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Essays on the Role of Accounting Information in Governance and Valuation

A dissertation presented

by

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Essays on the Role of Accounting Information in Governance and Valuation

Abstract

My dissertation is focused on understanding how firm-level accounting information affects resource allocation in capital markets, by : (1) interacting with mechanisms through which investors govern managers and (2) facilitating investment decisions. To this end, I use both analytical, and empirical methods, using both international and US data.

In the first essay I study shareholder activism, which is arguably the most salient corporate governance mechanism, currently. In particular, I examine the interaction of managerial incentives and reported performance, in the context of this phenomenon. I document that reporting better accounting performance at the onset of an activism campaign is associated with a lower likelihood of proxy fights and board turnover for target firms. Consequently managers, facing a threat to their control and careers, take actions to boost short-term earnings. Proxies of earnings management are significantly higher for target firms in the quarter following the launch of activism. Cross-sectional and time-series evidence suggests that this is driven by managers responding to the pressure of an activism campaign. Furthermore, target firms, which manage earnings, underperform over the next year, suggesting that the evidence is more consistent with costly short-term earnings management than improvement in operational efficiency due to activism.

In the second essay, co-authored with Matthew Lyle and Charles Wang, we attempt to make progress in establishing a standard for estimating firm-level expected returns. Consistent with existing work, we show that under fairly general and economically motivated assumptions, expected stock returns can be expressed as a linear combination of two firm-level characteristics — book-to-market (value) and profitability. More interestingly,

we show that empirical estimates based on this relation predict the cross-section of out-of-sample returns in 26 of 29 international equity markets. In sharp contrast, we find that firm-level estimates based on standard factor-models fail to exhibit any systematic predictive power internationally. We also show, both analytically and empirically that the importance of profitability in forecasting returns depends on the quality of information disclosed to investors.

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Introduction

Understanding how firm-level information affects the resource-allocation process in capital markets is a a central question in accounting, economics and finance. This broad question constitutes of two parts: (1) understanding the role of information in the mechanisms through which investors govern managers and (2) understanding the mechanisms through which information gets reflected in market prices and facilitates investors' investment decisions.

I examine these questions by using two approaches: (1) exploit an emerging governance phenomenon and (2) employ and innovate on existing analytical and empirical methodologies in the accounting and finance literature.

Shareholder activism, led primarily by hedge funds, has emerged as the most influential form of shareholder intervention over the last decade. Activist funds today manage more than $200bn, and this represents a more than eight-fold increase over the last decade. Given its disruptive impact, the emergence of shareholder activism has also been accompanied by an active and ongoing debate in both academic and policy circles about its long-term effects. In the first essay, I examine the interaction of managerial incentives and reported performance, in the context of this phenomenon. I document that reporting better accounting performance at the onset of an activism campaign is associated with a lower likelihood of proxy fights and board turnover for target firms. Consequently managers, facing a threat to their control and careers, take actions to boost short-term earnings. Proxies of earnings management are significantly higher for target firms in the quarter following the launch of activism. Cross-sectional and time-series evidence suggests that this finding is driven by managers responding to the pressure of an activism campaign and not by underlying trends in profitability, coincident with activism. In particular, earnings management is more pronounced when the market signals support for the activist, when the activist has higher ownership, and when private benefits of control for managers are higher. Furthermore, target firms which manage earnings underperform over the next year, implying that the evidence is more suggestive of costly short-term earnings management than improvement in operational efficiency due to activism.

Expected returns are a central input in asset allocation decisions. Estimating expected stock returns has been a centerpiece in financial economics since at least the derivation of the CAPM (Sharpe, 1964), but despite its importance, progress in establishing a standard for estimating expected returns has been limited, due to the unobserved nature of expected returns. In the second essay, co-authored with Matthew Lyle and Charles Wang, we attempt to make some progress in establishing a standard for estimating firm-level expected returns. Consistent with existing work, we show that under fairly general and economically motivated assumptions, expected stock returns can be expressed as a linear combination of two firm-level characteristics — book-to-market (value) and profitability. More interestingly, we show that empirical estimates based on this relation predict the cross-section of out-of-sample returns in 26 of 29 international equity markets. In sharp contrast, we find that firm-level estimates based on standard factor-models, even those based on value and profitability, fail to exhibit any systematic predictive power internationally. We also examine how variation in accounting systems and information quality interacts with this linear relationship. We show, both analytically and empirically that the importance of profitability in forecasting returns depends on the quality of information disclosed to investors. Overall, our results suggest that a tractable and theoretically consistent characteristics-based model provides a robust framework for estimating expected returns worldwide.

Chapter 1

Earnings Management during Activism Campaigns

1.1 Introduction

Shareholder activism has emerged as an influential corporate governance mechanism over the last decade. A few facts highlight the growing influence of shareholder activists: (1) activist funds today manage more than $120 billion, a seven-fold increase in assets under management from 2002; (2) the number of activism campaigns has jumped from 96 in 2001, to around 350 in 2014; and (3) the median target firm in 2014 had a market-capitalization of $1 billion, representing a five-fold increase over the last decade.[1]

An activism campaign typically involves a hedge fund investor, with a significant ownership in the target company, advocating for operational, governance or personnel changes. As Gantchev (2013) describes, this can be characterized as a sequential bargaining process between the activist and the firm, with an implicit threat of a proxy fight if negotiations fail to yield a resolution. Such campaigns have been documented to significantly alter firms' governance structures, capital structures, payout policies, investment patterns, and

[1] See, for example, Coffee and Palia (2015).

managers' careers.[2] Given its disruptive impact, the rise of shareholder activism has been accompanied by an active and ongoing debate in both academic and policy circles about its long-term effects on firm value and operational performance.[3] Regardless of its long-run value effects, the arrival of a shareholder activist represents a significant disruption to managerial decision-making and poses a real threat to the careers of CEOs and directors of targeted firms.[4] Chris Young, head of contested situations at Credit Suisse, explains:

> "it is literally a matter of career life and death for management teams and directors who are subjected to activism."[5]

Given these consequences for firms and managers, this essay seeks to understand how managers respond to this form of shareholder dissidence. In particular, I examine whether managers take actions to boost short-term reported performance during an activism campaign. Models of "short-termism" (e.g., Stein, 1988, 1989; Narayanan, 1985) predict that threats to control or concerns about reputation can lead managers to manage short-term earnings, potentially at the expense of long-term value. As applied to modern day activism, financial reporting can be important because targets of activism tend to be underperforming and arguments about undervaluation, flawed business strategies and operational inefficiencies form the crux of a majority of activist campaigns.[6] Consequently improved accounting performance, during the activism campaign, can aid the management in convincing other passive shareholders of their managerial abilities. Given that the

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[2]Brav *et al.* (2008, 2015a,b); Klein and Zur (2009) document the impact of activism on long-run firm outcomes.

[3]Cremers *et al.* (2015) and Bebchuk *et al.* (2014); Brav *et al.* (2015a) represent the two sides of this debate: the former argue that the pressure of hedge-fund activism inhibits long-term investment and innovation, and overall erodes long-run value whereas the latter provide evidence that hedge-fund activism is value and efficiency-enhancing in the long-run.

[4]Brav *et al.* (2008); Gow *et al.* (2014); Fos and Tsoutsoura (2014) document the impact of activism on managers' and directors' careers – CEO pay declines by more than $1 million and CEO turnover goes up by 10%, whereas the likelihood of a director's departure nearly doubles following an activism campaign.

[5]See "Defeat Activists by Giving Them What They Want" - Matt Levine, *Bloomberg*, Jan 6, 2014

[6]This is based on an updated sample (1994-2011) using the same data collection procedure and estimation methods as in Brav, Jiang, Partnoy, and Thomas (2008) and Brav, Jiang, and Kim (2010). For more information please see `https://faculty.fuqua.duke.edu/~brav/HFactivism_SEPTEMBER_2013.pdf`.

likelihood of eventual shareholder support in the case of a proxy fight is an important variable in the activist's tradeoff decision of continuing the campaign or not, this might lower the incentives for the activist to pursue the campaign. If improved accounting performance is accompanied by improved valuations, that would further lower the expected benefits of pursuing the campaign for the activist. This idea is echoed by eminent law firm Wachtell, Litpon, Rozen and Katz in its memo to CEOs discussing strategies to thwart an activist attack:

> "...strong performance, though not an absolute defense, is one of the best defenses....".[7]

I begin my empirical analysis by examining whether accounting performance, reported during the campaign, is indeed influential. Using a comprehensive sample of activism campaigns, initiated primarily by hedge funds, in the US from 2004–2014, I find that for target firms a one-standard deviation increase in return-on-assets in the quarter following activism, controlling for return-on-assets in the prior quarter, is associated with a 25% reduction in the likelihood of the campaign culminating in a proxy fight and a 14% reduction in the likelihood of the target firm experiencing director turnover in the following fiscal year. I focus my initial analysis on this quarter following the launch of a campaign, because it is is coincident with an important phase of an activism campaign. Activism campaigns are fairly short-lived events, with the median campaign lasting around 5 months and 65% of them being resolved within two quarters following their launch. Similarly, Gantchev (2013) documents that for the majority of campaigns, negotiations reach a culmination within 6–9 months from the launch of the campaign. Consequently, the earnings report for the quarter after the campaign launch, which for the median target firm is announced 173 days after the commencement of activism, is a key metric that becomes available to shareholders and the market during this negotiation period.

The remainder of my empirical analyses examines whether managers respond to these

[7]See "Dealing with Activist Hedge Funds" by Martin Lipton of Wachtell, Lipton, Rose and Katz, *The Harvard Law School Forum on Corporate Governance and Financial Regulation*, June 2, 2015.

incentives and engage in short-term earnings management. Using an interrupted time-series design, I analyze the behavior of discretionary accruals (DA) and proxies for real earnings manipulation (REM) in firms targeted by activists.[8] I document that DA and REM for target firms are on an average higher, by 0.32–0.44% of total assets, in the quarter following the launch of an activism campaign. The effects are economically important and represent around 10–14% (32–44%) of the median quarterly operating (net) income in my sample.

To argue that these deviations are indeed driven by activism, I conduct a battery of tests to provide evidence that this effect is more pronounced when showing better performance is likely to be more valuable. First, I show that managers are more likely to manage earnings when the threat from the activist is more credible. I proxy for the credibility of the threat from the activist by using two measures: whether the market responds positively to the announcement of activism and by the activist's ownership in the target company at the time of announcement. The former measure proxies for other shareholders' support for the activist and has been shown to influence managerial behavior (Fos and Jiang, 2016). Higher ownership or 'skin-in-the-game' by the activist, not only acts as a signal to other shareholders, but also makes the activist more likely to pursue a costly continuation of the campaign, because the activist internalizes more of the eventual gains (Edmans and Holderness, 2016; Gantchev, 2013). Second, I affirm that under-performing target firms, where a reversal in profitability can be argued as evidence of managerial efficacy, are more likely to engage in earnings management following activism. Third, I document that managers who are more likely to have greater private benefits threatened by activism (as proxied for by takeover defenses) are more likely to manage earnings. As Shin (2016) and Boyson and Pichler (2016) document, takeover defenses are also used as critiques against the management by activists and also lead to proxy fights. Even in the absence of private benefits, an improvement in financial performance could be an effective strategy for managers in such situations.

[8] A long empirical literature in accounting (e.g., Graham *et al.*, 2005; Roychowdhury, 2006; Cohen and Zarowin, 2010) shows that managers manipulate both real activities and accruals to increase short-term earnings.

An alternative explanation that may account for some of these findings is that activists time their campaigns to coincide with a reversal in performance for target firms. Such a mean-reversion in underlying economics could induce bias in the earnings management proxies (Kothari *et al.*, 2005b). I conduct two tests to argue that mean-reversion is unlikely to explain the effects I document. First, I show that earnings management is driven by campaigns where the firm and activist are still engaged, at the end of the quarter following the launch, in contrast to campaigns which get resolved prior to the quarter-end, where managers' incentives to manage earnings are arguably reduced. This is consistent with the earnings management interpretation of the baseline findings, and is hard to square with the mean-reversion argument. Second, I examine the pattern of earnings management and profitability for multiple quarters following activism and show that earnings management is short-lived, thereby suggesting that it is not reflecting some underlying trend. Moreover, target firms do not show any structural improvement in profitability in the three quarters following activism, which does not suggest any immediate mean-reversion in performance. Generally speaking, any firm-level shock which might bias these proxies, (Owens *et al.*, 2016), would have to vary in a particular manner to cause this short-lived effect. I also document parallel distortions in specific income statement and balance sheet accounts, further assuaging concerns surrounding using noisy proxies.

I conclude my analysis by examining whether the effect I observe can be interpreted as costly signaling by managers or is more indicative of opportunistic earnings management. I do this by examining the future stock market performance of target firms which seem to manage earnings, relative to other target firms. I find that target firms, which manage earnings, significantly underperform over a 12-month horizon suggesting that the effect I observe is not driven by managers signaling future good news but is more consistent with opportunistic earnings management. Interestingly, and consistent with prior work, (Cohen and Zarowin, 2010), I find that future underperformance is exacerbated for firms engaging in real earnings management, suggesting that some of these actions are potentially costly over the longer-term. This result also argues against a reversal in performance, whether coincident with activism or reflecting efficiencies engendered by activist pressure, driving the distortions in the earnings management proxies.

The findings of this paper contribute to several strands of literature in accounting and finance. First, by analyzing managerial strategies at the onset of activism campaigns, I contribute to the literature on activism by showing that managerial responses to activism are not limited to adopting hostile tactics, but can be more strategic and focused on short-term performance. The broader literature on blockholder intervention, both theoretical and empirical, has treated activism as a one-shot process.[9] The findings in my paper and some others, (Gantchev, 2013; Boyson and Pichler, 2016), show that the activism process is more complicated and the incentives and economic factors that shape this process, merit further investigation.

This paper also extends the literature studying how firms shape the information environment in response to pressure from institutional investors and activists, (e.g., DeAngelo, 1988; Dimitrov and Jain, 2011; Bourveau and Schoenfeld, 2015). DeAngelo (1988) studies the role of reported performance in the context of corporate control contests in the 1970s. I build on this paper by showing that the modern phenomenon of activism, which is not a battle for control, can similarly induce negative externalities by exacerbating the limited horizon problem of managers. The paper closest to mine is a contemporaneous paper (Khurana *et al.*, 2017), who also find evidence of managers suppressing bad news and engaging in real earnings management during activism. My results differ from theirs in that I provide more direct evidence of the effect of performance on the outcomes of activism; find evidence of both accruals-based and real earnings management; and tease apart the motivations behind earnings management. Other papers studying financial reporting and activism, (Cheng *et al.*, 2015; Hall and Trombley, 2012) focus on the years following activism. Distinct from their analysis, the short-duration design of this paper allows me to document how reported performance influences the outcome of activism.

[9]See Edmans and Holderness (2016) for a review of the different models of shareholder intervention and Brav *et al.* (2015b) for a summary of the empirical findings surrounding activism.

Overall, this paper provides empirical evidence consistent with models of "short-termism", (e.g., Stein, 1989, 1988) and contributes to the long and rich literature in accounting and finance which documents how various capital market phenomena influence earnings management behavior by executives.[10]

1.2 Activism: Institutional Setting

The phenomenon of hedge fund activism, that is the subject of this study, is still a fairly recent phenomenon. In this section I describe certain institutional features that have enabled this form of shareholder activism to have a significant influence on firm and managerial behavior. Thereafter I briefly summarize the literature on hedge fund activism, in particular focusing on findings which motivate my study.

Shareholder activism over the past decade has been primarily driven by hedge funds, that enjoy certain structural features, enabling this form of activism to have significantly more influence than activism initiated by other institutional or individual shareholders, for example dissidence in the form of shareholder proposals. Brav *et al.* (2008) identifies these structural features — lower regulation and lower diversification, translating into better incentives. The sophisticated clientele of hedge funds allow them to operate outside the ambit of security regulations that constrain the operation of other institutional shareholders such as mutual funds or pension funds. The investment portfolios of hedge funds are significantly less diversified than that of other institutional investors and they hold large stakes in a few investments. Moreover the lack of regulatory constraints enable hedge funds to lever up more aggressively and hence pursue much larger investments than the same asset size would dictate for a mutual fund. Hedge fund managers often have significant personal investments in the fund. All of these features incentivize hedge funds to pursue value improvements in target companies more aggressively.

[10]For example: mergers and acquisitions (e.g., Louis, 2004; Erickson and Wang, 1999; Cohen and Zarowin, 2010), IPOs and SEOs (e.g. Teoh *et al.*, 1998; Shivakumar, 2000), executive compensation contracts (e.g., Healy, 1985; Bergstresser and Philippon, 2006; Cheng and Warfield, 2005; Jiang *et al.*, 2010; Armstrong *et al.*, 2013), corporate governance (e.g., Klein, 2002) and regulation (e.g., Cohen *et al.*, 2008), to name a few.

A growing literature documents the long-term influence of this form of activism on firm outcomes such as profitability, productivity, and innovation (e.g., Brav *et al.*, 2008, 2015a,b). This literature also documents that this form of activism is not restricted to small, poorly covered firms but instead has grown to target much larger firms (Cremers *et al.*, 2015; Coffee and Palia, 2015). Of particular interest to my study are the findings about the substantial impact that this growing phenomenon is having on the careers of managers and board members. Greenwood and Schor (2009) documents that target firms are significantly more likely to be taken over following activism, Brav *et al.* (2008) documents that CEO turnover goes up by 10% and CEO pay declines by nearly $1 million following activism, while Gow *et al.* (2014) documents that the likelihood of a director's departure, over a two-year period, nearly doubles following activism.

This literature also documents two key findings about the evolution of the activism process that are important to my study. A consistent finding in the activism literature is that the announcement of an activism campaign is a significant economic event. The literature documents that the average stock price reaction to an activism campaign is around 5% (Brav *et al.*, 2008; Greenwood and Schor, 2009; Klein and Zur, 2009), which suggests that the broader market pays close attention to the intervention. Gantchev (2013), on the other hand, articulates the process of negotiation, following the arrival of the activist. The large majority of campaigns get resolved in the negotiation stage, when activists broadly make their demands and negotiate with management. This is typically a period extending 6-9 months from the initial announcement date. Unresolved campaigns are followed by demands for board representation and then proxy fights. This short-lived nature of activism is also corroborated in my paper — 65% of the activism events in my sample are resolved within two quarters following their launch. These findings suggests that the activism campaign is a fairly short negotiation between managers and activists and one that is closely followed by the market. This makes it an ideal window for examining the steps managers take to thwart activists.

1.3 Data and Estimation of Variables

This section describes the construction of the main treatment variable of interest - activism events, the estimation of the key outcome variables used in the paper - discretionary accruals and proxies of real earnings management, and finally describes the primary sources of other firm-level data.

1.3.1 Activism Events

I start by collecting information on the key treatment variable, activism campaigns, from the Factset Sharkwatch database. This data, similar to the data used in the literature on hedge fund activism, largely originates from 13D filings by investors with the SEC. Under rule 13d of the 1934 Securities and Exchange Act, the US SEC mandates investors to file a Schedule 13D with the SEC when they acquire more than 5% of the voting class of any security of a publicly traded company and have an intention to influence the control of the company.[11] In the absence of the latter, investors are required to file the more abbreviated Form 13G.[12] From Sharkwatch, I collect data on publicly disclosed shareholder activism events in the United States from the period 2004-2014. Excluding repeat targets within the same quarter and targets which were not an investment trust or a mutual fund, I obtain 2663 activism campaigns with GVKEY-PERMNO links. This does not include activism events for routine shareholder proposals filed under Rule 14a-8. I further exclude corporate control contests initiated by another firm and activism campaigns which were not accompanied by a 13D filing, barring those initiated by hedge funds. The resulting sample of 2399 activism events is further truncated by other restrictions: excluding financial firms and utilities(SICs 6000-6999, 4900-4999), and imposing data requirements, I arrive at a final sample of 1457 activism events for which I have data on the main earnings management variables and firm-level controls. This sample of activism events further change through the various

[11]See https://www.sec.gov/answers/sched13.htm.

[12]See http://www.sec.gov/divisions/corpfin/guidance/reg13d-interp.htm.

empirical analyses in the paper, as more data requirements are imposed.

1.3.2 Firm-level Data and Computation of Variables

Firm-level data is obtained from multiple sources. Firstly, the key outcome variables of interest, discretionary accruals and proxies of real earnings management, are computed from available quarterly data for the universe of firms in Compustat.

Discretionary Accruals

Discretionary accruals are computed by subtracting a model-implied estimate of non-discretionary accruals from total accruals. Following (Hribar and Collins, 2002), I compute total accruals from the statement of cash-flows. Specifically, total accruals are computed by differencing net cash-flow from operating activities (CFO), excluding discontinued operations (XIDOQ), from earnings before extraordinary items (IBQ), all scaled by lagged total assets(ATQ) [13]:

$$TA_{i,t} = \frac{IBQ_{i,t} - (CFO_{i,t} - XIDOQ_{i,t})}{ATQ_{i,t-1}} \tag{1.1}$$

For my main analyses, I compute discretionary accruals using the modified - Jones model (Dechow *et al.*, 1995)) augmented with return on assets data following Kothari *et al.* (2005b, 2015). More specifically, non-discretionary accruals are modeled as a linear function of changes in revenue (ΔREVTQ) less that contributed by changes in accounts receivables (ΔRECTQ); gross property, plant and equipment (PPENTQ); and lagged income before extraordinary items (IBQ):

$$\begin{aligned} \mathbb{E}[TA_{i,t}] &= \beta_0 + \beta_1 \frac{1}{ATQ_{i,t-1}} + \beta_2 \frac{\Delta REVTQ_{i,t} - \Delta RECTQ_{i,t}}{ATQ_{i,t-1}} \\ &\quad + \beta_3 \frac{PPENTQ_{i,t}}{ATQ_{i,t-1}} + \beta_4 \frac{IBQ_{i,t-1}}{ATQ_{i,t-1}}, \end{aligned} \tag{1.2}$$

Following Dou *et al.* (2014); Ball and Shivakumar (2006), I estimate the coefficients of (1.2)

[13] Note that I compute quarterly operating cash-flows (CFO) from the year-to-date number (OANCFY) available in Compustat.

by pooling observations for each three-digit SIC industry with more than 30 observations.[14] Discretionary accruals, DA are obtained as the residuals of these estimation regressions:

$$DA_{i,t} = TA_{i,t} - \widehat{TA_{i,t}} \tag{1.3}$$

In supplemental robustness tests I estimate (1.2) using a time-series model, an industry-quarter cross-sectional model and using other co-variates. For purposes of my analysis, the discretionary accruals estimates are winsorized outside the 1st and 99th percentile.

Real Earnings Management

To develop the other key outcome variable, proxies of real earnings management, I build on prior literature on this topic. Specifically, I focus on two metrics which the extant literature (Roychowdhury, 2006; Cohen and Zarowin, 2010) uses to study real activities manipulation: abnormal cash-flows from operations and abnormal discretionary expenses. These variables are intended to reflect the impact of strategic earnings manipulation using the following methods:

1. *Acceleration of sales* - Actions to increase sales temporarily through aggressive price discounts or more lenient credit terms will lead to a temporary increase in sales volumes, which are likely to reverse once the firm reverts to normal business practices. The increased sales will translate into higher earnings, as long as margins are positive, but their translation into commensurate cash-flows will be impaired by the increased price discounts and more lenient credit terms.

2. *Decrease in R&D and SG&A*: These are often viewed as discretionary and which can be cut to boost current period earnings. Whether reduction in these expenses result in higher accruals or higher cash-flows, for the period, will depend on the extent to which firms paid for these expenses in cash.

[14] Note that these estimations are conducted on the entire firm-quarter panel in Compustat. Given the very large estimation sample, concerns about outliers affecting the estimated coefficients are lower and so variables in these estimations are winsorized outside the 0.5th and 99.5th percentile of the pooled sample.

Similar to the construction of discretionary accruals, the real earnings management proxies are computed by subtracting a model-implied measure of the normal level of cash-flows and discretionary expenses from actual realizations. [15] I compute the normal level of cash-flows from operations using the model developed in Dechow *et al.* (1998) and implemented in Roychowdhury (2006); Cohen and Zarowin (2010), where normal cash-flow from operations (CFO) is modeled as a linear function of sales (REVTQ) and change in sales (ΔREVTQ):

$$\mathbb{E}\left[\frac{CFO_{i,t}}{ATQ_{i,t-1}}\right] = \beta_0 + \beta_1 \frac{1}{ATQ_{i,t-1}} + \beta_2 \frac{REVTQ_{i,t}}{ATQ_{i,t-1}} + \beta_3 \frac{\Delta REVTQ_{i,t}}{ATQ_{i,t-1}}, \quad (1.4)$$

Consistent with the estimation of discretionary accruals, I estimate the coefficients of (1.4) by pooling observations for each three-digit SIC industry having at least 30 observations available for the estimation exercise. In robustness tests, I also report results using proxies computed from an industry-quarter cross-sectional model. Abnormal cash-flows are obtained as residuals of the estimated regressions:

$$Ab\_CFO_{i,t} = \frac{CFO_{i,t}}{ATQ_{i,t-1}} - \frac{\widehat{CFO}_{i,t}}{ATQ_{i,t-1}} \quad (1.5)$$

The construction of abnormal discretionary expenses also involves modeling the normal level of discretionary expenses as a linear function of sales. For this particular exercise, I use lagged sales also used by Cohen and Zarowin (2010), since modeling discretionary expenses as a linear function of contemporaneous sales mechanically produces lower residuals if current period sales are being managed upwards. This implies that discretionary expenses and it's components are as follows:

$$\mathbb{E}\left[\frac{Y_{i,t}}{ATQ_{i,t-1}}\right] = \beta_0 + \beta_1 \frac{1}{ATQ_{i,t-1}} + \beta_2 \frac{REVTQ_{i,t-1}}{ATQ_{i,t-1}}, \quad (1.6)$$

[15] Similar to the previous exercize, all variables in these estimations are winsorized outside the 0.5th and 99.5th percentile of the pooled sample.

where $Y_{i,t}$ is sequentially replaced by SG&A, R&D and the sum of the two to estimate normal discretionary expenses. This treatment is prompted by the specific context of activism. Activism often brings with it associated administrative expenses related to proxy fights, hiring lawyers, and investment relation efforts, which are likely to generate higher SG&A expenses and thus might counter management's efforts to lower discretionary expenses. While this complicates the prediction on the behavior of this component of discretionary expenses, the prediction on how firms might manage R&D expenses is less ambiguous and thereby I disaggregate abnormal discretionary expenses into SG&A and R&D expenses and use the latter to construct my comprehensive measure of real earnings management. As in the case of discretionary accruals and abnormal cash-flows, (1.6) is modeled for each three-digit SIC industry and then the different proxies for abnormal discretionary expenses are computed as:

$$Ab\_Y_{i,t} = \frac{Y_{i,t}}{ATQ_{i,t-1}} - \frac{\widehat{Y_{i,t}}}{ATQ_{i,t-1}} \tag{1.7}$$

The prediction about the behavior of these proxies for real earnings management falls out of the preceding discussion. For a given sales level, firms that are managing earnings upwards are likely to have abnormally low cash flows from operations and/or unusually low R&D expenses. Consequently to capture the total effect of real activities manipulation, following Cohen and Zarowin (2010); Roychowdhury (2006), I multiply *Ab_CFO* and *Ab_R&D* by negative one to make them increasing in the direction of earnings management and then combine them to create my composite measure of real earnings management, *REM*.

