[40] By comparing the coefficients for BOLD in columns 1–2 and 5–6, it can be inferred that bolder analysts provide fewer 1-year-ahead forecast types but more longer-term forecast types. Interestingly, the coefficients for analyst forecast consistency (CONS) are significantly negative across columns 1–6, suggesting that NFT and CONS capture analyst ability from different perspectives. Consistent with Bayesian investors learning about analyst predictive ability through historical forecasting performance (Chen et al., 2005), the coefficient for firm-specific forecasting experience (FEXP) is significantly negative across all columns. More experienced analysts provide few forecast types than their less experienced peers in that these more experienced analysts' forecasting ability has been revealed by their historical forecasting performance. As a result, they have weaker incentives to use forecast type provision to signal their ability. Earnings forecasting frequency (FREQ) is significantly positively associated with all NFT components, consistent with the notion that NFT to some extent captures analyst effort. All NFT components are positively related to analyst forecasting timelines (LFR), a robust sign for lead analysts. Analysts who cover more industries provide fewer forecast types, consistent with more complex portfolios negatively affecting analysts' effort and attentiveness with regard to at least some stocks in their portfolios. In contrast, analysts who follow more firms provide more forecast types. A potential explanation is that analysts who follow more firms have higher innate ability. Except for the number of 1-year-ahead income statement forecast types (NFT1_IS), all other NFT components are significantly positively correlated with brokerage size (SIZE), consistent with superior resources facilitating analysts' research. The positive association between brokerage size and NFT may also stem from the non-random matching between

[40] ABLT captures analysts' earnings forecasting ability by definition. Although the number of balance sheet (NFT_BS) and the number of income statement forecast types (NFT_CS) are not correlated with ABLT, in later sections, I show that NFT_BS and NFT_CS signal analysts' ability to forecast price targets or make profitable stock recommendations.

brokerages and analysts—high-ability analysts are more likely to work at larger brokerage houses. The adjusted R^2s for all columns are small, ranging between 1.5% to 4.2%, suggesting that the analyst characteristics documented by prior literature can only explain a small proportion of the variation in NFT.

1.4.2 Regressing NFT on fixed effects

Panel B of Table 1.2 reports the adjusted R^2s for the regressions of NFT or selected analyst characteristics on brokerage fixed effects (column 1), analyst fixed effects (column 2), or firm-analyst fixed effects (column 3). In addition to providing analysts with better resources and distribution networks, brokerages may also affect analysts' forecast provision by internal policies—they may provide analysts with template forecasting models or instructions to disclosure. Column 1 shows that 21.2% (20.2%) of variation in NFT1 (NFT) can be explained by brokerage fixed effects, compared to 0.6% for boldness (BOLD), 3.2% for earnings forecasting frequency (FREQ), 4.1% for leader-follower ratio (LFR), 13.5% for number of firms followed (NFRM), and 8% for number of industries covered (NIND), indicating that factors at the brokerage level determine NFT more than determining other analyst characteristics. Nevertheless, only a moderate amount of variation in NFT can be explained by brokerage fixed effects. In addition, analysts following the same firm in the same year are usually affiliated to different brokerage houses. As a result, brokerage fixed effects and firm-analyst fixed effects may partially overlap, exaggerating the explanatory power of brokerage fixed effects for NFT.

Column 2 shows that 39% (37.8%) of variation in NFT1 (NFT) can be explained by analyst fixed effects, which capture analysts' average innate ability across all firms followed. Column 3 shows that firm-analyst fixed effects, which capture analysts' firm-specific innate ability as suggested by Clement et al. (2007), explain 49.5% (50.1%) of the variation in NFT1 (NFT), compared to 7.1% for BOLD, 17.2% for FREQ, 21.7% for LFR, 59.6% for NFRM, and 55.2% for NIND, indicating that NFT is a credible surrogate for analyst innate ability.

1.5 Main results

1.5.1 Results for tests of NFT and earnings forecast accuracy

Descriptive statistics

Table 1.3 shows descriptive statistics for the variables used in tests of NFT and earnings forecast accuracy. The sample consists of up to 301,839 firm-analyst-year observations from the period 2002–2019. Panel A shows summary statistics. The mean (median) of relative earnings forecast accuracy (RAFE) is 0.99 (0.97).[41] Transformed NFT components are distributed between 0 and 1 evenly. The untabulated correlation matrix shows that there is no severe multicollinearity problem.

Panel B shows the average relative absolute earnings forecast error (RAFE) conditional on NFT and on its components.[42] I first normalize NFT and its components to fall between 0 and 1 using the following equation:

$$\mathrm{VARIABLE\_N_{ijt}} = \frac{\mathrm{Rank(VARIABLE_{ijt})} - 1}{\max\{\mathrm{Rank(VARIABLE_{ijt})}\} - 1}, \tag{1.8}$$

where Rank(·) (max{·}) takes the rank (maximum) of VARIABLE within firm i and year t. I then sort relative absolute earnings forecast error (RAFE) into quartiles 1–4 based on the following intervals of NFT_N: [0, 0.25), [0.25, 0.5), [0.5, 0,75), and [0.75, 1]. The average relative earnings forecast error for the top quartile is smaller than that for the bottom quartile across all four NFT components. The spreads are statistically and economically significant. Within each firm-year, on average, EPS forecasts with NFT (NFT_IS) in the top quartile are 2.6% (3.8%) more accurate than the consensus relative to those in the bottom quartile. In particular, the average RAFE is monotonically decreasing across NFT_IS quartiles.

Regression results

Table 1.4 reports the regression results for Equation 1.2. Column 1 (column 2) shows that within each firm-year, the earnings forecast accompanied by the most (1-

[41] In principle, the mean of RAFE should equal 1 exactly. The slight deviation from one is due to winsorization at the 99th percentile. The main results are qualitatively similar without this treatment.

[42] I require a firm-year to have at least four analyst followings with unique raw NFTs in the univariate analysis. This requirement is too stringent for balance sheet and cash flow statement forecast types because of lack of within-firm-year variation.

year-ahead) forecast types is 1.41% (1.78%) more accurate ex-post than the consensus relative to that accompanied by the fewest forecast types, after controlling for analyst characteristics and brokerage fixed effects. Columns 3–4 show that the number of income statement forecast types (NFT_IS) have stronger effects on RAFE than the number of forecast types belonging to other categories of the financial statement. The marginal effect of NFT_IS (NFT1_IS) on RAFE is -2.57 (-2.23) with a t-statistic of -7.76 (-6.72). In columns 5–6, I include firm-analyst fixed effects to absorb analysts' firm-specific innate ability. The coefficient for NFT (NFT_IS) is -1.05 (-1.55) with a t-statistic of -2.24 (-3.47). This finding shows that when analysts have better information about the firm (through exerting higher effort to study the firms they follow), they would provide more forecast types to signal the credibility of their earnings forecasts.

Earnings forecast accuracy is also associated with other analyst characteristics. Relative earnings forecast error (RAFE) is increasing in lagged earnings forecast error (AFE_{t-1}), earnings forecasting frequency (FREQ), earnings forecasting horizon (HRZ), number of firms followed (NFRM), and brokerage size (SIZE). In addition, RAFE is decreasing in earnings forecasting timeliness (LFR) and walk-down bias (WKDN).

To rule out the possibility that the association between NFT and earnings forecast accuracy is purely driven by analysts' provision of specific forecast types, I re-estimate Equation 1.2 but further control for analysts' provision of specific forecast types. The sample used in each regression is restricted to firm-year observations with the related analyst forecast coverage.[43] I select 6 forecast types that are most negatively correlated with relative earnings forecast error in horse-racing regressions: Earnings Before Interest and Taxes (EBI), Earnings Before Interest, Taxes, Depreciation, and Amortization (EBT), GAAP Earnings (GPS), Net Income (NET), Pre-tax Profit (PRE), and Sales (SAL). The regression results are reported in Table 1.5. The coefficient for NFT_R is both statistically and economically significant throughout all columns, indicating that analysts do not merely rely on specific forecast types to signal their superior ability and effort to forecast earnings.

[43]This analysis is infeasible when the coverage of the related forecast types is very low. However, in that case, the provision of the related forecast types is even less likely to drive my results.

1.5.2 Results for tests of NFT and price target forecast accuracy

Descriptive statistics

Table 1.6 shows descriptive statistics for the variables used in tests of NFT and price target forecast accuracy. The sample consists of up to 839,601 observations at the firm-analyst-forecast level from the period 2002–2019. To prevent misaligned stock splits, I delete price targets whose ratios to 360-day-ahead stock prices are above the 99th percentile in the sample. I also remove observations with relative price target absolute forecast error (RPTAFE) greater than 2 to reduce the impact of ourliers.[44] Panel A shows summary statistics. The average (median) PTAFE is 0.34 (0.25), confirming the findings of Bonini et al. (2010) and Bradshaw et al. (2013) that analysts' price target forecasts are generally inaccurate. The untabulated correlation matrix denies the existence of sever multicollinearity problems. Panel B shows the average relative price target forecast error conditional on the number of forecast types provided by analysts normalized with Equation 1.8. The average RPTAFE for the top NFT1 and NFT quartile is smaller than that for the bottom quartiles. The spreads are statistically and economically significant. Within each firm-year, on average, price targets accompanied by NFT1 (NFT) in the top quartile are 3.2% (2.4%) more accurate than the consensus relative to those in the bottom quartile. In particular, the average RPTAFE is monotonically decreasing in NFT1 and NFT quartiles.

Regression results

Table 1.7 shows the regression results for Equation 1.3. Columns 1–5 show that except for the number of cash flow statement forecast types (NFT_CS), all other NFT components are negatively correlated with relative price target forecast errors (RPTAFE). The magnitudes are both statistically and economically significant. In each firm-year, on average, price targets accompanied by the most (1-year-ahead) forecast types are 1.31% (1.76%) more accurate than the consensus relative to those accompanied by the fewest (1-year-ahead) forecast types. In columns 6–7, I include firm-analyst fixed effects in the regressions. Interestingly, the effects of NFT1 and NFT become stronger, suggesting that

[44]The main results are qualitatively unchanged without these treatments.

innate analyst ability alone cannot explain the negative association between relative price target forecast error and NFT.

Price target forecast accuracy is correlated with several other analyst characteristics. Relative price target forecast error (RPTAFE) is increasing in concurrent earnings forecast error (AFE), indicating that earnings forecasts are an important input in analysts' price target forecasting models (Ertimur et al., 2007; Loh and Mian, 2006). RPTAFE is also increasing in boldness (BOLD), firm-specific (FEXP) and general forecast experience (GEXP), number of industries covered (NIND), and walk-down bias (WKDN). In addition, RPTAFE is decreasing in the brokerage size (SIZE), price target forecasting frequency (FREQ_PT), and forecasting timeliness (LFR).

Similar to Section 1.5.1, I separately re-estimate Equation 1.3 but further control for analysts' provision of specific forecast types. The sample used in each regression is restricted to firm-year observations with the related analyst forecast coverage when applicable. The unreported regression results reveal that the positive correlation between the number of forecast types provided by analysts and price target forecast accuracy is not merely driven by specific forecast types.

1.5.3 Results for tests of NFT and the profitability of stock recommendations

Descriptive statistics

Table 1.8 reports the univariate analysis for the number of forecast types provided by analysts and the profitability of analysts' stock recommendations. The sample consists of up to 200,631 (201,374) observations from the period 2002–2019 at the firm-analyst-recommendation level when REC_RET_180 (REC_RET_30), at-most 180-day (30-day) size-adjusted buy-and-hold abnormal return, is the dependent variable. The untabulated correlation matrix rules out the existence of sever multicollinearity problems.

Panel A presents summary statistics for the profitability of stock recommendations. The mean and median of REC_RET_180 (REC_RET_30) are 2.8% (2.4%) and 2.4% (1.9%), respectively. Panel B shows the average I/B/E/S recommendation code conditional on the number of forecast types provided by analysts normalized with Equation 1.8. Recommendations accompanied by relatively more (fewer) forecast types are more pessimistic (optimistic). Panel C (panel D) reports the average REC_RET_180

(REC_RET_30) conditional on the number of forecast types provided by analysts normalized with Equation 1.8. The average abnormal returns are in general monotonically increasing across quartiles sorted on NFT or its components. Investors who follow the stock recommendations in the top NFT quartile earn 1.97% (8.50%) higher szie-adjusted returns than those following the recommendations in the bottom NFT quartile when practicing a semi-annual (monthly) portfolio updating strategy.[45]

Regression results

Table 1.9 reports the regression results for Equation 1.4. In columns 1–6 (columns 7–8), the dependent variable is REC_RET_180 (REC_RET_30). In columns 1–5, the coefficients for all NFT components are significantly positive. The coefficient for NFT_R is 1.16% (t-statistic = 5.81), translating into a 2.32% (1.16×2) higher annualized return on following stock recommendations accompanied by the most forecast types than following those accompanied by the fewest forecast types. In column 6, I include firm-analyst fixed effects. Although the coefficient for NFT_R becomes smaller in magnitude (Coef = 0.99, t-statistic = 3.95), it remains statistically and economically significant. This finding shows that analysts provide more forecast types when their stock recommendations are more credible. Following Ertimur et al. (2007), I use an alternative measure of recommendation profitability, REC_RET_30, in columns 7–8. The results are even stronger.

Several analyst characteristics are associated with stock recommendation profitability. Consistent with Loh and Mian (2006) and Ertimur et al. (2007) that earnings forecasts are an important input in analysts' valuation models, earnings forecast error (AFE) is negatively related to stock recommendation profitability. Consistent with Jacob et al. (1999) that analysts' forecasting expertise is increasing in her firm-specific forecasting experience, FEXP is positively related to stock recommendation profitability. Consistent with Jacob et al. (1999) that earnings forecasting frequency is a proxy for analysts' effort, FREQ is positively related to stock recommendation profitability. Interestingly, analysts' stock recommendation frequency, FREQ_REC, is negatively related to stock recommendation profitability. Consistent with Cooper et al. (2001) and Shroff et al. (2014) that forecasting timeliness is a robust sign for high-quality analysts, leader-follower ratio (LFR) is significantly positively related to recommendation profitability. Consistent

[45]The returns are before transaction costs.

with the notion that large brokerages have better resources, brokerage size (SIZE) is positively related to stock recommendation profitability.

Similar to Section 1.5.1, I separately re-estimate Equation 1.4 but further control for analysts' provision of specific forecast types. The sample used in each regression is restricted to firm-year observations with the related analyst forecast coverage when applicable. The unreported regression results reveal that the positive association between the number of forecast types provided by analysts and stock recommendation profitability is not merely driven by specific forecast types.

1.5.4 Results for tests of NFT and market reactions

Descriptive statistics

Table 1.10 shows summary statistics for the variables used in tests of NFT and the stock market's reactions to analysts' stock recommendation revisions. The sample consists of up to 71,849 observations at the firm-analyst-revision level from the period 2002–2019. I require the distance between two consecutive stock recommendations not to exceed 365 days. The percentages of stock recommendation revisions accompanied by simultaneous forecast revisions in EPS, EBI, NET, PRE, and SAL are 36.3%, 12.3%, 26.1%, 23.9%, and 29.2%, respectively. The untabulated correlation matrix denies the existence of severe multicollinearity problems.

Before delving into the multivariate analysis, I first conduct a univariate analysis. Figure 1.3 shows the average 3-day cumulative market-adjusted abnormal returns (CAR3) in percentage conditional on the level of stock recommendation revisions and the number of forecast types provided by analysts normalized with Equation 1.8. I sort stock recommendation revisions at each level into quartiles based on normalized NFT using Equation 1.8. The absolute value of CAR3 is monotonically increasing across NFT quartiles for level -2 (upgrading by 2 levels) and level 2 (downgrading by 2 levels) and is generally increasing across NFT quartiles for level -1 and level 1. I do not plot extreme revisions (RECrev = -4, -3, 3, 4) because they are rare (¡ 1% in total) and trigger much larger market reactions compared to milder revisions, which would distort the figure.

Regression results

Table 1.11 shows the regression results for Equation 1.5. In the table, I do not report the coefficients for analyst characteristics and their interactions with recommendation revisions to reserve space. Column 1 (column 2) shows that the estimated coefficient for the interaction between RECrev and NFT1_R (NFT_R) is -0.35 (-0.41) with a t-statistic of -3.40 (-4.05), translating into that within each firm-year, on average, the absolute values of CAR3 around stock recommendation revisions accompanied by the most (1-year-ahead) forecast types are 0.35% (0.41%) higher per unit of revision than those around stock recommendations accompanied by the fewest (1-year-ahead) forecast types. Columns 3–5 show that the market reacts more strongly to recommendation revisions accompanied by more income statement forecast types too, whereas the market does not differentially react to the numbers of accompanying balance sheet forecast types or cash flow statement forecast types. The capital market also reacts more strongly to stock recommendations simultaneously accompanied by revisions in earnings and sales. This result extends the finding in Keung (2010) that the capital market reacts more strongly to the *earnings forecast revisions* along with concurrent sales forecast revisions.

1.5.5 Results for tests of NFT and analyst career outcomes

Descriptive statistics

Table 1.12 reports descriptive statistics for the variables used in tests of NFT and analyst career outcomes. The sample used to test analysts' career termination, promotion, and demotion contain 58,402, 13,958, and 15,834 observations, respectively, at the analyst-year level from the period 2002–2019. Panel A shows summary statistics. On average, 19.3% of analysts leave the sell-side equity research industry every year; 1.1% (1.2%) of analysts are promoted (demoted). Panel B shows average analyst career outcomes conditional on NFT′_Q, where NFT′_Q is the cross-sectional percentile of NFT′, a variable capturing the number of forecast types provided by analysts across all firms followed. The likelihood of termination (promotion) is monotonically decreasing (increasing) in NFT′_Q, whereas analysts' demotion status is not associated with NFT′_Q. The untabulated correlation matrix rules out the existence of sever multicollinearity problems.

Regression results

Table 1.13 shows the results for the conditional logistic regressions for Equation 1.6. Odd (even) columns show the estimated coefficients (marginal effects) and Z-scores. Columns 1–2 show that the number of forecast types provided by analysts (NFT′) is negatively associated with the likelihood of being fired by employers, after controlling for analysts' provision of other forecast types and analyst characteristics. Columns 3–4 show that analysts who provide more forecast types are more likely to be promoted to large brokerages from small brokerages. However, columns 5–6 show that NFT′ is not significantly associated with analysts' degradation. A potential explanation for this result is that analysts who provide fewer forecast types than their peers are more likely to be directly terminated rather than to be demoted to smaller brokerage houses.

Several analyst characteristics are related to analyst career outcomes. Consistent with Jung et al. (2012), providing long-term earnings growth forecasts has a positive effect on saving analysts' professional careers. However, the association between providing sales forecasts and analyst career outcomes is insignificant after controlling for analysts' overall forecast type provision (NFT′).[46] Consistent with Mikhail et al. (1999), analysts with relatively less accurate earnings forecasts are more likely to experience turnover. In addition, analysts who are bolder (BOLD), forecast earnings more frequently (FREQ), release earnings forecasts in a timelier manner (LFR), and cover more firms (NFRM) or industries (NIND), are less likely to be fired by their employers. Inconsistent with Ke and Yu (2006), walk-down bias (WKDN) is not correlated with analyst career outcomes in my sample and research design. A potential explanation is that my sample period is post-reg FD, in which it is harder for analysts to benefit from access to management.

There is a caveat about the above findings. From I/B/E/S data, I can only infer analysts' moves within the sell-side equity research industry. In fact, high-quality analysts have more career choices. They can become buy-side analysts, join the management teams of the firms they followed, or start their own businesses. The outside career options may bias the association between forecast type provision and analyst termination (promotion) upward (downward), to the extent that forecast type provision is positively associated with analyst ability.

[46]Untabulated results show that providing sales forecasts is significantly negatively associated with analysts' termination. Analysts' overall forecast type provision subsumes the power of sales forecast provision in explaining analysts' turnover.

1.6 Supplementary analyses

1.6.1 Subsample analyses in pre- and post-2010 periods

To preclude the possibility that analysts signal their higher ability and effort by providing more forecast types only in some sample years, I split the sample into pre- (including 2010) and post-2010 subsamples and re-estimate Equation 1.2, 1.3, 1.4, 1.5, and 1.6 on the two subsamples, respectively. The results hold in both pre- and post-2010 periods.

1.6.2 Differential post-recommendation drift

Despite the fact that stock recommendations revised by analysts who provide more forecast types have stronger short-term price impacts (Section 1.5.4), this does not imply that these analysts' stock recommendations are more profitable in the long run (Section 1.5.3). One reason is that if the stronger market reactions are solely driven by these analysts' superior information distribution networks (e.g. larger brokerage houses) rather than their superior ability to discover intrinsic firm values, the long-term returns on their stock recommendations should not be persistently higher than those of other analysts. Similarly, the results in Section 1.5.3 do not imply the results in Section 1.5.4 either.

To test whether investors can instantly identify more profitable stock recommendations by the number of accompanying forecast types, I examine the post-recommendation drifts for stock recommendations accompanied by low and high numbers of forecast types, respectively. Post-recommendation drift is defined as at most 180-day size-adjusted buy-and-hold returns which are accumulated from two days **after** the stock recommendation until the earlier of 180 days after the recommendation or two days before the recommendation is revised or reiterated. Unreported results show that stock recommendations accompanied by the most forecast types have a 0.81% ($2 \times 0.404\%$) higher annualized post-recommendation drift than those accompanied by the fewest forecast types—36.6% of the differential 180-day recommendation returns have not been realized within the three-day recommendation window.

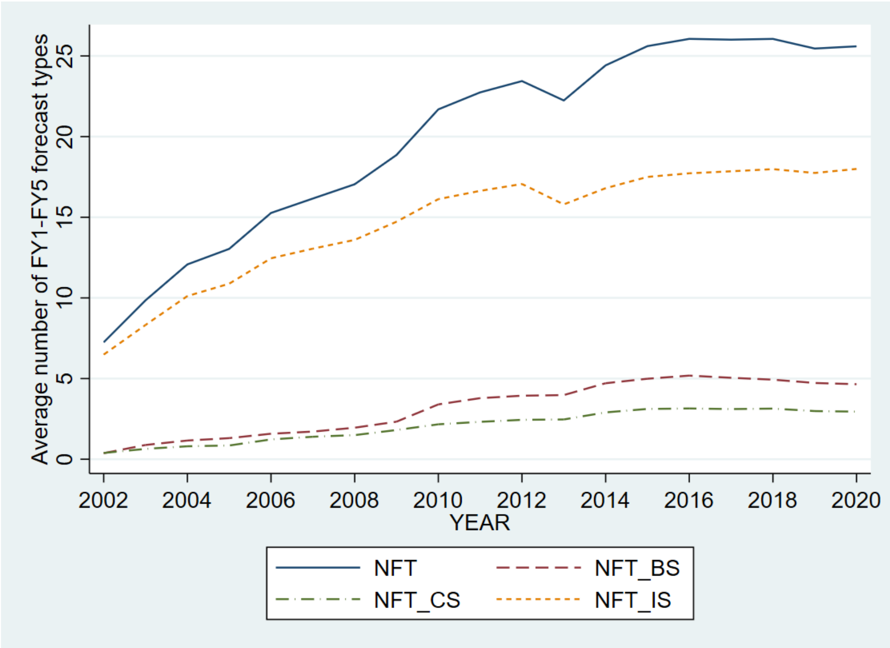
1.7 Conclusion

In this study, I first document substantial within-firm-year heterogeneity in the number of forecast types provided by financial analysts to I/B/E/S. This heterogeneity is beyond analysts' provision of any specific forecast types. I then provide an explanation for this phenomenon. I hypothesize that analysts provide additional forecast types as a means of signaling their superior ability and effort to forecast firm fundamentals. Consistent with my hypothesis, I find that analysts who provide more forecast types have more accurate earnings forecasts and price target forecasts, more profitable stock recommendations, more influential stock recommendation revisions, and better career outcomes.

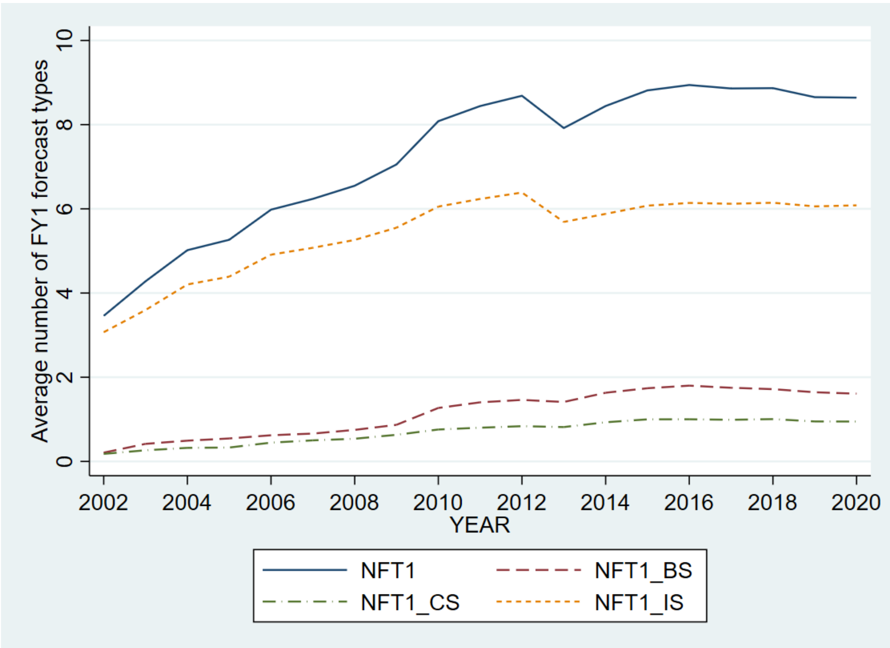
My study extends our understanding of what shapes analysts' voluntary forecast provision. I find that more able/diligent analysts provide a broad set of forecast types to distinguish themselves from other analysts rather than sticking to specific forecast types such as cash flow or sales. Moreover, I propose an ex-ante measure of analyst forecasting performance. The number of forecast types provided by analysts is parsimonious and applies to the following analysts of most firms in the I/B/E/S universe. It does not require a long time series of data to estimate, so it is particularly useful for discerning high-quality new analysts without a long track record. This paper also contributes to our understanding of the determinants of the profitability of stock recommendations and price target accuracy—a relatively under-researched area. My study also contributes to the literature of investors' differential reactions to stock recommendation revisions. Finally, my study improves our understanding of the labor market of sell-side financial analysts.

