Enterprise Risk Management and the Cost of Capital

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ENTERPRISE RISK MANAGEMENT AND THE COST OF CAPITAL

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ABSTRACT

Enterprise risk management (ERM) is a process that manages all risks in an integrated, holistic fashion by controlling and coordinating any offsetting risks across the enterprise. This research investigates whether the adoption of the ERM approach affects firms' cost of equity capital. We restrict our analysis to the U.S. insurance industry to control for unobservable differences in business models and risk exposures across industries. We simultaneously model firms' adoption of ERM and the effect of ERM on the cost of capital. We find that ERM adoption significantly reduces firm's cost of capital. Our results suggest that cost of capital benefits are one answer to the question how ERM can create value.

INTRODUCTION

Enterprise risk management (ERM) is a holistic approach to risk management. Traditionally, corporations managed risks arising from their business units separately in each unit. ERM improves on this traditional "silo"-based approach by coordinating and controlling any offsetting risks across the enterprise. A number of surveys document how firms implement ERM programs to achieve such synergies between different risk management activities (see, e.g., Colquitt, Hoyt, and Lee, 1999; Kleffner, Lee, and McGannon, 2003; Beasley, Clune, and Hermanson, 2005; Altuntas, Berry-Stölzle, and Hoyt, 2011), a number of studies on firms' decision to start an ERM program provide evidence that firms adopt ERM for direct economic benefits (see, e.g., Liebenberg and Hoyt, 2003; Pagach and Warr, 2011; Altuntas, Berry-Stölzle, and Hoyt, 2012), and a limited number of studies provide evidence that ERM is associated

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with improvements in firm performance and increases in firm value (see, e.g., Hoyt and Liebenberg, 2011; Eckles, Hoyt, and Miller, 2014; Farrell and Gallagher, 2015; Grace et al., 2015). While this prior literature argues that ERM can create value by creating synergies between different risk management activities, increasing capital efficiency, avoiding the underinvestment problem in financially constrained firms, and by reducing the cost of external financing, there is a lack of empirical evidence supporting these claims.

The goal of our research is to shed some light on the fundamental question of *how* ERM can create value. We specifically focus on the relationship between ERM adoption and firms' cost of external financing, and investigate whether ERM adoption is negatively associated with the cost of equity capital. Such a research design allows us to evaluate whether cost of capital benefits are one mechanism for value creation by the ERM approach.

There are multiple conceptual arguments why ERM adoption should reduce a firm's cost of capital. First, an ERM program improves the information available about a firm's risk profile, and this information can be shared with investors, reducing information asymmetries and leading to a lower cost of capital (see, e.g., Easley and O'Hara, 2004; Lambert, Leuz, and Verrecchia, 2007). Second, ERM decreases firms' cost of capital through reducing firms' systematic risk. Hann, Ogneva, and Ozbas (2013) originally used this argument to explain why diversified firms benefit from a lower cost of capital than their focused counterparts. When firms experience low cash flows, they incur certain deadweight losses, for example, the loss of valuable personnel. Such deadweight losses are more pronounced during economic down-turns. In other words, these deadweight losses are at least partially countercyclical and increase systematic risk. Hann, Ogneva, and Ozbas document that diversified firms with less correlated segment cash flows have a lower cost of capital, supporting the view that coinsurance reduces systematic risk. ERM improves on the traditional risk management approach by its focus on understanding and managing correla-tions and interaction of risk or, in other words, by its focus on managing the coinsurance effect, thereby reducing systematic risk. Third, ERM adoption reduces the probability that a firm needs expensive external financing (Froot, Scharfstein, and Stein, 1993). In addition, ERM adoption can improve firms' ratings, which are used by outside investors as a signal of financial strength; Standard & Poor's as well as other rating agencies explicitly evaluate firms' ERM program as part of the rating process.

To avoid possible spurious correlations caused by unobservable differences in business models and risk exposures across industries, we restrict our analysis to a single industry, an industry that is almost tailor-made for an empirical analysis of ERM programs and their cost of capital implications: the U.S. insurance industry. The insurance industry embraced the ERM approach, and a substantial fraction of insurers adopted an ERM program, providing the necessary variation for an empirical analysis. In addition, the U.S. insurance industry is the only insurance industry worldwide with a substantial number of publicly traded stock companies, providing the necessary stock price data for cost of equity capital calculations. Since insurance companies hardly ever issue bonds, we can simply

focus on their cost of equity capital to approximate their weighted average or total cost of capital.[1]

Our cost of equity capital measure is based on the implied cost of capital approach (see, e.g., Gebhardt, Lee, and Swaminathan, 2001), which equates the firm's market value of equity with its discounted future cash flow estimates, and solves for the required internal rate of return. We use an implied cost of capital measure because such measures better explain variations in expected stock returns than realized stock returns (see, e.g., Gebhardt, Lee, and Swaminathan, 2001; Pástor, Sinha, and Swaminathan, 2008; Li, Ng, and Swaminathan, 2013). The main differences between implied cost of capital measures are the valuation model used to describe future cash flows and the growth assumptions in perpetuity. To ensure that our results are robust to method choice, we calculate four different implied cost of capital measures and take the average across those four measures. This average is the main cost of capital measure used in our analysis.[2]

Following the procedure suggested by Beasley, Pagach, and Warr (2008), Hoyt and Liebenberg (2011), and Pagach and Warr (2011), we systematically search newswires and other media, as well as financial reports, for evidence of ERM program adoption by our sample insurance companies. We then use two procedures to test whether ERM adoption is actually accompanied by a decrease in firms' cost of capital. First, we use an event study methodology and test for an abnormal reduction in the cost of capital around the year of ERM adoption. Second, we explicitly model the determinants of ERM adoption and estimate a two-equation treatment effects model to assess the effect of ERM use on firms' cost of capital. For ERM adopters, the ERM indicator variable in this model is coded equal to 1 in the year of ERM adoption and all following years; the variable is equal to 0 in the years prior to ERM adoption. For firms that do not adopt ERM during our sample period, the ERM indicator is equal to 0 for

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[1]Insurance companies receive premium payments up front, invest the premium money in the capital markets, and pay claims once they occur. If premiums are calculated properly and investments are well managed, there is no need for additional liquidity. Capital has the important function to serve as a buffer that can absorb higher than expected losses. The insurance industry is a regulated industry and regulators monitor how much capital insurance companies have on their balance sheet relative to the liabilities to policyholders. There are regulatory capital requirements, and bonds do not count as capital. While the average industrial firm issues capital as well as bonds and focuses on its weighted cost of capital including the cost of debt to make investment decisions, for insurance companies, the weighted cost of capital is basically equivalent to the cost of equity capital. All articles measuring insurance companies' cost of capital we are aware of only focus on the cost of equity capital (see, e.g., Cummins and Phillips, 2005; Wen et al., 2008; Pottier and Xu, 2014). Cummins and Phillips (2005) even break down the overall cost of capital of a firm to the individual business lines, providing a methodology to use the cost of equity capital for financial decision making within insurance companies.

[2]The four implied cost of capital measures used in our analysis are Gebhardt, Lee, and Swaminathan's (2001) industry ROE method, Gordon and Gordon's (1997) finite horizon method, Gode and Mohanram's (2003) economy-wide growth method, and Easton's (2004) price-earnings-growth ratio.

all firm-year observations. In both the event study and the treatment effects model, we find that ERM adoption is significantly associated with a reduction in firms' cost of equity capital.

An open question is whether ERM adoption *causes* the reduction in firms' cost of capital. We provide additional evidence supporting that view. First, we address the reverse causality argument. An alternative explanation for the negative relationship between ERM adoption and firms' cost of capital in our empirical analysis is that firms with a lower cost of capital might be more likely to adopt ERM. We regress an ERM indicator on past levels of firms' cost of capital. The coefficients of 1-, 2-, and 3-year lagged cost of capital levels are either insignificant or positive and significant in these regressions, making reverse causality unlikely. Second, in addition to the two-equation treatment effects model, we use an alternative methodology to control for self-selection; we calculate endogenous treatment effects in the potential-outcomes framework (Wooldridge, 2010). The main idea of the potential-outcomes approach is to compare treated observations with estimated counterfactuals based on potential outcomes, that is, the potential outcomes had only the treatment assignment been changed. The estimated average treatment effect on the treated is negative and significant, supporting the view that ERM adoption reduces the cost of capital. Third, we provide additional time-series evidence on the cost of capital development of ERM adopters. Our event study analysis already provides evidence of abnormal changes in the cost of capital of ERM adopting firms around the year of ERM adoption. For the subsample of ERM adopters, we also regress firms' cost of capital on the ERM indicator as well as year and firm fixed effects. The focus of this regression is on cost of capital changes of adopters over time rather than on cross-sectional differences; by design the model controls for any time-invariant firm-specific factors. Again, the coefficient of the ERM indicator is negative and significant, supporting the view that ERM adoption reduces the cost of capital.

Our research design is motivated by a desire to better understand the drivers of firm value. The market value M of a firm can be described as $M = B + PV(abnormal\ earnings)$, where B denotes the book value of the firm's assets, *abnormal earnings* are earnings in excess of a charge for the cost of capital, and PV denotes the present value operator based on the cost of capital. The book value of a firm's assets should not be significantly affected by the firm's adoption of the ERM approach. So let us simply assume that the book value B stays constant. Then ERM adoption can either create value through its impact on the cost of capital, through its impact on the firm's cash flows and, hence, its abnormal earnings, or through a combination of these two mechanisms.[3]

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[3]The simple model of the market value of a firm could be extended by adding a term for the equity put option. Shareholders can walk away from the firm if liabilities exceed firm value. That option is especially valuable for firms in financial distress. Since the firms in our sample are on average well capitalized and financially strong, we argue that the equity put option is relatively less important for determining the overall value of the firm than the two other value drivers, namely, the cost of capital and the expected abnormal earnings. But let us ignore the relative impact of the three drivers of firm value for a moment. Taking Hoyt and Liebenberg's

The argument that risk management can reduce a firm's cost of capital is still relatively new. The mainstream view in the risk management literature to date is that risk management creates value through its impact on a firm's cash flows. Risk management can, for example, reduce a firm's tax liability, transaction costs of bankruptcy (Smith and Stulz, 1985), regulatory costs (Mayers and Smith, 1982), and mitigate the underinvestment problem in financially constrained firms leading to higher profits (Froot, Scharfstein, and Stein, 1993). More recently, some articles argue that ERM may not just impact a firm's cash flows and earnings, but may also reduce the firm's cost of capital (see, e.g., Beasley, Pagach, and Warr, 2008; Hoyt and Liebenberg, 2011). The only loosely related empirical analysis we are aware of is Hann, Ogneva, and Ozbas's (2013) analysis of firms' degree of diversification and their cost of capital. They find that diversified firms with less correlated segment cash flows have, on average, a lower cost of capital than focused firms. Assuming that firms diversify to achieve a coinsurance effect, Hann, Ogneva, and Ozbas provide the first evidence that a specific risk management tool can reduce a firm's cost of capital. Our article extends Hann, Ogneva, and Ozbas's work by examining the effect of ERM adoption on firms' cost of capital.

Our result that ERM adoption reduces the cost of capital is not just statistically but also economically significant. We can use the Gordon (1959) growth model with the 0 dividend growth assumption to calculate the increase in firm value resulting from our estimated changes in firms' cost of capital.[4] The mean cost of capital for the sample of ERM adopting firms is 10.958 percent (see Table 4). On average, the change of firms' cost of capital around the year of ERM adoption based on our event study results (see Table 3) is $(-0.00604 -0.00578 -0.00432)/3 = -0.00538$. This 0.538 percent reduction would result in an average cost of capital of 10.420 percent for ERM adopters. Inserting these cost of capital numbers into the Gordon growth model leads to an increase in firm value of $(10.958 \text{ percent}/10.420 \text{ percent}) - 1 = 5.163$ percent. For the 0.595 percent reduction in firms' cost of capital based on an OLS regression with firm and year fixed effects (see model 5 in Table 2), the resulting increase in firm value is

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(2011) result as a given, we know that ERM adoption leads to an increase in firms' market value by about 20 percent. Our results indicate that ERM adoption reduces the cost of capital, and a reduction in the cost of capital all else equal has a positive impact on firm value. It is theoretically possible that the positive impact of the cost of capital reduction on firm value is offset by a decrease in the value of the equity put option. In that case, ERM adoption has to have a strong positive impact on the abnormal future earnings that result in an increase in firm value of 20 percent, which seems implausible. We basically have two of the value drivers with a positive impact on firm value and one with a negative impact. Our empirical results only imply that the reduction in firms' cost of capital is one driver of value creation. Of course there are other factors that might come into play.