Although I use this composite measure as my main outcome variable for real earnings management, in additional tests I illustrate the behavior of each individual proxy of real earnings management. For purposes of my analysis, all the proxies for real earnings management are winsorized outside the 1st and 99th percentile.

Other Variables

These proxies are then matched to the CRSP/Compustat merged database to compute standard stock-level and firm-level information to be included as control variables in the empirical analysis. The literature on hedge-fund activism has consistently identified a set of firm-characteristics which drives an activist's target selection (e.g., Brav *et al.*, 2008; Gow *et al.*, 2014; Bebchuk *et al.*, 2014) and these findings inform the selection of control variables for my analysis. I compute the following variables at the quarterly level using fundamental data for the quarter and prices at the end of the quarter:*MCAP*, the market capitalization of the company; *BM*, the book-to-market ratio of equity (logged values of both of which are used in the regression); *ROA*, the ratio of net income to total assets; *Sales Growth*, the ratio of current-period sales to that in the previous quarter; *Leverage*, the ratio of long-term debt to total assets; *Payout*, the ratio of common dividends to net income; *Firm Age*, which is simply the time till date for which data on the firm has been available on CRSP and *Size Adj Returns*, the excess stock returns over the past twelve months. In addition, I also include *Lagged Net Operating Assets*, because Barton and Simko (2002) show that overstated net operating assets can act as a constraint on accruals management and the evidence on activism suggests that the mix of operating and non-operating assets does play a role in the activist's target selection.

This set of fundamentals and returns-based controls is augmented with a few additional variables. I obtain data on whether a firm had a staggered board or not, by parsing through changes in firm's bylaws and charters using data from Factset's Sharkrepellent database. I also compute the level of institutional ownership from 13F filing data compiled by Whalewisdom. The firm-level data is matched to I/B/E/S to obtain the extent of analyst coverage for each firm-quarter.

The overall exercise yields an unbalanced firm-quarter (calendar) panel containing an average of 27 quarters of data for 3652 firms.

1.3.3 Summary Statistics

The details in Table 1.1, i.e. descriptive statistics for target firms at the time of the campaign, relative to the pooled sample of non-target firms, are consistent with the findings in the literature on the activists' target selection process.[16]. Target firms tend to be smaller: the median target firm has a market capitalization of $362 million which is almost half that of the median non-target firm. This is largely due to the capital and diversification constraints hedge funds face when trying to target larger firms. The distribution of the market-cap of target firms is skewed by a few very large targets, primarily towards the end of the sample period. Activists also tend to behave like "value investors", targeting firms with unpriced potential for improvement i.e. firms with higher book-to-market ratios and which have been experiencing a decline in operating and stock-market performance, as evidenced in the lower median ROA, sales growth and past returns. Target firms, however are not distressed firms and tend to be mature firms, in fact more mature than non-target firms, with low leverage and substantial cash, but with low dividend payout. Interestingly, Brav *et al.* (2015a) shows that target firms were out-performing control firms in terms of profitability, three years prior to activism, suggesting that the promise of a reversal in performance underpins the activism process. Finally, the median target firm has comparable institutional ownership and only marginally lower analyst coverage relative to non-target firms.

1.4 Empirical Analysis and Results

This section contains the results of my analyses which motivate and demonstrate earnings management. I start with an investigation of the role of performance, reported during the activism campaign, on eventual outcomes of activism. Thereafter I present empirical evidence on managers takeing strategic actions to temporarily improve profitability when engaged with an activist.

[16]See Brav *et al.* (2015b) for a detailed summary

Table 1.1. Characteristics of Target and Non-Target Firms

Table 1.1 reports characteristics of firms targeted by activists in comparison to other CRSP-Compustat firms, with available data, which were never a target of an activism campaign. The observations are at the firm-quarter level for a time period extending from 2004-2014. All variables are measured as of quarter end. Characteristics of target firms are measured as at the end of the quarter in which the activism campaign is initiated against the firm. For non-target firms, the reported statistics are computed using the pooled firm-quarter panel. Variable definitions are as described in the appendix. All unbounded variables are winsorized outside the 1st and 99th percentile.

	Target Firms					Non-Activism Firms				
	(mean)	(p25)	(p50)	(p75)	(count)	(mean)	(p25)	(p50)	(p75)	(count)
Discretionary Accruals	-0.002	-0.020	0.001	0.019	1457	0.000	-0.019	0.000	0.020	99,481
Real Earnings Management Proxy	-0.019	-0.043	-0.018	0.004	1457	-0.023	-0.048	-0.022	0.001	99481
log(MCAP)	6.22	4.80	5.89	7.53	1457	6.51	5.26	6.43	7.69	99,481
log(BM)	-0.65	-1.10	-0.61	-0.15	1457	-0.85	-1.31	-0.80	-0.32	99,481
Sales Growth	1.04	0.94	1.01	1.09	1457	1.05	0.95	1.02	1.10	99,481
Leverage	0.16	0.00	0.10	0.28	1457	0.16	0.00	0.11	0.26	99,481
Past Size-Adj Return	-0.06	-0.33	-0.11	0.11	1457	0.03	-0.26	-0.04	0.21	99,481
ROA	-0.01	-0.02	0.00	0.01	1457	0.00	0.00	0.01	0.02	99,481
Lagged Net Operating Assets	3.10	1.07	2.08	3.66	1440	3.30	1.14	2.09	3.59	98,703
Payout	0.11	0.00	0.00	0.00	1457	0.12	0.00	0.00	0.09	99,481
Staggered Board	0.45	0.00	0.00	1.00	1457	0.49	0.00	0.00	1.00	99,481
Firm Age	19.85	8.08	15.16	26.17	1457	18.59	6.92	13.66	24.50	99,481
Institutional Ownership	0.7	0.5	0.7	0.9	1457	0.7	0.5	0.7	0.9	99,481
Analyst Following	7	1	4	10	1457	7	2	5	11	99,481

1.4.1 Does Performance Matter?

I begin my empirical analysis by examining whether performance, in the quarter following the launch of the activism campaign, controlling for performance at the time of the launch of activism, influences the eventual outcome of the campaign. The choice of focusing on this time-period is motivated by Gantchev (2013)'s finding that the negotiation period between the firm and the activist can be described as a period that starts approximately 3 months after the campaign launch and which, for the majority of campaigns, culminates 6-9 months after the campaign launch. Thereby, for this analysis, I focus on a set of campaigns which are still on-going at the end of the quarter following the launch of the campaign, and for which I can observe an eventual resolution of the campaign. This yields a smaller set of activism campaigns, for which I estimate probit equations of the form:

$$Y_i = \Phi(\alpha + \beta_1 ROA_{i,t} + \beta_2 ROA_{i,t+1} + \gamma X_{i,t} + f_t + \lambda_j) + \epsilon_i, \quad (1.8)$$

Y_i denotes a set of indicator variables which are used to capture various costly outcomes for the target firm. I model the likelihood of the target firm experiencing the following outcomes: (1) the activism campaign extends to a definitive proxy fight, and (2) the target firm experiences director turnover in the following fiscal period. $ROA_{i,t+1}$, the main variable of interest for this analyses, denotes the profitability of the target firm in the quarter following the one in which the activism campaign is launched. This is computed as income for the relevant quarter, scaled by total assets at the end of the quarter of activism. $ROA_{i,t}$, profitability in the quarter of activism, is also included in the regression to isolate the component of performance in $t+1$, which is orthogonal to that in t. For purposes of this analysis, these measures are multiplied by 100 to make the marginal effects easier to interpret.

Table 1.2 describes the result of the analyses. Higher return-on-assets, in the quarter following activism, is strongly negatively associated with the likelihood of the activism campaign ending in a definitive proxy fight and the target firm experiencing director turnover in the following fiscal. The effects are economically meaningful — marginal effects, computed at the means of the independent variables, implies that a one percentage point increase in return-on-assets is associated with a 5% and 3% reduction in the unconditional likelihood of a proxy fight or director turnover respectively. An inter-quartile increase in return-on-assets reduces the likelihood of a proxy fight and that of director turnover by 13% and 7% respectively.

As the results show, the other firm characteristics which have a statistically significant relationship with the different outcome variables are firm-size, past returns, leverage, firm-age and the presence of take-over defenses (*Staggered Board*, *Bulletproof Rating* and *Poison Pill Adopted*). The relationships of the outcome variables with firm-size, past returns and leverage are not economically meaningful, whereas the effect of takeover defenses on the likelihood of the campaign ending in a proxy fight is. The negative coefficient on *Staggered Board* and the positive coefficient on *Poison Pill Adopted* is also consistent with the findings in Shin (2016), which shows that staggered boards seem to impose costs on activists, and Boyson and Pichler (2016), which shows that activists use proxy fights as a counter-mechanism to targets which resist by adopting a poison-pill, following the launch of the activism campaign. Of the campaign-level controls, higher activist ownership is strongly positively associated with the likelihood of the campaign ending in a proxy fight or the target having to grant a board seat to the activist. This is consistent with theory, that higher ownership increases the threshold for costly intervention for the activist, and this evidence also serves as motivation for subsequent tests where I partition the activism events using the activist's ownership. The evidence in this table, even in the absence of any causal interpretation, suggests that better performance during the activism campaign is associated with less adverse consequences for managers.

1.4.2 Activism and Earnings Management

The arguments in the introduction and the evidence in the previous section suggests that managers have incentives to report better performance when they are targeted by an activist.

Table 1.2. Reported Performance and Outcomes of Activism

This panel reports results of Probit analyses examining the influence of profitability, in the quarter following the launch of the activism campaign, on the eventual outcomes of activism. The unit of analyses here is an activism campaign, unlike most of the following analyses which are at the firm-quarter level. The sample for this analyses is a subset of activism events — which persist beyond one quarter following launch and where the campaign has been concluded. The dependent variable in Columns (1) and (2) is an indicator variable set to 1 if the activism campaign ended in a definitive proxy fight, and that in Columns (3) and (4) is an indicator denoting whether the target firm experienced director turnover in the fiscal year, following the one in which the campaign was launched. The variable of interest in all specifications is $ROA_{(t+1)}$, which is computed as income in the quarter following the launch of the activism campaign, scaled by total assets at the end of the quarter of launch. Other firm-level controls are measured at the end of the quarter in which activism is launched. Columns (2), and (4) include campaign-level controls, as they are available, in addition to a set of firm-level controls. All specifications include year and one-digit SIC dummies. The variable of interest is multiplied by 100 to make marginal effects more interpretable. Robust standard errors are reported in the parentheses below the coefficients and levels of significance are indicated by *, **, and ***, representing 10 percent, 5 percent, and 1 percent, respectively.

	Proxy Fight		Board Turnover	
	(1)	(2)	(3)	(4)
ROA_t	-0.0004	0.0095	0.0009	0.0015
	[0.0105]	[0.0138]	[0.0114]	[0.0128]
$ROA_{(t+1)}$	-0.0228*	-0.0354**	-0.0257**	-0.0238*
	[0.0138]	[0.0166]	[0.0128]	[0.0144]
log(MCAP)	0.0504	0.1304*	0.1193**	0.1312**
	[0.0635]	[0.0793]	[0.0542]	[0.0616]
log(BM)	0.1375	0.1478	0.0827	0.0621
	[0.0920]	[0.1068]	[0.0751]	[0.0846]
Sales Growth	-0.1884	-0.2840	0.0251	0.0902
	[0.2502]	[0.2847]	[0.1741]	[0.1959]
Leverage	-0.1697	-0.5425	0.5107*	0.3704
	[0.3734]	[0.4459]	[0.2899]	[0.3168]
Past Size-Adj Return	-0.1919	-0.3254*	-0.0878	-0.0931
	[0.1452]	[0.1851]	[0.1373]	[0.1508]
Lagged NOA	-0.0127	-0.0217	0.0018	0.0013
	[0.0182]	[0.0237]	[0.0130]	[0.0135]
Payout	0.0048	0.0449	0.0005	-0.0338
	[0.1290]	[0.1332]	[0.1083]	[0.1205]
Staggered Board	-0.2100*	-0.5441***	-0.0216	-0.1561
	[0.1238]	[0.2091]	[0.0966]	[0.1538]
Firm Age	0.0047	0.0055	0.0059*	0.0047
	[0.0035]	[0.0039]	[0.0031]	[0.0036]
Institutional Ownership	0.0983	0.1612	0.0795	0.1252
	[0.3006]	[0.3261]	[0.2446]	[0.2693]
Analyst Following	0.0005	-0.0078	-0.0045	-0.0150
	[0.0143]	[0.0172]	[0.0119]	[0.0131]
Bulletproof Rating		0.0672*		0.0380
		[0.0375]		[0.0278]
Activist Ownership		0.0267***		0.0035
		[0.0103]		[0.0080]
Announcement Returns		-0.2552		-0.0956
		[0.3542]		[0.2124]
Poison Pill Adopted		1.1495***		0.2436
		[0.2714]		[0.2613]
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	786	659	797	666
Pseudo R^2	0.042	0.113	0.053	0.053

Consequently, to examine whether managers respond to these incentives, I focus on my entire sample of activism events to examine how the proxies of earnings management change as a function of activism. This is implemented by estimating equations of the form:

$$Y_{i,t} = \alpha + \beta Activism_{i,t-1} + \gamma X_{i,t} + \lambda_i + f_t + \epsilon_{i,t}, \tag{1.9}$$

This specification examines the behavior of the earnings management proxies in the quarter following the launch of the activism campaign, after controlling for a wide-set of contemporaneous variables. The main treatment variable of interest, $Activism_{i,t-1}$, only switches on for target firms when an activism campaign was initiated in the prior quarter, i.e $t-1$; (λ_i, f_t) are a set of firm and time fixed effects to control for unobserved firm-level heterogeneity or contemporaneous cross-sectional shocks, and $X_{i,t}$ are a matrix of firm controls, measured at time t. Standard errors are clustered at the firm level.

The results in Table 1.3, Panel A, confirm the main hypothesis. The coefficients on the treatment indicator are positive and highly statistically significant, for both DA and REM, in all specifications and are stable with the progressive inclusion of control variables. The regression specifications in columns (3) and (6) also include higher-order industry×time fixed effects which ensure that the results are not driven by contemporaneous industry-level shocks.

The effects are economically meaningful with the average coefficients for DA and REM each implying distortions of 0.35% of assets. Each of these effects translates to about 12% of median quarterly operating income. As I explained in the previous section, there is likely to be a certain degree of overlap between the underlying actions driving the distortion in the accruals measures and the real earnings management measures because real activities manipulation such as accelerating sales or reducing the component of discretionary expenses which are paid for with a lag will also result in higher accruals. Consequently the economic equivalent of the sum of coefficients on the DA and REM proxies represents the upper-bound of the impact of income-enhancing actions taken by management.

Table 1.3. Activism and Earnings Management

Panel A: Discretionary Accruals and Composite Real Earnings Management Proxy

This panel reports results of quarterly OLS regressions of proxies of accruals and real earnings management on an event-quarter dummy for activism and other firm characteristics. $Activism_{(t-1)}$ is an indicator variable which takes the value 1 only for target firms in the quarter following the one with the onset of the activism campaign and is 0 for all other observations. The dependent variable in columns 1,2 and 3, DA ,is discretionary accruals calculated using the cross-sectional modified-Jones model, augmented with ROA, and computed using cash-flow data. The dependent variable in columns 4,5 and 6, REM , is a composite real earnings management proxy computed as the sum of abnormal cash-flows from operations and abnormal R&D expenses. The proxy is multiplied by negative one to make it increasing in the direction of earnings management. All variables are measured as of quarter end. Time fixed effects are at the calendar-quarter level; industry fixed effects are at the two-digit SIC level; industry-time fixed effects are at the intersection of time and industry fixed effects.. Robust standard errors, clustered by firm, are reported in the parentheses below the coefficients and levels of significance are indicated by *, **, and ***, representing 10 percent, 5 percent, and 1 percent, respectively.

	DA			REM		
	(1)	(2)	(3)	(4)	(5)	(6)
Activism$_{(t-1)}$	0.0032**	0.0038***	0.0037***	0.0043***	0.0031***	0.0032***
	[0.0015]	[0.0014]	[0.0014]	[0.0012]	[0.0012]	[0.0012]
log(MCAP)		-0.0072***	-0.0075***		0.0005	0.0003
		[0.0006]	[0.0007]		[0.0006]	[0.0006]
log(BM)		-0.0034***	-0.0036***		0.0048***	0.0048***
		[0.0007]	[0.0007]		[0.0007]	[0.0007]
Sales Growth		0.0147***	0.0149***		0.0013	0.0014
		[0.0020]	[0.0020]		[0.0017]	[0.0018]
Leverage		0.0133***	0.0129***		0.0278***	0.0271***
		[0.0025]	[0.0026]		[0.0025]	[0.0025]
Past Size-Adj Return		-0.0038***	-0.0038***		-0.0023***	-0.0023***
		[0.0005]	[0.0005]		[0.0004]	[0.0004]
ROA		0.4756***	0.4762***		-0.2058***	-0.2043***
		[0.0108]	[0.0109]		[0.0091]	[0.0090]
Lagged NOA		-0.0000	-0.0001		0.0002**	0.0001
		[0.0001]	[0.0001]		[0.0001]	[0.0001]
Payout		0.0004	0.0004		0.0005	0.0004
		[0.0004]	[0.0004]		[0.0003]	[0.0004]
Staggered Board		-0.0005	-0.0004		-0.0009	-0.0009
		[0.0012]	[0.0012]		[0.0009]	[0.0009]
Firm Age		-0.0001	-0.0001		-0.0000	-0.0000
		[0.0001]	[0.0001]		[0.0001]	[0.0001]
Institutional Ownership		-0.0029	-0.0026		-0.0009	-0.0008
		[0.0019]	[0.0019]		[0.0018]	[0.0018]
Analyst Following		-0.0001*	-0.0002**		-0.0003***	-0.0003***
		[0.0001]	[0.0001]		[0.0001]	[0.0001]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Time FE	No	No	Yes	No	No	Yes
Observations	99,481	98,703	98,703	99,481	98,703	98,703
R^2	0.114	0.263	0.297	0.385	0.420	0.449

Panel B: Behavior of Individual Real Earnings Management Proxies

This panel reports results of quarterly OLS regressions on individual proxies of real earnings management on an event-quarter dummy for activism and other firm characteristics. $Activism_{(t-1)}$ is an indicator variable which takes the value 1 only for target firms in the quarter following the one with the onset of the activism campaign and is 0 for all other observations. All proxies are multiplied by negative one to make them increasing in the direction of earnings management. The dependent variable in column 1 is abnormal cash-flows, in column 2 it is abnormal R&D expenses while column 3 reports results using abnormal R&D expenses but computed using a sample where missing R&D is not recorded as zero. Column 4 reports results using abnormal SG&A expenses and finally the outcome variable in column 5 is the sum of abnormal R&D and abnormal SG&A expenses. The models used to construct these proxies are explained in greater detail in the text. All variables are measured as of quarter end. Time fixed effects are at the calendar-quarter level. Robust standard errors, clustered by firm, are reported in the parentheses below the coefficients and levels of significance are indicated by *, **, and ***, representing 10 percent, 5 percent, and 1 percent, respectively.

	(Ab_CFO)	(Ab_R&D)	(Ab_R&D2)	(Ab_SG&A)	(Ab_Discretionary)
$Activism_{(t-1)}$	0.0026**	0.0006*	0.0013**	-0.0006	-0.0004
	[0.0011]	[0.0004]	[0.0006]	[0.0006]	[0.0008]
log(MCAP)	-0.0025***	0.0031***	0.0046***	0.0102***	0.0125***
	[0.0005]	[0.0004]	[0.0006]	[0.0008]	[0.0010]
log(BM)	-0.0009	0.0062***	0.0090***	0.0106***	0.0144***
	[0.0006]	[0.0005]	[0.0007]	[0.0008]	[0.0011]
Sales Growth	0.0035**	-0.0028***	-0.0041***	-0.0277***	-0.0300***
	[0.0017]	[0.0004]	[0.0006]	[0.0012]	[0.0014]
Leverage	0.0165***	0.0126***	0.0171***	0.0272***	0.0369***
	[0.0022]	[0.0017]	[0.0027]	[0.0029]	[0.0039]
Past Size-Adj Return	-0.0023***	0.0001	0.0002	0.0002	0.0003
	[0.0004]	[0.0002]	[0.0003]	[0.0004]	[0.0004]
ROA	-0.2566***	0.0641***	0.0813***	0.0984***	0.1285***
	[0.0091]	[0.0062]	[0.0072]	[0.0074]	[0.0100]
Lagged NOA	-0.0000	0.0002***	0.0003***	0.0006***	0.0009***
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0002]
Payout	0.0004	-0.0000	-0.0000	0.0006***	0.0007***
	[0.0003]	[0.0001]	[0.0001]	[0.0002]	[0.0002]
Staggered Board	-0.0005	-0.0004	-0.0009	0.0002	-0.0002
	[0.0009]	[0.0005]	[0.0008]	[0.0010]	[0.0013]
Firm Age	0.0000	-0.0000**	-0.0001	-0.0002	-0.0002**
	[0.0001]	[0.0000]	[0.0001]	[0.0001]	[0.0001]
Institutional Ownership	-0.0030*	0.0024**	0.0028	0.0029*	0.0041*
	[0.0017]	[0.0011]	[0.0018]	[0.0018]	[0.0023]
Analyst Following	-0.0003***	-0.0000	-0.0000	-0.0000	-0.0000
	[0.0001]	[0.0000]	[0.0001]	[0.0001]	[0.0001]
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	98,703	98,703	54,840	90,994	90,994
R^2	0.487	0.649	0.707	0.865	0.850

Panel B of Table 1.3 reports results of the same specification as in (1.9) but with the composite *REM* proxy disaggregated into it's main components, *Ab_CFO* and *Ab_R&D*. As explained earlier, these proxies are multiplied by negative one to make them increasing in the direction of earnings management. The results in Columns (1) and (2) indicate that the main effect described earlier is indeed driven by both components of *REM*. The coefficient on *Ab_R&D* indicates that managers manipulate R&D expenses by 0.06% of assets to generate improvements in profitability in response to activism. This effect is economically important given that the R&D spending for the median firm is zero. The cutback in R&D spending is further highlighted in column 3 which reports results for a sample of firms with non-missing R&D expenses. Koh and Reeb (2015) suggest that a significant portion of firms with missing R&D expenses actually engage in innovative activity and missing R&D expenses in these cases might represent misreporting or a misclassification of expenses. Consequently recording these missing R&D expenses as zero could understate any distortion in R&D activity in response to a shock. Column 4 of Panel B shows the behavior of abnormal SG&A expenses and the results suggest that these do not change in response to activism. As highlighted earlier, interpretation of this effect becomes complicated by the fact that even if managers do try and reduce discretionary spending on SG&A, activism brings with it concomitant expenses related to lawyers, proxy advisory firms and investor relations which are likely to be classified under SG&A and hence might negate any strategic cut-backs in these spendings.

1.4.3 Tying Earnings Management to Activism

Do managers react more when the activist attack has more credibility?

Strategic actions to boost profits temporarily are likely to bear some costs for the manager: (1) such actions might be detectable which might have consequences for the manager's reputation and (2) to the extent that such myopic actions hurt long-term firm value and the manager cares about long-term value, this also imposes an additional cost to the manager. Consequently managers are likely to engage in such behaviors when they perceive the benefits of the performance improvement to be higher. Any strategic action to thwart the activist attack is likely to be more valuable to the manager when the activist threat is more credible. I demonstrate that the variation in earnings management is consistent with this argument. Empirically, this translates to re-estimating (1.9) but by splitting the main treatment variable, $Activism_{i,t-1}$ into two non over-lapping indicators, $Activism_{i,t-1} \times Less\ Credible$ and $Activism_{i,t-1} \times More\ Credible$. This results in estimating equations of the form:

$$\begin{aligned} Y_{i,t} &= \alpha + \beta_1 Activism_{i,t-1} \times Less\ Credible \\ &\quad + \beta_2 Activism_{i,t-1} \times More\ Credible + \gamma X_{i,t} + \lambda_i + f_t + \epsilon_{i,t}, \end{aligned} \tag{1.10}$$

I estimate the credibility of the activist attack with two measures. Given that the activist shareholder is usually a minority shareholder, in the eventually of a contest for control, the way public shareholders vote will eventually dictate the outcome of the activism event. The activism campaign can thereby be thought of as an exercise by the manager and the activist in persuading other shareholders. Thereby if public shareholders react positively to the announcement of activism it is likely to put the manager under greater pressure. Conversely if the market reacts negatively to the arrival of the activist it would suggest that the market does not regard the activist's thesis as credible. Fos and Jiang (2016) provide evidence of this in the context of a proxy fight, where they show that the market reaction to the announcement of a proxy fight influences manager's option exercise behavior. Consequently, I code activism events as *More Credible* when the compounded abnormal returns during the 20 days around the announcement of the activism event is positive.[17] Columns (1) and (2) of Table 1.4 report the results for this analysis. Both DA and REM are positive and significant when the market reaction suggests that the activist has support from other shareholders whereas DA and REM are not significantly different from zero when the market does

[17] Abnormal returns are estimated as compounded stock returns minus the compounded returns for the CRSP value-weighted index, measured over 20 days centered around the day of announcement of activism. The mean abnormal return is 5.7% whereas the median abnormal return is 3.1%. Although the market generally perceives activism as value-enhancing, in that 56% of the events were accompanied by a positive abnormal reactions, it is clearly not overwhelmingly so.

not signal any support to the activist. The effects of these two different treatments are statistically distinguishable at the 5% level for DA and at the 10% level for REM.

