ENTERPRISE RISK MANAGEMENT AND FIRM OPERATIONS:

EVIDENCE FROM INVENTORY MANAGEMENT

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Enterprise risk management (ERM) is a program that manages all firm risks in an integrated framework to control and coordinate offsetting risks. In this study, I provide the first archival evidence on how ERM affects firms' day-to-day, routine operations. Using hand-collected ERM adoption data and inventory information, I examine whether firms with an ERM program experience an improvement in their inventory management. My findings suggest that ERM adoption is associated with greater inventory turnover ratios and lower inventory impairments. These results are robust to a range of models in addressing endogeneity concerns. Additionally, I find that ERM's effect on inventory management is stronger among firms with greater financial distress, with less investments in innovation, or with higher information asymmetries, and when firms' ERM program grows more mature. My study documents ERM's real economic benefits to firms' operations and highlights how ERM contributes to operating performance.

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CHAPTER 1

INTRODUCTION

Enterprise risk management (ERM) utilizes an integrated framework to manage all risks faced by a firm in a risk portfolio. An ERM program enables effective and efficient use of firms' resources and reduces operational surprises and losses. Hence, ERM provides reasonable assurance for firms to achieve operations objectives (COSO 2004). ERM is also important in day-to-day operational decisions to accelerate firm growth and enhance performance (COSO 2017).

Prior research documents that ERM is associated with improvement in firm profitability ratios such as return on assets (ROA) and return on equity (ROE) (e.g., Callahan and Soileau 2017; Florio and Leoni 2017) as well as increased cost and revenue efficiencies for insurance companies (Grace, Leverty, Phillips, and Shimpi 2015). However, profitability and efficiencies are overall measures of firm operating performance. Firm operations span a wide range of activities, and it remains unknown which firms' day-to-day operation contributes to the improved performance associated with ERM. Without pinpointing the solid benefits, an ambiguous view of ERM's overall impact may restrain managers from perceiving ERM's real effects, resulting in a hesitance to adopt ERM or an underutilization of ERM in practice (Beasley, Branson, and Hancock 2015, 2020; Cohen, Krishnamoorthy, and Wright 2017). In this study, I open this black box by investigating *how* ERM substantiates the benefits to firm operations and examining ERM's real effects.

I focus on inventory management because it is vital to firm operations.[1] Best practices in firm operations rely on proper inventory management, requiring sufficient inventory to be available at the time that it is demanded by customers or required for production at reasonable

[1] Inventory is one of the most expensive assets of companies, representing as much as 50 percent of total invested capital (Heizer, Render, and Munson 2020).

costs (Gaur, Fisher, and Raman 2005). Firms with improved inventory management see enhancements in their core operations (Feng, Li, McVay, and Skaife 2015). Therefore, in this study I investigate whether ERM affects firms' day-to-day operations, focusing on inventory management, and shed some light on how ERM contributes to firm operating performance.

I expect ERM to improve firm inventory management and provide three theoretical arguments for the expectation. First, an ERM program strengthens risk control and coordinates risk management activities across business units (Ellul and Yerramilli 2013). Hence, ERM reduces operational risk due to inadequate or failed processes, people, and systems, or from external events (Girling 2013; Lam 2014). It helps smooth production, ease planning, and reduce operational surprises and losses in inventory transactions, tracking, shipping, and handling, making future inventory costs more predictable. Second, ERM focuses on strategic planning and long-term sustainability. It fosters a risk culture that fights against myopic activities and encourages innovation that involves short-run uncertainties but potential long-run gains (COSO 2017, 2018; Xu and Xie 2018). Innovation improves inventory management because innovative products and processes expedite selling and production cycles, which makes inventory purchase, tracking, and valuation more efficient (Lee, Zhou, and Hsu 2015). Third, ERM improves the information environment. ERM utilizes advanced risk identification and evaluation methods, such as PESTLE and SWOT, in analyzing the firm's external environment.[2] Hence, firms with ERM are better able to forecast future customer demands driven by varying customer tastes, or changes in demographics, technology trends, or social events (Ittner and Michels 2017; Elliott 2018). With

[2] PESTLE is an acronym for the external environment categories that the approach covers: political, economic, sociological, technological, legal, and environmental. It provides a framework to systematically investigate the impact of external events in these categories on a firm and its competitors. The SWOT approach incorporates the internal factors of strengths (S) and weaknesses (W) and the external factors of opportunities (O) and threats (T). The SWOT approach is often employed for each of the six PESTLE categories.

improved sales forecast, firms reduce the likelihood of inventory shortages, as well as the storage costs and risk of obsolescence and impairment associated with excess inventory (Yano and Lee 1995). Also, ERM reduces information asymmetries between firms and all parties involved in the supply chain including customers and suppliers. Enhanced communication and timely information sharing throughout the supply chain is key to effective inventory management because they help control expensive ordering capacity change adjustments including overtime, subcontracting, extra inventory, backorders, and equipment modifications (Cachón and Fisher 2000; DeHoratius and Raman 2008; Heizer et al. 2020).

To answer my research questions, I gather a sample of firms that appeared in the Standard and Poor's 500 index (S&P 500) for any fraction of time from 2001 to 2017, excluding the financial and utility industries. I hand-collect the ERM status for the sample firms systematically from newswire and firms' Securities and Exchange Commission (SEC) filings, complemented by Google searches. I code ERM as a binary variable that equals one in the years that a firm has an ERM program in place, and zero otherwise.

Following prior literature (Huson and Nanda 1995; Chen, Frank, and Wu 2005; Easton 2009; Feng et al. 2015), I use inventory turnover and inventory impairment to measure firm inventory management. I employ a FIFO (first in, first out) adjusted turnover ratio and industry-adjusted turnover ratio to measure inventory turnover, defined as the cost of goods sold divided by average inventory. Inventory impairment represents obsolete inventory with a lost market value that firms have to write down or write off. I manually search dozens of impairment-related keywords in firms' SEC filings and employ three measures: a dummy variable indicating whether an impairment exists, a continuous variable of impairment magnitude, and an industry-adjusted impairment magnitude.

My baseline regression models suggest that ERM significantly improves firm inventory turnover and reduces inventory impairment, controlling for a range of firm characteristics and internal control over financial reporting (ICFR).[3] My findings suggest that ERM increases the number of times inventory turned annually by around 23%, translating to 38.1 million U.S. dollars of cost saving. Also, ERM decreases the magnitude of inventory impairments by 3.03% of the average annual FIFO inventory, translating to a cost saving of nearly 50.9 million U.S. dollars.

I also find that ERM's effect on inventory management is more pronounced among firms with greater financial distress, with less investments in innovation, or with higher information asymmetries. The cross-sectional results provide empirical support to my three theoretical arguments for the relation between ERM and inventory management.

To address the endogeneity concerns of reverse causality and omitted variables, I use an instrumental variable approach (2SLS) and my results persist. Moreover, to alleviate the concern that firms self-select to adopt an ERM program, and that I use a linear probability model for an indicator in the first stage of 2SLS, I utilize a Heckman two-step model, also known as the treatment effect model, and my results still hold. Additionally, the propensity score matching analysis supports my findings that ERM improves inventory management.

To address the concern that my ERM measure is of a binary nature and has limited variation, I develop ERM maturity measures in an attempt to capture the quality of a firm's ERM implementation. The measures are based on the notion that a firm improves the quality of its ERM program over time through experimental learning and experience accumulation and sharing (Eckles, Hoyt, and Miller 2014; Eastman and Xu 2021). My results show that the economic

[3] ERM incorporates ICFR in its framework (COSO 2017) and literature (Feng el at. 2015) documents that ICFR improves inventory management. Hence, it is important to control for ICFR in our models to show that ERM has incremental effect on inventory management over ICFR.

benefits of ERM adoption on inventory management substantially increase over time when a firm's ERM program matures.

My research makes several contributions to the literature. First, to the best of my knowledge, this is the first archival study to empirically investigate the effect of ERM on firms' day-to-day, routine operations. It provides direct evidence on how ERM contributes to the improvement in firms' operating performance documented by prior literature (e.g., Callahan and Soileau 2017; Florio and Leoni 2017; Grace et al. 2015). Also, most existing studies on ERM focus on the financial sector (e.g., Hoyt and Liebenberg 2011; Baxter, Befard, Hoitash, and Yezegel 2013; Ellul and Yerramilli 2013; Bailey, Collins, and Abbott 2018), and whether the findings can be generalized to other industries is questionable (Eastman and Xu 2021). I extend the scope to firms in various industries and examine a research question that cannot be answered by the financial industry—whether ERM impacts the real economy. My results that ERM improves firms' day-to-day operations provide a positive answer to the question.

Further, despite prior evidence that ERM increases firms' overall value and performance, such as Tobin's Q, ROA, ROE, and efficiencies (e.g., Hoyt and Liebenberg 2011; Callahan and Soileau 2017), managers still hesitate to adopt ERM or underutilize ERM in practice (Beasley et al. 2015, 2020; Cohen et al. 2017). According to surveys that follow up for more than ten years (Beasley et al. 2015, 2020), one of the leading barriers for firms to embrace ERM is "lack of perceived value." The overall performance measures in prior literature only provide an overarching view of ERM's general impact, making it difficult for managers to truly perceive ERM's real effects. My findings that ERM improves inventory management pinpoint and substantiate the solid benefits of ERM to firm operations, helping managers perceive and appreciate the value of ERM.

Second, I contribute to the literature on firm operations and inventory management.

Operations research considers risk management in management science models (e.g., optimization, simulation, etc.) to develop specific operation decisions (such as the best ordering quantity and production planning under uncertainties) and suggests firms utilize the models in their operations (Wu and Olson 2008; Kim, Lu, Kvam, and Tsao 2011; Mirzapour Al-e-hashem, Malekly, and Aryanezhad 2011; Wu, Olson, and Dolgui 2015). Most of this literature utilizes case studies or field surveys (Choi, Ye, Zhao, and Luo 2015). However, it remains an empirical question whether firms with an ERM program *indeed* experience improvement in their operations when using such management science models in decision-making. I provide systematic archival evidence supporting the modeling work in operations research using a large panel of firms.

Most of the existing studies on inventory management come from industry-specific case studies, surveys, and questionnaires (e.g., Anderson, Fitzsimons, and Simester 2006; Blome and Schoenherr 2011), or examine the impacts of inventory management on firm performance (e.g., Huson and Nanda 1995; Chen et al. 2005; Alan, Gao, and Gaur 2014). The studies highlight the importance of effective inventory management. Thus, it is crucial to understand the driving force of effective inventory management. I extend the literature by presenting an institutional framework—ERM—that drives inventory management improvement.

Finally, I empirically support the notion that ERM is broader than ICFR in nature (COSO 2004; 2017) by delivering evidence that ERM further improves inventory management incrementally to ICFR. I argue that my sample of S&P 500 firms provides a clean setting to test the incremental effect of ERM over ICFR because these firms mostly have strong internal control so that ICFR should not matter for them.[4] My results indicate that ERM is broader in assuring the

[4] According to Table 2, over 96% of our sample firms do not have any internal control material weaknesses. Hence, we can attribute the effect of inventory management in our sample to ERM above and beyond internal control.

operations objectives that ERM and ICFR share in common, on top of the strategic objectives that ERM strives to achieve in addition to internal control (COSO 2004, 2013).[5] This finding is important since ERM is underemphasized and underutilized in practice by firm management and auditors (Cohen et al. 2017). Given the mandatory nature of firms' ICFR disclosures and voluntary ERM adoption, it calls for more attention from the standard-setters and practitioners.