[4]The Gordon (1959) growth model is a commonly used version of the dividend discount model. Gordon's model describes a firm's market value per share or stock price as:

$$\text{Stock Price} = D(1 + g)/(r - g),$$

where $D =$ the annual dividend, $g =$ the projected dividend growth rate, and $r =$ the required rate of return or cost of capital. Assuming dividend growth is 0, the model simplifies to

$$\text{Stock Price} = D/r.$$

5.742 percent. For the 1.999 percent reduction in firm's cost of capital after ERM adoption estimated with our treatment effects model (see Table 5), the corresponding increase in firm value is 22.313 percent; the increase in firm value based on the same model estimated with the Gebhardt, Lee, and Swaminathan (2001) cost of capital measure rather than the average cost of capital measure is 11.657 percent. Comparing those calculated changes in firm value to the 19.884 percent total impact of ERM adoption on firm value estimated by Hoyt and Liebenberg (2011, p. 813), we conclude that at least one-quarter of the total increase in firm value can be attributed to the reduction in the cost of capital.

The article proceeds as follows. In the next section, we discuss related literature and the conceptual background of our research design. This is followed by a description of the data, and sections discussing the methodology and the results. The final section concludes.

CONCEPTUAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

ERM is a structured approach to managing all risks faced by the enterprise in a holistic way. ERM emphasizes risk identification outside the standard risk "silos," the identification of interdependencies between different types of risks, the aggregation of risk at the enterprise level, and the measurement and management of the aggregated enterprise-wide risk. Thus, one benefit of an ERM program is that it improves the information available to the firm about its aggregate risk profile. This information can be shared with investors, leading to an increase in transparency about the firm's future earnings distribution. Consistent with this argument, Wade, Hoyt, and Liebenberg (2015) document that ERM adoption is associated with a decrease in firms' dispersion in analyst earnings forecasts. Improved disclosures and information sharing with investors can help mitigate information asymmetries. Disclosures are especially important for firms with complex operations because such firms are difficult to evaluate from the outside. A recent model developed by Lambert, Leuz, and Verrecchia (2007) demonstrates how the quality of information disclosed by a firm can reduce its cost of capital. Lambert, Leuz, and Verrecchia's model is consistent with the capital asset pricing model and incorporates multiple securities with correlated cash flows. In their model, investors' beliefs about the covariances of a firm's cash flows with the cash flows of other firms depend on the quality of information disclosed by the firm. Most importantly, this effect of information quality is not diversifiable and, hence, directly impacts the firm's cost of capital. Consistent with that view, a number of empirical studies show that less reliable accounting information is associated with a higher cost of capital (see, e.g., Francis et al., 2005; Francis, Khurana, and Pereira, 2005; Ashbaugh-Skaife et al., 2009). In an alternative model based on a market microstructure framework, Easley and O'Hara (2004) also come to the conclusion that increasing the amount of reliable information available to investors reduces the cost of capital. Their model includes both informed and uninformed investors. While informed investors receive all information, uninformed investors only receive a fraction of the released information. Thus, uninformed investors demand a higher return in exchange for the information risk they face. Supporting this view, Easley, Hvidjkaer, and O'Hara (2002) use a measure of information risk from a structural microstructure model and show that information

risk is a determinant of stock returns. In summary, we argue that ERM improves the information available about a firm's risk profile, and hence, ERM adoption should reduce a firm's cost of capital.

Furthermore, ERM should decrease firms' cost of capital through reducing firms' systematic risk. While the conventional view in the literature is that risk management in general can only reduce idiosyncratic risk and not systematic risk, there is recent empirical evidence that is contrary to this view. Hann, Ogneva, and Ozbas (2013) examine the relationship between corporate diversification and the cost of capital; they find that diversified firms have a lower cost of capital than matched portfolios of stand-alone firms. They also document that the reduction in the cost of capital is more pronounced for firms with less correlated segment cash flows; this finding is consistent with a coinsurance effect. Hann, Ogneva, and Ozbas argue that coinsurance is associated with a reduction in the cost of capital because coinsurance can reduce systematic risk through the avoidance of countercyclical deadweight costs. When firms experience low cash flow realizations, in other words, low or negative earnings, they incur certain deadweight losses. Such deadweight losses include, among others, the high cost associated with raising external capital, the loss of valuable personnel, suppliers or customers, price discounts demanded by risk sensitive customers, and the direct costs associated with financial distress. Since such deadweight losses tend to be higher during economic downturns and get further amplified through asset fire sales and rising financing costs, these deadweight losses are at least partially countercyclical and increase systematic risk. Similar to Hann, Ogneva, and Ozbas's argument that coinsurance reduces systematic risk, we argue that risk management in general reduces systematic risk through mitigating countercyclical deadweight costs and that any improvement in firms' risk management approach should reduce a firm's cost of capital. In addition, ERM improves on the traditional risk management approach by its focus on understanding and managing correlations and interaction of risk or, in other words, by its focus on managing the coinsurance effect. Through this focus on managing the coinsurance effect, ERM adoption should further reduce firms' systematic risk resulting in a decrease of their cost of capital.

Another benefit of an ERM program is that it reduces the probability that a firm needs expensive external financing to fund profitable investment projects (Froot, Scharfstein, and Stein, 1993). A structured approach to identify all risks faced by a firm may screen for risks outside the standard risk "silos" or business units and identify previously overlooked threats to the firm. Improved risk identification allows firms to choose the most effective tool to manage the identified risks instead of passively retaining them. In addition, ERM emphasizes the identification and management of interdependencies between different types of risks. Such an approach allows firms to coordinate risk management activities across all business units of a firm and to exploit natural hedges. Thus, ERM allows firms to avoid unforeseen accumulation of risks from different sources (e.g., fire risk, operational risk, commodity price risk, etc.). Large unforeseen losses, either from overlooked threats or risk accumulation, limit a firm's ability to invest in positive net present value projects and force a firm to raise external funds to address its financing constraints. Due to information asymmetries between managers and outside investors, however,

external sources of funds are more expensive than internal sources (Myers and Majluf, 1984); investors assume that only firms with less advantageous investment opportunities issue new capital and demand a substantial discount on the price of new shares. Therefore, firms that have to raise external funds face an increase in their cost of capital. Since ERM focuses on reducing the probability of large losses and capital shocks, ERM reduces the probability that a firm has to raise expensive external financing and, hence, reduces the firm's expected cost of capital.[5]

It is important for firms to have a strong financial strength rating. Standard & Poor's as well as other rating agencies explicitly evaluate companies' ERM program as part of the rating process. Following its announcement in October 2005 that ERM would "become a separate, major category" of its analysis for insurers, Standard & Poor's declared in May 2008 that it would add an additional dimension to its "ratings process for nonfinancial companies through an ERM review."[6] In February 2006, A.M. Best, the major rating agency in the insurance industry, followed Standard & Poor's example and released a special report describing its increased focus on ERM in the rating process. Therefore, a well-functioning ERM program positively impacts a firm's rating, which is used by outside investors as a signal of financial strength. This direct link between ERM programs and financial strength ratings creates an additional channel through which ERM adoption should lead to a lower cost of capital.

Based on the four conceptual arguments presented above, we can state the following testable hypothesis for ERM adoption:

Hypothesis: ERM adoption reduces firms' cost of equity capital.

Sample Selection

Our initial sample includes all publicly traded insurance companies in the merged CRSP/Compustat database for the years 1996–2012. We identify insurance companies based on the Standard Industrial Classification System (SIC) codes and keep all firms with SIC codes between 6311 and 6399. This initial sample consists of 371 unique firms. Our first screen excludes American Depository Receipts and firms with missing Compustat data for sales, assets, or equity. Following Zhang, Cox, and Van Ness (2009), we calculate the fraction of firms' sales revenue from insurance operations based on the Compustat Segment database and exclude firms with less than 50 percent of their sales in insurance. Next, we remove firms with insufficient stock return data from the CRSP monthly stock database. We then match the sample firms to the I/B/E/S database and eliminate firms that do

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[5]Campbell, Dhaliwal, and Schwartz (2012) use a similar argument to explain why mandatory contribution to corporate pension plans should increase firms' cost of capital. Their empirical results are consistent with this view.

[6]Standard & Poor's Rating Services published the ERM rating criteria for insurance companies and industrial firms in 2005 and 2008, respectively. The most recent updates were released in May 2013 and November 2012, respectively.

not have analyst earnings forecasts in I/B/E/S; as explained in more detail below, we need analyst earnings forecasts to calculate firms' implied cost of capital. This first set of screens reduces our sample to 250 firms, or 1,587 firm-year observations. We then classify all firms in the sample as ERM adopters or nonadopters using the method outlined in the next section. The resulting sample is the sample we used for our event study. Thus, we will refer to this sample as the event study sample throughout the article.

Our regression analysis includes a number of additional insurance specific control variables. We merge the firms in the sample with statutory accounting data filed with the National Association of Insurance Commissioners (NAIC), and we drop firms for which neither a property and casualty, a life, nor a health statement is available. We also eliminate firms for which a statement is available, but reported net premiums written are 0 or negative. Note that we aggregate statutory statements filed for individual subsidiaries of an insurance group to the group level, controlling for double counting of intragroup shareholdings. Our final sample for the regression analysis consists of 132 firms, of which 45 are life insurers and 87 are property and casualty insurers. The sample includes 761 firm-year observations, of which 246 firm-year observations are from life insurers and 515 observations are from property and casualty insurers.

CONSTRUCTION OF THE ERM ADOPTION INDICATOR

We follow the previous ERM literature and use a four-step procedure to classify firms as ERM adopter or nonadopters (see, e.g., Hoyt and Liebenberg, 2011; Pagach and Warr, 2011; Eckles, Hoyt, and Miller, 2014). In the first step, we conduct a comprehensive search of newswires and other news media for statements about an ERM program; the search includes Factiva, LexisNexis, Google, and other search engines. In the second step, we search firms' financial reports, filings with the U.S. Securities and Exchange Commission (SEC), and data libraries including Thomson One and Mergent Online. Our search strings consist of ERM-related key phrases and their abbreviations in conjunction with the individual firm names. The key phrases used in the search include "enterprise risk management," "chief risk officer," "risk committee," "strategic risk management," "consolidated risk management," "holistic risk management," and "integrated risk management" in different variations. In the third step, we manually review each search result to determine whether it is a true hit and the firm actually adopts an ERM program, or whether the search hit just mentions ERM in a different context. Such out-of-context search hits, as for, example, ERM product sales to clients, are ignored. Finally, we identify the earliest evidence of ERM adoption for each insurer based on the previous three steps and construct an *ERM* indicator variable. To be consistent with our cost of capital measure described in the next section, we code the *ERM* indicator for the current year equal to 1 if a firm adopts ERM between July 1st of the previous year and June 30th of the current year. The *ERM* indicator is set to 0 for years prior to ERM adoption, and set to 1 for all years after ERM adoption.

We repeated the manual search process used to identify the year of ERM adoption for all adopters and all years after adoption to verify whether these firms terminated their

ERM program or not in any of the years.[7] We could not find any instance of a firm terminating an ERM program. Thus, we conclude that all sample firms have maintained their ERM programs since adoption.

Our event study sample consists of 112 firms that have adopted ERM by the end of 2012, and 138 firms that have not. Our regression sample includes 89 firms that have adopted ERM by 2012, and 43 firms that have not. Figure 1 shows the cumulative number of sample firms with an ERM program over time. The black bars represent the number of ERM adopters in the event study sample, and the gray bars show the number of adopters in the regression sample.

THE IMPLIED COST OF EQUITY CAPITAL MEASURE

The cost of equity capital is the rate of return required by the shareholders of a company on their investment. To measure that required or expected rate of return, we use the implied cost of capital measures developed by Gordon and Gordon (1997), Gebhardt, Lee, and Swaminathan (2001), Gode and Mohanram (2003), and Easton (2004) because implied cost of capital measures better explain variations in expected stock returns than realized stock returns (see, e.g., Gebhardt, Lee, and Swaminathan, 2001; Pástor, Sinha, and Swaminathan, 2008; Li, Ng, and Swaminathan, 2013).[8] Each

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[7]It is theoretically possible that a firm adopts ERM, terminates its ERM program, and then re-adopts ERM in a later year. To ensure that we do not falsely code such a firm as having an ERM program in all years since the firm adopted ERM for the first time, we manually review each search result to verify that a firm did not terminate its ERM program in any of the years after ERM adoption.