Secondly I expect the pressure on the management to be higher when the activist has higher ownership in the target firm. Higher ownership by the activist increases the likelihood that the activist will engage in a costly intervention, such as a proxy fight, because the activist stands to internalize more of the gains from such an intervention (Edmans and Holderness, 2016; Gantchev, 2013). This is also consistent with the results in Table 1.2, which show that the activist's ownership is strongly positively associated with the likelihood of the campaign extending to a proxy fight or the target firm granting a board seat to the activvst. Higher ownership by the activist, could also serve as a signal to other shareholders that the activist has engaged in costly information acquisition and could also be valuable in the eventuality of a shareholder vote. Consequently, I code activism events as *More Credible* when the activist's ownership in the target firm is above the median ownership in my sample. [18] Columns (3) and (4) of Table 1.4 report the results for this analysis. Both DA and REM are positive and significant when the activist's ownership is above the median level and are not significantly different from zero when otherwise. The effects of these two different treatments are statistically distinguishable at the 5% level for REM.

Earnings management and entrenchment in target firms

Activism has emerged as a governance mechanism aimed at solving agency problems in capital markets and thereby it is natural to examine how management response to activism interacts with the governance framework of a target firm. I examine this empirically, following the approach in (1.10) by partitioning the main treatment variable into two mutually exclusive partitions: $Activism_{i,t-1} \times Less\ Entrenched$ and $Activism_{i,t-1} \times More\ Entrenched$.

I proxy for entrenchment using two measures. Columns (1) and (2) of Table 1.5 partitions target firms into two groups using Factset's Bulletproof rating system, which is a proprietary system Factset uses to accord a numerical rating to firms based on the presence

[18]The median ownership by activist's in my sample is 6.3% whereas the 75th percentile is 9.6%.

Table 1.4. Earnings Management and the Credibility of the Activist

Table 1.4 reports results using the same specification as in Table 1.3 with the difference being that the variable of interest, $Activism_{(t-1)}$, is partitioned into two complimentary variables, $Activism_{(t-1)}$×*More Credible* and $Activism_{(t-1)}$×*Less Credible*. For columns 1 and 2, *More Credible* indicates that the activism campaign initiated in the previous quarter was accompanied by positive cumulative abnormal returns in the 20 days surrounding the event. For columns 3 and 4, *More Credible* indicates that the activism campaign was initiated by an activist whose ownership in the target firm was above the median-level of ownership among all activist. Columns 1 and 3 report results for this specification using DA as the outcome variable whereas columns 2 and 4 use REM as the outcome variable. All control variables used in Table 1.3 are included in the analysis but are not reported for purposes of brevity. The last two rows report results of the F-test examining equality of the two event dummy partitions. All variables are measured as of quarter end. Time fixed effects are at the calendar-quarter level. Robust standard errors, clustered by firm, are reported in the parenthesis below the coefficients and levels of significance are indicated by *, **, and ***, representing 10 percent, 5 percent, and 1 percent, respectively.

	Announcement Returns		Activist's Ownership	
	(DA)	(REM)	(DA)	(REM)
$Activism_{(t-1)}$×*More Credible*	0.0065***	0.0052***	0.0060**	0.0062***
	[0.0018]	[0.0015]	[0.0024]	[0.0020]
$Activism_{(t-1)}$×*Less Credible*	0.0001	0.0004	0.0021	0.0001
	[0.0022]	[0.0020]	[0.0020]	[0.0017]
log(MCAP)	-0.0072***	0.0005	-0.0072***	0.0006
	[0.0006]	[0.0006]	[0.0006]	[0.0006]
log(BM)	-0.0034***	0.0048***	-0.0035***	0.0048***
	[0.0007]	[0.0007]	[0.0007]	[0.0007]
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Other Firm Controls	Yes	Yes	Yes	Yes
Observations	98,703	98,703	98,537	98,537
R^2	0.233	0.396	0.233	0.396
F-stat (more credible = less credible)	5.172	3.627	1.555	5.171
P-Val	0.023	0.057	0.212	0.023

and effectiveness of a number of important takeover defense measures. Columns (3) and (4) partition target firms by whether their boards were staggered or not at the time of activism. The results suggest that the evidence of earnings management, using both accruals and real activities, following activism, is driven by firms with more entrenched managers. The coefficient on $Activism_{i,t-1} \times More\ Entrenched$ is highly positive and significant across all four specifications whereas the coefficient on $Activism_{i,t-1} \times Less\ Entrenched$ is not statistically different from zero in any of the specifications.

The idea that firms who are already more protected against any threat to control would be engaging in this behavior more can be puzzling. One explanation is the private-benefits argument — these takeover defenses proxy for private benefits being extracted by the management and consequently the intervention gain is higher for the activist for these targets. This higher intervention gain trumps the higher intervention cost due to the presence of takeover defenses and thus still necessitates strategic action on the part of the manager. An alternative explanation is that dissidence from activists is not aimed at control through takeovers, which takeover defenses prevent, but rather activists highlight the presence of takeover defenses to other shareholders as evidence of agency problems. Consequently, even if managers are not seeking to protect higher private benefits, an improvement in performance becomes valuable to managers in countering the activist's criticism in such cases.

Earnings management and under-performing target firms

Any improvement in performance for the target firm is likely to be more salient, greater the extent of past under-performance which means that the incentives to take strategic actions to generate an immediate reversal in performance is likely to be higher for these target firms. Targets for whom financial performance is not objectively lower relative to peers are instead likely to point this out and also focus on other strategies to counter the activist. To investigate this hypothesis, I partition firms in each cross-section into two quantiles with an indicator variable, which assumes a value 1 for all firm-quarters which were above the

Table 1.5. Earnings Management, Activism and Takeover Defenses

This table reports results using the same specification as in Table 1.3 with the difference being that the variable of interest, $Activism_{(t-1)}$, is partitioned into two complimentary variables, $Activism_{(t-1)} \times$*More Entrenched* and $Activism_{(t-1)} \times$*Less Entrenched*. For columns 1 and 2 the partition uses *Bulletproof Rating*, a proprietary measure computed by Factset which captures the strength of takeover defenses in a company. Firms are rated from 0 to 10 based on the presence and strength of various takeover defenses. *More Entrenched* indicates that the target firm was above the median *Bulletproof Rating* among all target firms. For columns 3 and 4, *More Entrenched* focuses on a single takeover defense mechanism, the presence of a staggered board. Columns 1 and 3 report results for this specification using *DA* as the outcome variable whereas columns 2 and 4 use *REM* as the outcome variable. All control variables used in Table 1.3 are included in the analysis but are not reported for purposes of brevity. The last two rows report results of the F-test examining equality of the two event dummy partitions. All variables are measured as of quarter end. Time fixed effects are at the calendar-quarter level. Robust standard errors, clustered by firm, are reported in the parenthesis below the coefficients and levels of significance are indicated by *, **, and ***, representing 10 percent, 5 percent, and 1 percent, respectively.

	Bulletproof Rating		Staggered Board	
	(DA)	(REM)	(DA)	(REM)
$Activism_{(t-1)} \times$*More Entrenched*	0.0051**	0.0053***	0.0052**	0.0043**
	[0.0020]	[0.0018]	[0.0021]	[0.0018]
$Activism_{(t-1)} \times$*Less Entrenched*	0.0015	-0.0003	0.0027	0.0022
	[0.0020]	[0.0017]	[0.0019]	[0.0016]
log(MCAP)	-0.0072***	0.0005	-0.0072***	0.0005
	[0.0006]	[0.0006]	[0.0006]	[0.0006]
log(BM)	-0.0034***	0.0048***	-0.0034***	0.0048***
	[0.0007]	[0.0007]	[0.0007]	[0.0007]
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Other Firm Controls	Yes	Yes	Yes	Yes
Observations	98,703	98,703	98,703	98,703
R^2	0.233	0.396	0.233	0.396
F-stat(more entrenched = less entrenched)	1.639	5.197	0.783	0.777
P-Val low = high	0.200	0.023	0.376	0.378

median profitability for the cross-section in the previous quarter and 0 otherwise. Thereafter I test whether the earnings management behavior observed in the quarter following activism is higher for the under-performing firms. This translates into estimating the following equation:

$$
\begin{aligned}
Y_{i,t} &= \alpha + \beta_1 Activism_{i,t-1} + \beta_3 Activism_{i,t-1} \times Z_{i,t-1} \\
&\quad + \beta_2 Z_{i,t-1} + \gamma X_{i,t} + \lambda_i + f_t + \epsilon_{i,t},
\end{aligned} \tag{1.11}
$$

where $Z_{i,t}$ indicates the dummy partitioning the cross-section in terms of profitability. [19] Table 1.6 reports the results for estimating this equation using both DA and REM for the quarterly sample. The coefficient of interests here are that on $Activism_{(t-1)}$ and $Activism_{(t-1)} \times ROA_{i,t-1}$ *above median*. Indeed earnings management, following activism, is concentrated among the underperforming firms as indicated by the highly positive and significant coefficients on $Activism_{(t-1)}$ for both DA and REM. On the other hand, the sum of the coefficients on $Activism_{(t-1)}$ and $Activism_{(t-1)} \times ROA_{i,t-1}$ *above median* cannot be distinguished from zero for both DA and REM suggesting that there is no evidence of earnings management among the target firms which were actually ahead of their peers in terms of profitability when the activist showed up.

1.4.4 Is it just Mean-reversion in Performance?

An alternative explanation for the main empirical association and some of the cross-sectional tests could be that activists are successful stock-pickers and time their campaign when operating performance is about to reverse. Kothari *et al.* (2005a) show that performance trends are an important concern for modeling discretionary accruals, and more generally, Owens *et al.* (2016) suggest that economic shocks can bias earnings management proxies for many periods ahead. To argue against this possibility, I conduct a number of other tests.

[19] Note that $Z_{i,t}$ is labeled as $ROA_{i,t-1}$ *above median* in Table 1.6.

Table 1.6. Earnings Management and Underperforming Target Firms

This table reports results using the same specification as in Table 1.3 with the difference being that the variable of interest,$Activism_{(t-1)}$, is now interacted with another indicator, $ROA_{(t-1)}$ *above median*, which indicates whether an observations belongs to a firm which was above the cross-sectional median in terms of ROA in the previous quarter. The coefficient on $Activism_{(t-1)} \times ROA_{(t-1)}$ *above median* indicates the effect for the interaction of these two indicators. Column 1 reports results for this specification using *DA* as the outcome variable whereas column 2 uses *REM* as the outcome variable. All variables are measured as of quarter end. Time fixed effects are at the calendar-quarter level. Robust standard errors, clustered by firm, are reported in the parenthesis below the coefficients and levels of significance are indicated by *, **, and ***, representing 10 percent, 5 percent, and 1 percent, respectively.

	(DA)	(REM)
$Activism_{(t-1)}$	0.0050***	0.0050***
	[0.0019]	[0.0017]
$Activism_{(t-1)} \times ROA_{(t-1)}$ *above median*	-0.0044*	-0.0053**
	[0.0027]	[0.0024]
$ROA_{(t-1)}$ *above median*	-0.0180***	-0.0105***
	[0.0007]	[0.0006]
log(MCAP)	-0.0053***	0.0016***
	[0.0006]	[0.0006]
log(BM)	-0.0050***	0.0038***
	[0.0007]	[0.0007]
Sales Growth	0.0107***	-0.0010
	[0.0020]	[0.0017]
Leverage	0.0061**	0.0235***
	[0.0025]	[0.0025]
Past Size-Adj Return	-0.0031***	-0.0019***
	[0.0005]	[0.0004]
ROA	0.4994***	-0.1927***
	[0.0107]	[0.0089]
Lagged NOA	-0.0001	0.0001*
	[0.0001]	[0.0001]
Payout	0.0004	0.0005
	[0.0004]	[0.0003]
Staggered Board	-0.0008	-0.0010
	[0.0011]	[0.0009]
Firm Age	-0.0002**	-0.0001
	[0.0001]	[0.0001]
Institutional Ownership	-0.0030	-0.0010
	[0.0019]	[0.0018]
Analyst Following	-0.0001*	-0.0003***
	[0.0001]	[0.0001]
Firm FE	Yes	Yes
Time FE	Yes	Yes
Observations	98,652	98,652
R^2	0.249	0.401

Earnings management in resolved versus ongoing campaigns

The earnings management interpretation of the findings suggest that the evidence of earnings management, in the quarter following activism, should be driven by events where the firm and the activist are still engaged in negotiation. This is in contrast to campaigns which get resolved prior to the quarter-end, where the manager's incentives to focus on short-term earnings, to be reported in the future, are diluted. Thus to the extent, that earnings management is reversible or only requires a short-window of time to operationalize, the likelihood of finding an effect in this latter sample of events is lower. I examine this prediction with another empirical exercise, again similar to that in (1.10) in that the main treatment indicator is interacted with two mutually exclusive indicators, *Campaign Resolved* and *Campaign Ongoing*. Interaction with the former indicates that an activism campaign was initiated against the firm in the prior quarter but was resolved before the end of the current quarter, whereas the complementary treatment indicates that the activism campaign initiated in the prior quarter is still ongoing. I create the above partitions by using the end-date of activism events as coded by Factset. Manual examination of a random sample of activism campaigns suggests that this date captures one of the following events: 1) the firm accedes to the activists' demands and this is recognized in some formal communication from the firm or the activist 2) the firm and the activist engage in a proxy fight in which case the campaign end date is synonymous with the date of the proxy fight 3) the firm and the activist arrive at a mutual agreement and this is highlighted in communication from the firm or the activist and 4) the activism campaign ends in failure for the activist and the activist signals the end of the campaign reiterating their concerns. [20] The results for this exercise are reported in Table 1.7.

The results in Table 1.7 support the reasoning in this section in that evidence of earnings

[20]The variable denoting the end of an activism campaign is missing for 211 campaigns which were 13-D filings by hedge funds but were unaccompanied by any public activism campaign. Despite the absence of a formal campaign, I include them in my analysis because the average abnormal stock price reaction to the 13-D filings in these cases was 5%, suggesting that these are regarded as economically important events by the market. For the purposes of the current analysis these events are classified as ongoing as of the end of the following quarter. The results are insensitive to the exclusion of these events

Table 1.7. Earnings Management in Resolved vs Unresolved Campaigns

This table reports results using the same specification as in Table 1.3 with the difference being that the variable of interest, $Activism_{(t-1)}$, is partitioned into two complimentary variables, $Activism_{(t-1)} \times Campaign\ Ongoing$ and $Activism_{(t-1)} \times Campaign\ Resolved$. *Campaign Ongoing* indicates that the activism campaign which was initiated against the target firm in the previous quarter, is still ongoing as of the end of the current quarter. *Campaign Resolved* indicates that the campaign launched in the previous quarter has arrived at some resolution by the end of the current quarter. Column 1 report results for this specification using *DA* as the outcome variable whereas column 2 uses *REM* as the outcome variable. All variables are measured as of quarter end. Time fixed effects are at the calendar-quarter level. Robust standard errors, clustered by firm, are reported in the parenthesis below the coefficients and levels of significance are indicated by *, **, and ***, representing 10 percent, 5 percent, and 1 percent, respectively.

	(DA)	(REM)
$Activism_{(t-1)} \times Campaign\ Ongoing$	0.0045**	0.0035**
	[0.0017]	[0.0015]
$Activism_{(t-1)} \times Campaign\ Resolved$	0.0026	0.0024
	[0.0023]	[0.0019]
log(MCAP)	-0.0072***	0.0005
	[0.0006]	[0.0006]
log(BM)	-0.0034***	0.0048***
	[0.0007]	[0.0007]
Sales Growth	0.0147***	0.0013
	[0.0020]	[0.0017]
Leverage	0.0133***	0.0278***
	[0.0025]	[0.0025]
Past Size-Adj Return	-0.0038***	-0.0023***
	[0.0005]	[0.0004]
ROA	0.4756***	-0.2058***
	[0.0108]	[0.0091]
Lagged NOA	-0.0000	0.0002**
	[0.0001]	[0.0001]
Payout	0.0004	0.0005
	[0.0004]	[0.0003]
Staggered Board	-0.0005	-0.0009
	[0.0012]	[0.0009]
Firm Age	-0.0001	-0.0000
	[0.0001]	[0.0001]
Institutional Ownership	-0.0029	-0.0009
	[0.0019]	[0.0018]
Analyst Following	-0.0001*	-0.0003***
	[0.0001]	[0.0001]
Firm FE	Yes	Yes
Time FE	Yes	Yes
Observations	98,703	98,703
R^2	0.233	0.396

management, for both DA and REM, in the quarter following activism, can be found for the firms which are still engaged with the activist. The coefficient on $Activism_{t-1} \times$ $Campaign\ Resolved$ is not statistically distinguishable from zero for both DA and REM. Note that the coefficients for this partition are not economically insignificant however, which is consistent with the idea that some of the actions managers take to manage earnings are not easily reversible. I do not find any evidence that in the cases where the activism campaign get resolved quickly, managers try and manage earnings in the very quarter in which the activism campaign is initiated. This is consistent with the idea that in these cases managers do not have enough time to take actions to meaningfully improve earnings, but rather might be adopting more 'off-the-shelf' resistances, such as poison-pills (Boyson and Pichler, 2016).

Does Performance show a Reversal?

The finding from the previous analysis is hard to square with the mean-reversion argument. However, it is still possible that activists resolve their campaign quickly in firms which are unlikely to show a performance reversal. If the proxies are only reflecting reversals in underlying performance, that could still explain why the effect is observed only in campaigns where the firm and the activist are still engaged at the end of the quarter following the launch. To rule out this explanation, I examine the behavior of DA, REM, and ROA in other periods following activism to try to detect any evidence of a reversal in performance which should produce biased proxies for multiple quarters.

Thereby, I estimate equations of the form:

$$\begin{aligned} Y_{i,t} &= \alpha + \beta_1 Activism_{i,t} + \beta_2 Activism_{i,t-1} + \beta_3 Activism_{i,t-2} \\ &\quad + \beta_4 Activism_{i,t-3} + \gamma X_{i,t} + \lambda_i + f_t + \epsilon_{i,t}, \end{aligned} \tag{1.12}$$

which is equivalent to the specification in (1.9) but is augmented by indicators denoting time-periods, extending upto 3 quarters after the activism campaign was initiated. To make this clearer, the coefficient on $Activism_{i,t}$ indicates the impact of activism on the behavior of proxies in the quarter in which activism was initiated, whereas that on $Activism_{i,t-3}$ indicates the impact of activism on earnings management in the quarter, 3 quarters after activism. Columns 1 and 2 of Table 1.8 reports results of estimating (1.12) for the quarterly sample. The coefficient on both DA and REM are positive and significant only for $Activism_{i,t-1}$ and dissipate thereafter. If the effect I observe is driven by some unobserved changes happening in the firm which are also correlated with the likelihood of being targeted by an activist or if the earnings management proxies were in fact mis-measuring earnings management and reflecting some other firm response to the activism event, it has to be that such changes only arise in the quarter after activism and do not persist thereafter.

To make this point clearer, I examine the time dynamics of profitability in the same time periods around activism by replacing the earnings management proxies in (1.12) with ROA and by removing ROA from the vector of firm-controls. Columns (3) and (4) of Table 1.8 report the results of estimating these equations. For the specification without firm fixed effects, the coefficient on the time-dummies are negative and significant for all quarters except the quarter following activism, i.e. concurrent with earnings management. The same pattern is observed in column 4 except that the coefficient on $Activism_{i,t-3}$ is negative but insignificant. These results suggest that profitability at target firms do not show any structural improvement, immediately following activism, and the under-performance relative to the cross-section and the firm's average over time persists for a few quarters after activism.

1.4.5 Future Returns Following Earnings Management

It is still plausible that the effect I observe is evidence of short-term efficiency improvements in response to the pressure from the activist, rather than strategic earnings management. To tease apart these two competing explanations, I examine whether future stock market returns for target firms vary according to the levels of the proxies of earnings management. If the proxies reflect short-term efficiency improvements, it is arguable that they would predict positive returns in the future, or at the least, not predict negative returns. On

Table 1.8. Earnings Management and Activism: Mean Reversion in Profitability or Short-Term Effect

Table 1.8 reports results of OLS regression of discretionary accruals, real earnings management and profitability on event-quarter dummies for activism and firm characteristics. $Activism_{(t)}$ is a dummy variable which indicates the quarter featuring the start of the activism campaign against the target firm. $Activism_{(t-1)}$ denotes the quarter after,$Activism_{(t-2)}$ denotes two quarters after and finally $Activism_{(t-3)}$ denotes three quarters after the start of the campaign.The dependent variable in Column 1 is the baseline discretionary accrual proxy, DA, while that in column 2 is the baseline real earnings management proxy, REM. Dependent variables in Columns 3 and 4 are ROA, calculated as income before extraordinary items scaled by assets. The last six rows of the table report results of F-tests equating the coefficients on the event time dummies to each other and the corresponding p-values. All control variables used in Table 1.3 are included in the analysis but are not reported for purposes of brevity.All variables are measured as of quarter end. Time fixed effects are at the calendar-quarter level. Robust standard errors, clustered by firm, are reported in the parentheses below the coefficients and levels of significance are indicated by *, **, and ***, representing 10 percent, 5 percent, and 1 percent, respectively.

	(DA)	(REM)	(ROA)	(ROA)
$Activism_{(t)}$	0.0002	0.0014	-0.0046***	-0.0042***
	[0.0013]	[0.0011]	[0.0015]	[0.0013]
$Activism_{(t-1)}$	0.0034**	0.0026**	-0.0015	-0.0011
	[0.0014]	[0.0012]	[0.0013]	[0.0012]
$Activism_{(t-2)}$	-0.0005	-0.0011	-0.0033**	-0.0032**
	[0.0015]	[0.0013]	[0.0015]	[0.0014]
$Activism_{(t-3)}$	0.0007	0.0012	-0.0034**	-0.0020
	[0.0015]	[0.0014]	[0.0016]	[0.0014]
log(MCAP)	-0.0076***	0.0002	0.0116***	0.0207***
	[0.0007]	[0.0006]	[0.0005]	[0.0010]
log(BM)	-0.0035***	0.0045***	0.0158***	0.0124***
	[0.0008]	[0.0007]	[0.0012]	[0.0012]
Firm FE	Yes	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
Other Firm Controls	Yes	Yes	Yes	Yes
Observations	91,471	91,471	91,471	91,471
R^2	0.238	0.395	0.220	0.551
F-stat ($Activism_{(t)}$ = $Activism_{(t-1)}$)	2.867	0.653	4.398	4.425
P-Val	0.090	0.419	0.036	0.035
F-stat ($Activism_{(t-1)}$ = $Activism_{(t-2)}$)	3.596	4.183	1.372	1.647
P-Val	0.058	0.041	0.242	0.199
F-stat ($Activism_{(t-1)}$ = $Activism_{(t-3)}$)	1.544	0.614	1.267	0.253
P-Val	0.214	0.433	0.260	0.615

the other hand, if the proxies reflect short-term earnings management, to the extent that such earnings management is costly, they are more likely to predict negative returns in the future. If I observe negative return predictability, that would also allow me to shed light on whether earnings management is in fact evidence of costly signaling of future good news by managers, or evidence of costly earnings management by self-interested managers.

The choice of conducting this test at the target level, exploiting variation between targets, is driven by the fact average returns of activism targets will be confounded by the changes activists implement in target firms. To the extent that some of these changes are value-accretive, it lowers the likelihood of being able to detect underperformance of target firms who manage earnings.

To identify target firms which manage earnings, I follow prior literature (Cohen and Zarowin, 2010) and sort target firms into quantiles based on their levels of DA and REM in the quarter following the launch of activism. In particular, I test whether firms in the top quantile of these proxies have lower size-adjusted returns over the following 6 or 12 months. This translates into tests of the form:

$$Y_i = \alpha + \beta Top\_Quantile + \gamma X_{i,t} + f_t + \epsilon_i, \quad (1.13)$$

Y_i captures size-adjusted returns for target firms, measured from the end of the quarter following activism, and measured over horizons of six months and twelve months. $Top\_Quantile$ is an indicator variable capturing whether the target firm was in the top quantile of DA or REM, with sorting being done among all target firms and using the levels of the proxies as of the end of the quarter following activism. In untabulated tests, I also examine results where firms are instead sorted into quintiles of DA and REM by cross-section and industry. The results are insensitive to these alternate specifications. X_i denote a set of firm-level controls, again measured at the end of the quarter following the launch of activism. f_t denotes year-quarter fixed effects.

Table 1.9 captures the results of this analysis. I find that across all specifications, target firms in the top quantile of the earnings management proxies, underperform other target firms. This underperformance is magnified at the 12 month horizon and target firms in the top quantile of the *REM* proxy underperform other targets by as much as 9%. The underperformance of firms in the top quantile of the *DA* proxy is much less severe at around 5%. In fact, untabulated tests reveal that the subset of firms which are only in the top quantile of *DA* and not in the top quantile of *REM*, around 100 observations, do not exhibit any long-term relative underperformance. This is consistent with the findings in Cohen and Zarowin (2010), which shows that return reversals are higher for firms engaging in real earnings management.

It is to be noted that this long-term underperformance cannot be exclusively attributed to earnings management or evidence of bad news being masked by earnings management. To the extent that earnings management is able to adversely influence the outcome of activism, it could be that these target firms experience reversal of earlier announcement gains, reflected in poorer returns in the future. However at the least, these results do suggest that the evidence is more consistent with opportunistic earnings management than efficiency enhancements. Moreover, it also suggests that earnings management does not seem to be functioning as a costly signal of future good news.

1.5 Robustness Tests

In this section I show that the main effect demonstrated in Table 1.3 is also reflected in specific income statement and balance sheet accounts which are likely to capture earnings management. The results of this analysis are tabulated in Table 1.10. Thereafter I also show that some of the empirical choices used in the estimation of *DA* and *REM*, such as the choice of the particular model of estimating discretionary accruals or the estimation sample do not influence inferences. Table 1.11 tabulates these results.

