Why does operating profitability predict returns? New evidence on risk versus mispricing explanations

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Abstract: This study develops new evidence on risk versus mispricing explanations of the well-known profitability premium. First, we examine whether exposure to expected downside risk is a plausible explanation. We find that high profitability is associated with both lower *ex-ante* and ex-post probabilities of future price crashes. Thus, less profitable firms exhibit greater downside risk than highly profitable firms, making a downside risk explanation implausible. Although this fact is overlooked by the market in general, it is anticipated by options traders; we find that put options of low profitability firms are relatively more expensive. Simultaneously, these firms do not exhibit greater probability of jumps, indicating that volatility(risk)-based explanations for the profitability premium are unlikely to be descriptive. Second, we find that the sticky-expectations model of Bouchard et al. (2019) only partially explains the profitability premium. While on average, analysts' forecast revisions correct in the same direction as recent profitability, the profitability premium still exhibits a strong relationship to the *non-sticky* component of analysts' forecast revisions. Third, institutional investors trade profitability-based signals but do so with a delay, likely contributing to the premium. Overall, our evidence favors the explanation that the profitability premium is related to investor mispricing of potential downside risk and provides greater clarity on recent findings in the literature.

Keywords: Profitability premium; Operating profitability; Stock Returns; Expected Crash Risk; Underreaction

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1. Introduction

A large body of literature documents that future returns are increasing in profitability. This profitability premium is robust in multiple international settings, including the U.S. (e.g., Ball et al. 2016), China (Jiang et al. 2018), ASEAN markets (Kim and Phan 2020), and broad indexes of both developed and emerging markets (Wahal and Repetto 2020). Although this effect is well documented, there is considerable tension in the literature regarding two major competing explanations for its existence. One view is that profitability is a proxy for risk that is not captured by existing asset-pricing models (Barinov 2022). For example, Fama and French (2006) state that "Controlling for other variables, more profitable firms…are more risky", while Barinov (2023) argues that the profitability premium is driven by volatility risk. Yet, an alternative view is that the relationship between profitability and future returns is driven by mispricing based on a combination of trading frictions and behavioral factors (Haugen and Baker 1996; Barberis and Thaler 2003; Bouchard et al. 2019).[1]

Given this tension in the literature, we develop new evidence on these competing explanations and shed new light on recent findings. In summary, we examine whether exposure to expected downside risk explains the profitability premium and investigate whether the sticky-expectations model of Bouchard et al (2019) provides a complete description of this effect; our findings do not support either hypothesis. We also find that institutional investors trade profitability signals but with a delay, potentially contributing to the profitability premium. We

[1] A third possible explanation for return predictability of any "anomaly" variable is data mining (Fama 1998). We do not believe that data mining is likely to explain the profitability premium which has been shown in multiple settings based on numerous definitions of profitability: the unexpected component of earnings (Ashley 1962; Ball and Brown 1968; Foster, Olsen and Shevlin 1984; Bernard and Thomas 1989), total earnings (Fama and French 2006; Fama and French 2008), gross profitability (Novy-Marx 2013), operating profitability (Ball, Gerakos, Linnainmaa and Nikolaev 2015) and cash-based operating profitability (Ball, Gerakos, Linnainmaa and Nikolaev 2016). Moreover, Engelberg et al. (2018) show that data mining is unlikely to fully explain all anomaly returns.

perform tests using both accounting as well as cash-based operating profitability.[2] Our tests comprise U.S. firms with the data required for daily stock option volatilities, institutional investors, and sell-side analysts, in addition to market and financial statement data.

Distinguishing between the risk and mispricing explanations for the profitability premium is important from both academic and investor perspectives. Academics vigorously debate the sources of return predictability to understand the pricing of risky assets, while investors are interested in taking advantage of potential mispricing to enhance their investment returns. Standard asset pricing tests attempt to explain differences in returns across assets by relating them to exposure to risk factors. While theoretically elegant, these tests have historically failed to produce satisfactory explanations of several return anomalies in the literature. Even when a risk-factor model can explain returns to a particular anomaly, it is often the case that the same model cannot explain other anomalies (the Fama and French (1993) multi-factor model, for example).

We develop a research design that does not appeal to a factor structure of stock returns, and our analysis proceeds in three stages. In the first stage, we examine differences in the ex-ante stock crash risk of low and high profit firms. The advantage of this approach is that it simultaneously provides evidence about both risk-based and mispricing-based explanations for the profitability premium. On the one hand, the last 25 years have seen a groundswell in research indicating that risk premia are actually compensation for holding stocks with high downside risk (i.e., a high likelihood of large future stock crash), as opposed to high volatility, per se.[3] Thus,

[2] Ball et al. (2015) show that operating profitability exhibits a stronger relation with future returns then either net income or gross profit (Novy-Marx, 2013), while Ball et al. (2016) show that cash-based operating profitability (an operating profitability measure that excludes accruals) better explains future returns than net income, gross profitability, and operating profitability. In our empirical tests we find that our inferences hold for both operating profitability and cash-based operating profitability, so we generally refer to both measures as "profitability" unless specified otherwise.
[3] See, for example, Reitz (1988); Harvey and Siddique (2000); Barro (2006); Harvey et al. (2010); Bollerslev and Todorov (2011); Kozhan et al. (2013); Kelly and Jiang (2014); van Oordt and Zhou (2016); Lemperiere et al. (2017).

correlating profitability and ex-ante crash risk is an intuitive approach to validate or refute a risk-based explanation for the premium. On the other hand, Jang & Kang (2019) observe that anomaly returns are often concentrated in an anomaly's short leg. Therefore, showing that firms in the short leg are relatively overvalued would provide evidence that mispricing is driving the anomaly returns. Jang and Kang (2019) propose and validate a firm's ex-ante stock crash risk as a measure of this overvaluation. Thus, correlating profitability and ex-ante crash risk is also an intuitive approach to validate or refute a mispricing-based explanation for the premium.

We use two approaches to measure ex-ante stock crash risk. The first measure relies on historic relationships between firm characteristics and subsequent stock crashes (Jang & Kang 2019). The second measure relies on stock option traders' revealed beliefs about the likelihood that a stock will subsequently crash, as reflected in the relative volatilities of a firm's call and put options. Prior research reports that informed traders prefer to use the options market rather than the stock market to capitalize on potential mispricing (Black 1975; Amin and Lee 1977; Cox and Rubenstein 1985; Cao et al. 2005). Furthermore, options traders are better at processing firm disclosures (Jin et al. 2012). We follow prior studies and measure options-based ex-ante stock crash risk as the difference in the implied volatility of a stock's out-of-the-money put options and at-the-money call options (Kim and Zhang 2014; Kim et al. 2016; Kim et al. 2019). Higher values indicate that option traders perceive a greater likelihood of a large negative price movement.

We find that profitability is <u>negatively</u> associated with both measures of ex-ante stock crash risk. This result has two important implications. First, if the high average returns of high-profit firms in the US market could be explained by <u>greater</u> exposure to downside risk (vis-à-vis the downside risk of low profit firms), it would have to be the case that high profit firms are, in fact, exposed to greater downside risk. Our findings strongly reject this hypothesis using two unique approaches to estimating expected crash risk probabilities. Empirically, low profitability firms embody greater expected downside risk (but not greater upside risk), a finding that is inconsistent with a risk-based explanation. Second, consistent with the intuition in Jang & Kang (2019), our results demonstrate that low profit firms are overvalued to the point that traders bid up the price of options that pay off following a large decline in their stock. These previously undocumented findings are consistent with options traders recognizing and exploiting potential mispricing of profitability in the stock market. We also find comparable results when we estimate models of annual or daily realized crash risk, as in Ohlson and Bilinski (2015), rather than ex-ante crash risk.

In the second stage of our analysis, we take a closer look at the findings of Bouchard et al. (2019) who report that the profitability anomaly can be explained by the 'sticky' expectations of stock analysts who fail to adequately revise upwards (downwards) the earnings expectations of high (low) profitability firms conditional on their past forecast behavior. They show that the profitability premium is related to the persistence of analysts' previous forecasts. Prima facie, their findings suggest that the stickiness of professional analysts' expectations explains the profitability premium. While their findings support an underreaction story, we find that their theory does not reflect the entire story. This is because they do not show that the profitability premium is unrelated to the 'non-sticky' component of analysts' expectations. When we decompose analyst expectations into a 'sticky' and 'non-sticky' component, we find that the 'non-sticky' component has greater explanatory power for the profitability premium. With this test, we develop deeper insight into the Bouchard et al (2019) findings.[4]

[4] It is important to note that while Bouchard et al. (2019) focus on operating cash flows as a measure of profitability, our study focuses on profitability variables studied by Ball et al. (2016) which include both accounting-based operating profitability and a comprehensive measure of cash-based profitability. We should expect that if the Bouchard et al. (2019) explanation holds, it should hold for the latter measures as well.

In the third stage of our analysis, we examine institutional investor underreaction to the information in operating profitability as plausible sources of mispricing. Richardson et al. (2010) recommend that researchers the joint hypothesis problem entirely by observing the actions of specific capital market participants to identify investor underreactions. We examine the relationship between profitability and changes in institutional investors' demand for a firm's stock. We find that profitability is positively associated with institutional demand in both the profitability year and the subsequent year. We interpret this as evidence that institutions initially underreact to the information in profits but subsequently revise their expectations and demand for firms' shares, driving at least a portion of the profitability premium.

We perform three additional stock price-based tests to address the joint hypothesis problem. First, we show that firms with high operating profitability significantly outperform those with low operating profitability on days with large negative market-wide returns. This is inconsistent with a risk-based explanation that predicts that high-operating-profit firms should exhibit worse performance than low-operating-profit firms on days with large negative market declines. Second, we show that returns on operating profitability are concentrated around subsequent quarterly earnings announcements. This is also indicative of mispricing since a risk-based explanation for the positive relationship between operating profitability and earnings announcement returns would require improbably momentous changes in risk over these short windows (Richardson et al. 2010). Third, we extend Ball et al. (2015), who report that operating profitability explains the cross-sectional variation in monthly returns for up ten ten years. We show that this long-horizon correlation is present mainly during months in which earnings announcements occur. These are the months when new information is revealed to the market and suggest that a significant portion of the operating profitability premium is likely to reflect mispricing.

In summary, our study makes several new contributions to the literature on the profitability premium. First, we document an asymmetry in the relationship between operating profitability and expected crash risk, suggesting that the profitability premium is not explained by exposure to downside risk. Second, prior studies establish that informed option traders are better at processing and interpreting information and firms' disclosures.[5] However, there is less evidence on the specific sources of information that affect option demand, and recent studies have generally focused on the role of firms' overall information environment and monitoring.[6]. We show that demand for call and put options is consistent with the notion that options traders use the options market to exploit mispricing related to profitability.

Third, our study sheds new light on the literature related to analyst forecasts and their role in explaining potential mispricing. Bradshaw, Richardson, and Sloan (2001) find that analysts are delayed in incorporating operating accruals into EPS forecasts. Other studies also show that analysts' EPS forecast errors are correlated with past profitability (Gu and Xue 2007; Solliman 2008). Recently, Bouchard et al. (2019) propose that it is the stick expectations of analysts that explain the profitability anomaly. Our findings augment this literature by showing that the non-sticky component of analysts' forecasts remains a strong predictor of the profitability premium.

Fourth, our study is related to the literature that examines the relationship between changes in institutional demand and both contemporaneous returns (Wermers 1999; Nofsinger and Sias

[5] See, for example, studies related to informed investors' use of the option market (Cao, Chen, and Griffin 2005; Cox and Rubenstein 1985; Amin and Lee 1977; Black 1975), option demand and informed trading (Skinner 1990; Chakravarty, Gulen, and Mayhew 2004; Lee and Yi 2001; Jin et al. 2012; Cremers and Weinbaum 2010), and option demand and the implied volatility spread (Easley et al. 1998; Bollen and Whaley 2004).
[6] See, for example, Kim and Zhang (2014), Kim, Li, Lu, and Yu (2016), Callen and Fang (2017), Kim, Lu, and Yu (2019), Chowdhury, Faff, and Hoang (*forthcoming*), and Mamum, Balachandan, Duong, and Gul (*forthcoming*).

1999; Lehavy and Sloan 2008) and future returns (Sias 2004).[7] Our test of institutional demand is most closely related to Choi and Sias (2012), who examine institutions' delayed responses to firms' fundamentals as a potential explanation for the relationship between fundamentals and future returns. Our results show that institutional investors initially underreact to profitability but subsequently revise their demand for shares. Thus, institutional investors appear to contribute to mispricing and profitability premium. In other words, institutions' delayed response to a broad index

The remainder of this paper is organized as follows. Section 2 discusses the motivation behind the tests. Section 3 presents our construct measurements and sample. Section 4 provides the design of the tests and empirical results. Finally, Section 5 presents the conclusions of this study.