[8]Another relatively crude measure of *ex ante* expected returns used in the literature is the average of *ex post* realized returns (see, e.g., Cummins and Rubio-Misas, 2006). However, that approach has been widely criticized for producing very noisy estimates of expected returns (see, e.g., Blume and Friend, 1973; Sharpe, 1978; Froot and Frankel, 1989; Elton, 1999). Elton (1999), for example, shows that average realized returns can diverge substantially from expected returns over lengthy periods of time. Alternatively, expected returns can be estimated using asset pricing models such as the CAPM and the Fama and French (1993) three-factor model (FF3). There are also two recent studies using an asset-pricing-model-based approach to investigate the cost of capital specifically for the insurance industry. Cummins and Phillips (2005) estimate the cost of equity for property–liability insurance companies using the CAPM and FF3 models, and Wen et al. (2008) compare the estimates of property–liability insurers' cost of capital based on the CAPM with estimates from the Rubinstein-Leland (RL) model. However, cost of capital estimates based on asset pricing models are still based on realized returns, and Fama and French (1997) show that such estimates are imprecise and have huge standard errors. In their study, Fama and French (1997) use the CAPM and the FF3 to estimate the cost of capital for 48 different industries, excluding the financial services sector. An additional disadvantage of such asset pricing models is that they require a large number of consecutive returns to estimate firms' cost of capital. The standard approach is to use a rolling window of the previous 5 years of return data to estimate firms' cost of capital for a given year. A firm's cost of capital estimate for year t will be based on 20 percent new observations and 80 percent old ones that have also been used to calculate the cost of capital in year $t-1$. While such a rolling window approach is appropriate for a cross-sectional comparison of firms, a rolling window approach lacks the time-series variation necessary for a longitudinal study. Our

FIGURE 1
Cumulative Numbers of Sample Insurers Engaged in ERM by Year
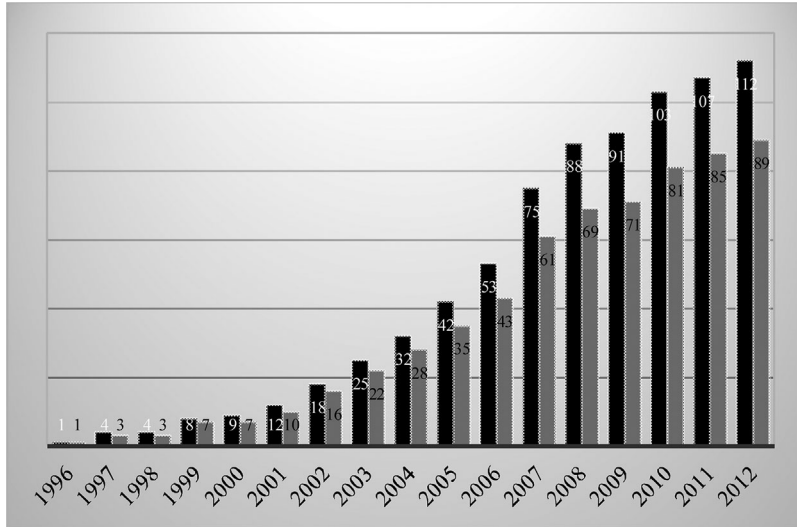
Notes: Each black bar represents the cumulative number of ERM adopters in the event study sample, and each gray bar represents the cumulative number of adopters in the regression sample. We classify firms as ERM users based on a comprehensive search of SEC filings, annual reports, newswires, and other media.

of these models is derived from the dividend discount model and basically equates the firm's market value of equity with its discounted future cash flow estimates. Solving for the discount rate that balances the equation gives the implied cost of capital.[9] The following paragraphs briefly summarize the models; a more detailed overview of the formulas and data sources is presented in Table A1 of the Appendix.

The dividend discount model describes the price per share of common stock P_t at the end of year t as

$$P_t = \sum_{i=1}^{\infty} \frac{E_t(D_{t+i})}{(1 + r_{icc})^i}, \tag{1}$$

where $E_t(D_{t+i})$ denotes the expected future dividends per share for period $t+i$, conditional on the information available at time t, and r_{icc} is the cost of equity capital at time t. Assuming "clean surplus" accounting that requires all gains and losses affecting firms' book value to be included in earnings, the book value B_t at the end of

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research focuses on changes in firms' cost of capital after ERM adoption. A 5-year rolling window CAPM or Fama–French three-factor cost of capital measure does not fit to our research design.

[9]Assuming that capital markets are efficient and share prices reflect all relevant information, including information about firms' size and firms' bankruptcy risk, then implied cost of capital measures reflect that information, too.

year t can be expressed as the book value at the end of the previous year plus earnings minus dividends: $B_t = B_{t-1} + NI_t - D_t$. Using that relationship, the dividend discount model from Equation (1) can be rewritten as the so-called residual income model that is based on standard accounting numbers:

$$P_t = B_t + \sum_{i=1}^{\infty} \frac{E_t[NI_{t+i} - r_{icc}B_{t+i-1}]}{(1 + r_{icc})^i},\qquad(2)$$

where B_t is the book value per share at the end of period t, $E_t[\cdot]$ is the expected value operator conditional on the information available at time t, NI_{t+i} is net income per share for period $t+i$, and r_{icc} is the cost of equity capital at time t.

Equation (2) is based on an infinite series. Different implied cost of capital models use different assumptions to approximate the stream of expected abnormal earnings in perpetuity, where abnormal earnings are earnings in excess of a charge for the cost of capital. Gebhardt, Lee, and Swaminathan (2001) express Equation (2) in terms of firms' return on equity (with $ROE_{t+i} = NI_{t+i}/B_{t+i-1}$) rather than net income, and slice the infinite series into three parts for practical purposes. For the first 3 years, explicit earnings forecasts of financial analysts from the I/B/E/S database are used to approximate expected earnings.[10] From year $t+4$ to year $t+12$, earnings are implicitly forecasted by mean reverting the third-period ROE to the twelfth-period ROE, which is assumed to be the industry median ROE.[11,12] The simple linear interpolation between the year $t+3$ ROE and the industry median ROE is used for the mean reversion process. For year $t+12$ and beyond, the value is estimated by calculating year 12's present value of the residual income as a perpetuity. Such a modeling approach assumes that firms cannot sustain earnings superior to their industry peers in a competitive market in the long run, and that abnormally high earnings will return to the industry median over time.[13]

Gordon and Gordon (1997) basically assume that forecasts of abnormal returns have a finite time horizon and that for all years beyond that finite horizon corporations

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[10]In the full regression sample, 6 firm-year observations have earnings forecasts from only one analyst, 25 firm-years have forecasts from two analysts, 38 firm-years have forecasts from three analysts, and all other firm-years have forecasts from four or more analysts. To address the concern of the quality of the ICC estimates when a firm is only followed by a single analyst, we remove the firm-year observations with earnings forecasts from only one analyst and re-run the analysis. Our results are robust to dropping those observations.

[11]Following Gebhardt, Lee, and Swaminathan (2001), loss firms are excluded when calculating the industry median ROE.

[12]Note that we treat the life insurance industry and the non-life insurance industry as separate industries in this context. The classification of life versus non-life insurers is based on NAICS codes. We classify insurers with NAICS code of 524113 as life insurers and all others as non-life insurers.

[13]The 12-year time period after which firms earnings return to the industry median is chosen arbitrarily by Gebhardt, Lee, and Swaminathan (2001). However, they also present robustness checks and conclude that the "results are very similar" if a 6-, 9-, 15-, 18-, or 21-year time period is used.

simply earn the expected return or cost of capital. Following Gordon and Gordon, we assume the finite time horizon to be 5 years. The cost of capital is then computed as the discount rate that equates the current share price with expected dividends, which are equal to their expected values for the first 5 years and expected earnings in year 6 for all years after year 5. Proxies for expected dividends per share for the first 5 years are derived by multiplying earnings forecasts from the I/B/E/S database with a dividend payout ratio, defined as the ratio of the actual dividends from the most recent fiscal year divided by earnings over the same time period for firms with positive earnings, or divided by the long-term industry median ROA multiplied with total assets for firms with negative earnings.[14]

Gode and Mohanram (2003) assume that there is an economy-wide long-term growth in abnormal earnings changes and that the short-term growth rate decays to that long-term rate. They set the long-term rate equal to expected inflation and approximate expected inflation with the (nominal) risk-free rate minus 3 percent, which is a rough estimate of the real risk-free rate for their sample period. We follow their approach directly for the years 1996 through 2007 and set the long-term growth rate equal to the yield on 10-year U.S. Treasury bonds minus 3 percent. However, the 10-year Treasury bond yield decreased substantially after 2007 and even dropped below 3 percent after 2010. Therefore, we use the difference between yields of 10-year Treasury bonds and yields of 10-year Treasury Inflation-Indexed Securities for years after 2007 as our long-term growth rate.

Easton (2004) shows that the price-earnings-growth (PEG) ratio used by financial analysts and investors in the industry actually measures a firm's cost of capital and can be derived from the general residual income model under some restrictive assumptions. PEG is calculated as the square root of the change in forecasted earnings between years 4 and 5 relative to the current share price.

For all four measures, we collect analysts' forecasts from the I/B/E/S database as of June of the following year, and calculate firms' cost of capital as of June of that year (see, e.g., Gebhardt, Lee, and Swaminathan, 2001; Dhaliwal, Heitzman, and Li, 2006; Pástor, Sinha, and Swaminathan, 2008).[15] To ensure that our results are robust to method choice, we then calculate the mean of the four cost of capital measures for each firm-year observation.[16] This mean implied cost of capital is the main cost of capital measure used in our analysis.

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[14]More precisely, we determine the median ROA separately for publicly traded life insurers and non-life insurers for the 1980–2012 period. The median ROA for life insurers is approximately 1.2 percent and the median ROA for non-life insurers is approximately 3.4 percent. Therefore, we use the factors 0.012 and 0.034 in our calculation.

[15]Prior studies (see, e.g., Campbell, Dhaliwal, and Schwartz, 2012) winsorize calculated cost of capital measures from above at 0.5. None of our calculated cost of capital values are greater than or equal to 0.5 or 50 percent.

[16]There are five observations for which the Easton (2004) measure could not be calculated and there are two different observations for which the Gode and Mohanram (2003) measure could not be calculated. For those seven observations, we simply use the mean across the three remaining cost of capital measures.

FIGURE 2

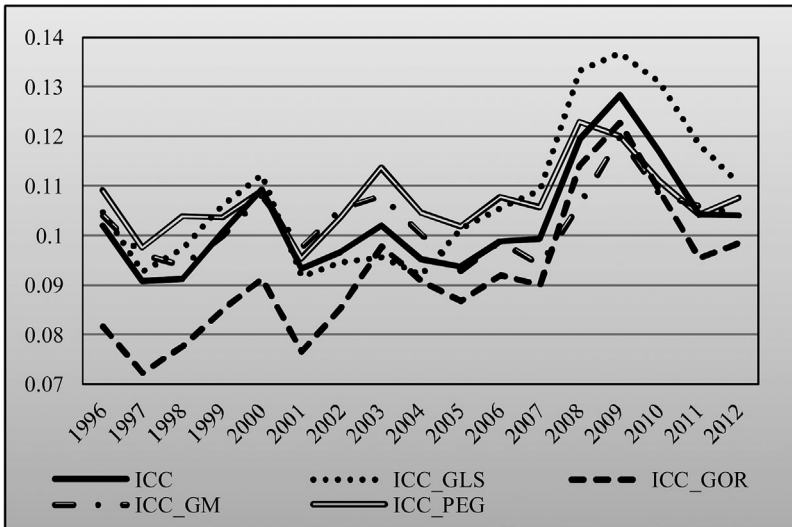Insurers' Median Implied Cost of Equity Capital Over Time

Figure 2 presents the annual median cost of equity capital over the 1996 through 2012 period for the cost of capital measures calculated with Gebhardt, Lee, and Swaminathan's (2001) industry ROE method (*ICC_GLS*), Gordon and Gordon's (1997) finite horizon method (*ICC_GOR*), Gode and Mohanram's (2003) economy wide growth method (*ICC_GM*), and Easton's (2004) price-earnings-growth ratio (*ICC_PEG*) as well as the main cost of capital measure used in our analysis, the average across those four measures (*ICC*). The graph is based on the event study sample, which consists of 250 firms, or 1,587 firm-year observations. The important takeaway from this graph for the purpose of our study is that the time-series variation of all five measures follows a similar pattern; the different assumptions about abnormal earnings growth in perpetuity seem to primarily impact the level of the cost of capital estimates.

For the 761 firm-year observations with all control variables necessary for the regression analysis, the mean ICC is 10.079 percent with a standard deviation of 2.841 percent. The first quartile of the cost of capital measure is 8.229 percent and the third quartile is 11.691 percent, so half of the ICC values are within that range. There is variation in the level of the different cost of capital measures. Mean values range from 8.976 percent for Gordon and Gordon's (1997) measure to 10.674 percent for Gebhardt, Lee, and Swaminathan's (2001) measure.