The remainder of the dissertation is organized as follows. Chapter 2 reviews the literature on ERM and inventory management, and develops hypotheses. Chapter 3 describes my data and research design. Chapter 4 presents the results of my baseline regression model as well as cross-sectional analysis. Chapter 5 reports the tests to alleviate endogeneities. Chapter 6 investigates the impact of ERM maturity on inventory management. Chapter 7 tests if the results are robust to the use of impairment-related measures of inventory management performance, and Chapter 8 concludes.

[5] In the COSO (2004) ERM framework, ERM assists firms to achieve four categories of objectives: strategic, operations, reporting, and compliance. In the COSO (2013) internal control framework, internal control assists firms to achieve three categories of objectives: operations, reporting, and compliance.

CHAPTER 2

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

This chapter provides a review of relevant literature including a section on Erm literature and a section on inventory managmenet literature. In the last section, I develop the main hypothesis of my research.

2.1 Enterprise Risk Management Literature

ERM is a holistic risk management approach that employs an integrated framework to identify and address all types of risk that an organization might encounter (COSO 2004). ERM is a process applied in both strategy setting and throughout the firm that provides justifiable assurance regarding the achievement of firms' goals. To this aim, ERM defines a system of monitoring and learning that addresses internal control, strategy-setting, governance, communicating with stakeholders, and measuring performance (COSO 2017). While traditional risk management practices aim to manage risks within each business unit separately, ERM handles risks in an integrated framework across the entity (Nocco and Stulz 2006). As such, in contrast to the traditional methods that ignore potential across-silos offsetting risks, ERM utilizes natural hedges to effectively manage enterprise risks.

Earliest adoptions of ERM program date back to the 1990s and were concentrated among financial firms (i.e., insurers and banks). Later on, a series of major events attracted attentions towards risk management and accelerated the adoption of ERM among other industries. The corporate failures such as Enron and WorldCom in the early 2000s triggered the Sarbanes-Oxley Act of 2002. The financial crisis of 2007-2008 inspired regulators to raise risk management responsibilities of the board of directors and senior executives. In 2008, Standard & Poor's (S&P) included ERM adoption in its corporate credit ratings (S&P 2008). In 2010, the U.S. Securities and Exchange Commission (SEC) issued Rule 33-9089 that requires listing firms to disclose details about the Board of Directors' role in risk oversight as well as the firm's risk management approach in the proxy statements. Corporate failure incidences rooted in mismanagement of risks on the one hand, and the effectiveness of ERM programs on the other hand, convinced more managers to consider ERM seriously. By the end of 2017, more than 60% of S&P 500 firms have adopted ERM (see Figure 1).

ERM studies generally fall into three categories. First, studies investigating the factors that determine ERM adoption. These studies find a positive association between the decision to engage in ERM and factors such as firm size (Colquitt et al. 1999), leverage (Liebenberg and Hoyt 2003), board independence (Beasley et al. 2005), institutional ownership (Pagach and Warr 2011), and earnings volatility (Hoyt and Liebenberg 2011). Second, research that document the implications of ERM value creation. Hoyt and Liebenberg (2011) find empirical evidence that ERM adoption significantly increases Tobin's Q. Other studies show that not only the adoption, but also the quality (Baxter et al. 2013; Ai et al. 2018) and the maturity (Farrell and Gallagher 2015) of ERM programs are associated with higher Tobin's Q. The third group of studies aim to explain the mechanisms through which ERM creates value. Prior literature documents that ERM creates value through its negative association with stock return volatility risk (Eckles et al. 2014), default risk (Lundqvist and Vilhelmsson 2016), and cost of capital (Berry-Stölzle and Xu 2018), as well as its positive association with resilience to financial crisis (Aebi et al. 2012), cost efficiency, return on asset (Grace et al. 2015), transparency (Wade et al. 2015), and innovation efficiency (Xu and Xie 2018). Moreover, the adoption of ERM significantly improves the quality of financial reporting and internal controls (Cohen et al. 2017), reduce audit fees, audit delay, and the likelihood of late filing (Bailey et al. 2018), and deters financial reporting misconduct (Eastman et al. 2020).

Despite the steady surge in ERM adoption across diverse industries, existing literature mainly concentrates on financial firms and specifically insurance companies. The regulations specific to financial firms along with the unique risk-centric business model of insurance companies raise doubts regarding the implication of previously documented results among other industries. The generalizability of previous results is therefore limited, and further research on broader samples is called for.

2.2 Inventory Management Literature

Inventory management is vastly studied in accounting and operations management literature. Inventory turnover ratio—defined as the firm's cost of goods sold divided by average inventory holdings—is commonly used to measure inventory management performance, and to conduct industry competitive analysis (Easton 2009). Balakrishnan et al. (1996) show that inventory turnover is positively correlated with capital intensity and suggest that firms investing in more fixed assets need to generate higher inventory turnover in order to cover their high overhead costs. Gaur et al. (2005) document a negative association between inventory turnover and gross margin and explain that gross margin can be related to inventory turnover directly (through determining the optimal service level) or indirectly (through price, product variety, and product life cycle). Gaur and Kesavan (2009) report a positive association between sales growth and inventory turnover. Based on them, higher sales growth implies greater demand for products and hence lower inventory holdings. Feng et al. (2015) show that inventory turnover is negatively associated with sales volatility and explain that firms with highly volatile sales face uncertainty in demand and have difficulties holding efficient inventory levels. Feng et al. (2015) also document that the number of geographic and operating segments, firm age, and engagement in foreign sale are all negatively associated with inventory turnover. Lee et al. (2015) propose that more innovative firms have higher inventory turnover ratios.

The quality of internal control over financial reporting has a positive association with inventory turnover. Doyle et al. (2007) suggest that higher financial reporting quality improvers firms' inventory turnover. Feng et al. (2015) show that having inventory-related material weaknesses significantly decreases inventory turnover. They explain that since inventory-related material weaknesses indicate inaccuracy in inventory valuation or tracking, it is expected that managers, relying on this inaccurate information, make decisions that result in inefficient inventory management.

Another stream of research on inventory management seeks to predict future performance. Huson and Nanda (1995) find that, holding profit margins constant, higher inventory turnover ratios are associated with more profitable operations. Chen et al. (2005) show that firms with abnormally high inventory holdings have abnormally poor long-term stock returns. Alan et al. (2014) find that inventory productivity strongly predicts future stock returns. They show that a zero-cost portfolio consisting of long (short) position in highest (lowest) inventory productive firms earns more than 1% average monthly abnormal return.

2.3 Hypotheses Development

I expect that ERM improves inventory management and provide three theoretical arguments for the expectation. First, ERM involves an integrated risk management framework that mitigates firm operational surprises. ERM involves a strengthened risk identification technique and coordinates risk management activities across business units (Ellul and Yerramilli 2013). Hence, ERM adopters may spot certain previously overlooked operational hazards that fall into cracks of traditional risk silos and in a timelier manner, reducing their inventory holdings accordingly. Also, less surprises in operations and finances helps managers make more efficient decisions including those related to inventory management. Consistent with the view, operations research documents that ERM reduces firm operational risks (Mikes 2009; Huang et al. 2011; Blome and Schoenherr 2011).

Second, ERM adoption fosters innovative activities. ERM reduces the managerial short-termism problem through mitigating managers' career concerns, and increases managers willingness to make long-term beneficial strategic decisions such as engaging in innovative activities. Moreover, stakeholder orientation inherent in ERM framework cultivates a work environment of long-term commitment that encourages engagement in experimentation (Tian and Wang 2014; Flammer and Kacperczyk 2016), encouraging workers to adopt long-term horizons and create novel ideas (Turban and Greening 1997). Consequently, ERM triggers the creation and communication of new ideas, and enables managers to make more informed decisions regarding innovation projects and accelerate the turnover of innovative ideas (COSO 2012). Consistent with the view, Xu and Xie (2018) document a positive association between ERM adoption and innovation.

Balakrishnan et al. (1996) and Huson and Nanda (1995) show that adopting just-in-time (JIT) manufacturing, which is a type of process innovation that improves the supply chain, positively impacts inventory turnover. Lee et al. (2015) show that not only process innovation but also product innovation positively impacts inventory turnover ratio. Process innovation improves inventory turnover by facilitating ordering/delivery and generating flexible, collaborative, and team-oriented workflow, which expedites the operations and reduces inventory holdings in the production cycle (Lee et al. 2015). Moreover, if a process innovation reduces production costs through decreasing waste/buffer in operations, it will help the firm lower the price of its products and, ultimately, increase its sales. Product innovation involves introducing new products that satisfy everchanging customer demands, and therefore boosts sales. While sales increase may lead to an increase in inventory, such increase is usually less than proportional because of the economy of scale (Olivares and Cachón 2009) and inventory turns faster. Due to short product life cycles in recent decades, product innovation may have a short-term impact on inventory turnover. Yet, if the firm creates a work environment that consistently seeks making innovative products, one can expect impacts on inventory management to remain persistent.

Third, ERM improves external information environment and reduces information asymmetries between firms and stakeholders, including customers and suppliers in the supply chain. To keep inventory holdings at optimal levels, managers need to have access to accurate and punctual information on inventory holdings, transactions, tracking, shipping, and handling. Yet, many firms suffer from inaccurate inventory records. DeHoratius and Raman (2008) suggest that inventory auditing practices can improve the accuracy on inventory records. ERM requires regular internal auditing. Moreover, ERM assesses and incorporates firm-specific key risks in designing safety systems, employee training programs, procedures, and checks and balances. Consequently, ERM adoption improves the quality and accuracy of operational records including those related to inventory. Ineffective sharing of information throughout the supply chain is another factor that can deteriorate inventory management performance (Cachón and Fisher 2000). ERM reduces the information asymmetry among all stakeholders, including those within the supply chain. Enhanced communication and timely information sharing throughout the supply chain is key to effective inventory management because they help control expensive ordering capacity change adjustments including overtime, subcontracting, extra inventory, backorders, and equipment modifications (Cachón and Fisher 2000; DeHoratius and Raman 2008; Heizer et al. 2020).

Based on the above three arguments, I propose my first hypothesis as follows:

Hypothesis 1. ERM adoption improves inventory management.

Eckles et al. (2014) investigate the association between ERM adoption and stock return volatility, and show that the reduction in return volatility becomes stronger over time after the adoption of ERM. They argue that their results are consistent with anecdotal evidence that ERM implementation is a complicated process that matures over time and that it takes time for the adopters to fully realize the economic benefits of ERM. Based on this argument, I expect the impacts of ERM adoption on inventory management to intensify over time. This leads to my second hypothesis:

Hypothesis 2. As a firm's ERM program grows more mature over time, its impacts on inventory mangement become stronger.