First, I focus on accounts receivables to understand if managers take strategic actions to accelerate sales. To the extent that managers extend credit terms to bring future sales forward, this is likely to be reflected in an increase in accounts receivables. Even in the absence of acceleration of sales, receivables could reflect the considerable discretion

Table 1.9. Future Performance of Target Firms

This table examines future returns of target firms, following earnings management, and reports results of OLS regressions of six-month ahead, and twelve-month ahead size-adjusted returns, on firm characteristics and an indicator for whether the particular observation's levels of discretionary accruals, DA, and real earnings management, REM, was in the highest quintile among all target firms. Similar to Table 1.2, the unit of analysis here is an activism campaign, unlike the previous analyses which were at the firm-quarter level. Returns are measured from the end of the quarter following the launch of activism. Firm characteristics are measured at the end of, and firms are sorted into quintiles based on their levels of DA and REM in this quarter, i.e., when earnings management appears to occur. The analysis is conducted on a consistent sample of target firms for whom past, and future twelve months' returns are available. The first four columns pertain to results when firms are sorted based on DA and the following four report results when firms are sorted into quintiles based on REM. Time fixed effects are at the calendar-quarter level. Robust standard errors, clustered by time, are reported in the parentheses below the coefficients and levels of significance are indicated by *, **, and ***, representing 10 percent, 5 percent, and 1 percent, respectively.

	DA				REM			
	6-month returns		*12-month returns*		*6-month returns*		*12-month returns*	
Highest Quintile of EM Proxy	-0.0191	-0.0216	-0.0427	-0.0520*	-0.0637**	-0.0611**	-0.0901**	-0.0914**
	[0.0192]	[0.0242]	[0.0259]	[0.0293]	[0.0250]	[0.0237]	[0.0408]	[0.0357]
log(MCAP)		-0.0059		-0.0109		-0.0069		-0.0121
		[0.0092]		[0.0144]		[0.0091]		[0.0143]
log(BM)		0.0113		0.0168		0.0112		0.0173
		[0.0169]		[0.0315]		[0.0164]		[0.0322]
Sales Growth		0.0579*		0.0716		0.0645*		0.0754
		[0.0336]		[0.0567]		[0.0336]		[0.0576]
Leverage		0.0583		-0.0664		0.0534		-0.0719
		[0.0658]		[0.0922]		[0.0664]		[0.0917]
Past Size-Adj Return		-0.0089		0.0212		-0.0100		0.0195
		[0.0205]		[0.0385]		[0.0201]		[0.0378]
ROA		0.4959*		0.4963		0.4038		0.3575
		[0.2916]		[0.4019]		[0.2891]		[0.3815]
Lagged NOA		-0.0027		-0.0034		-0.0028		-0.0036
		[0.0038]		[0.0057]		[0.0037]		[0.0056]
Payout		0.0165		0.0316		0.0163		0.0315
		[0.0172]		[0.0274]		[0.0174]		[0.0275]
Staggered Board		0.0403		0.0747**		0.0400		0.0744**
		[0.0249]		[0.0318]		[0.0250]		[0.0320]
Firm Age		0.0003		0.0004		0.0004		0.0005
		[0.0005]		[0.0006]		[0.0005]		[0.0006]
Institutional Ownership		-0.0108		0.0161		-0.0137		0.0126
		[0.0489]		[0.0710]		[0.0489]		[0.0706]
Analyst Following		0.0011		0.0016		0.0012		0.0017
		[0.0021]		[0.0033]		[0.0021]		[0.0033]
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1201	1186	1201	1186	1201	1186	1201	1186
R^2	0.040	0.056	0.047	0.061	0.046	0.061	0.051	0.065

Table 1.10. Earnings Management and Activism: Examining Specific Accounts

Table 1.10 reports results of OLS regressions of the same specification as in Table 1.3 with the difference being that the outcome variables used here are not residuals of estimated quantities but instead are directly computed from specific balance sheet and income statement accounts. Column 1 reports results using changes in accounts receivables, scaled by sales, while column 2 also uses changes in accounts receivables but scaled by assets instead. Column 3 reports results using total accruals, scaled by lagged assets, as the outcome variable while column 4 reports results using R&D expenses, scaled by lagged assets, as the outcome variable. The results reported in column 4 are estimated on a sample of observations with non-missing R&D values. All variables are measured as of quarter end. Time fixed effects are at the calendar-quarter level;industry-time fixed effects are at the two-digit SIC and calendar-quarter level. Robust standard errors, clustered by firm, are reported in the parantheses below the coefficients and levels of significance are indicated by *, **, and ***, representing 10 percent, 5 percent, and 1 percent, respectively.

	(Rec/Sales)	(Rec/Assets)	(Accruals)	(R&D)
$Activism_{(t-1)}$	0.0088*	0.0013	0.0040**	-0.0014**
	[0.0046]	[0.0008]	[0.0016]	[0.0005]
log(MCAP)	0.0125***	0.0013***	-0.0039***	-0.0047***
	[0.0017]	[0.0002]	[0.0009]	[0.0007]
log(BM)	0.0021	-0.0009***	-0.0005	-0.0089***
	[0.0020]	[0.0003]	[0.0011]	[0.0007]
Sales Growth	0.2467***	0.0379***	-0.0065**	0.0058***
	[0.0091]	[0.0017]	[0.0029]	[0.0006]
Leverage	0.0275***	0.0041***	0.0160***	-0.0171***
	[0.0077]	[0.0010]	[0.0032]	[0.0027]
Past Size-Adj Return	0.0047***	0.0010***	-0.0030***	-0.0001
	[0.0016]	[0.0002]	[0.0009]	[0.0003]
ROA	0.1271***	0.0275***	0.7143***	-0.0870***
	[0.0267]	[0.0037]	[0.0211]	[0.0073]
Lagged NOA	-0.0017***	-0.0003***	0.0001	-0.0003***
	[0.0005]	[0.0000]	[0.0001]	[0.0001]
Payout	-0.0002	-0.0005*	0.0002	0.0000
	[0.0016]	[0.0003]	[0.0004]	[0.0001]
Staggered Board	0.0015	-0.0002	-0.0011	0.0004
	[0.0027]	[0.0004]	[0.0013]	[0.0008]
Firm Age	-0.0002	-0.0000	-0.0001	0.0001
	[0.0004]	[0.0000]	[0.0001]	[0.0001]
Institutional Ownership	-0.0086	-0.0014*	0.0008	-0.0035*
	[0.0053]	[0.0007]	[0.0027]	[0.0018]
Analyst Following	-0.0003	-0.0001***	-0.0003***	-0.0000
	[0.0002]	[0.0000]	[0.0001]	[0.0001]
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	98,703	98,703	98,703	54,858
R^2	0.150	0.134	0.228	0.805

managers exercise over revenue recognition. Arthur Levitt in his famous 1998 speech, "The Numbers Game", lists premature recognition of revenues as one of the five tools used in managing earnings.[21]. Academics alike have deliberated on the role of revenue recognition practices on firms' earnings management behaviors (Healy and Wahlen, 1999; Altamuro *et al.*, 2005). Therefore I investigate whether receivables increase systematically following activism. This translates into estimating equations of the form of (1.9), but using a scaled measure of changes in accounts receivables ($\Delta Rec/Sales$,$\Delta Rec/Assets$) as the main outcome variable. Columns (1) and (2) of Table 1.10 show that receivables increase significantly in the quarter following activism. The coefficient on $\Delta Rec/Sales$ is that the contribution of receivables to sales is higher by 0.88% and this effect is statistically significant at the 10% level. This is an economically large effect, given that the median contribution of receivables to sales in the overall sample is 0.57%. The coefficient on $\Delta Rec/Assets$ is 0.0013 but is statistically insignificant (t-stat of 1.62). But this is an economically significant effect given the median level of this variable in the overall sample is similar at 0.0012.[22]

The next model-free measure of earnings management I examine is total accruals, calculated as in (1.1). The reasons for focusing on total accruals are as follows: (1) conditional on hypothesizing accruals management, this effect should mechanically be reflected in total accruals as well since non-discretionary accruals are, by definition, assumed to be the same between the treatment and control groups ; (2) as explained earlier, several real actions to manipulate earnings could also result in inflated accruals even though these would not be traditionally described as 'accruals management'. Column (3) of Table 1.10 reports results of estimating (1.9), but using total accruals as the main outcome variable. The coefficient on $Activism_{i,t-1}$ is highly positive and significant and is also comparable in magnitude to that estimated using discretionary accruals.

Third, I focus on R&D expenses, obtained directly from the income statement, to

[21]See http://www.sec.gov/news/speech/speecharchive/1998/spch220.txt

[22]In untabulated tests I find evidence that the increase in receivables is indeed concentrated in the sub-sample of activism events where the market reacted positively to the announcement.

highlight that managers take strategic actions to reduce discretionary expenses. For this analysis, I focus on a sub-sample with non-missing R&D expenses. Similar to the exercise in column (4) of Panel B of 1.3, this empirical choice is motivated by the finding in Koh and Reeb (2015) who show that coding missing R&D expenses as zero might understate spending on R&D and thereby bias against a researcher trying to understand distortions in R&D spending.[23] The results in Column (4) of Table 1.10 suggests that the cut-back in R&D spending is sharp at 0.14% of assets which is comparable to the median level of R&D spending in the broader sample used for this particular analysis.

Finally, in Table 1.11, I re-estimate (1.9), but using a restricted sample for which I can calculate a number of alternative DA and REM measures instead of the baseline measures used in the main regressions. Column (1) reports the results using the baseline measure of discretionary accruals, that computed using the modified Jones model, augmented with lagged return-on-assets. Columns (2) - (4) report results using measures which are common in the earnings management literature and vary from the baseline model in their choice of co-variates. Column (2) reports results using the original modified Jones model without the performance adjustment as in Dechow *et al.* (1995) while column (3) uses the original (Jones, 1991) model with an adjustment for performance. As with the baseline model, these measures are estimated for each three-digit SIC industry with at least 30 observations. Column (4) reports results using the Jones model but without the adjustment for performance. Column (5) reports results using the same modified-Jones model as in (2) with the difference being that the model is estimated separately for each firm, using it's own time series and imposing the restriction of the availability of at least 10 observations. Column (6) reports results using the same model as used for the baseline measure but estimated cross-sectionally for each 2-digit SIC industry with at least 10 observations, as in Cohen and Zarowin (2010). Finally in column (7), I report results using my baseline measure of real earnings management, but again estimated cross-sectionally for each 2-digit SIC

[23]The availability of R&D spending is comparable in the treatment and overall sample - R&D is missing in approximately 44% of both samples.

industry with at least 10 observations. The coefficient on $Activism_{t-1}$ is positive, comparable in magnitude to those in Table 1.3 and significant at the 5% level for all specifications suggesting that the relationship between earnings management and activism is robust to alternative measurements and estimation samples.

Table 1.11. Robustness Test: Alternative Specifications of Earnings Management Proxies

Table 1.11 reports results of OLS regressions of the same specification as in Table 1.3 with the difference being that the earnings management proxies are calculated using alternative models. Dependent variable in column 1 is DA, the baseline discretionary accrual measure used in prior regressions, column 2 reports results using discretionary accruals estimated using the modified-Jones model but without the Kothari *et al.* (2005a) adjustment for performance, column 3 uses the Jones model augmented with ROA and column 4 uses the traditional Jones model. Column 5 uses the baseline model but estimated separately for each firm using time-series data for each firm while Column 6 reports results using the baseline measure but estimated using a cross-sectional model at the two-digit SIC and calendar-quarter level. Similarly, column 7 reports results using an alternate composite proxy for real earnings management which is estimated using a cross-sectional model for each 2-digit SIC industry and for each calendar quarter. All control variables used in Table 1.3 are included in the analysis but are not reported for purposes of brevity. All variables are measured as of quarter end. Time fixed effects are at the calendar-quarter level. Robust standard errors, clustered by firm, are reported in the parenthesis below the coefficients and levels of significance are indicated by *, **, and ***, representing 10 percent, 5 percent, and 1 percent, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Activism_{(t-1)}$	0.0042***	0.0029**	0.0044***	0.0030**	0.0025**	0.0047***	0.0026**
	[0.0014]	[0.0013]	[0.0015]	[0.0013]	[0.0012]	[0.0017]	[0.0013]
log(MCAP)	-0.0075***	-0.0028***	-0.0071***	-0.0024***	-0.0038***	-0.0076***	-0.0016***
	[0.0006]	[0.0005]	[0.0006]	[0.0005]	[0.0006]	[0.0007]	[0.0006]
log(BM)	-0.0034***	-0.0019***	-0.0034***	-0.0019***	-0.0022***	-0.0031***	0.0025***
	[0.0007]	[0.0006]	[0.0007]	[0.0006]	[0.0007]	[0.0008]	[0.0007]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	94,723	94,723	94,723	94,723	94,723	94,723	94,723
R^2	0.235	0.389	0.209	0.361	0.274	0.193	0.375

1.6 Conclusion

There is growing evidence on the importance of hedge fund activism in shaping firm policies and managerial careers. There is however little evidence on the actions managers take in response to activism. My paper sheds light on this and shows that reported performance has a significant role to play in this setting. In fact, the perceived shortening of managerial horizons, as a result of activism, leads to managers taking myopic actions to improve short-term performance. Further analysis reveals specific conditions under which this problem is exacerbated - when the perceived threat from the activist is higher, when the firm has been under-performing and when managerial entrenchment is higher. I also show that this distortion is not reflective of signaling of future good news, but rather predicts future underperformance. Collectively the evidence in my study shows that a mechanism intended to resolve agency problems in capital markets can have negative externalities of managers taking costly short-term actions.

Chapter 2

Accounting Data and the Cross Section of Expected Returns[1]

2.1 Introduction

Expected returns are a central input in asset allocation decisions. Estimating expected stock returns has been a centerpiece in financial economics since at least the derivation of the CAPM (Sharpe, 1964), but despite its importance, progress in establishing a standard for estimating expected returns has been limited, due to the unobserved nature of expected returns. We posit that such a standard should, by definition, produce empirical proxies that on average forecast the cross-section of future returns and across multiple equity markets. Despite extensive work on this problem, to our knowledge no method satisfying these criteria exists.

For example, there is ample evidence now that the capital asset pricing model and the Fama and French (1993) factor model produce unreliable proxies of *ex ante* expected returns in the U.S., as they fail to exhibit out-of-sample predictive ability (Lee *et al.*, 2014; Lyle and Wang, 2015). The accounting literature's development of the implied cost of capital (ICC) class of expected return proxies (ERPs), as an alternative to factor-based proxies, have so

[1] Co-authored with Matthew Lyle, and my advisor Charles C.Y. Wang

far failed to produce a well-accepted standard.[2] The empirical challenges involved in the implementation of these proxies are exacerbated in the international setting (Lee *et al.*, 2009), given the varying degrees in the integration with global markets, differences in regulatory and governance institutions, the relative paucity of international data, and differences in accounting reporting standards which represent significant barriers to a uniform standard or framework for estimating firm-level expected returns worldwide. Indeed, prior work shows that factors known to explain the in-sample variation of returns in the U.S. do not necessarily explain returns in other markets internationally (Fama and French, 2012; Hou *et al.*, 2011).

Motivated by this, we provide a parsimonious and tractable approach to estimating expected returns that can be applied across international markets. We show that under fairly general assumptions, a valuation-based approach allows expected returns to be expressed as a linear function of two easily measured firm-characteristics, book-to-market (BM) and profitability (return on equity). The model-derived estimates of expected returns significantly and reliably predict the cross section of out-of-sample stock returns in 26 of 29 equity markets worldwide. Fama-MacBeth (FM) regression tests—regressing one-month-ahead returns on ex-ante proxies of expected returns—yield an average predictive slope coefficient of 1.05 (relative to the benchmark of 1). For 21 (20) of the 29 countries the predictive slope is not significantly different from 1 at the 10% (5%) level. Portfolio-based tests yield similar conclusions on the proxies' predictive power. In contrast, we demonstrate that factor-based models—even those based on the BM and profitability factors—fail to forecast stock returns in all but one international market. On average, the implied model parameters based on our estimates are economically plausible and consistent with the

[2]Recent examples of papers that explore the performance of these and other expected-return proxies include: Botosan and Plumlee (2005); Botosan *et al.* (2011); Easton and Monahan (2005); Lyle *et al.* (2013); Lee *et al.* (2014); Lyle and Wang (2015); and Wang (2015). This literature suggests an overall lack of evidence that ICCs, in the cross section, line up well with expected returns (Easton and Monahan, 2005; Lee *et al.*, 2014). Moreover, the assumptions that underlie ICC models are often restrictive (e.g., constant expected returns, ad-hoc terminal growth assumptions) and the implementation of these proxies are often difficult (e.g., solving non-linear equations by numerical methods that may or may not converge, or that may converge to multiple solutions) – which have limited the usefulness of this class of expected return proxies.

findings of prior work focused on US markets.

This valuation-based model of expected returns preserves the economic predictions of more complex analytical models that link expected equity returns to firm characteristics (e.g., Berk *et al.*, 1999; Liu *et al.*, 2009; Zhang, 2005). These latter models offer insights on the the economic mechanisms driving these linkages; however, they tend to be mathematically complex or highly stylized, and most importantly difficult to calibrate with firm-level data. On the other hand, our model is easy to calibrate and can be derived using only two plausible assumptions: 1) book values are expected to carry value-relevant information, and 2) expected growth rates in market and book are persistent and mean-reverting. Assumption 1) is consistent with the design of accounting systems, which are in place to provide stakeholders with value-relevant information. Assumption 2) is broadly consistent with prior research showing that expected returns (e.g., Campbell, 1991; van Binsbergen and Koijen, 2010; Pástor and Stambaugh, 2012) and profitability (e.g., Beaver, 1970; Penman, 1991; Pástor and Veronesi, 2003; Healy *et al.*, 2014) are persistent and mean-reverting, consistent with the intuition that neither expected returns nor profitability are expected to stay abnormally high or low indefinitely. We find support for both assumptions in our empirical analyses.

Because our model-based estimates depend on outputs of accounting systems, which vary across international markets, we further analyze how the variation in the quality of information about firms' profitability affects expected returns. We extend the model to a setting where investors dynamically learn about profitability through time and show that, holding all other sources of information constant, higher-quality information about firm profitability—defined by lower measurement error variance—increases the importance of profitability in determining expected returns. Relying on measures of country-level earnings quality derived from Leuz *et al.* (2003) and employing an instrumental variables estimation strategy, we confirm these predictions in our empirical tests. Overall, our findings point to the commonality of two firm characteristics—BM and profitability—and the role of accounting information quality in explaining the cross section of expected returns worldwide.

Our work builds on the large implied cost of capital literature in accounting (e.g., Botosan, 1997; Gebhardt *et al.*, 2001; Claus and Thomas, 2001; Gode and Mohanram, 2003; Easton, 2004) in that we also seek to infer expected returns implied by observed stock prices and accounting data. Our approach, though similar in principle, has several distinct practical advantages. Ours is motivated by a fairly general valuation model that allows for time varying expected returns, it is applicable to non-dividend paying firms and a broad class of accounting systems, is easy to implement, and does not require solving non-linear equations. Further, our ERPs line up well with the cross section of future returns across international equity markets—i.e., obtain a slope coefficient close to 1 and a constant coefficient close to 0 in regressions of future returns on ERPs.

We also contribute to the rich empirical literature linking stock returns to firm characteristics.[3] Unlike the prior work of Haugen and Baker (1996) and Lewellen (2015), who assess the out-of-sample predictive ability of expected return estimates derived from historical FM regressions, but using a large set of *ad hoc*, and short-lived in the case of Haugen and Baker (1996), predictors, our empirical approach is guided by valuation theory. Moreover, our findings suggest that reliable proxies of expected returns can be extracted with merely two firm characteristics, consistent with Lewellen (2015)'s findings.[4]

Closest to ours is Lyle and Wang (2015) (hereafter "LW15"), who derive a similar model of expected returns—based on a linear combination of book-to-market and profitability—and test it using US equities. We generalize their findings both analytically and empirically. Analytically, we outline a set of minimalistic conditions under which such a model can be derived. Indeed, we show that the linear relation between expected returns and accounting-based characteristics hold even if firms do not pay dividends, unlike the assumption of firm-level dividend payments implicit in the Vuolteenaho (2002) approach utilized by LW15.

[3]See Green *et al.* (2013) or Lewellen (2015) for a summary and an examination of the relative importance of the firm characteristics that have been identified to be associated with future returns.

[4]Lewellen (2015)'s results suggest that increasing the number of predictors does not improve the predictive slope coefficient (towards 1).

Empirically, we generalize and validate the findings of LW15 internationally, and show that the model-implied proxies line up well with expected returns across international markets.[5]

Finally, our analysis of information quality offers new insights that would not be possible using traditional CAPM or other factor-based models used when studying expected returns and anomalies. This extension provides a framework for understanding why various characteristics (and financial performance metrics) relate to future stock returns: they carry information about expected profitability. If investors update their beliefs about expected profitability based on a collection of signals/variables, then variables that systematically forecast future profitability should also forecast future stock returns. For example Sloan (1996) finds that accruals are negatively related to future stock returns, but accruals are also negatively related to future profitability. Similarly, while Piotroski (2000)'s F-score is negatively related to future stock returns, it is also a strong negative predictor of future profitability.

While we cannot definitively speak to market rationality, as we do not derive or test an equilibrium asset pricing model, our findings are consistent with rational expectations. If our results were driven by spurious correlations between firm characteristics and stock returns, it is unlikely that we could derive a simple model that relates these characteristics to expected returns based on assumptions that are consistent with economic intuition and with empirical data. This is also validated by the fact that the predictions from the model are borne out in empirical data over long periods of time and across multiple countries. If anything, our work suggests that it would be surprising if value (e.g., Fama and French, 1992) and profitability (e.g., Ball *et al.*, 2015, 2016; Novy-Marx, 2013) were not associated with expected returns. The poor out-of-sample predictive ability of value-factor and profitability-factor-based estimates suggest that, in measuring firm-level expected returns, a characteristics-based model that preserves the same intuition as the factor-based counterpart (e.g., Fama and French, 2014) might offer a way forward in constructing estimates of expected returns.

[5]We also differ from Lewellen (2015) and Haugen and Baker (1996) on this front. Lewellen (2015) studies the U.S. market exclusively, while Haugen and Baker (1996) focuses mainly on the U.S. but also performs an analysis on France, Japan, Germany, and the U.K.

2.2 The Model

In this section, we derive a statistical model of expected returns that is a linear combination of BM and expected profitability, as in LW15. However, our derivation is based on a valuation model that relies on a milder set of assumptions, allowing us to generalizes the result of LW15 and apply this model to a wide range of accounting systems and firms (i.e., non-dividend payers). This model provides guidance on the firm characteristics that are predicted to be related to average future returns, and its structure allows us to empirically assess whether our underlying assumptions are plausible (i.e., magnitudes of persistence parameters).

2.2.1 Set Up and Main Assumptions

We begin by writing down a tautological relation between the log book-to-market multiple and expected future growth in log market and log book values. Let M_t, B_t, $G_{b,t+1}$, and $G_{m,t+1}$ denote market value, book value, growth in book value, and growth in market value, respectively. By definition, the growth variables are net of distributions and connect current and future book and market values:

$$B_{t+1} = G_{b,t+1}B_t \text{ and } M_{t+1} = G_{m,t+1}M_t. \tag{2.1}$$

Taking logs and subtracting log market (m) from log book (b) values yields

$$bm_t = bm_{t+1} + g_{m,t+1} - g_{b,t+1}. \tag{2.2}$$

Iterating (2.2) forward and taking expectations conditional on information known at time t, we arrive at the following identity:

$$bm_t = \lim_{j\to\infty} \mathbb{E}_t\left[bm_{t+j}\right] + \sum_{i=1}^{\infty} \mathbb{E}_t[g_{m,t+i} - g_{b,t+i}]. \tag{2.3}$$

Because equation (2.3) is a tautology, it must be true. However, the tautology is only helpful if it can be used to obtain a tractable solution for bm_t. In order to do so, we must make assumptions about the long-run expected value of the book-to-market ratio,

$\lim_{j\to\infty} \mathbb{E}_t\left[bm_{t+j}\right]$, and how book growth, $g_{b,t+i}$, and market growth, $g_{m,t+i}$, evolve over time.

We assume that the long-run book-to-market ratio is expected to be a finite and fixed constant: $\lim_{j\to\infty} \mathbb{E}_t\left[bm_{t+j}\right] = \overline{bm} \in (-\infty, \infty)$. This assumption is an expression about the accounting system, it is expected to be "value-relevant"—book values are tied to market values—in the future. To build intuition, it is helpful to consider the implications if this assumption fails. If bm_{t+j} is expected to diverge to $+\infty$, then book values must be expected to grow faster than market values indefinitely. Such an outcome would imply an accounting system that aggressively books assets or rarely writes them off, such that book values eventually become detached from market values and thus lose relevance. Because accounting regimes around the world tend to be conservative in nature, it is difficult to envision an accounting system that would imply that investors expect bm_{t+j} to diverge to $+\infty$.[6] Conversely, if bm_{t+j} is expected to diverge to $-\infty$, then market values are expected to grow faster than book values indefinitely. Such an outcome is consistent with an accounting system that is extremely conservative in terms of booking assets or very quick in writing off assets, such that book values become detached from, and become irrelevant for, market values. Not only is this divergence unlikely, but it is also inconsistent with the data. For example, Pástor and Veronesi (2003) show that while the market-to-book ratio does decline on average as firms age, the ratio settles to a stable value above 1.[7]

A historical cost accounting system would satisfy this assumption. Consider, for illustration, a firm that purchases a productive asset at market value with a finite useful life. Historical cost accounting systems dictate that, at the time of the purchase, book and market values are equal. Moving forward in time, however, market and book values will deviate since the accounting system will record shareholder equity as the asset at cost less depreciation plus retained cash, whereas the market value will be the fair market value for

[6]Under mark-to-market accounting, which may considered an aggressive regime, book values and market values are guaranteed to converge by the definition of marking to market.

[7]See Figure 5 of their paper.

the asset plus retained cash. This difference between book and market will persist up to the point where the asset becomes unproductive and no longer has economic value. At this point, the book value of equity will be the cumulative retained cash plus a value of zero for the asset (either the asset will have been fully depreciated or it will be marked down to zero when it becomes unproductive). Similarly, the market value of equity will also be equal to cumulative retained cash because the asset has become unproductive and has value zero. This implies that book values and market values will once again be equal, i.e., they will have converged. The same intuition applies at the firm level, since a firm can be thought of as an aggregation of projects or assets; furthermore, if we allow the firms to have growth options (so that the market value of the retained cash in the firm can be greater than the book value), we would expect the market to book multiple to converge to a constant above 1. To conclude, because assumption 2.2.1 implies an accounting system that is neither very conservative nor very aggressive, we view assumption 2.2.1 to be fairly general and applicable to the various accounting regimes—i.e., variants of GAAP or IFRS—around the world.