This paper has several limitations. First, this paper only studies financial statement line items. However, I/B/E/S and FactSet along with other data vendors collect hundreds of forecast types (Givoly et al., 2019; Hand et al., 2021). Future research can consider those forecast types to extend the findings in this paper. Second, this paper only considers analysts' forecast provision to I/B/E/S. Future research can compare analysts' provision to I/B/E/S with their forecast provision in research reports.

1.8 Figures

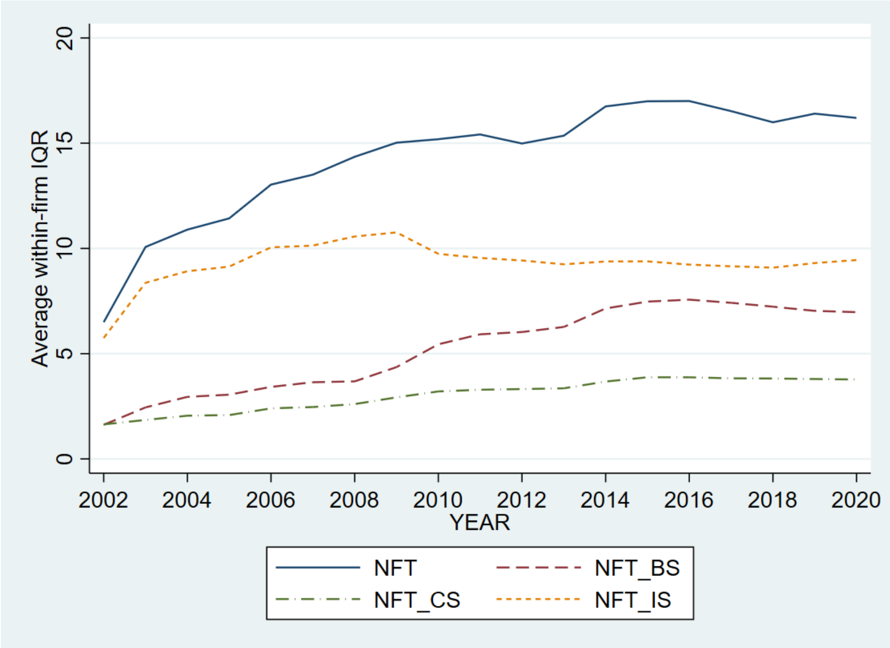


(A) Average number of total forecast types

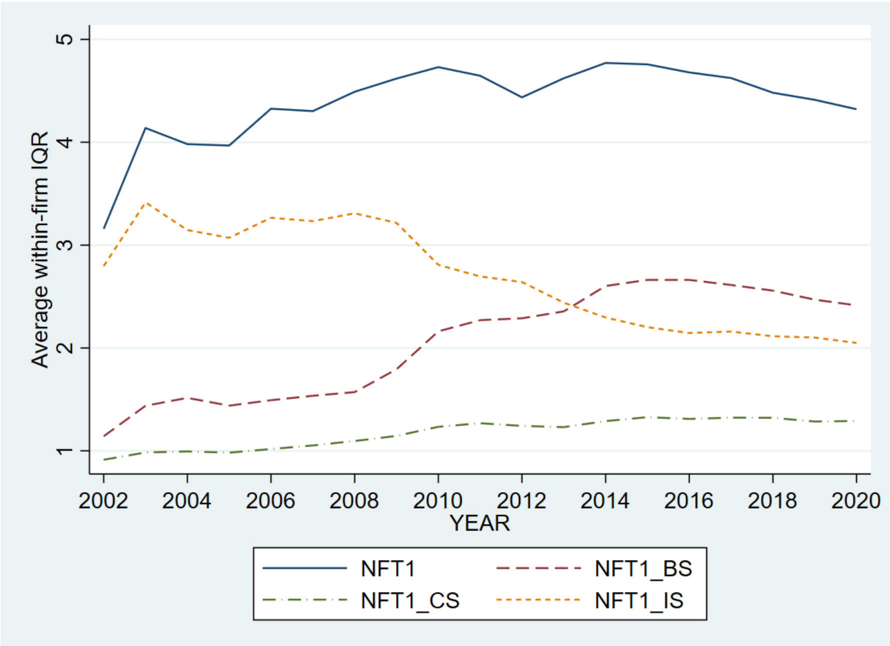


(B) Average number of one-year ahead forecast types

Figure 1.1: Average number of forecast types an analyst provides for a firm in a given year over years. NFT (1), NFT (1)_BS, NFT (1)_CS, and NFT (1)_IS are numbers of (1-year-ahead) forecast types belonging to the whole financial statement, balance sheet, cash flow statement, and income statement, respectively.



(A) Average within-firm IQR for total number of forecast types—NFT



(B) Average within-firm IQR for number of one-year-ahead forecast types—NFT1

Figure 1.2: Average within-firm interquartile range (IQR) for number of forecast types over years. NFT (1), NFT (1)_BS, NFT (1)_CS, and NFT (1)_IS are numbers of (1-year-ahead) forecast types belonging to the whole financial statement, balance sheet, cash flow statement, and income statement, respectively.

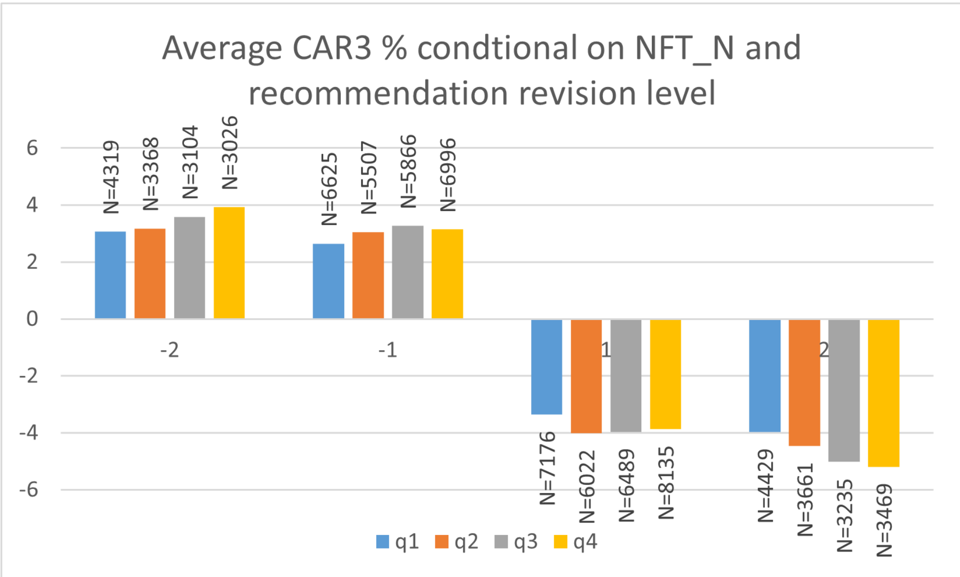


Figure 1.3: Average 3-day cumulative market-adjusted abnormal returns (CAR3) in percentage conditional on NFT_N and recommendation revision level. NFT_N is defined as the number of forecast types provided by analyst j for firm i during the past 3 months prior to the month of stock recommendation revisions (NFT), transformed following Equation 1.8. The numbers above the bars are numbers of observations.

1.9 Tables

Table 1.1: Descriptive statistics for NFT and analyst characteristics.

Panel A: Summary statistics for raw variables

	N	Mean	Sd	Q1	Median	Q3
NFT1	310,534	7.879	3.697	6.000	8.000	10.000
NFT	310,534	20.971	12.847	12.000	19.000	28.000
NFT_BS	310,534	3.100	4.638	0.000	0.000	5.000
NFT_CS	310,534	1.903	2.528	0.000	1.000	3.000
NFT1_IS	310,534	6.055	2.426	5.000	7.000	8.000
NFT_IS	310,534	15.969	8.555	10.000	16.000	21.000
FEXP	310,534	4.813	3.642	2.000	4.000	6.000
FREQ	310,534	5.101	2.600	3.000	5.000	6.000
GEXP	310,534	10.368	6.334	5.000	9.000	14.000
NFRM	310,534	17.297	7.667	13.000	16.000	21.000
NIND	310,534	4.084	2.443	2.000	4.000	5.000
SIZE	310,534	67.595	61.677	22.000	48.000	104.000
STAR	310,534	0.102	0.302	0.000	0.000	0.000

Panel B: Summary statistics for transformed variables

	N	Mean	Sd	Q1	Median	Q3
NFT1_R	308,613	0.490	0.341	0.182	0.500	0.769
NFT_R	310,534	0.439	0.337	0.143	0.394	0.696
NFT_BS_R	290,120	0.281	0.367	0.000	0.056	0.500
NFT_CS_R	284,450	0.322	0.372	0.000	0.200	0.600
NFT1_IS_R	306,707	0.564	0.356	0.250	0.667	0.857
NFT_IS_R	309,818	0.471	0.341	0.162	0.458	0.750
ABLT_R	310,534	0.518	0.329	0.260	0.532	0.786
BOLD_R	310,534	0.372	0.344	0.071	0.268	0.606
CONS_R	310,534	0.588	0.352	0.293	0.666	0.918
FEXP_R	310,534	0.428	0.358	0.100	0.364	0.714
FREQ_R	310,534	0.452	0.343	0.167	0.429	0.700
GEXP_R	310,534	0.422	0.340	0.125	0.357	0.684
LFR_R	310,534	0.311	0.350	0.028	0.156	0.497
NFRM_R	310,534	0.455	0.332	0.176	0.417	0.714
NIND_R	310,534	0.418	0.351	0.000	0.353	0.667
SIZE_R	310,534	0.349	0.337	0.065	0.238	0.511
WKDN_R	310,534	0.498	0.343	0.200	0.500	0.800

Table 1.1: This table reports summary statistics for NFT and analysts characteristics. Panel A (panel B) reports summary statistics for the raw (transformed) variables. Variables with a postfix "_R" are transformed following Equation 1.1 to fall between 0 and 1. NFT is the number of forecast types analyst j provides for firm i during year t. NFT1, NFT_BS, NFT_CS, and NFT_IS (NFT1_IS) count 1-year-ahead forecasts, balance sheet forecasts, cash flow statement forecasts, and (1-year-ahead) income statement forecasts, respectively. The sample period is 2002–2015. All variables are defined in the text.

Table 1.2: Regressions of NFT on analyst characteristics.

Panel A: Regressions of NFT on analyst characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. VARIABLE	NFT1	NFT	NFT_BS	NFT_CS	NFT1_IS	NFT_IS
ABLT_R	1.410***	1.816***	−0.112	−0.030	2.723***	2.714***
	(3.38)	(4.40)	(-0.22)	(-0.06)	(6.25)	(6.64)
BOLD_R	−0.679**	0.805***	2.419***	1.551***	−2.804***	−0.179
	(-2.47)	(2.98)	(7.49)	(4.90)	(-9.77)	(-0.67)
CONS_R	−1.959***	−2.793***	−2.852***	−3.034***	−1.049**	−2.572***
	(-4.36)	(-6.27)	(-5.00)	(-5.75)	(-2.25)	(-5.87)
FEXP_R	−4.465***	−3.727***	−2.588***	−2.824***	−4.344***	−3.379***
	(-8.47)	(-7.20)	(-3.89)	(-4.42)	(-7.97)	(-6.57)
FREQ_R	3.692***	6.143***	4.067***	4.621***	2.498***	6.161***
	(7.18)	(12.14)	(6.56)	(7.86)	(4.66)	(12.27)
GEXP_R	−0.501	−1.995*	−2.007	0.512	0.599	−1.440
	(-0.49)	(-1.95)	(-1.46)	(0.40)	(0.57)	(-1.40)
LFR_R	1.482***	2.061***	2.652***	2.208***	0.756	1.652***
	(3.07)	(4.41)	(4.23)	(3.94)	(1.53)	(3.65)
NFRM_R	6.460***	6.375***	3.536***	0.992	7.523***	7.176***
	(6.68)	(6.65)	(2.80)	(0.84)	(7.40)	(7.58)
NIND_R	−2.057***	−2.461***	−0.687	−2.757***	−0.890	−1.908**
	(-2.61)	(-3.09)	(-0.66)	(-2.83)	(-1.10)	(-2.44)
SIZE_R	7.622***	8.357***	15.951***	21.511***	0.610	3.321***
	(7.42)	(7.61)	(12.22)	(19.54)	(0.56)	(3.11)
STAR	−0.237	−0.731	−0.316	−0.198	−2.587**	−2.284**
	(-0.21)	(-0.62)	(-0.20)	(-0.15)	(-2.21)	(-2.01)
WKDN_R	−0.132	−0.001	0.057	0.148	−0.299	0.001
	(-0.52)	(-0.00)	(0.20)	(0.52)	(-1.11)	(0.00)
Ajd R^2	0.015	0.020	0.028	0.042	0.008	0.013
N	308,613	310,534	290,120	284,450	306,707	309,818

Panel B: Adj R^2s for regressions of NFT on fixed effects

	(1)	(2)	(3)
Fixed Effects	Broker	Analyst	Firm-Analyst
NFT1	0.212	0.390	0.495
NFT	0.202	0.378	0.501
BOLD	0.006	0.028	0.071
FREQ	0.032	0.128	0.172
LFR	0.041	0.127	0.207
NFRM	0.135	0.481	0.596
NIND	0.080	0.402	0.552

Table 1.2: (Continued on the following page)

Table 1.2: Panel A reports regression results for the following regression equation:

$$
\begin{aligned}
&100 \times \text{VARIABLE\_R}_{\text{ijt}} = \\
&\beta_0 + \beta_1 \text{ABLT\_R}_{\text{ijt}} + \beta_2 \text{BOLD\_R}_{\text{ijt}} + \beta_3 \text{CONS\_R}_{\text{ijt}} + \beta_4 \text{FEXP\_R}_{\text{ijt}} + \beta_5 \text{FREQ\_R}_{\text{ijt}} \\
&+ \beta_6 \text{GEXP\_R}_{\text{ijt}} + \beta_7 \text{LFR\_R}_{\text{ijt}} + \beta_8 \text{NFRM\_R}_{\text{ijt}} + \beta_9 \text{NIND\_R}_{\text{ijt}} + \beta_{10} \text{SIZE\_R}_{\text{ijt}} \\
&+ \beta_{11} \text{STAR}_{\text{ijt}} + \beta_{12} \text{WKDN\_R}_{\text{ijt}} + \epsilon_{\text{ijt}},
\end{aligned}
$$

where VARIABLE $\in$ {NFT1, NFT, NFT_BS, NFT_CS, NFT1_IS, NFT_IS}. NFT is the number of forecast types analyst j provides for firm i during year t. Other NFT components are defined accordingly. Variables with a postfix "_R" are transformed following Equation 1.1 to fall between zero and one. An intercept is estimated for each model specification but unreported. All variables are defined in the text. The sample period is 2002–2015. Standard errors are clustered at the analyst level. *, **, and *** denote significance at 0.10, 0.05, and 0.01 level, respectively.
Panel B reports the adjusted R^2s for the following regression equation:

$$\text{VARIABLE\_R}_{\text{ijt}} = \beta_0 + \beta_1 \text{FixedEffects} + \epsilon_{\text{ijt}},$$

where VARIABLE $\in$ {NFT1, NFT, BOLD, FREQ, LFR, NFRM, NIND}; Fixed Effects $\in$ {brokerage house fixed effects, analyst fixed effects, firm-analyst fixed effects}. The sample period is 2002–2015.

Table 1.3: Descriptive statistics for variables used in tests of NFT and earnings forecast accuracy.

Panel A: Summary statistics

	N	Mean	Sd	Q1	Median	Q3
RAFE	301,839	0.990	0.514	0.698	0.977	1.200
NFT1_R	298,885	0.488	0.353	0.154	0.500	0.800
NFT_R	301,839	0.443	0.348	0.125	0.396	0.724
NFT1_IS_R	295,861	0.560	0.369	0.200	0.667	0.875
NFT_IS_R	300,563	0.473	0.352	0.133	0.462	0.769
I_AFEBI	301,839	0.494	0.500	0.000	0.000	1.000
I_AFEBT	301,839	0.546	0.498	0.000	1.000	1.000
I_AFGPS	301,839	0.543	0.498	0.000	1.000	1.000
I_AFNET	301,839	0.777	0.416	1.000	1.000	1.000
I_AFPRE	301,839	0.706	0.456	0.000	1.000	1.000
I_AFSAL	301,839	0.833	0.373	1.000	1.000	1.000
FEXP_R	301,839	0.434	0.368	0.091	0.364	0.750
FREQ_R	301,839	0.453	0.354	0.143	0.429	0.750
GEXP_R	301,839	0.429	0.352	0.111	0.364	0.714
HRZ_R	301,839	0.507	0.396	0.079	0.457	0.983
LFR_R	301,839	0.329	0.364	0.024	0.167	0.559
NFRM_R	301,839	0.449	0.344	0.150	0.400	0.727
NIND_R	301,839	0.422	0.359	0.000	0.364	0.667
SIZE_R	301,839	0.369	0.351	0.060	0.263	0.585
WKDN_R	301,839	0.493	0.352	0.174	0.500	0.809

Panel B: Average RAFE conditional on NFT_N

	[0, 0.25)	[0.25, 0.5)	[0.5, 0.75)	[0.75, 1]	Low-High	t-statistic
NFT1_N	1.007	0.976	0.975	0.987	0.020	8.08
NFT_N	1.006	0.981	0.979	0.980	0.026	11.48
NFT1_IS_N	1.017	0.986	0.971	0.979	0.038	14.31
NFT_IS_N	1.012	0.984	0.977	0.974	0.038	16.05

Table 1.3: This table reports descriptive statistics for variables used in tests of NFT and earnings forecast accuracy. NFT is the number of forecast types analyst j provides for firm i during the first half of year t. Other NFT components are defined accordingly. I_AF^k equals 1 if analyst j issues at least one 1-year-ahead type k forecast for firm i during the first half of year t, and 0 otherwise. $I_AF^k \in \{$earnings before interest and taxes (EBI), earnings before interest, taxes, depreciation, and amortization (EBT), GAAP earnings per share (GPS), net income (NET), pre-tax profit (PRE), sales (SAL)$\}$. All variables with a postfix "_R" ("_N") are transformed following Equation 1.1 (Equation 1.8) to fall between 0 and 1. The sample period is 2002–2019. All variables are defined in the text. Panel A reports summary statistics for variables used in tests of NFT and earnings forecast accuracy. Panel B reports average RAFE conditional on NFT components.

Table 1.4: Regression results for tests of NFT and earnings forecast accuracy.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLE	NFT1	NFT	NFT1_IS	NFT_IS	NFT	NFT_IS
VARIABLE_R	–1.410***	–1.784***	–2.229***	–2.571***	–1.050**	–1.554***
	(-4.08)	(-5.20)	(-6.72)	(-7.76)	(-2.24)	(-3.47)
AFE_R_{t-1}	7.271***	7.222***	7.337***	7.230***	-16.197***	-16.271***
	(22.71)	(22.80)	(22.62)	(22.73)	(-45.20)	(-45.16)
FEXP_R	–0.121	–0.125	–0.101	–0.173	–0.098	–0.123
	(-0.39)	(-0.40)	(-0.32)	(-0.56)	(-0.16)	(-0.20)
FREQ_R	2.033***	2.016***	2.034***	2.040***	3.990***	3.991***
	(6.49)	(6.50)	(6.46)	(6.55)	(10.55)	(10.44)
GEXP_R	0.081	0.048	0.046	0.054	–0.016	0.097
	(0.19)	(0.12)	(0.11)	(0.13)	(-0.02)	(0.12)
HRZ_R	6.481***	6.411***	6.530***	6.445***	6.268***	6.306***
	(24.1)	(24.08)	(24.09)	(24.11)	(20.31)	(20.33)
LFR_R	–0.977***	–1.004***	–0.953***	–0.966***	–0.519	–0.486
	(-3.42)	(-3.55)	(-3.32)	(-3.41)	(-1.51)	(-1.41)
NFRM_R	0.759*	0.734*	0.656*	0.707*	0.011	–0.033
	(1.96)	(1.92)	(1.66)	(1.84)	(0.02)	(-0.06)
NIND_R	0.020	0.054	0.089	0.081	0.364	0.400
	(0.05)	(0.15)	(0.24)	(0.22)	(0.70)	(0.76)
SIZE_R	1.209***	1.309***	1.010**	1.212***	0.556	0.552
	(2.79)	(3.05)	(2.29)	(2.79)	(0.82)	(0.81)
WKDN_R	–0.588*	–0.590*	–0.661**	–0.619*	–1.241***	–1.256***
	(-1.77)	(-1.79)	(-1.97)	(-1.87)	(-3.34)	(-3.36)
Fixed Effects	Broker	Broker	Broker	Broker	Firm-Analyst	Firm-Analyst
Adj R^2	0.011	0.011	0.011	0.011	0.062	0.062
N	298,826	301,781	295,801	300,504	271,374	270,098

Table 1.4: This table reports the regression results for the following regression equation:

$$\begin{aligned}
&100 \times RAFE_{ijt(d)} = \\
&\beta_0 + \beta_1 VARIABLE_R_{ijt(d)} + \beta_2 AFE_R_{ijt-1} + \beta_3 FEXP_R_{ijt} + \beta_4 FREQ_R_{ijt} \\
&+ \beta_5 GEXP_R_{ijt} + \beta_6 HRZ_R_{ijt(d)} + \beta_7 LFR_R_{ijt} + \beta_8 NFRM_R_{ijt} + \beta_9 NIND_R_{ijt} \\
&+ \beta_{10} SIZE_R_{ijt} + \beta_{11} WKDN_R_{ijt} + \text{Brokerage } (+ \text{ Firm-Analyst}) + \epsilon_{ijt},
\end{aligned}$$

where RAFE is the relative absolute forecast error for the most recent 1-year-ahead EPS forecast provided by analyst j for firm i outstanding on June 30th year t. VARIABLE $\in$ {NFT1, NFT, NFT1_IS, NFT_IS }. NFT is the number of forecast types analyst j provides for firm i during the first half year of year t. Other NFT components are defined accordingly. All variables with a postfix "_R" are transformed following Equation 1.1 to fall between zero and one. An intercept is estimated for each model specification but unreported. The sample period is 2002–2019. All variables are defined in the text. Standard errors are clustered at the analyst level. *, **, and *** denote significance at 0.10, 0.05, and 0.01 level, respectively.

Table 1.5: Regression results for tests of NFT and earnings forecast accuracy with additional control variables.

	(1)	(2)	(3)	(4)	(5)	(6)
Non-EPS AF	EBI	EBT	GPS	NET	PRE	SAL
Coef. NFT_R	–1.618***	–1.972***	–1.659***	–0.769**	–1.167***	–1.358***
	(-3.77)	(-4.95)	(-4.14)	(-2.01)	(-3.02)	(-3.72)
I_AF	–0.931***	–0.504	–0.047	–2.300***	–1.311***	–1.415***
	(-3.04)	(-1.51)	(-0.15)	(-5.93)	(-3.72)	(-3.16)
Control VARs			Yes			
Fixed Effects			Broker			
Adj R^2	0.012	0.012	0.011	0.011	0.011	0.011
N	239,004	262,824	267,229	294,882	291,569	297,734

Table 1.5: This table reports the regression results for the following regression equation:

$$
\begin{aligned}
&100 \times \mathrm{RAFE}_{\mathrm{ijt(d)}} = \\
&\beta_0 + \beta_1 \mathrm{NFT\_R}_{\mathrm{ijt(d)}} + \beta_2 \mathrm{I\_AF}^{\mathrm{k,1}}_{\mathrm{ijt}} + \beta_3 \mathrm{AFE\_R}_{\mathrm{ijt-1}} + \beta_4 \mathrm{FEXP\_R}_{\mathrm{ijt}} + \beta_5 \mathrm{FREQ\_R}_{\mathrm{ijt}} \\
&+ \beta_6 \mathrm{GEXP\_R}_{\mathrm{ijt}} + \beta_7 \mathrm{HRZ\_R}_{\mathrm{ijt(d)}} + \beta_8 \mathrm{LFR\_R}_{\mathrm{ijt}} + \beta_9 \mathrm{NFRM\_R}_{\mathrm{ijt}} + \beta_{10} \mathrm{NIND\_R}_{\mathrm{ijt}} \\
&+ \beta_{11} \mathrm{SIZE\_R}_{\mathrm{ijt}} + \beta_{12} \mathrm{WKDN\_R}_{\mathrm{ijt}} + \epsilon_{\mathrm{ijt}},
\end{aligned}
$$

where RAFE is the relative absolute forecast error for the most recent 1-year-ahead EPS forecast provided by analyst j for firm i outstanding on June 30th year t. NFT is the number of forecast types analyst j provides for firm i during the first half of year t. $\mathrm{I\_AF}^{\mathrm{k,1}}_{\mathrm{ijt}}$ is an indicator variable that equals 1 if analyst j provides at least one 1-year-ahead forecast of type k for firm i during the first half if yer t, and 0 otherwise. $\mathrm{AF} \in \{\mathrm{EBI}, \mathrm{EBT}, \mathrm{GPS}, \mathrm{NET}, \mathrm{PRE}, \mathrm{SAL}\}$. All variables with a postfix "_R" are transformed following Equation 1.1 to fall between zero and one. An intercept is estimated for each model specification but unreported. The sample period is 2002–2019. All variables are defined in the text. Column (1)–(6) report the regression results for Equation 1.2 after controlling for analysts' provision of Earnings Before Interest and Taxes (EBI), Earnings Before Interest, Taxes, Depreciation, and Amortization (EBT), GAAP Earnings (GPS), Net Income (NET), Pre-tax Profit (PRE), and Sales (SAL), restricted to firms with the related forecast coverage, respectively. Please see Appendix for detailed definitions of forecast types. Standard errors are clustered at analyst level. *, **, and *** denote significance at 0.10, 0.05, and 0.01 level, respectively.

Table 1.6: Descriptive statistics for variables used in tests of NFT and price target forecast accuracy.