CHAPTER 3

DATA AND RESEARCH DESIGN

This chapter provides information on the sources of data and describes the sample selection process, and the methodology used in my baseline analyses.

3.1 Data

Table 1 summarizes the sample selection procedure. I begin with a sample of 12,367 firm-year observations (864 unique firms) on all firms that appeared in the S&P 500 index during any fraction of time from 2001 to 2017. I apply certain sample screening procedures to the initial dataset. Following the inventory literature (i.e., Demerjian et al. 2012; Cheng et al. 2018), I remove financial firms (SIC codes 6000 to 6999; 2,234 observations on 158 unique firms) and utility firms (SIC codes 4900 to 4999; 838 observations on 56 unique firms) from the sample. Next, I drop observations with missing information on internal control variables (2,634 observations), resulting in an analysis period that begins in 2004.[6] Finally, I remove observations with missing values on explanatory variables (1,746 observations), yielding in the final sample of 4,915 firm-years (513 unique firms) from 2004 to 2017.

I use several sources to collect the data used in this study. I obtained firm financial statement data from Compustat annual and quarterly files, and business and geographic segments data from Compustat segments files. Data on daily stock return and firm age are attained from CRSP. I collect data on internal control material weakness from Audit Analytics and institutional ownership from firms' 13-F filings. I retrieve analysts' data from I/B/E/S.

[6] That is due to the fact that our sample firms, all of which are accelerated filers, have been subjected to Sarbanes-Oxley (SOX) Section 404(a) and 404(b) since 2004.

3.2 Construction of ERM Adoption Variable

I follow the ERM literature (Eckles et al. 2014; Berry-Stölzle and Xu 2018; Kamiya, Kang, Kim, Milidonis, and Stulz 2021) and construct an indicator variable to measure firms' ERM status. Specifically, I use the following phrases to capture signs of ERM adoption: "enterprise risk management," "chief risk," "risk committee," "risk management committee," "strategic risk management," "consolidated risk management," "holistic risk management," and "integrated risk management."[7] For all firm-years in my initial sample, I search for disclosure of any of the above-mentioned phrases in the news media captured by Factiva, supplemented by Google searches. I also search the U.S. SEC filings—including, but not limited to, 10-K, 8-K, and proxy statements—for the same set of phrases. Next, I manually review reports and news in chronological order to check for the earliest convincing implication of ERM adoption.[8] For ERM-adopters, I also check reports and news on years after the engagement of ERM and find that none of my sample firms have terminated their ERM programs at any later time. Figure 1 presents the historical trend of ERM adoption among S&P 500 firms in my final sample of 513 unique firms.

3.3 Methodology

As my main analysis, I use the following baseline regression to test for the association between adopting ERM and inventory turnover ratio.

$$InvtTurnRatio_{i,t} = \alpha + \delta ERM_{i,t-1} + \gamma ERM\_Ever_i + \beta Controls_{i,t-1} + Year\ Dummies + Industry\ Dummies + \varepsilon_{i,t} + \varepsilon_{i,t} \quad \text{(Eq. 1)}$$

In equation (1), firms and years are indexed by i and t, respectively, and $Controls_{i,t-1}$ represents the

[7] Instead of the term "chief risk officer" suggested in ERM literature, we use "chief risk" in order to capture other relevant terms such as "Chief Risk, Compliance and Ethics Officer", "Chief Risk and Strategy Officer", and "Chief Risk Management Officer".

[8] Manual screening is necessary as in many cases ERM-related terms are used, but in a different context.

following vector of independent variables:

$$Controls_{i,t-1} = [\ GrossMargin_{i,t-1},\ CapitalIntensity_{i,t-1},\ Size_{i,t-1},\ Book\text{-}to\text{-}Market_{i,t-1},\ ROA_{i,t-1},\ Loss_{i,t-1},\ SalesGrowth_{i,t-1},\ SalesVolatility_{i,t-1},\ Age_{i,t-1},\ ForeignSales_{i,t-1},\ Segments_{i,t-1},\ Auditor_{i,t-1},\ Invt\_MWIC_{i,t-1},\ \beta_{13}\ Rev\_MWIC_{i,t-1},\ \beta_{14}\ Other\_MWIC_{i,t-1}\ ] \qquad \text{(Eq. 2)}$$

Detailed descriptions of all the variables are presented in the appendix. In selecting the control variables, I follow Feng et al (2015). Since firms that are able to maintain high gross margins tend to have lower inventory turnover (Gaur et al. 2005), I expect the coefficient on *GrossMargin* to be significant and negative. Firms with high capital intensity need to maintain a high inventory turnover ratio to cover their overwhelming fixed costs (Balakrishnan et al. 1996) and hence I expect a significant and positive coefficient on *CapitalIntensity*. Gaur and Kesavan (2009) suggest that higher sales growth implies greater product demand and therefore lower inventory holdings. Consequently, I expect the coefficient on *SalesGrowth* to be significant and positive. I follow Feng et al (2015) and include other firm characteristics such as complexity (*Segments* and *ForeignSales*), firm age (*Age*), audit quality (*Auditor*), and resource availability (*ROA* and *Loss*) in my model, as well as three indicators that capture disclosures of material weaknesses over internal control (MWIC); inventory-related MWIC dummy (*Invt_MWIC),* revenue related MWIC dummy *(Rev_MWIC),* and the natural log of the number of other MWIC *(Other_MWIC)*. Feng et al (2015) document a negative association between inventory-related MWIC (*Invt_MWIC*) and inventory turnover ratio. Since ERM encompasses internal control within its framework (COSO 2004; Cohen et al. 2017) and has additional features that contribute further to the impact of ERM on inventory turnover, I do not expect the same results in my regression model.

In equation (1), *InvtTurnRatio* represents each of the following two dependent variables: 1) *Invt_Turnover,* defined as the cost of goods sold divided by average annual FIFO inventory, where the annual average is computed using beginning and ending FIFO inventory.[9] 2) *Invt_AdjTurn,* defined as the firm's *Invt_Turnover* less the median industry-year *Invt_Turnover*, where industry is defined using Fama and French 30-industry classification.[10, 11] I use equation (1) to run two separate OLS regressions using my two dependent variables.

My variable of interest, *ERM*, is a dummy variable that equals one if the firm has an active ERM program, and zero otherwise. With reference to Hypothesis (1), I expect δ to be significant and positive no matter which of the two dependent variables is used in equation (1). *ERM_Ever* is a time-invariant dummy variable that equals one if the firm has ever adopted ERM, and zero otherwise. *ERM_Ever* controls for the differences in time-invariant unobserved firm characteristics across firms with and without ERM program. By including both *ERM* and *ERM_Ever* in the regression, I isolate the incremental impact of ERM adoption on inventory turnover ratio. In addition to the control variables, I include both year and industry fixed effects (using Fama and French 30-industry classification) in my model, and cluster standard errors at the firm level.

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[9] Following Feng et al. (2015) we adjust all LIFO (last in, first out) inventory amounts to its FIFO (first in, first out) basis using the disclosure of LIFO reserves. Consistently, cost of goods sold and gross margin are also adjusted to their FIFO basis.

[10] Using *median* to define our industry-adjusted dependent variables is based on Feng et al. (2015). As a robustness check, we also define *Invt_AdjTurn* using industry-year *mean* and re-run all our tests. Results are robust to this change.

[11] Available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_30_ind_port.html

CHAPTER 4

RESULTS

In this chapter, descriptive statistics and baseline results are presented. Moreover, a cross-sectional analysis is provided with the aim to identify the channels through which ERM adoption impacts inventory management.

4.1 Descriptive Statistics and Univariate Analysis

Table 2 shows descriptive statistics for all variables used in the main analysis for the full sample. All continuous variables are winsorized at the 1st and 99th percentiles. *ERM* has a mean of 0.418 which implies that out of 4,915 firm-year observations in my sample, 2,053 observations have an active ERM program. In terms of the number of firms, 314 unique firms (61.2% of the total of 513 firms) in my sample have adopted ERM by the end of their 2017 fiscal year. The mean (median) for inventory turnover is 13.933 (5.525) which is very similar to the mean (median) of 14.032 (5.955) in Feng et al. (2015). The distributions of other key variables are comparable to those found in prior studies (e.g., Gaur et al. 2005; Feng et al. 2015) with the exception of material weaknesses variables. The frequency of observations with inventory (non-inventory) related material weakness over financial reporting in my study is 0.6% (2.8%); however, Feng et al. (2015) report the considerably larger rates of 1.8% (5.3%). This difference is consistent with prior literature. My sample focuses on extremely large (S&P 500) firms, and larger firms are more likely to have effective ICFR (Ashbaugh-Skaife et al. 2007; Doyle et al. 2007)

Table 3 reports descriptive statistics for firm-years with (column (I)) and without (column (II)) ERM program. Column (III) shows the differences in the means and medians across ERM status. The mean and median of *Invt_Turnover* and *Invt_AdjTurn* are significantly higher for ERM-adopter firm-years which is consistent with my hypothesis that the adoption of ERM is associated with higher inventory turnover ratios. Given the average annual FIFO inventory holdings of 1873.6 million dollars in my sample, the 2.155 (1.315) units difference in the means of *Invt_Turnover* (*Invt_AdjTurn*) between the two groups has economic significance as well.

While firm-years with an active ERM program consist 41.8% of my sample, they account for less than 17%, 16%, and 23% of observations with inventory-related, revenue-related, and other-related material weaknesses, respectively. These results imply that adopting ERM can considerably improve the quality of internal control over financial reporting, and hence, decrease incidences of material weaknesses.

Table 4 presents Pearson (top) and Spearman (bottom) correlations among the dependent variables, my main independent variable (*ERM*), and the rest of the independent variables. As expected, ERM adoption is positively correlated with inventory turnover. Moreover, consistent with the literature, I find gross margin and sales growth (capital intensity) to be negatively (positively) correlated with inventory turnover.

4.2 Baseline Regressions Results

Table 5 presents the results for my baseline regression, presented by equation (1), on the association between ERM adoption and inventory turnover. We find the coefficient on my ERM indicator variable (*ERM*) to be positive and significant (3.224 with a t-statistic of 2.23 when using *Invt_Turnover* as the dependent variable, and 3.066 with a t-statistic of 2.13 when using *Invt_AdjTurn* as the dependent variable). This result indicates that, consistent with Hypothesis 1, inventory turnover ratio - either unadjusted (column (I)), or industry-adjusted (column (II)) - is significantly higher for firms with an active ERM program. The magnitude of the coefficient suggests that the inventory turnover ratio of a firm with an active ERM program is, on average, about 3.2 units higher than that of a firm without an ERM program. Since the average inventory turnover ratio in my final sample is 13.933, the coefficient of 3.224 implies that for an average firm in my sample, adoption of ERM increases the number of times inventory is turned throughout the year by around 23% (= 3.224 / 13.933). This is equivalent to a decrease in days inventory outstanding from 26.2 days to 21.3 days. Given the average annual FIFO inventory holdings of 1,873.6 million dollars in my final sample, for an average firm in the sample, the adoption of ERM decreases annual FIFO inventory to 1,492.3 million dollars, all else equal.[12] Assuming a cost of capital of 10%, this translates to 38.1 million dollars of cost saving per year (= (1,873.6 - 1,492.3) × 10%).