2. Hypothesis development

2.1 Is the profitability premium compensation for bearing risk?

2.1.1 Ex-ante downside risk

The concept of risk premia holds that investors should be compensated with higher long-run returns when they own riskier investments. However, the nature of what might be considered "risk" has evolved over time. Historically, risk has been considered in the context of mean and variance (Markowitz 1952). All else being equal, a higher expected variance (i.e., volatility) demands a higher return premium. This was followed by asset pricing models espousing the notion of compensated systematic risk, broadly characterized under the umbrella of a stochastic discount

[7] Additionally, prior studies examine the trading behavior of institutions and show that institutional demand is positively correlated over adjacent quarters (Sias 2004), institutions buy shares from (sell shares to) individuals in response to positive (negative) cash-flow news (Cohen, Gompers and Vuolteenaho 2002), and institutional investors (as opposed to individual investors) drive sentiment-based trading (DeVault, Sias and Starks 2019).

factor (Cochrane, 2005). A quarter century after Markowitz (1952), Kraus and Litzenberger (1976) extended the traditional capital asset pricing model to include tail risks. This perspective holds that, to a large degree, the risk premium is compensation for holding stocks with a higher likelihood of occasional large declines, as opposed to volatility per se (Reitz 1988; Harvey and Siddique 2000; Barro 2006; Harvey et al. 2010; Bollerslev and Todorov 2011; Kozhan et al. 2013; Kelly and Jiang 2014; van Oordt and Zhou 2016). Thus, investors demand a premium to hold stocks that are more likely to crash.

Lemperiere et al. (2017) apply this logic to a wide array of data over multiple asset classes. They report that virtually all the previously documented risk premia they examine are only weakly (if at all) related to volatility. Instead, the premia are related to the existence of negative skewness (i.e., occasional large price declines). Notable exceptions are those arising from “trend following” strategies, which exhibit a smaller likelihood of large negative returns (and, in fact, exposure to positive skewness). Thus, trend-following, which has been shown to be profitable (Lemperiere et al. 2014), has the added benefit of low exposure to downside risk (Lemperiere et al. 2017). These regularities lead Lemperiere et al. (2017) to categorize “trend following” as a genuine market anomaly that plausibly hinges on behavioral biases.

This raises two possibilities related to profitability premiums. First, the premium is simply compensation for holding high-profit firms that have greater exposure to downside risk. Thus, a positive association between profitability and downside risk provides a risk-based explanation for the premium. However, within the broader context of trend-following, it is possible that more profitable firms are not actually exposed to downside risk. In other words, a strategy that buys past winners (high profits) and sells past losers (low profits) earns positive returns without excessive exposure to downside risk. This lack of a positive relationship could manifest in one of two ways.

First, it might be the case that *low profit* firms have more exposure to downside risk than high profit firms. Jang and Kang (2019) report that firms with more ex-ante downside risk (based on estimated stock crash probabilities) have lower subsequent returns, suggesting that investors misprice that risk. Thus, the profitability premium may reflect a negative association between profitability and ex-ante downside risk that is not priced by the market. Moreover, the results in Lemperiere et al. (2014) related to "momentum" type strategies raise the possibility that high profit firms have higher exposure to large stock jumps rather than large crashes. Alternatively, profitability and downside risk may be uncorrelated.

The lack of a positive association between profitability and downside risk, whether due to a negative or no association, would diminish the plausibility of the downside risk explanation for the premium. In our tests, we proxy for investors' ex-ante expectations of downside risk using both stock option volatilities and a crash risk expectations model. (For completeness, we also consider realized return outcomes in Section 2.1.2.) We state our first hypothesis in the null:

H1*: Profitability is positively associated with ex-ante downside risk*

2.1.2 Realized downside and upside risk

We triangulate the analysis of ex-ante downside risk by examining the likelihood that firms will experience a realized stock crash. We follow recent studies and consider extreme negative annual returns (< -50%) to identify stock crashes (Jang and Kang 2019; Ohlson and Bilinski 2015). This analysis allows us to explore the possibility that the profitability premium reflects compensation for bearing downside risk that is not captured by the ex-ante measures considered in Section 2.1.1.

To ensure that our results do not simply capture volatility in stock returns, we also examine large realized price jumps, which we identify based on extreme positive annual returns (> 50%).

By including the likelihood of realized stock jumps in our analysis, we can additionally validate or refute the more traditional concept of risk (i.e., volatility) as an explanation for the profitability premium. Asset pricing theory suggests that stock returns follow a factor structure in which a stock's exposure to systematic risk factors determines expected returns. Because there is no consensus regarding the identity of these factors, it is typically difficult for known factors to distinguish between risk and mispricing explanations for a broad range of anomalies. All else being equal, high-risk stocks should have a higher likelihood of large positive ***and*** negative returns relative to low-risk stocks. By contrast, a variable that has opposite correlations with large positive and negative returns is unlikely to capture risk.

If the profitability premium reflects the rational pricing of profitable firms' exposure to high volatility, we should observe symmetry in the measured relationship between profitability and extreme upside vs. downside returns. In other words, we should observe a higher likelihood of price jumps ***and*** crashes among high-profit firms than in low profit firms. Alternatively, a higher likelihood of price jumps but a lower likelihood of crashes among high-profit firms makes volatility-based explanations unlikely. Our null hypothesis is as follows:

H2a*: Profitability is equally and positively associated with price jumps and crashes using annual returns.*

A potential critique of using low frequency measures of stock crashes and jumps (i.e., annual returns) is the exposure of the long window expected returns to risk. Thus, differences in downside and upside volatility related to profitability may be driven by variation in expected returns if our empirical model omits unknown risk factors. We address this concern by using market-adjusted ***daily*** returns because differences in expected returns become negligibly small at very short horizons. Therefore, tests using daily returns are more accurate and powerful because they diminish the influence of risk on expected returns. We model the probability of a firm outperforming or underperforming the market by at least 100 basis points on any given day, a threshold that cannot be reasonably attributed to risk. Our null hypothesis is as follows:

***H2b**: Profitability is equally and positively associated with price jumps and crashes using daily returns.*

2.2 Does the profitability premium reflect expectation errors?

Section 2.1 focuses on whether downside risk is a plausible source of the profitability premium. In this section, we explore an alternative, non-risk-based explanation. Specifically, we focus on the relationship between profitability and subsequent revision in investors' earnings expectations. A large literature finds an initial optimistic bias in earnings expectations and a subsequent downward drift leading up to the announcement. However, the magnitude of this drift provides insight into whether analysts initially underreact to specific information. La Porta (1996) finds that forecast revisions are negatively associated with past growth. Bradshaw et al. (2001) report that high accruals are associated with a larger subsequent downward drift in forecasts. We build on Bouchard et al. (2019) who report that higher profit firms exhibit higher subsequent forecast errors related to next year's earnings. In other words, analysts are overly optimistic about low profit firms and pessimistic about high profit firms. However, they measure these errors immediately following the profit announcement. Therefore, we begin with these early earnings expectations, but investigate whether the initial underreaction to past profitability resolves as new information is revealed.

We expect this underreaction to past profitability to put upward (downward) pressure on the subsequent forecast drift among high-profit (low-profit) firms. We isolate this profitability effect on forecast drift by removing the systematic component of drift due to the well-documented forecast walk-down. Specifically, we examine the abnormal drift after adjusting for drift among industry-matched peers. We expect a positive abnormal drift among high-profit firms and a negative abnormal drift among low-profit firms. Thus, we test the following hypothesis:

H3*: The abnormal drift in forecast revisions is in the same direction as past profitability.*

Our next two hypotheses investigate the association between this forecast drift and the profitability premium. First, we examine whether the subsequent drift in forecast revisions can predict the magnitude of the premium. H3 implies that there will be larger positive and negative relative forecast drifts for high- and low-profit firms, respectively. In turn, we expect prices to respond to these drifts. We test whether the profitability premium is concentrated in firms with an upward abnormal drift. Similarly, the short side of the premium should be concentrated in firms with a downward abnormal drift. We state our next hypothesis as follows.

H4a*: The profitability premium is concentrated in (i) high profit firms with a subsequent upward forecast drift and (ii) low profit firms with a downward drift.*

Next, we examine the persistent and idiosyncratic components of the drift to better understand the underlying mechanisms behind the premium. Bouchard et al. (2019) propose a sticky expectations model in which analysts can vary in the persistence of their EPS forecast revisions (i.e., expectation stickiness). Stickier expectations are characterized by a higher persistence of forecast revisions that reflect more persistent EPS overestimation and underestimation. Bouchard et al. (2019) conclude that the profitability premium is more pronounced for stocks that are followed by analysts characterized by more sticky expectations. In other words, analysts repeatedly make forecasting errors and subsequent corrections in the same direction, and the market fails to anticipate this predicable bias. If this is the case, then the persistent component of forecast revisions should have (at least the majority of) the explanatory power for the profitability premium. However, Hughes and Liu (2008) report that trading strategies based on the predictable component of forecast errors are typically not profitable. Thus, it is not clear whether the results in Bouchard et al. (2019) are an outcome of analyst persistence or a reflection of firms with difficult to forecast performance.

Therefore, we examine whether the implication of forecast revisions for the profitability premium differs for the revision's persistent (sticky or persistent) and idiosyncratic (non-persistent) components. To test this, we state the following hypothesis in the null.

***H4b**: The profitability premium is unrelated to the idiosyncratic (non-persistent) component of analysts' forecast revisions.*

2.3 Profitability and institutional investor demand for shares

Our final hypothesis examines institutional demand for shares. These arguments have two implications for the trading behavior of institutions. First, institutions exhibit a delayed increase in demand for the shares of high-profit firms as their earnings expectations drift upward. Second, institutions also exhibit a delayed decrease in demand for low-profit firms as their earnings expectations drift downward. This analysis is in the spirit of Choi and Sias (2012), who report that institutional investors exhibit delayed demand for firms conditional on their fundamentals. However, profitability is arguably the most salient performance measure observed by investors, and thus differs from the broad index of fundamental signals examined in Choi and Sias (2012). We thus state our final hypothesis as follows:

***H5**: Profitability is positively associated with subsequent institutional demand for shares.*

3. Variable measurement and sample

3.1 Operating profitability

Following prior research, we measure operating profitability using annual operating profit (Ball et al. 2015) and cash operating profit (Ball et al. 2016), scaled by total assets:

Operating Profit (*OP*) = Sales – COGS – (SG&A – R&D)

Cash Operating Profit (*COP*) = Sales – COGS – (SG&A – R&D) – ΔREC – ΔINV – ΔXPP + ΔDR + ΔAP + ΔXACC.

Where COGS is the cost of goods sold; SG&A is selling, general, and administrative expenses; R&D is research and development expenses; REC is accounts receivable; INV is inventory; XPP is prepaid expenses; DR is deferred revenue; AP is accounts payable; and XACC is accrued expenses.

3.2 Ex-ante stock crash risk

3.2.1 Stock option implied volatility skewness

Our first measure of ex-ante stock crash risk is stock option-implied volatility skewness (*IVSKEW*). We measure *IVSKEW* as the difference between the daily implied volatility of an out-of-the-money (OTM) put option and that of an at the money (ATM) call on the same day (Kim and Zhang 2014). Larger positive values for *IVSKEW* indicate that put options have become relatively more expensive than similar call options, revealing options traders' belief that a large negative movement in price has become more likely. We obtain daily option data from OptionMetrics. We define option moneyness using the option delta value, with OTM puts defined as put options with a delta value between -0.375 and -0.125, and ATM calls defined as call options with a delta value between 0.375 and 0.625. Consistent with Kim and Zhang (2014), we additionally apply the following restrictions to the options: (i) the implied volatility of the option is not missing and is between 0.03 and 2.00, (ii) the open interest of the option is not missing and is greater than zero, (iii) the total volume of option contracts is not missing, and (iv) the best offer price is equal to or greater than the best bid price and the best bid price is not zero. When there are multiple put or call option contracts for a stock on the same day, we calculate *IVSKEW* as the weighted average of the implied volatilities for the put or call options using option open interest. Finally, we compute *IVSKEW3* as the average *IVSKEW* over the three months beginning in the fourth month, following the end of the prior fiscal year.

3.2.2 Crash probability

Our second measure of ex-ante stock crash probability follows Jang and Kang's (2019) approach, which estimates stock crash probabilities using parameters estimated out of sample. Our approach proceeds in the following steps. First, for a given firm-year, we compute the forward 12 month return beginning in the fourth month following the fiscal year-end. We identify returns of 100% or larger as price jumps and returns of -50% or less as price crashes. We generate a ternary variable that equals 1 for price jumps, -1 for price crashes, and 0 otherwise.