Panel A: Summary statistics

	N	Mean	Sd	Q1	Median	Q3
PTAFE	839,601	0.341	0.313	0.113	0.251	0.472
RPTAFE	839,601	1.000	0.632	0.530	0.945	1.360
NFT1_R	837,921	0.509	0.303	0.286	0.529	0.750
NFT_R	839,601	0.435	0.295	0.203	0.405	0.636
NFT1_BS_R	774,697	0.288	0.368	0.000	0.000	0.500
NFT1_CS_R	743,617	0.265	0.367	0.000	0.000	0.500
NFT1_IS_R	836,720	0.599	0.321	0.333	0.667	0.857
AFE_R	839,601	0.442	0.344	0.128	0.400	0.717
BOLD_R	839,601	0.377	0.346	0.071	0.278	0.615
FEXP_R	839,601	0.439	0.358	0.118	0.375	0.750
FREQ_R	839,601	0.507	0.341	0.250	0.500	0.800
FREQ_PT_R	839,601	0.570	0.341	0.333	0.545	1.000
GEXP_R	839,601	0.422	0.336	0.125	0.364	0.667
LFR_R	839,601	0.326	0.349	0.036	0.182	0.517
NFRM_R	839,601	0.470	0.330	0.200	0.444	0.727
NIND_R	839,601	0.432	0.349	0.125	0.400	0.667
SIZE_R	839,601	0.371	0.339	0.076	0.284	0.539
WKDN_R	839,601	0.493	0.342	0.192	0.500	0.789

Panel B: Panel B: Average RPTAFE conditional on NFT

	[0,0.25)	[0.25,0.5)	[0.5,0.75)	[0.75,1]	Low-High	t-statistic
NFT1_N	1.019	1.000	0.995	0.987	0.032	15.60
NFT_N	1.014	0.999	0.994	0.990	0.024	12.41

Table 1.6: This table reports descriptive statistics for variables used in tests of NFT and price target forecast accuracy. PTAFE is absolute price target error, defined as the absolute value of the difference between analyst j's 1-year-ahead price target issued on day d and firm i's realized stock price on d+360, divided by firm i's stock price on day d. RPTAFE is relative price target error, defined as PTAFE divided by the mean of all absolute price target errors for firm i in year t. NFT is the number of forecast types provided by analyst j for firm i during the past 3 months prior to the price target issuance month. Other NFT components are defined accordingly. All variables with a postfix "_R" ("_N") are transformed following Equation 1.1 (Equation 1.8) to fall between zero and one. An intercept is estimated for each model specification but is unreported. The sample period is 2002–2019. All variables are defined in the text. Panel A reports summary statistics for the variables; panel B reports average RPTAFE conditional on NFT components.

Table 1.7: Regression results for tests of NFT and price target forecast accuracy.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLE	NFT1	NFT	NFT1_BS	NFT1_CS	NFT1_IS	NFT1	NFT
VARIABLE_R	–1.763***	–1.305***	–0.994***	–0.246	–1.575***	–2.700***	–2.408***
	(-5.39)	(-3.66)	(-2.85)	(-0.78)	(-5.15)	(-7.41)	(-6.07)
AFE_R	3.599***	3.604***	3.752***	3.847***	3.600***	2.927***	2.940***
	(14.40)	(14.43)	(13.93)	(13.78)	(14.38)	(10.06)	(10.11)
BOLD_R	2.380***	2.399***	2.600***	2.597***	2.360***	0.989***	0.992***
	(9.89)	(9.98)	(9.98)	(9.63)	(9.80)	(3.63)	(3.65)
FEXP_R	1.677***	1.706***	1.630***	1.872***	1.693***	3.427***	3.448***
	(5.88)	(5.99)	(5.25)	(5.84)	(5.94)	(6.68)	(6.74)
FREQ_R	0.096	0.065	0.028	0.049	0.102	–0.248	–0.274
	(0.35)	(0.24)	(0.09)	(0.16)	(0.37)	(-0.78)	(-0.86)
FREQ_PT_R	–0.980***	–0.984***	–0.809**	–0.847**	–0.988***	0.481	0.470
	(-3.25)	(-3.25)	(-2.50)	(-2.54)	(-3.27)	(1.39)	(1.36)
GEXP_R	0.781**	0.783**	0.918**	0.687	0.755**	0.404	0.347
	(2.11)	(2.12)	(2.28)	(1.64)	(2.03)	(0.58)	(0.50)
LFR_R	–0.421*	–0.409	–0.492*	–0.498*	–0.445*	–0.491*	–0.476*
	(-1.69)	(-1.64)	(-1.83)	(-1.78)	(-1.78)	(-1.71)	(-1.67)
NFRM_R	0.302	0.278	0.362	0.373	0.308	–0.272	–0.285
	(0.77)	(0.71)	(0.86)	(0.85)	(0.79)	(-0.51)	(-0.54)
NIND_R	0.814**	0.813**	0.731*	0.770*	0.827**	0.354	0.350
	(2.32)	(2.31)	(1.94)	(1.95)	(2.35)	(0.77)	(0.76)
SIZE_R	–2.287***	–2.312***	–2.192***	–2.260***	–2.432***	–0.662	–0.646
	(-5.99)	(-6.07)	(-5.04)	(-4.96)	(-6.34)	(-1.19)	(-1.17)
WKDN_R	0.423*	0.426*	0.404	0.502*	0.403*	0.058	0.053
	(1.76)	(1.78)	(1.56)	(1.85)	(1.68)	(0.21)	(0.19)
Fixed Effects	Broker	Broker	Broker	Broker	Broker	Firm-Analyst	Firm-Analyst
Adj R^2	0.004	0.004	0.004	0.004	0.004	0.036	0.036
N	837,864	839,544	774,662	743,563	836,665	827,449	829,063

Table 1.7: (Continued on the following page)

Table 1.7: This table reports the regression results for the following regression equation:

$$100 \times \text{RPTAFE}_{\text{ijt(d)}} =$$
$$\beta_0 + \beta_1\text{VARIABLE\_R}_{\text{ijt(d)}} + \beta_2\text{AFE\_R}_{\text{ijt}} + \beta_3\text{BOLD\_R}_{\text{ijt}} + \beta_4\text{FEXP\_R}_{\text{ijt}} + \beta_5\text{FREQ\_R}_{\text{ijt}}$$
$$+ \beta_6\text{FREQ\_PT\_R}_{\text{ijt}} + \beta_7\text{GEXP\_R}_{\text{ijt}} + \beta_8\text{LFR\_R}_{\text{ijt}} + \beta_9\text{NFRM\_R}_{\text{ijt}} + \beta_{10}\text{NIND\_R}_{\text{ijt}}$$
$$+ \beta_{11}\text{SIZE\_R}_{\text{ijt}} + \beta_{12}\text{WKDN\_R}_{\text{ijt}} + \text{Brokerage (+ Firm-Analyst)} + \epsilon_{\text{ijt(d)}},$$

where RPTAFE is relative absolute price target error, defined as absolute price target error divided by the mean of all absolute price target error for firm i in year t. Absolute price target error, PTAFE, is defined as the absolute value of the difference between analyst j's 1-year-ahead price target issued on day d and firm i's realized stock price on d+360, divided by firm i's stock price on day d. VARIABLE $\in$ {NFT1, NFT, NFT1_BS, NFT1_CS, NFT1_IS}. NFT is the number of forecast types provided by analyst j for firm i during the past 3 months prior to the price target issuance month. Other NFT components are defined accordingly. All variables with a postfix "_R" are transformed following Equation 1.1 to fall between zero and one. An intercept is estimated for each model specification but is unreported. The sample period is 2002–2019. All variables are defined in the text. Standard errors are clustered at analyst level. *, **, and *** denote significance at 0.10, 0.05, and 0.01 level, respectively.

Table 1.8: Descriptive statistics for variables used in tests of NFT and stock recommendation profitability.

Panel A: Summary statistics for recommendation profitability						
	N	Mean	Sd	Q1	Median	Q3
REC_RET_180	200,631	0.028	0.285	–0.101	0.024	0.157
REC_RET_30	201,374	0.027	0.147	–0.039	0.019	0.085
Panel B: Average I/B/E/S recommendation code conditional on NFT						
	[0,0.25)	[0.25,0.5)	[0.5,0.75)	[0.75,1]	High-Low	t-statistic
NFT1_N	2.482	2.542	2.547	2.562	0.080	15.34
NFT_N	2.483	2.525	2.553	2.578	0.095	17.84
NFT_IS_N	2.483	2.524	2.664	2.568	0.085	16.13
Panel C: Average at most 180-day recommendation profitability conditional on NFT						
	[0,0.25)	[0.25,0.5)	[0.5,0.75)	[0.75,1]	High-Low	t-statistic
NFT1_N	1.795	2.605	2.541	2.797	1.002	5.68
NFT_N	1.902	2.684	2.806	2.888	0.986	5.80
NFT_IS_N	1.903	2.798	2.560	2.942	1.039	6.09
Panel D: Average at most 30-day recommendation profitability conditional on NFT						
	[0,0.25)	[0.25,0.5)	[0.5,0.75)	[0.75,1]	High-Low	t-statistic
NFT1_N	1.701	2.393	2.585	2.326	0.625	6.96
NFT_N	1.823	2.462	2.522	2.531	0.708	8.10
NFT_IS_N	1.782	2.528	2.467	2.526	0.744	8.45

Table 1.8: Panel A reports summary statistics for the profitability of stock recommendations. REC_RET_180 (REC_RET_30) is at most 180-day (30-day) size-adjusted buy-and-hold abnormal returns. Panel B reports average I/B/E/S recommendation code conditional on NFT. Strong buy: 1; buy: 2; hold: 3; sell: 4; strong sell: 5. Panel C (panel D) reports average at most 180-day (30-day) size-adjusted buy-and-hold abnormal returns conditional on NFT (components). NFT is the number of forecast types analyst j provides for firm i during the past 3 months prior to stock recommendation issuance month. Other NFT components are defined accordingly. Variables with a postfix "_N" are transformed following Equation 1.8 to fall between zero and one. The sample period is 2002–2019.

Table 1.9: Regression results for tests of NFT and stock recommendation profitability.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. VARIABLE	Column (1)–(6): REC_RET_180						REC_RET_30	
VARIABLE	NFT1	NFT	NFT_BS	NFT_CS	NFT_IS	NFT	NFT	NFT
VARIABLE_R	0.934***	1.160***	0.908***	0.661***	0.983***	0.989***	0.772***	0.610***
	(4.76)	(5.81)	(4.29)	(3.23)	(5.09)	(3.95)	(7.25)	(4.88)
AFE_R	–0.776***	–0.759***	–0.720***	–0.784***	–0.744***	–0.910***	–0.171*	–0.190*
	(-4.49)	(-4.41)	(-3.85)	(-4.01)	(-4.32)	(-3.82)	(-1.86)	(-1.70)
BOLD_R	0.297*	0.302*	0.166	0.107	0.296*	0.126	0.213**	–0.080
	(1.76)	(1.80)	(0.93)	(0.56)	(1.76)	(0.51)	(2.47)	(-0.68)
FEXP_R	0.612***	0.621***	0.618***	0.676***	0.617***	–0.144	0.510***	–0.058
	(3.13)	(3.17)	(2.91)	(2.94)	(3.14)	(-0.40)	(4.73)	(-0.32)
FREQ_R	0.596***	0.579***	0.613***	0.856***	0.593***	0.225	0.246**	–0.018
	(3.30)	(3.20)	(3.22)	(4.25)	(3.26)	(0.87)	(2.55)	(-0.14)
FREQ_REC_R	–0.770***	–0.800***	–0.537***	–0.643***	–0.797***	–0.936***	–0.080	–0.233**
	(-4.55)	(-4.72)	(-3.09)	(-3.55)	(-4.70)	(-3.98)	(-0.96)	(-2.02)
GEXP_R	–0.065	–0.044	–0.230	–0.271	–0.042	–0.280	0.026	–0.232
	(-0.30)	(-0.20)	(-0.98)	(-1.08)	(-0.19)	(-0.64)	(0.20)	(-1.10)
LFT_R	0.581***	0.577***	0.416**	0.377*	0.585***	0.050	0.304***	0.088
	(3.20)	(3.20)	(2.21)	(1.87)	(3.24)	(0.20)	(3.23)	(0.75)
NFRM_R	0.406*	0.434*	0.207	0.465*	0.438*	0.412	0.262**	0.189
	(1.78)	(1.92)	(0.84)	(1.82)	(1.93)	(1.19)	(2.02)	(1.10)
NIND_R	0.086	0.024	0.073	0.077	0.032	–0.487	0.002	–0.210
	(0.41)	(0.12)	(0.34)	(0.34)	(0.15)	(-1.50)	(0.02)	(-1.29)
SIZE_R	1.706***	1.679***	1.014***	0.947***	1.746***	–0.052	0.930***	–0.089
	(6.51)	(6.43)	(3.59)	(2.98)	(6.66)	(-0.15)	(6.19)	(-0.44)
WKDN_R	0.118	0.124	0.277	0.453**	0.129	0.379	0.302***	0.450***
	(0.66)	(0.70)	(1.46)	(2.28)	(0.73)	(1.53)	(3.16)	(3.81)
Fixed Effects	Broker	Broker	Broker	Broker	Broker	Firm-Analyst	Broker	Firm-Analyst
Adj R^2	0.006	0.006	0.004	0.004	0.006	0.017	0.011	0.046
N	198,518	200,553	158,571	148,557	199,849	176,178	201,296	176,817

Table 1.9: (Continued on the following page)

Table 1.9: This table reports regression results for the following regression equation:

$$100 \times \text{REC\_RET\_}\{180, 30\}_{\text{ijt(d)}} =$$
$$\beta_0 + \beta_1\text{VARIABLE\_R}_{\text{ijt(d)}} + \beta_2\text{AFE\_R}_{\text{ijt}} + \beta_3\text{BOLD\_R}_{\text{ijt}} + \beta_4\text{FEXP\_R}_{\text{ijt}} + \beta_5\text{FREQ\_R}_{\text{ijt}}$$
$$+ \beta_6\text{FREQ\_REC\_R}_{\text{ijt}} + \beta_7\text{GEXP\_R}_{\text{ijt}} + \beta_8\text{LFR\_R}_{\text{ijt}} + \beta_9\text{NFRM\_R}_{\text{ijt}} + \beta_{10}\text{NIND\_R}_{\text{ijt}}$$
$$+ \beta_{11}\text{SIZE\_R}_{\text{ijt}} + \beta_{12}\text{WKDN\_R}_{\text{ijt}} + \text{Brokerage (+ Firm-Analyst)} + \epsilon_{\text{ijt(d)}},$$

where REC_RET_{180,30} is either at most 180-day or at most 30-day size-adjusted buy-and-hold abnormal return. VARIABLE ∈ {NFT1, NFT, NFT_BS, NFT_CS, NFT_IS}. NFT is the number of forecast types analyst j provides for firm i during the past 3 months prior to the stock recommendation issuance month. Other NFT components are defined accordingly. Variables with a postfix "_R" are transformed following Equation 1.1 to fall between zero and one. An intercept is estimated for each model specification but not reported. All variables are defined in the text. In column (1)–(6), the dependent variable is REC_RET_180. In column (7)–(8), the dependent variable is REC_RET_30. The sample period is 2002–2019. Standard errors are clustered at the analyst level. *, **, and *** denote significance at 0.10, 0.05, and 0.01 level, respectively.

Table 1.10: Summary statistics for variables used in tests of NFT and the capital market's reactions to revisions in recommendation revisions.

	N	Mean	Sd	Q1	Median	Q3
CAR3	71,849	–0.003	0.103	–0.033	0.000	0.031
RECrev	71,849	–0.002	1.321	–1.000	0.000	1.000
NFT1_R	69,317	0.494	0.415	0.000	0.500	1.000
NFT_R	71,849	0.466	0.411	0.000	0.400	1.000
NFT_BS_R	48,257	0.337	0.434	0.000	0.000	1.000
NFT_CS_R	46,094	0.340	0.432	0.000	0.000	1.000
NFT_IS_R	70,852	0.481	0.414	0.000	0.462	1.000
EPSrev	71,849	–0.020	0.280	0.000	0.000	0.000
EBIrev	71,849	–0.005	0.126	0.000	0.000	0.000
NETrev	71,849	–0.012	0.244	0.000	0.000	0.000
PRErev	71,849	–0.014	0.235	0.000	0.000	0.000
SALrev	71,849	–0.001	0.029	0.000	0.000	0.000
I_EPSrev	71,849	0.363	0.481	0.000	0.000	1.000
I_EBIrev	71,849	0.123	0.328	0.000	0.000	0.000
I_NETrev	71,849	0.261	0.439	0.000	0.000	1.000
I_PRErev	71,849	0.239	0.427	0.000	0.000	0.000
I_SALrev	71,849	0.292	0.455	0.000	0.000	1.000
AFE_R_{t-1}	71,849	0.481	0.405	0.000	0.500	1.000
BOLD_R	71,849	0.460	0.407	0.000	0.500	1.000
FEXP_R	71,849	0.465	0.400	0.000	0.500	1.000
FREQ_R	71,849	0.500	0.398	0.000	0.500	1.000
FREQ_REC_R	71,849	0.579	0.402	0.250	0.500	1.000
GEXP_R	71,849	0.466	0.405	0.000	0.500	1.000
LFR_R	71,849	0.440	0.412	0.000	0.384	1.000
NFRM_R	71,849	0.489	0.405	0.000	0.500	1.000
NIND_R	71,849	0.471	0.402	0.000	0.500	1.000
SIZE_R	71,849	0.434	0.412	0.000	0.375	1.000
WKDN_R	71,849	0.500	0.404	0.000	0.500	1.000

Table 1.10: This table reports summary statistics for the variables used in tests of NFT and market reactions to stock recommendation revisions. NFT is the number of forecast types analyst j provides for firm i during the past 3 months prior to the month in which the stock recommendation is revised. Other NFT components are defined accordingly. AFrev is the level of analyst j's simultaneous 1-year-ahead forecast revision for firm i on day d. AFs include EPS, Earnings Before Interest and Taxes (EBI), Net Income (NET), Pre-tax Earnings (PRE), and Sales (SAL). I_AFrev equals 1 if analyst j simultaneously revises a stock recommendation and a related 1-year ahead forecast, and 0 otherwise. Variables with a "_R" postfix are transformed following Equation 1.1. The sample period is 2002–2019. All variables are defined in the text.

Table 1.11: Regression results for tests of NFT and market reactions to recommendation revisions.

	(1)	(2)	(3)	(4)	(5)
VARIABLE	NFT1	NFT	NFT_BS	NFT_CS	NFT_IS
RECrev	–1.228***	–1.193***	–1.183***	–1.262***	–1.191***
	(-9.04)	(-8.95)	(-8.72)	(-8.81)	(-8.91)
VARIABLE_R	–0.092	–0.058	0.026	0.129	–0.123
	(-0.96)	(-0.61)	(0.29)	(1.34)	(-1.30)
RECrev × VARIABLE_R	–0.348***	–0.411***	–0.131	0.061	–0.384***
	(-3.40)	(-4.05)	(-1.20)	(0.56)	(-3.91)
EPSrev	2.457***	2.425***	2.013***	1.903***	2.417***
	(5.84)	(5.83)	(5.73)	(4.95)	(5.78)
EBIrev	0.802	0.877	0.926	1.317**	0.861
	(1.32)	(1.45)	(1.42)	(2.31)	(1.42)
NETrev	–0.269	–0.199	0.088	–0.014	–0.230
	(-0.68)	(-0.51)	(0.22)	(-0.03)	(-0.59)
PRErev	0.567	0.507	0.461	0.459	0.512
	(1.50)	(1.34)	(1.18)	(1.20)	(1.36)
SALrev	25.210***	25.251***	19.038***	16.034***	25.455***
	(7.18)	(7.32)	(7.57)	(7.03)	(7.31)
RECrev × I_EPSrev	–0.554***	–0.561***	–0.402***	–0.398***	–0.564***
	(-4.48)	(-4.70)	(-3.60)	(-3.42)	(-4.69)
RECrev × I_EBIrev	0.532***	0.525***	0.280*	0.346**	0.535***
	(3.71)	(3.67)	(1.93)	(2.33)	(3.75)
RECrev × I_NETrev	0.193	0.232	0.135	0.137	0.195
	(1.01)	(1.20)	(0.72)	(0.71)	(1.03)
RECrev × I_PRErev	–0.184	–0.226	–0.211	–0.303	–0.192
	(-0.99)	(-1.20)	(-1.13)	(-1.64)	(-1.03)
RECrev × I_SALrev	–0.488***	–0.516***	–0.496***	–0.422***	–0.506***
	(-3.35)	(-3.49)	(-3.33)	(-2.70)	(-3.42)
Analyst Charateristics			Yes		
RECrev × AnalystCharacteristics			Yes		
Fixed Effects			Firm-Year		
Adj R^2	0.234	0.232	0.186	0.208	0.233
N	69,317	71,849	48,257	46,094	70,852

Table 1.11: (Continued on the following page)

Table 1.11: This table reports the regression results for the following regression equation:

$$
\begin{aligned}
&100 \times \mathrm{CAR3}_{\mathrm{ijt(d)}} = \\
&\beta_0 + \beta_1 \mathrm{RECrev}_{\mathrm{ijt(d)}} + \beta_2 \mathrm{VARIABLE\_R}_{\mathrm{ijt(d)}} + \beta_3 \mathrm{RECrev}_{\mathrm{ijt(d)}} \times \mathrm{VARIABLE\_R}_{\mathrm{ijt(d)}} \\
&+ \sum_{\mathrm{k=4}}^{8} \beta_{\mathrm{k}} \textit{Other Forecast Revision}^{\mathrm{k-3}} + \sum_{\mathrm{k=9}}^{13} \beta_{\mathrm{k}} \mathrm{RECrev} \times \mathrm{I\_}\textit{Other Forecast Revision}^{\mathrm{k-8}} \\
&+ \sum_{\mathrm{k=14}}^{24} \beta_{\mathrm{k}} \textit{Analyst Characteristics}\mathrm{\_R}^{\mathrm{k-13}} + \sum_{\mathrm{k=25}}^{35} \beta_{\mathrm{k}} \mathrm{RECrev} \times \textit{Analyst Characteristics}\mathrm{\_R}^{\mathrm{k-24}} \\
&+ \text{Firm-Year} + \epsilon_{\mathrm{ijt(d)}},
\end{aligned}
$$

where CAR3 is 3-day market-adjusted abnormal returns around stock recommendation revisions; RECrev is the level of stock recommendation revisions. VARIABLE $\in$ {NFT, NFT1, NFT_BS, NFT_CS, NFT_IS}. NFT is the number of forecast types analyst j provides for firm i during the past 3 months prior to the month in which the stock recommendation is revised. Other NFT components are defined accordingly. *Other Forecast Revisions* = {EPSrev, EBIrev, NETrev, PRErev, SALrev}. I_*Other Forecast Revision* = {I_EPSrev, I_EBIrev, I_NETrev, I_PRErev, I_SALrev}. *Analyst Characteristics* = {$\mathrm{AFE}_{\mathrm{t-1}}$, BOLD, FEXP, FREQ, FREQ_REC, GEXP, LFR, NFRM, NIND, SIZE, WKDN}. Variables with a postfix "_R" are transformed following Equation 1.1 to fall between 0 and 1. An intercept is estimated for each model specification but unreported. Estimated coefficients for analyst characteristics and their interactions with stock recommendation revisions are unreported to reserve space. All variables are defined in the text. The sample period is 2002–2019. Standard errors are clustered at the analyst level. *, **, and *** denote significance at 0.10, 0.05, and 0.01 level, respectively.

Table 1.12: Descriptive statistics for variables in tests of NFT and analyst career outcomes.

Panel A: Summary statistics

	N	Mean	Sd	Q1	Median	Q3
Career outcomes						
TERMINATION	58,402	0.193	0.395	0.000	0.000	0.000
PROMOTION	13,958	0.011	0.103	0.000	0.000	0.000
DEMOTION	15,834	0.012	0.110	0.000	0.000	0.000
NFT and non-EPS forecasts provision						
NFT′	58,402	0.433	0.282	0.206	0.419	0.643
I_AFLTG′	58,402	0.401	0.490	0.000	0.000	1.000
I_AFSAL′	58,402	0.891	0.312	1.000	1.000	1.000
Analyst characteristics						
AFE_M	58,402	0.329	0.201	0.193	0.289	0.423
BOLD_M	58,402	0.355	0.180	0.240	0.332	0.441
COMP_M	58,402	0.474	0.247	0.288	0.489	0.654
FREQ_M	58,402	0.435	0.226	0.260	0.445	0.592
GEXP_M	58,402	0.331	0.295	0.073	0.251	0.537
LFR_M	58,402	0.274	0.203	0.124	0.236	0.380
NFRM_M	58,402	0.289	0.255	0.057	0.241	0.460
NIND_M	58,402	0.282	0.263	0.000	0.233	0.467
SIZE_M	58,402	0.328	0.288	0.077	0.247	0.520
WKDN_M	58,402	0.494	0.197	0.393	0.495	0.596

Panel B: Average analyst career outcomes conditional on NFT

NFT′_Q	[0,25)	[25,50)	[50,75)	[75,100]	High-Low	t-statistic
TERMINATION	0.286	0.201	0.156	0.132	–0.154	-33.51
PROMOTION	0.003	0.011	0.015	0.016	0.013	5.69
DEMOTION	0.010	0.012	0.014	0.013	0.003	0.98

Table 1.12: Panel A reports summary statistics for variables used in the tests of NFT and analyst career outcomes. Panel B reports average analyst career outcomes conditional on NFT. VARIABLE_M is the average of VARIABLE_R across all firms followed by analyst j in year t, where VARIABLE_R is VARIABLE transformed following Equation 1.1. NFT′_Q is the cross-sectional percentile of NFT′. The sample period is 2002–2019. All variables are defined in the text.

Table 1.13: Regression results for tests of NFT and analyst career outcomes.