UNIVARIATE DIFFERENCES IN THE COST OF CAPITAL AND TIME-SERIES TRENDS

Table 1 presents univariate differences in firms' cost of capital between different sets of observations. Out of the 761 firm-year observations in the regression sample, 130 firm-year observations are from firms that do not adopt ERM during our sample period, and 631 firm-year observations are from firms that adopt ERM. Out of the 631 observations from ERM adopters, 272 are observations from years before firms adopt

TABLE 1
Differences in the Cost of Capital Between ERM Adopters and Nonadopters

Panel A:	All Years and Firms		
	ERM Adopters (1)	Nonadopters (2)	Difference (1)–(2)
N	631	130	
Mean	0.10227	0.09361	0.00866***
Median	0.10040	0.08926	0.01114***

Panel B:	Before ERM Is Adopted		
	Adopters Before ERM Adoption (1)	Nonadopters (2)	Difference (1)–(2)
N	272	130	
Mean	0.09263	0.09361	–0.00098
Median	0.09474	0.08926	0.00548

Panel C:	After ERM Is Adopted		
	Adopters After ERM Adoption (1)	Nonadopters (2)	Difference (1)–(2)
N	359	130	
Mean	0.10958	0.09361	0.01597***
Median	0.10753	0.08926	0.01827***

Panel D:	ERM Firms		
	Adopters After ERM Adoption (1)	Adopters Before ERM Adoption (2)	Difference (1)–(2)
N	359	272	
Mean	0.10958	0.09263	0.01695***
Median	0.10753	0.09474	0.01279***

Notes: ICC is firm's *ex ante* implied cost of equity capital calculated as the average of the four cost of capital measures developed by Gebhardt, Lee, and Swaminathan (2001), Gordon and Gordon (1997), Gode and Mohanram (2003), and Easton (2004). Statistical significance of difference in means is based on a *t*-test. Statistical significance of difference in medians is based on a nonparametric Wilcoxon rank-sum test. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively. Panel A compares all firm-years of firms that adopt ERM during our sample period with firms that do not. Panel B compares observations of ERM adopters before the year of ERM adoption with all firm-years of nonadopters. Panel C compares observations of ERM adopters after ERM adoption with all firm-years of nonadopters, and Panel D compares observations of ERM adopters before the year of ERM adoption with observation of the same firms after ERM adoption.

an ERM program, and 359 observations are from years after ERM adoption. Panel A of Table 1 compares firms that adopt ERM during our sample period with firms that do not. The difference in means test is significant at the 1 percent level and indicates that ERM adopters have, on average, a higher cost of capital than nonadopters. The analysis presented in Panel D focuses on ERM adopters only and compares their cost of capital before and after ERM adoption. Both the mean and median cost of capital are significantly higher after ERM adoption. These results could simply be driven by a time-series effect. More firms adopt ERM as the years go by (see Figure 1) and the average cost of capital is higher for the years 2008–2012 than for earlier years (see Figure 2). Similarly, the results in Panels B and C could be explained by a time-series effect.

To control for a time-series effect, we run a simple OLS regression with year dummies. More precisely, we estimate the following model: $ICC_{i,t} = \alpha + \beta \ ERM_{i,t} + \gamma_t + \varepsilon_{i,t}$, where ICC is the implied cost of capital; $ERM_{i,t}$ is an indicator variable coded equal to 1 if firm i has an ERM program in year t, and 0 otherwise; γ_t denotes year fixed effects; and $\varepsilon_{i,t}$ is the error term. The results in column (1) of Table 2 are based on the full regression sample of all firms and years. The coefficient of the ERM indicator is positive and significant, indicating that, even after controlling for industry-wide changes in the cost of capital over time, firm-year observations with an ERM program in place have, on average, a higher cost of capital than firm-year observations without an ERM program. That result could be driven by differences in cost of capital levels between adopters and nonadopters. We will explore this theme in more detail later. The model in column (2) is estimated with observations from ERM adopters before ERM is adopted as well as with those from nonadopters. The *ERM Firm* indicator is equal to 1 for firms that adopt ERM during the sample period, and 0 for nonadopters. The coefficient of the *ERM Firm* indicator is insignificant. The model in column (3) is estimated with observations from the ERM adopters after ERM is adopted as well as with those from nonadopters. The coefficient of the ERM indicator is positive and significant. When adding firm fixed effects to the model, however, the sign changes and the coefficient becomes insignificant, indicating that differences across firms cannot be ignored in the analysis. The model in column (4) is based on data from ERM adopters only. The coefficient of the ERM indicator is insignificant. When we add firm fixed effects to the model the coefficient of the ERM indicator becomes negative and significant, indicating that ERM adoption is associated with a 0.595 percent reduction in firms' cost of capital. Since the estimation only includes firms that adopt ERM, the focus of the last two regressions is on cost of capital changes of adopters over time rather than on cross-sectional differences.

Changes in Firms' Cost of Capital Around the Adoption of ERM

To provide a more rigorous longitudinal test for the effect of ERM adoption on firm's cost of capital, we employ an event study methodology similar to the approach used by Lee, Mayers, and Smith (1997). We adjust for industry-wide time-series trends in the cost of capital by subtracting the industry average in a given year from the ICC measure of each firm in that year. We then test for significant changes of this industry-adjusted ICC measure in the $(t-1)$ to $(t+1)$ event window around the year of ERM adoption.

TABLE 2

OLS Regressions of the Cost of Capital on the ERM Indicator and Year Fixed Effects

	(1) ICC	(2) ICC	(3) ICC	(4) ICC	(5) ICC
ERM	0.00557**		0.01177***	0.00220	−0.00595**
	(0.00243)		(0.00376)	(0.00272)	(0.00287)
ERM Firm		−0.00296			
		(0.00251)			
Constant	0.07714***	0.07778***	0.08450***	0.07142***	0.06101***
	(0.00404)	(0.00391)	(0.00605)	(0.00550)	(0.01911)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects					Yes
No. of observations	761	402	489	631	631
R^2	0.229	0.158	0.193	0.269	0.663

Notes: The OLS regressions are based on the following equation: $ICC_{i,t} = \alpha + \beta\, ERM_{i,t} + \gamma_t + \varepsilon_{i,t}$, where *ICC* is firm's *ex ante* implied cost of equity capital calculated as the average of the four cost of capital measures developed by Gebhardt, Lee, and Swaminathan (2001), Gordon and Gordon (1997), Gode and Mohanram (2003), and Easton (2004). *ERM* is an indicator variable coded equal to 1 if firm i has an ERM program in year t and 0 otherwise, and γ_t are year fixed effects. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively. Results in column (1) are based on the full sample of all firms and years. Model (2) is estimated with observations from ERM adopters before ERM is adopted as well as with the observations from nonadopters. The *ERM Firm* indicator is equal to 1 for firms that adopt ERM during the sample period, and 0 for nonadopters. Model (3) is estimated with observations from the ERM adopters after ERM is adopted as well as with the observations from nonadopters. Models (4) and (5) are based on data from ERM adopters only. Model (5) also includes firm fixed effects.

More precisely, we compute the industry-adjusted change in firm i's implied cost of capital in the event window as

$$\Delta AdjICC_i = AdjICC_{i,t+1} - AdjICC_{i,t-1}, \qquad (3)$$

where $AdjICC_i = ICC_{i,t} - IndustryAverage_{i,t}$ represents firm i's industry-adjusted cost of capital, $ICC_{i,t}$ denotes firm i's firm-specific cost of capital, and $IndustryAverage_{i,t}$ is the average cost of capital across all sample firms in the industry. Note that we use three alternative ways to calculate the $IndustryAverage_{i,t}$. First, we use the entire insurance industry to calculate the industry average cost of capital for each year. Second, we distinguish between life insurers and non-life insurers based on the North American Industry Classification System (NAICS) and calculate the industry average separately for life insurers (NAICS code of 524113) and non-life insurers.[17]

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[17]Following the standard in the literature (see, e.g., Fama and French, 1997; Wen et al., 2008; Hoyt and Liebenberg, 2011), we use the SIC codes to define the insurance industry when pulling data from Compustat, CRSP, and I/B/E/S. However, the Compustat Segment database on corporate sales is based on NAICS codes. Thus, we use NAICS codes to define different segments or sectors within the insurance industry.

TABLE 3

Changes in Firms' ICC Around the Adoption of ERM

	Event Window	No. of Firms	Changes in ICC	
			Mean	Median
Industry adjustment based on insurance industry as a whole	$(t-1,$ $t+1)$	64	-0.00604^{**} (0.030)	-0.00493^{**} (0.027)
Separate industry adjustments for life insurers and non-life insurers	$(t-1,$ $t+1)$	64	-0.00578^{**} (0.035)	-0.00433^{**} (0.020)
Separate industry adjustments for five sectors defined by NAICS codes	$(t-1,$ $t+1)$	64	-0.00432^{*} (0.086)	-0.00461^{**} (0.048)

Notes: The null hypotheses are that the mean and/or median of the industry-adjusted changes in firms' implied cost of equity capital measured by *ICC* around the year of ERM adoption are 0. *ICC* is defined as firm's *ex ante* implied cost of equity capital calculated as the average of the four cost of capital measures developed by Gebhardt, Lee, and Swaminathan (2001), Gordon and Gordon (1997), Gode and Mohanram (2003), and Easton (2004). Firm *i*'s industry-adjusted *ICC* is the difference between the firm's *ICC* in a particular year and the industry average *ICC* in that year. The table presents three test versions that differ with respect to the industry adjustment. The *p*-values for the difference of the mean from 0 are based on a *t*-test, and *p*-values for the difference of the median from 0 are based on the Wilcoxon signed-ranks test. The *p*-values appear in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Third, we distinguish between five sectors defined by NAICS codes and calculate separate industry average costs of capital for them; we classify the NAICS code of 524113 as the life insurance sector, 524114 as the health insurance sector, 524126 and 524128 as the property–casualty (P/C) sector, 524127 as the title insurance sector, and 524130 as the reinsurance sector. We use the *t*-test and the Wilcoxon signed-ranks test to analyze whether the industry-adjusted change in firms' cost of capital around the adoption of an ERM program as defined in Equation (3) differs significantly from 0.

Table 3 presents the results of the *t*-tests and Wilcoxon signed-ranks tests. In all three versions of the tests, which only differ with respect to how the industry adjustment is calculated, the mean and median of the changes in the industry-adjusted implied cost of capital are negative and significantly different from 0. Overall these results indicate that ERM adoption leads to a reduction in firms' cost of capital. The average reduction in firm's cost of capital 1 year after ERM adoption ranges from 0.432 to 0.604 percentage points.

TWO-EQUATION TREATMENT EFFECTS REGRESSION MODEL

Our main test of ERM's impact on firms' cost of equity capital is based on a two-equation treatment effects regression model. We follow the prior literature and model the cost of capital as a function of firm-specific characteristics (see, e.g., Botosan and Plumlee, 2005; Dhaliwal, Heitzman, and Li, 2006; Hail and Leuz, 2006; Pástor, Sinha, and Swaminathan, 2008; Campbell, Dhaliwal, and Schwartz, 2012; Hann, Ogneva,

and Ozbas, 2013); we then extend this baseline model to include the ERM adoption indicator. Since firms self-select to implement an ERM program and some of the factors affecting the selection decision may also impact the firms' cost of capital, we use a two-equation maximum-likelihood treatment effects model that jointly estimates firms' decision to adopt an ERM program and the effect of that decision (or treatment) on the firms' cost of capital. We adjust standard errors for clustering at the firm level. The specification of the model is as follows:

$$ICC_{i,t+1} = X_{it}\beta + \delta ERM_{it} + \varepsilon_{it}, \tag{4}$$

where ICC_{it} is firm i's implied cost of equity capital in year t; ERM_{it} is an indicator variable coded equal to 1 if firm i has adopted an ERM program in year t, and 0 otherwise; X_{it} is a vector of control variables; and ε_{it} is the error term. A firm's choice to adopt an ERM program is then modeled as the outcome of an unobservable latent variable ERM_{it}^*, which is a linear function of firm characteristics:

$$ERM_{it}^* = \omega_{it}\gamma + u_{it}, \tag{5}$$

where ω_{it} is a vector of firm characteristics and u_{it} is the error term. Assuming that the decision to adopt ERM is observed if and only if the latent variable is positive, and assuming that the two error terms are bivariate normal with a 0 mean and a specific covariance matrix, the two equations can be estimated with the maximum-likelihood method; see Maddala (1983) for details. The following sections discuss the firm specific variables included as explanatory variables in Equations (4) and (5).

Variables Included in the Cost of Capital Equation

Our selection of explanatory variables for the firms' cost of capital model (Equation (4)) is based on the previous literature (see, e.g., Gebhardt, Lee, and Swaminathan, 2001; Campbell, Dhaliwal, and Schwartz, 2012; Hann, Ogneva, and Ozbas, 2013). The CAPM suggests a positive link between a stock's market beta and the corresponding firm's cost of equity capital, and hence, we include beta as an explanatory variable in our model. We estimate each firm's beta based on the market model, using the value-weighted CRSP (NYSE/AMEX) index and a minimum of 24 monthly returns over the prior 60 months.

We expect firm size to be inversely related to the cost of capital because information on larger firms is more readily available than information on smaller firms. Consistent with this view, there is substantial empirical evidence on a negative relationship between firms' size and cost of capital (see, e.g., Gebhardt, Lee, and Swaminathan, 2001; Hou, van Dijk, and Zhang, 2012). We use the natural logarithm of the book value of assets to measure firm size.

Modigliani and Miller (1958) theorize that a firm's cost of equity, unlike its average cost of capital, is positively associated with the debt proportion in its capital structure, or, in other words, with the firm's leverage. Fama and French (1992) empirically

demonstrate that the *ex post* mean stock returns are an increasing function of firms' leverage. More recently, a number of studies also document a positive relation between implied cost of equity capital measures and leverage (see, e.g., Dhaliwal, Heitzman, and Li, 2006). To capture differences in leverage across firms, we include a measure of leverage in our model. The *Leverage* variable is calculated as the ratio of the total book value of liabilities to the market value of equity.