Second, we employ a generalized logit model (GLM) to jointly estimate parameters for the probability that a firm experiences a stock crash or jump over the subsequent 12 months. This approach has the advantage of defining crashes and jumps as exclusive, but mutually dependent. For a given two-digit SIC industry-year *t*, we collect all available firms for years *t-1 to t-10*, requiring a minimum of 50 firms for each group. We then estimate the GLM for this group with the ternary dependent variable and a vector of explanatory variables to predict extreme negative and positive outcomes. These include past 12 month market return (*RM12*), past 12 month individual market-adjusted return (*EXRET12*), total volatility equal to the standard deviation of daily returns over 6 months preceding the crash measurement period (*TVOL*), skewness of daily returns over prior 6 months (*TSKEW*), log of firm market value of equity (*SIZE*), turnover equal to of the average monthly trading volume divided by total shares outstanding over the 12 months preceding the crash measurement period (*TURN*), years since first appearance on the CRSP monthly file (*AGE*), tangible assets equal to gross PP&E scaled by total assets (*TANG*), and sales growth equal to the log of sales minus prior year sales (*SALESG*).

Third, we compute each firm's crash probability using its year *t* values for the explanatory variables and industry-level parameters (based on years *t-1* to *t-10*) obtained from estimating the GLM:

$$CRASHP = \frac{\exp{(\alpha + \beta X)}}{1 + \exp(\alpha + \beta X) + \exp{(\delta + \theta X)}}. \tag{1}$$

In Eq. (1), α and β are the industry-specific stock crash intercept and slopes (estimated over years *t*-10 to *t*-1) that model the likelihood of a stock crash relative to a non-event (i.e., no crash or jump). Similarly, δ and θ are the stock jump parameters that model the likelihood of a stock jump relative to a non-event (i.e., no crash or jump). The firm-specific year *t* vector of explanatory variables is represented by *X*. Thus, *CRASHP* is a firm-year estimate of the probability that a firm's stock will crash by at least 50% over the following 12 months, conditional on the firm's current characteristics and historic industry crash patterns. See Jang and Kang (2019) for additional details regarding this measure.

3.3 Analyst forecast errors and revisions

Bouchaud et al. (2019) measure the annual forecast error based on the first *IBES* forecasts available within 45 days of the previous fourth-quarter earnings announcement. This approach creates a single point estimate of the consensus forecast error early in an earnings year. We also collect this early error but follow Bradshaw et al. (2001) by conducting our tests across all twelve forecast months for each annual earnings realization. We compute monthly forecasts as the monthly median *IBES* annual EPS forecast (month = 1 to 12) scaled by the stock price from the first month in the series (i.e., month = 1). Similarly, we compute monthly forecast errors (*FE*) by subtracting the monthly consensus EPS forecast from the actual EPS realization scaled by the month 1 stock price. This approach results in a series of up to twelve values for both the forecast and forecast errors. Ultimately, these two measures reveal patterns in expected earnings. However, a series of forecast errors has the added benefit of expressing this pattern in the context of optimism and pessimism. To identify abnormal levels of analyst optimism or pessimism (*ADJFE*), we also adjust the forecast errors using the average two-digit SIC industry forecast error for the given month.

3.4 Institutional investor demand

We obtain institutional ownership from Thomson-Reuters 13F data and measure the change in institutional ownership as quarterly growth or decline in the number of institutional investors holding a stock (e.g., Lehavy and Sloan 2008; Choi and Sias 2012). This measure captures the change in ownership breadth, which should provide a strong signal for changes in institutional demand for a stock (Sias, Starks, and Titman 2006; Brown, Wei, and Wermers 2014). Our primary measure, ΔIO, is the quarterly change in the number of institutional investors holding a stock.[8] We include only 13(f) filers present on Thomson-Reuters in both the current and prior quarters to mitigate bias due to changes in the universe of filers (Lehavy and Sloan 2008). Our second measure, ΔAIO, is the quarterly change in institutional breadth less the average quarterly change in institutional breadth for securities within the same NYSE capitalization decile. Thus,

[8] We obtain institutional ownership from Thomson-Reuters 13F data. We note that the 13(f) data, however, are an inexact measure. For example, small institutions (less than $100 million in assets) and positions (less than $200,000) may be excluded from the 13(f) filings.

this measure captures the abnormal change in the breadth of a firm relative to similarly sized firms. The remaining two measures normalize this adjusted change in institutional breadth by using general institutional ownership levels. Following Choi and Sias (2012), we calculate Δ*AIO1%* by dividing the abnormal change in breadth by the average number of institutional shareholders at the end of quarter $q = 0$ for securities in the same capitalization decile. Furthermore, following Lehavy and Sloan (2008), we calculate Δ*AIO2%* by dividing the abnormal change in breadth by the total number of 13(f) filers for quarter $q = 0$.

To test *H5* we examine the change in institutional ownership during an 'Information Period' which includes the four quarters ending three months after the operating profitability fiscal year (Quarters $q = -3$ to 0) and a 'Post Information Period', which includes the four subsequent quarters (Quarters $q = 1$ to 4).[9] We use the Information Period quarters to identify institutional investors' *timely* incorporation of operating profitability information and the Post Information Period quarters to identify institutional investors' *delayed* incorporation of operating profitability information (Choi and Sias 2012).

3.5 Sample

We obtain stock return data from the Center for Research in Security Prices (CRSP), financial statement data from Compustat, analyst forecast data from the Institutional Brokers Estimates System (*I/B/E/S*), stock option data from OptionMetrics, and institutional investor ownership data from Thomson-Reuters. Our maximum sample period spans the period 1991–2018.

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[9] For example, a firm with a fiscal year ending on March 31, 2010 is assigned an 'Information Period' that lasts from July 2009 through June 2010 and a 'Post Information Period' that lasts from July 2010 through June 2011. Extending the Information Period to three months following the fiscal year end provides time for the financial reports to be issued.

We begin in 1991 because the data for several of our tests (such as option quotes and analyst forecasts) are primarily available beyond this date.

Panel A of Table 1 reports the pooled descriptive statistics of the profitability variables used in our study. The average operating profit (*OP*) and cash operating profit (*COP*) are 11.1% and 12.2% of total assets, respectively. Panel B compares variable means for firms allocated to the high (Decile 10) and low (Decile 1) operating profit portfolios. Consistent with prior research, firms with high operating profits exhibit higher average annual returns. However, high operating profit firms exhibit lower return volatility, smaller market betas, larger market capitalization, and lower BM ratios relative to firms with low operating profits. Taken together, high operating profit firms generally fit a lower-risk profile rather than a higher-risk profile.

4. Results

4.1 Profitability and the ex-ante likelihood of a stock price crash

We test *H1* by estimating pooled OLS regressions of either *IVSKEW3* or *CRASHP* on the decile ranks of profitability (*COP* or *OP*). We include several control variables taken from prior studies that examine ex-ante crash likelihood, two-digit SIC industry effects, and year effects. We determine significance based on standard errors two-way clustered by firm and year. Table 2 reports the results. Columns (1) and (2) show that both *COP* and *OP* are negatively associated with the implied volatility skew during the period following the release of the financial statements ($p < 0.01$). Similarly, columns (3) and (4) show that both *COP* and *OP* are also negatively associated with ex-ante crash probability, as measured by Jang and Kang's (2019) expectations model ($p < 0.01$). These results suggest that more profitable firms are less likely to experience future stock crashes. Thus, the results are inconsistent with the profitability premium reflecting compensation for investors bearing downside risk when they own high profit firms.

4.2 Profitability and the likelihood of realized stock crashes and jumps

4.2.1 Annual returns

We expect that under *H2a*, the likelihood of large positive annual returns is *increasing* in past profitability, while the likelihood of large negative annual returns is *decreasing* in past profitability. We test *H2a* using annual cross-sectional logistic regressions that model the likelihood of large positive or negative annual returns as a function of profitability as follows:

$$P(Low\_return) = \alpha_1 + \beta_1 * Profitability + \Gamma_1 * RiskControls. \tag{2}$$

$$P(High\_return) = \alpha_2 + \beta_2 * Profitability + \Gamma_2 * RiskControls \tag{3}$$

Where Low_return and $High\_return$ are indicator variables that equal 1 when a firm's annual stock return is below -50% or above 50%, respectively, and 0 otherwise. *Profitability* is either *OP* or *COP*, and $RiskControls$ is a vector of risk variables including the stock's return volatility (*VOL*), market beta (*BETA*), market value of equity (*SIZE*), and book-to-market ratio (*BM*). We calculate profitability and control variables at the end of each calendar year and rank them into annual deciles with a range (0, 1). We calculate the annual return as the 12-month return beginning in the following April, attaching the CRSP delisting returns when available. Thus, these tests identify an association between large returns and past profitability. In our tests, the risk hypotheses would not be supported if we find that profitability is associated with a *lower* likelihood of large negative annual returns (i.e., $\beta_1 < 0$) but a *higher* likelihood of large positive annual returns ($\beta_2 > 0$).

Table 3 reports the results from estimating Eq. (2) and (3). Panel A provides estimates from Eq. (2) which models the likelihood of large negative returns.[10] The estimated coefficients on *COP*

[10] The estimated coefficients are reported as time series averages using the Fama and MacBeth (1973) approach. We find equivalent results when we used pooled regressions (not reported).

and *OP* for the full sample are -0.99 and -1.12, respectively ($p < 0.01$). This negative association between profitability and the likelihood of a realized stock crash corroborates our results based on ex-ante expected crash risk in section 4.1. Panel B provides estimates from Equation (3) which models the likelihood of large positive returns. The coefficients on *COP* and *OP* for the full sample are now positive, 0.49 and 0.44 ($p < 0.01$). Results excluding microcaps in both panels are similar.[11] If high profit firms are riskier in the volatility sense, then we would expect past profitability to be positively correlated with both large positive and large negative returns. Thus, these results support *H2a* and are inconsistent with the risk hypothesis.

4.2.2 Daily returns

In this section, we adapt an approach based on Eqs. (2) and (3) in a daily setting: The outcome variables now identify whether a firm experiences a market-adjusted daily return of -1% or less (Eq. 2), or 1% or more (Eq. 3).[12] We measure the market-adjusted daily market returns using the CRSP value-weighted index return. We obtain daily returns over the 12-month period beginning in the following April and estimate daily cross-sectional logistic regressions over this period. The results of these tests are presented in Table 4. In Panel A, the estimated coefficients on *COP* and *OP* for the full sample are both negative ($p < 0.01$). In Panel B, the estimated coefficients on *COP* and *OP* for the full sample are both positive ($p < 0.01$). Results excluding microcaps are similar. Thus, profitability is associated with a lower likelihood of large negative daily returns and a higher likelihood of large positive daily returns. These results corroborate those for the 12-month return window reported above.

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[11] The reported annual results are also robust to using a return magnitude of 70% (as opposed to 50%) as the threshold.

[12] Note that a stock having a higher likelihood of overperforming/underperforming the market by 1% daily cannot reasonably be attributed to differentials in risk.

4.3 Performance in periods of negative market news

The results in sections 4.1 and 4.2 refute downside risk and symmetric risk as explanations for the profitability premium. We also use tests of daily returns to examine whether systematic risk provides a plausible explanation. Asset-pricing models suggest that stocks with high exposure to systematic risk experience more negative returns during periods of systematic bad news. Accordingly, if high-profit stocks are exposed to higher systematic risk, then we expect their returns to be more negative on days of large negative market shocks. As a direct test, we examine whether high-profit firms outperform on days with negative market news. Outperformance on these days would be contrary to greater systematic risk. We identify a large market shock as a daily CRSP value-weighted index return of -5% or lower. During the sample period of 1991-2018, we find only 17 such days, which suggests that daily market returns of -5% or more are rare and therefore reflect significant bad news at the aggregate level. We estimate the following logistic model for each of the 17 days:

$$P(AdjRet > 0) = \alpha_1 + \beta_1 * Profitability + \Gamma_1 * RiskControls. \quad (4)$$

Eq. (4) is identical to Eq. (3) except that the dependent variable now equals 1 when the market-adjusted daily return is positive rather than 1% or higher. Thus. estimates from Eq. (4) inform us of the likelihood that high-profit firms outperform ($\hat{\beta}_1$>0) or underperform ($\hat{\beta}_1$<0) the market on days of extreme bad news. In these tests, $\beta_1 > 0$ indicates that high-profit firms exhibit relatively low exposure to negative market-wide events, suggesting that these firms exhibit less systematic risk.