The coefficients on *ERM_Ever* are insignificant suggesting that compared to non-ERM firms (*ERM_Ever* =0), ERM adapters (*ERM_Ever* =1) do not have a systematically higher inventory turnover ratio *prior to* their ERM adoption. As such, the reverse causality seems unlikely. Consistent with existing literature (Nissim and Penman 2001; Gaur et al. 2005; Feng et al. 2015), I find significant negative coefficients on *GrossMargin, Size, Book-to-Market, and Segments,* and significant positive coefficients on *CapitalIntensity* and *SaleGrowth*.

4.3 Cross-Sectional Tests

I propose that ERM improves inventory turnover through three channels and use cross-sectional settings to test my propositions. I define a proxy for each channel, and for each proxy, I divide my sample into high versus low subsamples where high (low) implies higher (lower) than the industry-year median value for that proxy. Next, I re-estimate equation (1) on each subsample, separately. Each panel of Table 6 represents one of the channels.

The first channel (Panel A) is related to the inherent risk management function of the ERM

[12] After-adoption inventory holdings = (13.933 / (13.933 + 3.224)) × 1,873.6 = 1,492.3 million U.S. dollars.

program. ERM provides the firm with an integrated framework that mitigates operational and financial surprises. Fewer surprises in operations and finances help managers make more efficient decisions including those related to inventory management. Firms under financial distress use aggressive pricing to convert their inventory holdings into cash (Hendel 1996; Whitaker 1999), and a reduction in inventory holdings is more noticeable among firms that manage to resolve their financial distress (Steinker et al. 2016). As such, I argue that ERM's function in reducing operational risk is more important in firms with financial distress than firms without it. Hence, I expect the impact of ERM adoption on inventory turnover to be more pronounced among firms with financial distress. I use Ohlson's O-score (Ohlson 1980; Griffin and Lemmon 2002) to measure financial distress. As Panel A of Table 6 shows, consistent with my arguments, estimated coefficients on *ERM* are positive and significant (insignificant) among firms with a higher (lower) probability of default. The coefficient difference between the two subsamples is significant at 1% level.

Fostering innovation is the second channel through which ERM adoption increases inventory turnover. ERM reduces the managerial short-termism problem through mitigating managers' career concerns and increases managers' willingness to make long-term beneficial strategic decisions such as engaging in innovative activities. ERM framework has built-in features that trigger persistent collaboration and renovation in operational processes, as well as a long-term strategic view towards product competition in the market. Hence, I expect ERM to facilitate innovation in both products and processes and consequently increase inventory turnover. Therefore, I propose that the impact of ERM adoption on inventory turnover should be more pronounced among firms that invest less in innovative activities. I use research and development expenditures scaled by sales (*R&DExpnd*) to measure investment in innovation. Panel B of Table

6 shows that coefficients on *ERM* are significant among firms investing less in innovation and insignificant among firms investing more in innovation. The coefficient difference between the two subsamples is significant at 5% level.

The role of ERM in enhancing the accuracy and availability of information builds the third channel that contributes to the impact of ERM adoption on inventory turnover. ERM provides managers with accurate and punctual information on inventory holdings, transactions, tracking, shipping, and handling, and integrates risk-adjusted information into future plans which itself reduces forecast errors (Ittner and Michels 2017) and enables managers to better plan for their inventory holdings. Consequently, ERM adoption improves the quality and accuracy of operational records including those related to inventory. Further, ERM reduces information asymmetries among all stakeholders, including those within the supply chain, improving inventory management performance (Cachón and Fisher 2000). Therefore, I expect the positive association between ERM adoption and inventory turnover to be more noticeable among firms with uncertain information environment. I use forecast dispersion (*ForecastDispersion*) as the proxy for information asymmetry, where greater forecast dispersion implies greater asymmetry. Panel C of Table 6 supports my expectation by showing significant (insignificant) estimated coefficients on *ERM* on the subsample with high (low) forecast dispersion.

CHAPTER 5

ADDITIONAL TESTS

One important concern with my results thus far is that the adoption of ERM is an endogenous choice by firms. If there are unobservable correlated omitted variables that affect both the choice of firm to adopt ERM and the firm's inventory turnover, then the documented association between *ERM* and inventory turnover in Table 5 could be biased and possibly spurious. To address endogeneity, I use instrumental variable estimation, treatment effect model, and propensity score matching.

5.1 Instrumental Variable Estimation

In my instrumental variable estimation, *ERM* is instrumented in the first-stage using the ratio of ERM adopters within a firm's industry in a particular year *(ERM_IndRatio)* as the instrumental variable. This instrument is likely to be positively correlated with *ERM* because a greater ratio of ERM adoption within the firm's industry peers increases the chance of adopting ERM. In addition to satisfying the relevance condition, the ERM adoption rate within the industry does not directly affect individual firms' inventory turnover. In that capacity, I suggest that the instrument affects the second-stage inventory turnover variable only through its effect on the ERM adoption decision, thus satisfying the exogeneity condition.

In the first stage of the 2SLS estimation, I regress *ERM* on the instrumental variable *(ERM_IndRatio)*, the vector of control variables defined in (2), and year and industry dummies. Results of the first stage are presented in column (I) of Table 7. Consistent with my arguments, first stage results show that *ERM_IndRatio* has a significant positive association with the decision to adopt ERM.

In the second stage, I regress inventory turnover ratio (*Invt_Turnover* and *Invt_AdjTurn*, in two separate regressions) on the predicted values of *ERM* from the first stage, while including the same set of control variables and industry and year dummies as in the first stage. Columns (II) and (III) of Table 7 represent the results of the second stage using *Invt_Turnove*r and *Invt_AdjTurn* as the dependent variable, respectively. Based on the results, after controlling for endogeneity, ERM has a statistically and economically significant impact on inventory turnover ratio. In both columns, the coefficient is significant and positive implying that the adoption of ERM is associated with an increase in inventory turnover ratio – either unadjusted or industry-adjusted. Thus, Hypothesis 1 is robust to the use of the instrumental variable.

5.2 Treatment Effect Model

To alleviate the concern of the endogenous choice of adopting ERM, and to address the concern of linear probability regression in modeling a dummy variable *(ERM)* using the 2SLS method, I use a treatment effect model (Chang et al. 2009; Kini et al. 2009; Eckles et al. 2014; Acharya and Xu 2017; Berry- Stölzle and Xu 2018).

In the first stage of the treatment effect model, I use a subset of my explanatory variables, the instrumental variable *(ERM_IndRatio)*, and a set of eight firm-specific variables[13] to estimate *ERM* using a probit model.

$$ERM_{i,t-1} = \alpha_0 + \gamma\ (ERM\_IndRatio)_{i,t-1} + \alpha_1\ DailyRtnVol_{,t-1} + \alpha_2 CashRatio_{i,t-1} + \alpha_3 Opacity_{i,t-1} + \alpha_4 CashFlowVol_{i,t-1} + \alpha_5 Z\text{-}score_{i,t-1} + \alpha_6\ ValueChange_{i,t-1} + \alpha_7\ Leverage_{i,t-1} + \alpha_8\ InstOwnership_{,t-1} + \alpha_9 Inventory\text{-}MW_{i,t-1} + \alpha_{10} Revenue\text{-}MW_{i,t-1} +$$

[13] These eight variables are the determinants of the adoption of ERM adoption. In selecting these variables, we follow prior literature. (e.g., Hoyt and Liebenberg 2011; Pagach and Warr 2011). The variables are: 1) *DailyRtnVol:* natural logarithm of the standard deviation of the firm's daily returns over the year, 2) *CashRatio*: cash plus short term investments divided by book value of assets, 3) *Opacity:* intangible assets divided by total assets, 4) *CashFlowVol*: natural log of the standard deviation of the error term from a regression of a firm's quarterly operating cash flow on the prior quarter's operating cash flow, scaled by total assets, 5) *Z-score:* Altman's Z-score 6) *ValueChange:* annual growth in market value, 7) *Leverage:* book value of liabilities divided by book value of assets 8) *InstOwnership:* percentage of equity held by institutions.

$$\alpha_{11} Other\text{-}MW_{i,t-1} + Year\ Dummies + Industry\ Dummies + \varepsilon_{i,t} \qquad \text{(Eq. 3)}$$

I model the probability of ERM adoption in the first stage using equation (3), and control for the potential self-selection bias due to the omitted variable issue by including the Inverse Mills ratio (IMR) derived from the first stage in the second stage (equation (1)).

Table 8 shows the results of the treatment effect model in the association between ERM adoption and inventory turnover ratio. I present the first-stage results in column (I). The coefficient on the inverse Mills ratio is negative and significant, which suggests that self-selection can be a serious concern. Column (II) and Column (III) of Table 8 show the second-stage results using *Invt_Turnover* and *Invt_AdjTurn* as the dependent variable, respectively. The results document a positive association between ERM and inventory turnover. Moreover, using this model, the coefficients on both dependent variables become significant at one percent level (p-value <0.01).

5.3 Propensity Score Matching

To determine whether firm-years with an active ERM program would have generated a significantly lower inventory turnover ratio had they not had an ERM program, I use the propensity score matching (PSM) technique. In doing so, I use a logit model to estimate the probabilities of possessing an active ERM program. The logit estimation includes all the independent variables defined in vector (2), as well as industry and year dummies. Following Blanco and Wehrheim (2017), I then use the predicted probabilities, or propensity scores, from the logit estimation and perform the matching using three different matching procedures: nearest-neighbor matching (in which the treated firm-year is matched with a certain number of controls that have the closet propensity score), kernel matching (in which the more similar the untreated observations are to the treated observations, the more weight they are given), and radius matching (in which each treated observation is matched only with the control unit whose propensity score falls in a predefined neighborhood of the propensity score of that treated unit).

Table 9 reports the average treatment effect estimates. Panel A reports the results using nearest-neighbor matching that allows each treated firm to be matched with four controls. The results are, however, robust to any number of matches between one and six. Column (I) of Panel A suggests that the average inventory turnover ratio would be 4.587 units higher if all firm-years were to have an active ERM program, as opposed to none had an active ERM program. Panels B and C show the results using kernel matching and radius matching, respectively. The results in Panel C are based on setting the radius limited to 0.1; nonetheless, the coefficients remain significant using any radius greater than or equal to 0.05. Overall, Table 9 suggests that the non-random assignment of ERM adoption to firms with higher inventory turnover does not explain my findings.

CHAPTER 6

THE MATURITY OF ERM

While my baseline regression model documents the effects of ERM adoption on inventory turnover and the instrumental variable and the treatment effect models address concerns of endogeneity and self-selection bias, none of these models consider the impacts of changes in the quality of ERM program through time. As Eckles et al. (2014) suggest, since ERM implementation is a complex process, it takes time for the benefits of it to be fully realized. Assuming that ERM matures as time passes, the number of years past from the adoption of ERM is a sensible proxy for the quality of an ERM program. Based on this assumption, it is reasonable to expect the economic benefits of the ERM program to have a positive association with the number of years since ERM was initially adopted. In this capacity, I argue that as the quality of an ERM program improves through time, its impacts on inventory management performance magnifies. To test this argument, I develop two ERM maturity models.