We next make the common assumption that expected book-growth and expected market-growth evolve according to AR(1) processes: Expected growth rates in the market value of equity, $\mathbb{E}_t[g_{m,t+1}] \equiv \mu_t$, and the book value of equity, $\mathbb{E}_t[g_{b,t+1}] \equiv h_t$, can be persistent and time-varying and follow AR(1) processes, with persistence parameters, κ and ω, that are less than 1 in absolute value

$$\mu_{t+1} = \mu + \kappa(\mu_t - \mu) + \xi_{t+1}, \tag{2.4}$$

$$h_{t+1} = \mu + \omega(h_t - \mu) + \epsilon_{t+1}. \tag{2.5}$$

Under these assumptions, the Appendix shows that the expression for bm_t simplifies to

$$bm_t = \overline{bm} + \frac{1}{1-\kappa}(\mu_t - \mu) - \frac{1}{1-\omega}(h_t - \mu). \tag{2.6}$$

Assumption 2.2.1 models the stochastic processes governing expected market and book growth to be AR(1). The parameters κ and ω of equations (2.4) and (2.5) represent the levels of persistence in expected market and book growth, respectively; μ represents the unconditional mean of expected growth rate for both market and book; and the vector of innovations $(\xi_{t+1}, \epsilon_{t+1})$ are IID through time with zero means and a positive semi-definite covariance matrix.[8]

Although this second assumption is statistical in nature, it captures empirical regularities and economic intuition. The AR(1) assumption for expected market growth captures the possibility, consistent with a growing body of empirical evidence, that expected returns can be time-varying (e.g., Cochrane, 2011; Ang and Liu, 2004; Fama and French, 2002; Jagannathan *et al.*, 2001) and persistent (e.g., Fama and French, 1988; Campbell and Cochrane, 1999; Pástor and Stambaugh, 2009). The assumption for expected book growth captures the idea that, while firms can experience periods of unusually high or low profitability, competitive forces drive a tendency for accounting rates of returns to revert to a steady-state mean (e.g., Beaver, 1970; Penman, 1991; Pástor and Veronesi, 2003; Healy *et al.*, 2014).

Two additional observations on these assumptions are worth noting. First, the reversion of expected market and book growth to a common mean (μ) is not an additional assumption, but rather an implication of, the "value-relevance" and AR(1) assumptions. Under assumption 2.2.1, the identity of (2.3) implies that growth rates of book and market values *must* converge in expectation,

$$\lim_{T\to\infty} \mathbb{E}_t[g_{m,t+T} - g_{b,t+T}] \quad = \quad 0. \tag{2.7}$$

By assumption 2.2.1, convergence is only possible if expected growth in market and book values share a common mean. This implication is consistent with the economic intuition that in the long-run abnormal growth in book values should converge to 0 due to competition (e.g., Ohlson, 1995). Second, under these assumptions and fixed persistence parameters, bm_t is weakly stationary and $\overline{bm}$ is the unconditional mean of bm. However, even under the

[8]Contemporaneous correlations between the innovation in expected book and market growth are possible under this assumption. Thus, while innovations in expected market growth are not correlated over time, i.e., $cov_t(\xi_{t+n}, \xi_{t+k}) = 0$, and the innovations in book growth are not correlated over time, i.e., $cov_t(\epsilon_{t+n}, \epsilon_{t+k}) = 0$, the only restriction on the contemporaneous covariance between innovations in book and market growth is boundedness, i.e., $|cov_t(\epsilon_{t+k}, \xi_{t+k})| < \infty$.

scenario of an *ex post* change in the persistence parameters, which would imply a structural break in bm_t, the relation of (2.6) would continue to hold so long as the processes remain AR(1) and the "value relevance" assumption is valid.

Overall, the two assumptions that we impose on the identity of (2.3) are fairly general, applicable to a wide range of accounting systems, and are consistent with empirical data and economic intuition. In untabulated tests we also find empirical support for these assumptions.[9] These assumptions deliver a parsimonious (2.6) relating bm to expected growth in market and book values, which are related to, but more general than, the familiar residual-income model. In the formulations of Ohlson (1995) and Feltham and Ohlson (1995), for example, accounting numbers are relevant through dividends, which are substituted out using the clean surplus relation. Our valuation equation circumvents the dependence on dividends through the "value relevance" assumption.

2.2.2 Expected Returns

Our goal is to solve for next period's expected returns, conditional on information known at time t. Expected log-returns, is defined as:

$$\mathbb{E}_t[r_{t+1}] = \mathbb{E}_t\left[\log\left(\frac{M_{t+1}+D_{t+1}}{M_t}\right)\right] = \mu_t + \mathbb{E}_t\left[\log\left(1+\frac{D_{t+1}}{M_{t+1}}\right)\right], \tag{2.8}$$

where M_t and D_t are the time-t market value and dividends, respectively.

Armed with the bm ratio in (2.6), expected returns are easily recovered for non-dividend payers by solving (2.6) for μ_t, which is a function of BM and expected profitability. That is, the model does not require firms to pay dividends. However, if a firm is expected to pay dividends, mild additional structure on the dividend payout policy over the next interval is required to handle the dividend-yield portion of (i.e., the second term in) (2.8). We do so by assuming, following Pástor and Veronesi (2003), that dividends are proportional to

[9] In a vast majority of the countries in our sample, we find substantial support for the hypothesis that the realized aggregate series in the growth in market and book values are generated by ARMA(1,1) processes, consistent with expected book and market growth being AR(1) (Hamilton, 1994). Moreover, in all of the countries in our sample, we are unable to reject the null that the mean growth in book and the mean growth in market values are different from one another.

book value over the next interval and that clean surplus is expected to hold. Under these assumptions we show in the Appendix that expected returns for dividend-paying firms is also a linear combination of BM and expected profitability (ROE):[10]

$$\mathbb{E}_t[r_{t+1}] = A_1 + A_2 bm_t + A_3 \mathbb{E}_t[roe_{t+1}], \tag{2.9}$$

where $A_1 = K - (1 - \kappa + \rho\kappa)\overline{bm} - A_3 \log(1+\delta) + \frac{(\kappa-\omega)(1-\rho)}{(1-\omega)}\mu$, $A_2 = 1 - \kappa + \rho\kappa$, and $A_3 = \frac{\rho(\kappa-\omega)+1-\kappa}{1-\omega}$; δ is the proportion of dividends paid out of book; the constants K and ρ are by-products of a log-linearization around the unconditional *bm* ratio and close to zero in value. For non-dividend-payers, the coefficient values simplify considerably by setting $\rho = 0$. Thus, even under these rather mild assumptions, as in LW15, expected log returns can be determined by a constant, *bm*, and expected profitability (*roe*).[11,12]

The intuition for why *bm* and *roe* provide information on expected returns resides in the present value relation between prices, expected future payoffs, and expected returns. Accounting fundamentals provide information on expected future payoffs (cash flows), while market prices provide information on both expected future payoffs and how they are discounted. Thus combining market values with accounting numbers, rather than the latter *per se*, reveal expected returns.

Consider for illustration the classic Gordon Growth Model, which relates market values (M_t) to dividends (D_t) as well as constant dividend growth (g) (i.e., expected future payoffs) and constant expected return (r):

$$M_t = D_t \frac{1+g}{r-g}.$$

This model implies that the expected return is a function of expected future fundamentals

[10]Our assumption of dividends being proportional to book values over one interval, for those expected to pay dividends, does not imply that dividends are proportional to book for all time. We make this assumption for tractability and for one-period-ahead returns only. Outside of one-period-ahead returns for current dividend-paying firms, we do not rely on dividend-payout policies to generate any of our results.

[11]The interpretation of the coefficients in this paper, however, is slightly different. In LW15, $A_1 = \frac{(\omega-\kappa)k_1}{1-\omega k_1}\mu$, $A_2 = 1 - \kappa k_1$, and $A_3 = \frac{1-\kappa k_1}{1-\omega k_1}$, where k_1 is a linearization constant assumed to be close to one.

[12]Under the assumption of constant expected returns, or $\kappa = 0$, whereby no growth is expected, expected returns boils down to a function of the earnings-to-price multiple, similar to the approach advocated by Penman *et al.* (2015).

(i.e., dividends and dividend growth) and market price:

$$r = \frac{D_t}{M_t}(1+g)+g.$$

While contrived, this example illustrates the intuition that expected returns are revealed by combining market values and "adding back" expected future payoffs.

We note that the predictions of this simple model are broadly consistent with those from more complex economic models. For example, similar to us, the models of Papanikolaou (2011) and Zhang (2005) predict that value firms have higher future returns. Whereas Papanikolaou (2011) attributes this relation to value firms' lower exposure to investment shocks, which carry a negative risk premium, Zhang (2005)'s model, based on Q-theory, suggest value firms have greater discount rates because in bad times they are burdened with larger amounts of unproductive capital. Hou *et al.* (2014) use Q-theory to argue that expected profitability is related to discount rates in equilibrium. For a given level of investment, relatively high expected profitability must imply high discount rates, since the firm would prefer to invest more otherwise. Similarly, relatively low profitability must imply low discount rates, since the firm would prefer to invest less otherwise. Our model captures the predictions of these more complex models, but is anchored on only two simple assumptions, applicable to a broad set of firms and accounting systems, and is easy to calibrate with data.

2.3 Calibration and Main Empirical Tests

This section describes the process of estimating (2.9), including the data requirements and key inputs, to compute the model-implied estimates of expected returns. We then present our main empirical tests to assess the out-of-sample cross-sectional performance of these estimates.

2.3.1 Data and Calibration

To calibrate the model we make the following assumptions on the relations between realized and expected, returns and profitability (*roe*):

$$r_{i,t+1} = \mathbb{E}_t[r_{i,t+1}] + \eta_{i,t+1}, \tag{2.10}$$

$$roe_{i,t+1} = \mathbb{E}_t[roe_{i,t+1}] + \nu_{i,t+1}, \tag{2.11}$$

where $(\eta_{i,t+1}, \nu_{i,t+1})$ are IID noise terms with zero mean and a positive semi-definite covariance matrix.[13] Substituting into (2.9) and applying the AR(1) assumption to expected log book growth yields the following estimable equation relating one-period ahead realized returns to current *bm* ratios and *roe*:

$$r_{i,t+1} = \beta_1 + \beta_2 bm_{i,t} + \beta_3 roe_{i,t} + \zeta_{i,t+1}, \tag{2.12}$$

where $\beta_1 = K + \left(1 - \kappa + \frac{(\kappa-\omega)(1-\rho\omega)}{1-\omega}\right)\mu - (1-\kappa+\rho\kappa)\overline{bm} - \omega A_3 log(1+\delta)$, $\beta_2 = A_2 = 1 - \kappa + \rho\kappa$, $\beta_3 = \omega A_3 = \omega\frac{\rho(\kappa-\omega)+1-\kappa}{1-\omega}$, and $\zeta_{i,t+1} = A_3(\epsilon_t - \omega\nu_t) - \eta_{t+1}$. Again, $K = \log(1 + \delta\exp(\overline{bm}))$ and $\rho = \frac{\delta\exp(\overline{bm})}{1+\delta\exp(\overline{bm})}$ are by-products of the log linearization.

Calibrating the model requires us to specify the frequency with which expected returns and expected *roe* evolve according to the assumed dynamics. For example, LW15 choose quarterly and annual frequencies. A challenge in the international setting is that the mandatory frequency of interim reporting is not uniform across markets in different countries; moreover, some countries changed their mandatory interim financial-reporting frequency during our sample period (e.g., Link, 2012).

Because annual reporting is required in all countries in our sample, a natural empirical specification would be to match annual stock returns to annual *bm* and *roe*. Given that fundamental data for most countries become available for a suitable cross section only between the early and mid-1990s, using annual data imposes serious limitations on the time

[13] The uncorrelatedness and zero mean assumptions follow from the properties of conditional expectations (e.g., Angrist and Pischke, 2008). Note that while expected return and expected return-on-equity innovations are independent over time, they can be contemporaneously correlated.

series of data available to us. The lack of consistency in quarterly reporting across countries also limits the usefulness of switching to interim reporting.

Our approach to resolving this empirical issue, similar to that of Fama and French (1992), is to match one-month-ahead returns to annual fundamental data (i.e., matching one-month-ahead returns to *bm* and annual *roe*). This can be thought of as treating the annual version of (2.12) as the sum of 12 equations that contain monthly returns and news. In this framework, each of the 12 months in a given year is an estimation equation, using the same BM and annual ROE, and the sum of the 12 estimated monthly coefficients translates to the coefficients of an annual model. We assume fundamental data to be known publicly and observable to the researcher four months after the fiscal-year-end date.[14] Thus, in computing a firm's BM, we use its market capitalization on the last trading day of the fourth month after the last fiscal-year-ending month.

Our data on returns and fundamentals come from Compustat Global and Compustat North America (in the case of Canada and the U.S.).[15] Monthly returns are computed using Compustat's price variable (variable *prccd* from the price file) by applying adjustments for splits and dividends using the respective adjustment factors (variables *ajexdi* and *trfd* from the price file).[16] Gross annual ROE is calculated as $ROE_{i,t} = \left(1 + \frac{X_{i,t}}{Book_{i,t-1}}\right)$, where $X_{i,t}$ is Net Income before Extraordinary Items (variable *ib* from the fundamentals file) and $Book_{i,t-1}$ is the lagged Book Value of Common Equity (variable *ceq* from the fundamentals file).

We make forecasts of expected future monthly (log) returns by estimating (2.12), via FM regressions, using historical realized monthly returns, the *bm* ratio, and *roe* that are observable as of the forecast date to avoid look-ahead bias. To ensure stability in the FM

[14] This assumption is necessitated by the sparseness of the earnings announcement date variable for a number of countries in Compustat Global. However, among those firms in our sample with earnings announcement dates, greater than 90 percent of them report annual earnings within four months of the fiscal year end.

[15] While our use of Compustat for international fundamentals and returns data follows some prior literature (e.g., Bushman and Piotroski, 2006, Novy-Marx, 2013), the international capital markets literature has also used Datastream as a common alternative. Though ex ante we do not expect our findings to be influenced by this choice, we re-estimate our main results, in untabulated robustness tests, for a set of major countries using Datastream and find nearly identical results.

[16] Specifically, log gross returns from t to $t+1$ is computed as $log\left(\frac{prccd_{t+1} \times trfd_{t+1}}{ajexdi_{t+1}} \times \frac{ajexdi_t}{prccd_t \times trfd_t}\right)$

coefficients, we use a training (or burn-in) sample consisting of 40 months in each country, after which out-of-sample forecasting and testing begins. We use a "cumulative" window approach, or recursive estimation, in that all historical data available at the time of the forecast are used to estimate (2.12) in order to form expected returns. In other words, we forecast one-month-ahead expected r at the end of each calendar month by applying historically-estimated FM coefficients on the *bm* and *roe* values observed as of the forecast date.

Embedded in our country-specific and recursive estimation choices are the implicit assumptions that 1) expected market growth and expected book growth follow AR(1) processes with a common long-run mean; 2) these model parameters are country-specific and may be time-varying; and 3) expected dividend payout ratios are country-specific and time-varying. The latter assumption differs slightly from LW15, which assumes that the model parameters are industry-specific. These implementation choices reflect a trade off between parsimony and realism necessitated by the relative sparsity, both in time series and cross section, of international equity fundamentals data. In the section on robustness tests we describe how relaxing the assumption of constant dividend payouts in the cross section affects our model parameters.

2.3.2 Sample Selection

We begin with a set of 34 countries whose capital markets and related institutions have been commonly studied in the international asset pricing literature—Australia, Austria, Belgium, Canada, China, Denmark, Finland, France, Germany, Greece, Hong Kong, India, Indonesia, Israel, Italy, Ireland, Japan, Malaysia, Netherlands, New Zealand, Norway, Pakistan, the Philippines, Portugal, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, the United Kingdom, and the U.S. These include the 31 countries examined by Leuz *et al.* (2003) and the 23 countries recognized to have developed capital markets (e.g., Ang *et al.*, 2009; Fama and French, 2012). Because our estimation requires the use of the log of book-to-market multiple and the log of the gross return-on-equity ratio, firms with negative book values are excluded from our analyses.

We impose three sets of filters to mitigate the influence of unusual observations on our estimation and calibration of the paper's model. First, in each country and on each forecast date, we eliminate very small and illiquid firms—any firm belonging to the bottom 2 percent of the cross-section in either market capitalization or liquidity.[17] Second, we exclude observations whose stock price belongs to the bottom 5 percent of the cross-section or is trading below 1 unit of the home currency. Third, to further ensure the reliability of the cross-sectionally-estimated coefficients, we impose the requirement that each cross section, after applying the above filters, must have a minimum of 100 observations.

These restrictions, in conjunction with a minimum of 40 months of data, eliminate the following 5 countries from our empirical analyses: Austria, Ireland, New Zealand, Singapore, and Portugal. Thus, the empirical analyses in our paper examine the efficacy of our model-implied estimates for a set of 29 countries worldwide.

We also take measures to ensure that our data are not corrupted by inconsistencies arising from the use of different currencies to report financial data within a given country. For the eurozone countries that switched currencies following adoption of the *euro*, we convert all pre-adoption financial data to *euros* using the conversion rate mandated by the European Central Bank. This translation simply makes the within-country currency amounts comparable pre- and post-euro conversion. For all other occasions where companies switch currencies, we drop the two years surrounding the change.[18]

2.3.3 Summary Statistics

Table 2.1 summarizes, by country, our data on the model inputs of (2.12). It reports time-series averages of the distributional statistics of *bm* and *roe*. With the exception of South

[17]Following prior research (e.g., LaFond *et al.*, 2007), we proxy for a stock's liquidity using the proportion of zero-return days over the prior month. This approximation is necessitated by a lack of a well-populated trading-volume variable in the Compustat Global price files.

[18]We set the one-month-ahead returns to missing whenever the given fiscal year's financials are reported in a different currency than the following year's financials. This adjustment affects less than 1% of the sample.

Korea, all countries on average have (cross-sectional) median *bm* values that are negative, a reflection of the tendency for book values to be smaller than market values. There is wide variation in the central tendency of *bm* across countries, ranging from a median *bm* of 0.11 in South Korea to -1.17 in China. Despite this variation in central tendency, the spread in the distribution appears similar across most countries. In contrast, the (time-series) averages of (cross-sectional) median and mean *roe* values are relatively uniform across all the countries in our sample.

The last two columns of Table 2.1 report the initial and final dates for which we have fundamentals and returns data for each country (after imposing the sample selection requirements described above). There is some variation in how early the data begins. For three countries (Canada, Japan, and the U.S.), data became available in the mid- to late-1980s; for most countries data became available in the early- to mid-1990s. For a small handful of countries (Belgium, China, Finland, Greece, Israel, Norway, Pakistan, and the Philippines), data are not available until the 2000s.

Table 2.2 presents FM coefficients from monthly regressions of one-month-ahead returns (r) on *bm* and *roe*, i.e., the time-series mean of the cross-sectionally-estimated coefficients. These two accounting-based characteristics explain between 1% and almost 5% of the cross sectional *contemporaneous* variation in returns, averaging 2.2%.[19] Our findings suggest that *roe* exhibits a stronger association with returns compared to *bm*. The FM coefficient on *roe* is positive and significant (at the 10-percent level) in 27 of the 29 countries in our sample; on the other hand, the coefficient on *bm* is significant (at the 10-percent level) for 21 of the 29 countries.

[19] As noted in Lewellen (2015), FM R^2 is not an indicator of predictive power, but reflects the degree to which the ERP explains contemporaneous variation in returns. To see why, consider the following simple example. Suppose that expected returns are constant for all firms (i.e., no cross-sectional variation), but news has the following structure:

$$r_{i,t+1} = er + \epsilon_{i,t+1},$$
$$\epsilon_{i,t+1} = C_{t+1} \times erp_{i,t},$$

where C_{t+1} is a cross-sectional random variable taking a positive or a negative value with 50% probability in a given time period. In this case, even though the proxy ($erp_{i,t}$) has no predictive ability, in cross-sectional regressions it will completely explain the ex post contemporaneous variation in realized returns, i.e., 100% R^2.

Table 2.1. Summary Statistics of Model Inputs

Table 2.1 reports summary statistics by country for inputs to the regression of (2.12), bm_t and roe_t. The distributional summary statistics reported here are time-series averages of the corresponding cross-sectional statistics. N represents the average number of observations per cross section in a particular country. *Min Date* and *Max Date*, respectively, denote the first and last calendar month for which data are available for the country in question, after imposing our sample selection requirements.

	bm							*roe*									
Country	*q5*	*q25*	*Med*	*q75*	*q95*	*Mean*	*sd*	*q5*	*q25*	*Med*	*q75*	*q95*	*Mean*	*sd*	*N*	**Start**	**End**
Australia	-2.11	-1.13	-0.61	-0.18	0.28	-0.72	0.78	-0.17	0.06	0.12	0.20	0.43	0.13	0.25	287	1993m11	2014m9
Belgium	-1.57	-0.68	-0.22	0.11	0.64	-0.32	0.70	-0.24	0.03	0.09	0.15	0.36	0.08	0.24	106	2001m5	2014m3
Canada	-1.58	-0.83	-0.38	0.00	0.63	-0.42	0.74	-0.33	0.00	0.09	0.15	0.34	0.06	0.30	170	1985m5	2010m9
China	-2.25	-1.56	-1.17	-0.82	-0.37	-1.23	0.61	-0.09	0.03	0.08	0.15	0.30	0.09	0.21	1,188	2001m5	2014m8
Denmark	-1.76	-0.65	-0.15	0.24	0.78	-0.27	0.83	-0.39	0.00	0.08	0.15	0.34	0.05	0.29	134	1999m5	2014m8
Finland	-1.69	-0.95	-0.45	-0.01	0.48	-0.50	0.67	-0.13	0.05	0.12	0.19	0.34	0.11	0.18	105	2001m5	2014m9
France	-1.76	-0.94	-0.45	0.01	0.71	-0.46	0.84	-0.25	0.04	0.10	0.16	0.31	0.08	0.25	441	1991m5	2014m9
Germany	-1.94	-1.05	-0.56	-0.12	0.62	-0.60	0.80	-0.37	0.01	0.08	0.15	0.37	0.06	0.34	388	1991m5	2014m9
Greece	-1.77	-0.85	-0.31	0.14	0.75	-0.38	0.79	-0.11	0.02	0.08	0.15	0.36	0.09	0.18	141	2002m5	2010m9
Hong Kong	-1.68	-0.67	-0.05	0.52	1.25	-0.12	0.91	-0.11	0.05	0.11	0.18	0.37	0.11	0.23	250	1995m8	2014m9
India	-2.05	-0.84	-0.09	0.55	1.47	-0.17	1.08	-0.21	0.05	0.13	0.22	0.42	0.12	0.26	967	1997m8	2014m9
Indonesia	-1.78	-0.81	-0.19	0.37	1.10	-0.26	0.95	-0.34	0.00	0.11	0.21	0.47	0.10	0.41	210	1999m5	2014m9
Israel	-1.67	-0.51	-0.07	0.25	0.67	-0.21	0.75	-0.33	0.02	0.10	0.18	0.47	0.09	0.30	183	2008m5	2014m8
Italy	-1.72	-0.90	-0.43	0.02	0.73	-0.44	0.84	-0.21	0.02	0.08	0.14	0.29	0.07	0.24	181	1998m5	2014m9
Japan	-1.55	-0.71	-0.27	0.10	0.57	-0.35	0.67	-0.13	0.02	0.05	0.09	0.20	0.04	0.18	2,530	1989m2	2014m9
Malaysia	-1.64	-0.79	-0.34	0.06	0.55	-0.41	0.70	-0.10	0.05	0.10	0.16	0.30	0.10	0.19	322	1993m3	2014m9
Netherlands	-2.09	-1.17	-0.62	-0.16	0.42	-0.70	0.81	-0.25	0.04	0.13	0.22	0.47	0.12	0.30	131	1997m5	2011m8
Norway	-1.81	-0.91	-0.36	0.19	1.38	-0.33	0.96	-0.60	-0.03	0.09	0.17	0.42	0.03	0.37	118	2001m5	2014m9
Pakistan	-1.59	-0.71	-0.16	0.41	1.23	-0.16	0.91	-0.21	0.06	0.17	0.28	0.52	0.16	0.29	195	2004m12	2014m9
Philippines	-2.51	-1.08	-0.49	0.07	0.82	-0.63	1.18	-0.12	0.04	0.11	0.18	0.41	0.12	0.32	138	2007m5	2014m9
South Africa	-1.99	-1.06	-0.53	-0.08	0.76	-0.57	0.87	-0.05	0.11	0.19	0.27	0.54	0.21	0.26	186	1997m11	2014m9
South Korea	-1.24	-0.40	0.11	0.59	1.20	0.06	0.76	-0.40	0.00	0.06	0.13	0.28	0.03	0.31	893	1994m5	2014m9
Spain	-2.07	-1.08	-0.62	-0.27	0.35	-0.70	0.77	-0.14	0.06	0.12	0.18	0.38	0.12	0.21	114	1998m5	2014m4
Sweden	-2.10	-1.20	-0.62	-0.10	0.56	-0.67	0.83	-0.70	-0.02	0.11	0.20	0.41	0.02	0.48	246	1998m5	2014m9
Switzerland	-1.78	-0.91	-0.36	0.08	0.94	-0.39	0.88	-0.20	0.04	0.10	0.16	0.31	0.08	0.22	171	1998m5	2014m9
Taiwan	-1.41	-0.72	-0.29	0.09	0.50	-0.35	0.59	-0.16	0.02	0.08	0.15	0.29	0.07	0.18	488	1999m5	2014m9
Thailand	-1.50	-0.65	-0.14	0.32	0.91	-0.20	0.77	-0.27	0.03	0.11	0.19	0.38	0.10	0.27	289	1993m5	2014m9
UK	-2.16	-1.16	-0.52	0.02	0.43	-0.63	0.88	-0.10	0.04	0.13	0.22	0.46	0.14	0.27	656	1990m6	2014m9
US	-2.04	-1.12	-0.60	-0.20	0.37	-0.70	0.77	-0.34	0.03	0.11	0.17	0.38	0.08	0.36	3,249	1984m5	2014m9