Table 5 reports results from estimating Eq. (4). In Panel A, the full sample coefficients on *COP* and *OP* are both positive ($p < 0.01$), which indicates that past profitability increases the likelihood that a firm will outperform (rather than underperform) the market on days when the market experiences substantial negative shocks.[13] To take a deeper look into these findings, we restrict the previous sample to the 2008 financial crisis when the economy experienced substantial aggregate credit, financial, and macroeconomic shocks. We report these results in Panel B. We find that there are 11 days during the 2007-2009 period when the market return was -5% or less. Despite our expectation that fewer sample days will lower power even further, we find a stronger result during the financial crisis. The estimated coefficients on both *COP* and *OP* are larger than those in Panel A.

Collectively, the evidence from our tests examining extreme price movements provides consistent evidence that refutes three risk-based explanations for the profitability premium (i.e., downside risk, symmetric risk, and systematic risk).

4.3 Profitability and expectation errors

4.3.1 Forecast drift for extreme profitability firms

Figure 1 plots the monthly time series of year *t+1* industry-adjusted forecast errors (*ADJFE*) for firms with either high profitability (top decile) or low profitability (bottom decile) in year *t*. The results for *COP* and *OP* provide similar inferences, so we limit our discussion to the former. In month 1, immediately following the prior fourth quarter earnings announcement, analyst forecasts for low *COP* firms are optimistic relative to their industry peers. The size of this effect is meaningful at about 1.2% of price. In contrast, high *COP* firms have forecasts that are more pessimistic than their industry peers. This effect is about 1.5% of price. These results confirm those in Bouchaud et al. (2019) for our setting. Consistent with *H3*, this excess optimism for low profit

[13] This evidence is especially noteworthy for two reasons. First, when we drop microcap stocks, the evidence becomes stronger. For example, the estimated coefficient on *COP* more than doubles. Second, the Fama-Macbeth *t*-statistics are based on only 17 cross-sectional estimates which normally would provide low power to detect an effect. Yet, we can achieve statistical significance which indicates a high degree of consistency in higher profit firms outperforming the market when the aggregate news is bad.

firms and pessimism for high profit firms attenuates over the following 12 months. This confirms that earnings forecasts tend to drift in the same direction as past profitability.[14] While descriptive in nature, Figure 1 provides an intuitive view of (1) the excessive levels of analyst optimism and pessimism related to past profitability, and (2) the attenuation of this bias over the subsequent 12 months.

4.3.2 Forecast drift for all profitability levels

Figure 1 is restricted to firms in extreme profitability deciles, which is a common basis for measuring the profitability premium. Next, we focus on the entire profitability distribution. Given the correlation between extreme profitability levels and forecast revisions reported above, we examine whether this correlation extends to all profitability levels. To keep the analysis tractable, we examine the association between profitability and total forecast revision between months 1 and 12. We define *REVEST* as the month 12 consensus EPS forecast minus the month 1 consensus forecast scaled by price in month 1. Thus, larger positive (negative) values for *REVEST* indicate a larger total positive (negative) forecast revision during the 12 months. Next, we independently sort firms into annual deciles of profitability (*COP* or *OP*) and annual terciles of *REVEST*, resulting in 30 portfolios. Figure 2 shows the proportion of firms in each 3×10 cell. The cells with proportions above the expected level are shaded.[15] The patterns for both *COP* and *OP* suggest that the positive relationship between profitability and forecast revisions generalizes to the full distribution of profitability. Generally, firms with higher profitability exhibit higher subsequent revisions, whereas the opposite is true for lower-profit firms.

[14] Recall that the forecast error equals actual EPS minus the EPS forecast. Because actual EPS is fixed, the signed forecast error become smaller (i.e., less positive, or more negative) as the forecast increases, and become larger (i.e., more positive or less negative) as the forecast decreases.
[15] Assuming that profitability and that total change in expected earnings are uncorrelated, the expected proportion in each cell is 3.33% (or 1/30).

To formally test *H3*, we compute the average monthly (1–12) *ADJFE* for each year for each profitability portfolio.[16] Following Bradshaw et al. (2001), we regress this average *ADJFE* on decile-ranked profitability (0, 1). We conduct these regressions for each of the 12 months in the series. The regression intercept measures the average *ADJFE* for low-profit firms and the regression slope measures the average incremental *ADJFE* for a high-versus low-profit firm. This results in a time series of 12 intercepts and slopes. Table 6 reports the intercepts and slopes of the regressions. Panel A reports the results for *COP*. Consistent with Figures 1 and 2, the intercept exhibits a significant increase from -0.88 in month 1 to -0.17 in month 12 ($p < 0.01$). This finding confirms that low-profit firms experience a downward drift in forecasts that converge towards actual earnings. Additionally, the slope is large and positive in month one, again confirming Bouchaud et al. (2019) in our setting. However, the slope exhibits a significant decrease from 2.73 to 0.94 ($p < 0.01$) over 12 months. This convergence in forecast errors towards zero statistically confirms hypothesis *H3* that forecast revisions drift in the same direction as past profitability. The results for operating profit (*OP*) in Panel B lead to similar inferences.

4.3.3 Forecast drift and the profitability premium

Hypothesis 4a is highlighted in Figure 3. In particular, the lower-right green region describes firms with high profitability and subsequent forecast revisions. We expect to observe the strongest positive returns on the long-term side of the profitability premium in this region. The top-left green region describes firms with low profitability and low subsequent forecast revisions. We expect to observe the strongest negative returns on the short side of the profitability premium in this region.

[16] We repeat these tests using unadjusted forecast errors and continue to find significant support for *H3*.

We operationalize Figure 3 by independent two-way sorting firms at the median annual profitability and *REVEST*. We then generate two mutually exclusive samples. The first sample includes firms with above (below) median profitability and above (below) median *REVEST*. In these firms, subsequent forecasts drift in the same direction as profitability. The second sample includes firms with above (below) median profitability and below (above) the median *REVEST* (red region). In these firms, subsequent forecasts drift in the opposite direction to profitability. We test for the presence of the profitability premium in these two samples based on three-factor alphas.[17]

The results are presented in Table 7. Panels A and B report the results when we measure profitability using *COP* and *OP*, respectively. We restrict our discussion to Panel A because both profitability measures lead to identical inferences. We begin with the sample in which the subsequent total forecast revision is in the Same Direction as profitability. The monthly alphas increase monotonically from the lowest profit quintile (-0.93%; $p < 0.01$) to the highest profit quintile (0.97%; $p < 0.01$). The long-short hedge portfolio generates monthly risk-adjusted returns of 1.91% ($p < 0.01$). Thus, the profitability premium is pronounced among firms whose analysts initially underweight the profitability signal.[18]

The results are starkly different for the sample in which the subsequent total forecast revision is in the Opposite Direction to profitability. The monthly alphas now ***decrease*** monotonically from a ***positive*** return for the lowest profit quintile (0.61%; $p < 0.01$) to a ***negative*** return for the highest profit quintile (-0.62%; $p < 0.01$). Thus, the premium reverses, with the long-

[17] The alphas we report are based on monthly returns to portfolios firmed on April 1 of each year. We sort firms into five portfolios based on the most recent profitability announced prior to April 1. We include the MktRf, HML, and SMB risk controls. Our inferences do not change when we use pricing models that include investment (CMA) and momentum (MOM) factors.

[18] In unreported tests we also confirm the presence of the profitability premium in the full sample.

short hedge portfolio generating negative monthly risk-adjusted returns of -1.24% ($p < 0.01$). The profitability strategy would have generated significant negative returns among firms whose analysts initially ***overweight*** the profitability signal. We also confirm that hedge returns significantly differ between the two samples ($p < 0.01$). The analysis above is consistent with hypothesis H4b and suggests that the profitability premium is largely driven by expectation errors and mispricing.[19]

4.3.4 The persistent and nonpersistent components of the forecast revision

We show above that the profitability premium is restricted to firms for which the subsequent forecast revision is in the same direction as profitability. We further examine this by decomposing the subsequent 12-month forecast revision (*REVEST*) into a persistent (*REVPERS*) and nonpersistent component (*REVNPERS*).[20] We repeat the above analysis. However, we now generate two new samples based on annual median cuts of profitability and either *REVPERS* or *REVNPERS*. We focus on firms where the revision component and profitability are in the same direction. Thus, both samples are restricted to firms with above (below) median profitability and above (below) median *REVPERS* (*REVNPERS*).

The results are also presented in Table 7. For the persistent component of the revision, the profitability strategy generates a monthly alpha of 0.51% ($p < 0.05$). While weakly significant, the return is only one-quarter as large as the return we found above when the full revision is in the

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[19] One could argue that the "Opposite Direction" sample is something of a straw man. However, for that to be the case the literature would have to have determined that expectation errors and mispricing are the root cause of the profitability premium. We are unaware of anything like broad agreement in that regard.

[20] We estimate forecast revision persistence parameters for each NYSE size decile using rolling regressions of *REVEST* on three lags of *REVEST*. We then apply those parameters to all firms in each annual size decile. For example, to decompose $REVEST_{t+1}$ relative to year t profitability, we regress $REVEST_t$ on $REVEST_{t-1}$, $REVEST_{t-2}$, and $REVEST_{t-3}$ using all firms in a size decile. We then compute the persistent component (*REVPERS*) of $REVEST_{t+1}$ by applying those parameters to year t to year t-2 *REVEST*. We compute the nonpersistent component (*REVNPERS*) as the actual $REVEST_{t+1}$ minus $REVPERS_{t+1}$. This approach has the advantage of generating the persistent component of the subsequent revisions using only data that is available as of the portfolio formation dates.

same direction as profitability (i.e., 1.91%). For the non-persistent component of the revision, the results are very similar to what we find for the full revision. The monthly alphas increase monotonically from the lowest profit quintile (-0.87%; $p < 0.01$) to the highest (0.98%; $p < 0.01$). The long-short hedge portfolio generates monthly risk-adjusted returns of 1.85% (p < 0.01). We also confirm that the hedge return is significantly larger when the sample construction is based on the nonpersistent component of the revision (p < 0.01). Together, these results confirm Bouchard et al.'s (2019) contention that sticky expectations play a role in profitability premium. However, the significantly larger premium we find based on the non-persistent component of the forecast error points to the large impact of mispricing that is not predictable based on prior analyst behavior.[21]

4.4 Institutional investor demand

Table 8 reports the profitability and institutional demand results. We require firm-year data to be available for all eight quarters surrounding the profitability announcement, and we rank this sample into ten profitability portfolios every year. In Panel A, we compute the time-series means of the quarterly cross-sectional averages for both an information period (i.e., months *t-9* to *t+3* relative to the profitability year-end) and a post-information period (i.e., months *t+4* to *t+15* following the profitability year-end). We report the average quarterly change in institutional breadth during the information period and post-information period for the low (decile 1) and high (decile 10) profitability deciles.

First, we examine the Information Period (i.e., profit year) and validate that our design can detect predictable changes in institutional demand. We find a larger increase in institutional

[21] Our inferences are unchanged if we estimate firm-specific persistence parameters using rolling windows. However, our sample size is substantially reduced.

demand among high profit firms (Decile 10) than among profit firms (Decile 1) ($p < 0.01$). This extends to all the ownership and profitability measures. These results serve as a baseline and provide us with reasonable confidence that our test design is well specified to detect variations in institutional demand during the post-information period.

Consistent with *H5*, and institutions' delayed incorporation of information, profitability continues to be positively associated with changes in institutional demand during the four quarters after the profitability announcement. High *COP* firms add 1.32 institutions per quarter (or about 5.3 institutions over the year), while low *COP* firms add only 0.40 per quarter (or about 1.6 institutions over the year).[22] High *COP* firms also gain institutions relative to their size-matched peers, whereas low *COP* firms lose institutions. Moreover, this difference in the growth in institutional demand between high- and low-profit firms equates to about 5.4% (1.34% × 4) of the average firms' initial institutional ownership and about 0.1% (0.024% × 4) of the universe of 13(f) filers. Thus, these effects are economically meaningful and statistically significant ($p < 0.01$). The results for *OP* led to identical inferences.

As with the analyst forecast-based tests reported previously, we also examine the changes in institutional demand across the full distribution of profitability. We estimate OLS regressions of the change in institutional ownership on profitability and several common firm characteristics. We report the estimated slopes from the pooled OLS regressions of the quarterly change in institutional ownership on profitability and several controls. For each dependent variable, we estimate two regressions: one during the Information Period and one during the post-information period. We use a decile rank transformation of profitability that ranges from zero to one. We follow

[22] While we only report results for the high and low profit deciles, we find that the change in institutional demand increases monotonically across all ten profitability deciles. In regression tests reported later we identify variation in institutional demand across the entire distribution of profitability.

Choi and Sias (2012) by including four control variables that jointly capture common risk characteristics and momentum. These include the natural log of firm size and the natural log of the book-to-market ratio, both measured at $q = -1$ (i.e., the Information Period fiscal year-end), lag percent asset growth measured during the four quarters from $q = -4$ through $q = -1$ (i.e., the information period fiscal year), and the market-adjusted return measured over $q = -1$ through $q = 0$ (i.e., the final two quarters of the information period). We also included quarter- and two-digit SIC industry effects. We report *t*-statistics based on standard errors clustered by firm and quarter.