6.1 ERM Maturity Dummies Using Baseline Regression Model

First, I address the maturity of an ERM program based on my baseline regression model. Consistent with Eckles et al. (2014), I substitute *ERM* with a set of dummies defined to measure the maturity of an ERM program. *ERM_Maturity-D1* is a dummy that takes the value of one within the first and second year of ERM adoption, and zero otherwise. *ERM_Maturity-D2* is a dummy that takes the value of one within the third and fourth year of ERM adoption, and zero otherwise. *ERM_Maturity-D3* is a dummy that takes the value of one after the fourth year of ERM adoption, and zero otherwise. Equation (4) shows the baseline regression model with ERM maturity dummies:

$$InvtTurnRatio_{i,t} = \alpha + \delta_1 ERM\_Maturity\text{-}D1_{i,t} + \delta_2 ERM\_Maturity\text{-}D2_{i,t} +$$

$\delta_3 ERM\_Maturity\text{-}D3_{i,t} + \gamma ERM\_Ever_i + \beta Controls_{i,t-1} + Year\ Dummies + Industry\ Dummies + \varepsilon_{i,t}$ (Eq. 4)

I present the results for this model in Panel A of Table 10. The coefficients on *ERM_Maturity-D1, ERM_Maturity-D2,* and *ERM_Maturity-D3* are of my interest and are all significant at 5% level. Moreover, taking each dependent variable into account separately, there is always an increasing trend in the magnitude of the coefficients as I move from ERM*_Maturity-D1* to *ERM_Maturi*ty-D3. The results support my Hypothesis 2 that the economic effects of ERM adoption on inventory turnover strengthen as the ERM program evolves over time.

6.2 Categorical ERM Maturity Using Instrumental Variable Estimation

To address endogeneity, I develop a two-stage least square method (2SLS) where *ERM_Maturity* is instrumented in the first-stage using the ratio of ERM-adopters within the firm's industry-year *(ERM_IndRatio),* as the instrumental variable. In the first stage of this model, I regress *ERM_Maturity* on the instrumental variable *(ERM_IndRatio)*, the vector of control variables defined in (2), and year and industry dummies. Results of the first stage are presented in column (I) of Panel B of Table 10. Consistent with my arguments, *ERM_IndRatio* has a significant positive association with *ERM_Maturity*.

In the second stage, I regress inventory turnover ratio (*Invt_Turnover* and *Invt_AdjTurn*, in two separate regressions) on the predicted values of *ERM_Maturity* from the first stage, while including the same set of control variables and industry and year dummies as in the first stage. Columns (II) and (III) of Panel B of Table 10 represent the results of the second stage using *Invt_Turnove*r and *Invt_AdjTurn* as the dependent variable, respectively. The positive and significant coefficients on *ERM_Maturity* suggest that even after addressing endogeneity, the evolvement in the maturity ERM programs throughout time results in incremental improvements in inventory turnover ratio. These results support my Hypothesis 2.

CHAPTER 7

INVENTORY IMPAIRMENT

Among different measures of inventory productivity proposed in the literature, inventory turnover ratio and inventory impairment seem to be the two most commonly used measures (Feng et al. 2015). Thus far, I show that the adoption of ERM significantly increases inventory turnover ratio. In this section, as a robustness check, I test the association between ERM adoption and inventory impairment.

Hendricks and Singhal (2009) document that excess inventory announcements are associated with significant negative stock market reactions. Larson et al. (2014) provide empirical evidence suggesting that inventory write-downs lead to severe negative impacts on firms' operating performance, and that extreme sales growth firms are more likely to experience a future inventory write-down. Feng et al. (2015) report a positive association between inventory impairment and inventory-related material weaknesses. Overall, a lower level of inventory impairment is an indicator of a better operational performance. With reference to my propositions on the association between ERM adoption and operational performance, I expect that ERM adoption lowers both the incidences and magnitude of inventory impairment, and that these impacts amplify throughout time.

7.1 Construction of Inventory Impairment Variables

Inventory mismanagement can result in holdings of considerable amounts of excess or obsolete inventory with a market value below cost. Since U.S. Generally Accepted Accounting Principles (GAAP) requires reporting inventory at the lower of cost or market, in certain cases, firms need to impair their inventory to its market value. This write-down of value is recorded as an operating cost and reduces the firm’s net income.

To collect impairment data, I manually search for any sign of inventory impairment in 10-K filings of all firm-years in my final sample. Existing literature (e.g., Hendricks and Singhal 2009; Larson et al. 2011; Allen et al. 2013) suggest searching for terms such as "obsolescence," "obsolete," "impairment," "write-down," and "write-off" within a few words of the word "inventory." Impairment, however, can be stated using diverse phrases some of which cannot be captured by the aforementioned terms.[14] As such, in addition to searching dozens of impairment-related terms,[15] I also check for the context around *every* appearance of the word "inventory" or "inventories" in 10-K filings in order to make sure that I capture as many incidences of inventory impairment as possible.

Most firms report their inventory impairment charges in a direct and accurate manner even if the amount is relatively small. However, since it is not required to disclose the exact amount of inventory impairment, some firms tend not to report the impairment amount directly and precisely. As a result, in my final sample of 4,915 firm-years, 1,095 observations show circumstantial evidence of inventory impairment but the amount is not clearly stated.[16] To solve this inconsistency in reporting the impairment amount, I follow Allen et al. (2013) and remove these 1,095 firm-year observations from my impairment dataset. Moreover, I exclude 95 firm-years with impairment records related to acquisition or natural catastrophe as these impairment charges are caused by exogenous forces that are not captured by my models. In addition, for 180 firm-years

[14] For instance, "inventories were *written* off," and "reserve for obsolescence" (without the word inventory close to it).

[15] Including the terms suggested in literature, plus "inventory allowance," "reserve(s) for inventory," "reserve(s) for obsolescence," "inventory shrinkage," and "provision(s) for inventory".

[16] For example, beginning and end of year "reserves for inventory" is reported, but the amount charged throughout the year in form of actual inventory write-down is not stated. In such cases, annual *change* in "reserves for inventory" can be easily computed; however, it is not clear how much of the change, if any, is due to actual inventory impairments. In some cases, the change in inventory reserves is huge, suggesting that the *potential* amount of impairment can probably be big.

no 10-K filings are reported on SEC. As a result, my final sample for the impairment analysis consists of 3,545 firm-years. In the final sample, I find 1,096 firm-year observations with an identifiable non-zero amount of impairment reported on SEC.

To scale impairment amount, I divide it by the average annual FIFO inventory, where the annual average is computed using beginning and ending FIFO inventory. Out of 1,096 firm-year observations that reported non-zero inventory impairment amounts, 200 observations had impairments less than one percent of average annual FIFO inventory. These relatively small impairments are inevitable and mainly caused by the use of the allowance accounting method, and hence, do not necessarily imply inefficiency in inventory management. Consequently, in defining my impairment-related variables, I consider incidences of impairment amounts less than one percent of average annual FIFO inventory as zero. [17] The number of observations with impairment amounts between1% and 2%, 2% and 3%, 3% and 5%, 5% and 10%, and greater than 10% of average annual FIFO inventory is 170, 131, 218, 215, and 162, respectively

My first impairment-related dependent variable, *Impair_Magn*, is defined as the annual amount of impaired inventory divided by average annual FIFO inventory, times a hundred, where annual impairments of less than one percent of average annual FIFO inventory are considered zero. My next impairment-related dependent variable, *Impair_AdjMagn*, is computed as the firm's *Impair_Magn* less the median industry-year *Impair_Magn*, where industry is defined using Fama and French 30-industry classification. Finally, I define an indicator, *Impair_Dum*, that equals one

[17] Some firms report insignificant write-downs each and every year as a result of using indirect or allowance method in which managers estimate the expected amount of inventory that will go obsolete in the next fiscal year and expense it to a reserve account – which will be revised accordingly in each year. Since this is a *routine* annual process, the occurrence and magnitude of such small amounts of inventory write-downs should not be interpreted as a sign of low performance in inventory management. Hence, we suggest that these impairments should be treated as zero. Yet, as a robustness check, we re-define all of our impairment-related dependent variables, *without* considering even the smallest amounts of impairment as zero. The results are robust to this change, implying that ERM adoption significantly reduces the magnitude and possibility of all inventory impairments including routine insignificant write-downs.

if *Impair_Magn* is greater than zero (implying an impairment amount greater than one percent of average annual FIFO inventory), and zero otherwise. [18]

7.2 Empirical Results Using Inventory Impairment Variables

Following Feng et al. (2015) I use the exact same set of independent and fix effect variables in my inventory impairment tests as those I use in inventory turnover tests, and cluster standard errors at the firm level. Table 11 shows the results of my inventory impairment tests.

Panel A of Table 11 shows the results for my baseline model. Since *Impair_Magn* is a truncated continuous variable with the lower bound of one, I use a tobit estimation in Column (I). For *Impair_AdjMagn* there is no limiting bound and hence I use OLS estimation in Column (II). *Impair_Dum* is an indicator that takes the values of either one or zero and therefore I use probit estimation in Column (III). As expected, the coefficients are all significant and negative implying that ERM adoption is associated with a lower impairment magnitude, either unadjusted (columns (I)) or industry-adjusted (columns (I)), and a smaller likelihood of a notable inventory impairment (column (III)). Untabulated results of the marginal effects show that the adoption of ERM, on average, decreases the magnitude of inventory impairments by 0.753 percent of the average annual FIFO inventory. Given the average annual FIFO inventory of 1,681.4 million dollars in my final sample of 3,545 firm-years, this translates to an average annual cost savings of nearly 12.6 million dollars (= 1,681.4 × 0.753%).

To address endogeneity and self-selection bias, I run a two-stage least square model and a treatment effect model using each of my impairment-related variables as the dependent variable.

[18] *Impair_Magn, Impair_AdjMagn, and Impair_Dum* are all defined based on setting "1% of average annual FIFO inventory" as the lower bound to consider an impairment non-zero. As a robustness check, we re-define these three variables using 2%, 3%, 5%, and 10% of average annual FIFO inventory as the lower bound. The results are robust to the change. In addition, the results are robust to the use of total assets (following Larson et al. 2011 and Allen et al. 2013) as the denominator to scale impairment amounts.

Panel B (Panel C) of Table 11 shows the results for my two-stage least square (treatment effect) model. The regression settings, including the use of *ERM_IndRatio* as the instrumental variable, are exactly the same as the ones used for inventory turnover tests. In Panels B and C, Column (I) reports the first stage results, and the negative and significant coefficients on *ERM* in columns (II) to (IV) show the negative association between ERM adoption and inventory impairment magnitude (Column (II)), industry-adjusted inventory impairment magnitude (Column (III)), and the likelihood of facing a notable inventory impairment (Column (IV)).