Table 2.2. Summary Statistics of Estimated Coefficients

Table 2.2 reports the coefficients on bm_t and roe_t. The coefficients are estimated by Fama and MacBeth (1973) cross-sectional regressions, in which monthly log-returns are regressed on firm characteristics for each calendar month. We assume accounting data is known four months after the fiscal-year end date. Publicly available financial data on book values and ROE are matched to one-month-ahead returns for twelve months, starting four months after the fiscal-year end date as in Lewellen (2015). The estimation uses the cross-section of firms in a given country for a particular calendar month. Columns (1)–(3) report the Fama-MacBeth coefficients and standard errors (in square brackets below coefficients). Column (4) reports the average number of firms per cross section, column (5) reports the total number of months included in the Fama-Macbeth estimates, and column (6) reports the average of the cross-sectional-regression adjusted R^2 values. Levels of significance are indicated by *, **, and ***, representing 10 percent, 5 percent, and 1 percent, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Country	***bm***	***roe***	***cons***	**N**	**Periods**	**Adj R^2**
Australia	0.0033***	0.0103***	0.0048*	286	252	0.019
	[0.001]	[0.004]	[0.002]			
Belgium	0.0047***	0.0242***	0.0015	106	139	0.020
	[0.001]	[0.006]	[0.004]			
Canada	-0.0004	0.0095**	-0.0004	170	300	0.016
	[0.001]	[0.004]	[0.003]			
China	0.0051***	0.0031	0.0086	1,182	161	0.022
	[0.001]	[0.005]	[0.008]			
Denmark	0.0000	0.0136***	0.0003	134	185	0.028
	[0.002]	[0.004]	[0.004]			
Finland	0.0091***	0.0318***	-0.0014	106	108	0.039
	[0.002]	[0.009]	[0.005]			
France	0.0030***	0.0155***	0.0021	440	282	0.019
	[0.001]	[0.003]	[0.003]			
Germany	0.0025***	0.0103***	-0.0016	387	282	0.015
	[0.001]	[0.002]	[0.003]			
Greece	0.0006	0.0287***	-0.0133	141	100	0.021
	[0.002]	[0.008]	[0.009]			
HongKong	0.0067***	0.0223***	-0.0015	250	229	0.020
	[0.001]	[0.007]	[0.005]			
India	0.0016	0.0129**	0.0026	963	207	0.029
	[0.002]	[0.005]	[0.007]			
Indonesia	0.0060***	0.0136***	0.0090	210	186	0.015
	[0.002]	[0.003]	[0.006]			
Israel	0.0007	0.0234***	-0.0008	182	77	0.017
	[0.002]	[0.006]	[0.009]			
Italy	0.0021**	0.0182***	-0.0019	181	198	0.025
	[0.001]	[0.004]	[0.004]			

Table 2.2 Continued

Country	(1) *bm*	(2) *roe*	(3) *cons*	(4) N	(5) Periods	(6) Adj R^2
Japan	0.0067***	0.0069***	-0.0007	2,522	309	0.017
	[0.001]	[0.002]	[0.004]			
Malaysia	0.0064***	0.0238***	0.0009	321	260	0.017
	[0.001]	[0.005]	[0.006]			
Netherlands	0.0034*	0.0113**	0.0002	131	172	0.030
	[0.002]	[0.006]	[0.004]			
Norway	0.0013	0.0211***	0.0014	118	152	0.024
	[0.001]	[0.006]	[0.004]			
Pakistan	-0.0004	0.0105**	0.0120*	195	116	0.022
	[0.002]	[0.005]	[0.006]			
Philippines	0.0036**	0.0100*	0.0095	138	79	0.010
	[0.002]	[0.006]	[0.006]			
South Africa	0.0027**	0.0010	0.0098***	185	204	0.015
	[0.001]	[0.004]	[0.003]			
South Korea	0.0097***	0.0159***	-0.0054	889	246	0.022
	[0.002]	[0.004]	[0.006]			
Spain	0.0029**	0.0256***	0.0001	115	184	0.031
	[0.001]	[0.007]	[0.004]			
Sweden	0.0012	0.0120***	0.0001	246	198	0.029
	[0.001]	[0.003]	[0.004]			
Switzerland	0.0022**	0.0080*	0.0027	170	198	0.024
	[0.001]	[0.005]	[0.003]			
Taiwan	0.0063**	0.0314***	-0.0015	486	186	0.048
	[0.003]	[0.007]	[0.007]			
Thailand	0.0074***	0.0208***	0.0002	289	258	0.019
	[0.001]	[0.006]	[0.005]			
UK	0.0022***	0.0083***	0.0045*	654	293	0.011
	[0.001]	[0.002]	[0.003]			
US	0.0030***	0.0047***	0.0065**	3,244	366	0.011
	[0.001]	[0.001]	[0.003]			

It is worthwhile noting that these coefficients, on average, imply plausible values for the underlying model parameters. Based on the cross-country mean market-to-book of 0.44 and a payout ratio of 0.03, the mean coefficients on *bm* and *roe* imply persistence parameters of $\kappa \approx 0.97$ and $\omega \approx 0.87$, values that are consistent with those documented in Lyle and Wang (2015) and van Binsbergen and Koijen (2010). Moreover, these values are largely unaffected for assumed payout ratios that range from 0 to 6%.[20]

Finally, we form the model-implied expected one-month-ahead return proxy on each forecast date using historically-estimated FM coefficients. Recall, at the end of each calendar month after the initial 40-month burn-in period, we construct a forecast of one-month-ahead returns by applying the cumulative average of all the cross-sectional coefficients from estimating (2.12) to the currently-available annual *bm* and *roe*.

Table 2.3 reports the time-series average of the cross-sectional distributional summary statistics for the estimated expected one-month-ahead log returns. We observe substantial within-country variation in the estimates as well as cross-country variation in the (cross-sectional) mean of the estimates. Comparing the mean expected log return (column 3) to the mean realized log return (column 10) suggests that our estimates are on average similar to future average realized returns for all the countries.[21]

For ease of interpretation, column (4) reports the mean of expected *simple* returns ($R_{i,t+1}$) implied by our model-implied estimates. Based on the assumption that log returns are conditionally normally distributed, conditional expected simple returns can be constructed as follows:

$$\hat{\mathbb{E}}_t[R_{i,t+1}] = \exp(\hat{\mu}_{i,t} + 0.5 \times \hat{\sigma}^2_{i,t+1}), \tag{2.13}$$

where $\hat{\mu}_{i,t}$ is our expected log return estimate, and $\hat{\sigma}^2_{i,t+1}$ is an estimate of the expected

[20] On average, the (within-country) pooled mean payout ratio is 1.4%. The cross-country standard deviation in the mean payout is 1.7%.

[21] As can be observed in Table 2.3, both estimates of expected log returns implied by our model as well as average realized log returns can be negative, and are always smaller than average simple returns. Because log-returns are a concave function of gross stock returns, by Jensen's inequality expected log-returns must be weakly less than expected simple stock returns. Moreover, because average monthly simple returns are low, we can expect average monthly log returns to often be negative.

Table 2.3. Summary Statistics of Expected Return Proxies

Table 2.3 columns (1)-(3) and (5)-(9) report summary statistics by country for the monthly ERPs calculated using (2.12). The table reports time-series averages of the corresponding cross-sectional statistics. Expected-return proxies for a particular calendar month are calculated using firm characteristics and the cumulative rolling average of the estimated cross-sectional coefficients as of the end of the previous calendar month. For calculating cumulative averages, we use a burn-in period of forty months. Column(4) reports the time-series average of the cross-sectional mean of a proxy for expected simple returns, computed as $\hat{\mathbb{E}}_t[R_{i,t+1}] = \exp(\hat{\mu}_{i,t} + 0.5 \times \hat{\sigma}^2_{i,t+1})$, where $\hat{\mu}_{i,t}$ is our expected log return estimate, and $\hat{\sigma}^2_{i,t+1}$ is an estimate of the expected volatility in log returns based on the average squared daily returns from the prior month scaled by 252/12. Finally, the last three columns report the time-series averages of the cross-sectional mean realized log monthly returns, variance of realized log monthly returns, and mean realized simple monthly returns.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	q5	*q25*	*Mean*	*Mean (Simple)*	**Median**	**q75**	*q95*	*sd*	*N*	*Mean Log Returns*	*Variance Log Returns*	*Mean Simple Returns*
Australia	-0.0034	0.0029	0.0050	0.0106	0.0069	0.0095	0.0043	0.0053	268	0.0040	0.0116	0.0095
Belgium	-0.0061	0.0013	0.0037	0.0086	0.0055	0.0098	0.0030	0.0057	76	0.0021	0.0119	0.0071
Canada	-0.0043	0.0007	0.0020	0.0156	0.0032	0.0062	0.0016	0.0047	153	-0.0002	0.0280	0.0115
China	-0.0105	-0.0054	-0.0027	0.0074	-0.0004	0.0028	-0.0032	0.0048	1,118	0.0028	0.0184	0.0123
Denmark	-0.0023	0.0027	0.0040	0.0129	0.0049	0.0069	0.0035	0.0033	110	-0.0003	0.0183	0.0074
Finland	-0.0120	-0.0043	0.0006	0.0066	0.0051	0.0117	0.0003	0.0078	68	0.0024	0.0141	0.0078
France	-0.0031	0.0023	0.0036	0.0110	0.0047	0.0074	0.0030	0.0047	421	0.0018	0.0144	0.0084
Germany	-0.0072	-0.0033	-0.0020	0.0072	-0.0008	0.0017	-0.0023	0.0035	366	-0.0029	0.0170	0.0041
Greece	-0.0126	-0.0064	-0.0042	0.0058	-0.0019	0.0055	-0.0041	0.0072	93	-0.0104	0.0170	-0.0012
HongKong	-0.0167	-0.0079	-0.0047	0.0043	-0.0017	0.0038	-0.0055	0.0088	229	0.0010	0.0199	0.0125
India	-0.0043	0.0002	0.0014	0.0148	0.0026	0.0053	0.0011	0.0041	928	0.0048	0.0292	0.0207
Indonesia	-0.0038	0.0026	0.0064	0.0277	0.0102	0.0149	0.0061	0.0070	182	0.0082	0.0466	0.0263
Israel	-0.0108	-0.0043	-0.0028	0.0003	-0.0016	0.0036	-0.0031	0.0063	108	0.0013	0.0132	0.0105
Italy	-0.0077	-0.0034	-0.0019	0.0028	-0.0006	0.0017	-0.0023	0.0041	150	-0.0025	0.0107	0.0033
Japan	-0.0110	-0.0051	-0.0020	0.0064	0.0006	0.0040	-0.0026	0.0049	2,371	-0.0035	0.0176	0.0041
Malaysia	-0.0075	-0.0018	0.0010	0.0073	0.0033	0.0064	0.0004	0.0050	301	0.0008	0.0310	0.0122
Netherlands	-0.0081	-0.0026	0.0000	0.0101	0.0021	0.0048	-0.0007	0.0051	98	-0.0014	0.0190	0.0101
Norway	-0.0080	0.0027	0.0051	0.0074	0.0071	0.0111	0.0040	0.0068	88	0.0014	0.0152	0.0056
Pakistan	0.0047	0.0076	0.0092	0.0148	0.0106	0.0132	0.0091	0.0030	148	0.0137	0.0253	0.0102
Philippines	-0.0013	0.0071	0.0090	0.0199	0.0107	0.0132	0.0081	0.0057	78	0.0044	0.0197	0.0237
South Africa	-0.0023	0.0034	0.0063	0.0196	0.0086	0.0132	0.0060	0.0050	158	0.0092	0.0251	0.0150
South Korea	-0.0227	-0.0135	-0.0087	0.0129	-0.0045	0.0007	-0.0096	0.0078	855	-0.0041	0.0159	0.0162
Spain	-0.0071	0.0004	0.0025	0.0067	0.0042	0.0075	0.0018	0.0066	90	0.0008	0.0099	0.0059
Sweden	-0.0132	-0.0029	-0.0007	0.0091	0.0010	0.0039	-0.0019	0.0067	212	-0.0012	0.0222	0.0079
Switzerland	-0.0028	-0.0003	0.0012	0.0068	0.0023	0.0046	0.0010	0.0027	145	0.0020	0.0117	0.0067
Taiwan	-0.0147	-0.0072	-0.0049	0.0006	-0.0032	-0.0001	-0.0059	0.0064	449	-0.0002	0.0150	0.0088
Thailand	-0.0263	-0.0106	-0.0058	0.0114	-0.0023	0.0030	-0.0076	0.0111	272	0.0021	0.0331	0.0150
UK	0.0023	0.0043	0.0053	0.0095	0.0063	0.0082	0.0053	0.0026	599	0.0042	0.0083	0.0096
US	0.0014	0.0045	0.0059	0.0173	0.0069	0.0084	0.0055	0.0027	3,004	0.0051	0.0219	0.0145

volatility in log returns based on the average squared daily returns from the prior month scaled by 252/12. Across the 29 countries in our analysis, the cross-sectional mean (median) monthly expected simple returns is 0.99% (0.91%) or 12.60% (11.43%) annualized. Though these implied expected simple return estimates are not the main focus of the paper, we discuss them in more detail in robustness tests to assess their performance relative to factor-based estimates of expected simple returns.

2.3.4 Cross-Sectional Validation Tests

We next turn to validating the model-implied expected return estimates and assessing their reliability across worldwide markets. We first examine how the proxies, on average, are associated with future returns. We then assess their performance relative to standard factor-model-based proxies.

Regression Based Tests

Our primary test for assessing the reliability of our estimates is the standard regression-based test as employed by, for example, Lewellen (2015) and Lyle and Wang (2015). In particular, we separately estimate for each country cross-sectional predictive regressions of 1-month-ahead r on our estimate:

$$r_{i,t+1} = \delta_0 + \delta_1 \mathbb{E}_t[r_{i,t+1}] + w_{i,t+1}. \tag{2.14}$$

A perfect proxy of expected returns implies $\delta_0 = 0$ and $\delta_1 = 1$. In particular, having a slope coefficient close to 1 suggests that the magnitudes of the cross-sectional differences in the estimates are informative of the magnitude of differences in expected returns, which facilitate inferences in regression settings. More generally, positive and significant δ_1 coefficients imply positive return sorting ability on average. To reduce the influence of unusually large values in our estimates, we winsorize the expected return measures at the top and bottom 1 percent.

Table 2.4 reports FM regression estimates of (2.14) for the 29 countries in the sample.

The results in this table indicate that the model-implied estimates strongly and significantly predict realized returns for a vast majority of the countries. Coefficients on expected returns (the "predictive slope coefficient") are statistically significant at the 5-percent and 10-percent levels for 24 and 26 of the 29 countries, respectively. Greece, Pakistan, and South Africa's predictive slope coefficients do not differ significantly from 0 at the 10% level; in the case of Pakistan, the slope is also indistinguishable from 1.

The average slope coefficient across the 29 countries is 1.05. Based on the F-test for the null hypothesis that the slope is equal to 1 (reported in the last row of Table 2.4), we reject the null for only 9 (10) of the 29 countries at the 10-percent (5-percent) level. Furthermore, we fail to reject the null that the constant term is equal to 0 at the 5-percent level for all but 2 countries in our sample. In the aggregate, these regression-based test results suggest that our characteristic-based estimates line up well with expected returns and are reliably associated with the cross section of future returns across international markets.[22]

Portfolio Sort Tests

We supplement the above parametric return regression tests with portfolio-level analysis. To conduct these non-parametric tests, we construct equal-weighted portfolios at the end of each calendar month based on the quintile rankings of the ex ante ERP, and summarize the average 1-month-ahead returns realized by each portfolio. Our choice of quintile portfolios is intended to ensure that, for any given country on any given month, there are at least 20 stocks in each portfolio.

Table 2.5 provides further evidence that, consistent with the regression tests of Table 2.4, the model-implied proxies exhibit significant ability to predict the cross-section of future returns. We document in column (6) significant average spreads between the top and bottom quintile portfolios for 24 countries. Though these results are statistically slightly weaker, they are broadly consistent with the regression-based tests. In fact, the portfolio

[22]In untabulated robustness tests, we find that winsorizing the inputs at the top and bottom 1 percent of each cross section yields estimates that produce virtually identical results.

Table 2.4: Return Regressions

Table 2.4 reports the results of Fama-MacBeth regressions of one-month-ahead log returns on the ERPs for each country. Expected returns are winsorized at the top and bottom one-percent. Standard errors are reported in brackets below the coefficient estimates. The last row reports the p-value for the F-test of the null hypothesis that the slope coefficient is equal to 1. Levels of significance are indicated by *, **, and ***, representing 10 percent, 5 percent, and 1 percent, respectively.

	Australia	*Belgium*	*Canada*	*China*	*Denmark*	*Finland*	*France*	*Germany*	*Greece*	*Hong Kong*
$\hat{\mathbb{E}}[r_{i,t+1}]$	0.5577**	1.0484***	0.7340**	0.4085**	1.5072***	0.4111*	1.3956***	1.7270***	0.2810	0.8958***
	[0.238]	[0.319]	[0.335]	[0.204]	[0.530]	[0.221]	[0.347]	[0.333]	[0.303]	[0.170]
Cons	0.0007	-0.0017	-0.0028	0.0121	-0.0004	-0.0013	-0.0042	-0.0002	-0.0116	0.0102*
	[0.003]	[0.005]	[0.003]	[0.009]	[0.005]	[0.007]	[0.003]	[0.003]	[0.011]	[0.005]
N	67,239	9,991	45,514	178,906	20,186	6,779	118,351	102,838	9,236	52,309
R^2	0.016	0.025	0.016	0.008	0.025	0.014	0.012	0.009	0.012	0.016
p-Value	0.064	0.880	0.428	0.004	0.340	0.010	0.255	0.030	0.021	0.541

	India	*Indonesia*	*Israel*	*Italy*	*Japan*	*Malaysia*	*Netherlands*	*Norway*	*Pakistan*	*Philippines*
$\hat{\mathbb{E}}[r_{i,t+1}]$	0.7374**	1.0454***	1.6767***	1.3071***	0.9429***	1.4109***	0.8810**	1.1139**	1.0769	1.1622**
	[0.299]	[0.227]	[0.414]	[0.255]	[0.155]	[0.206]	[0.406]	[0.440]	[0.879]	[0.487]
Cons	0.0029	0.0056	0.0158**	0.0010	-0.0001	-0.0004	-0.0043	-0.0029	0.0004	-0.0033
	[0.008]	[0.005]	[0.007]	[0.004]	[0.003]	[0.006]	[0.005]	[0.005]	[0.012]	[0.008]
N	191,194	33,691	8,183	29,548	730,374	78,049	16,696	13,307	16,883	6,050
R^2	0.008	0.013	0.015	0.02	0.013	0.012	0.024	0.025	0.019	0.012
p-Value	0.380	0.842	0.111	0.231	0.713	0.047	0.770	0.796	0.931	0.741

	South Africa	*South Korea*	*Spain*	*Sweden*	*Switzerland*	*Taiwan*	*Thailand*	*UK*	*US*
$\hat{\mathbb{E}}[r_{i,t+1}]$	-0.0378	1.5412***	1.0350***	1.0922***	0.7494*	0.9327***	0.6660***	1.1200***	1.2794***
	[0.170]	[0.245]	[0.249]	[0.253]	[0.409]	[0.167]	[0.141]	[0.255]	[0.350]
Cons	0.0146***	0.0105	-0.0000	0.0030	0.0016	0.0097*	0.0082*	-0.0022	-0.0039
	[0.003]	[0.007]	[0.004]	[0.004]	[0.004]	[0.006]	[0.005]	[0.003]	[0.004]
N	32,104	209,537	16,290	41,673	28,656	82,991	69,932	174,792	1,096,559
R^2	0.012	0.017	0.027	0.022	0.018	0.013	0.015	0.007	0.008
p-Val	0.000	0.028	0.888	0.716	0.540	0.687	0.019	0.638	0.425

sorts are robust enough that for the majority of the countries (20), even the spread between the portfolio *median* returns, reported in column (7), are statistically significant.

Collectively, these results imply that reliable firm-level expected stock returns that are applicable to worldwide markets can be constructed with a linear combination of *bm* and *roe*. These findings also demonstrate, consistent with Lewellen (2015), that firm-level expected return estimates obtained from FM regressions exhibit strong cross-sectional predictive properties.

2.3.5 Robustness Tests

In this section we assess the performance of factor-model-based estimates of expected returns to contextualize our main findings. We also describe how relaxing the assumption of dividend payouts being constant in the cross section affects our model parameters. Finally, we discuss untabulated analyses on the sensitivity of our estimates to variations in the training sample period as well as performance based on alternative evaluative frameworks.

Factor-Based Estimates

To contextualize our main empirical results, we assess the performance of firm-level estimates of expected returns derived from the global and regional four-factor models described in Fama and French (2012). These are global and regional versions of the Fama and French (1993) three-factor model augmented with the momentum factor, but the factor returns are based on portfolios that encompass 23 countries in four regions: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Switzerland, Sweden, U.K., and U.S. We obtain monthly global and regional factor returns from Ken French's data library.[23]

At the end of each calendar month (t), one-month-ahead factor-based estimates for a

[23] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 2.5: Stock Returns of Portfolios Sorted on Expected Return Estimates

Table 2.5 reports the country-specific average one-month-ahead log returns for each quintile portfolio of the ERP. Quintile portfolios are constructed for each calendar month between and including *Min Date* and *Max Date* in Table 2.1. Column (6) [(7)] reports the average spread in mean [median] log returns between the fifth and first quintile portfolios. OLS standard errors are used in significance tests, using the time-series of mean or median quintile spreads. Levels of significance are indicated by *, **, and ***, representing 10 percent, 5 percent, and 1 percent, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Country	***Q1***	***Q2***	***Q3***	***Q4***	***Q5***	***Spread Mean*** *Q5 - Q1*	***Spread Median*** *Q5 - Q1*
Australia	-0.0008	0.0045	0.0036	0.0044	0.0046	0.0054**	0.0040**
Belgium	-0.0048	0.0031	0.0005	0.0057	0.0067	0.0115***	0.0034
Canada	-0.0087	-0.0002	0.0026	0.0018	-0.0010	0.0077**	0.0035
China	0.0060	0.0095	0.0121	0.0116	0.0113	0.0053**	0.0037
Denmark	-0.0083	-0.0013	0.0037	0.0044	0.0041	0.0124***	0.0117***
Finland	-0.0008	-0.0010	0.0010	0.0057	0.0045	0.0053	0.0030
France	-0.0075	0.0006	0.0024	0.0043	0.0052	0.0127***	0.0088***
Germany	-0.0124	-0.0043	0.0000	0.0010	-0.0018	0.0106***	0.0085***
Greece	-0.0205	-0.0118	-0.0107	-0.0085	-0.0135	0.0070	0.0075
HongKong	-0.0076	0.0051	0.0072	0.0089	0.0097	0.0173***	0.0142***
India	0.0026	0.0098	0.0109	0.0124	0.0053	0.0027	0.0029
Indonesia	0.0046	0.0080	0.0119	0.0145	0.021	0.0164***	0.0049
Israel	-0.0043	0.0099	0.0116	0.0116	0.0159	0.0203***	0.0125***
Italy	-0.011	-0.0009	-0.0014	0.0001	0.0008	0.0118***	0.0122***
Japan	-0.0099	-0.0030	-0.0013	0.0006	0.0013	0.0112***	0.0100***
Malaysia	-0.0122	-0.0037	-0.0009	0.0020	0.0034	0.0156***	0.0105***
Netherlands	-0.0084	-0.0047	-0.0019	-0.0006	0.0011	0.0095**	0.0089***
Norway	-0.0122	-0.0001	0.0033	0.0056	0.0027	0.0149***	0.0194***
Pakistan	0.0073	0.0132	0.0125	0.0124	0.0118	0.0045	0.0135**
Philippines	0.0003	0.0047	0.0085	0.0095	0.0149	0.0147**	0.0090**
South Africa	0.0116	0.0113	0.0124	0.0121	0.0134	0.0018	-0.0009
South Korea	-0.0224	-0.0074	-0.0040	0.0035	0.0069	0.0294***	0.0238***
Spain	-0.0064	0.0000	0.0029	0.0075	0.0056	0.0120***	0.0107***
Sweden	-0.0125	0.0018	0.0047	0.0052	0.0053	0.0178***	0.0180***
Switzerland	0.0004	0.0037	0.0015	0.0039	0.0054	0.0050*	0.0042
Taiwan	-0.0029	0.0043	0.0076	0.0070	0.0054	0.0083***	0.0090***
Thailand	-0.0062	-0.0014	0.0062	0.0087	0.0102	0.0163***	0.0120***
UK	0.0001	0.0038	0.0035	0.0053	0.0053	0.0053***	0.0031**
US	-0.0010	0.0034	0.0049	0.0067	0.006	0.0070***	0.0033*

firm (i) are constructed as follows:

$$\begin{aligned}\hat{\mathbb{E}}_t[r_{i,t+1}] &= rf_{t+1} + \hat{\gamma}_{i,RMRF}\hat{\mathbb{E}}_t[RMRF_{t+1}] + \hat{\gamma}_{i,SMB}\hat{\mathbb{E}}_t[SMB_{t+1}] \\ &\quad + \hat{\gamma}_{i,HML}\hat{\mathbb{E}}_t[HML_{t+1}] + \hat{\gamma}_{i,WML}\hat{\mathbb{E}}_t[WML_{t+1}].\end{aligned} \tag{2.15}$$

Here $\hat{\mathbb{E}}_t[RMRF_{t+1}]$, $\hat{\mathbb{E}}_t[SMB_{t+1}]$, $\hat{\mathbb{E}}_t[HML_{t+1}]$, and $\hat{\mathbb{E}}_t[WML_{t+1}]$ represent the expected global or regional market, size, value, and momentum factor returns, respectively, which we estimate based on the trailing average 40-month realized factor returns. $\hat{\gamma}_{i,j}$ represents the factor j loadings for a firm, estimated in time-series for each firm i using monthly stock and factor returns over the 40 months prior to the forecast date. U.S. treasury yields are used as a proxy for risk-free rates. Because the global and regional factors are calculated using US-Dollar-denominated returns, for consistency in this exercise we convert all price series to U.S. Dollars and compute U.S.-Dollar-denominated returns for all firms in our sample.

Because these factor-based models yield expected simple returns, we compare them against our model-implied estimate of expected simple returns following (2.13). Table 2.6 reports the results of regression-based tests for the global- and regional-factor-based estimates for the 29 countries in our sample alongside the results of the model-implied estimates of simple returns. To facilitate comparisons, we use a common set of firm-year observations for which all three estimates are available. Like our results in Table 2.4, the model-implied estimate of simple returns perform very well across all 29 countries. In fact, the predictive slope coefficient is positive and significant for all 29 countries. In striking contrast, with the exception of one country, the global- and regional-factor-based estimates do not exhibit out-of-sample return predictability. The exception is in Pakistan, for which the global four-factor model exhibits a modest slope coefficient of 0.2548 that is significant at the 10% level. For the remaining countries the slope coefficients are either significantly negative (4 countries) or indistinguishable from zero at the 10-percent level.