In Panel B of Table 8, we show that during the information period, all four measures of growth in institutional demand continue to be positively associated with *COP* ($p < 0.01$) after including additional controls. This provided us with a baseline. Turning to the post information period, moving from low to high *COP* predicts an additional 1.28 institutions (0.32 x 4) over the four quarters in both absolute terms and relative to size-matched peers ($p < 0.05$). Thus, we can show that the delayed response of institutions to the information conveyed by profitability is not fully subsumed by risk and momentum. This difference in institutional growth between high and low *COP* firms equates to about 3.16% (0.79 × 4) of the average firms' institutional ownership at the time of the information release ($p < 0.01$) and about 0.08% (0.02 × 4) of the universe of 13(f) filers ($p < 0.01$). Thus, the profitability effect continues to exhibit a reasonable level of economic significance even with additional controls. The results in Panel C for *OP* again lead to similar, but somewhat stronger inferences. In summary, institutional demand for shares continues to be positively associated with profitability for up to four quarters, following earnings announcements.

4.5 Additional analysis

We perform two additional stock price-based tests that address the joint hypothesis problem present when testing for an anomaly.

4.5.1 Earnings announcement tests

A useful approach to distinguish between risk and underreaction is to study subsequent earnings announcement returns. If a significant amount of the returns generated by an investment strategy long in high-profitability firms and short in low-profitability firms occur around earnings announcements, it is likely that the returns to the strategy are driven by earnings or cash flow news that surprises the market rather than risk-related expected returns (La Porta et al. 1997). We directly test for evidence of earnings announcement returns in a long-short investment strategy based on operating profits. For each calendar year, we rank all firms into deciles based on their profitability. We then obtain the 5-day announcement window returns around the next four quarterly earnings announcements, beginning in April. Next, we average the returns across firms to obtain the portfolio returns. Finally, we computed the time-series mean returns of each portfolio.

Panel A of Table 9 shows that the market-adjusted announcement return of the low *COP* portfolio is -4.51%, while the high *COP* portfolio experiences an average return of 1.36%, a difference of 5.87% ($p < 0.01$) for the long/short hedge portfolio. When microcaps are excluded, we find similar results, with an average difference of 4.12% for the hedged portfolio. We find similar results when we use raw returns. The returns are slightly smaller for portfolios based on *OP* in Panel B; however, the differences remain statistically significant.

For context, we compare these results with the findings of Ball et al. (2016, Table 4, Panel A), where a long-short portfolio based on the ranked decile of cash profitability produces a CAPM-adjusted monthly average return of 0.65% per month or 7.8% per year. Our findings in Panel A suggest that approximately half of these returns occur around earnings announcements. We interpret this evidence to be ***inconsistent*** with a risk-based explanation of the profitability-return relationship.

4.5.2 Long horizon tests

Ball et al. (2015) report that operating profitability explains the cross-sectional variation in monthly returns for up 10 ten years, consistent with a risk-based explanation for the profitability premium. We have added this discussion by repeating the tests of Ball et al. (2015).[23] However, in addition to examining all monthly returns (All), as in Ball et al. (2015), we examine two subsamples that include either months with a quarterly earnings announcement (EA) or months without a quarterly earnings announcement (Non-EA). Like the earnings announcement tests, the risk hypothesis predicts that returns to the profitability premium should occur evenly over time. In contrast, Figure 4 shows that the ability of past profits to predict future returns is driven by months with earnings announcements. First, we show that the results from tests that include all months (All) follow a pattern similar to that of Ball et al. (2015), with the slope of both cash operating profitability (*COP*) and operating profitability (*OP*) decaying over time, but remaining reliably positive over most of the 10-year prediction period. Next, we repeat the test on the sample restricted to months that contain a quarterly earnings announcement and show that the slope on both *COP* and *OP* decays more slowly and is reliably positive for all but one of the horizons we examine. Finally, we repeat the tests on the sample restricted to months without a quarterly earnings announcement and show that the slopes on *COP* and *OP* fail to reach significance at the 5% level over almost every horizon examined. These tests suggest that any long-horizon

[23] These tests are based on regressions estimated monthly using data from January 2003 through December 2017 for stocks with a market value of equity above the 20th percentile of NYSE market capitalization. The independent variables are prior one-month return, prior one-year return skipping one month, log-book-to-market, log-size, and either operating profitability (*OP*) or cash operating profitability (*COP*). We lag only the operating profitability variables and keep all other independent variables current. The lags range up to ten years, increasing in increments of six months.

correlation between profitability and future returns is driven by subsequent earnings announcements when new market information is likely to be revealed.

5. Conclusion

A growing body of literature documents that profitability predicts future returns (Fama and French 2006; Novy-Marx 2013; Ball et al. 2015, 2016). More recently, Ball et al. (2015, 2016) show that operating profitability and cash-based operating profitability are the strongest predictors of future returns. We provide evidence of competing explanations for these findings by investigating risk and mispricing. Our first set of tests examine the relation between profitability and extreme return outcomes. Profitability is negatively related to ex-ante stock crash risk. Profitability is also negatively related to the likelihood of large negative future returns, but positively related to the likelihood of large positive returns. High-profitability firms also outperform low-profitability firms on days with extremely large negative market returns. Taken together, this evidence is inconsistent with a risk-based explanation of this relationship. Our second set of tests investigates the potential underreaction by analysts and institutional investors to information on profitability as a mechanism for profitability mispricing. We find that both analysts and institutional investors underreact to profitability information. This suggests that the profitability premium is more consistent with mispricing than with risk. Our study sheds light on the risk versus mispricing explanations for the positive relationship between profitability and future returns documented in prior studies. This is an important issue from the investor's perspective. If returns to profitability are due to risk, this affects their portfolio selection or asset allocation decisions. On the other hand, if the returns are driven by mispricing, this offers an opportunity to take advantage of that mispricing.

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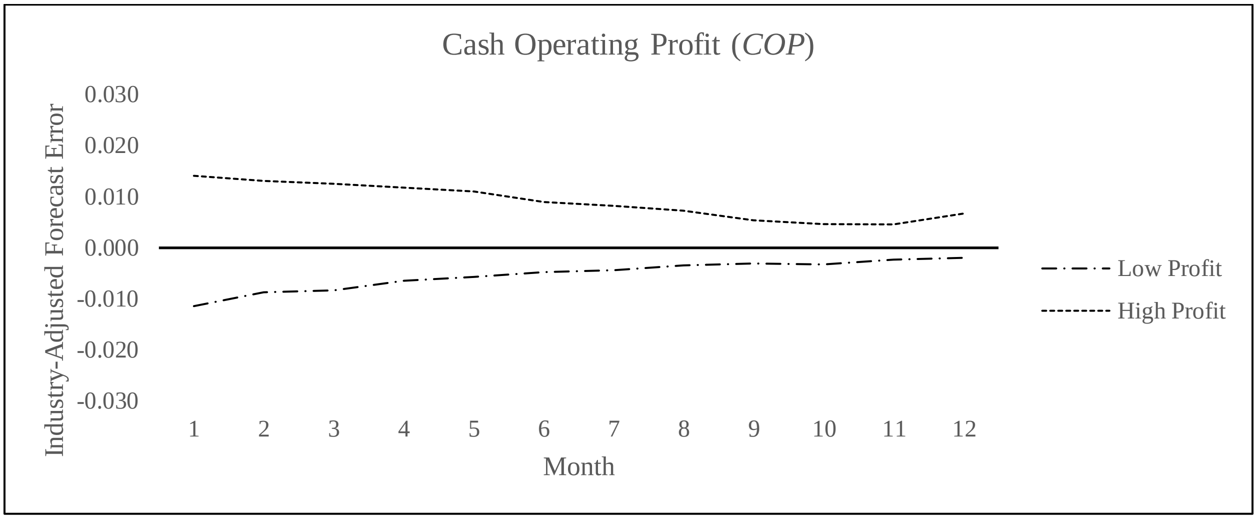
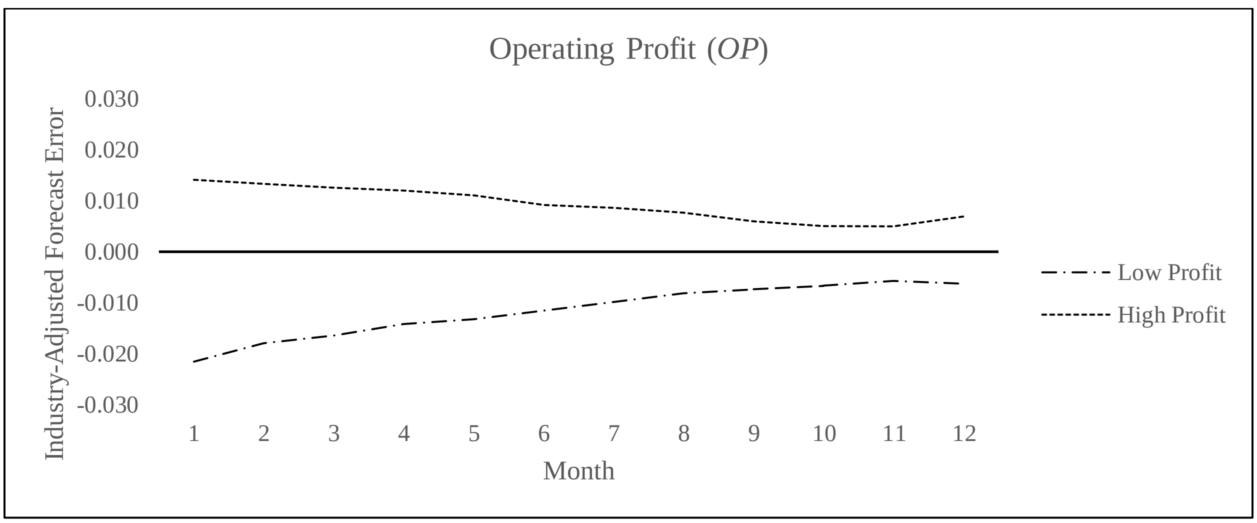
Figure 1 Industry-adjusted forecast errors for low and high operating profitability firms





This figure plots industry-adjusted annual forecast errors for low-profit and high-profit firms over the 12 months following the prior year's earnings announcement. We identify firms as having low and high profits if they are in the bottom and top annual operating profitability deciles, respectively. We define the monthly forecast error as the actual EPS minus the consensus (median) *IBES* EPS forecast for that month divided by the price at the end of the first month in the series (i.e., month 1). We adjust each monthly forecast error by subtracting the average error for the two-digit SIC industry-matched firms. This approach results in a measure of the optimism or pessimism of firms' forecasts relative to those of their industry peers. To include in the sample, we require a firm to have an available forecast in the first month of this series (i.e., month 1). We plot the time-series means of the monthly (1–12) cross-sectional averages for each operating profitability portfolio.