Panel D of Table 11 reports the average treatment effect estimates when using impairment-related variables as the dependent variable. The procedure to run the matching is the same as the one explained in section 5.3 of Chapter 5. Each matching model is reported in a separate panel, and each column shows the dependent variable used. All the coefficients are negative and significant suggesting that the non-random assignment of ERM adoption to firms with lower inventory impairment (in terms of magnitude and/ or incidences) does not explain my findings.

Next, I test for changes in the impacts of ERM adoption on inventory impairment as the ERM program matures using the same regression settings described in Chopater 6. In Table 11, Panel E shows the results of the OSL regression setting that includes my three ERM maturity dummies. The coefficients are all negative, significant, and with an increasing trend in the absolute value. Column (IV), for instance, suggests that ERM adoption decreases the likelihood of facing an inventory impairment greater that 1% of average annual FIFO inventory, and that this impact increases as time passes and the ERM program becomes more mature. Panel F of Table 11 shows that when I run the 2SLS regression using my categorical ERM maturity variable the results are still significant.

CHAPTER 8

CONCLUSIONS

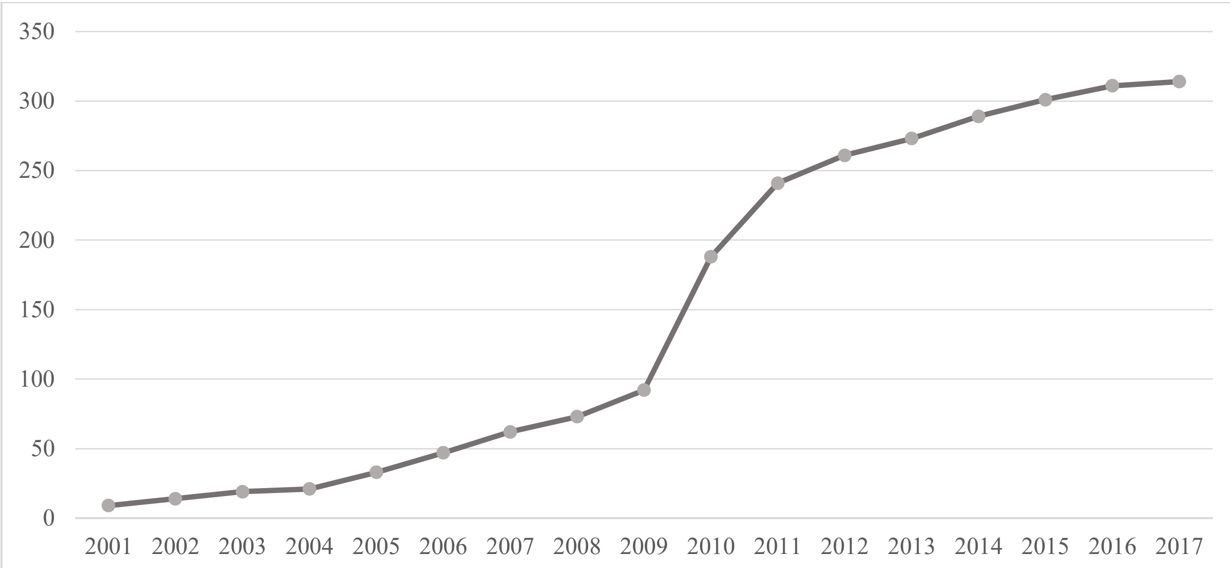
COSO (2004) emphasizes the operations-related objective of ERM, providing a roadmap for firms to move toward a more complete risk management process that satisfies more needs than that of their internal control. COSO (2017) further stresses the role of day-to-day operational decisions in the integrated ERM framework in driving firm performance. In addition, the widely-accepted risk quadrants include operational risk as one of the major categories of risk ERM addresses. Given the importance of firm operations in the ERM framework, I provide the first evidence on how ERM affects firm day-to-day, routine operations. I focus on inventory management since it is at the core of firm operations, and I measure it by inventory turnover ratio and impairment.

Using a hand-collected sample of ERM adopters from firms that have ever been listed on the S&P 500 index between 2001 and 2017, I find that firms with ERM implementation experience an improvement in their inventory management during my sample period from 2004 to 2017. More specifically, I show that, controlling for ICFR, ERM adoption is associated with a greater inventory turnover ratio and less impairment. These results are robust to addressing the endogeneity concerns using an instrumental variable (2SLS) approach, treatment effect model, and propensity score matching.

I also find that ERM's effect on inventory management is more pronounced among firms with greater financial distress, with less investments in innovation, or with higher information asymmetries. Consequently, I document three channels thorugh which ERM adoption improves inventory turnover; risk mitigation, innovation boost, and information environment improvement.

In addition, I show that ERM's impacts on inventory management tend to increase as time passes after the adoption. My research documents ERM's real economic benefits to firms' operations and provides evidence that ERM is broader than internal control functions by presenting the incremental effects of ERM on inventory management to ICFR. Given the under-appreciation and under-utilization of ERM in practice, my study calls for more attention from the standard-setters and practitioners on ERM.

Figure 1: Historical Trend of ERM Adoption



Note: This figure shows the historical trend of ERM adoption among S&P 500 firms in my final sample of 513 unique firms. The vertical axis shows the cumulative number of firms in my sample that have adopted ERM. The sample is consisted of firms that appeared in S&P 500 index during any fraction of time between 2001 and 2017, excluding financial (6000 <= SIC <= 6999) and utility firms (4900 <= SIC <= 4999).

Table 1: Sample Selection

Description	Firm-years
Observations on all firms that appeared in the S&P 500 index during any fraction of time from 2001 to 2017	12,367
Less: Financial firms (SIC codes 6000 to 6999)	2,234
Less: Utility firms (SIC codes 4900 to 4999)	838
Less: Observations with missing information on internal control variables	2,634
Less: Observations with missing values on explanatory variables	1,746
Final sample	4,915

Note: This table presents the sample selection process. The final sample includes 4,915 firm-years (513 unique firms) over the 2004 – 2017 period.

Table 2: Descriptive Statistics

Variable	N	Mean	StDev	25th	Median	75th
ERM	4,915	0.418	0.493	0.000	0.000	1.000
ERM_Ever	4,915	0.681	0.466	0.000	1.000	1.000
ERM_IndRatio	4,915	0.401	0.266	0.154	0.405	0.611
Invt_Turnover	4,915	13.933	26.634	3.386	5.544	11.388

Variable	N	Mean	StDev	25th	Median	75th
Invt_AdjTurn	4,915	5.525	23.760	-1.548	-0.002	2.098
GrossMargin	4,915	41.768	20.582	26.214	39.332	56.175
CapitalIntensity	4,915	8.215	1.519	7.183	8.088	9.256
Size	4,915	8.944	1.263	8.071	8.839	9.719
Book-to-Market	4,915	0.391	0.299	0.198	0.325	0.503
ROA	4,915	0.064	0.080	0.034	0.067	0.105
Loss	4,915	0.122	0.327	0.000	0.000	0.000
SalesGrowth	4,915	6.182	17.970	-1.710	5.372	12.669
SalesVolatility	4,915	0.145	0.126	0.065	0.108	0.177
Age	4,915	3.385	0.712	2.890	3.434	3.892
ForeignSales	4,915	0.161	0.368	0.000	0.000	0.000
Segments	4,915	1.488	0.315	1.386	1.386	1.609
Auditor	4,915	0.989	0.105	1.000	1.000	1.000
Invt_MWIC	4,915	0.004	0.064	0.000	0.000	0.000
Rev_MWIC	4,915	0.005	0.067	0.000	0.000	0.000
Other_MWIC	4,915	0.036	0.247	0.000	0.000	0.000

Note: This table reports the descriptive statistics of the variables used in the empirical analysis. The sample includes 2004 – 2017 observations for firms that appeared in S&P 500 index anytime from 2001 to 2017, excluding financial (6000 <= SIC <= 6999) and utility (4900 <= SIC <= 4999) firms. See the Appendix for variable definitions. All continuous variables are winsorized at the extreme 1 percent and 99 percent.

Table 3: Univariate Differences across ERM Status

	(I) *ERM* = 1 N = 2,053		(II) *ERM* = 0 N = 2,862		Difference (I) - (II)	
Variables	Mean	Median	Mean	Median	Mean	Median
Invt_Turnover	15.187	6.099	13.033	5.136	2.154***	0.964***
Invt_AdjTurn	6.291	0.035	4.976	-0.150	1.315**	0.186***
ERM_IndRatio	0.576	0.583	0.275	0.227	0.301***	0.356***
GrossMargin	40.430	38.560	42.729	39.798	-2.298***	-1.239*
CapitalIntensity	8.689	8.644	7.874	7.777	0.815***	0.867***
Size	9.303	9.204	8.685	8.614	0.618***	0.591***
Book-to-Market	0.381	0.316	0.398	0.333	-0.017*	-0.016**
ROA	0.059	0.060	0.068	0.072	-0.009***	-0.011***
Loss	0.117	0.000	0.126	0.000	-0.009	0.000

	(I) *ERM* = 1 N = 2,053		(II) *ERM* = 0 N = 2,862		Difference (I) - (II)	
SalesGrowth	4.102	3.906	7.675	6.680	-3.572***	-2.773***
SalesVolatility	0.135	0.100	0.152	0.117	-0.017***	-0.017***
Age	3.509	3.714	3.297	3.258	0.212***	0.457***
ForeignSales	0.141	0.000	0.175	0.000	-0.034**	0.000***
Segments	1.508	1.609	1.473	1.386	0.036***	0.223***
Auditor	0.998	1.000	0.983	1.000	0.015***	0.000
Invt_MWIC	0.003	0.000	0.005	0.000	-0.003	0.000
Rev_MWIC	0.003	0.000	0.006	0.000	-0.003	0.000
Other_MWIC	0.028	0.000	0.041	0.000	-0.013	0.000

Note: This table presents the univariate difference across ERM status for the sample firms. See the Appendix for variable definitions. All continuous variables are winsorized at the extreme 1 percent and 99 percent. Statistical significance of difference in means is based on 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.