	(1)	(2)	(3)	(4)	(5)	(6)
	TERMINATION		PROMOTION		DEMOTION	
	Coef	ME	Coef	ME	Coef	ME
NFT′	–0.761***	–0.112***	1.063**	0.246**	0.319	0.062
	(-7.72)	(-6.16)	(2.16)	(2.16)	(0.70)	(0.66)
I_AFLTG′	–0.301***	–0.044***	–0.502	–0.116	–0.267	–0.052
	(-3.97)	(-4.37)	(-1.62)	(-1.62)	(-1.23)	(-1.15)
I_AFSAL′	0.036	0.005	0.682	0.158	0.688	0.135
	(0.53)	(0.52)	(1.24)	(1.33)	(1.41)	(1.24)
AFE_M	2.670***	0.394***	0.140	0.032	1.772***	0.347***
	(22.11)	(10.87)	(0.22)	(0.22)	(5.01)	(4.40)
BOLD_M	–0.825***	–0.122***	–1.227**	–0.285**	–0.728*	–0.142**
	(-9.73)	(-7.78)	(-2.32)	(-2.21)	(-1.85)	(-2.07)
COMP_M	0.076	0.011	–0.592	–0.137	0.695**	0.136
	(0.85)	(0.82)	(-1.11)	(-1.08)	(2.03)	(1.51)
FREQ_M	–2.081***	–0.307***	–0.567	–0.132	–3.042***	–0.595***
	(-22.96)	(-12.11)	(-0.76)	(-0.75)	(-4.67)	(-6.93)
GEXP_M	0.115*	0.017*	0.714	0.165	0.704***	0.138**
	(1.68)	(1.74)	(1.58)	(1.64)	(2.71)	(2.33)
LFR_M	–0.165**	–0.024**	–0.268	–0.062	–0.427	–0.084
	(-2.28)	(-2.22)	(-0.42)	(-0.42)	(-1.16)	(-1.28)
NFRM_M	–1.945***	–0.287***	0.834	0.193	–0.106	–0.021
	(-19.22)	(-15.30)	(1.61)	(1.56)	(-0.28)	(-0.28)
NIND_M	–0.346***	–0.051***	–1.081**	–0.251	–0.263	–0.051
	(-4.70)	(-4.17)	(-2.14)	(-2.11)	(-0.75)	(-0.75)
SIZE_M	0.077	0.011	–1.032	–0.239	–0.356	–0.070
	(0.27)	(0.27)	(-0.65)	(-0.64)	(-0.57)	(-0.57)
WKDN_M	–0.049	–0.007	0.358	0.083	–0.556	–0.109*
	(-0.72)	(-0.74)	(0.77)	(0.77)	(-1.59)	(-1.82)
Fixed Effects			Broker			
Pseudo R^2	0.171		0.036		0.069	
Prob > χ^2	0.000		0.000		0.000	
N	57,937		4,276		15,636	

Table 1.13: (Continued on the following page)

Table 1.13: This table reports the regression results for the following equation estimated by the conditional logistic model matched at brokerage house level:

$$\text{VARIABLE}_{\text{jt+1}} = \beta_1\text{NFT}'_{\text{jt}} + \beta_2\text{I\_AFLTG}'_{\text{jt}} + \beta_3\text{I\_AFSAL}'_{\text{jt}} + \beta_4\text{AFE\_M}_{\text{jt}} + \beta_5\text{BOLD\_M}_{\text{jt}} + \beta_6\text{COMP\_M}_{\text{jt}} + \beta_7\text{FREQ\_M}_{\text{jt}} + \beta_8\text{GEXP\_M}_{\text{jt}} + \beta_9\text{LFR\_M}_{\text{jt}} + \beta_{10}\text{NFRM\_M}_{\text{jt}} + \beta_{11}\text{NIND\_M}_{\text{jt}} + \beta_{12}\text{SIZE\_M}_{\text{jt}} + \beta_{13}\text{WKDN\_M}_{\text{jt}} + \text{Brokerage} + \epsilon_{\text{ijt+1}},$$

where VARIABLE $\in$ {TERMINATION, PROMOTION, DEMOTION}. NFT$'$ is average of analyst j's relative rank of total number of forecast types in year t. Specifically, I first use Equation 1.1 to scale analyst j's total forecast types within each firm she follows in year t. Then I take average across all firms analyst j follows in year t. I_AFLTG$'$ (I_AFSAL$'$) equals 1 if analyst j provides at least one long-term earnings growth (sales) forecast for any firm she follows in year t, and 0 otherwise. Variables with a postfix "_M" are average of VARIABLE_R across all firms followed by analyst j in year t, where VARIABLE_R is VARIABLE transformed following Equation 1.1 to fall between zero and one. All variables are defined in the text. The sample period is 2002–2019. Odd (even) columns display estimated coefficients (marginal effects) and z-scores. Standard errors are clustered at analyst level. *, **, and *** denote significance at 0.10, 0.05, and 0.01 level, respectively.

Appendix

Categorization of I/B/E/S forecast types by financial statement sections

Balance sheet forecast types:[1]

BPS	book value per share
ENT	enterprise value (non per share)
NAV	net asset value (non per share)
NDT	net debt (non per share)
ROA	return on asset (percent)
ROE	return on equity (percent)

Cash flow statement forecast types:

CPS	cash flow per share
CSH	cash earnings per share
CPX	capital expenditure (non per share)
DPS	dividend per share
FFO	funds from operations per share

Income statement forecast types:[2]

EBI	earnings before interest and taxes (non per share)
EBG	earnings per share – before goodwill
EBS	earnings before interest, taxes, depreciation, and amortization per share
EBT	earnings before interest, taxes, depreciation, and amortization (non per share)
EPS	earnings per share
EPX	earnings per share – alternate
GPS	GAAP earnings per share
GRM	gross margin (percent)
NET	net income (non per share)
OPR	operating profit (non per share)
PRE	pre-tax profit (non per share)
SAL	revenue/sales (non per share)
LTG	long-term earnings growth (percent)

[1] I categorize ROA and ROE as balance sheet forecast types because the denominators of them are average total assets and average common equity, respectively, which require forecasting next period's balance sheet items. The numerator for ROA and ROE are forecasts for operating incomes and net incomes, respectively, which are counted as income statement forecast types.

[2] LTG is categorized as a one-year-ahead forecast type because unlike other long-term growth forecast types, which are scarce, LTG forecast type is common in I/B/E/S and in analysts' research reports.

Table A1: Analysts' provision of specific forecast types to I/B/E/S.

	BPS		CPS		CPX		CSH		DPS		EBI		EBG		EBS	
Year	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
1995	0.000	n.a	0.086	0.370	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a
1996	0.000	n.a	0.061	0.465	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a
1997	0.000	n.a	0.066	0.456	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a
1998	0.000	n.a	0.069	0.420	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a
1999	0.000	n.a	0.183	0.337	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a
2000	0.000	n.a	0.197	0.360	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a
2001	0.000	n.a	0.158	0.404	0.000	n.a	0.015	0.288	0.000	n.a	0.000	n.a	0.103	0.528	0.000	n.a
2002	0.394	0.210	0.299	0.264	0.000	n.a	0.017	0.086	0.215	0.207	0.204	0.145	0.288	0.915	0.116	0.147
2003	0.453	0.276	0.385	0.340	0.000	n.a	0.022	0.168	0.283	0.282	0.310	0.210	0.008	0.188	0.247	0.179
2004	0.480	0.308	0.415	0.360	0.000	n.a	0.024	0.148	0.383	0.325	0.360	0.241	0.012	0.228	0.295	0.202
2005	0.522	0.309	0.441	0.345	0.000	0.083	0.002	0.099	0.464	0.326	0.399	0.234	0.008	0.154	0.318	0.202
2006	0.510	0.289	0.442	0.341	0.426	0.252	0.002	0.149	0.442	0.313	0.405	0.245	0.000	n.a	0.313	0.195
2007	0.536	0.297	0.443	0.348	0.522	0.314	0.003	0.074	0.441	0.322	0.415	0.246	0.000	n.a	0.310	0.185
2008	0.563	0.314	0.453	0.360	0.548	0.335	0.005	0.131	0.442	0.338	0.449	0.261	0.000	n.a	0.311	0.183
2009	0.566	0.337	0.460	0.360	0.562	0.375	0.005	0.144	0.467	0.354	0.478	0.292	0.000	n.a	0.311	0.186
2010	0.593	0.358	0.535	0.350	0.633	0.432	0.005	0.101	0.572	0.408	0.639	0.377	0.000	n.a	0.301	0.178
2011	0.608	0.355	0.531	0.368	0.648	0.432	0.001	0.102	0.561	0.427	0.725	0.480	0.000	n.a	0.299	0.161
2012	0.625	0.349	0.530	0.366	0.661	0.443	0.004	0.122	0.583	0.438	0.877	0.759	0.000	n.a	0.282	0.161
2013	0.634	0.360	0.524	0.337	0.662	0.436	0.017	0.148	0.591	0.438	0.895	0.784	0.000	n.a	0.256	0.157
2014	0.665	0.393	0.588	0.373	0.686	0.457	0.044	0.152	0.605	0.479	0.914	0.813	0.000	n.a	0.321	0.151
2015	0.684	0.404	0.594	0.380	0.698	0.482	0.039	0.146	0.604	0.494	0.926	0.825	0.000	n.a	0.437	0.165
2016	0.705	0.410	0.593	0.369	0.704	0.485	0.046	0.136	0.591	0.476	0.934	0.827	0.000	n.a	0.441	0.164
2017	0.686	0.410	0.585	0.370	0.693	0.487	0.054	0.131	0.594	0.478	0.930	0.830	0.000	n.a	0.428	0.172
2018	0.681	0.410	0.587	0.361	0.703	0.494	0.056	0.138	0.630	0.484	0.939	0.835	0.000	n.a	0.416	0.171
2019	0.677	0.401	0.569	0.355	0.694	0.488	0.049	0.138	0.587	0.483	0.939	0.838	0.000	n.a	0.383	0.161
2020	0.658	0.389	0.564	0.337	0.689	0.485	0.045	0.147	0.587	0.504	0.945	0.844	0.000	n.a	0.364	0.164

Table A1: (Continued on the following page)

	EBT		ENT		EPX		FFO		GPS		GRM		NAV		NDT	
Year	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
1995	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a
1996	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a
1997	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a
1998	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a
1999	0.051	0.165	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a
2000	0.044	0.166	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a
2001	0.025	0.140	0.000	n.a	0.000	n.a	0.012	0.935	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a
2002	0.446	0.322	0.000	n.a	0.125	0.116	0.021	0.840	0.000	n.a	0.000	n.a	0.030	0.127	0.101	0.139
2003	0.532	0.433	0.000	n.a	0.213	0.207	0.023	0.917	0.347	0.188	0.000	n.a	0.021	0.123	0.157	0.169
2004	0.599	0.493	0.000	n.a	0.207	0.221	0.028	0.916	0.495	0.275	0.000	n.a	0.010	0.126	0.206	0.189
2005	0.652	0.524	0.000	n.a	0.290	0.204	0.030	0.905	0.528	0.290	0.000	n.a	0.013	0.123	0.311	0.215
2006	0.688	0.537	0.240	0.133	0.411	0.317	0.029	0.871	0.583	0.333	0.519	0.510	0.012	0.106	0.398	0.232
2007	0.711	0.552	0.295	0.164	0.346	0.314	0.027	0.841	0.674	0.417	0.573	0.597	0.019	0.148	0.426	0.250
2008	0.736	0.584	0.310	0.178	0.381	0.328	0.025	0.874	0.805	0.559	0.581	0.619	0.063	0.130	0.453	0.265
2009	0.700	0.618	0.360	0.190	0.334	0.294	0.027	0.779	0.856	0.733	0.567	0.608	0.117	0.133	0.453	0.276
2010	0.789	0.682	0.387	0.197	0.341	0.301	0.029	0.815	0.895	0.764	0.624	0.595	0.705	0.406	0.471	0.280
2011	0.800	0.700	0.448	0.216	0.299	0.266	0.033	0.737	0.886	0.769	0.643	0.576	0.738	0.436	0.494	0.286
2012	0.798	0.704	0.478	0.219	0.256	0.213	0.034	0.753	0.885	0.761	0.632	0.566	0.765	0.441	0.519	0.294
2013	0.799	0.701	0.429	0.214	0.185	0.154	0.036	0.840	0.888	0.744	0.617	0.550	0.764	0.437	0.497	0.306
2014	0.823	0.735	0.492	0.273	0.183	0.110	0.042	0.747	0.904	0.754	0.626	0.537	0.784	0.450	0.539	0.381
2015	0.837	0.749	0.511	0.279	0.169	0.095	0.042	0.782	0.925	0.767	0.660	0.553	0.801	0.473	0.560	0.386
2016	0.836	0.764	0.517	0.288	0.201	0.094	0.044	0.797	0.941	0.767	0.653	0.562	0.823	0.471	0.583	0.405
2017	0.823	0.777	0.520	0.293	0.213	0.099	0.045	0.781	0.945	0.774	0.639	0.564	0.800	0.432	0.585	0.412
2018	0.810	0.785	0.521	0.298	0.196	0.107	0.045	0.781	0.959	0.788	0.631	0.559	0.802	0.436	0.587	0.419
2019	0.805	0.784	0.522	0.288	0.181	0.106	0.041	0.835	0.957	0.785	0.636	0.570	0.797	0.440	0.579	0.404
2020	0.806	0.786	0.517	0.289	0.187	0.108	0.043	0.821	0.957	0.796	0.604	0.583	0.793	0.437	0.580	0.400

Table A1: (Continued on the following page)

	NET		OPR		PRE		ROA		ROE		SAL		LTG	
Year	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
1995	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.617	0.418
1996	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.198	0.291	0.646	0.460
1997	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.324	0.296	0.654	0.477
1998	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.478	0.372	0.638	0.442
1999	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.530	0.378	0.610	0.412
2000	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.596	0.412	0.603	0.383
2001	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.000	n.a	0.653	0.514	0.667	0.448
2002	0.648	0.407	0.580	0.368	0.605	0.380	0.143	0.160	0.334	0.194	0.761	0.642	0.697	0.453
2003	0.774	0.589	0.684	0.520	0.724	0.552	0.278	0.237	0.485	0.305	0.826	0.729	0.679	0.447
2004	0.844	0.701	0.751	0.603	0.788	0.651	0.320	0.292	0.525	0.350	0.871	0.790	0.701	0.449
2005	0.881	0.730	0.796	0.633	0.829	0.673	0.345	0.283	0.563	0.352	0.891	0.800	0.694	0.423
2006	0.879	0.754	0.794	0.649	0.834	0.689	0.345	0.276	0.568	0.343	0.887	0.805	0.630	0.373
2007	0.898	0.769	0.804	0.652	0.861	0.702	0.383	0.268	0.587	0.338	0.901	0.822	0.612	0.337
2008	0.914	0.795	0.828	0.669	0.872	0.731	0.432	0.286	0.611	0.361	0.907	0.812	0.609	0.327
2009	0.872	0.790	0.782	0.651	0.843	0.728	0.447	0.298	0.610	0.384	0.922	0.845	0.606	0.330
2010	0.917	0.852	0.837	0.707	0.892	0.797	0.502	0.294	0.682	0.444	0.962	0.882	0.615	0.314
2011	0.929	0.862	0.857	0.707	0.906	0.807	0.522	0.289	0.695	0.455	0.956	0.889	0.604	0.311
2012	0.925	0.849	0.770	0.537	0.902	0.788	0.555	0.300	0.697	0.456	0.950	0.873	0.597	0.300
2013	0.926	0.844	0.257	0.178	0.894	0.759	0.577	0.305	0.707	0.444	0.947	0.868	0.555	0.273
2014	0.947	0.869	0.298	0.198	0.923	0.785	0.599	0.315	0.743	0.490	0.963	0.889	0.550	0.271
2015	0.963	0.886	0.281	0.195	0.938	0.802	0.625	0.343	0.751	0.487	0.975	0.920	0.535	0.271
2016	0.976	0.894	0.316	0.205	0.949	0.805	0.648	0.355	0.759	0.494	0.971	0.922	0.540	0.273
2017	0.976	0.896	0.320	0.200	0.952	0.804	0.644	0.366	0.752	0.502	0.973	0.930	0.523	0.275
2018	0.977	0.899	0.272	0.201	0.953	0.815	0.632	0.363	0.746	0.501	0.978	0.927	0.522	0.271
2019	0.978	0.895	0.225	0.213	0.949	0.796	0.618	0.359	0.732	0.494	0.977	0.921	0.467	0.255
2020	0.979	0.893	0.187	0.232	0.943	0.793	0.605	0.352	0.717	0.482	0.978	0.922	0.454	0.259

Table A1: (Continued on the following page)

Table A1: This table shows analysts' provision of different forecast types available in the I/B/E/S US file via Wharton's WRDS database through 1995 to 2020. Numbers below 0.5% are rounded to zero. To be included in the sample, a firm-analyst-year observation must 1) have at least one one-year ahead earnings per share (EPS) forecast; 2) the analyst can be identified; 3) both the analyst's estimates and the firm's reporting accounting numbers are denominated in US dollar. Column (a)s present the ratio between the number of firms with at least one forecast of related type in year t and the total number of firms in year t. Column (b)s present the cross-firm average ratio between the number of analysts providing at least one forecast of related type for firm i (firm i must have at least one forecast of related type in year t) and the total number of analysts following firm i in year t.

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Chapter 2

Second Paper

Capacity overhang, investment, and accruals

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Abstract

Capacity overhang is the difference between a firm's installed production capacity and its optimal capacity. When investment is costly to reverse, firms can ex post have capacity overhang due to negative demand shocks. Based on real options theory, we empirically show that future investment and investment-cash flow sensitivity are negatively related to capacity overhang after controlling for existing investment determinants. Given the role played by accruals in reflecting firms' growth in the scale of business operations, we also find a negative accruals-capacity overhang relationship. Finally, we augment optimal investment models, the Performance-adjusted Modified Jones Model, and an investment-based accruals model, with capacity overhang. We find that investment efficiency and accruals management estimates may be biased if capacity overhang is ignored.

JEL Classification: D25; G31; M41

Keywords: Investment; Accruals; Capacity overhang; Real options

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2.1 Introduction

Investment is a key driver of economic growth. Understanding the determinants of corporate investment is central to financial economics. Numerous studies model firms' optimal investment using firm characteristics capturing growth opportunities and profitability. Failure to account for any key investment determinants may bias the estimated future investment. In this study, we propose a fundamental determinant of firm-level investment that captures firms' investment and demand dynamics—capacity overhang—the difference between a firm's installed capacity and its optimal capacity under the current economic fundamentals. We then show that this measure also predicts accruals, consistent with accruals reflecting growth in the scale of business operations.

Most of the theoretical and empirical literature on the economics of investment is based on the "q theory" of Tobin (1969). The theory compares the capitalized value of the marginal investment to its purchase costs, i.e. replacement costs, where the value can be either the price of the investment in a secondary market or the expected present value of the profits it would generate during the useful life. Tobin's marginal q is the ratio of the marginal investment's capitalized value to its replacement costs. An investment should be undertaken if and only if q is greater than 1. An investment should not be undertaken, or the installed capacity should be reversed, if and only if q is below 1. However, the market value of the marginal investment is unobservable. What we can observe is average q, the ratio of the market value of capital in place to its replacement costs. Hayashi (1982) argues with a neoclassical framework that average q is equivalent to marginal q if and only if a number of conditions are satisfied.[1] However, these conditions are unrealistic in general. The deviation from the theory makes average q a potentially biased proxy for Tobin's marginal q.[2]

The situation is further complicated after introducing options to postpone investment and costly-to-reverse investment. In an extension of Pindyck (1988)'s real options model of investment allowing for costly investment reversibility, Aretz and Pope (2018) show that firms can produce below full capacity even if investment is partially reversible. Intuitively,

[1] The conditions are: (1) constant returns to scale production technology, (2) homogeneous capital goods, (3) efficiency stock market, and (4) competitive product market. However, in reality, conditions (1), (2), and (4) obviously do not hold for all firms, and the validity of (3) is still under debate.

[2] Although Erickson and Whited (2000) propose an approach to eliminating the measurement error in Tobin's average q, their approach is based on strong statistical assumptions. Therefore, it is unlikely that their method can converge Tobin's marginal q and average q perfectly.

at the optimality, the firm invests if and only if the value of the new capacity is larger than the sum of the investment costs and the value of the option to install that capacity later; the firm divests if and only if the value of the installed capacity is less than the divestment proceeds and the value of the acquired growth option. Under this model, the firm's investment is a discontinuous function with respect to demand, holding other parameters constant. When demand falls between some interval, the firm neither invests nor divests—it just retains the option to produce if demand increases and to sell it if demand falls. Therefore, there is a wedge between a firm's installed capacity and its optimal capacity—capacity overhang. A firm's capacity overhang at some point in time is shaped by two forces: the optimal capacity at the point of time and the firm's installed capacity. The former is a function of demand, volatility, investment cost, production cost, irreversibility of investment, systematic risk, and interest rate, while the latter is determined by the historical capacity choices of the firm and the evolution of demand.

Aretz and Pope (2018) estimate firm-level capacity overhang using a stochastic frontier model.[3] They decompose the natural log of a firm's installed capacity into two components: the natural log of optimal capacity and a capacity overhang term. The natural log of optimal capacity is a linear function of a vector of optimal capacity determinants and a normally distributed error term. The capacity overhang term follows the normal distribution truncated from below at zero, whose mean is a linear function of a vector of capacity overhang determinants. The model is estimated recursively with the Maximum Likelihood (MLE) method. We will elaborate on the estimation of capacity overhang in Section 2.3.

This capacity overhang estimate may have important implications for firms' investment behaviors, both in the cross-section and in the time series. Consider two firms with different capacity overhang. Recall that capacity overhang is shaped by optimal capacity and installed capacity. The high-capacity overhang firm might either have experienced abnormally low demand recently or unusually high demand in the more distant past, leading to excess capacity relative to current demand. In addition to low demand, higher-capacity overhang may also depend on demand volatility, investment irreversibility, production cost, or investment cost. All these factors deter the high-capacity overhang firm from investing. For example, fixing demand constant, high demand volatility

[3] See ? for more technical details.

increases the value of growth option, reducing the firm's optimal capacity. Overall, we expect a negative investment-capacity overhang relationship.

Our empirical results show that capacity overhang negatively predicts firms' year-ahead investment both in the panel regressions and in the Fama and MacBeth (1973) cross-sectional regressions. This negative association is robust to other investment determinants documented by the prior literature. Interestingly, the correlation between capacity overhang and Tobin's q is positive, while they predict investment in opposite directions. This may be caused by the effect of accounting conservatism on the denominator of Tobin's q, the book value of total assets. This finding reveals a new source of measurement error in Tobin's q.[4]

Our next goal is to examine the ability of capacity overhang to explain accruals. The accounting literature has identified three roles of accruals: (1) mitigating timing differences between business transactions and their associated cash flows effects (**?**), (2) capturing the conditional conservatism of accouting (**??**) and, (3) reflecting investments related to growth in the scale of business operations (Arif et al., 2016; Dechow et al., 2008; Fairfield et al., 2003; Jones, 1991; Larson et al., 2018; Wu et al., 2010; Zhang, 2007). The investment view of accruals posits that accruals at least partially reflect deliberate investment choices by the firm. For example, Larson et al. (2018) show that accruals are positively correlated with growth in operating activities, measured as growth in employees. Under real options-based arguments, Arif et al. (2016) hypothesize and find that working capital accruals are negatively associated with uncertainty modeled by the volatility of stock returns. To the extent that capacity overhang shapes investment and accruals reflect investment, we expect to find a negative accruals-capacity overhang relationship. As working capital accruals are more easily reversible than long-term operating accruals, and working capital accruals mainly reflect firms' short-term demand rather than long-term growth, we expect a weaker negative relationship between working capital accruals and capacity overhang. As firms sometimes use debt to finance investments in operating assets, we expect a positive association between capacity overhang and financing accruals. This positive association is driven by the positive effect of capacity overhang on financial liability accruals. Finally, we hypothesize that capacity overhang is more (less) negatively related to operating (financial) asset accruals than to operating

[4] Please see the discussion in Section 2.5.2.

(financial) liability accruals because firms' investment has first-order effects on operating asset accruals but affect operating liability accruals only to the extent that firms use operating or financial liabilities to finance investment. Our empirical results support our hypotheses.

Finally, we examine the potential bias induced by failure to account for capacity overhang in estimating optimal investment or discretionary accruals. A number of studies first rely on statistical models to estimate firms' optimal investment and then link the in-sample residuals, i.e. the difference between the realized investment and the estimated optimal investment, to other variables of interest. Some studies call these in-sample residuals "investment inefficiency". Biddle et al. (2009) test the association between accruals quality and managers' over-investment in a one-step regression. McNichols and Stubben (2008) examine the association between earnings management and investment efficiency also in a one-step regression. In more recent work, Choi et al. (2020) use a two-step regression to first obtain the in-sample residuals of an optimal investment model as a proxy for investment inefficiency, and then regress the residuals on firms' analyst coverage of capital expenditure forecasts. Their optimal investment model is largely identical to McNichols and Stubben (2008)'s. Some studies do not directly focus on optimal investment. Instead, they look at investment-cash flow sensitivity. For example, Biddle and Hilary (2006) use investment-cash flow sensitivity as a measure of investment inefficiency under the assumption that Tobin's q is a sufficient statistic for investment if there is no imperfection of the market. They then link this investment inefficiency to lower accounting quality. Nonetheless, to the extent that capacity overhang is potentially correlated with investment-cash flow sensitivity, omitting capacity overhang from such models could be an important source of bias.

To examine the potential impact of failure to account for capacity overhang in estimating optimal investment, we augment typical investment models with capacity overhang. We find that a significant proportion of firms may be incorrectly identified as efficiently- or inefficiently- investing firms if capacity overhang is neglected.

Analogous to the concept of optimal investment, non-discretionary accruals are the component of accruals that is driven by economic forces, whereas discretionary accruals are assumed to be subject to managers' manipulations. Numerous studies use discretionary accruals to detect earnings management (e.g. Dechow et al., 1995; Jones, 1991;

Kothari et al., 2005). To the extent that accruals reflect growth, Arif et al. (2016) take an investment approach to modeling discretionary accruals, and they show that the discretionary accruals derived from their model are better than the Performance-adjusted Jones Model at detecting companies that just meet or beat analysts' earnings forecasts. Inspired by their study, we examine the consequences of failure to consider capacity overhang in modeling discretionary accruals. We augment the Performance-adjusted Jones Model and an investment-based accruals model with capacity overhang and find that a large proportion of firms are misidentified as earnings manipulators or truthful reporters.