Figure 2 Proportion of firms with a Low, Mid and High total analyst forecast revision by profitability deciles

		COP									
		Low	2	3	4	5	6	7	8	9	High
	Low	4.2%	3.4%	3.6%	4.0%	3.6%	3.3%	3.0%	2.9%	2.7%	2.6%
REVEST	Mid	2.3%	3.2%	3.0%	2.9%	3.2%	3.4%	3.6%	3.8%	3.9%	3.7%
	High	3.5%	3.4%	3.3%	3.2%	3.2%	3.3%	3.4%	3.3%	3.4%	3.7%

		OP									
		Low	2	3	4	5	6	7	8	9	High
	Low	4.4%	2.6%	3.9%	4.0%	3.6%	3.2%	3.1%	2.9%	2.7%	2.8%
REVEST	2	2.0%	3.7%	2.8%	2.7%	3.1%	3.5%	3.7%	3.8%	3.9%	3.8%
	High	3.6%	3.7%	3.3%	3.3%	3.2%	3.3%	3.3%	3.3%	3.3%	3.5%

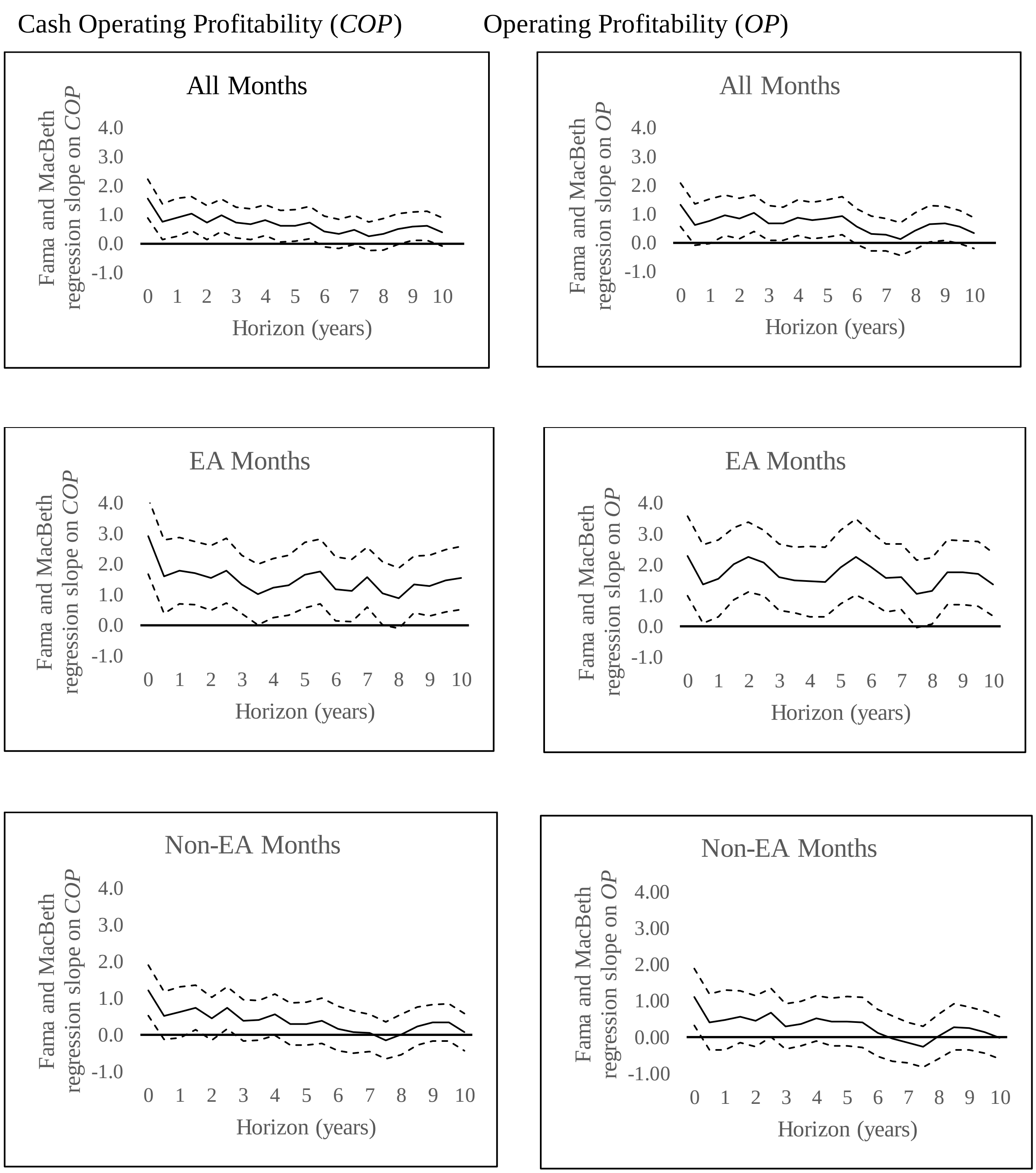
This figure reports the proportion of firms in 30 portfolios based on independent annual decile sorts of profitability and annual tercile sorts of the 12-month forecast revision (*REVEST*)). Profitability is the year *t COP* or *OP*. *REVEST* is the total 12 month change in the consensus year *t*+1 EPS forecast scaled by the price in month 1. Month 1 is the first month following the announcement of year *t* earnings. High (low) values of *REVEST* indicate upward (downwards) EPS forecast revisions that occurred during the EPS year. To include in the sample, we require a firm to have an available forecast in the first month of this series (i.e., month 1). Cells with a proportion larger than the expected value (3.33%) are shaded.

Figure 3 Hypothesized return patterns for the profitability premium conditional on the subsequent change in expected earnings

	Low Profitability	High Profitability
Low *REVEST*	Low profit firms with subsequent decrease in expected earnings. **Low Profit → Low Returns**	High profit firms with subsequent decrease in expected earnings. **High Profit → Low Returns**
High *REVEST*	Low profit firms with subsequent increase in expected earnings. **Low Profit → High Returns**	High profit firms with subsequent increase in expected earnings. **High Profit → High Returns**

This figure highlights the relationship between profitability, subsequent forecast revisions, and stock return. Green areas are where we expect to observe the strongest evidence of profitability premium.

Figure 4 Slopes and 95% confidence intervals from Fama and MacBeth regressions of monthly stock returns on lagged operating profitability



This figure plots the average Fama and MacBeth (1973) regression slopes and 95% confidence intervals from the cross-sectional regressions that predict monthly returns. The regressions are estimated monthly using data from January 2003 through December 2017 for stocks with a market value of equity above the 20th percentile of the NYSE market capitalization. The independent variables are the prior one-month return, prior one-year return skipping one month, log-book-to-market, log-size, and either cash operating profitability (C*OP*) or operating profitability (*OP*). See section 3.1 for variable definitions. We lag only the operating profitability variables and keep all other independent variables current. The lags range up to ten years, increasing in increments of six months. For example, the slopes reported for Horizon = 10 explain the cross-sectional variation in monthly returns using the operating profitability recorded ten years earlier. We separately estimate the regressions for a sample that includes all monthly returns (All), a sample that includes only months with quarterly earnings announcements (EA), and a sample that excludes all months with quarterly earnings announcements (Non-EA).

Table 1 Descriptive statistics

Panel A: Full sample

	Mean	Median	SD
Annual Return	0.173	0.054	0.934
COP	0.111	0.117	0.174
OP	0.122	0.121	0.168
VOL	0.149	0.126	0.099
BETA	1.113	0.992	0.990
MV ($M)	2,682	188	15,039
BM	0.619	0.518	3.402
n = 98,613			

Panel B: Averages for High (decile 10) and Low (decile 1) operating profit

	COP			*OP*		
	High	Low	H - L	High	Low	H – L
Annual Return	0.192	0.094	0.098	0.165	0.098	0.068
COP	0.412	-0.238	0.650	0.364	-0.180	0.544
OP	0.380	-0.138	0.518	0.421	-0.206	0.627
VOL	0.157	0.238	-0.082	0.156	0.259	-0.102
BETA	1.287	1.376	-0.089	1.302	1.463	-0.161
MV ($M)	6,443	292	6,150	6,489	211	6,277
BM	0.258	0.525	-0.267	0.277	0.500	-0.223

Panel A reports the descriptive statistics of the variables used for the overall sample. Panel B reports the statistics for high and low operating profit portfolios based on *COP* and *OP* and the difference (H – L). We identify high and low operating profits based on the top and bottom annual deciles of operating profitability, respectively.

Annual Return is the 12 month buy-and-hold return beginning in April of the year following the year in which we establish profitability ranks. *OP* and *COP* are operating profit and cash operating profit, respectively. *Vol* is the stock's return volatility, *BETA* is the market beta, *MV* is the market capitalization, and *BM* is the ratio of the book value of common equity to the market value of common equity. The sample period is 1991-2018.

Table 2 Profitability and the ex-ante likelihood of a stock price crash

Dependent Variable:	*IVSKEW3*		*CRASHP*	
	(1)	(2)	(3)	(4)
COP	-0.009***		-0.647***	
	(-3.69)		(-2.98)	
OP		-0.011***		-0.559***
		(-4.10)		(-2.86)
SIZE	-0.012***	-0.012***	-0.858***	-0.861***
	(-19.15)	(-19.25)	(-5.48)	(-5.49)
LEV	0.005	0.004	-0.159	-0.110
	(0.83)	(0.71)	(-0.34)	(-0.24)
MB	-0.005***	-0.005***	-0.414***	-0.414**
	(-4.40)	(-3.99)	(-2.83)	(-2.75)
CFVOL	0.034**	0.034**	2.481**	2.517**
	(2.17)	(2.20)	(2.61)	(2.64)
EVOL	0.003	0.002	2.514***	2.492***
	(0.28)	(0.16)	(3.66)	(3.57)
SVOL	-0.003	-0.002	0.787***	0.795***
	(-0.85)	(-0.75)	(4.19)	(4.26)
TURN	-0.053***	-0.052***	15.070***	15.081***
	(-10.40)	(-10.24)	(14.99)	(15.17)
BETA	-0.001	-0.001	-0.086	-0.085
	(-1.20)	(-1.24)	(-0.41)	(-0.41)
IVOL	0.367***	0.368***	33.861	33.632
	(2.98)	(2.99)	(0.71)	(0.71)
TVOL	-0.290**	-0.291**	57.713	57.873
	(-2.33)	(-2.33)	(1.15)	(1.15)
NSKEW	0.000	0.000	0.410***	0.409***
	(0.29)	(0.33)	(4.67)	(4.65)
RET	-0.001	-0.001	-0.260	-0.268
	(-0.86)	(-0.91)	(-1.02)	(-1.05)
HHI	-0.003	-0.003	-0.482	-0.471
	(-0.47)	(-0.47)	(-1.37)	(-1.32)
STRATEGY	0.009	0.011	22.284***	22.407***
	(0.42)	(0.50)	(8.28)	(8.42)
OIV	0.096***	0.095***		
	(7.75)	(7.64)		
Industry and Year Effects	Yes	Yes	Yes	Yes
Observations	24,037	24,037	53,256	53,256
Adj R^2	22.2%	22.2%	52.4%	52.4%

This table presents regression slopes and *t*-statistics (in parentheses) from pooled OLS regressions that provide evidence of the ability of operating profitability to predict ex-ante stock crash probability. The dependent variable in columns 1 and 2 is *IVSKEW3*, and the average daily stock option implied volatility skew is measured over months

4 to 6 following the fiscal year end. The dependent variable in columns 3 and 4 is *CRASHP*, an out-of-sample estimate of the probability that a firm's stock will crash by 50% or more over the 12 months beginning four months after the fiscal year end. See section 3.2, The regressions uses data from 1996 to 2017 for all stocks with available data. We use OLS and regress *IVSKEW3* or *CRASHP* on the annual decile rank (0, 1) of either the cash operating profit (*COP*) or operating profit (*OP*). We include a vector of control variables taken from the literature, including industry (two-digit SIC) and year fixed effects and two-way cluster standard errors by firm and year. Regression slopes were multiplied by 100.

SIZE is the log of market capitalization. *LEV* is the ratio of long-term total debt to total assets. *MB* is the ratio of the market value of common equity to its book value of common equity. *CFVOL* is the standard deviation of operating cash flows (scaled by lagged total assets) over the past five years. *EVOL* is the standard deviation of income before extraordinary items (scaled by lagged total assets) over the prior five years. *SVOL* is the standard deviation of sales revenue (scaled by lagged total assets) over the prior five years. *TURN* is the average monthly share turnover over fiscal year. *BETA* is the market beta estimated from CAPM using daily stock and market returns over the fiscal year. *IVOL* is the standard deviation of weekly firm-specific returns over the fiscal year. *TVOL* is the standard deviation of weekly stock returns over the fiscal year. *NSKEW* is the negative skewness of weekly stock returns over the fiscal year. *RET* is the return during the fiscal year. *HHI* is the Herfindahl-Hirschman index measured within the three-digit SIC industry year. *STRATEGY* is the business strategy composite measure of Bentley et al. (2013) scaled by 100. *OIV* is the daily open interest-weighted implied volatility of at the money call options, computed as the average over the fiscal year.