We include the ratio of book-to-market value of equity in the model to control for differences in growth opportunities across firms. Prior research (see, e.g., Fama and French, 1992, 1993; Berk, Green, and Naik, 1999; Petkova and Zhang, 2005) points out that stocks with a high book-to-market ratio, indicating relatively low growth opportunities, have relatively high systematic risk and time-varying risk, resulting in a high risk premium. Consistent with that view, a number of empirical studies (see, e.g., Fama and French, 1992, 1993; Dhaliwal et al., 2005) provide evidence of a positive link between the book-to-market ratio and cost of capital. Thus, we expect a positive sign for the *BooktoMkt* variable. Following Campbell, Dhaliwal, and Schwartz (2012), we include firms' mean long-term growth forecasts from I/B/E/S as an additional control variable for growth opportunities in our model. However, Gode and Mohanram (2003) argue that it is difficult to predict the effect of firms' long-term growth rate on the cost of equity capital.

Forecasts from different analysts provide different views on a firm's earnings prospects. The dispersion of forecasts reflects analysts' uncertainty about the firm's expected earnings and, hence, can be interpreted as a measure of information asymmetry between managers and outside analysts and investors (see, e.g., Madden, 1998; Botosan and Plumlee, 2005; Zhang, 2006). However, prior empirical studies generally find a negative relationship between forecast dispersion and firms' cost of capital (see, e.g., Gebhardt, Lee, and Swaminathan, 2001; Gode and Mohanram, 2003; Dhaliwal et al., 2005; among others). To control for any effect of analysts' forecast dispersion we include the *Foredispers* variable in our model; *Foredispers* is calculated as the natural logarithm of the standard deviation of analyst earnings forecasts for the next year divided by the consensus earnings estimate for the same period.

DeAngelo, DeAngelo, and Stulz (2006) provide evidence that a firm's dividend policy is related to its life cycle; more mature firms are more likely to pay dividends. Baker and Wurgler (2004) on the other hand argue that firms' dividend policy caters to time-varying investor demand for dividend payers; firms pay dividends when investors put higher prices on payers. Hence, dividend payments should be relevant to share prices and firms' cost of capital, but in different directions at different times. To control for any effect of dividend payments on firms' cost of capital, we include the *Dividend* indicator variable in our model. This indicator is coded equal to 1 if a firm pays a dividend in year t, and 0 otherwise.

In addition, we control for differences in the cost of equity capital across the life, health, and P/C sectors of the insurance industry, by including the mean for each sector as a control variable in the model. Firms with an NAICS code of 524113 are classified as life insurers, firms with an NAICS code of 524114 as health insurers, and firms with an NAICS code of 524126, 524127, 524128, or 524130 as P/C insurers,

respectively. Finally, we include year dummies in the model to control for variations in the cost of capital over time.

Variables Included in the ERM Equation

Our selection of explanatory variables for the ERM model (Equation (5)) is also based on the previous literature (see, e.g., Hoyt and Liebenberg, 2011; Pagach and Warr, 2011). A substantial number of studies find evidence that ERM adoption is more likely among larger firms (see, e.g., Colquitt, Hoyt, and Lee, 1999; Hoyt, Merkley, and Thiessen, 2001; Beasley, Clune, and Hermanson, 2005; Standard & Poor's, 2005). Explanations for the positive relationship between firm size and ERM adoption include the argument that larger firms are more complex and face a wider spectrum of heterogeneous risks and may, hence, benefit more from a holistic approach toward risk identification. In addition, larger firms can spread the fixed costs of running an ERM program over multiple business units. To control for differences in size across firms, we include the natural logarithm of the firms' book value of assets in our model.

Liebenberg and Hoyt (2003) argue that firms with greater financial leverage should benefit more from reducing earnings volatility by managing their risks in an enterprise-wide fashion. Their empirical results support that view. On the other hand, the implementation of an ERM program requires a substantial initial investment, and firms with higher levels of capital or lower levels of leverage may find it easier to start a new ERM program. To capture any possible effect of leverage on firms' ERM adoption decision, our model includes the ratio of the total book value of liabilities to the market value of equity as a measure of firm leverage.

Firms with a high book-to-market ratio are usually large, established firms with substantial franchise value, whereas those with a low book-to-market ratio have most of their growth opportunities still ahead. Thus, we expect ERM implementation to be more valuable to firms with a high book-to-market ratio, since ERM adoption allows these firms to protect their franchise value. To control for differences in the book-to-market ratio across firms, we include the *BooktoMkt* variable in our model; this variable is calculated as the ratio of the book value of equity to the market value of equity.

Implementing an ERM program is a challenging task that requires substantial resources. If a company is involved in merger and acquisition (M&A) activities, it may not be able to devote additional resources to the implementation of an ERM program. Therefore, we expect a negative relationship between recent M&A activities and a firm's probability of starting an ERM program. To control for differences in M&A activities across firms, we add a *RecentM&A* measure to our model; it is calculated as the ratio of intangible assets to the book value of total assets. A merger or an acquisition usually results in a significant amount of goodwill and other intangible assets for companies (see, e.g., Caves, 1989; Dubin, 2007; Boone and Mulherin, 2008).[18]

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[18]Boone and Mulherin (2008) study 308 U.S. corporate takeovers during an 11-year period and find that the ratio of intangible assets to the total assets of the target firms averages 65 percent across the sample at the time of M&As.

Hence, the fraction of intangible assets relative to the total assets can be interpreted as a measure of recent M&A activities.[19]

If an insurance company belongs to a conglomerate with firms from other industries, the board may include members without insurance-specific expertise. For such a conglomerate, ERM with its focus on identifying, measuring, aggregating, and communicating risk across the entire corporation may be especially helpful to ensure that all board members, regardless of insurance specific expertise, understand the firm's risk profile. Thus, we include the indicator variable *OthIndus* in our model; this variable is coded equal to 1 for firms with positive sales outside the insurance industry (NAICS codes less than 524100 or greater than 524199), and 0 otherwise.

Insurers' lines of business diversification may also impact the ERM adoption decision. However, the direction of this effect is unclear. On the one hand, more diversified insurers are more complex and may, hence, benefit more from an ERM program than their more focused counterparts. On the other hand, more diversified insurers should already benefit from a substantial coinsurance effect. Hence, additional expected benefits from an ERM program may be marginal and hardly worth the investment, especially if implementation cost is increasing in the number of lines an insurer writes. To capture any effect of line of business diversification on ERM adoption, we include the *Divers* variable in our model. This variable is calculated as one minus the Herfindahl index of net premiums written across all 47 P/C, life and health insurance lines.[20]

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[19]To examine whether our measure really captures M&A activities, we sort our sample firm-year observations into deciles with respect to the ratio of intangible assets to total assets. We then specifically examine the 10-K reports of the companies in the largest decile. We find strong evidence linking firms' intangible assets ratio to their recent merger and acquisition activities. Three representative examples include Wellpoint Inc., UnitedHealth Group Inc., and Fidelity National Financial Inc. Specifically, on page 32 of Wellpoint's 2008 10-K, there is the following statement: "Due largely to our past mergers and acquisitions, goodwill and other intangible assets represent a substantial portion of our assets. Goodwill and other intangible assets were approximately $22.3 billion as of December 31, 2008, representing approximately 46 percent of our total assets and 104 percent of our consolidated shareholders' equity at December 31, 2008. If we make additional acquisitions it is likely that we will record additional intangible assets on our consolidated balance sheets." On page 40 of United Health Group's 2005 10-K form, there is the following statement: "Due largely to our recent acquisitions, goodwill and other intangible assets represent a substantial portion of our assets. Goodwill and other intangible assets were approximately $18.2 billion as of December 31, 2005, representing approximately 44 percent of our total assets. If we make additional acquisitions it is likely that we will record additional intangible assets on our books." On page 27 of Fidelity National Financial's 2002 10-K form there is the following statement: "We have made acquisitions in the past that resulted in recording a significant amount of goodwill. As of December 31, 2001, cost in excess of net assets acquired, net, was $808.6 million, of which $762.3 million relates to goodwill recorded in connection with the Chicago Title merger in 2000."

[20]The by line Herfindahl index is calculated across 47 business lines. For P/C insurance business, we collect the net premiums written (NPW) by line from the Underwriting and Investment Exhibit (Part 1B—Premiums Written) in the NAIC annual statements. Note that

We include three indicator variables in the model to control for the potential heterogeneity in the likelihood of ERM adoption across the three insurance industry sectors. The three indicators *PCPrem*, *LifePrem*, and *HlthPrem* are coded equal to 1 if firms have positive net premiums written in the P/C, life, or health insurance segments respectively, and 0 otherwise. We expect P/C insurers to be more likely to adopt ERM because the models used to aggregate risks within an ERM framework are closely related to those models employed in the actuarial pricing of P/C insurance contracts (Wang and Faber, 2006), reducing the cost of ERM adoption for P/C insurers.[21]

Given the common goal of reducing income volatility, reinsurance and ERM may act as substitutes (see, e.g., Cole and McCullough, 2006). If the volatility is effectively controlled by reinsurance use, the additional benefits from an ERM program may be minimal, resulting in a decreased likelihood of ERM adoption. To control for differences in reinsurance use across insurers, we include the *Reinsuse* variable in the model. This variable is calculated as the ratio of reinsurance ceded to direct premiums

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we aggregate some lines as follows: Fire and Allied lines is calculated as the sum of "Fire" and "Allied lines"; Accident and Health is calculated as the sum of "Group Accident and Health," "Credit Accident and Health," and "Other Accident and Health"; Medical Malpractice is calculated as the sum of "Medical Malpractice–Occurrence" and "Medical Malpractice–Claims Made"; Products Liability is calculated as the sum of "Products Liability–Occurrence" and "Products Liability–Claims Made"; Auto is calculated as the sum of "Private Passenger Auto Liability," "Commercial Auto Liability," and "Auto Physical Damage"; Reinsurance is calculated as the sum of "Nonproportional Assumed Property," "Nonproportional Assumed Liability," and "Nonproportional Assumed Financial Lines." The resulting 25 P/C lines used to calculate the Herfindahl index are Accident and Health, Aircraft, Auto, Boiler and Machinery, Burglary and Theft, Commercial Multi-Peril, Credit, Earthquake, Farmowners, Financial Guaranty, Fidelity, Fire and Allied lines, Homeowners, Inland Marine, International, Medical Malpractice, Mortgage Guaranty, Ocean Marine, Other, Other Liability, Products Liability, Reinsurance, Surety, Workers' Compensation, and Warranty. For life insurance business, we collect the NPW by line from the Exhibit−1 Part 1–Premiums and Annuity Considerations for Life and Accident and Health Contracts in the NAIC annual statements. The 10 life insurance lines used in the calculation of the Herfindahl index are Industrial Life, Ordinary Life Insurance, Ordinary Individual Annuities, Credit Life (Group and Individual), Group Life Insurance, Group Annuities, Group Accident and Health, Credit Accident and Health (Group and Individual), Other Accident and Health, and Aggregate of All Other Lines of Life Business. For health insurance business, we collect the NPW by line from the Underwriting and Investment Exhibit (Part 1–Premiums) in the NAIC annual statements. The 12 health insurance lines used in the calculation of the Herfindahl index are Comprehensive (Hospital and Medical), Dental Only, Disability & Long-Term Care & Stop Loss and Other, Disability Income, Federal Employee Health Benefits Plan, Long-Term Care, Medicare Supplement, Other Health, Stop Loss, Title XIX Medicaid, Title XVIII Medicare, and Vision Only.

[21]In addition, there is more guidance for P/C insurers how to implement an ERM program. In May 2013, Standard & Poor's published an ERM rating criteria guide for insurers. The ERM rating guidelines are very detailed for P/C insurers, less so for health insurers and life insurers.

written plus reinsurance assumed (see, e.g., Cummins, Phillips, and Smith, 2001; Berry-Stölzle et al., 2012).[22]

Pagach and Warr (2011) argue that financial slack may be correlated with ERM adoption. Firms with higher levels of financial slack may find it easier to pay for the initial costs associated with implementing an ERM program. We include the fraction of cash and marketable securities to total assets as a measure of financial slack in our model.

ERM adoption should also be correlated with firms' earnings volatility (see, e.g., Liebenberg and Hoyt, 2003; Hoyt and Liebenberg, 2011; Pagach and Warr, 2011). One of the goals of an ERM program is to stabilize earnings. Therefore, firms with more volatile earnings can benefit more from adopting ERM and should be more likely to actually start an ERM program. To control for differences in earnings volatility across firms, we include the $CV(EBIT)$ variable in our model. This variable is calculated as the coefficient of variation of the quarterly earnings before interest and taxes (EBIT) for the previous 3 years.

Altuntas, Berry-Stölzle, and Hoyt (2012) argue that managerial career concerns about keeping their job influence the decision to adopt ERM. An ERM program reduces the volatility of earnings and, hence, improves the informativeness of earnings as a signal of the CEO's ability. In a career concern model, it is optimal for a CEO with high initial reputation to only adopt ERM after a period of poor performance. Consistent with that view, Altuntas, Berry-Stölzle, and Hoyt document a positive relation between firms' likelihood to adopt ERM and adverse changes in past performance for a sample of German insurers. We include firms' 1-year percentage change in market value in our model to capture any effect of changes in past performance on ERM adoption.[23]

Lastly, we include year dummies in the *ERM* equation to control for time variation in firms' probability to implement an ERM programs. The next section presents descriptive statistics for all variables included in the regression model.