Our study makes several contributions. First, our empirical evidence lends support to the real options-based investment literature. Based on real options theory, we document a strong and robust link between investment and capacity overhang. In contrast to Tobin's q, the capacity overhang estimate uses accounting numbers rather than stock prices as a first-order input.[5] This feature makes capacity overhang less vulnerable to the effects of short-term mispricing of stocks. Second, our findings also contribute to the financial accounting literature by extending our understanding of the determinants of different categories of accruals. Our findings provide guidance for estimating (non-) discretionary accruals using an investment approach.

The rest of paper is arranged as follows. Section 2.2 presents the theoretical background and develops the hypotheses; Section 2.3 reviews the estimation of capacity overhang; Section 2.4 introduces the regression models; Section 2.5 describes the sample and descriptive statistics; Section 2.6 reports and discusses the empirical results; Section 2.7 concludes the paper.

2.2 Theoretical background and hypothesis development

2.2.1 Theoretical background

Our empirical analysis is motivated by the model of investment under uncertainty by Dixit and Pindyck (2012). Consider a monopolistic all-equity firm that continuously makes production and capacity adjustment decisions to maximize its value. The price of outputs is driven by a downward-sloping demand curve with a stochastic demand and a constant elasticity of demand. The cost of production takes a quadratic form in the

[5] Stock prices are a second-order input into the capacity overhang estimate: volatility and market beta.

quantity of outputs. Investment in capacity is costly to reverse. In other words, if the firm divests its installed capacity, the divestment proceeds are lower than its purchase prices. The firm holds the option to delay investment, i.e. the option to grow. There is no adjustment time, and capacity can be acquired and sold without restriction. Intuitively, to maximize value, the firm invests if and only if the value of the newly added capacity is larger than the sum of the investment costs and the value of the growth option; the firm divests if and only if the value of the installed capacity is less than the sum of the divestment proceeds and the value of the acquired growth option.

The mathematical solution to the model implies that for a given unit of installed capacity, there is an interval where investment does not change with respect to demand, fixing other parameters constant.[6] When demand is below a lower critical value, θ_1, the firm sells the unit of capacity, i.e. the option to produce, in exchange for divestment proceeds and an option to repurchase the option to produce at a later date, i.e. a growth option; when demand is larger than θ_1 but lower than the upper critical value, θ_2, the firm retains the unit of capacity, i.e. the option to produce, but does not use it—the firm can exercise the option to produce if demand rises and to sell it when demand drops; when demand is above θ_2, the firm exercises the option to produce. In terms of the option to grow, the firm keeps it but does not use it when demand is below the critical value, θ^*, and exercise it when demand is above θ^*, in exchange for an option to produce less the investment costs.

The model implies that the optimal installed capacity increases with demand and investment reversibility, and decreases with demand volatility, systematic risk, investment cost, and production cost. Intuitively, higher demand induces higher capitalized profits, and hence the value of a newly added unit of capacity increases; higher investment reversibility gives the firm more flexibility to adjust capacity downward if demand falls, so the firm is more likely to exercise the growth option; higher demand volatility raises the value of the growth option—facing higher uncertainty, the firm prefers to "wait and see".

In the model, the firm's investment decisions are sequential. Hence, the theory implies that capacity overhang, defined as the difference between the firm's installed capacity and its optimal capacity, is path-dependent. Capacity overhang is determined by the firm's historical investment decisions and current economic fundamentals such as demand

[6]For a formal version of the model and its solution, please see Pindyck (1988), Dixit and Pindyck (2012), and Aretz and Pope (2018).

and demand volatility. Fixing installed capacity, capacity overhang increases as demand decreases (volatility increases); fixing demand, capacity overhang increases as installed capacity increases (volatility decreases).[7]

2.2.2 Hypothesis development

Based on the real options arguments in Section 2.1, firms with higher capacity overhang may have excess installed capacity, deteriorating demand, higher demand uncertainty, more costly-to-reverse investment, higher production cost, or larger market betas. All these factors deter firms from investing. We state our first hypothesis as follows:

H1: Firms' future investment is negatively associated with capacity overhang.

The effect of capacity overhang on the investment-cash flow sensitivity is unclear ex-ante. On the one hand, as high-capacity overhang firms may have been experiencing deteriorating demand, they are more likely to be experiencing financial distress. If the investment-cash flow sensitivity is a valid measure of financial constraints as suggested by Fazzari et al. (1988), we would observe a positive association between capacity overhang and the investment-cash flow sensitivity.

On the other hand, high-capacity overhang firms have more installed capacity. When these firms are faced with positive demand shocks, they can reactivate the unused installed capacity before building new capacity, leading to less need for external financing and lower investment-cash flow sensitivity. In summary, the two counteracting effects make the role played by capacity overhang unclear in affecting the investment-cash flow sensitivity. Overall, we state our second hypothesis in the null form:

H2 (Null): Capacity overhang is not associated with the investment-cash flow sensitivity.

Accruals are not only a component of profitability but also a component of investment (Arif et al., 2016; Dechow et al., 2008; Fairfield et al., 2003; Jones, 1991; Larson et al., 2018;

[7] Of course, capacity overhang also depends on other parameters like investment reversibility, systematic risk, investment cost, production cost, and interest rate. We assume these factors are more slow-moving that demand and volatility.

Wu et al., 2010; Zhang, 2007). If the negative investment-capacity overhang relationship is true, we also expect a negative association between accruals and capacity overhang.

Recall that by definition, capacity overhang deters firms from investing in long-lived operating assets rather than current assets, despite the association between the two. In addition, working capital accruals are less irreversible than long-term operating accruals. Hence, we expect a weaker (stronger) negative association between capacity overhang and working capital accruals (long-term operating accruals).

When firms acquire operating assets, firms generate financial obligations to the extent that firms at least partially rely on external finance. High- (low-) capacity overhang firms engage in less (more) investment in operating assets, so they have less (more) demand for external finance and generate fewer (more) financial obligations. Overall, we conjecture an opposite direction of the effect of capacity overhang on financial accruals to the extent that capacity overhang does not affect financial assets. We state our third set of hypotheses as follows:

H3: Future operating accruals are negatively associated with capacity overhang.

H3a: The negative association of capacity overhang with future working capital accruals is weaker than that with future long-term operating accruals.

H3b: Future financial accruals are positively associated with capacity overhang.

We expect capacity overhang to have differential effects on the asset component and the liability component of accruals. Specifically, we expect the negative association of capacity overhang with operating liability accruals to be weaker than that with operating asset accruals.[8] The reason is that although firms sometimes use liabilities to finance their investment in operating assets, firms can use internally generated cash flow alternatively or as a complement.

During the investment in operating assets, financial liabilities are generated. However, capacity overhang does not directly affect financial asset accruals. Overall, we expect capacity overhang to be more negatively related to financial liability accruals than to fi-

[8] We multiply liability accruals by -1 to reflect the intensity of investment. For example, more positive asset accruals and more negative liability accruals reflect more intensive investment.

nancial asset accruals. We state our fourth hypothesis as follows:

H4: Capacity overhang is more (less) negatively associated with operating (financial) asset accruals than with operating (financial) liability accruals.

2.3 Measuring capacity overhang

Aretz and Pope (2018) estimate firm-level capacity overhang using a stochastic frontier model. We briefly review their approach in this section. The real options theory suggests that capacity overhang is truncated from below at zero, giving rise to the scenario where stochastic frontier models are suitable.[9] At time t, firm i's installed capacity, $\overline{\mathrm{K}}_{\mathrm{it}}$, is measured as the sum of gross property plant and equipment (PPE) and intangible assets. $\overline{\mathrm{K}}_{\mathrm{it}}$ can be decomposed into optimal capacity, $\mathrm{K}^*_{\mathrm{it}}$, and a capacity overhang term ξ_{it}: $\overline{\mathrm{K}}_{\mathrm{it}} = \mathrm{K}^*_{\mathrm{it}}\xi_{\mathrm{it}}$, where $\xi_{\mathrm{it}} \in [1, +\infty)$. After taking natural log of both sides, we obtain: $\ln(\overline{\mathrm{K}}_{\mathrm{it}}) = \ln(\mathrm{K}^*_{\mathrm{it}}) + \ln(\xi_{\mathrm{it}}) = \ln(\mathrm{K}^*_{\mathrm{it}}) + \mathrm{u}_{\mathrm{it}}$, where $\mathrm{u}_{\mathrm{it}} = \ln(\xi_{\mathrm{it}}) \in [0, +\infty)$. Aretz and Pope (2018) assume that the natural log of of optimal capacity, $\ln(\mathrm{K}^*_{\mathrm{it}})$, is a linear function of optimal capacity determinants, and a normally distributed error term $\mathrm{v}_{\mathrm{it}} \sim \mathrm{N}(0, \sigma^2_{\mathrm{v}})$. We can then write

$$\ln(\overline{\mathrm{K}}_{\mathrm{it}}) = \alpha_{\mathrm{k}} + \boldsymbol{\beta}'\mathbf{X}_{\mathrm{it}} + \mathrm{v}_{\mathrm{it}} + \mathrm{u}_{\mathrm{it}},$$

where α_{k} is industry fixed effects;[10] the vector of the determinants of optimal capacity, $\mathbf{X}$, includes Sales, costs of goods sold (COGS), selling, general and administrative expenses (SG&A), stock volatility, market beta, and risk-free rate.

To implement the Maximum Likelihood Estimation (MLE) method, Aretz and Pope (2018) assume the normal distribution truncated from below at zero for the natural log of capacity overhang term: $\mathrm{u}_{\mathrm{it}} \sim \mathrm{N}^+(\boldsymbol{\gamma}'\mathbf{Z}_{\mathrm{it}}, \sigma^2_{\mathrm{u}})$, where the vector of capacity overhang determinants, $\mathbf{Z}_{\mathrm{it}}$, includes recent sales decline, more distant sales decline, and a loss dummy. The model parameters are estimated recursively using MLE on a monthly basis. The recursive estimation window ends in December of the prior calendar year, ensuring

[9]The real options-based investment model in Aretz and Pope (2018) abstracts from fixed investment costs and time-to-build. As a result, if the firm's installed capacity is below optimal capacity, the firm instantaneously raises its installed capacity to optimal capacity.

[10]Industry fixed effects capture unobservable industry-wide variables such as the elasticity of demand and the capacity adjustment prices so that the capacity overhang estimates across industries are directly comparable.

that economic agents can incorporate the latest financial data into the estimation. As our empirical analysis is at the firm-year level, for each firm-year, we use the capacity overhang for the fiscal year-end month.

2.4 Models

2.4.1 Models for tests of the investment-capacity overhang relationship (H1) and the association between capacity overhang and the investment-cash flow sensitivity (H2)

We test the investment-capacity overhang relationship (H1) and the association between capacity overhang and the investment-cash flow sensitivity (H2) by estimating the following regression model:[11]

$$\begin{aligned}
&\mathrm{INVESTMENT}_{\mathrm{it+1}} \\
&= \beta_0 + \beta_1 \mathrm{OH}_{\mathrm{it}} + \beta_2 \mathrm{LN_AT}_{\mathrm{it}} + \beta_3 \mathrm{Q}_{\mathrm{it}} + \beta_4 \mathrm{ROA}_{\mathrm{it}} + \beta_5 \mathrm{CFO}_{\mathrm{it+1}} + \beta_6 \mathrm{OH_CFO}_{\mathrm{it+1}} \\
&+ \beta_7 \mathrm{LEV}_{\mathrm{it}} + \beta_8 \mathrm{VOL}_{\mathrm{it+1}} + \beta_9 \mathrm{R}^{\mathrm{f}}_{\mathrm{it+1}} + \mathrm{Firm} + \mathrm{Year} + \epsilon_{\mathrm{it+1}}.
\end{aligned} \tag{2.1}$$

In the tests of H1, the variable of interest is fiscal year-end capacity overhang (OH). In the tests of H2, the variable of interest is the interaction between capacity overhang and year-ahead operating cash flow ($\mathrm{OH\_CFO}_{\mathrm{it+1}}$).

Since different studies on investment define investment in different ways, to examine the ability of capacity overhang to predict investment of differnet categories, we consider four investment variables. First, we consider the annual growth rate in the sum of property, plant, and equipment (PPE) and intangible assets (denoted as ΔPPEINT). We include intangibles because they are increasingly important in a service- and technology-

[11] The model we use is very similar to the models used by Eisdorfer (2008) and Arif et al. (2016) except for some minor differences. To control for firms' size, we use log of book total assets, while they use log of market total assets; to control for firms' growth opportunity, we use Tobin's q, while they use market-to-book equity; to control for firms' profitability, we use return on assets (ROA), while they use current period operating cash flow; to control for leverage effects, we use market leverage, while they use book leverage; to control for volatility, we use realized standard deviation of daily stock returns in year t+1, while they estimate expected volatility using the generalized autoregressive conditional heteroskedasticity (GARCH) model; to control for firms' financial constraints, we use year-ahead operating cash flow; while they do not control for financial constraints. In addition, we do not control for recession indicator or default spread. Instead, we control for year and firm fixed effects to absorb any omitted macroeconomic factors and unobservable time-invariant firm characteristics, respectively. Our results are qualitatively similar if we use the same research design as Eisdorfer (2008) and Arif et al. (2016).

based economy like the US.[12] In Compustat item names, $\Delta\mathrm{PPEINT_t} = \Delta(\mathrm{PPEGT} + \mathrm{INTAN})_\mathrm{t}/(\mathrm{PPEGT} + \mathrm{INTAN})_{\mathrm{t-1}}$. Second, we consider the annual growth rate in PPE (denoted as ΔPPE). In Compustat item names, $\Delta\mathrm{PPE_t} = \Delta\mathrm{PPEGT_t}/\mathrm{PPEGT_{t-1}}$. This measure is wide-used by the prior literature to capture firms' physical capital investment.[13] Third, we consider firms' total investment (denoted as TOTINV), defined as the sum of annual changes in PPE and intangibles, research and development (R&D) expenses, and 30% of selling, general and administrative expense (SG&A), divided by lagged total assets. This measure of investment not only accounts for intangible assets on the balance sheet, but also considers the expensed proportion of intangible investment. In Compustat item names, $\mathrm{TOTINV_t} = [\Delta\mathrm{PPEGT} + \Delta\mathrm{INTAN} + \mathrm{XRD} + 0.3 \times (\mathrm{XSGA} - \mathrm{XRD})]_\mathrm{t}/\mathrm{AT_{t-1}}$. We choose a 30% capitalization rate for SG&A following Eisfeldt and Papanikolaou (2013).[14] Finally, we consider capital expenditures divided by lagged gross PPE (denoted as CAPX). Although this measure ignores disinvestment and hence may not accurately reflect growth in physical capital, this measure is widely-used in finance and accounting literature.[15]

In addition, following the prior literature, we control for firm characteristics that are associated with investment. The control variables are firms' size (denoted as LN_AT), Tobin's q (denoted as Q), profitability (denoted as ROA), year-ahead operating cash flow (denoted as CFO), leverage (denoted as LEV), volatility of stock returns (denoed as VOL), and interest rate (denoted as $\mathrm{R^f}$). Firms' size is defined as the natural log of firms' total book assets (Compustat item AT). Tobin's q is the sum of market equity and total assets minus book equity and deferred taxes, divided by total assets. In Compustat item names, $\mathrm{Q_t} = (\mathrm{PRCC\_F} \times \mathrm{CSHO} + \mathrm{AT} - \mathrm{CEQ} - \mathrm{TXDB})_\mathrm{t}/\mathrm{AT_t}$.[16]. The measure of profitability we use is return on assets (ROA). In Compustat item names, $\mathrm{ROA_t} = \mathrm{OIADP_t}/\mathrm{AT_{t-1}}$, where OIADP is operating income after depreciation. Operating cash flow is defined as

[12] **?** document that intangible capital makes up 34% of firms' total capital in recent years.

[13] For example, Fazzari et al. (1988). See Table B2 in Cooper et al. (2020) for a review.

[14] Also see Cooper et al. (2020), Hulten and Hao (2008), Peters and Taylor (2017), and Zhang et al. (2014).

[15] For example, Biddle et al. (2009), Goodman et al. (2014), Kaplan and Zingales (1997), and McNichols and Stubben (2008).

[16] Since Tobin's marginal q is unobservable, we follow the literature to use Tobin's average Q as a proxy for firms' growth opportunity. Under the some conditions, marginal Q is equivalent to average Q (Hayashi, 1982). However, the conditions are generally not satisfied. Hence the average Q contains measurement errors (Erickson and Whited, 2000). As a robustness check, we use the errors-in-variables model using high-order cumulants and moments proposed by Erickson and Whited (2000). Our results are robust.

the sum of earnings before extraordinary items and depreciation amortization, divided by lagged total assets. In Compustat item names, $\mathrm{CFO_t = (IB + DP)_t/AT_{t-1}}$. Leverage is defined as total liabilities divided by the sum of market equity and total liabilities. In Compustat item names, $\mathrm{LEV_t = LT_t/(PRCC\_F \times CSHO + LT)_t}$. Volatility of stock returns is calculated as the standard deviation of daily stock returns in the years when investment is made for firms with at least 200 trading days of data. Interest rate is the nominal returns on 30-day T-Bills at the middle of years when investment is made.

In the main analysis, we include firm and year fixed effects to absorb any unobservable time-invariant firm characteristics and omitted macroeconomic factors that may be associated with firms' investment behaviors, respectively. To examine whether the negative investment-capacity overhang relationship exists in the cross section, we conduct Fama and MacBeth (1973) cross-sectional regressions for Eq 2.1 excluding fixed effects and interest rate.

We expect a negative coefficient for capacity overhang (β_1) for all investment definitions. We do not have a prejudgement about the sign of the coefficient for the interaction between capacity overhang and year-ahead operating cash flow (β_6).

2.4.2 Models for tests of accruals-capacity overhang relationship (H3) and asset accruals versus liability accruals (H4)

Following Arif et al. (2016), we take an investment approach to modeling accruals. Specifically, we estimated the following regression equation:

$$\begin{aligned}
&\mathrm{ACCRUALS_{it+1}} \\
&= \beta_0 + \beta_1\mathrm{OH_{it}} + \beta_2\mathrm{LN_AT_{it}} + \beta_3\mathrm{Q_{it}} + \beta_4\mathrm{ROA_{it}} + \beta_5\mathrm{LEV_{it}} + \beta_6\mathrm{VOL_{it+1}} \\
&+ \beta_7\mathrm{R^f_{it+1}} + \mathrm{Firm} + \mathrm{Year} + \epsilon_{\mathrm{it+1}}.
\end{aligned} \tag{2.2}$$

To examine the associations of capacity overhang with different accruals components, we follow Larson et al. (2018)'s approach to decomposing accruals. First, we define firms' comprehensive accruals (denoted as COMPACC) as the difference between changes in the book value of common equity and changes in cash and cash equivalents, divided by beginning total assets.[17] In Compustat item names, $\mathrm{COMPACC_t = (\Delta CEQ - \Delta CHE)_t/AT_t}$.

[17] Larson et al. (2018) argue that their comprehensive measure of accruals is a more complete measure of accruals than the aggregated accruals of **?** and the total accruals of **?**. They suggest that future research use their comprehensive accruals if the research does not focus on a specific subset of accruals.

Comprehensive accruals can be further decomposed into two components, operating accruals (denoted as OPACC) and financial accruals (denoted as FINACC). In Compustat item names, $\mathrm{OPACC_t} = [(\Delta\mathrm{AT} - \Delta\mathrm{CHE} - \Delta\mathrm{IVAEQ} - \Delta\mathrm{IVAO}) - (\Delta\mathrm{LT} - \Delta\mathrm{DLC} - \Delta\mathrm{DLTT})]_\mathrm{t}/\mathrm{AT_{t-1}}$. Financial accruals are the difference between comprehensive accruals and operating accruals. To further examine the different effects of capacity on the short-term and long-term components of operating accruals, we decompose operating accruals into working capital accruals (denoted as WCACC) and long-term operating accruals (LTACC). In Compustat item names, $\mathrm{WCACC_t} = [(\Delta\mathrm{ACT} - \Delta\mathrm{CHE}) - (\Delta\mathrm{LCT} - \Delta\mathrm{DLC})]_\mathrm{t}/\mathrm{AT_{t-1}}$. LTACC is the difference between OPACC and WCACC.

To investigate the differential effects of capacity overhang on asset accruals and liability accruals, we decompose each of the five accrual components into asset accruals and liability accruals. Variables with a "_A" ("_L") postfix denotes the asset (liability) component of accruals. In Compustat item names, $\mathrm{COMPACC\_A_t} = (\Delta\mathrm{AT} - \Delta\mathrm{CHE})_\mathrm{t}/\mathrm{AT_{t-1}}$, $\mathrm{OPACC\_A_t} = (\Delta\mathrm{AT} - \Delta\mathrm{CHE} - \Delta\mathrm{IVAEQ} - \Delta\mathrm{IVAO})_\mathrm{t}/\mathrm{AT_{t-1}}$, $\mathrm{FINACC\_A_t} = (\Delta\mathrm{IVAEQ} + \Delta\mathrm{IVAO})_\mathrm{t}/\mathrm{AT_{t-1}}$, and $\mathrm{WCACC\_A_t} = (\Delta\mathrm{ACT} - \Delta\mathrm{CHE})/\mathrm{AT_{t-1}}$. The asset component of long-term operating accruals, LTACC_A, is the difference between the asset component of operating accruals (OPACC_A) and the asset component of working capital accruals (WCACC_A). Liability accruals are the differences between the related accruals and their asset components. We multiply liability accruals by -1 to make the coefficients comparable across asset accruals and liability accruals.

We expect a negative (positive) coefficient for capacity overhang (β_1) when the dependent variable in Eq 2.2 is operating (financial) accruals, and the negative relationship is weaker for working capital accruals than for long-term accruals. In addition, we expect the negative accruals-capacity overhang relationship is stronger (weaker) for operating (financial) asset accruals than for operating (financial) liability accruals.

2.4.3 Optimal investment models augmented with capacity overhang

To investigate the potential bias in the optimal investment derived from statistical models that ignore capacity overhang, we compare the residuals from the original models and those from the same models augmented with capacity overhang. The residuals from an optimal investment model are a measure of firms' investment inefficiency. A positive (negative) residual indicates over- (inder-) investment.

First, following Fazzari et al. (1988), we model firms' optimal investment using the following regression equation:

$$\mathrm{TOTINV}_{\mathrm{it+1}} = \beta_0 + \beta_1 \mathrm{Q}_{\mathrm{it}} + \beta_2 \mathrm{CFO}_{\mathrm{it+1}} + \epsilon_{\mathrm{it+1}}, \tag{2.3}$$

where TOTINV is year-ahead total investment, Q is Tobin's q, and CFO is year-ahead operating cash flow. We use total investment in place of physical capital investment to cater to the increasing importance of intangible capital in the modern economy.[18] The model is estimated by 2-digit SIC industry and year with at least 20 available observations.[19] Correspondingly, we estimated an augmented version of Eq 2.3 with capacity overhang (OH):

$$\mathrm{TOTINV}_{\mathrm{it+1}} = \beta_0 + \beta_1 \mathrm{Q}_{\mathrm{it}} + \beta_2 \mathrm{CFO}_{\mathrm{it+1}} + \beta_3 \mathrm{OH}_{\mathrm{it}} + \epsilon'_{\mathrm{it+1}}. \tag{2.4}$$

Second, we consider a model used by McNichols and Stubben (2008):[20]

$$\mathrm{TOTINV}_{\mathrm{it+1}} = \beta_0 + \beta_1 \mathrm{Q}_{\mathrm{it}} + \beta_2 \mathrm{CFO}_{\mathrm{it+1}} + \beta_3 \Delta \mathrm{AT}_{\mathrm{it}} + \beta_4 \mathrm{TOTINV}_{\mathrm{it}} + \epsilon_{\mathrm{it+1}}. \tag{2.5}$$

Eq 2.5 has two additional variables to Eq 2.3: growth in total assets, and concurrent investment. The former serves to accounting for potential measurement errors in Tobin's q and firms' growth options; the latter captures a firm-specific component to investment decisions (McNichols and Stubben, 2008). Correspondingly, we estimated an augmented version of Eq 2.5 with capacity overhang (OH):

$$\begin{aligned} &\mathrm{TOTINV}_{\mathrm{it+1}} \\ &= \beta_0 + \beta_1 \mathrm{Q}_{\mathrm{it}} + \beta_2 \mathrm{CFO}_{\mathrm{it+1}} + \beta_3 \Delta \mathrm{AT}_{\mathrm{it}} + \beta_4 \mathrm{TOTINV}_{\mathrm{it}} + \beta_5 \mathrm{OH}_{\mathrm{it}} + \epsilon'_{\mathrm{it+1}}. \end{aligned} \tag{2.6}$$

For each pair of models, we calculate the percentage of firm-years with: (1) $\hat{\epsilon}$ and $\hat{\epsilon}'$ with different signs; (2) $\hat{\epsilon}$ and $\hat{\epsilon}'$ in different quartiles; (3) $\hat{\epsilon}$ ($\hat{\epsilon}'$) in either of two extreme quartiels but $\hat{\epsilon}'$ ($\hat{\epsilon}$) not so; (4) $|\hat{\epsilon}|$ and $|\hat{\epsilon}'|$ in different quartiles; (5) $|\hat{\epsilon}|$ ($|\hat{\epsilon}'|$) in either of

[18] Our results are even stronger when we use other investment variables.

[19] This treatment implicitly assumes that the coefficients for variables in the model are constant within industry-year. This approach to accounting for industry-wide heterogeneity is standard in corporate finance and accounting literature.

[20] Choi et al. (2020) and Goodman et al. (2014) and a number of other studies also employ this model.

two extreme quartiles but $|\hat{\epsilon}'|$ ($|\hat{\epsilon}|$) not so. $|\cdot|$ denotes absolute value.

2.4.4 Accruals models augmented with capacity overhang

Similar to optimal investment models, accruals models assume that firms' normal accruals, i.e. non-discretionary accruals, are determined by economic forces, whereas the abnormal accruals, i.e. discretionary accruals, are subject to managers' manipulation. To examine the potential bias in the estimated discretionary accruals resulting from neglecting capacity overhang, we compare the residuals from the original models and the augmented models with capacity overhang along the lines of Section 2.4.3.