We also consider the recent Fama and French (2014) five-factor model, which augments Fama and French (1993)'s original three-factor model with a profitability factor and an investment factor. Fama and French (2014) show that this expanded model better explains

Table 2.6: Return Regressions: Factor-Based-Model Expected-Return Estimates

Table 2.6 reports the results of Fama-MacBeth regressions of future simple returns on different ERPs. Columns under FF Global and FF Regional report regression of realized simple returns on ERPs generated using firm-specific loadings on the Fama-French global four factors and the regional four factors, respectively. Expected factor returns are estimated based on trailing 40-month averages, and factor loadings are estimated based using data available in the 40 months prior to the forecast date. For comparison, we create proxies of expected simple returns computed as $\hat{\mathbb{E}}_t[R_{i,t+1}] = \exp(\hat{\mu}_{i,t} + 0.5 \times \hat{\sigma}^2_{i,t+1})$, where $\hat{\mu}_{i,t}$ is our expected log return estimate, and $\hat{\sigma}^2_{i,t+1}$ is an estimate of the volatility in log returns based on the average squared daily returns from the prior month scaled by 252/12. Regression-based tests using simple returns and these proxies are reported in columns under the heading CLW. The analyses are conducted on a common set of firm-year observations for which all ERPs are available. All ERPs are winsorized at the top and bottom one percent. Columns under the heading $\hat{\mathbb{E}}[r_{i,t+1}]$ reports the slope coefficient on the ERP, *Cons* reports the coefficient on the constant term, and p reports p-values corresponding to the F-test of the null that the slope coefficient is equal to 1. Levels of significance are indicated by *, **, and ***, representing 10 percent, 5 percent, and 1 percent, respectively.

	CLW			FF Global			FF Regional			
Country	$\hat{\mathbb{E}}[r_{i,t+1}]$	Cons	p	$\hat{\mathbb{E}}[r_{i,t+1}]$	Cons	p	$\hat{\mathbb{E}}[r_{i,t+1}]$	Cons	p	N
Australia	0.5530**	0.0082**	0.047	-0.0772	0.0026	0.000	-0.0082	0.0118***	0.000	64,374
Belgium	0.6807**	0.0045	0.227	-0.2375	-0.0185*	0.000	0.0284	0.0070	0.004	9,654
Canada	0.4700***	0.0059**	0.000	0.0019	0.0234	0.000	-0.2233***	0.0123***	0.000	43,212
China	3.5899***	-0.0073	0.000	-0.0100	0.0271**	0.000	-0.1794	0.0222**	0.000	172,531
Denmark	1.0543***	-0.0006	0.816	-0.3165**	0.0370***	0.000	-0.0174	0.0124**	0.000	19,089
Finland	0.4946**	0.0028	0.039	-0.1025	0.0167	0.000	-1.1804**	0.0005	0.000	6,438
France	1.0689***	-0.0008	0.715	0.0194	0.0101	0.000	-0.0187	0.0083**	0.000	112,612
Germany	0.7193***	0.0016	0.121	-0.0255	-0.0126	0.000	-0.1012	0.0048	0.000	99,671
Greece	1.0357**	-0.0059	0.933	-0.0277	-0.0120	0.000	0.7443	0.0021	0.638	9,058
HongKong	2.2628***	0.0070*	0.000	-0.2135*	-0.0029	0.000	0.1131	0.0140***	0.000	50,424
India	3.7759***	-0.0331***	0.000	-0.0797	0.0232*	0.000	-0.0447	0.0222***	0.000	183,428
Indonesia	2.1836***	-0.0173	0.051	-0.2492**	0.0365***	0.000	-0.1593	0.0302***	0.000	30,706
Israel	1.3927***	0.0145	0.372	-0.3088**	0.0188**	0.000	-0.1569	0.0157*	0.000	7,801
Italy	2.9696***	0.0033	0.000	-0.1301	0.0091	0.000	-0.2258	0.0052	0.000	28,681
Japan	2.3393***	-0.0069**	0.000	-0.0058	-0.0141	0.000	0.0278	0.0039	0.000	683,671
Malaysia	1.7983***	-0.0100*	0.000	-0.0444	0.0055	0.000	0.1053	0.0067	0.000	75,221
Netherlands	0.7825***	0.0071	0.424	-0.2979	0.0120	0.000	0.3090	0.0102*	0.001	16,211
Norway	1.3719***	-0.0065	0.109	-0.1321	0.0016	0.000	-0.2061	0.0079	0.000	12,457
Pakistan	2.0903***	-0.0221***	0.005	0.2596*	0.0143*	0.000	-0.0936	0.0163*	0.000	16,179
Philippines	1.9876***	-0.0217**	0.023	-0.1057	0.0183**	0.000	0.2794	0.0167*	0.027	5,813
South Africa	0.6764***	0.0103*	0.019	0.0044	0.0403***	0.000	0.2063	0.0170***	0.000	30,745
South Korea	3.0504***	0.0011	0.000	-0.0023	0.0278	0.000	-0.0699	0.0160*	0.000	204,707
Spain	1.9934***	0.0002	0.003	-0.1359	-0.0059	0.000	0.3016	0.0095*	0.007	15,847
Sweden	1.2380***	0.0070	0.188	0.0204	0.0142	0.000	-0.0884	0.0143**	0.000	40,511
Switzerland	1.0388***	0.0080**	0.873	-0.1153	-0.0107	0.000	-0.0330	0.0084**	0.000	27,691
Taiwan	3.5363***	0.0147**	0.000	-0.0783	0.0027	0.000	0.1934	0.0157**	0.000	81,252
Thailand	1.6473***	0.0096	0.000	-0.0212	-0.0196	0.000	-0.2078*	0.0172**	0.000	65,056
UK	1.0344***	0.0025	0.873	-0.0126	0.0091	0.000	-0.1291	0.0080***	0.000	161,469
US	0.7782***	0.0033*	0.051	-0.0924	0.0233*	0.000	-0.0660*	0.0132***	0.000	1,069,316
5-Factor							-0.0385	0.0127***	0.000	1,069,316
3-Factor							-0.1031*	0.0134***	0.000	1,069,316

the cross section of average returns *in-sample* compared to the three-factor model, similar to the conclusions of Hou *et al.* (2014) and Novy-Marx (2013). We complement these findings by assessing the out-of-sample performance of five-factor-based estimates, reported in the second-to-last row of Table 2.6. Our regression-based tests of this model are restricted to the U.S. since profitability and investment factor returns are not available globally. As with the four-factor model, we find that this expanded model does not produce ERPs that are robustly associated with future returns. We document a negative but insignificant slope coefficient.

Finally, we consider a variation of the new factor model that incorporates only the market, value, and profitability factors, representing a close factor-based counterpart to our paper's characteristic-based model. The out-of-sample performance, reported in the last row of Table 2.6, continues to be poor, as the proxy exhibits a negative and significant slope coefficient at the 10-percent level.

Juxtaposed against the performance of our model-implied estimates of simple returns, these results overall show that the out-of-sample cross-sectional predictive ability of our estimates dramatically outperform that of alternative factors-based proxies. We note that these findings need not necessarily invalidate the factor models per se, but could be consistent with the possibility that firm characteristics better capture time-varying factor loadings and premiums (e.g., Cochrane, 2011), which are notoriously difficult to estimate (Fama and French, 1997). This evidence is also consistent with and generalizes the findings of LW15 across international markets and accounting systems, broadly echoing the views of Campbell *et al.* (2010) that accounting information is useful in explaining firm level expected rate of returns. Indeed, our evidence suggests that an accounting-based characteristic model provides a robust framework for estimating firm-level expected rates of returns around the world.

Dividend Payout Variation

To help validate the assumptions used in the model we analytically and empirically examine how the coefficients A2 and A3 embedded in (2.12) depend on the dividend payout ratio. We show in the Appendix that the loading on *bm* and *roe* is expected to increase with the payout ratio.[24] We test these formal predictions empirically by estimating the following contemporaneous Fama-MacBeth regression:

$$\begin{aligned} r_{i,t+1} = \quad & \beta_1 + \beta_2 \times bm_{i,t} + \beta_3 \times roe_{i,t+1} + \beta_4 \times payout_{i,t+1} \\ & + \beta_5 \times bm_{i,t} \times payout_{i,t+1} + \beta_6 \times roe_{i,t+1} \times payout_{i,t+1} + \zeta_{i,t+1}, \end{aligned} \tag{2.16}$$

where $payout_{i,t+1} = Dividends_{i,t+1}/Book_{i,t+1}$, which is consistent with the model presented in the paper. The empirical results, reported in Table 2.7, largely support the theoretical predictions. The coefficients on the interactions of *bm* and *roe* with *payout* are positive and statistically significant in a large number of countries. Specifically, the coefficient on $bm \times payout$ is positive in all but one country in our sample, and is statistically significant at the 10-percent level in 23 countries. The coefficient on $roe \times payout$ is positive for all but two countries; however, the statistical significance of this coefficient is less strong, with 14 being significant at the 10-percent level. We note that the statistical significance of these results are likely in part attenuated by noise in the dividend data. Our discussions with the S&P revealed that there is a variation in the accuracy with which Compustat Global captures dividends across countries. Nevertheless, these estimates are broadly consistent with the model's predictions that firms with higher future payouts should produce higher loadings on the accounting-based characteristics.

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[24]This is true so long as the persistence of expected returns is positive and is greater than the persistence of expected profitability, i.e., $\kappa > \omega$. As mentioned above, the average coefficients on *bm* and *roe* across countries implies persistence parameters of $\kappa \approx 0.97$ and $\omega \approx 0.87$.

Table 2.7: Dividend Payout and Relations between Expected Returns and Accounting-Based Characteristics

Table 2.7 reports the country-level results on the estimation of (2.17). We run Fama-MacBeth regressions of future realized annual log stock returns, r_{t+1}, on firm characteristics, bm_t, roe_{t+1}, labeled as $froe$ in the table, and $payout_{t+1}$, a continuous variable computed as $Dividends_{t+1}/Book_{t+1}$. The variables $bm \times payout$ and $froe \times payout$represent interactions of $payout$ with bm and $froe$, respectively. $payout$ is winsorized at the 1-percent level. Standard errors are reported in brackets below the coefficient estimates. Levels of significance are indicated by *, **, and ***, representing 10 percent, 5 percent, and 1 percent, respectively.

	Australia	*Belgium*	*Canada*	*China*	*Denmark*	*Finland*	*France*	*Germany*	*Greece*	*Hong Kong*
bm	0.0424**	0.0206	0.0602**	0.0721***	0.0344	0.0947*	0.0554***	0.0581***	0.0761**	0.0859***
	[0.020]	[0.042]	[0.023]	[0.016]	[0.033]	[0.030]	[0.014]	[0.021]	[0.023]	[0.022]
$froe$	0.1183**	0.4580***	0.3951***	0.2718***	0.4020***	0.5090***	0.4231***	0.2707***	0.4907***	0.4655***
	[0.056]	[0.058]	[0.101]	[0.069]	[0.091]	[0.072]	[0.049]	[0.037]	[0.091]	[0.156]
$payout$	0.3582	2.1520**	-0.1976	-0.6139	1.4684**	1.2045*	0.5462	0.8191***	2.0232***	0.8740**
	[0.214]	[0.442]	[0.395]	[1.162]	[0.569]	[0.408]	[0.320]	[0.209]	[0.499]	[0.343]
$bm \times payout$	0.4629***	1.4412*	0.2061	0.8498**	1.2337***	0.6640**	-0.0775	0.5326**	1.3149***	0.4819**
	[0.151]	[0.580]	[0.343]	[0.361]	[0.354]	[0.168]	[0.291]	[0.217]	[0.361]	[0.214]
$froe \times payout$	1.8429**	1.5300	2.0541	4.8886	3.5593*	1.5894	-0.9048	3.8656**	1.9315	1.1293
	[0.747]	[3.268]	[1.547]	[3.904]	[1.954]	[1.816]	[1.294]	[1.611]	[1.241]	[1.514]
$Cons$	0.0927***	-0.1203	0.0312	0.0929	0.0010	-0.1041	0.0224	-0.0038	-0.0820	0.0395
	[0.031]	[0.122]	[0.033]	[0.091]	[0.075]	[0.158]	[0.043]	[0.042]	[0.108]	[0.044]
N	4,849	424	3,867	14,207	1,886	416	9,707	8,608	1,088	3,965
Adj R^2	0.086	0.175	0.121	0.091	0.185	0.145	0.128	0.143	0.135	0.130

	India	*Indonesia*	*Israel*	*Italy*	*Japan*	*Malaysia*	*Netherlands*	*Norway*	*Pakistan*	*Philippines*
bm	0.0437**	0.1212***	0.0249	0.0309	0.0594***	0.0933***	0.0644*	0.0199	0.0352	0.0480
	[0.018]	[0.019]	[0.026]	[0.020]	[0.010]	[0.023]	[0.033]	[0.021]	[0.024]	[0.032]
$froe$	0.0428	0.4699***	0.3244***	0.3959***	0.0677***	0.3676***	0.4499***	0.2972***	0.2220**	0.1309
	[0.058]	[0.099]	[0.055]	[0.064]	[0.023]	[0.119]	[0.126]	[0.061]	[0.075]	[0.089]
$payout$	2.5548***	1.5426	0.8666**	1.3632***	1.3688	1.7060**	1.0725***	1.3328**	0.1186	-0.2669
	[0.708]	[4.648]	[0.222]	[0.437]	[0.807]	[0.624]	[0.350]	[0.509]	[0.512]	[0.334]
$bm \times payout$	0.6496**	7.3759	1.0607**	1.3288***	0.9676***	1.3732***	0.8743**	1.1769**	0.7299***	1.3879**
	[0.230]	[11.419]	[0.309]	[0.393]	[0.338]	[0.357]	[0.301]	[0.395]	[0.182]	[0.378]
$froe \times payout$	-0.4167	11.6932	2.4046	3.2815	4.7387**	4.5108**	2.0722	2.0203*	4.3875***	10.6006***
	[1.403]	[17.377]	[1.404]	[2.970]	[2.027]	[1.732]	[1.326]	[0.960]	[1.169]	[1.063]
$Cons$	0.0312	0.0988	0.0167	0.0116	-0.0175	0.0257	-0.0072	0.0122	0.0437	0.1713**
	[0.085]	[0.083]	[0.076]	[0.067]	[0.055]	[0.070]	[0.062]	[0.086]	[0.121]	[0.030]
N	13,663	2,973	1,060	2,786	60,045	5,917	1,878	1,193	1,658	570
Adj R^2	0.079	0.146	0.137	0.164	0.058	0.122	0.178	0.131	0.123	0.093

Table 2.7 Continued.

	South Africa	*South Korea*	*Spain*	*Sweden*	*Switzerland*	*Taiwan*	*Thailand*	*UK*	*US*
bm	0.0649***	0.0954***	0.0696**	0.0328	0.0252	0.1377***	0.1484***	0.0420***	0.0571***
	[0.016]	[0.026]	[0.024]	[0.029]	[0.019]	[0.034]	[0.022]	[0.011]	[0.014]
froe	0.1977**	0.2752***	0.5459***	0.2897***	0.2940***	0.7741***	0.8335***	0.2037***	0.1544***
	[0.077]	[0.066]	[0.142]	[0.054]	[0.094]	[0.132]	[0.176]	[0.057]	[0.025]
payout	0.0978	1.6930*	0.4924	1.1439***	0.5812	14.0831	-0.2767	0.3312**	0.0705
	[0.371]	[0.856]	[0.393]	[0.321]	[0.527]	[13.795]	[0.329]	[0.152]	[0.138]
$bm \times payout$	0.3029*	3.5678***	0.7707*	0.7656***	1.2231***	31.1406	0.8280***	0.1066	0.0732
	[0.162]	[0.342]	[0.359]	[0.178]	[0.206]	[38.190]	[0.268]	[0.083]	[0.083]
$froe \times payout$	0.9042	14.6233***	2.6362*	1.8357**	6.6188**	156.3112	5.3548**	0.0851	0.6971***
	[1.231]	[2.748]	[1.458]	[0.742]	[2.416]	[141.621]	[2.064]	[0.208]	[0.245]
Cons	0.1144**	-0.0758	0.0179	0.0018	0.0038	-0.0085	-0.0274	0.0714**	0.0948***
	[0.052]	[0.103]	[0.070]	[0.058]	[0.060]	[0.062]	[0.075]	[0.028]	[0.028]
N	2,922	17,042	1,530	3,828	2,605	7,447	5,784	14,609	92,534
Adj R^2	0.104	0.154	0.186	0.153	0.161	0.163	0.149	0.069	0.053

Sensitivity to Training Sample Window

In untabulated tests we also assess the sensitivity of our proxies to the choice of the burn-in period. Our baseline results use the first 40 months of data as the training sample before constructing ERPs and conducting out-of-sample tests. Our choice of 40 months, which we view to be a relatively short training period, was motivated by the relatively short sample of available data in certain countries (e.g., Israel and Pakistan).

We vary the training window to include 30 and 50 months and, for nearly all countries, these variations in the training sample period do not affect our inferences. For Finland and the Netherlands, widening the training sample and reducing the testing window reduces the statistical significance slightly, with t-statistics of 1.56 and 1.33, respectively. Reducing the training window to 30 months marginally affects one country—Switzerland—whose predictive coefficient remains positive and large in magnitude with a borderline t-statistic of 1.63. Overall, however, our main findings on the association with the cross section of future returns across countries are not very sensitive to the training window period.

2.4 Accounting Quality: Implications and Tests

While the empirical evidence presented above establishes the usefulness of accounting information in estimating expected returns across the world, accounting systems, and the quality of the information they produce, can significantly vary from one market and institutional setting to another. This section analyzes, both analytically and empirically, how our model of expected returns is affected by the quality of accounting information provided to investors.

2.4.1 Model Setup and Key Implication

To investigate this issue analytically, we extend the baseline model of expected returns to a setting where information is imperfect. To introduce the concept of imperfections in the accounting system vis-à-vis return prediction, we assume that investors do not directly observe expected growth in book value, h_t, but learn about it dynamically over time using realized accounting reports.[25]

In the spirit of Dechow *et al.* (2010), we assume that investors observe financial reports of book growth, $g_{b,t+1}$, which reflects both "true" firm performance ($g_{true,t+1}$) and noise (ζ^r_{t+1}) from the accounting system:

$$g_{b,t+1} = g_{true,t+1} + \zeta^r_{t+1}, \text{ and} \tag{2.17}$$

$$g_{true,t+1} = h_t + \zeta^{true}_{t+1}. \tag{2.18}$$

It follows that observed reports of book growth ($g_{b,t+1}$) have two sources of noise: (1) true "fundamental" or "innate" noise (ζ^{true}_{t+1}) and (2) measurement errors from the accounting system (ζ^r_{t+1}). We assume that the noise in the reports is captured by two independent error terms, $\zeta^{true}_{t+1} \sim N(0, \sigma^2)$ and $\zeta^r_{t+1} \sim N(0, \sigma_r^2)$.[26] Mapping this back into the assumptions about growth in book value (2.5), we have:

$$g_{b,t+1} = h_t + \zeta^{true}_{t+1} + \zeta^r_{t+1}. \tag{2.19}$$

Since investors observe only realized growth in book values, they form expectations of book growth by making inferences (or learning) about the unobserved h_t using relevant information to optimally update their beliefs over time. We denote $f_t = \mathbb{E}[h_t|\mathcal{F}_t]$ as investors' beliefs about mean book growth given $\mathcal{F}_t$, where $\mathcal{F}_t = \{g_{b,\tau}\}_{\tau \in \{0,1,\ldots,t\}}$ represents the history of accounting reports available to investors. Assuming that h_t is also conditionally Gaussian, it can be shown that investors' optimal dynamic updates to their beliefs take the following form:

$$f_{t+1} = \mu + \omega(f_t - \mu) + \frac{\omega v_t}{\sigma^2 + \sigma_r^2 + v_t}(g_{b,t+1} - f_t), \tag{2.20}$$

where $v_t = \mathbb{E}[(h_t - \mathbb{E}[f_t|\mathcal{F}_t])^2|\mathcal{F}_t]$ is the conditional variance of f_t with respect to investors

[25]Unlike related studies in the literature (e.g., van Binsbergen and Koijen, 2010), we do not assume that investors need to filter expected returns. Our rationale is that since investors set prices, given their expectations of book growth they must also set expected market returns. Our setting is thus closely related to that of Pástor and Veronesi (2003, 2006), except that we do not assume an exogenous discount factor.

[26]While the assumption of Gaussian error terms is common and somewhat restrictive, the assumption of independence is without loss of generality.

filtration $\mathcal{F}_t$, or the dispersion in investors' prior beliefs; σ_h^2 is the conditional variance of h_t; and $v_{t+1} = \omega^2 v_t + \sigma_h^2 - \frac{\omega^2 v_t^2}{\sigma^2+\sigma_r^2+v_t}$.[27]

Using this updating rule, we show in the Appendix that when the accounting system is imperfect, expected stock returns are a linear combination of *bm* and *roe*:

$$\mathbb{E}[r_{t+1}|\mathcal{F}_t] = C_1(t) + C_2(t)f_{t-1} + C_3 bm_t + C_4(t) roe_t, \quad (2.21)$$

in which the coefficient on *roe* takes the following form

$$C_4(t) = A_3 \frac{\omega v_{t-1}}{\sigma^2 + \sigma_r^2 + v_{t-1}}. \quad (2.22)$$

This model provides the key insight that, all else equal, better accounting information quality elevates the importance of profitability in forecasting future returns. Specifically, conditional on the dispersion of investors' prior beliefs (v_{t-1}), the volatility of the underlying fundamentals (σ^2), and the persistence in expected returns and expected profitability, the coefficient on *roe* is increasing with accounting information quality (or decreasing in σ_r^2).

The above analytical approach also allows a reconciliation of our model with the various alternative firm characteristics and signals (e.g., valuation ratios and accounting data) that relate to future stock returns. In particular, generalizing the above to include multiple information sources in investors' information set, if a signal systematically forecasts future profitability (i.e., future *roe*), conditional on *bm*, it follows that such a variable is also systematically associated with expected returns.

2.4.2 Empirical Tests

We proceed to empirically test the prediction that, all else equal, higher-quality accounting information leads investors to place greater weight on profitability in inferring expected returns. Accounting information quality, specifically the variance in measurement errors in the context of the model above, is difficult to measure. Under the view that greater variation in information quality exist across (rather than within) countries, our empirical

[27] This follows directly from Theorem 13.4 of Liptser and Shiryaev (1977).

approach exploits cross-country variation in the data. To do so, we adopt the methodology of Leuz *et al.* (2003) which creates a composite country-level measure of accounting quality by averaging a given country's rankings across four dimensions.

The first two dimensions of information quality capture the extent to which firms in a given country engage in earnings smoothing. The first earnings-smoothing measure (*Variability*) takes each country's median ratio of firm-level standard deviation of operating earnings divided by the firm-level standard deviation of cash-flow from operations, and ranks these median ratios across countries in descending order. A lower ratio implies a greater degree of earnings smoothing, and hence lower earnings quality, resulting in a higher rank. The second earnings-smoothing measure (*Correlation*) takes the magnitude of the contemporaneous correlation between changes in accounting accruals and changes in operating cash flows in each country, and ranks this correlation across countries in ascending order. This correlation is estimated by pooling all firm-years within a country; a greater magnitude implies greater earnings smoothing and lower earnings quality, resulting in a higher rank.

The third and fourth dimensions of information quality measures the extent of the use of accruals to manage earnings in a given country. The third measure (*Accruals Magnitude*) takes the median of the ratio between the absolute value of firm accruals and the absolute value of firm cash-flow from operations in a given country, and ranks this measure across countries in ascending order. A higher median ratio implies a greater use of accruals to manage earnings, and lower earnings quality, resulting in a higher rank. The fourth and final dimension of poor information quality (*Small Loss Avoidance*) takes the ratio between instances of small profits and instances of small losses, calculated by pooling all firm-years within a country, and ranks the measure across countries in ascending order. Small profits and small losses are calculated using earnings scaled by total assets, where small losses are defined as in the range $[-0.01, 0)$ and small profits are defined as in the range $[0.00, 0.01]$. A higher ratio implies greater use of managerial discretion in managing earnings, and lower earnings quality, resulting in a higher rank.

Our main empirical test, reported in Table 2.8, exploits the cross-country variations between this proxy, *Poor Information Quality*, and the median *roe* coefficient, generated from monthly regressions of (2.12). That is, we assess the cross-country relation between the the average level of information quality and the average importance of *roe* in forecasting returns over the relevant time frame.[28]

Column (1) of the table reports OLS estimates of regressions of each country's median *roe* coefficient on its *Poor Information Quality* measure and a control for the size of each country's equity market.[29] The rationale for such a control is to address the "all else equal" aspect of the theoretical predictions. Holding accounting information quality constant, the presence of more information intermediaries may reduce the importance of the accounting representation of profitability. Consistent with this intuition, our result shows a negative and significant coefficient on market size. Moreover, consistent with the model predictions, we report a negative coefficient on *Poor Information Quality*, but it is not statistically significant.[30]

We interpret the lack of significance in *Poor Information Quality* as, at least in part, a result of errors in measuring countries' accounting systems' measurement error variances—the underlying theoretical variable of interest—which is consistent with the coefficient's attenuation to 0. We resolve this issue empirically by using an instrumental-variables approach to identify the effect of information quality on the importance of profitability.

Our instruments capture the quality of governance institutions in a given country. Our identifying assumption is that the strength of such institutions affects the importance of profitability in forecasting future returns only by improving the information quality produced by firms in equity markets. Our instrument, *Quality of Governance Institutions*, is constructed using data from the World Bank's Worldwide Governance Indicators project, which compiles

[28]This approach is consistent with, but need not depend on, the assumption that earnings quality in a country is constant through time.

[29]Specifically, we take the log of the median total market capitalization over the relevant time frame for a given country.

[30]These results exclude Greece, Pakistan, and South Africa, for which the model does not generate reliable proxies. Taiwan is also excluded because information on the strength and quality of its governance institutions is unavailable.