Descriptive Statistics and Univariate Differences of Regression Variables

Table 4 presents the descriptive statistics for all variables used in the treatment effects regression. The average implied cost of capital across our sample is 10.079 percent and the median cost of capital is 9.920 percent. Noteworthy is also that we have a more recent sample that includes substantially more ERM firms than previous studies; over

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[22]More precisely, given the inclusion of the P/C, life, and health insurance sectors, the numerator of *Reinsuse* is calculated as the sum of reinsurance ceded by life subsidiaries, by health subsidiaries, and to nonaffiliates by P/C subsidiaries; the denominator is computed as the sum of total direct premiums written by P/C, life, and health subsidiaries, and total reinsurance assumed by life subsidiaries, by health subsidiaries, and from non-affiliates by P/C subsidiaries.

[23]Firms' market value is calculated as the product of the year-end closing stock price and the number of shares outstanding.

TABLE 4
Descriptive Statistics and Univariate Differences Across ERM Status

Variable	Full Sample Mean	Full Sample Median	(1) ERM = 1 Mean	(1) ERM = 1 Median	(2) ERM = 0 Mean	(2) ERM = 0 Median	Difference (1)–(2) Mean	Difference (1)–(2) Median
ICC	0.10079	0.09920	0.10958	0.10753	0.09295	0.09257	0.01663***	0.01496***
ICC_GLS	0.10674	0.10612	0.11671	0.11647	0.09782	0.09608	0.01889***	0.02039***
ICC_GOR	0.08976	0.09029	0.10174	0.09949	0.07906	0.07912	0.02268***	0.02037***
ICC_GM	0.10164	0.09932	0.10852	0.10431	0.09550	0.09368	0.01302***	0.01063***
ICC_PEG	0.10462	0.10326	0.11055	0.10781	0.09939	0.09948	0.01116***	0.00833***
ERM	0.47175	0.00000						
Beta	0.82310	0.70595	0.99946	0.79669	0.66560	0.63897	0.33386***	0.15772***
Size	9.19088	9.04347	9.92030	9.75175	8.53949	8.26865	1.38081***	1.48310***
Leverage	4.84371	2.61211	5.90125	2.82631	3.89930	2.32549	2.00194***	0.50082***
BooktoMkt	0.80906	0.73445	0.91349	0.82789	0.71579	0.64767	0.19769***	0.18022***
Foredispers	-3.87537	-3.94481	-3.85042	-3.90399	-3.89764	-3.97029	0.04722	0.06630
LongGrow	11.57272	11.25000	10.93942	10.50000	12.13828	12.00000	-1.19887***	-1.50000***
Dividend	0.76610	1.00000	0.83287	1.00000	0.70647	1.00000	0.12640***	0.00000
Sector_ICC	0.13945	0.14475	0.13948	0.14475	0.13943	0.14475	0.00005	0.00000
RecentM&A	0.03438	0.00954	0.03469	0.00913	0.03410	0.01072	0.00059	-0.00159
OthIndus	0.00394	0.00000	0.00557	0.00000	0.00249	0.00000	0.00308	0.00000
Divers	0.56476	0.67175	0.57394	0.69443	0.55657	0.65921	0.01737	0.03522*
PCPrem	0.78581	1.00000	0.80501	1.00000	0.76866	1.00000	0.03636	0.00000
LifePrem	0.50197	1.00000	0.48468	0.00000	0.51741	1.00000	-0.03273	-1.00000
HlthPrem	0.12221	0.00000	0.14763	0.00000	0.09950	0.00000	0.04813**	0.00000**
Reinsuse	0.15103	0.10605	0.14700	0.10563	0.15463	0.10702	-0.00763	-0.00139
Slack	0.10605	0.07267	0.10518	0.08268	0.10683	0.06304	-0.00165	0.01964***
CV(EBIT)	0.21067	0.39504	0.22917	0.45363	0.19415	0.34625	0.03501	0.10738***
ValueChange	0.14932	0.08809	0.07051	0.04591	0.21970	0.16539	-0.14919***	-0.11948***
No. of firm-year obs.	761		359		402			

Notes: ICC is firm's *ex ante* implied cost of equity capital calculated as the average of *ICC_GLS, ICC_GOR, ICC_GM,* and *ICC_PEG. ICC_GLS* is Gebhardt, Lee, and Swaminathan's (2001) cost of capital measure, *ICC_GOR* is the cost of capital measure developed by Gordon and Gordon (1997), *ICC_GM* is the the cost of capital measure developed by Gode and Mohanram (2003), and *ICC_PEG* is Easton (2004) price-earnings-growth ratio. *ICC_GM* has 759 observations; 358 for ERM = 1 and 401 for ERM = 0. *ICC_PEG* has 756 observations; 354 for ERM = 1 and 402 for ERM = 0. *ERM* is an indicator variable coded equal to 1 for the year of ERM adoption and all following years, and 0 otherwise. ERM classification is based on a comprehensive search of SEC filings, annual reports, newswires, and other media. *Beta* is the capital market beta based on the market model; *Beta* is estimated with a minimum of 24 monthly returns over the 60 prior months and the value-weighted market index. *Size* is measured as the natural logarithm of the book value of equity. *Leverage* is the ratio of the book value of liabilities to the market value of equity. *BooktoMkt* is defined as the ratio of the book value of equity to market value of equity. *Foredispers* is calculated as the natural logarithm of the standard deviation of the analyst earnings forecasts for the next year divided by the consensus earnings estimate for the same period. *LongGrow* is the firm's mean long-term growth rate from I/B/E/S. *Dividend* is an indicator coded equal to 1 if a firm paid dividends in a particular year, and 0 otherwise. *Sector_ICC* is the average implied cost of equity capital in the following three sectors of the insurance industry: the life sector (NAICS code = 524113), the health sector (NAICS code = 524114), and the property–casualty (P/C) sector (NAICS code = 524126, 524127, 524128, or 524130). *RecentM&A* is equal to the ratio of intangible assets to the book value of assets. *OthIndus* is an indicator variable coded equal to 1 for firm-years with positive sales outside the insurance industry (NAICS code < 524100 or > 524199), and 0 otherwise. *Divers* is equal to the complement of the Herfindahl index of net premiums written across the different lines of insurance. *PCPrem, LifePrem,* and *HlthPrem* are indicators coded equal to 1 if a firm has positive net premiums written in the P/C, life, and health insurance sectors, respectively. *Reinsuse* is equal to the ratio of reinsurance ceded to the sum of direct premiums written and reinsurance assumed. *Slack* is the ratio of cash and short-term investments to the book value of assets. *CV(EBIT)* is the coefficient of variation of quarterly earnings before interest and taxes of the previous 3 years. *ValueChange* is defined as (firm value$_t$ − firm value$_{t-1}$)/firm value$_{t-1}$. Accounting and market data are collected from the Compustat Industrial and the Compustat Segments databases. Insurance specific accounting data are from statutory filings of insurance companies with the National Association of Insurance Commissioners. Firm and market returns are taken from the CRSP monthly stock database. Analysts' forecasts are collected from I/B/E/S. Statistical significance of difference in means is based on a *t*-test. Statistical significance of difference in medians is based on a nonparametric Wilcoxon rank sum test. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

47percent of the firm-year observations in our sample are from firms with an ERM program.[24]

Table 4 also reports differences in the means and medians of the variables across ERM adoption status. ERM adopters differ substantially from nonadopters. Contrary to our hypothesis, ERM adopters have, on average, a higher implied cost of capital than nonadopters. However, when interpreting this result, it is important to keep in mind that a univariate analysis does not control for time-trends and other factors that may also affect firms' cost of capital. On average, ERM adopters tend to have a larger market beta, higher leverage, and a higher book-to-market ratio, and more ERM adopters than nonadopters pay dividends. All these characteristics may also contribute to a higher cost of capital.

Results

Table 5 presents the results of the maximum-likelihood treatment effects model that simultaneously estimates Equations (4) and (5). The estimation results for Equation (4), which models firms' implied cost of capital as a function of the ERM adoption indicator and other firm-specific control variables, are reported in the first column. Most importantly, the coefficient of the *ERM* indicator is negative and significant at the 1 percent level. This negative coefficient indicates that firms with an ERM program have on average a 1.999 percent lower cost of capital than firms without an ERM program, after controlling for other firm-level determinants of the cost of capital as well as firms' self-selection of an ERM program.[25] Consistent with the theoretical predictions, a number of our control variables are also significantly related to firms' cost of capital. The coefficient of the *Beta* variable is positive and significant, indicating that firms with larger systematic risk face a higher cost of capital. We find a positive relationship between the *Leverage* variable and firms' cost of capital, supporting Modigliani and Miller's (1958) prediction. The *BooktoMkt* variable and the *Dividend* variable are positively associated with firms' cost of capital, consistent with the notion that firms with a high book-to-market ratio and firms that pay dividends are relatively mature firms with high systematic risk and time-varying risk. Consistent with prior empirical studies, firms with a lower dispersion in analyst forecasts and firms operating in an industry sector with a higher average cost of

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[24]In Hoyt and Liebenberg's (2011) sample, for example, ERM users account for only 8.5 percent of the firm-year observations.

[25]We perform a number of robustness checks. Following Hoyt and Liebenberg (2011), we estimate the treatment effects model with 10 different specifications of the ERM equation, while holding the specification of the ICC equation constant. The first specification of the ERM equation only includes four identifying variables from the baseline model, namely *RecentM&A*, *PCPrem*, *LifePrem*, and *HlthPrem*. The other specifications stepwise add the remaining ERM determinants. The coefficient of the ERM indicator variable is negative and significant in all 10 regressions. In addition, we estimate 8 alternative specifications of the ICC equation, leaving the ERM equation unchanged. The first ICC equation specification only includes the size variable and the ERM indicator. We then iteratively add additional control variables. Again, the negative relationship between ERM adoption and a firm's cost of capital is robust to all of these alternative specifications. These results are available upon request.

TABLE 5
Full Maximum-Likelihood Treatment Effects Estimates

	ICC (Equation (4))	ERM (Equation (5))
ERM	−0.01999 (0.00556)***	
Beta	0.00569 (0.00293)*	
Size	0.00145 (0.00119)	0.62252 (0.09195)***
Leverage	0.00070 (0.00025)***	−0.03085 (0.01363)**
BooktoMkt	0.01915 (0.00554)***	0.25388 (0.36484)
Foredispers	−0.00230 (0.00115)**	
LongGrow	0.00155 (0.00031)***	
Dividend	0.00673 (0.00372)*	
Sector_ICC	0.45968 (0.21060)**	
RecentM&A		−4.87296 (1.38893)***
OthIndust		1.75033 (0.37770)***
Divers		−0.96251 (0.43328)**
PCPrem		1.24564 (0.27293)***
LifePrem		−0.63326 (0.25734)**
HlthPrem		1.90739 (0.44391)***
Reinsuse		−0.04721 (0.50172)
Slack		−1.70193 (0.99330)*
CV(EBIT)		−0.00056 (0.00617)
ValueChange		−0.18850 (0.17460)
Constant	−0.00207 (0.02558)	−4.06877 (0.94523)***
No. of observations		761
No. of clusters		132
Log pseudolikelihood		1610.23
Wald test of independent equations		19.93*

Alternative ICC Measures:	ICC_GLS	ICC_GOR	ICC_GM	ICC_PEG
ERM	−0.01144** (0.00495)	−0.02550*** (0.00745)	−0.03013*** (0.01022)	−0.02652*** (0.00702)

Notes: The two-equation treatment effects model is defined as: $ICC_{i,t+1} = X_{it}\beta + \delta ERM_{it} + \varepsilon_{it}$, where ERM adoption is modeled as a latent unobservable variable $ERM_{it}^* = \omega_{it}\gamma + u_{it}$. ω_{it} is a vector of firm variables. Year dummies are included in both equations, but not reported. The two equations are jointly estimated with the maximum-likelihood method. Standard errors are adjusted for firm-level clustering and are reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively. The bottom panel presents coefficient estimates of the *ERM* indicator using the following alternative cost of capital measures as dependent variable in Equation (4): Gebhardt, Lee, and Swaminathan's (2001) measure (*ICC_GLS*), Gordon and Gordon's (1997) measure (*ICC_GOR*), Gode and Mohanram's (2003) measure (*ICC_GM*), and Easton's (2004) price-earnings-growth ratio (*ICC_PEG*).

capital seem to have a higher cost of capital. We also find a positive relationship between firms' forecasted long-term growth rate and their cost of capital. The Wald test for independent equations rejects the null hypothesis that the error terms of the two equations are uncorrelated and, hence, justifies a joint estimation. The fact that a number of firm characteristics are significantly related to firms' ERM adoption decision further supports a two-equation model. More precisely, the results of the ERM equation provide evidence that *Size*, *Leverage*, *RecentM&A*, *OthIndust*, *Divers*, *PCPrem*, *LifePrem*, *HlthPrem*, and *Slack* are significantly associated with firms' use of ERM.[26]

We also estimate the treatment effects model with the implied cost of capital measures developed by Gordon and Gordon (1997), Gebhardt, Lee, and Swaminathan (2001), Gode and Mohanram (2003), and Easton (2004) separately in addition to our average cost of capital measure. The coefficient estimates of the *ERM* indicator are presented in the bottom panel of Table 5. The coefficients are all significant and range from −1.144 percent to −3.013 percent, indicating that firms with an ERM program have a 1 percent to 3 percent lower cost of capital than firms without an ERM program.