First, we consider the Performance-adjusted Modified Jones Model, which is initially developed by Jones (1991) and modified by Dechow et al. (1995) and Kothari et al. (2005). This model is widely-used the literature of (detecting) earnings management. Specifically, we estimated the following model by 2-digit SIC industry and year with at least 20 observations:[21]

$$\begin{aligned} &\mathrm{OPACC_{it+1}} \\ &= \beta_0 + \beta_1 1/\mathrm{AT_{it}} + \beta_2 \Delta(\mathrm{SALE} - \mathrm{AR})_{\mathrm{it+1}} + \beta_3 \mathrm{PPE_{it+1}} + \beta_4 \mathrm{ROA_{it+1}} \\ &+ \epsilon_{\mathrm{it+1}}, \end{aligned} \tag{2.7}$$

where OPACC is operating accruals; 1/AT is inverse total assets; SALE is sales divided by lagged total assets; AR is account receivables (Compustat item: RECT) scaled by lagged total assets; PPE is gross property, plant, and equipment (Compustat item: PPEGT) divided by lagged total assets; ROA is return on assets. We use operating accruals as the dependent variable out of the following two considerations. First, financial accruals are highly reliable as they are specified in legal contracts or traded on transparent secondary markets (**?**). As a result, the possibility of managing financial accruals is low. Second, in contrast to operating accruals, financial accruals are negatively related to investment intensity. The reason is that firms sometimes use debt to finance investment in operating assets, leading more negative financial accruals, which is resulted from higher financial liability accruals.

Correspondingly, we estimate an augmented version of Eq 2.7 with capacity overhang

[21] Bartov et al. (2000) show that the Cross-sectional Modified Jones Model outperforms its time-series counterpart in terms of detecting earnings management.

(OH):

$$\begin{aligned}&\mathrm{OPACC}_{\mathrm{it+1}}\\&=\beta_0+\beta_1 1/\mathrm{AT}_{\mathrm{it}}+\beta_2\Delta(\mathrm{SALE}-\mathrm{AR})_{\mathrm{it+1}}+\beta_3\mathrm{PPE}_{\mathrm{it+1}}+\beta_4\mathrm{ROA}_{\mathrm{it+1}}+\beta_5\mathrm{OH}_{\mathrm{it}}\\&+\epsilon'_{\mathrm{it+1}}.\end{aligned}\tag{2.8}$$

Next, following Arif et al. (2016), we take an investment approach to modeling accruals. Specifically, we estimate the following regression model by 2-digit SIC industry and year with at least 20 observations:

$$\begin{aligned}&\mathrm{OPACC}_{\mathrm{it+1}}\\&=\beta_0+\beta_1\mathrm{LN\_AT}_{\mathrm{it}}+\beta_2\mathrm{Q}_{\mathrm{it}}+\beta_3\mathrm{ROA}_{\mathrm{it}}+\beta_4\mathrm{LEV}_{\mathrm{it}}+\beta_5\mathrm{VOL}_{\mathrm{it+1}}+\epsilon_{\mathrm{it+1}}.\end{aligned}\tag{2.9}$$

We then estimate an augmented version of Eq 2.9 with capacity overhang (OH):

$$\begin{aligned}&\mathrm{OPACC}_{\mathrm{it+1}}\\&=\beta_0+\beta_1\mathrm{LN\_AT}_{\mathrm{it}}+\beta_2\mathrm{Q}_{\mathrm{it}}+\beta_3\mathrm{ROA}_{\mathrm{it}}+\beta_4\mathrm{LEV}_{\mathrm{it}}+\beta_5\mathrm{VOL}_{\mathrm{it+1}}+\mathrm{OH}_{\mathrm{it}}+\epsilon'_{\mathrm{it+1}}.\end{aligned}\tag{2.10}$$

All variables have been defined in previous sections. Unlike the Performance-adjusted Jones Model, this investment-based accruals model does not rely on information in year t+1 if we replace the realized volatility with alternative measures of expected volatility such as historical standard deviation of stock returns or volatility derived from the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. This feature allows investors to calculate discretionary accruals in real time.

2.5 Sample and descriptive statistics

2.5.1 Sample selection

The financial statement data are from Compustat. The stock returns data are from CRSP. The capacity overhang estimate is downloaded from Kevin Aretz's website.[22] Tab 2.1 summarizes our sample selection procedures. We begin with all firm-year observations in the CRSP/Compustat Merged annual file from the period 1970–2018. We delete financial firms (SIC $\geq$ 4900 & SIC $\leq$ 4949) and utilities (SIC $\geq$ 6000 & SIC $\leq$ 6999). We

[22] https://www.kevin-aretz.com/data.

only keep firms whose stocks are traded at NYSE (EXCHG = 11), NASDAQ (EXCHG = 12), or AMEX (EXCHG = 14). To be included in the sample, a firm-year must have non-missing year-end stock prices (PRCC_F), common shares outstanding (CSHO), income before extraordinary items (IB), common equity (CEQ), total assets (AT), capital expenditures (CAPX), current assets (ACT), and gross property, plant, and equipment (PPEGT). Other missing variables are treated as zero. We further delete firm-years with non-positive book common equity, with missing year-end capacity overhang estimate (OH), with missing year-ahead investment or accruals variables, or with missing other control variables. Finally, we eliminate firms with less than two years of data. The final sample contains 81,036 firm-year observations from the period 1971–2017 because we use lagged and 1-year-ahead variables to construct variables used in the tests. To mitigate the impact of outliers, we winsorize all variables at the 1st and the 99th percentile for each cross section.

2.5.2 Descriptive statistics

Tab 2.2 presents the summary statistics for the main variables. Firms in the sample have sizable investment rates. The mean (median) of investment in PPE and intangibles is 0.170 (0.075). Mean (median) investment in PPE is 0.138 (0.083), slightly lower than that of CAPX, capital expenditures (mean = 0.161, median = 0.111), indicating that firms engage in divestitures. As a result, capital expenditures may not accurately capture growth in physical capital. Total investment is the largest in terms of mean and median among the four investment variables, with a mean (median) of 0.207 (0.163), suggesting that a substantial portion of firms' investment is off-balance sheet.

The mean (median) of comprehensive accruals (COMPACC) is 0.041 (0.031), while the means (medians) of operating accruals (OPACC) and financial accruals (FINACC) are 0.068 (0.033) and -0.027 (0.000), respectively, indicating that comprehensive accruals are mainly driven by operating accruals. Within operating accruals, long-term operating accruals (LTACC) dominate working capital accruals (WCACC) in terms of magnitude. The mean (median) of OPACC is 0.068 (0.033), while the means (medians) of LTACC and WCACC are 0.059 (0.017) and 0.016 (0.008), respectively. [23] Moreover, LTACC also has the largest standard deviation among all accrual components, reflecting the importance

[23] By construction, COMPACC = OPACC + FINACC and OPACC = WCACC + LTACC. The slight violation of the equality is due to winsorization. Our main results still hold without winsorization.

of long-term capital investments in determining total operating accruals. Operating asset accruals are larger than operating liability accruals, implying that operating accruals are mainly determined by asset accruals. In contrast, financial liability accruals are much larger that financial asset accruals. The above findings are consistent with Larson et al. (2018).

The mean of capacity overhang (OH) is 0.499, indicating that the average difference between the installed capacity and the optimal capacity is 50%. The average Tobin's q (Q) is 1.796, consistent with the positive average investment rates in the sample. The distributions of other control variables are consistent with prior studies in general.

Tab 2.3 reports Pearson and Spearman correlation coefficients of capacity overhang (OH) with year-ahead investment, year-ahead accruals, and firm characteristics, in the pooled sample. Capacity overhang is significantly negatively correlated with all four year-ahead investment variables, consistent with the negative investment-capacity overhang relationship. The negative association is the strongest for capital expenditure (CAPX). Additionally, capacity overhang is significantly negatively correlated with comprehensive accruals (COPMACC), operating accruals (OPACC), working capital accruals (WCACC), and long-term operating accruals (LTACC), whereas capacity overhang is positively correlated with financial accruals (FINACC). This finding is consistent with the negative accruals-capacity overhang relationship. The positive correlation between financial accruals and capacity overhang stems from the positive correlation between financial liability accruals and capacity overhang—high-capacity overhang firms invest less, so they need less external funds to finance their investment. Capacity overhang is also correlated with other firm characteristics. High-capacity overhang firms are larger, lower in Tobin's q, lower in profitability, lower in current demand, lower in year-ahead demand changes, lower in year-ahead operating cash flow, lower in leverage, and higher in volatility. Capacity overhang is positively correlated with interest rate.

Interestingly, capacity overhang is positively correlated with Q, whereas they predict investment in opposite directions. This finding indicates that capacity overhang and Tobin's q capture firms' investment behaviors from distinct perspectives.[24]

[24] We propose a potential explanation for the positive correlation between Tobin's q and capacity overhang. Firms of higher capacity overhang have worsening demand. As a consequence, the numerator of Tobin's q, the market prices of equity and liabilities of these firms drop. However, according to accounting conservatism, these firms might have written down the book value of PPE and intangibles through impairments, leading to a lower denominator. Recall that the capacity proxy in the capacity

2.6 Empirical results

2.6.1 Investment-capacity overhang relationship (H1)

Univariate analysis

Before delving into regression analyses, we first conduct several univariate analyses. Tab 2.4 shows year-ahead investment, year-ahead accruals, and firm characteristics, conditional on year-end capacity overhang (OH). Specifically, we sort firm-year observations into low-, medium-, and high-capacity overhang groups based on the 30th and 70th percentiles. Note that at this stage, we do not sort firms at each cross-section to take into account the variation in the time series. Consistent with Tab 2.3, both the mean and median of investment and accruals (excluding financial accruals) are decreasing across the low-, medium-, and high-capacity overhang groups.

Fig 2.1 shows the average investment rates of low- and high-capacity overhang firms over the prior and subsequent 5 years relatively to the year when the portfolios are sorted. Low- (high-) capacity overhang firms are defined as firms with a capacity overhang estimate below the 20th percentile (above the 80th percentile) at the end of year t. Through year t-5 to year t-1, high-capacity overhang firms' investment is higher than that of low-capacity overhang firms. This tendency reverses from year t and maintains until year t+5 and onward. This pattern is consistent with the notion that high-capacity overhang firms are "fallen angels" who have experienced good times and built excess capacity in the past but their fundamentals are starting to deteriorate recently (Aretz and Pope, 2018; Chan and Chen, 1991).

Regression analysis

Tab 2.5 shows the regression results for Eq 2.1[25]. In columns (1)–(4), the coefficients for capacity overhang are significantly negative, the t-statistics ranging from -8.84 to

overhang estimate is gross PPE and intangibles, only reflecting the purchase costs of these assets. The fall in the denominator outweighing the fall in the numerator forms the positive association between q and capacity overhang. This observation gives rise to a potential improvement about measuring Tobin's q by using gross total book assets instead of net total book assets. We leave this issue for future research.

[25]We do not report the results for pooled regressions because the regressions of investment-q and investment-cash flow sensitivities are typically run with firm and year fixed effects to absorb unobservable time-invariant firm characteristics and year trends (Wang and Zhang, 2021). Nevertheless, we conduct Fama and MacBeth (1973) regressions to confirm the effects of capacity overhang on investment in the cross section.

-17.30, after controlling for other firm characteristics and clustering standard errors at the firm level, showing that capacity overhang is negatively associated with firms' future investment, incrementally to investment determinants documented by prior studies.[26] Importantly, the magnitudes of t-statistics for the estimated coefficients for capacity overhang are as large as those for Tobin's q. When investment in PPE and intangibles (ΔPPEINT) or total investment (TOTINV) being the dependent variable, capacity overhang is even better able to predict investment than Tobin's q.

In addition to capacity overhang and q, firms' future investment is negatively associated with firms' size, leverage, and interest rate, while future investment is positively associated with year-ahead cash flow. Inconsistent with Eisdorfer (2008) and Arif et al. (2016), except for total investment, other investment variables are not significantly associated with volatility. Untabulated analysis shows that the potentially negative association between investment and volatility is absorbed by *market leverage*.[27]

The above regressions include firm and year fixed effects, so the interpretation of the estimated coefficients is within-firm. To examine the ability of capacity overhang to predict investment in the cross-section, we run Fama and MacBeth (1973) regressions of year-ahead investment on capacity overhang and firm characteristics. Specifically, we run Eq 2.1 without firm and year fixed effects and interest rate for each cross-section. Panel A of Tab 2.6 shows the average estimated coefficients and the autocorrelation-adjusted t-statistics using the Newey and West (1987) method with the maximum lag of 10 years. The average coefficients for capacity overhang are significantly negative throughout columns (1)–(4).

Panel B shows the number of years in which the estimated coefficients are positive. Over the 47 years, capacity overhang positively predicts investment in PPE and intangibles (ΔPPEINT), investment in PPE (ΔPPE), total investment (TOTINV), and capital expenditures (CAPX) only in 5, 14, 1, and 13 years, respectively. In the cross section, the negative associations of capacity overhang with ΔPPEINT and TOTINV are the strongest.

The above findings show that capacity overhang negatively predicts firms' investment

[26]As a robustness check, we use two-way clustered standard errors at the firm and year level for all panel regressions. Our results are unchanged.

[27]Eisdorfer (2008) and Arif et al. (2016) use book leverage in their regression analyses. Investigating the interplay between investment, leverage, and volatility is beyond the scope of this paper. We leave this for future research.

incrementally to other firm characteristics documented by the existing literature. The predictive ability of capacity overhang is valid both in the time-series and in the cross-section.

2.6.2 Capacity overhang and the investment-cash flow sensitivity (H2)

Tab 2.5 and Tab 2.6 support the existence of the well-documented positive investment-cash flow relationship. The coefficient for year-ahead operating cash flow is significantly positive for each model specification. However, capacity overhang is negatively associated with this investment-cash flow sensitivity. The coefficient for the interaction between capacity overhang and year-ahead operating cash flow is significantly negative in the panel data for each model specification (Tab 2.5) and in the cross section (Tab 2.6). Hence, H2 is rejected by data.

This finding shows that the investment behaviors of high-capacity overhang firms are less sensitive to their financial situations because facing the same investment opportunity, high-capacity overhang firms can reactivate unused installed capacity before building up new productive capacity. Prior studies (e.g. Almeida and Campello, 2007; Beatty et al., 2009; Biddle and Hilary, 2006) use investment-cash flow sensitivity as a measure of investment inefficiency. One underlying assumption for their analyses is that Tobin's q is a sufficient statistic for firms' investment if the financial market is frictionless.[28] Our findings show that the investment-cash flow sensitivity may not fully capture firms' investment inefficiency in that the investment-cash flow sensitivity is a function of capacity overhang.

2.6.3 Accruals-capacity overhang relationship (H3)

Univariate analysis

Tab 2.4 shows year-ahead accruals conditional on capacity overhang. In general, the mean and median of accruals, asset accruals, and liability accruals are monotonically decreasing across low-, medium-, and high-capacity overhang groups, except for financial accruals (FINACC).[29] The reason is that financial accruals are mainly determined by

[28] Investment-cash flow sensitivity as a measure of financial constraints is actually controversial (e.g. Chen and Chen, 2012; Kaplan and Zingales, 1997).

[29] The mean of long-term operating accruals (LTACC) for the medium-capacity overhang group is larger than that for the low-capacity overhang group.

financial liability accruals while financial liability accruals are generated during financing operations and investment. High-capacity overhang firms invest less, so they have less financial liability accruals, leading to higher financial accruals.

Fig 2.2 shows the average accruals of low- and high-capacity overhang firms over the prior and subsequent 5 years relative to the year when the portfolios are sorted. Low- (high-) capacity overhang firms are defined as firms with a capacity overhang estimate below the 20th percentile (above the 80th percentile) at the end of year t. Panel (a) shows that similar to investment, high-capacity overhang firms' comprehensive accruals (COMPACC) are higher than those of low-capacity overhang firms through year t-5 to year t-2, but the relation reverses in year t-1 and maintains until year t+5 and onward. Operating accruals (OPACC, panel [b]) and long-term operating accruals (LTACC, panel [e]) show similar patterns. Unlike long-term operating accruals, working capital accruals (WCACC, penal [d]) of high-capacity overhang firms are lower than those of low-capacity overhang firms through year t-5 to year t+5, and in year t, high-capacity overhang firms have negative working capital accruals. Financial accruals (FINACC, panel [c]) are negative through year t-5 to year t+5 and show patterns opposite to operating accruals, consistent with the view that financial (liability) accruals are generated during financing operations and investment.

Regression analysis

Tab 2.7 shows the regression results for Eq 2.2. Columns (1)–(3) and (6) show that capacity overhang (OH) negatively predicts comprehensive accruals (COMPACC), operating accruals (OPACC), and long-term operating accruals (LTACC) while positively predicts financial accruals (FINACC). In addition to capacity overhang, firms' future non-financial accruals are negatively associated with firms' size, volatility, and interest rate while are positively associated with Tobin's q (Q). The above findings support the role played by accruals to reflect firms' growth in the scale of business operations. Interestingly, unlike regressions of investment where the effect of volatility (VOL) is absorbed by market leverage (LEV), volatility is negatively associated with non-financial accruals. Leverage is negatively related to operating accruals, working capital accruals (WCACC), and long-term operating accruals, while leverage is positively related to financial accruals. The opposite effects of leverage on operating accruals and financial accruals neutralize the effect of leverage on comprehensive accruals.

Column (4) shows that when expected demand, measured by return on asset (ROA), is not controlled for, capacity overhang is significantly negatively related to working capital accruals.[30] This result is consistent with the argument that high-capacity overhang firms have been experiencing worsening demand. However, column (5) shows that after controlling for expected demand, the association between capacity overhang and working capital accruals is no longer significantly different from zero. The reason is that investment in working capital assets such as inventories is less irreversible than other operating accruals like long-term operating accruals. Additionally, working capital accruals are only loosely related to firms' investment in long-lived capital.

In Tab 2.8, we run Fama and MacBeth (1973) regressions of accruals on capacity overhang and control variables. The average estimated coefficients for capacity overhang are significantly negative across all components of operating accruals, but the relationship is positive for financial accruals. The findings in the cross-sectional analysis are consistent with the negative accruals-capacity overhang relationship.

2.6.4 Asset accruals versus liability accruals (H4)

Tab 2.9 shows the results for panel regressions of asset accruals versus liability accruals on capacity overhang and control variables (Eq 2.2). For comprehensive accruals (COMPACC), operating accruals (OPACC), and long-term operating accruals (LTACC), the coefficients for capacity overhang for their asset components are more negative than the related liability components. The F-tests reject the equality of the coefficients for capacity overhang between asset components and liability components at 0.001 level. In contrast, capacity overhang has first-order effects on financial liability accruals (FINACC). The coefficients for capacity overhang for working capital asset accruals (WCACC_A) and working capital liability accruals (WCACC_L) are not significantly indifferent (F-statistic = 0.24, p-value = 0.622).

The above results support our hypothesis that capacity overhang has stronger effects on the asset (liability) components of non-financial (financial) accruals.

[30] We implicitly assume a random-walk evolution of demand. Our results are robust to alternative expected demand measures such as sales and analysts' sales forecasts.

2.6.5 Controlling for realized demand shock

Note that we control for current-period profitability (ROA) to capture firms' expected demand. This treatment is based on the assumption that the evolution of demand follows a random walk. We acknowledge that this assumption may not hold at least for some firms. Nevertheless, using analysts' sales forecasts may not fully resolve this issue. For example, analysts' sales forecasts may be biased under the asymmetric information between managers and financial analysts. In addition, using analysts' estimates reduces the our sample size aggressively. Controlling for realized stock returns may not perfectly fix the problem either. As stock prices are forward-looking, stock returns not only capture short-term demand but also capture long-term demand. Moreover, stock returns reflect risks or investor sentiment, too. Therefore, to mitigate the concern that current-period ROA is unable to fully capture firms' expected demand, we control for realized demand shock, measured as changes in realized sales scaled by beginning total assets (ΔSALE). Tab 2.10 shows that our findings are robust to controlling for realized demand shock.

2.6.6 Augmenting optimal investment models with capacity overhang

Tab 2.11 compares the optimal investment models with and without capacity overhang as an investment determinant (Eq 2.3–2.6). In panel A, we consider the simplest investment model used by Fazzari et al. (1988) and others (e.g. McNichols and Stubben, 2008) as a baseline model.

The average estimated coefficient for capacity overhang (OH) is significantly negative. After including capacity overhang, the average adjusted-R^2 increases from 0.137 to 0.152. We find that 5.65% of the residuals from the two models have different signs, suggesting that these firms may be misclassified as over- or under- investing firms. We then sort the residuals into quartiles at each cross-section. We find that 14.62% of firms' residuals fall into different quartiles under different models. Some studies classify firms as over- (under-) investing firms if their signed residuals are in the top (bottom) quartile. We find that 10.31% (7.51%) of firms may be misclassified as under- (over-) investing firms if capacity overhang is ignored in estimating optimal investment. In the context of investment efficiency, a number of studies focus on the absolute value of residuals (e.g. Choi et al., 2020). We sort absolute residuals into quartiles for each cross-section. We find that

21.23% of firms' absolute residuals are sorted into different quartiles under different models. Moreover, 20.01% (9.14%) of firms may be misclassified as efficiently (inefficiently) investing firms if capacity overhang is ignored in estimating optimal investment.

Panel B of Tab 2.11 shows the same contents as panel A but focuses on the optimal investment model used by McNichols and Stubben (2008). McNichols and Stubben (2008) augment Fazzari et al. (1988)'s model with changes in total assets (ΔAT) and concurrent investment rate (TOTINV). The average estimated coefficient for capacity overhang is significantly negative. After including capacity overhang, the adjusted-R^2 increases from 0.262 to 0.273.

We find that under the two models, 5.96% of the residuals have different signs and 14.50% (21.2%) of firms' (absolute) residuals are sorted into different quartiles. Moreover, 9.64% (7.83%) of firms might be misclassified as under- (over-) investing firms if capacity overhang is ignored. Regarding investment efficiency, 20.70% (8.72%) of firms might be misclassified as engaging in efficient (inefficient) investment if capacity overhang is ignored in estimating optimal investment.

Although McNichols and Stubben (2008)'s model outperforms the model of Fazzari et al. (1988) by partially capturing the effects of capacity overhang on firms' investment, neglecting capacity overhang from their model may still lead to substantial bias.

2.6.7 Augmenting accrual models with capacity overhang

Tab 2.12 compares the accruals models with and without capacity overhang as a determinant of accruals. Panel A shows the analysis of the Performance-adjusted Modified Jones Model (Eq 2.7–2.8).

The average estimated coefficient for capacity overhang is significantly negative, consistent with our findings in Section 2.6.3. After including capacity overhang, the average adjusted-R^2 increases from 0.262 to 0.276. We find that 5.55% of firms' abnormal accruals have different signs under the two models. We then sort the (absolute) abnormal accruals into quartiles for each cross-section and find that 13.62% (20.62%) of firms' (absolute) abnormal accruals fall into different quartiles under different models. Additionally, we find that 9.31% (7.66%) of firms may be misidentified as firms with abnormally low (high) operating accruals if capacity overhang is ignored in estimating discretionary accruals. In addition, 19.39% (9.20%) of firms may be misidentified as firms with moderate (extreme) unsigned abnormal accruals if capacity overhang is neglected in estimating discretionary accruals.

Panel B shows the analysis of an investment-based accruals model proposed by Arif et al. (2016) (Eq 2.9–2.10). Under this investment framework, the estimated discretionary accruals may be substantially biased too, if capacity overhang is ignored.

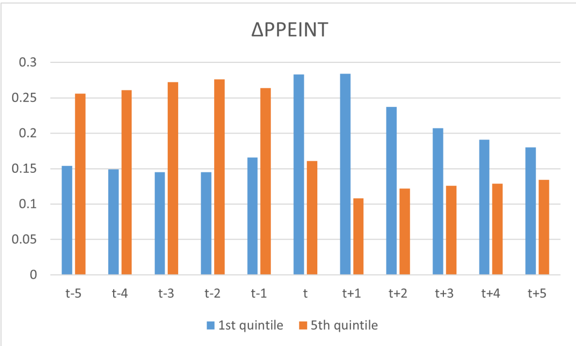
The above findings show that as capacity overhang captures firms' investment behaviors and accruals at least partially reflect the firms' deliberate investment choices, ignoring capacity overhang from the estimation of discretionary accruals may confound firms' opportunistic behaviors with their rational behaviors determined by economic forces.

2.7 Conclusion

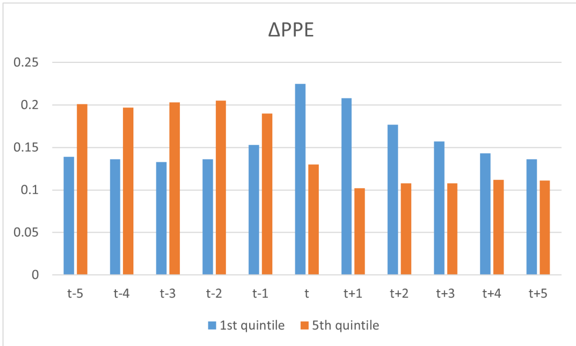
Featuring costly-to-reverse investment, the real options-based investment models suggest that firms' optimal productive capacity can often be lower than installed capacity. We hypothesize that the difference between a firm's installed capacity and its optimal capacity, i.e. capacity overhang, is negatively related to firms' future investment, after controlling for other investment determinants. We test our hypothesis using a firm-level capacity overhang measure estimated by Aretz and Pope (2018). We find that capacity overhang robustly predicts investment in a negative way. The negative association is robust to alternative definitions of investment and exists both in the panel data and in the cross section. Additionally, we document a negative association between capacity overhang and investment-cash flow sensitivity.

Consistent with the view that accruals at least partially reflect firms' deliberate investment choices, capacity overhang is negatively (positively) related to operating (financial) accruals. The negative relationship is stronger for long-term operating accruals than for working capital accruals, since working capital accruals are less irreversible and are less related with firms' investment in long-lived capital. Furthermore, capacity overhang is more (less) negatively associated with operating (financial) asset accruals than with operating (financial) liability accruals. The above findings support the investment approach to modeling accruals. Finally, we examine the potential impact of failure to account for capacity overhang in estimating optimal investment or discretionary accruals. We find that failure to account for capacity overhang in estimating these variables may lead to substantial bias.