Table 3: Profitability and the Likelihood of Realized Stock Crashes and Jumps

Panel A: Likelihood of a Stock Crash (Ret <= -50%)

	All Firms		Microcaps Excluded	
Intercept	-3.61***	-3.55***	-4.65***	-4.66***
	(-16.05)	(-15.88)	(-14.73)	(-14.61)
COP	-0.99***		-1.07***	
	(-13.68)		(-9.17)	
OP		-1.12***		-0.99***
		(-8.06)		(-6.73)
VOL	3.03***	2.99***	3.87***	3.85***
	(15.45)	(14.92)	(13.99)	(13.77)
BETA	-0.04	-0.02	-0.11	-0.10
	(-0.49)	(-0.32)	(-0.75)	(-0.67)
Size	-1.03***	-0.94***	-0.94***	-0.97***
	(-5.54)	(-5.66)	(-3.15)	(-3.31)
BM	-0.45***	-0.49***	-0.32*	-0.33**
	(-4.06)	(-4.56)	(-1.90)	(-1.97)
Avg. R^2	0.20	0.20	0.19	0.19
Avg. # of Firms	3,436	3,436	1,838	1,838
No. of Years	26	26	26	26

Panel B: Likelihood of Stock Jump (Ret >= 50%)

	All Firms		Microcaps Excluded	
Intercept	-2.65***	-2.64***	-2.94***	-2.91***
	(-13.01)	(-13.17)	(-10.79)	(-10.86)
COP	0.49***		0.42***	
	(6.32)		(3.79)	
OP		0.44***		0.35***
		(5.28)		(2.92)
VOL	1.02***	1.02***	1.46***	1.46***
	(5.93)	(5.99)	(8.48)	(8.59)
BETA	0.01	0.01	-0.11	-0.11
	(0.21)	(0.15)	(-0.91)	(-0.93)
Size	-0.52***	-0.51***	-0.39**	-0.38**
	(-3.14)	(-3.14)	(-2.10)	(-2.05)
BM	0.31***	0.33***	0.16	0.15
	(2.99)	(3.18)	(0.91)	(0.90)
Avg. R^2	6.6%	6.6%	8.0%	7.9%
Avg. # of Firms	3,436	3,436	1,838	1,838
No. of Years	26	26	26	26

(Continued)

This table shows the results of logistic regressions that provide evidence of the ability of operating profitability to predict relatively high and low one-year returns in the future. The dependent variable in Panel A is a binary variable that takes the value of 1 if the 12 month buy-and-hold return is less than -50%, and 0 otherwise. The dependent variable in Panel B is a binary variable that takes the value of 1 if the 12 month buy-and-hold return is greater than 50% and 0 otherwise. *OP* and *COP* are operating profit and cash operating profit, respectively. *VOL* is the stock's monthly return volatility over three years ending with the most recent calendar year; *BETA* is estimated from the market model over the same period as *VOL*; *MV* is market capitalization; and *BM* is the ratio of the book value of common equity to the market value of common equity. We calculate all independent variables at the end of each calendar year and form annual decile ranks that range (0 to 1).

Following the Fama-Macbeth methodology, each regression is estimated on annual cross sections from 1991 to 2018. The reported coefficients are time series means with Fama-Macbeth t-statistics. We perform tests using both a full sample and a sample that excludes microcaps (stocks that fall into the bottom 20% of market capitalization based on NYSE breakpoints).

Table 4: Profitability and the likelihood of high and low market-adjusted daily returns

Panel A: Likelihood of relatively high daily returns (Mkt. Adj Ret < -1%)

	All Firms		Microcaps Excluded	
Intercept	-1.09***	-1.09***	-1.34***	-1.35***
	(-96.83)	(-96.01)	(-82.30)	(-81.09)
COP	-0.087***		-0.074***	
	(-23.82)		(-13.22)	
OP		-0.094***		-0.07***
		(-22.56)		(-10.00)
VOL	0.80***	0.80***	0.94***	0.938***
	(89.35)	(89.45)	(83.92)	(84.08)
BETA	-0.03***	-0.03***	-0.08***	-0.08***
	(-5.27)	(-4.95)	(-11.37)	(-11.10)
Size	-047***	-0.47***	-0.30***	-0.31***
	(-48.78)	(-48.55)	(-24.74)	(-24.95)
BM	-0.04***	-0.05***	-0.06***	-0.06***
	(-11.07)	(-12.56)	(-9.14)	(-8.92)
Avg. R^2	6.30%	6.40%	6.80%	6.90%
Avg. # of Firms	3,259	3,259	1,798	1,798
No. of Days	6,546	6,546	6,546	6,546

Panel B: Likelihood of relatively low daily returns (Mkt. Adj Ret > 1%)

	All Firms		Microcaps Excluded	
Intercept	-1.18***	-1.18***	-1.40***	-1.41***
	(-105.96)	(-105.46)	(-88.07)	(-87.15)
COP	0.017***		0.024***	
	(4.84)		(4.40)	
OP		0.02***		0.039***
		(4.87)		(6.13)
VOL	0.621***	0.62***	0.771***	0.778***
	(68.84)	(68.81)	(69.39)	(69.23)
BETA	-0.04***	-0.04***	-0.09***	-0.09***
	(-7.84)	(-7.76)	(-12.89)	(-12.65)
Size	-0.41***	-0.41***	-0.26***	-0.26***
	(-42.57)	(-42.80)	(-21.91)	(-22.06)
BM	0.02***	0.02***	-0.03***	-0.02***
	(5.06)	(5.50)	(-4.70)	(-3.65)
Avg. R^2	5.1%	5.20%	5.90%	6.0%
Avg. # of Firms	3,259	3,259	1,798	1,798
No. of Days	6,546	6,546	6,546	6,546

This table presents the average Fama and MacBeth (1973) regression slopes and *t*-values from logistic regressions using daily market-adjusted stock returns that provide evidence of the ability of operating profitability to predict relatively high and low daily returns in the future. The regressions use data from 1991 to 2018 for all stocks and all-but-microcaps (stocks that fall in the bottom 20% of market capitalization based on NYSE breakpoints). The dependent variable in Panel A is a binary variable that takes the value of 1 if the daily market-adjusted return is less than -1% and 0 otherwise. The dependent variable in Panel B is a binary variable that takes the value of 1 if the daily market-adjusted return is greater than 1% and 0 otherwise. We adjust the returns using the CRSP value-weighted index returns. *OP* and *COP* are operating profit and cash operating profit, respectively. *VOL* is the stock's monthly return volatility over three years ending with the most recent calendar year; *BETA* is estimated from the market model over the same period as *VOL*; *MV* is market capitalization; and *BM* is the ratio of the book value of common equity to the market value of common equity. We calculate all independent variables at the end of each calendar year and form annual decile ranks that range (0,1). Profitability and control variables are attached to future stock returns for the following April-March period.

Table 5: Profitability and the likelihood of future positive daily market adjusted returns on days of extreme negative market news

Panel A: Days on which the return of the CRSP value-weighted index is below -5%

	All Firms		Microcaps Excluded	
Intercept	1.78***	1.80***	1.37***	1.35***
	(11.90)	(11.92)	(3.83)	(3.65)
COP	0.26***		0.68***	
	(3.53)		(5.25)	
OP		0.21***		0.68***
		(2.71)		(4.41)
VOL	-1.35***	-1.34***	-1.52***	-1.51***
	(-5.79)	(-5.69)	(-6.38)	(-6.17)
BETA	-0.72***	-0.72***	-0.76***	-0.77***
	(-9.01)	(-9.07)	(-8.22)	(-8.18)
Size	-1.51***	-1.50***	-0.90***	-0.88***
	(-12.96)	(-12.95)	(-3.45)	(-3.36)
BM	-0.18	-0.18*	-0.35**	-0.32**
	(-1.63)	(-1.69)	(-2.14)	(-2.01)
Avg. R^2	13.2%	13.1%	14.6%	14.7%
Avg. # of Firms	3,277	3,277	1,805	1,805
No. of Days	17	17	17	17

Panel B: Financial crisis (12/2007 - 06/2009)

	All Firms		Microcaps Excluded	
Intercept	1.59***	1.58***	0.87***	0.85**
	(10.22)	(10.24)	(2.10)	(1.98)
COP	0.35***		0.88***	
	(4.10)		(6.22)	
OP		0.33***		0.86***
		(3.80)		(4.91)
VOL	-0.81***	-0.79***	-1.03***	-1.00***
	(-6.23)	(-6.02)	(-5.83)	(-5.70)
BETA	-0.74***	-0.74***	-0.65***	-0.66***
	(-8.08)	(-8.15)	(-6.07)	(-6.10)
Size	-1.59***	-1.57***	-0.76***	-0.73**
	(-14.74)	(-14.75)	(-2.23)	(-2.16)
BM	-0.41***	-0.40***	-0.55***	-0.53***
	(-4.95)	(-5.11)	(-4.17)	(-4.32)
Avg. R^2	9.2%	9.1%	9.9%	9.9%
Avg. # of Firms	3,057	3,057	1,754	1,754
No. of Days	11	11	11	11

This table presents the average Fama and MacBeth (1973) regression slopes and *t*-values from daily logistic regressions that provide evidence of the ability of operating profitability to predict market outperformance on days of extreme negative market news. The regressions use data from 1991 to 2018 for all stocks and all-but-microcaps (stocks that fall in the bottom 20% of market capitalization based on NYSE breakpoints).

In Panel A, we restrict the sample to days on which the return of the CRSP value-weighted index is below -5%. Panel B is additionally restricted to days that occurred during the financial crisis (12/2007–06/2009). The dependent variable is a binary variable that takes the value of 1 if the daily market-adjusted buy-and-hold return is positive and 0 otherwise. We adjust the returns using the CRSP value-weighted index returns. *OP* and *COP* are operating profit and cash operating profit, respectively. (see Section 3.1). *VOL* is the stock's monthly return volatility over three years ending with the most recent calendar year; *BETA* is estimated from the market model over the same period as *VOL*; *MV* is market capitalization; and *BM* is the ratio of the book value of common equity to the market value of common equity. We calculate all independent variables at the end of each calendar year and form annual decile ranks that range (0,1).

Table 6: Regressions of subsequent forecast errors on ranked operating profitability

Panel A: Cash operating profit (*COP*)

$ADJFE_{, t+1} = \beta_0 + \beta_1 * COP + \varepsilon_{t+1}$						
Month	β_0	$t(\beta_0)$	β_1	$t(\beta_1)$	R^2	N
1 (First)	-0.88	-4.46	2.73	9.16	0.37	270
2	-0.66	-3.33	2.36	8.06	0.31	270
3	-0.58	-3.22	2.18	7.98	0.32	270
4	-0.48	-2.88	1.98	7.87	0.31	270
5	-0.44	-2.83	1.82	7.65	0.30	270
6	-0.36	-2.55	1.53	7.52	0.31	270
7	-0.34	-2.77	1.40	7.78	0.33	270
8	-0.25	-2.07	1.17	6.78	0.28	270
9	-0.22	-2.29	0.92	6.53	0.27	270
10	-0.24	-3.78	0.86	8.13	0.32	270
11	-0.17	-2.55	0.75	7.26	0.27	270
12 (Last)	-0.17	-1.81	0.94	6.07	0.23	270
Last - First	0.71	3.26	-1.79	-5.31		

Panel B: Operating profit (*OP*)

$ADJFE_{, t+1} = \beta_0 + \beta_1 * OP + \varepsilon_{t+1}$						
Month	β_0	$t(\beta_0)$	β_1	$t(\beta_1)$	R^2	N
1 (First)	-0.99	-4.10	2.94	7.93	0.27	270
2	-0.76	-3.29	2.55	7.27	0.24	270
3	-0.68	-3.18	2.36	7.20	0.24	270
4	-0.58	-3.00	2.16	7.31	0.24	270
5	-0.55	-3.10	2.02	7.30	0.25	270
6	-0.47	-2.93	1.74	7.36	0.25	270
7	-0.42	-2.97	1.55	7.37	0.27	270
8	-0.32	-2.35	1.31	6.51	0.23	270
9	-0.30	-2.64	1.07	6.25	0.22	270
10	-0.31	-4.28	1.00	7.93	0.31	270
11	-0.24	-3.09	0.88	7.22	0.27	270
12 (Last)	-0.31	-2.88	1.18	6.51	0.26	270
Last - First	0.68	2.57	-1.76	-4.23		

This table presents the regression slopes and t-statistics (based on Newey-West standard errors) from pooled OLS regressions that provide evidence on the ability of operating profitability to predict future forecast errors.

We conduct our tests using monthly *IBES* consensus (median) forecasts of annual EPS. We collect forecasts beginning with the first forecast available following the prior year's fourth-quarter earnings announcement date. We define the forecast error (*FE*) for month *t* (*t* = 1 to 12) as the actual EPS minus the consensus EPS forecast available for month *t* divided by the price at the end of the first month in the series (i.e., month = 1). This approach provides a time series of forecast errors for a firm during an earnings year. We compute the adjusted forecast error (*ADJFE*) by subtracting the average monthly *FE* for the matched industry year based on the two-digit SIC. All coefficients are multiplied by 100.

In Panel A, we rank the sample into ten portfolios every year based on the prior year's cash operating profitability (*COP*) and compute the average *ADJFE* for each month (1 to 12) of every year for each portfolio. We then regress the average *ADJFE* on the decile *COP* ranking assigned to the firm year (0, 1). We conduct these regressions for each of the 12 months between the prior year's fourth-quarter earnings announcement and the current year's fourth-quarter earnings announcement. Thus, the regression intercept β_0 measures the average *ADJFE* for low *COP* firms. The slope measures the incremental *ADJFE* for a firm with a high *COP* versus one with a low *COP*. Panel B reports the same results using operating profitability (*OP*). See section 3.1 for *COP* and *OP* definitions.