On Reverse Causality

A negative relationship between ERM adoption and firms' cost of capital could just be driven by a higher likelihood of firms with relatively low cost of capital to adopt ERM. To investigate this reverse causality argument, we estimate a logistic regression model of the ERM indicator variable on past levels of firms' cost of capital. We adjust standard errors for firm-level clustering. In the five different specifications of the model, we use firm's 1-year lagged *ICC* variable and then add successively the 2-, 3-, 4-, and 5-year lagged *ICC*. All five model specifications include all independent variables from the first-stage ERM equation of the treatment effects model as well as year indicators as control variables. The results are reported in Table 6. The coefficients of 1-, 2-, and 3-year lagged cost of capital levels are either insignificant or positive and significant in these regressions, making reverse causality unlikely.

TREATMENT EFFECTS REGRESSION WITH SURVIVAL DATA SET

The use of binary choice models for studying the determinants of ERM adoption has been criticized in the literature (see, e.g., Pagach and Warr, 2011). The estimation of a logit or probit model assumes that all the observations of a firm are independent. This assumption implies that the firm makes a separate ERM adoption decision every year, or in other words that the firm can switch back and forth between having and not having an ERM program every year. However, starting an ERM program requires a substantial investment, and firms making that initial investment commit to the ERM approach in the long term. When coding the ERM indicator, we could not identify a single firm that discontinued its ERM program. Therefore, a model of the determinants of ERM adoption should just focus on the one-time decision to adopt

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[26]The results are robust to adding the *Divers* variable as a measure of firm diversification to the ICC equation. The coefficient of *Divers* is insignificant and all other coefficients stay qualitatively the same.

TABLE 6
Logit Regression of the ERM Indicator on Lagged ICC Levels

	(1) ERM	(2) ERM	(3) ERM	(4) ERM	(5) ERM
ICC_{t-1}	21.0457***	18.0654***	16.6542***	23.8844**	22.8203
	(5.1579)	(4.5510)	(5.0774)	(12.0655)	(15.2175)
ICC_{t-2}		6.5371	8.6901*	9.4954	21.4246*
		(8.0250)	(5.1238)	(5.9647)	(12.7293)
ICC_{t-3}			−0.0413	12.1055**	15.1561***
			(7.5466)	(6.0411)	(5.6555)
ICC_{t-4}				−16.0169*	5.2949
				(8.4111)	(10.6625)
ICC_{t-5}					−28.9009**
					(11.8075)
All control variables from the ERM Equation (5) included	Yes	Yes	Yes	Yes	Yes
Constant	−9.4956***	−9.8632***	−8.6016***	−8.4118***	−9.2795***
	(2.0547)	(2.2688)	(2.2059)	(2.3450)	(2.8384)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
No. of observations	732	685	647	600	534
No. of clusters	129	121	113	102	86
Log pseudolikelihood	−214.3	−200.7	−189.0	−163.3	−127.3

Notes: ICC is firm's *ex ante* implied cost of equity capital (ICC) calculated as the average of *ICC_GLS, ICC_GOR, ICC_GM,* and *ICC_PEG*. All the control variables from the *ERM* Equation (5) are included, but are not reported. Standard errors are adjusted for firm-level clustering, and are reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

ERM. Hazard models and dynamic binary choice models based on so-called survival data sets have such a focus on the determinants of one-time events (Shumway, 2001). The main characteristic of a survival data set is that it includes firm-year observations of firms before a firm-specific event (e.g., ERM adoption) occurs, that it includes observations of firms in the year the event occurs, but that observations of firms after the occurrence of the event are dropped from the sample.

Since our treatment effects model specification basically uses a binary choice model for the first-stage ERM equation, it is subject to the same criticism as stand-alone models on ERM adoption. To show the robustness of our results, we therefore create a survival data set by removing firm-year observations of ERM adopting firms in the years after ERM adoption from the sample. We then re-estimate the treatment effects model with this survival data set. The downside of such an approach is a further reduction in sample size and, hence, statistical power. The survival data set consists of 100 firms, or 449 firm-year observations.

Table 7 reports the results of the treatment effects model with the survival data set. The coefficients and signs are very similar to those estimated with the full sample.[27] Most importantly, we still find the significantly negative relation between *ICC* and the *ERM* indicator. The difference in the cost of capital between ERM users and nonusers is 2.669 percentage points for the average measure and ranges from −1.879 percent to −3.884 percent for the four individual cost of capital measures. These estimates are over 0.5 percent larger than the estimates from the full sample.

Analyst Forecast Biases

A potential source of imprecision of implied cost of capital measures is biases in analyst forecasts. Following Hann, Ogneva, and Ozbas (2013), we employ two approaches to address this concern. First, we control for analyst forecast biases in our treatment effects regressions by including 1- and 2-year-ahead unexpected analyst forecast errors as well as the average of the 1- and 2-year-ahead expected analyst forecast errors as control variables in the model. Expected forecast errors are derived from a prediction model of actual forecast errors, and unexpected errors are the difference between actual errors and predicted errors (Ogneva, Subramanyam, and Raghunandan, 2007).[28] Our main result does not change when including these

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[27]Note that we dropped the *OthIndust* variable from the model. The standard error of this variable could not be estimated with the reduced sample.

[28]We estimate the following model of analyst forecast errors separately for 1- and 2-year-ahead forecast errors for our 1996 through 2012 sample: $Ferr_i = \beta_0 + \beta_1 \Delta PPE_i + \beta_2 LTG_i + \beta_3 FEP_i + \beta_4 Rev1_i + \beta_5 Rev2 + \beta_6 Ret_i + \varepsilon_i$, where $Ferr_i$ denotes the 1- or 2-year-ahead analyst forecast error calculated as actual I/B/E/S earnings per share (EPS) minus either the 1- or 2-year-ahead median EPS forecast issued in June of year $t+1$ ("forecast date"), scaled by the stock price on the "forecast date"; ΔPPE_i is the change in property, plant, and equipment (Compustat item "PPEGT") over year t scaled by the beginning-of-year total assets (Compustat item "AT"); LTG_i is the median long-term growth in earnings forecast on the "forecast date"; FE_P_i is the forward earnings-to-price ratio, defined as the 1-year-ahead median EPS forecast issued on the "forecast date," divided by the stock price on the "forecast

TABLE 7
Full Maximum-Likelihood Treatment Effects Estimates (Survival Data Set)

	ICC (Equation 1)		ERM (Equation 2)
ERM	−0.02669 (0.00707)***		
Beta	0.00073 (0.00419)		
Size	−0.00075 (0.00127)		0.45845 (0.08486)***
Leverage	0.00116 (0.00027)***		−0.01965 (0.01895)
BooktoMkt	0.01483 (0.00612)**		0.67827 (0.43105)
Foredispers	−0.00319 (0.00133)**		
LongGrow	0.00157 (0.00050)***		
Dividend	0.00025 (0.00425)		
Sector_ICC	0.44523 (0.23265)*		
RecentM&A			−3.43272 (1.18648)***
Divers			−1.08909 (0.40113)***
PCPrem			0.89015 (0.29029)***
LifePrem			−0.39846 (0.23336)*
HlthPrem			1.32138 (0.50592)***
Reinsuse			−0.56687 (0.49090)
Slack			−0.93974 (1.02703)
CV(EBIT)			0.01011 (0.00578)*
ValueChange			0.14342 (0.21971)
Constant	0.01698 (0.03487)		−4.24730 (1.04134)***
No. of observations		449	
No. of clusters		100	
Log pseudolikelihood		1015.72	
Wald test of independent equations		16.30***	

Alternative ICC Measures:	ICC_GLS	ICC_GOR	ICC_GM	ICC_PEG
ERM	−0.02094*** (0.00422)	−0.03884*** (0.00789)	−0.01879** (0.00862)	−0.02766** (0.01107)

Notes: The survival data set is created by removing firm-year observations of ERM adopting firms in the years after ERM adoption from the sample. The data, hence, just include the first year in which a firm adopts ERM as well as all observations with ERM = 0. The two-equation treatment effects model is defined as: $ICC_{i,t+1} = X_{it}\beta + \delta ERM_{it} + \varepsilon_{it}$, where ERM adoption is modeled as a latent unobservable variable $ERM_{it}^* = \omega_{it}\gamma + u_{it}\cdot\omega_{it}$ is a vector of firm variables. The *OthIndust* variable is not included in the model; the standard error of this variable could not be estimated with the reduced sample. Year dummies are included in both equations, but not reported. The two equations are jointly estimated with the maximum-likelihood method. Standard errors are adjusted for firm-level clustering, and are reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively. The bottom panel presents coefficient estimates of the *ERM* indicator using the following alternative cost of capital measures as dependent variable in Equation (4): Gebhardt, Lee and Swaminathan's (2001) measure (*ICC_GLS*), Gordon and Gordon's (1997) measure (*ICC_GOR*), Gode and Mohanram's (2003) measure (*ICC_GM*), and Easton's (2004) price-earnings-growth ratio (*ICC_PEG*).

additional control variables in the treatment effects regression models for the full sample and the survival sample (see Table 8, Panel A): the coefficient of the ERM variable continues to be negative and significant, indicating that ERM adoption is associated with a reduction in firms' cost of capital.

Second, Easton and Monahan (2005) document that the reliability of implied cost of capital measures increases with the accuracy of analyst forecasts. Therefore, we sort our sample based on the absolute value of the 1-year-ahead forecast errors, split the sample into two parts, and estimate the treatment effects regression model separately for the two subsamples. While the coefficient of the ERM variable is negative and significant ($\beta = -0.02365$) for the subsample with low absolute forecast errors, the coefficient is insignificant for the subsample with high absolute forecast errors (see Panel B of Table 8). These results suggest that our main finding that ERM reduces firms' cost of capital is unlikely driven by measurement errors in the implied cost of capital measures due to analyst forecast biases. Rather, measurement errors may weaken our results.

ENDOGENOUS TREATMENT EFFECTS IN THE POTENTIAL-OUTCOMES FRAMEWORK

The potential-outcomes framework provides an alternative approach to estimate treatment effects that builds on the statistical tradition of randomized experiments (Guo and Fraser, 2015). The advantage of randomized experiments is that statistical difference tests can be performed virtually without assumptions. If treatment assignment is based on covariates that also influence the outcome measure, a simple test for differences in means is invalid. The main idea of the potential-outcomes approach is to compare treated (and untreated) observations with estimated counterfactuals based on potential outcomes, that is, the potential outcomes had only the treatment assignment been changed. Counterfactuals for treated (untreated) observations are derived from untreated (treated) observations that are similar with respect to their covariates. Note that the potential-outcomes approach is often referred to as propensity score analysis because many specific estimators condense the information included in the covariates to a one-dimensional score, the so-called propensity score, defined as the probability of assignment to the treatment group conditional on a vector of observable covariates (Guo and Fraser, 2015). All variables that simultaneously influence the treatment assignment and the outcome variable have to be included in the estimation of the counterfactuals (Caliendo and Kopeinig, 2008, p. 35); standard estimators do not use the identifying variables that are only included in the first stage of a two-equation treatment effects regression model to derive counterfactuals.

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date"; $Rev1_i$ is the revision in the 1-year-ahead consensus forecast over the 3 months prior to the "forecast date," scaled by the stock price on the "forecast date"; $Rev2_i$ is the revision in the 2-year-ahead consensus forecast over the 3 months prior to the "forecast date," scaled by the stock price on the "forecast date"; and Ret_i is the stock return over the 12 months prior to the "forecast date." The predicted values of these two regressions are our estimates of the 1- and 2-year-ahead expected analyst forecast errors. Since the 1- and 2-year-ahead expected analyst forecast errors are highly correlated, we calculate the average of these two variables and use the average as a control for expected forecast errors in our regression models.