Table 2.8: Earnings Quality and Importance of ROE

Table 2.8 reports the results of OLS and instrumental-variables (IV) regressions of country-level median *roe* coefficients, from monthly regressions of (2.12), on measures of earnings quality. Our overall earnings quality measure follows Leuz *et al.* (2003): a simple average of a country's in-sample ranks on four dimensions of earnings quality: earnings smoothness, correlation of accruals and cash flows, accruals magnitude, and loss avoidance. These four variables are defined in Table 2.9. A higher score on each of these dimensions, and on the overall earnings-quality measure, implies lower or poorer earnings quality. The leftmost column reports the results of an OLS regression of the median *roe* coefficients on overall earnings quality. The second and third columns report the first and second stage results, respectively, of instrumental variables regressions where earnings quality is instrumented with a measure for a country's quality of governance institutions. This quality of governance measures combines information on a country's *Rule of Law*, *Accountability*, *Political Stability*, *Government Effectiveness*, and *Control of Corruption*, as reported by the World Bank's Worldwide Governance Indicators project. *Rule of Law* captures perceptions of the quality of contract enforcement, property rights, and the courts; *Accountability* captures perceptions of the extent to which citizens have the ability to exert their voices and influence to create accountability in society, including freedom to select their government and the presence of a free media; *Political Stability* measures perceptions of the likelihood of political instability; *Government Effectiveness* captures perceptions of the quality of public services and the robustness of the policy formulation process; and *Control of Corruption* captures perceptions of the extent to which public power is exercised for private benefits. We take the median value of each variable over the relevant time frame for each country and then standardize each measure using the cross-section of countries. Our final country-level measure is the simple average of these standardized measures. In the last column we report reduced-form versions of the IV estimation. The F-statistic on the instrument is reported in the last row. In each of these regressions we control for the log of a given country's median total market capitalization over the relevant time frame. Levels of significance are indicated by *, **, and ***, representing 10 percent, 5 percent, and 1 percent, respectively.

	OLS	IV First Stage	IV Second Stage	Reduced Form
Poor Information Quality (Leuz et al., 2003)	-0.0001		-0.0007**	
	[0.000]		[0.000]	
Quality of Governance Institutions		-3.9260***		0.0027*
		[1.264]		[0.001]
Log Market Size	-0.0023***	-0.1859	-0.0030***	-0.0029***
	[0.001]	[0.883]	[0.001]	[0.001]
Constant	0.0750***	20.6885	0.1041***	0.0898***
	[0.023]	[23.082]	[0.025]	[0.018]
Observations	25	25	25	25
First Stage F		9.65		

five metrics on countries' governance institutions.[31] *Rule of Law* captures perceptions of the quality of contract enforcement, property rights, and the courts; *Accountability* captures perceptions of the extent to which citizens have the ability to exert their voices and influence to create accountability in society, including freedom to select their government and the presence of a free media; *Political Stability* measures perceptions of the likelihood of political instability; *Government Effectiveness* captures perceptions of the quality of public services and the robustness of the policy formulation process; and *Control of Corruption* captures perceptions of the extent to which public power is exercised for private benefits. We take the median value of each variable over the relevant time frame for each country and then standardize each measure using the cross-section of countries. Our final country-level variable, *Quality of Governance Institutions*, is the simple average of the five standardized governance measures.

Columns (2) and (3) report the first- and second-stage results, respectively, of an instrumental-variables estimation in which we instrument *Poor Information Quality* with *Quality of Governance Institutions*. The first-stage estimation results suggest that higher-quality or stronger governance institutions in a country are significantly associated (at the 1% level) with higher-quality accounting information, consistent with economic intuition. In the second stage we find that, all else equal, better earnings quality increases the importance of *roe* in forecasting returns. Specifically, improving a country's earnings-quality rank by 1 unit increases the *roe* coefficient by about 0.001, representing an economically significant increase of approximately 10 percent for the median country. Consistent with measurement errors influencing the OLS results, the magnitude of the coefficient in the instrumental-variables specifications is substantially larger compared to the baseline OLS specification. Finally, the last column of the table reports the reduced-form OLS estimates from regressing the median *roe* coefficients on the governance-quality variable and the market size control. Consistent with our instrumental-variables estimates, these results show that stronger and higher-quality governance institutions elevate the importance of *roe* in forecasting returns.

[31] http://info.worldbank.org/governance/wgi/index.aspx\#home

Table 2.9 provides further analyses of the impact of information quality on the *roe* coefficient by examining the four different dimensions of *Poor Information Quality* separately. All four measures produce negative coefficients, and all but *Variability* are significant at the 10% level. *Accruals Magnitude* yields the strongest results, with statistical significance at the 5% level. Together with Table 2.8, these findings as consistent with the analytical prediction that *roe* plays a reduced role in forecasting returns when accounting information quality is lower.

2.5 Conclusion

We show that, under fairly general assumptions, expected returns is related to book-to-market and profitability. This parsimonious linear relation is not only theoretically applicable to various accounting systems, but also supported empirically: the model-implied estimates predict the cross section of future returns and line up well with expected returns across international markets. Our work promotes a characteristic-based approach to expected returns, and contributes to the stream of empirical studies devoted to developing the estimation of, and understanding the behavior of, expected returns. It also provides a practical tool that can be used to analyze investment choices in international equity markets.

This tractable model not only performs well empirically but can easily incorporate and generate analytical predictions that are not possible in traditional factor-based models. In particular, our analytical work in integrating the model of expected returns to a dynamic information setting allows for an analysis of how characteristics of accounting systems—specifically the quality of information produced—affects the inference of expected returns.

Although our model produces estimates of expected returns which are consistent with rational expectations, we cannot definitively speak to market rationality, as we do not derive or test an equilibrium asset pricing model. Such an endeavor would require further theoretical investigation, which would be fruitful for future research. Finally, although this paper anchors market values of equity to book values of equity, which we believe to be a natural choice and broadly consistent with traditional accounting-based valuation (e.g., Ohlson, 1995), it might also be possible to derive expected returns as a function of alternative multiples and ratios using the structure laid out in this paper. We believe that developing a more general theory for the appropriate use of the various valuation multiples and performance ratios observed in practice would be an important area of future work.

Table 2.9: Earnings Quality and Importance of ROE: Alternative Measures

Table 2.9 reports the same specifications reported in Table 2.8 but uses Leuz *et al.* (2003)'s four measures of poor Information quality. *Variability* measures the extent to which a country's firms engage in earnings smoothing. In descending order, we rank each country's median ratio of firm-level standard deviation of operating earnings to the firm-level standard deviation of cash-flow from operations. A lower ratio implies a greater degree of earnings smoothing and thus lower earnings quality, resulting in a higher rank in *Poor Information Quality*. *Correlation* also measures the extent of earnings smoothing in a country. Across countries, in ascending order, we rank the magnitude of the contemporaneous correlation between changes in accounting accruals and changes in operating cash flows. This correlation is estimated by pooling all firm-years within a country. A greater magnitude of correlation implies greater earnings smoothing and lower earnings quality, resulting in a higher rank on *Poor Information Quality*. *Accruals Magnitude* proxies for the extent of the use of accruals to manage earnings. We rank, in ascending order, the median of the absolute value of firm accruals scaled by the absolute value of firm cash-flow from operations. A higher median ratio implies a greater use of accruals in managing earnings and lower earnings quality, resulting in a higher rank on *Poor Information Quality*. Lastly the *Small Loss Avoidance* measure ranks across countries, in ascending order, the ratio of instances of small profits to instances of small losses: this ratio is calculated by pooling all firm-years within a country. Small profits and small losses are calculated using earnings scaled by total assets. Small losses are defined as in the range $[-0.01, 0)$ and small profits are defined as in the range $[0.00, 0.01]$. A higher ratio implies greater use of managerial discretion in managing earnings and lower earnings quality, and results in a higher rank in *Poor Information Quality*. Our instruments and control variables remain the same as in Table 2.8. Levels of significance are indicated by +, *, **, and ***, representing 15 percent, 10 percent, 5 percent, and 1 percent, respectively.

	Variability			Correlation			Accruals Magnitude			Small Loss Avoidance		
	OLS	IV First Stage	IV Second Stage	OLS	IV First Stage	IV Second Stage	OLS	IV First Stage	IV Second Stage	OLS	IV First Stage	IV Second Stage
Poor Information Quality	0.0001		-0.0009	0.0000		-0.0006*	-0.0002		-0.0006**	-0.0000		-0.0008*
	[0.000]		[0.001]	[0.000]		[0.000]	[0.000]		[0.000]	[0.000]		[0.000]
Quality of Governance		-2.9232			-4.5851***			-4.8061***			-3.3898+	
		[2.059]			[1.537]			[1.474]			[2.145]	
Log Market Size	-0.0022***	-0.2771	-0.0032**	-0.0022***	0.0738	-0.0029***	-0.0027***	-1.4518+	-0.0037***	-0.0022***	0.9117	-0.0022**
	[0.001]	[1.332]	[0.001]	[0.001]	[1.253]	[0.001]	[0.001]	[0.919]	[0.001]	[0.001]	[1.142]	[0.001]
Constant	0.0701***	22.4796	0.1107***	0.0725***	14.2393	0.0982***	0.0860***	53.8144**	0.1203***	0.0731***	-7.7792	0.0835***
	[0.021]	[35.373]	[0.041]	[0.019]	[33.039]	[0.030]	[0.027]	[24.410]	[0.025]	[0.018]	[30.393]	[0.023]
Observations	25	25	25	25	25	25	25	25	25	25	25	25
First Stage F		2.02			8.90			10.63			2.50	

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Appendix A

Appendix to Chapter 1

A.1 Variable Definitions

This section provides definition of the main variables used in the study.

A.1.1 Earnings Management Measures:

- *DA*: The baseline measure of discretionary accruals used in the main analyses in the paper is discretionary accruals as computed using cash-flow data and the Modified Jones model with an adjustment for performance. The empirical specification of non-discretionary implied by this model, as described by (1.3), is estimated for the sample of Compustat firms using quarterly data and by pooling all observations in every three-digit SIC industry with more than 30 observations. Data is obtained from Compustat.
- *REM*: The baseline measure of real earnings management is computed by adding abnormal cash-flows from operations, computed using (1.5), and abnormal R&D expenses, computed using (1.7). The empirical models for these proxies estimated for the sample of Compustat firms using quarterly data and by pooling all observations in every three-digit SIC industry with more than 30 observations. The proxies are multiplied by negative one to make them increasing in the direction of earnings

management. Data is obtained from Compustat.

A.1.2 Treatment Indicators

- $Activism_t$: Indicator variable that takes the value 1 for a target firm for the quarter during which an activism campaign is first launched against the firm, and 0 for all other observations. Activism data is obtained from the Factset Sharkwatch database.
- $Activism_{t-1}$: Indicator variable that takes the value 1 for a target firm for the quarter, following the one in which the activism campaign is first launched against the firm, and 0 for all other observations.
- $Activism_{t-2}$: Indicator variable that takes the value 1 for a target firm for the quarter, which is two quarters after the one in which the activism campaign is first launched against the firm, and 0 for all other observations.
- $Activism_{t-3}$: Indicator variable that takes the value 1 for a target firm for the quarter, which is three quarters after the one in which the activism campaign is first launched against the firm, and 0 for all other observations.

A.1.3 Campaign Details and Outcomes

- *Announcement Returns*: Abnormal returns are estimated as compounded stock returns minus the compounded returns for the CRSP value-weighted index, measured over 20 days centered around the day of announcement of activism
- *Activist Ownership*: The activist's ownership in the target company at the time of the announcement of activism. Factset obtains this from 13D filings for most campaigns. This data is not completely populated for campaigns, which were initiated by hedge funds owning less than 5% and hence were not accompanied by a 13D. For these campaigns Factset obtains this data from public announcements at the time of the launch of the campaign.
- $Bulletproof\ Rating$: A proprietary score accorded by Factset to each activism target and is computed as a weighted sum of the presence of various takeover measures in

the target firm. Higher bulletproof rating indicates the presence of greater takeover defenses.

- *Poison Pill Adopted*: Indicator variable that takes the value 1 for all campaigns where the target firm adopted a poison pill in response to activism.
- *Proxy Fight*: Indicator variable that takes the value 1 for all activism campaigns where the firm and the activist engaged in a definitive proxy fight. Sharkwatch captures data on whether an activist filed a definitive proxy statement.
- *Board Turnover*: Indicator variable that takes the value 1 for all activism campaigns, where the target firm experienced director turnover in the fiscal year following the year in which the activism campaign was launched. Director turnover for a particular firm, for each fiscal year, is computed by observing whether a director, who was on the board as of the end of the previous fiscal year, is still on the board at the end of the current fiscal year. The data on directors is obtained from Equilar.
- *Granting Board Seat*: Indicator variable that takes the value 1 for activism campaigns where the activist won at least one board seat at the end of the campaign.

A.1.4 Firm Controls

- *log(MCAP):* Natural logarithm of the market capitalization of the firm, measured in $MN. Market capitalization is calculated using the price and shares outstanding at the end of the quarter using data from CRSP.
- *log(BM):* Natural logarithm of the book-to-market ratio of the firm. Book-to-market is computed as the ratio of the common equity of the firm to it's market capitalization at the end of the quarter using data from Compustat and CRSP. Observations with negative book values are treated as missing.
- *Sales Growth:* Ratio of the total revenue for the current quarter to that for the preceding quarter. Data is obtained from Compustat.
- *Staggered Board:* Indicator variable, measured at the annual level, which takes the value 1 if the firm had a staggered board during that time-period and is 0 otherwise. Data

on staggered boards is obtained by parsing through changes in firms' bylaws and charters using data from Factset's Sharkrepellent database.

- *Leverage:* Ratio of the long-term debt of the firm to it's total assets, measured at the end of the quarter using data from Compustat. This variable is truncated at 1.
- *Size Adj Return:* Computed as the cumulative stock returns minus the returns for the corresponding size decile over the corresponding time period using data from CRSP.
- *ROA:* Net income before extraordinary items and discontinued operations divided by total assets using data obtained from Compustat and measured at the end of the quarter.
- *Lagged Net Operating Assets:* The lagged value of net operating assets, which is computed as common equity minus cash and marketable securities, plus total debt, scaled by sales as at the end of the quarter using data from Compustat.
- *Payout:* Computed as the ratio of dividends to net income before extraordinary items using quarterly data from Compustat. Quarterly dividend is calculated from the year-to-date cash dividends reported in the statement of cash-flows. Dividends are assumed to be 0 for observations with missing dividend data.
- *Age:* Computed as the number of years between the date at the end of the quarter and the first date on which a particular firm appears in the CRSP database.
- *Institution:* Relative institutional ownership is computed as the ratio of the total number of shares held by institutions to the number of shares, outstanding at the end of the quarter. Institutional ownership is obtained from 13F filing data, compiled by Whalewisdom.
- *Analyst:* Analyst coverage is calculated as the number of earnings estimates for the relevant fiscal period as reflected in the I/B/E/S summary file. Coverage is assumed to be 0 for observations, which have all other relevant variables, but is missing data on coverage.

Appendix B

Appendix to Chapter 2

B.1 Derivations

B.1.1 Book-to-Market Derivation

We begin with the definitions of gross realized market and book equity growth:

$$G_{m,t+1} = \frac{M_{t+1}}{M_t}, \tag{B.1}$$

$$G_{b,t+1} = \frac{B_{t+1}}{B_t}, \tag{B.2}$$

where M_t and B_t are the market value and book value of equity at the end of period t. These lead to the following definition for the book-to-market ratio:

$$\frac{B_t}{M_t} = \frac{G_{b,t+1}^{-1} B_{t+1}}{G_{m,t+1}^{-1} M_{t+1}}. \tag{B.3}$$

Taking logs of both sides of (B.3), the log book-to-market ratio (bm_t) can be written as

$$bm_t = bm_{t+1} + g_{m,t+1} - g_{b,t+1}, \tag{B.4}$$

where $g_{m,t+1} = \log(G_{t+1})$ and $g_{b,t+1} = \log(G_{B,t+1})$. Iterating (B.4) forward obtains

$$bm_{t+1} = bm_{t+2} + g_{m,t+2} - g_{b,t+2}, \tag{B.5}$$

which implies that (B.4) can be expressed as

$$bm_t = bm_{t+2} + g_{m,t+2} - g_{b,t+2} + g_{m,t+1} - g_{b,t+1}. \tag{B.6}$$

Thus, progressive substitution yields the following expression of the log book-to-market ratio:

$$bm_t = bm_{t+\tau} + \sum_{i=1}^{\tau}[g_{m,t+i} - g_{b,t+i}]. \tag{B.7}$$

Taking conditional expectations on both sides with respect to information known at time t, we obtain

$$bm_t = \mathbb{E}_t[bm_{t+\tau}] + \sum_{i=1}^{\tau}\mathbb{E}_t[g_{m,t+i} - g_{b,t+i}], \tag{B.8}$$

and letting $\tau \to \infty$ yields

$$bm_t = \lim_{\tau\to\infty}\mathbb{E}_t[bm_{t+\tau}] + \sum_{i=1}^{\infty}\mathbb{E}_t[g_{m,t+i} - g_{b,t+i}]. \tag{B.9}$$

Under our of a finite and time invariant unconditional mean for bm, i.e., $\lim_{\tau\to\infty}\mathbb{E}_t[bm_{t+\tau}] = \overline{bm}$, we simplify the above to

$$bm_t = \overline{bm} + \sum_{i=1}^{\infty}\mathbb{E}_t[g_{m,t+i} - g_{b,t+i}]. \tag{B.10}$$

Finally, under the assumption that expected market growth (denoted $\mu_t = E_t[g_{m,t+1}]$) and expected book growth (denoted $h_t = E_t[g_{b,t+1}]$) follow AR(1) processes, i.e.,

$$\mu_{t+1} = \mu + \kappa(\mu_t - \mu) + \xi_{t+1}, \text{ and} \tag{B.11}$$

$$h_{t+1} = \mu + \omega(h_t - \mu) + \epsilon_{t+1}, \tag{B.12}$$

we can rewrite (B.10) as

$$bm_t = \overline{bm} + \sum_{i=1}^{\infty}(\mathbb{E}_t[\mu_{t+i-1}] - \mathbb{E}_t[h_{t+i-1}]) \tag{B.13}$$

$$= \overline{bm} + \sum_{i=1}^{\infty}(\kappa^{i-1}(\mu_t - \mu) - \omega^{i-1}(h_t - \mu)). \tag{B.14}$$

Solving the infinite sum yields (2.6) in the text:

$$bm_t = \overline{bm} + \frac{1}{1-\kappa}(\mu_t - \mu) - \frac{1}{1-\omega}(h_t - \mu). \tag{B.15}$$

B.1.2 Expected Returns Derivation

This subsection describes in detail the derivation of expected returns as a function of bm and expected roe. We begin with the observation that expected stock returns are given by:

$$\mathbb{E}_t[r_{t+1}] = \mu_t + \mathbb{E}_t\left[\log\left(1 + \frac{D_{t+1}}{M_{t+1}}\right)\right]. \tag{B.16}$$

We follow Pástor and Veronesi (2003) and assume that dividends are proportional to book value over the next interval, such that:

$$\log\left(1 + \frac{D_{t+1}}{M_{t+1}}\right) = \log\left(1 + \delta\frac{B_{t+1}}{M_{t+1}}\right) = \log\left(1 + \delta\exp(bm_{t+1})\right). \tag{B.17}$$

Log-linearization around the unconditional mean of bm, $\overline{bm}$, and using (2.6), we have:

$$\log\left(1 + \frac{D_{t+1}}{M_{t+1}}\right) \approx \log(1 + \delta\exp(\overline{bm})) + \frac{\delta\exp(\overline{bm})}{1+\delta\exp(\overline{bm})}(bm_{t+1} - \overline{bm}) \tag{B.18}$$

$$= \log(1 + \delta\exp(\overline{bm})) + \frac{\delta\exp(\overline{bm})}{1+\delta\exp(\overline{bm})}\left[\frac{1}{1-\kappa}(\mu_{t+1} - \mu) - \frac{1}{1-\omega}(h_{t+1} - \mu)\right]. \tag{B.19}$$

Taking conditional expectations and substituting for expected growth in market using (2.6) yields:

$$\mathbb{E}_t\left[\log\left(1 + \frac{D_{t+1}}{M_{t+1}}\right)\right] \approx K + \rho\left[\frac{\kappa}{1-\kappa}(\mu_t - \mu) - \frac{\omega}{1-\omega}(h_t - \mu)\right] \tag{B.20}$$

$$= K + \rho\left[\kappa(bm_t - \overline{bm}) + \frac{\kappa - \omega}{1-\omega}(h_t - \mu)\right], \tag{B.21}$$

where $K = \log(1 + \delta\exp(\overline{bm}))$ and $\rho = \frac{\delta\exp(\overline{bm})}{1+\delta\exp(\overline{bm})}$.

Finally, under the proportional dividend assumption and clean-surplus accounting, growth in book and ROE can be related: $log(ROE_{t+1}) = log((B_{t+1} + D_{t+1})/B_t) = log(1 + \delta) + log(B_{t+1}/B_t)$ and $\mathbb{E}_t[roe_{t+1}] = log(1+\delta) + h_t$. Combining this with (B.16) and (B.21) above obtains the desired linear expression as summarized in (2.9) in the body of the paper:

$$\begin{aligned}
\mathbb{E}_t[r_{t+1}] &= \underbrace{\left[K + \frac{(\kappa-\omega)(1-\rho)}{1-\omega}\mu - (1-\kappa+\rho\kappa)\bar{bm} - A_3 log(1+\delta)\right]}_{A_1} \\
&+ \underbrace{[1-\kappa+\rho\kappa]}_{A_2} bm_t \\
&+ \underbrace{\left[\frac{\rho(\kappa-\omega)+1-\kappa}{1-\omega}\right]}_{A_3} \mathbb{E}_t[roe_{t+1}]. \qquad \text{(B.22)}
\end{aligned}$$

B.1.3 Dividend Payout and Expected Returns

The relation between expected returns and dividend payout is derived by combining equations (B.16) and (B.21) and differentiating with respect to δ:

$$\begin{aligned}
\frac{\partial E_t[r_{t+1}]}{\partial \delta} &= \frac{\partial \mu_t}{\partial \delta} + \frac{\partial E_t\left[\log(1+\frac{D_{t+1}}{M_{t+1}})\right]}{\partial \delta} \\
&= 0 + \frac{\partial K}{\partial \delta} + \frac{\partial \rho}{\partial \delta}\left[\kappa(bm_t - \bar{bm}) + \frac{\kappa-\omega}{(1-\omega)}(h_t-\mu)\right],
\end{aligned}$$

where

$$\begin{aligned}
\frac{\partial K}{\partial \delta} &= \frac{\exp(\bar{bm})}{1+\delta\exp(\bar{bm})} > 0 \text{ and} \\
\frac{\partial \rho}{\partial \delta} &= \frac{\exp(\bar{bm})}{(1+\delta\exp(\bar{bm}))^2} > 0.
\end{aligned}$$

Thus, the coefficients on bm_t and h_t increase with dividend payout, so long as expected returns are more persistent than expected profitability: i.e., $\kappa > 0$ and $\kappa > \omega$.

B.1.4 Expected Returns under Incomplete Information

This subsection derives expected returns when investors do not directly observe book growth. To solve for stock returns in this setting, we must first solve the present-value problem; we do so by applying the law of iterated expectations to (2.6). (See the appendix of Pástor and Veronesi, 2009, for a simple and related example.) We deduce:

$$bm_t = \overline{bm} + \frac{1}{1-\kappa}(\mu_t - \mu) - \frac{1}{1-\omega}(f_t - \mu). \tag{B.23}$$

Now, using the log-linearization in the previous subsection, we have:

$$\log\left(1+\frac{D_{t+1}}{M_{t+1}}\right) \approx \log(1+\delta\exp(\overline{bm})) + \frac{\delta\exp(\overline{bm})}{1+\delta\exp(\overline{bm})}(bm_{t+1} - \overline{bm}), \tag{B.24}$$

$$= \log(1+\delta\exp(\overline{bm})) + \frac{\delta\exp(\overline{bm})}{1+\delta\exp(\overline{bm})}\left[\frac{1}{1-\kappa}(\mu_{t+1}-\mu) - \frac{1}{1-\omega}(f_{t+1}-\mu)\right]. \tag{B.25}$$

Taking expectations conditional on $\mathcal{F}_t$, we have:

$$\mathbb{E}\left[\log\left(1+\frac{D_{t+1}}{M_{t+1}}\right)\Big|\mathcal{F}_t\right] \approx K + \rho\left(\frac{\kappa}{1-\kappa}(\mu_t-\mu) - \frac{\omega}{1-\omega}(f_t-\mu)\right), \tag{B.26}$$

where K and ρ are given in the prior subsection. This implies that expected returns are given as follows:

$$\mathbb{E}[r_{t+1}|\mathcal{F}_t] = A_1 + A_2 bm_t + A_3(f_t + y). \tag{B.27}$$

Here $A_1 = K - \rho\kappa\overline{bm} - (1-\kappa)\overline{bm} - A_3 y + \frac{(\kappa-\omega)(1-\rho)}{(1-\omega)}\mu$, $A_2 = \rho\kappa + (1-\kappa)$, and $A_3 = \frac{\rho(\kappa-\omega)+1-\kappa}{1-\omega}$; $y = \log(1+\delta)$

From the updating rule ((2.20)), we can express this in terms of current *roe* by noting that:

$$f_t - \mu = \omega(f_{t-1}-\mu) + \frac{\omega v_{t-1}}{\sigma^2 + \sigma_r^2 + v_{t-1}}(roe_t - y - f_{t-1}). \tag{B.28}$$

Plugging this into the expected-returns (B.27), we have:

$$\mathbb{E}[r_{t+1}|\mathcal{F}_t] = A_1 + A_2 bm_t + A_3\left[\mu + y + \omega(f_{t-1} - \mu) + \frac{\omega v_{t-1}}{\sigma^2 + \sigma_r^2 + v_{t-1}}(roe_t - y - f_{t-1})\right]. \quad \text{(B.29)}$$

Re-arranging, we obtain:

$$\mathbb{E}[r_{t+1}|\mathcal{F}_t] = C_1(t) + C_2(t) f_{t-1} + C_3 bm_t + C_4(t) roe_t, \quad \text{(B.30)}$$

where

$$\begin{aligned} C_1(t) &= A_1 + A_3\left[\mu(1-\omega) + y\left(1 - \frac{\omega v_{t-1}}{\sigma^2 + \sigma_r^2 + v_{t-1}}\right)\right], \\ C_2(t) &= A_3\left(\omega - \frac{\omega v_{t-1}}{\sigma^2 + \sigma_r^2 + v_{t-1}}\right), \\ C_3 &= A_2, \\ C_4(t) &= A_3 \frac{\omega v_{t-1}}{\sigma^2 + \sigma_r^2 + v_{t-1}}. \end{aligned}$$