Table 4: Pearson (bottom) and Spearman (top) Correlation Coefficients

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ERM	(1)		**0.521**	**0.573**	**0.079**	**0.065**	**-0.048**	**0.266**	**0.251**	*-0.036*	**-0.083**
ERM_Ever	(2)	0.521		**0.145**	**0.125**	**0.082**	**-0.078**	**0.219**	**0.232**	0.007	*-0.039*
ERM_IndRatio	(3)	**0.579**	**0.156**		**0.060**	**0.044**	**-0.053**	**0.207**	**0.179**	**-0.088**	**-0.067**
Invt_Turnover	(4)	**0.037**	0.019	*0.031*		**0.628**	**-0.331**	**0.291**	**0.196**	**0.050**	**-0.161**
Invt_Adj-Turn	(5)	0.025	0.002	0.025	**0.950**		**-0.233**	**0.078**	**0.090**	-0.014	**-0.067**
GrossMargin	(6)	**-0.050**	**-0.076**	**-0.057**	**-0.135**	**-0.124**		**-0.199**	**-0.316**	**-0.209**	**0.327**
CapitalIntensity	(7)	**0.267**	**0.222**	**0.201**	**0.081**	-0.010	**-0.185**		**0.766**	**0.134**	**-0.133**
Size	(8)	**0.248**	**0.228**	**0.175**	-0.017	**-0.063**	**-0.298**	**0.780**		**0.044**	-0.021
Book-to-Market	(9)	-0.018	-0.005	**-0.063**	-0.017	**-0.042**	**-0.202**	**0.117**	0.025		**-0.414**
ROA	(10)	**-0.053**	-0.024	*-0.030*	**-0.062**	**-0.041**	**0.288**	**-0.062**	**0.053**	**-0.345**	
Loss	(11)	-0.008	**-0.053**	0.007	0.026	*0.028*	**-0.155**	*-0.032*	**-0.140**	**0.213**	**-0.683**
SalesGrowth	(12)	**-0.135**	**-0.070**	**-0.167**	0.024	*0.035*	**0.138**	**-0.150**	**-0.084**	**-0.126**	**0.285**
SalesVolatility	(13)	**-0.078**	**-0.049**	**-0.083**	**-0.058**	-0.018	**-0.251**	**-0.141**	0.025	**0.094**	**-0.056**
Age	(14)	**0.146**	**0.103**	**0.140**	**-0.119**	**-0.105**	**-0.081**	**0.316**	**0.298**	0.006	-0.014
ForeignSales	(15)	**-0.037**	0.008	*-0.035*	-0.003	-0.006	*0.036*	-0.004	**-0.039**	**0.043**	-0.020
Segments	(16)	**0.061**	**0.063**	0.010	**-0.199**	**-0.169**	**-0.071**	**0.139**	**0.220**	**0.054**	-0.024
Auditor	(17)	**0.061**	**0.068**	**0.041**	0.024	0.012	0.001	**0.118**	**0.063**	**-0.037**	**0.044**
Invt_MWIC	(18)	*-0.033*	**-0.042**	**-0.046**	-0.024	-0.020	**-0.044**	**-0.053**	**-0.044**	0.008	**-0.058**
Rev_MWIC	(19)	*-0.037*	**-0.045**	**-0.043**	-0.023	-0.021	-0.026	**-0.048**	**-0.042**	-0.012	**-0.051**
Other_MWIC	(20)	**-0.050**	*-0.034*	**-0.070**	*-0.031*	-0.026	-0.003	**-0.062**	**-0.061**	0.022	**-0.086**

		(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
ERM	(1)	-0.008	**-0.162**	**-0.116**	**0.181**	**-0.037**	**0.066**	**0.061**	*-0.033*	*-0.037*	**-0.048**
ERM_Ever	(2)	**-0.053**	**-0.062**	**-0.081**	**0.136**	0.008	**0.069**	**0.068**	**-0.042**	**-0.045**	*-0.030*
ERM_IndRatio	(3)	0.002	**-0.209**	**-0.123**	**0.170**	*-0.030*	0.016	**0.038**	**-0.051**	**-0.049**	**-0.076**
Invt_Turnover	(4)	0.011	0.001	-0.026	**-0.058**	-0.028	**-0.068**	**0.030**	-0.016	-0.016	-0.021
Invt_Adj-Turn	(5)	-0.015	0.027	**0.058**	**-0.054**	*-0.028*	0.022	-0.001	-0.024	*-0.036*	-0.023
GrossMargin	(6)	**-0.149**	**0.097**	**-0.253**	**-0.103**	*0.031*	**-0.103**	0.004	**-0.046**	*-0.028*	-0.008
CapitalIntensity	(7)	-0.013	**-0.159**	**-0.191**	**0.344**	-0.017	**0.140**	**0.122**	**-0.051**	**-0.047**	**-0.055**
Size	(8)	**-0.112**	**-0.098**	**-0.039**	**0.327**	**-0.049**	**0.216**	**0.048**	*-0.034*	*-0.034*	**-0.053**
Book-to-Market	(9)	**0.131**	**-0.122**	**0.060**	*0.032*	0.028	**0.097**	*-0.029*	0.008	-0.017	0.011
ROA	(10)	**-0.552**	**0.287**	**-0.045**	*-0.032*	-0.010	**-0.050**	**0.029**	**-0.067**	**-0.064**	**-0.103**
Loss	(11)		**-0.251**	**0.109**	*-0.028*	0.020	**-0.063**	**-0.045**	*0.028*	**0.055**	**0.078**
SalesGrowth	(12)	**-0.241**		**0.078**	**-0.194**	0.005	**-0.078**	0.009	0.003	-0.004	0.008
SalesVolatility	(13)	**0.079**	**0.070**		**-0.113**	-0.008	**-0.081**	*-0.030*	*0.028*	*0.030*	*0.033*
Age	(14)	-0.022	**-0.170**	**-0.135**		0.009	**0.346**	**0.070**	-0.003	-0.003	-0.016
ForeignSales	(15)	0.020	0.003	-0.019	0.007		**0.071**	0.004	0.009	0.012	0.013
Segments	(16)	**-0.049**	**-0.079**	**-0.111**	**0.318**	**0.078**		-0.003	**0.041**	0.026	0.021
Auditor	(17)	**-0.045**	0.006	**-0.046**	**0.071**	0.004	-0.005		**-0.066**	**-0.039**	-0.018
Invt_MWIC	(18)	*0.028*	0.008	0.006	0.002	0.009	**0.038**	**-0.066**		**0.665**	**0.470**
Rev_MWIC	(19)	**0.055**	0.000	0.008	0.002	0.012	0.025	**-0.039**	**0.665**		**0.493**
Other_MWIC	(20)	**0.078**	0.010	0.025	-0.012	0.014	0.025	-0.021	**0.483**	**0.511**	

Notes: This table presents the Pearson (below diagonal) and Spearman (above diagonal) correlation coefficients for the main variables of interest used in our study. Bold values are significant at $p \leq 0.01$ (two-tailed) and italicized values are significant at $p \leq 0.05$ (two-tailed). See the appendix for variable definitions.

Table 5: Baseline Model

	(I) Invt_Turnover	(II) Invt_AdjTurn
ERM	**3.224****	**3.064****
	(2.23)	(2.13)
ERM_Ever	-1.634	-1.525
	(-0.81)	(-0.75)
GrossMargin	-0.417***	-0.417***
	(-5.34)	(-5.34)
CapitalIntensity	2.723**	2.715**
	(2.31)	(2.29)
Size	-4.362***	-4.355***
	(-3.08)	(-3.07)
Book-to-Market	-5.430**	-5.362*
	(-1.97)	(-1.94)
ROA	7.042	7.350
	(0.62)	(0.65)
Loss	-0.502	-0.443
	(-0.26)	(-0.22)
SalesGrowth	0.077**	0.073**
	(2.44)	(2.33)
SalesVolatility	-3.731	-3.965
	(-0.81)	(-0.86)
Age	-0.967	-0.987
	(-0.75)	(-0.76)
ForeignSales	-1.382	-1.307
	(-0.78)	(-0.73)
Segments	-8.018**	-7.923**
	(-2.19)	(-2.17)
Auditor	-0.751	-0.718
	(-0.37)	(-0.36)
Invt_MWIC	-3.824	-3.748
	(-1.30)	(-1.29)

	(I) Invt_Turnover	(II) Invt_AdjTurn
Rev_MWIC	-1.502	-1.421
	(-0.45)	(-0.45)
Other_MWIC	-0.861	-0.825
	(-0.84)	(-0.79)
Constant	56.536***	51.021***
	(5.25)	(4.72)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	4,915	4,915
Clusters	513	513
Adj. R-squared	0.344	0.171

Note: This table reports results of the baseline regression of the effect of ERM adoption (*ERM*) on inventory turnover (column (I)) and industry-adjusted inventory turnover (Column (II)). The model is defined in equation (1). See the Appendix for variable definitions. All continuous variables are winsorized at the extreme 1 percent and 99 percent. The standard errors are heteroscedasticity-consistent and allow for clustering at the firm level. Test statistics are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 6: Cross-Sectional Variation in the Effect of ERM Adoption

Panel A: Impact of risk on the association between ERM adoption and inventory turnover				
	O-Score			
	Invt_Turnover		Invt_AdjTurn	
	High Subsample	Low Subsample	High Subsample	Low Subsample
ERM	**6.131*****	**0.194**	**5.805*****	**0.1903**
	(3.3)	(0.11)	(4.09)	(0.16)
ERM_Ever	-4.614	1.807	-4.514	1.938
	(-1.47)	(0.94)	(-1.43)	(1.01)
GrossMargin	-0.475***	-0.378***	-0.475***	-0.380***
	(-4.51)	(-3.92)	(-4.52)	(-3.88)
CapitalIntensity	1.808	3.515**	1.758	3.529**
	(0.85)	(2.16)	(0.82)	(2.15)
Size	-4.925**	-4.302**	-4.823**	-4.404**
	(-2.35)	(-2.01)	(-2.28)	(-2.05)
Book-to-Market	-7.280**	-3.136	-7.378**	-2.868
	(-2.12)	(-0.76)	(-2.15)	(-0.70)

Panel A: Impact of risk on the association between ERM adoption and inventory turnover				
	O-Score			
	Invt_Turnover		Invt_AdjTurn	
	High Subsample	Low Subsample	High Subsample	Low Subsample
ROA	7.579	6.564	7.053	7.234
	(0.55)	(0.39)	(0.52)	(0.42)
Loss	-2.088	1.262	-2.154	1.511
	(-0.93)	(0.35)	(-0.93)	(0.41)
SalesGrowth	0.045	0.079**	0.036	0.079**
	(0.98)	(2.09)	(0.81)	(2.07)
SalesVolatility	-3.127	-5.384	-3.319	-5.564
	(-0.50)	(-0.96)	(-0.53)	(-0.99)
Age	-0.103	-2.282*	-0.120	-2.196*
	(-0.06)	(-1.71)	(-0.07)	(-1.65)
ForeignSales	-0.619	-0.435	-0.591	-0.255
	(-0.21)	(-0.31)	(-0.20)	(-0.18)
Segments	-7.165*	-6.799	-7.085*	-6.981
	(-1.73)	(-1.19)	(-1.70)	(-1.23)
Auditor	-0.987	-1.232	-1.206	-1.13
	(-0.23)	(-0.56)	(-0.28)	(-0.52)
Invt_MWIC	-2.668	4.433	-2.545	4.232
	(-0.95)	(1.27)	(-0.89)	(1.17)
Rev_MWIC	-2.185	-2.963	-1.978	-2.493
	(-0.58)	(-1.05)	(-0.54)	(-0.98)
Other_MWIC	-0.805	-0.741	-0.863	-0.658
	(-0.61)	(-0.57)	(-0.65)	(-0.50)
Constant	69.203***	49.552***	63.216***	44.799***
	(4.72)	(3.02)	(4.30)	(2.71)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,372	2,379	2,372	2,379
Clusters	388	372	388	372
Adj. R-squared	0.354	0.356	0.180	0.200
Test of Difference in ERM coefficient	Chi-square = 6.76		Chi-square = 6.01	
	p-value < 0.01		*p*-value = 0.01	