TABLE 8
Full Maximum-Likelihood Treatment Effects Estimates: Analyst Forecast Bias

Panel A: Controlling for Analyst Forecast Errors

	Full Sample	Survival Datat Set
	ICC (Equation (4))	
	(1)	(2)
ERM	−0.02062***	−0.02466***
	(0.00545)	(0.00716)
Pred_FerrAvg	−0.03151	−0.06670
	(0.07816)	(0.09049)
Unexp_Ferr1	−0.01544	0.00468
	(0.04614)	(0.03856)
Unexp_Ferr2	−0.15384***	−0.20401***
	(0.03350)	(0.04207)
All control variables from the ICC Equation (4) included	Yes	Yes
Constant	−0.03619	−0.03119
	(0.02884)	(0.03810)
Year fixed effects	Yes	Yes
No. of observations	469	278
No. of clusters	79	60
Log pseudolikelihood	1,011.21	657.26
Wald test of independent equations	23.63***	13.36***

Panel B: Partitions Based on Absolute Forecast Errors

	Below Median	Above Median
	ICC (Equation (4))	
	(3)	(4)
ERM	−0.02365**	0.02344
	(0.00947)	(0.01552)
All control variables from the ICC Equation (4) included	Yes	Yes
Constant	0.02059	−0.01657
	(0.04269)	(0.03784)
Year fixed effects	Yes	Yes
No. of observations	250	249
No. of clusters	72	74
Log pseudolikelihood	535.15	534.12
Wald test of independent equations	5.40**	1.21

Notes: This table presents treatment effects regressions of firm's *ex ante* implied cost of capital (ICC) on the ERM indicator, controlling for effects of analyst forecast errors. The two-equation treatment effects model is defined as: $ICC_{i,t+1} = X_{it}\beta + \delta ERM_{it} + \varepsilon_{it}$, where ERM adoption is modeled as a latent unobservable variable $ERM_{it}^* = \omega_{it}\gamma + u_{it}$; ω_{it} is a vector of firm variables. The two equations are jointly estimated with the maximum-likelihood method. Only the results of the ICC equation are presented. Panel A reports the results adding expected and unexpected forecast errors as additional controls to the ICC Equation (4). Columns (1) and (2) present the results based on the full sample and survival data set, respectively. *Pred_FerrAvg* is the average of the 1- and 2-year-ahead expected analyst forecast errors. The expected forecast errors are estimated using the prediction model based on Ogneva, Subramanyam, and Raghunandan (2007) and Hann, Ogneva, and Ozbas (2013). *Unexp_Ferr1* (*Unexp_Ferr2*) is the 1- (2-) year-ahead unexpected analyst forecast error. The unexpected forecast errors are computed as the difference between realized errors and their predicted component. Panel B reports results of the treatment effects regression on two subsamples. Column (3) is estimated on observations with an absolute forecast error below the sample median, and column (4) is estimated on observations with an absolute forecast error above the sample median. All four models include the full set of control variables from the ICC Equation (4), but the coefficients are not reported. Standard errors are adjusted for firm-level clustering, and are reported in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

More recently, a new genre of treatment effects estimators emerged that allows for self-selection into treatment based on unobservable, idiosyncratic characteristics that also affect the outcome (see, e.g., Basu et al., 2007; Wooldridge, 2010). These methods include instrument variables in the propensity score regression model. We employ an extension of the regression adjustment estimator described in Wooldridge (2010). This estimator controls for endogeneity by including the residuals of the propensity score regression model as a regressor in the models for the potential outcomes.

Propensity score methods are designed for cross-sectional data. We follow Villalonga (2004), the one propensity score analysis with a panel data set we found. Our analysis is based on the survival data set that includes all firm-year observations before ERM adoption, the observations of firms in the year they adopt ERM, but not the observations of firms after ERM adoption. We calculate the propensity score as the predicted probability $\hat{p}(x, z)$ from a probit regression model of the ERM indicator on all explanatory variables (X) that appear in both Equations (4) and (5) as independent variables, namely, firm *Size*, *Leverage*, the book-to-market ratio, and the year dummies, as well as instrument variables (Z). We use two sets of instruments. First, we use all identifying variables from the ERM Equation (5) of the treatment effects regression model as instruments. Second, we use only the significant identifying variables in the ERM equation of the treatment effects regression with the survival data set (see Table 7). To ensure that ERM observations and non-ERM observations are comparable, we restrict the analysis to observations on the common support. More precisely, we determine the minimum of the propensity scores of the ERM observations as well as the minimum of the propensity scores of the non-ERM observations, and we drop all observations with propensity scores below the maximum of the two minimums. Similarly, we drop all observations with propensity scores above the minimum of the two maximums of ERM and non-ERM observations.

Table 9 presents the results. We explicitly test for endogeneity and can reject the null hypothesis that treatment and outcome unobservables are uncorrelated at the 1 percent level. This test result indicates that the conditional mean independence assumption underlying all standard propensity score methods is violated. Therefore, basic propensity score matching would yield inconsistent estimates. The results of the endogenous treatment effects estimator are presented in column 2 of Table 9. For both sets of instrument variables, the average treatment effect on the treated (ATT) is approximately −3.7 percent and significant at the 5 percent level, supporting our hypothesis that ERM adoption reduces the cost of capital. For ERM adopters the average cost of capital would be approximately 13.7 percent if none of these firms adopted ERM, and ERM adoption reduces their cost of capital by 3.7 percent to roughly 10 percent.[29]

The bottom panel of Table 9 presents ATTs for the four cost of capital measures of Gordon and Gordon (1997), Gebhardt, Lee, and Swaminathan (2001), Gode and Mohanram (2003), and Easton (2004); the ATTs range from −0.928 percent for the Gebhardt, Lee, and Swaminathan measure to −8.597 percent for the Gode and

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[29]These results stay qualitatively the same if we add the *Divers* variable as a measure of diversification to the models for the potential outcomes.

TABLE 9
Endogenous Treatment Effects

	ATT	p-Value	Potential Outcome Mean (ERM = 0)	p-Value	Test of Endogeneity (χ^2)	p-Value
All variables from ERM Equation (5) used to derive propensity scores	−0.03762** (0.01670)	0.024	0.13694*** (0.01561)	0.000	22.98***	0.000
Significant variables from ERM equation of treatment effects regression with survival dataset used to derive propensity scores	−0.03734** (0.01671)	0.025	0.13667*** (0.01562)	0.000	19.91***	0.000

Alternative ICC Measures:	ICC_GLS	ICC_GOR	ICC_GM	ICC_PEG
ATT (all control vars.)	−0.00928 (0.00991)	−0.03498* (0.02038)	−0.08597*** (0.02653)	−0.02024 (0.02229)
ATT (significant control vars.)	−0.00644 (0.00983)	−0.03413* (0.01994)	−0.07903*** (0.02710)	−0.01881 (0.02257)

Notes: Average treatment effect on the treated (ATT) are based on an extension of the regression adjustment estimator described in Wooldridge (2010). This estimator controls for endogeneity by including the residuals of the the propensity score regression model as a regressor in the models for the potential outcomes. The test for endogeneity is based on the null hypothesis that treatment and outcome unobservables are uncorrelated. The potential outcome mean describes the average cost of capital for ERM adopters if none of these firms adopted ERM. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively. The bottom panel presents ATT estimates using the following alternative cost of capital measures: Gebhardt, Lee and Swaminathan's (2001) measure (*ICC_GLS*), Gordon and Gordon's (1997) measure (*ICC_GOR*), Gode and Mohanram's (2003) measure (*ICC_GM*), and Easton's (2004) price-earnings-growth ratio (*ICC_PEG*).

Mohanram measure. Only the ATTs based on Gordon and Gordon's (1997) and Gode and Mohanram's (2003) cost of capital measures are significant, indicating that the endogenous treatment effects results may be more sensitive to modeling assumptions of the implied cost of capital measures than the treatment effects regression estimates.

CONCLUSION

ERM is a process that manages all risks faced by the firm in an integrated, holistic fashion. There is empirical evidence that ERM is associated with improvements in firm performance and increases in firm value. We take the positive valuation effect of ERM as given and focus on the fundamental question of how ERM can create value. We specifically focus on the relationship between ERM adoption and firms' cost of external financing, and investigate whether ERM adoption is negatively associated with the cost of equity capital. Such a research design allows us to evaluate whether cost of capital benefits are one mechanism for value creation by the ERM approach.

Our analysis is based on the sample of publicly traded U.S. insurance companies; focusing on just one industry avoids possible spurious correlations caused by unobservable differences across industries. We calculate firm's cost of capital based on implied cost of capital models, which equate the firm's market value of equity with its discounted future cash flow estimates and solve for the required internal rate of return. We then test for an abnormal reduction in the cost of capital around the year of ERM adoption, and estimate a two-equation treatment effects model to assess the effect of ERM on firms' cost of capital. In both tests, ERM adoption is significantly associated with a reduction in firms' cost of capital. These results are also economically significant; at least one-quarter of the total increase in firm value due to ERM adoption documented by Hoyt and Liebenberg (2011) can be attributed to a reduction in the cost of capital.

It would be interesting to distinguish between the different mechanisms that may result in a reduction in firms' cost of capital after ERM adoption and to examine which of those mechanisms is relatively more important. We leave that question for future research.

APPENDIX

TABLE A1
Detailed Description of Individual ICC Measures

ICC	Formula and Assumptions	Source
GLS	$P_t = B_t + \sum_{i=1}^{11} \frac{FROE_{t+i}-r_{GLS}}{(1+r_{GLS})^i} B_{t+i-1} + \frac{FROE_{t+12}-r_{GLS}}{r_{GLS}(1+r_{GLS})^{11}} B_{t+11}$ where, P_t is the price per share of common stock in year t, r_{GLS} is the implied cost of equity capital, B_t is the book equity value	Gebhardt, Lee, and Swaminathan (2001)

(*Continued*)

TABLE A1
Continued

ICC	Formula and Assumptions	Source

per share, $(FROE_{t+i} - r_{GLS}) \times B_{t+i-1}$ is the residual income in year $t+1$, and $FROE_{t+i}$ is the expected return on book equity. Book equity is determined based on clean surplus accounting, that is, $B_{t+i} = B + FEPS_{t+i} \times (1-k)$, where, k is the current dividend payout ratio defined as the ratio of the actual dividends from the most recent fiscal year divided by earnings over the same time period for firms with positive earnings, or divided by 0.012 (0.034) × total assets for life (non-life) insurers with negative earnings. For the first 3 years, the expected return on book equity is approximated using analysts' earnings forecasts. More precisely, $FEPS_1$ and $FEPS_2$ are equal to the 1- and 2-year-ahead consensus earnings per share (EPS) forecasts, $FEPS_3$ is equal to $FEPS_2 \times (1 + LTG)$, where LTG is the long-term growth EPS forecast. From year $t+4$ to year $t+12$, earnings are implicitly forecasted by mean reverting $FROE_{t+3}$ to $FROE_{t+12}$, which is assumed to be the industry median ROE for the prior 5 years (excluding loss firm-years) on a rolling window basis. Life and non-life insurers are treated as separate industries; simple linear interpolation is used for the mean reversion process.

GOR $P_t = \sum_{i=1}^{5} \frac{FDPS_{t+i}}{(1+r_{GOR})^i} + \frac{FEPS_{t+5}(1+LTG)}{r_{GOR}(1+r_{GOR})^5}$ where, P_t is the price per share of common stock in year t, and r_{GOR} is the implied cost of equity capital. $FDPS_{t+i}$ is the expected dividend per share calculated as $FEPS_{t+i} \times (1-k)$, where, k is the current dividend payout ratio, defined as the ratio of the actual dividends from the most recent fiscal year divided by earnings over the same time period for firms with positive earnings, or divided by 0.012 (0.034) × total assets for life (non-life) insurers with negative earnings. $FEPS_{t+5}$ is the 5-year-ahead expected EPS, which are approximated by the 5-year-ahead consensus EPS forecast by analysts when available, and $FEPS_{t+i} = FEPS_t \times (1 + LTG)$ if $FEPS_t \geq 0$ when not available, where LTG is the long-term growth EPS forecast.

Gordon and Gordon (1997)

GM $P_t = \frac{FEPS_{t+1}}{r_{GM}} + \frac{FEPS_{t+2} - FEPS_{t+1} - r_{GM}(FEPS_{t+1} - FDPS_{t+1})}{r_{GM}[r_{GM} - (\gamma - 1)]}$ where, P_t is the price per share of common stock in year t, and r_{GM} is the implied cost of equity capital. $FEPS_{t+1}$ and $FEPS_{t+2}$ are equal to the 1- and 2-year-ahead consensus EPS forecasts. $FDPS_{t+1}$ is the expected dividend per share calculated as

Gode and Mohanram (2003)

(*Continued*)

TABLE **A1**
Continued

ICC	Formula and Assumptions	Source
	$FEPS \times (1-k)$, where k is the current dividend payout ratio, defined as the ratio of the actual dividends from the most recent fiscal year divided by earnings over the same time period for firms with positive earnings, or divided by 0.012 (0.034) $\times$ total assets for life (non-life) insurers with negative earnings. $(\gamma - 1)$ is the constant perpetual earnings growth rate and is set equal to the 10-year Treasury Bond rates minus 3% for the period from 1996 to 2007 and minus the 10-year Treasury Inflation Protected Securities (TIPS) rates for the period from 2008 to 2012.	
PEG	$P_t = \frac{FEPS_{t+5} - FEPS_{t+4}}{(r_{PEG})^2}$ where, P_t is the price per share of common stock in year t, and r_{PEG} is the implied cost of equity capital. $FEPS_t$ and $FEPS_{t+4}$ are the 5- and 4-year-ahead expected EPS, which are set equal to the 5- and 4-year-ahead consensus EPS forecast by analysts when available, and $FEPS_{t+i} = FEPS_t \times (1 + LTG)$ if $FEPS_t \geq 0$ when not available, where LTG is the long-term growth EPS forecast. We require $FEPS_{t+5} \geq FEPS_{t+4} > 0$ to ensure the existence of a positive root for r_{PEG}.	Easton (2004)

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