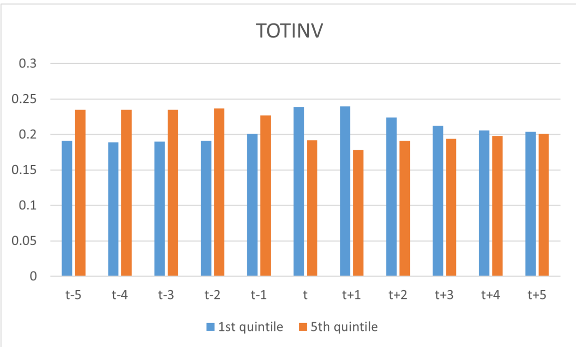
2.8 Figures



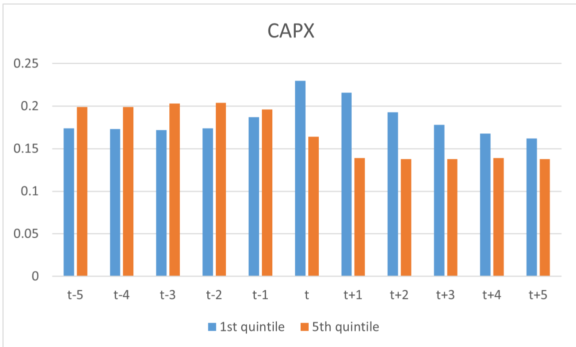
(A)



(B)

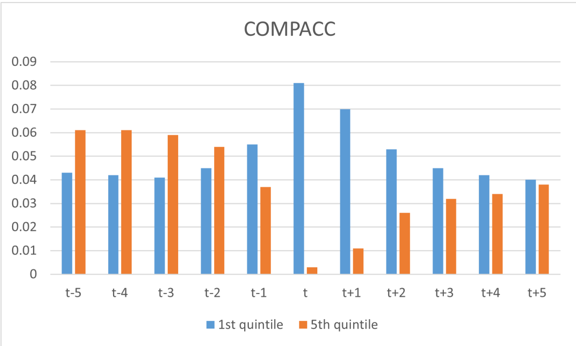


(C)

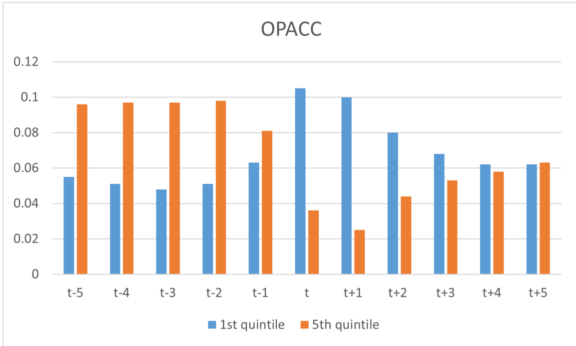


(D)

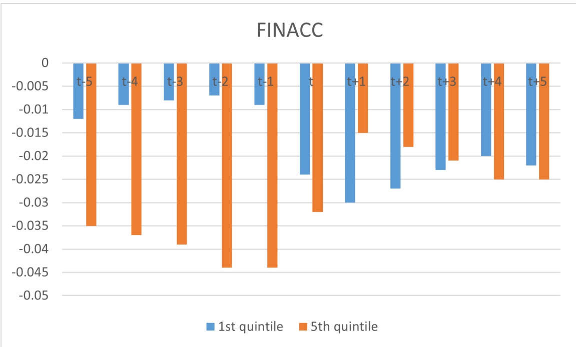
Figure 2.1: Panels (a)–(d) of this figure plot annual changes in PPE plus intangibles, annual changes in PPE, annual total investment, and annual CAPX, over the prior and post 5 fiscal years relative to portfolio sorting year (t), for low- and high-capacity overhang firms, respectively. High- (low-) capacity overhang firms are defined as firms with a capacity overhang value above the 4th quintile (below the 1st quintile) at the end of fiscal year t.



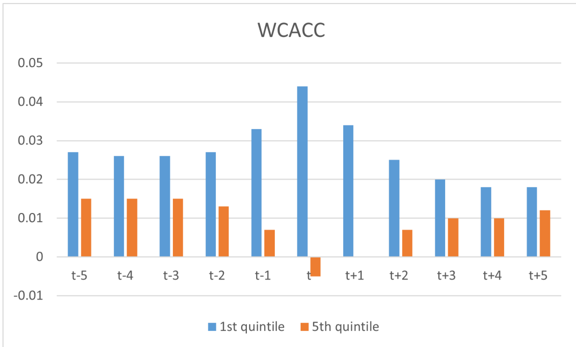
(A)



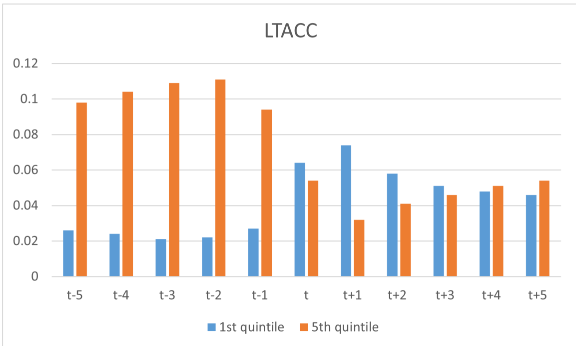
(B)



(C)



(D)



(E)

Figure 2.2: Panels (a)–(e) of this figure plot annual comprehensive accruals, operating accruals, financial accruals, working capital accruals, and long-term operating accruals, over the prior and post 5 fiscal years relative to portfolio sorting year (t), for low- and high-capacity overhang firms, respectively. High- (low-) capacity overhang firms are defined as firms with a capacity overhang value above the 4th quintile (below the 1st quintile) at the end of fiscal year t.

2.9 Tables

Table 2.1: Sample selection.

	Reduction	N.Obs
Compustat firm-years from the period 1970-2018		280,725
(Financial and utility firms: SIC $\geq$ 4900 & SIC $\leq$ 4949 or SIC $\geq$ 6000 & SIC $\leq$ 6999)	(75,067)	205,658
(Non-NYSE, NASDAQ, or AMEX listed firm-years: EXCHG $\neq$ 11, 12, or 14)	(64,059)	141,599
(Firm-years with missing year-end stock price, PRCC_F, Common Shares Outstanding, CSHO, Income Before Extraordinary Items, IB, Common Equity, CEQ, Total Assets, AT, Capital Expenditures, CAPX, Current Assets, ACT, or Gross Property, Plant and Equipment, PPEGT)	(1,367)	140,232
(Firm-years with non-positive Common Equity, CEQ)	(3,977)	136,255
(Firm-years with missing year-end OH)	(44,626)	91,629
(Firm-years with missing year-ahead investment variables)	(7,176)	84,453
(Firm-years with missing year-ahead accruals variables)	(1,418)	83,035
(Firm-years with missing other variables)	(1,370)	81,665
(Firms with less than two years of data)	(629)	81,036

Table 2.1: This table shows the selection procedure to construct the main sample.

Table 2.2: Descriptive statistics.

	N	Mean	Sd	Q1	Median	Q3
Investment variables						
ΔPPEINT	81,036	0.170	0.490	0.012	0.075	0.186
ΔPPE	81,036	0.138	0.280	0.025	0.083	0.180
TOTINV	81,036	0.207	0.224	0.089	0.163	0.268
CAPX	81,036	0.161	0.181	0.065	0.111	0.188
Accrual variables						
COMPACC	81,036	0.041	0.149	–0.020	0.031	0.087
COMPACC_A	81,036	0.105	0.261	–0.018	0.057	0.162
COMPACC_L	81,036	0.064	0.192	–0.024	0.025	0.098
OPACC	81,036	0.068	0.206	–0.026	0.033	0.116
OPACC_A	81,036	0.101	0.253	–0.018	0.054	0.156
OPACC_L	81,036	0.033	0.085	–0.008	0.020	0.057
FINACC	81,036	–0.027	0.144	–0.049	0.000	0.028
FINACC_A	81,036	0.003	0.036	0.000	0.000	0.000
FINACC_L	81,036	0.030	0.141	–0.020	0.000	0.045
WCACC	81,036	0.016	0.082	–0.021	0.008	0.046
WCACC_A	81,036	0.041	0.109	–0.009	0.022	0.074
WCACC_L	81,036	0.025	0.069	–0.008	0.014	0.046
LTACC	81,036	0.059	0.346	–0.015	0.017	0.072
LTACC_A	81,036	0.067	0.365	–0.012	0.020	0.078
LTACC_L	81,036	0.009	0.056	–0.002	0.002	0.012
Firm characteristics						
OH	81,036	0.499	0.289	0.315	0.470	0.615
LN_AT	81,036	5.516	2.010	4.031	5.347	6.883
Q	81,036	1.796	1.418	1.006	1.352	2.022
ROA	81,036	0.085	0.163	0.037	0.099	0.163
SALE	81,036	1.418	0.936	0.797	1.251	1.799
ΔSALE	81,036	0.136	0.295	–0.002	0.090	0.232
CFO	81,036	0.079	0.150	0.050	0.098	0.147
LEV	81,036	0.353	0.222	0.166	0.324	0.515
VOL	81,036	0.032	0.018	0.020	0.027	0.038
Macroeconomic Variables						
R^f	81,036	0.522	0.244	0.303	0.567	0.785

Table 2.2: This table shows descriptive statistics for variables used in the main tests. The sample period is 1971–2017. All variables are winsorized at the 1st and the 99th percentile for each cross section. Variables are defined in the text.

Table 2.3: Correlation coefficients between capacity overhang and other variables.

	Pearson	p-value	Spearman	p-value
Year-ahead investment variables				
$\Delta \mathrm{PPEINT}_{t+1}$	–0.057	0.000	–0.226	0.000
$\Delta \mathrm{PPE}_{t+1}$	–0.083	0.000	–0.189	0.000
TOTINV_{t+1}	–0.028	0.000	–0.113	0.000
CAPX_{t+1}	–0.103	0.000	–0.241	0.000
Year-ahead accrual variables				
$\mathrm{COMPACC}_{t+1}$	–0.124	0.000	–0.182	0.000
$\mathrm{COMPACC\_A}_{t+1}$	–0.119	0.000	–0.240	0.000
$\mathrm{COMPACC\_L}_{t+1}$	–0.062	0.000	–0.156	0.000
OPACC_{t+1}	–0.110	0.000	–0.206	0.000
$\mathrm{OPACC\_A}_{t+1}$	–0.119	0.000	–0.239	0.000
$\mathrm{OPACC\_L}_{t+1}$	–0.086	0.000	–0.149	0.000
FINACC_{t+1}	0.027	0.000	0.074	0.000
$\mathrm{FINACC\_A}_{t+1}$	–0.029	0.000	–0.057	0.000
$\mathrm{FINACC\_L}_{t+1}$	–0.035	0.000	–0.096	0.000
WCACC_{t+1}	–0.144	0.000	–0.174	0.000
$\mathrm{WCACC\_A}_{t+1}$	–0.173	0.000	–0.238	0.000
$\mathrm{WCACC\_L}_{t+1}$	–0.100	0.000	–0.145	0.000
LTACC_{t+1}	–0.024	0.000	–0.184	0.000
$\mathrm{LTACC\_A}_{t+1}$	–0.022	0.000	–0.202	0.000
$\mathrm{LTACC\_L}_{t+1}$	0.002	0.605	–0.090	0.000
Firm characteristics				
LN_AT	0.119	0.000	0.209	0.000
Q	0.103	0.000	0.147	0.000
ROA	0.524	0.000	0.485	0.000
SALE	–0.481	0.000	–0.577	0.000
$\Delta \mathrm{SALE}_{t+1}$	–0.189	0.000	–0.264	0.000
CFO_{t+1}	–0.400	0.000	–0.316	0.000
LEV	–0.103	0.000	–0.106	0.000
VOL	0.267	0.000	0.192	0.000
Macroeconomic variables				
R^{f}_{t+1}	0.528	0.000	0.572	0.000

Table 2.3: This table shows Pearson and Spearman correlation coefficients between OH and investment variables, accruals variables, and firm characteristics. The sample period is 1971–2017. All variables are winsorized at the 1st and the 99th percentile for each cross-section. Variables are defined in the text.

Table 2.4: Mean and median of variables conditional on capacity overhang.

Capacity overhang	*Low*		*Medium*		*High*	
	Mean	Median	Mean	Median	Mean	Median
Year-ahead investment variables						
$\Delta PPEINT_{t+1}$	0.211	0.107	0.177	0.076	0.121	0.037
ΔPPE_{t+1}	0.181	0.111	0.132	0.083	0.104	0.057
$TOTINV_{t+1}$	0.211	0.173	0.216	0.171	0.191	0.137
$CAPX_{t+1}$	0.200	0.141	0.151	0.108	0.135	0.087
Year-ahead accrual variables						
$COMPACC_{t+1}$	0.059	0.044	0.048	0.034	0.015	0.010
$COMPACC\_A_{t+1}$	0.136	0.097	0.116	0.060	0.060	0.013
$COMPACC\_L_{t+1}$	0.077	0.045	0.068	0.025	0.046	0.008
$OPACC_{t+1}$	0.089	0.059	0.078	0.036	0.035	0.004
$OPACC\_A_{t+1}$	0.131	0.093	0.112	0.057	0.058	0.012
$OPACC\_L_{t+1}$	0.042	0.031	0.034	0.021	0.023	0.011
$FINACC_{t+1}$	–0.030	–0.001	–0.030	0.000	–0.020	0.000
$FINACC\_A_{t+1}$	0.004	0.000	0.003	0.000	0.002	0.000
$FINACC\_L_{t+1}$	0.034	0.000	0.033	0.000	0.022	0.000
$WCACC_{t+1}$	0.033	0.022	0.015	0.009	0.000	0.000
$WCACC\_A_{t+1}$	0.068	0.047	0.040	0.024	0.015	0.006
$WCACC\_L_{t+1}$	0.035	0.024	0.025	0.015	0.016	0.007
$LTACC_{t+1}$	0.058	0.026	0.070	0.020	0.044	0.000
$LTACC\_A_{t+1}$	0.066	0.031	0.079	0.024	0.052	0.000
$LTACC\_L_{t+1}$	0.008	0.003	0.009	0.003	0.008	0.000
Firm characteristics						
OH	0.207	0.172	0.469	0.470	0.831	0.743
LN_AT	4.751	4.586	5.862	5.772	5.821	5.727
Q	1.566	1.133	1.935	1.517	1.839	1.357
ROA	0.154	0.138	0.115	0.111	–0.023	0.030
SALE	1.968	1.714	1.459	1.327	0.815	0.720
$\Delta SALE_{t+1}$	0.221	0.168	0.126	0.093	0.065	0.041
CFO_{t+1}	0.117	0.114	0.107	0.111	0.005	0.061
LEV	0.403	0.398	0.315	0.280	0.353	0.324
VOL_{t+1}	0.029	0.025	0.030	0.026	0.037	0.032
Macroeconomic variables						
R^f_{t+1}	0.281	0.192	0.607	0.671	0.649	0.686

Table 2.4: This table shows mean and median of investment and accruals variables and firm characteristics conditional on capacity overhang. Firm-years are sorted into Low-, Medium-, and High-capacity overhang subsamples using the 30th and the 70th percentile cutoffs. The sample period is 1971–2017. All variables are winsorized at the 1st and the 99th percentile for each cross-section. Variables are defined in the text.

Table 2.5: Panel regressions of year-ahead investment on capacity overhang.

	(1)	(2)	(3)	(4)
Dep. VAR	ΔPPEINT$_{t+1}$	ΔPPE$_{t+1}$	TOTINV$_{t+1}$	CAPX$_{t+1}$
OH	–0.246***	–0.098***	–0.112***	–0.052***
	(-13.10)	(-10.40)	(-17.30)	(-8.84)
LN_AT	–0.066***	–0.035***	–0.066***	–0.014***
	(-11.47)	(-10.96)	(-27.67)	(-6.31)
Q	0.070***	0.030***	0.026***	0.027***
	(6.51)	(12.20)	(12.59)	(15.20)
ROA	0.100*	0.124***	–0.042***	0.117***
	(1.86)	(5.89)	(-3.01)	(8.34)
CFO$_{t+1}$	0.249***	0.275***	0.242***	0.131***
	(2.73)	(8.27)	(8.81)	(6.61)
OH_CFO$_{t+1}$	–0.238**	–0.237***	–0.205***	–0.150***
	(-2.25)	(-5.65)	(-6.91)	(-5.71)
LEV	–0.333***	–0.286***	–0.202***	–0.146***
	(-9.72)	(-22.72)	(-20.44)	(-17.80)
VOL$_{t+1}$	0.017	–0.170	–0.338***	0.030
	(0.08)	(-1.56)	(-4.05)	(0.45)
R^f_{t+1}	–1.396	–1.227**	–0.981**	–0.649*
	(-1.53)	(-2.30)	(-2.53)	(-1.79)
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year
Adj R^2	0.160	0.250	0.332	0.374
N	81,036	81,036	81,036	81,036

Table 2.5: This table shows estimated coefficients and t-statistics (in parentheses) for the following regression equation:

$$\begin{aligned}\mathrm{INVESTMENT}_{it+1} = {} & \beta_0 + \beta_1\mathrm{OH}_{it} + \beta_2\mathrm{LN\_AT}_{it} + \beta_3\mathrm{Q}_{it} + \beta_4\mathrm{ROA}_{it} + \beta_5\mathrm{CFO}_{it+1} \\ & + \beta_6\mathrm{OH\_CFO}_{it+1} + \beta_7\mathrm{LEV}_{it} + \beta_8\mathrm{VOL}_{it+1} + \beta_9\mathrm{R}^f_{t+1} + \mathrm{Firm} \\ & + \mathrm{Year} + \epsilon_{it+1},\end{aligned}$$

where $\mathrm{INVESTMENT} \in \{\Delta\mathrm{PPEINT}, \Delta\mathrm{PPE}, \mathrm{TOTINV}, \mathrm{CAPX}\}$. The sample period is 1971–2017. All variables are winsorized at the 1st and the 99th percentile for each cross-section. An intercept is estimated for each model specification but not reported. Standard errors are clustered at the firm level. *, **, and *** denote significance at 0.10, 0.05, and 0.01 level, respectively. Variables are defined in the text.

Table 2.6: Fama–MacBeth regressions of year-ahead investment on capacity overhang.

		(1)	(2)	(3)	(4)
Dep. VAR	Predicted sign	$\Delta PPEINT_{t+1}$	ΔPPE_{t+1}	$TOTINV_{t+1}$	$CAPX_{t+1}$
Panel A: Average estimated coefficients					
OH	-	–0.153***	–0.085**	–0.086***	–0.054***
		(-6.43)	(-2.51)	(-15.62)	(-2.92)
LN_AT	-	–0.007***	–0.006**	–0.011***	–0.002
		(-2.67)	(-2.22)	(-7.16)	(-0.78)
Q	+	0.053***	0.043***	0.038***	0.041***
		(10.47)	(5.95)	(15.80)	(4.99)
ROA	+	0.101***	0.100***	–0.128***	0.072***
		(4.50)	(4.39)	(-5.99)	(3.53)
CFO_{t+1}	+	0.330***	0.303***	0.322***	0.204**
		(2.78)	(2.97)	(2.72)	(2.32)
OH_CFO_{t+1}	?	–0.194***	–0.151***	–0.199***	–0.213**
		(-2.77)	(-2.66)	(-2.66)	(-2.01)
LEV	-	–0.146***	–0.092***	–0.117***	–0.062**
		(-3.24)	(-2.76)	(-4.00)	(-2.15)
VOL_{t+1}	-	1.002***	0.646***	0.439***	1.077***
		(5.36)	(5.61)	(3.36)	(7.07)
Average Adj R^2		0.109	0.124	0.187	0.168
Average N		1,438	1,438	1,438	1,438
Panel B: Number of positive estimated coefficients (total sample years = 47)					
OH		5	14	1	13
LN_AT		11	13	0	20
Q		47	47	47	47
ROA		34	39	5	35
CFO_{t+1}		38	42	38	38
OH_CFO_{t+1}		18	19	15	16
LEV		7	8	5	11
VOL_{t+1}		37	37	32	43

Table 2.6: Panel A shows average estimated coefficients and t-statistics (in parentheses) from Fama-MacBeth regressions of year-ahead investment on OH:

$$\begin{aligned} \mathrm{INVESTMENT}_{it+1} = \beta_0 + \beta_1 \mathrm{OH}_{it} + \beta_2 \mathrm{LN\_AT}_{it} + \beta_3 \mathrm{Q}_{it} + \beta_4 \mathrm{ROA}_{it} + \beta_5 \mathrm{CFO}_{it+1} \\ + \beta_6 \mathrm{OH\_CFO}_{it+1} + \beta_7 \mathrm{LEV}_{it} + \beta_8 \mathrm{VOL}_{it+1} + \epsilon_{it+1}, \end{aligned}$$

where $\mathrm{INVESTMENT} \in \{\Delta\mathrm{PPEINT}, \Delta\mathrm{PPE}, \mathrm{TOTINV}, \mathrm{CAPX}\}$. The sample period is 1971–2017. All variables are winsorized at the 1st and the 99th percentile for each cross-section. An intercept is estimated for each model specification but not reported. Standard errors are corrected for autocorrelation according to Newey and West (1987) with a lag of 10 years. *, **, and *** denote significance at 0.10, 0.05, and 0.01 level, respectively. Variables are defined in the text.
Panel B shows number of years in which the estimated coefficients are positive.

Table 2.7: Panel regressions of year-ahead accruals on capacity overhang.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. VAR	$COMPACC_{t+1}$	$OPACC_{t+1}$	$FINACC_{t+1}$	$WCACC_{t+1}$	$WCACC_{t+1}$	$LTACC_{t+1}$
OH	–0.048***	–0.073***	0.026***	–0.016***	–0.002	–0.088***
	(-9.60)	(-12.22)	(6.25)	(-7.78)	(-0.91)	(-7.04)
LN_AT	–0.035***	–0.052***	0.017***	–0.012***	–0.014***	–0.055***
	(-23.93)	(-24.14)	(11.92)	(-16.55)	(-18.55)	(-12.18)
Q	0.025***	0.020***	0.004***	0.004***	0.003***	0.043**
	(12.49)	(9.36)	(4.06)	(6.70)	(5.43)	–2.230
ROA	0.163***	0.156***	0.020**		0.064***	0.064*
	(16.24)	(12.91)	(2.52)		(13.11)	(1.94)
LEV	0.005	–0.238***	0.240***	–0.069***	–0.059***	–0.137**
	(0.66)	(-23.69)	(38.38)	(-19.80)	(-17.42)	(-2.39)
VOL_{t+1}	–0.641***	–0.667***	0.020	–0.278***	–0.237***	–0.423***
	(-9.50)	(-8.25)	(0.37)	(-7.98)	(-6.93)	(-3.13)
R^f_{t+1}	–0.787***	–0.913**	0.155	–0.094	–0.124	–1.744***
	(-3.02)	(-2.50)	(0.62)	(-0.60)	(-0.81)	(-2.75)
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
Adj R^2	0.148	0.187	0.087	0.114	0.119	0.089
N	81,036	81,036	81,036	81,036	81,036	81,036

Table 2.7: This table shows estimated coefficients and t-statistics (in parentheses) for the following regression equation:

$$\begin{aligned} \mathrm{ACCRUALS}_{it+1} &= \beta_0 + \beta_1 \mathrm{OH}_{it} + \beta_2 \mathrm{LN\_AT}_{it} + \beta_3 \mathrm{Q}_{it} + \beta_4 \mathrm{ROA}_{it} + \beta_5 \mathrm{LEV}_{it} \\ &+ \beta_6 \mathrm{VOL}_{it+1} + \beta_7 \mathrm{R}^f_{t+1} + \mathrm{Firm} + \mathrm{Year} + \epsilon_{it+1}, \end{aligned}$$

where ACCRUALS $\in$ {COMPACC, OPACC, FINACC, WCACC, LTACC}. The sample period is 1971–2017. All variables are winsorized at the 1st and the 99th percentile for each cross-section. An intercept is estimated for each model specification but not reported. Standard errors are clustered at the firm level. *, **, and *** denote significance at 0.10, 0.05, and 0.01 level, respectively. Variables are defined in the text.

Table 2.8: Fama–MacBeth regressions of year-ahead accruals on capacity overhang.

		(1)	(2)	(3)	(4)	(5)
Dep. VAR	Predicted sign	$COMPACC_{t+1}$	$OPACC_{t+1}$	$FINACC_{t+1}$	$WCACC_{t+1}$	$LTACC_{t+1}$
Panel A: Average estimated coefficients						
OH	-	–0.025***	–0.051***	0.028*	–0.028***	–0.024**
		(-4.77)	(-3.25)	(1.77)	(-3.15)	(-2.02)
LN_AT	-	–0.008***	–0.008***	0.000	–0.005***	–0.004**
		(-4.12)	(-3.21)	(0.09)	(-4.26)	(-2.06)
Q	+	0.020***	0.020***	–0.000	0.005**	0.019***
		(6.54)	(4.83)	(-0.26)	(2.42)	(6.00)
ROA	+	0.160***	0.184***	–0.011	0.078***	0.099***
		(7.45)	(6.71)	(-1.16)	(2.72)	(10.47)
LEV	-	–0.009*	–0.065***	0.059***	–0.009***	–0.046***
		(-1.93)	(-7.24)	(7.31)	(-3.05)	(-4.48)
VOL_{t+1}	-	–0.336**	–0.370*	0.051	–0.169**	–0.222
		(-2.43)	(-1.92)	(0.54)	(-2.50)	(-1.37)
Average Adj R^2		0.116	0.094	0.018	0.061	0.050
Average N		1,438	1,438	1,438	1,438	1,438
Panel B: Number of positive estimated coefficients (total sample years = 47)						
OH		8	6	33	6	14
LN_AT		3	10	23	3	12
Q		47	47	25	38	45
ROA		47	47	21	43	43
LEV		19	3	45	14	6
VOL_{t+1}		12	15	31	14	16

Table 2.8: Panel A shows average estimated coefficients and t-statistics (in parentheses) from Fama-MacBeth regressions of year-ahead accruals on capacity overhang and control variables:

$$\begin{aligned} \mathrm{ACCRUALS}_{it+1} = \beta_0 + \beta_1 \mathrm{OH}_{it} + \beta_2 \mathrm{LN\_AT}_{it} + \beta_3 \mathrm{Q}_{it} + \beta_4 \mathrm{ROA}_{it} + \beta_5 \mathrm{CFO}_{it+1} \\ + \beta_6 \mathrm{LEV}_{it} + \beta_7 \mathrm{VOL}_{it+1} + \epsilon_{it+1}, \end{aligned}$$

where $\mathrm{ACCRUALS} \in \{\mathrm{COMPACC}, \mathrm{OPACC}, \mathrm{FINACC}, \mathrm{WCACC}, \mathrm{LTACC}\}$. The sample period is 1971–2017. All variables are winsorized at the 1st and the 99th percentile for each cross-section. An intercept is estimated for each model specification but not reported. Standard errors are corrected for autocorrelation according to Newey and West (1987) with a lag of 10 years. *, **, and *** denote significance at 0.10, 0.05, and 0.01 level, respectively. Variables are defined in the text.
Panel B shows number of years with a positive related estimated coefficient.