Table 7 Profitability premium and forecast drift

Panel A: Cash Operating Profitability

	Profitability Quintiles					
	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Same Direction	-0.93	-0.89	0.04	0.89	0.97	1.91
	(-5.47)	(-5.27)	(0.24)	(6.59)	(4.75)	(10.74)
Opposite Direction	0.61	0.82	0.05	-0.61	-0.62	-1.24
	(2.72)	(5.12)	(0.36)	(-3.69)	(-2.81)	(-6.36)
Same - Opposite	-1.55	-1.71	-0.02	1.51	1.60	3.14
	(-10.58)	(-15.11)	(-0.31)	(13.24)	(11.81)	(18.10)
Same Direction						
(i) Persistent forecast revision	-0.17	-0.09	0.07	0.08	0.34	0.51
	(-0.88)	(-0.55)	(0.52)	(0.63)	(1.81)	(2.37)
(ii) Nonpersistent forecast revision	-0.87	-0.89	-0.23	0.78	0.98	1.85
	(-6.16)	(-4.59)	(-1.39)	(6.90)	(5.06)	(9.42)
(ii) - (i)	-0.70	-0.80	-0.30	0.70	0.64	1.35
	(-7.02)	(-12.21)	(-4.44)	(7.81)	(8.75)	(14.50)

Panel B: Operating Profitability

	Profitability Quintiles					
	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Same Direction	-0.68	-0.60	0.01	0.57	0.81	1.48
	(-3.13)	(-3.14)	(0.05)	(4.77)	(4.34)	(6.44)
Opposite Direction	0.51	0.68	0.10	-0.46	-0.62	-1.13
	(2.20)	(3.83)	(0.51)	(-3.21)	(-3.06)	(-4.55)
Same - Opposite	-1.18	-1.28	-0.09	1.03	1.43	2.61
	(-5.64)	(-12.78)	(-1.31)	(9.66)	(11.46)	(11.93)
Same Direction						
(i) Persistent forecast revision	-0.07	0.00	0.05	0.05	0.28	0.35
	(-0.40)	(-0.01)	(0.28)	(0.32)	(1.70)	(1.66)
(ii) Nonpersistent forecast revision	-0.62	-0.60	-0.11	0.47	0.90	1.52
	(-3.53)	(-2.62)	(-0.73)	(4.96)	(4.75)	(7.04)
(ii) - (i)	-0.55	-0.60	-0.16	0.42	0.62	1.17
	(-7.64)	(-14.22)	(-3.63)	(4.56)	(8.77)	(14.15)

This Table reports three-factor alphas based on monthly returns to portfolios formed on April 1 and held for one year. We sort firms into five portfolios based on their most recent profitability announced prior to April 1. We included the MktRf, HML, and SMB risk controls. We report the alphas for the full sample as well as the two subsamples. The Same Direction includes firms with above-(below-) median profitability and above-(below-) median *REVEST*. In these firms, subsequent forecasts drift in the same direction as profitability. The Opposite Direction' includes firms with above (below) median profitability and below (above) the median *REVEST*. In these firms, subsequent forecasts drift in the opposite direction to profitability. Standard errors were adjusted for heteroskedasticity and autocorrelation for up to twelve lags. *t*-statistics are in parentheses.

We also decomposed *REVEST* into persistent and non-persistent components. We form two subsamples, which include firms with above (below) median profitability and above (below) median persistent and non-persistent components of *REVEST*. We estimate the forecast revision persistence parameters for each NYSE size decile using rolling regressions of *REVEST* on three lags of *REVEST*. We apply these parameters to all the firms in each annual size decile. For example, to decompose $REVEST_{t+1}$ relative to year *t* profitability, $REVEST_t$ is regressed on $REVEST_{t-1}$, $REVEST_{t-2}$, and $REVEST_{t-3}$ using all firms in a size decile. We then computed the persistent component (*REVPERS*) of $REVEST_{t+1}$ by applying these parameters to year *t* to year *t-2 REVEST*. We computed the nonpersistent component (*REVNPERS*) as the actual $REVEST_{t+1}$ minus $REVPERS_{t+1}$.

Table 8: Quarterly change in the number of institutional investors by ranks of profitability

Panel A: Univariate portfolio tests (*n* = 322,856)

	Information Period (*q* = -3 to 0)				Post Information Period (*q* = 1 to 4)			
	Δ*IO*	Δ*AIO*	Δ*AIO1%*	Δ*AIO2%*	Δ*IO*	Δ*AIO*	Δ*AIO1%*	Δ*AIO2%*
Low *COP* (Decile 1)	0.39	-0.06	-0.41%	0.00%	0.40	-0.22	-1.02%	-0.01%
High *COP* (Decile 10)	2.94	1.43	1.65%	0.07%	1.32	0.29	0.32%	0.01%
High *COP* - Low *COP*	2.55	1.50	2.06%	0.07%	0.92	0.51	1.34%	0.02%
(*t*-stat)	(8.99)	(8.36)	(7.82)	(7.55)	(3.78)	(3.22)	(4.70)	(3.60)
Low *OP* (Decile 1)	0.02	-0.36	-1.43%	-0.01%	0.30	-0.28	-1.37%	-0.01%
High *OP* (Decile 2)	3.15	1.60	2.10%	0.08%	1.22	0.18	0.16%	0.01%
High *OP* - Low *OP*	3.13	1.96	3.53%	0.09%	0.93	0.46	1.53%	0.02%
(*t*-stat)	(10.56)	(9.43)	(8.45)	(7.35)	(3.58)	(2.72)	(4.38)	(2.93)

Panel B: Regressions using cash operating profit (*COP*) (*n* = 322,856)

	Information Period (*q* = -3 to 0)				Post Information Period (*q* = 1 to 4)			
Dependent Variable:	Δ*IO*	Δ*AIO*	Δ*AIO1%*	Δ*AIO2%*	Δ*IO*	Δ*AIO*	Δ*AIO1%*	Δ*AIO2%*
$COP_{q\,=\,-4\text{ to }-1}$	0.77***	0.70***	1.27***	0.03***	0.32**	0.32**	0.79***	0.02**
	(7.96)	(7.22)	(6.75)	(6.69)	(2.05)	(2.02)	(2.99)	(2.58)
$ARET_{q\,=\,-1\text{ to }0}$	0.03***	0.03***	0.05***	0.00***	0.02***	0.02***	0.05***	0.00***
	(13.45)	(12.59)	(14.24)	(15.47)	(6.39)	(6.31)	(8.33)	(6.30)
$log(MV)_{q\,=\,-1}$	0.29***	-0.17***	-0.22***	-0.01***	0.18***	-0.01	0.11***	0.00
	(5.43)	(-4.22)	(-5.51)	(-4.38)	(3.05)	(-0.33)	(3.37)	(0.04)
$log(B/M)_{q\,=\,-1}$	-1.00***	-0.96***	-1.48***	-0.04***	-0.13**	-0.11*	-0.15	-0.00
	(-14.38)	(-13.78)	(-16.85)	(-18.30)	(-2.08)	(-1.82)	(-1.57)	(-1.13)
$Asset\ Growth_{q\,=\,-4\text{ to }-1}$	2.07***	2.08***	3.31***	0.10***	0.05	0.07	0.42**	0.00
	(14.57)	(15.38)	(22.14)	(20.85)	(0.46)	(0.63)	(2.48)	(0.13)
Industry and Qtr Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	5.8%	3.8%	4.2%	4.2%	1.9%	1.1%	1.8%	1.1%

(Continued)

Table 8: Continued

Panel C: Regressions using operating profit (*OP*) (n = 322,856)

	Information Period (q = -3 to 0)				Post Information Period (q = 1 to 4)			
Dependent Variable:	ΔIO	ΔAIO	$\Delta AIO1\%$	$\Delta AIO2\%$	ΔIO	ΔAIO	$\Delta AIO1\%$	$\Delta AIO2\%$
$OP_{q\ =\ -4\ to\ -1}$	0.86***	0.82***	2.34***	0.04***	0.38*	0.40**	1.09***	0.02**
	(6.40)	(6.18)	(8.41)	(6.58)	(1.91)	(2.03)	(3.12)	(2.23)
$ARET_{q\ =\ -1\ to\ 0}$	0.03***	0.03***	0.05***	0.00***	0.02***	0.02***	0.05***	0.00***
	(13.47)	(12.60)	(14.48)	(15.40)	(6.40)	(6.32)	(8.35)	(6.30)
$log(MV)_{q\ =\ -1}$	0.29***	-0.18***	-0.27***	-0.01***	0.17***	-0.02	0.10***	-0.00
	(5.22)	(-4.37)	(-6.30)	(-4.67)	(2.96)	(-0.46)	(3.05)	(-0.06)
$log(B/M)_{q\ =\ -1}$	-0.99***	-0.95***	-1.42***	-0.04***	-0.13**	-0.11*	-0.13	-0.00
	(-14.44)	(-13.81)	(-16.63)	(-18.58)	(-1.97)	(-1.70)	(-1.32)	(-1.01)
$Asset\ Growth_{q\ =\ -4\ to\ -1}$	1.98***	1.99***	3.03***	0.10***	0.01	0.03	0.30*	-0.00
	(13.92)	(14.63)	(22.03)	(20.02)	(0.07)	(0.22)	(1.76)	(-0.26)
Industry and Qtr Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	5.8%	3.8%	4.3%	4.2%	1.9%	1.1%	1.8%	1.1%

This table presents the time-series means of the quarterly cross-sectional average changes in institutional ownership for ten portfolios sorted by operating profitability. We report t-values based on Newey-West standard errors. The portfolios use data from 1992 to 2017 for all stocks with available data on institutional ownership. Like Choi and Sias (2012), our tests include an 'Information Period, ' which includes the four quarters ending three months after the operating profitability fiscal year (Quarters q = -3 to 0) and a 'Post Information Period, which includes the four subsequent quarters (Quarters q = 1 to 4). We use the 'Information Period' quarters to identify institutional investors' timely incorporation of operating profitability information and the 'Post Information Period' quarters to identify institutional investors' delayed incorporation of operating profitability information.

Our primary measure, ΔIO, is the quarterly change in the number of institutional investors holding stock. We include only 13(f) filers present in the current and prior quarters to mitigate bias due to changes in the universe of filers. Our second measure, ΔAIO, is the quarterly change in institutional breadth less the average quarterly change in institutional breadth for securities within the same NYSE capitalization decile. Thus, this measure captures the abnormal change in the breadth of a firm relative to similarly sized firms. The remaining two measures normalize this adjusted change in institutional breadth by using general institutional ownership levels. Following Choi and Sias (2012), we calculate $\Delta AIO1\%$ by dividing the abnormal change in breadth by the average number of institutional shareholders at the end of quarter q = 0 for securities in the same capitalization decile. Following Lehavy and Sloan (2008), $\Delta AIO2\%$ was normalized by the total number of 13(f) filers for quarter q = 0.

Table 9: Subsequent earnings announcement returns for profitability-based portfolios

Panel A: Cash operating profit (*COP*)

	Full Sample		Microcaps Excluded	
	Return	Mkt. Adj. Return	Return	Mkt. Adj. Return
Low (Decile 1)	-3.88***	-4.51***	-1.85*	-2.39***
t-statistic	(-4.50)	(-6.54)	(-1.88)	(-3.46)
High (Decile 10)	2.23***	1.36***	2.61***	1.74***
t-statistic	(3.88)	(2.81)	(3.85)	(2.98)
Hedge (D10-D1)	6.11***	5.87***	4.46***	4.12***
t-statistic	(11.03)	(10.59)	(4.49)	(4.59)

Panel B: Operating profit (*OP*)

	Full Sample		Microcaps Excluded	
	Return	Mkt. Adj. Return	Return	Mkt. Adj. Return
Low (Decile 1)	-3.42***	-4.03***	-1.70*	-2.37***
t-statistic	(-4.12)	(-5.88)	(-1.86)	(-3.54)
High (Decile 10)	1.42**	0.59	1.71***	0.87
t-statistic	(2.57)	(1.29)	(2.86)	(1.64)
Hedge (D10-D1)	4.85***	(4.62)***	3.41***	3.24***
t-statistic	(7.98)	(7.68)	(3.75)	(3.83)

This table provides the average earnings announcement returns for the high (decile 10) and low (decile 1) operating profitability portfolios. The portfolios are based on data from 1991 to 2018 for all stocks and all-but-microcapsules (stocks that fall into the bottom 20% of market capitalization based on NYSE breakpoints).

For each calendar year, we collected data on cash operating profitability (*COP*) and operating profitability (*OP*) (see Section 3.1) and ranked all firms into deciles based on operating profitability. We then collect the 5-day announcement window returns around the next four quarterly earnings announcements during the 12-month period starting in April and averaged them across firms to obtain the portfolio return. The results reflect the time-series mean return of each portfolio using both raw returns and returns adjusted by subtracting the value-weighted CRSP index return. Microcap stocks are defined as stocks that would fall into the bottom 20% of market capitalization, based on NYSE breakpoints.