Table 2.9: Panel regressions of year-ahead asset accruals or liability accruals on capacity overhang.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. VAR	$COMPACC_{t+1}$		$OPACC_{t+1}$		$FINACC_{t+1}$		$WCACC_{t+1}$		$LTACC_{t+1}$	
	Asset	Liability	Asset	Liability	Asset	Liability	Asset	Liability	Asset	Liability
OH	–0.095***	–0.047***	–0.091***	–0.017***	–0.002*	–0.028***	–0.016***	–0.014***	–0.092***	–0.004**
	(-13.01)	(-8.91)	(-13.00)	(-7.19)	(-1.90)	(-7.15)	(-5.96)	(-7.83)	(-7.32)	(-2.26)
LN_AT	–0.078***	–0.043***	–0.074***	–0.022***	–0.002***	–0.019***	–0.033***	–0.019***	–0.060***	–0.004***
	(-27.08)	(-20.73)	(-26.93)	(-25.11)	(-5.21)	(-13.65)	(-30.37)	(-27.46)	(-12.40)	(-7.76)
Q	0.030***	0.005***	0.026***	0.005***	0.003***	–0.001	0.007***	0.005***	0.044**	0.001**
	(11.7)	(4.10)	(10.36)	(9.17)	(7.41)	(-0.65)	(12.41)	(10.67)	(2.27)	(2.33)
ROA	0.138***	–0.036***	0.138***	–0.016***	0.003	–0.016**	0.042***	–0.022***	0.067**	0.004
	(8.88)	(-3.33)	(9.27)	(-3.17)	(1.19)	(-2.03)	(7.14)	(-5.50)	(1.97)	(0.93)
LEV	–0.324***	–0.328***	–0.323***	–0.084***	–0.003**	–0.242***	–0.117***	–0.058***	–0.167***	–0.029***
	(-25.97)	(-38.61)	(-26.58)	(-24.22)	(-2.13)	(-39.38)	(-25.60)	(-21.16)	(-2.89)	(-12.56)
VOL_{t+1}	–0.855***	–0.197***	–0.838***	–0.169***	–0.021	–0.022	–0.417***	–0.180***	–0.408***	0.016
	(-8.19)	(-2.67)	(-8.29)	(-4.79)	(-1.46)	(-0.43)	(-9.47)	(-6.27)	(-2.96)	(0.63)
R^f_{t+1}	–1.523***	–0.752**	–1.474***	–0.528***	–0.008	–0.158	–0.768***	–0.589***	–1.746**	–0.002
	(-3.19)	(-2.15)	(-3.19)	(-3.47)	(-0.11)	(-0.64)	(-3.81)	(-4.90)	(-2.52)	(-0.02)
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
Adj R^2	0.215	0.142	0.209	0.127	0.017	0.106	0.204	0.142	0.091	0.028
N	81,036	81,036	81,036	81,036	81,036	81,036	81,036	81,036	81,036	81,036
F-test	27.34		25.92		9.04		0.24		21.53	
p-value	0.000		0.000		0.003		0.622		0.000	

Table 2.9: This table shows estimated coefficients and t-statistics (in parentheses) for the following regression equation:

$$\mathrm{ACCRUALS}_{\mathrm{it}+1} = \beta_0 + \beta_1\mathrm{OH}_{\mathrm{it}} + \beta_2\mathrm{LN\_AT}_{\mathrm{it}} + \beta_3\mathrm{Q}_{\mathrm{it}} + \beta_4\mathrm{ROA}_{\mathrm{it}} + \beta_5\mathrm{LEV}_{\mathrm{it}} + \beta_6\mathrm{VOL}_{\mathrm{it}+1} + \beta_7\mathrm{R}^{\mathrm{f}}_{\mathrm{t}+1} + \mathrm{Firm} + \mathrm{Year} + \epsilon_{\mathrm{it}+1},$$

where $\mathrm{ACCRUALS} \in \{\mathrm{COMPACC\_A}, \mathrm{COMPACC\_L}, \mathrm{OPACC\_A}, \mathrm{OPACC\_L}, \mathrm{FINACC\_A}, \mathrm{FINACC\_L}, \mathrm{WCACC\_A}, \mathrm{WCACC\_L}, \mathrm{LTACC\_A}, \mathrm{LTACC\_L}\}$. The postfix "_A" ("_L") denotes asset (liability) accruals. The sample period is 1971–2017. All variables are winsorized at the 1st and the 99th percentile for each cross-section. An intercept is estimated for each model specification but not reported. Standard errors are clustered at the firm level. *, **, and *** denote significance at 0.10, 0.05, and 0.01 level, respectively. F-tests and p-values are testing the equality of the estimated coefficients for OH (β_1) between the asset and liability components of accruals. Variables are defined in the text.

Table 2.10: Panel regressions of investment or accruals on capacity overhang controlling for realized demand shock.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. VAR	ΔPPEINT$_{t+1}$	ΔPPE$_{t+1}$	TOTINV$_{t+1}$	CAPX$_{t+1}$	COMPACC$_{t+1}$	OPACC$_{t+1}$	WCACC$_{t+1}$	LTACC$_{t+1}$
OH	–0.226***	–0.082***	–0.099***	–0.042***	–0.045***	–0.068***	0.000	–0.083***
	(-12.19)	(-9.22)	(-16.15)	(-7.12)	(-9.16)	(-11.98)	(0.04)	(-6.76)
LN_AT	–0.031***	–0.013***	–0.050***	–0.007***	–0.021***	–0.028***	–0.006***	–0.037***
	(-6.03)	(-4.63)	(-22.78)	(-3.15)	(-15.99)	(-14.70)	(-8.41)	(-8.70)
Q	0.057***	0.022***	0.019***	0.024***	0.020***	0.011***	0.000	0.037*
	(5.48)	(9.36)	(10.09)	(14.01)	(10.25)	(5.58)	(-0.23)	(1.88)
ROA	0.141***	0.176***	0.005	0.135***	0.161***	0.153***	0.063***	0.061*
	(3.09)	(8.93)	(0.37)	(9.84)	(16.99)	(13.82)	(13.62)	(1.89)
ΔSALE$_{t+1}$	0.452***	0.311***	0.245***	0.113***	0.161***	0.276***	0.100***	0.223***
	(34.15)	(37.66)	(42.00)	(29.82)	(42.44)	(48.00)	(40.66)	(22.41)
LEV	–0.279***	–0.253***	–0.177***	–0.137***	0.029***	–0.196***	–0.045***	–0.104*
	(-8.04)	(-22.53)	(-19.24)	(-17.63)	(4.06)	(-21.31)	(-14.59)	(-1.81)
VOL$_{t+1}$	0.548***	0.149	–0.099	0.156**	–0.424***	–0.296***	–0.103***	–0.124
	(2.77)	(1.50)	(-1.29)	(2.39)	(-6.80)	(-4.15)	(-3.30)	(-0.92)
R$^{f}_{t+1}$	–0.659	–0.752	–0.616*	–0.505	–0.486**	–0.398	0.062	–1.327**
	(-0.77)	(-1.56)	(-1.75)	(-1.45)	(-2.04)	(-1.24)	(0.45)	(-2.18)
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
Adj R^2	0.214	0.327	0.406	0.398	0.223	0.302	0.214	0.116
N	81,036	81,036	81,036	81,036	81,036	81,036	81,036	81,036

Table 2.10: This table shows estimated coefficients and t-statistics (in parentheses) for the following regression equation:

$$\{\text{INVESTMENT}, \text{ACCRUALS}\}_{it+1} = \beta_0 + \beta_1 \text{OH}_{it} + \beta_2 \text{LN\_AT}_{it} + \beta_3 \text{Q}_{it} + \beta_4 \text{ROA}_{it} + \beta_5 \Delta\text{SALE}_{t+1} + \beta_6 \text{LEV}_{it} + \beta_7 \text{VOL}_{it+1} + \beta_8 \text{R}^{f}_{t+1} + \text{Firm} + \text{Year} + \epsilon_{it+1},$$

where INVESTMENT $\in \{\Delta\text{PPEINT}, \Delta\text{PPE}, \text{TOTINV}, \text{CAPX}\}$, ACCRUALS $\in \{\text{COMPACC}, \text{OPACC}, \text{WCACC}, \text{LTACC}\}$. The sample period is 1971–2017. All variables are winsorized at the 1st and the 99th percentile for each cross-section. An intercept is estimated for each model specification but not reported. Standard errors are clustered at the firm level. *, **, and *** denote significance at 0.10, 0.05, and 0.01 level, respectively. Variables are defined in the text.

Table 2.11: Augmenting optimal investment models with capacity overhang.

Panel A: Fazzari et al. (1988)'s investment model		
(1): $\mathrm{TOTINV}_{\mathrm{it+1}} = \beta_0 + \beta_1 \mathrm{Q}_{\mathrm{it}} + \beta_2 \mathrm{CFO}_{\mathrm{it+1}} + \epsilon_{\mathrm{it+1}}$ (2): $\mathrm{TOTINV}_{\mathrm{it+1}} = \beta_0 + \beta_1 \mathrm{Q}_{\mathrm{it}} + \beta_2 \mathrm{CFO}_{\mathrm{it+1}} + \beta_3 \mathrm{OH}_{\mathrm{it}} + \epsilon'_{\mathrm{it+1}}$		
	(1)	(2)
Q	0.037***	0.036***
	(14.86)	(14.43)
$\mathrm{CFO}_{\mathrm{t+1}}$	0.312***	0.279***
	(15.45)	(12.76)
OH		–0.094***
		(-8.15)
Average adj R^2	0.137	0.152
N	67,606	67,606
#Different sign$(\hat{\epsilon}, \hat{\epsilon}')$	3,820 (5.65%)	
#Different qtr$(\hat{\epsilon}, \hat{\epsilon}')$	9,886 (14.62%)	
#Different qtr$(\lvert\hat{\epsilon}\rvert, \lvert\hat{\epsilon}'\rvert)$	14,350 (21.23%)	
	qtr$(\hat{\epsilon}') > 1$	qtr$(\hat{\epsilon}') < 4$
qtr$(\hat{\epsilon}) = 1$	1.744	
	(10.31%)	
qtr$(\hat{\epsilon}) = 4$		1.268
		(7.51%)
	qtr$(\lvert\hat{\epsilon}\rvert) > 1$	qtr$(\lvert\hat{\epsilon}'\rvert) < 4$
qtr$(\lvert\hat{\epsilon}\rvert) = 1$	3.386	
	(20.01%)	
qtr$(\lvert\hat{\epsilon}'\rvert) = 4$		1.543
		(9.14%)

Table 2.11: (Continued on the following page)

(Table 2.11 continued)

Panel B: McNichols and Stubben (2008)'s investment model		
(1): $TOTINV_{it+1} = \beta_0 + \beta_1 Q_{it} + \beta_2 CFO_{it+1} + \beta_3 \Delta AT_{it} + \beta_4 TOTINV_{it} + \epsilon_{it+1}$		
(2): $TOTINV_{it+1} = \beta_0 + \beta_1 Q_{it} + \beta_2 CFO_{it+1} + \beta_3 \Delta AT_{it} + \beta_4 TOTINV_{it} + \beta_5 OH_{it} + \epsilon'_{t+1}$		
	(1)	(2)
Q	0.025***	0.025***
	(11.11)	(10.56)
CFO_{t+1}	0.331***	0.307***
	(16.46)	(13.99)
ΔAT	–0.120***	–0.126***
	(-11.95)	(-11.53)
TOTINV	0.403***	0.403***
	(31.58)	(29.51)
OH		–0.059***
		(-5.54)
Average adj R^2	0.262	0.273
N	67,606	67,606
#Different sign$(\hat{\epsilon}, \hat{\epsilon}')$	4,030 (5.96%)	
#Different qtr$(\hat{\epsilon}, \hat{\epsilon}')$	9,850 (14.50%)	
#Different qtr$(\|\hat{\epsilon}\|, \|\hat{\epsilon}'\|)$	14,344 (21.22%)	
	qtr$(\hat{\epsilon}') > 1$	qtr$(\hat{\epsilon}') < 4$
qtr$(\hat{\epsilon}) = 1$	1.603	
	(9.64%)	
qtr$(\hat{\epsilon}) = 4$		1.322
		(7.83%)
	qtr$(\|\hat{\epsilon}\|) > 1$	qtr$(\|\hat{\epsilon}'\|) < 4$
qtr$(\|\hat{\epsilon}\|) = 1$	3.501	
	(20.70%)	
qtr$(\|\hat{\epsilon}'\|) = 4$		1.471
		(8.72%)

Table 2.11: Panel A (panel B) shows average coefficients (t-statistics in parentheses) and some properties of residuals for the optimal investment model used by Fazzari et al. (1988) (McNichols and Stubben, 2008) and the same model augmented with capacity overhang. The models are estimated by 2-digit SIC industry and year with at least 20 available observations. "qtr(·)" denotes cross-sectional quartile. "| · |" denotes absolute value. The sample period is 1971–2017. All variables are winsorized at the 1st and the 99th percentile for each cross-section. An intercept is estimated for each model specification but not reported. *, **, and *** denote significance at 0.10, 0.05, and 0.01 level, respectively. Variables are defined in the text.

Table 2.12: Augmenting accruals models models with capacity overhang.

Panel A: Performance-adjusted Modified Jones Model

(1): $\text{OPACC}_{\text{it+1}} = \beta_0 + \beta_1 1/\text{AT}_{\text{it}} + \beta_2 \Delta(\text{SALE–AR})_{\text{it+1}} + \beta_3 \text{PPE}_{\text{it+1}} + \beta_4 \text{ROA}_{\text{it+1}} + \epsilon_{\text{it+1}}$
(2): $\text{OPACC}_{\text{it+1}} = \beta_0 + \beta_1 1/\text{AT}_{\text{it}} + \beta_2 \Delta(\text{SALE} - \text{AR})_{\text{it+1}} + \beta_3 \text{PPE}_{\text{it+1}} + \beta_4 \text{ROA}_{\text{it+1}} + \beta_5 \text{OH}_{\text{it}} + \epsilon'_{\text{it+1}}$

	(1)	(2)
1/AT	0.386***	0.411***
	(3.42)	(3.31)
$\Delta(\text{SALE} - \text{AR})_{\text{t+1}}$	0.266***	0.266***
	(31.75)	(31.32)
$\text{PPE}_{\text{t+1}}$	0.097***	0.103***
	(24.39)	(24.99)
$\text{ROA}_{\text{t+1}}$	0.271***	0.238***
	(20.74)	(17.88)
OH		–0.092***
		(-6.77)
Average adj R^2	0.262	0.276
N	67,606	67,606
#Different sign$(\hat{\epsilon}, \hat{\epsilon}')$	3,806 (5.55%)	
#Different qtr$(\hat{\epsilon}, \hat{\epsilon}')$	9,331 (13.62%)	
#Different qtr$(\lvert\hat{\epsilon}\rvert, \lvert\hat{\epsilon}'\rvert)$	14,131 (20.62%)	
	qtr$(\hat{\epsilon}') > 1$	qtr$(\hat{\epsilon}') < 4$
qtr$(\hat{\epsilon}) = 1$	1.596	
	(9.31%)	
qtr$(\hat{\epsilon}) = 4$		1.311
		(7.66%)
	qtr$(\lvert\hat{\epsilon}\rvert) > 1$	qtr$(\lvert\hat{\epsilon}'\rvert) < 4$
qtr$(\lvert\hat{\epsilon}\rvert) = 1$	3.326	
	(19.39%)	
qtr$(\lvert\hat{\epsilon}'\rvert) = 4$		1.574
		(9.20%)

Table 2.12: (Continued on the following page)

(Table 2.12 continued)

Panel B: An investment-based accruals model		
(1): $\text{OPACC}_{\text{it+1}} = \beta_0 + \beta_1\text{LN\_AT}_{\text{it}} + \beta_2\text{Q}_{\text{it}} + \beta_3\text{ROA}_{\text{it}} + \beta_4\text{LEV}_{\text{it}} + \beta_5\text{VOL}_{\text{it+1}} + \epsilon_{\text{it+1}}$ (2): $\text{OPACC}_{\text{it+1}} = \beta_0+\beta_1\text{LN\_AT}_{\text{it}}+\beta_2\text{Q}_{\text{it}}+\beta_3\text{ROA}_{\text{it}}+\beta_4\text{LEV}_{\text{it}}+\beta_5\text{VOL}_{\text{it+1}}+\beta_6\text{OH}_{\text{it}}+\epsilon'_{\text{it+1}}$		
	(1)	(2)
LN_AT	–0.009***	–0.008***
	(-10.61)	(-9.23)
Q	0.020***	0.022***
	(7.03)	(7.45)
ROA	0.289***	0.251***
	(16.11)	(13.13)
LEV	–0.069***	–0.068***
	(-8.59)	(-8.08)
$\text{VOL}_{\text{t+1}}$	–0.158	0.004
	(-1.14)	(0.02)
OH		–0.062***
		(-4.69)
Average adj R^2	0.127	0.134
N	67,606	67,606
#Different sign$(\hat{\epsilon}, \hat{\epsilon}')$	3,190 (4.72%)	
#Different qtr$(\hat{\epsilon}, \hat{\epsilon}')$	7,899 (11.68%)	
#Different qtr$(\lvert\hat{\epsilon}\rvert, \lvert\hat{\epsilon}'\rvert)$	11,684 (17.28%)	
	qtr$(\hat{\epsilon}') > 1$	qtr$(\hat{\epsilon}') < 4$
qtr$(\hat{\epsilon}) = 1$	1.380	
	(7.73%)	
qtr$(\hat{\epsilon}) = 4$		1.090
		(6.46%)
	qtr$(\lvert\hat{\epsilon}\rvert) > 1$	qtr$(\lvert\hat{\epsilon}'\rvert) < 4$
qtr$(\lvert\hat{\epsilon}\rvert) = 1$	2.793	
	(16.51%)	
qtr$(\lvert\hat{\epsilon}'\rvert) = 4$		1.270
		(7.52%)

Table 2.12: Panel A (panel B) shows average coefficients, t-statistics for coefficients, and some properties of residuals, for the Performance-adjusted Modified Jones Model (investment-based accruals model) and the same model augmented with capacity overhang. The models are estimated by 2-digit SIC industry and year with at least 20 available observations. "qtr(·)" denotes cross-sectional quartile. "|·|" denotes absolute value. The sample period is 1971–2017. All variables are winsorized at the 1st and the 99th percentile for each cross-section. An intercept is estimated for each model specification but not reported. *, **, and *** denote significance at 0.10, 0.05, and 0.01 level, respectively. Variables are defined in the text.

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Chapter 3

Third Paper

How do asset pricing models capture leverage effects?

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Abstract

This paper investigates how empirical asset pricing models capture leverage effects. Generally, empirical asset pricing models do not directly model leverage in their theoretical frameworks and/or empirical constructs. Nevertheless, prominent asset pricing models can explain expected stock returns satisfactorily well. To shed light on this issue, first, we use an illustrative conceptual framework to show that differentiating between unlevered factors related to firms' operating risks and a leverage multiplier is crucial to understanding expected stock returns. We then empirically show that popular asset pricing factors like value, investment, or profitability, can only absorb leverage effects to a limited degree. Finally, we empirically demonstrate that abnormal leverage—the component of leverage unexplained by asset pricing factors, is positively priced in the cross section—Failure to handle leverage properly in asset pricing models may lead to pricing errors.

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3.1 Introduction

In the friction-free Modigliani–Miller world, holding everything else constant, equity returns should increase (decrease) in leverage, provided expected returns on assets are higher (lower) than expected borrowing costs. Interestingly, the discussion of financial leverage is largely absent from mainstream asset pricing models. Bhandari (1988) documents a positive relationship between expected stock returns and leverage, which is robust to the inclusion of market beta and size. Fama and French (1992) find that the effects of leverage is fully absorbed by book-to-price ratio (B/P)—Leverage becomes redundant in explaining cross-sectional expected stock returns after controlling for B/P. Hou et al. (2015) and Hou et al. (2020) assume a representative unlevered firm in the development of their q model and q5 model, respectively. Given the fact that these popular asset pricing models can explain expected stock returns to a satisfactory degree, leverage must have been confounded with asset pricing factors. The very first question we want to investigate is that in addition to B/P, what other asset pricing factors capture leverage effects?

Penman et al. (2007) decompose book-to-price ratio into an enterprise book-to-price ratio pertaining to business operations and a leverage adjustment component[1]. They find that when enterprise book-to-price ratio and leverage are simultaneously included in the regressions of subsequent stock returns, enterprise book-to-price ratio is positively linked to subsequent stock returns while leverage is negatively related to subsequent stock returns. In addition, the correlation between enterprise book-to-price ratio and leverage is still positive. They conclude that the B/P effects on stock returns has a deeper-rooted foundation and the negative price for leverage in the cross-section is a puzzle. The accounting-absed equity valuation model of Penman et al. (2018) implies that B/P alone is unable to capture firms' all operating risks, and as a consequence, earnings-to-price ratio (E/P) must also be controlled for. They show that in the absence of expected earnings growth, stock returns should only load on E/P; when earnings grow, the weight shifts to B/P. They also find that once operating risks (e.g., enterprise E/P) are properly controlled for, a positive return-leverage relationship can be observed.

The development of computational power gives rise to the prosperity of dynamic

[1] After some algebra, $\mathrm{B/P} = \frac{\mathrm{NOA}}{\mathrm{P^{NOA}}} + \frac{\mathrm{ND}}{\mathrm{P}}(\frac{\mathrm{NOA}}{\mathrm{P^{NOA}}-1})$, where $\mathrm{P^{NOA}}$ is the market price of net operating assets; ND is net debt, the difference between financial liabilities and financial assets.

modeling in economics. The endogeneity of leverage has largely been recognized by academia. Hennessy and Whited (2005) use a dynamic investment model to show that there is no optimal leverage, and the static trade-off diagram should not hold. Gomes and Schmid (2010) study the relationship between stock returns and leverage using a dynamic model of endogenous investment and financing, predicting that highly-levered firms are typically mature firms with higher B/P and lower profitability. These dynamic economic models further reinforce that asset pricing factors and leverage are inextricably linked.

Ferguson and Shockley (2003) conceptually show that the failure of CAPM and the emergence of size effect and B/P effect are the consequences of using an equity-only portfolio for the true market portfolio. Their empirical evidence shows that in the cross section, the loadings on portfolios formed on relative leverage and relative distress completely subsume the effects of loadings on the size portfolio (SMB) and value portfolio (HML) in Fama and French (1993). However, their results do not hold in the time series and the high-minus-low relative leverage and distress portfolios do not yield significantly positive returns. Based on Modigliani and Miller (1958), Doshi et al. (2019) reverse-engineer the weighted average cost of capital (i.e., unlevered returns) using levered equity returns. They find that the value premium and volatility anomalies disappear, and size effect weakens in the cross-section. Doshi et al. (2019)'s results are not surprising given the strong positive correlation between leverage and B/P and the strong positive correlation between B/P and stock returns.

Although B/P and other asset pricing factors are potentially associated with leverage, we are unaware of their capability to absorb leverage effects in explaining expected stock returns. The second question we want to investigate is to what extent can asset pricing models capture leverage effects.

3.2 Methodologies and main findings

First of all, we conceptually demonstrate the relationship between stock returns and leverage using an illustrative model under the assumptions of Modigliani and Miller (1958). The simplified framework shows that in a typical asset pricing model, leverage must have been perfectly confounded with asset pricing factors so that the asset pricing models can explain expected stock returns.

Secondly, we replicate the results of Bhandari (1988), Penman et al. (2007), and Penman et al. (2018) using the latest data to check whether the well-documented negative return-leverage relationship still holds. Recent literature documents that the size premium has weakened (see Van Dijk (2011)). Green et al. (2011) document a declined accruals anomaly since the discovery of Sloan (1996). As firms' business models and global economy have been changing dramatically, it is important to examine the documented economic phenomena in the latest sample. We confirm that the results of the above studies still hold until today.

Thirdly, we study the relationship between leverage and firm characteristics used as asset pricing factors. At this stage, we focus on Fama-French three factor model (FF3), Fama-French five factor model (FF5), the q model, and the q5 model. We run leverage regressions as in Rajan and Zingales (1995) and run cross-sectional leverage regressions on asset pricing factors. We find that leverage heavily loads on size, B/P, profitability, and expected investment growth.

In the fourth place, we split each of the 25 Size-Book-to-Market portfolios into high- and low- leverage sub-portfolios and run Fama and French (1993) time series regressions on FF5 and q5 mimicking portfolio factors. We find that value and profitability capture leverage effects in FF5, and asset growth, ROE, and expected investment growth capture leverage effects in the q5 model. Also, both FF5 and q model fail to explain the returns of the low-leverage portfolios. These findings imply that the existing asset pricing models are not able to perfectly manage leverage effects.

Finally, on the basis of Gomes and Schmid (2010), we extract the component of leverage that is directly related to firm fundamentals by running cross-sectional leverage regressions on firm fundamentals. We define the component of leverage explained by firm fundamentals as expected leverage and the component unexplained by firm fundamentals as abnormal leverage. We find that abnormal leverage is positively priced even after controlling for other asset pricing characteristics.

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