Panel B: Impact of innovation on the association between ERM adoption and inventory turnover				
	R&DExpnd			
	Invt_Turnover		**Invt_AdjTurn**	
	High Subsample	**Low Subsample**	**High Subsample**	**Low Subsample**
ERM	**0.267**	**5.566****	**0.246**	**5.266****
	(0.28)	(2.32)	(0.25)	(2.22)
ERM_Ever	-0.369	-3.275	-0.356	-3.085**
	(-0.23)	(-0.90)	(-0.22)	(-2.20)
GrossMargin	-0.279**	-0.332**	-0.277**	-0.331***
	(-2.38)	(-2.42)	(-2.37)	(-7.45)
CapitalIntensity	-1.259	1.239	-1.220	1.226
	(-1.02)	(0.68)	(-0.98)	(1.53)
Size	1.149	-4.912**	1.098	-4.854***
	(0.72)	(-2.29)	(0.68)	(-5.50)
Book-to-Market	-8.486**	-3.247	-8.423**	-3.202*
	(-2.43)	(-0.86)	(-2.41)	(-1.65)
ROA	-10.136	19.947	-10.279	20.566*
	(-0.92)	(1.11)	(-0.93)	(1.86)
Loss	1.087	1.085	1.148	1.117
	(0.44)	(0.40)	(0.46)	(0.50)
SalesGrowth	0.076*	0.051	0.078*	0.042
	(1.94)	(1.15)	(1.97)	(1.26)
SalesVolatility	-6.330	3.486	-6.656	3.172
	(-1.03)	(0.49)	(-1.08)	(0.75)
Age	0.519	-1.474	0.549	-1.529*
	(0.64)	(-0.62)	(0.69)	(-1.89)
ForeignSales	-0.873	-0.825	-0.883	-0.649
	(-0.81)	(-0.22)	(-0.82)	(-0.41)
Segments	-9.883*	-3.276	-10.059*	-3.023
	(-1.77)	(-0.62)	(-1.81)	(-1.54)
Auditor	3.365	0.067	3.503	0.056
	(1.54)	(0.02)	(1.61)	(0.01)
Invt_MWIC	-4.613	0.091	-4.965	0.709
	(-1.56)	(0.01)	(-1.52)	(0.07)
Rev_MWIC	-3.515	1.336	-3.142	0.544
	(-1.37)	(0.19)	(-1.25)	(0.03)

Panel B: Impact of innovation on the association between ERM adoption and inventory turnover				
	R&DExpnd			
	Invt_Turnover		Invt_AdjTurn	
	High Subsample	**Low Subsample**	**High Subsample**	**Low Subsample**
Other_MWIC	1.217	-4.281**	1.340	-4.404*
	(0.80)	(-2.46)	(0.83)	(-1.73)
Constant	29.338**	62.098***	23.881*	64.242***
	(2.06)	(2.86)	(1.68)	(6.04)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,454	2,461	2,454	2,461
Clusters	272	266	272	266
Adj. R-squared	0.181	0.385	0.114	0.226
Test of Difference in ERM coefficient	Chi-square = 4.32		Chi-square = 3.96	
	p-value = 0.038		*p*-value = 0.046	

Panel C: Impact of information asymmetry on the association between ERM adoption and inventory turnover				
	ForecastDispersion			
	Invt_Turnover		Invt_AdjTurn	
	High Subsample	**Low Subsample**	**High Subsample**	**Low Subsample**
ERM	**5.339*** **	**0.901**	**5.138** **	**0.696**
	(2.64)	(0.47)	(2.56)	(0.36)
ERM_Ever	-2.881	-1.066	-2.787	-0.943
	(-1.28)	(-0.42)	(-1.24)	(-0.37)
GrossMargin	-0.434***	-0.412***	-0.436***	-0.413***
	(-5.44)	(-3.73)	(-5.47)	(-3.70)
CapitalIntensity	4.022***	0.247	4.019***	0.307
	(3.27)	(0.12)	(3.24)	(0.15)
Size	-7.036***	-0.116	-7.000***	-0.211
	(-4.63)	(-0.05)	(-4.61)	(-0.09)
Book-to-Market	-3.585	-12.128**	-3.349	-12.432**
	(-1.28)	(-2.03)	(-1.21)	(-2.05)
ROA	4.503	13.004	4.596	13.011
	(0.38)	(0.74)	(0.39)	(0.74)
Loss	-0.871	-1.162	-0.881	-0.786
	(-0.46)	(-0.27)	(-0.46)	(-0.18)

Panel C: Impact of information asymmetry on the association between ERM adoption and inventory turnover				
	ForecastDispersion			
	Invt_Turnover		Invt_AdjTurn	
	High Subsample	Low Subsample	High Subsample	Low Subsample
SalesGrowth	0.079**	0.083	0.073**	0.082
	(2.49)	(1.59)	(2.32)	(1.57)
SalesVolatility	-8.145**	4.163	-8.646**	4.368
	(-1.98)	(0.48)	(-2.11)	(0.50)
Age	-1.155	-0.285	-1.207	-0.203
	(-0.82)	(-0.15)	(-0.86)	(-0.11)
ForeignSales	-2.000	-1.442	-1.780	-1.530
	(-1.24)	(-0.54)	(-1.09)	(-0.57)
Segments	-5.129	-12.098**	-4.815	-12.233**
	(-1.26)	(-2.02)	(-1.19)	(-2.04)
Auditor	0.107	-0.788	0.216	-1.054
	(0.03)	(-0.25)	(0.07)	(-0.33)
Invt_MWIC	-3.395	-12.116	-3.230	-11.880
	(-1.02)	(-1.46)	(-0.95)	(-1.54)
Rev_MWIC	-2.910	6.382	-2.746	5.633
	(-0.84)	(0.87)	(-0.82)	(0.82)
Other_MWIC	-1.134	1.150	-1.109	1.371
	(-0.90)	(0.74)	(-0.88)	(0.87)
Constant	69.682***	40.816***	63.718***	35.741***
	(5.21)	(3.05)	(4.76)	(2.65)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2408	2414	2408	2414
Clusters	409	375	409	375
Adj. R-squared	0.337	0.405	0.201	0.216
Test of Difference in ERM coefficient	Chi-square = 3.06		Chi-square = 3.06	
	p-value = 0.080		*p*-value = 0.080	

Note: This table reports results of cross-sectional variation in the effect of ERM adoption (*ERM*) on inventory turnover (*Invt_Turnover*) and industry-adjusted inventory turnover (*Invt_AdjTurn*), using baseline regression settings (defined by equation (1)). Panel A presents results related to Ohlson O-score (*O-score*). Panel B presents results related to R&D expenditure (*R&DExpnd*). Panel C presents results related to analyst forecast dispersion (*ForecastDispersion*). See the appendix for variable definitions.

Table 7: Instrumental Variable Model

	(I) first stage ERM	(II) Invt_Turnover	(III) Invt_AdjTurn
ERM		**13.774****	**13.591****
		(2.21)	(2.17)
ERM_Ever	0.454***	-6.633*	-6.513*
	(25.68)	(-1.90)	(-1.85)
GrossMargin	0.001	-0.421***	-0.421***
	(1.14)	(-5.50)	(-5.49)
CapitalIntensity	0.038***	2.271*	2.264*
	(2.95)	(1.82)	(1.80)
Size	0.001	-4.361***	-4.355***
	(-0.01)	(-3.12)	(-3.11)
Book-to-Market	0.007	-5.521**	-5.453**
	(0.25)	(-2.00)	(-1.97)
ROA	-0.169	9.163	9.466
	(-1.19)	(0.82)	(0.84)
Loss	-0.003	-0.459	-0.400
	(-0.11)	(-0.23)	(-0.20)
SalesGrowth	0.001	0.080**	0.076**
	(-0.45)	(2.57)	(2.46)
SalesVolatility	0.041	-4.049	-4.282
	(0.63)	(-0.87)	(-0.92)
Age	0.002	-0.983	-1.002
	(0.13)	(-0.76)	(-0.78)
ForeignSales	-0.028	-1.105	-1.031
	(-1.42)	(-0.62)	(-0.57)
Segments	0.002	-7.747**	-7.653**
	(0.06)	(-2.16)	(-2.14)
Auditor	0.017	-0.793	-0.760
	(0.29)	(-0.39)	(-0.37)
Invt_MWIC	0.053	-4.470	-4.392
	(0.88)	(-1.53)	(-1.52)
Rev_MWIC	0.052	-2.154	-2.071
	(0.75)	(-0.64)	(-0.66)

	(I) first stage ERM	(II) Invt_Turnover	(III) Invt_AdjTurn
Other_MWIC	-0.005	-0.795	53.197***
	(-0.24)	(-0.80)	(4.74)
ERM_IndRatio	**0.794*** **		
	(11.00)		
Constant	-0.613***	58.939***	51.021***
	(-4.63)	(5.26)	(4.72)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	4,915	4,915	4,915
Clusters	513	513	513
Adj. R-squared	0.544	0.326	0.149

Note: This table reports results of the two-stage least squares model of the effect of ERM adoption (*ERM*) on inventory turnover (column (II)) and industry-adjusted inventory turnover (Column (III)). First-stage results are reported in columns (I). See the Appendix A for variable definitions. All continuous variables are winsorized at the extreme 1 percent and 99 percent. The standard errors are heteroscedasticity-consistent and allow for clustering at the firm level. Test statistics are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 8: Treatment Effect Model

	(I) first stage ERM	(II) Invt_Turnover	(III) Invt_AdjTurn
ERM		**8.665*** **	**8.197*** **
		(3.77)	(3.56)
ERM_Ever		-0.260	-0.149
		(-0.31)	(-0.18)
GrossMargin		-0.351***	-0.350***
		(-16.44)	(-16.35)
CapitalIntensity		3.830***	3.798***
		(7.90)	(7.80)
Size		-5.176***	-5.148***
		(-9.82)	(-9.72)
Book-to-Market		-3.987***	-3.841***
		(-3.19)	(-3.06)
ROA		5.738	5.959
		(0.95)	(0.99)

	(I) first stage ERM	(II) Invt_Turnover	(III) Invt_AdjTurn
Loss		-1.909	-1.857
		(-1.40)	(-1.36)
SalesGrowth		0.087***	0.082***
		(4.51)	(4.21)
SalesVolatility		-1.296	-1.637
		(-0.47)	(-0.59)
Age		-1.406***	-1.404***
		(-2.86)	(-2.85)
ForeignSales		0.231	0.332
		(0.27)	(0.38)
Segments		-5.492***	-5.436***
		(-4.53)	(-4.46)
Auditor		-2.141	-1.909
		(-0.58)	(-0.52)
Invt_MWIC	-0.067	0.920	0.768
	(-0.09)	(0.14)	(0.12)
Rev_MWIC	-0.196	0.337	0.550
	(-0.20)	(0.05)	(0.08)
Other_MWIC	-0.111	-0.541	-0.591
	(-0.93)	(-0.39)	(-0.42)
DailyRtnVol	-0.503***		
	(-6.21)		
CashRatio	-0.768***		
	(-2.98)		
Opacity	-0.790***		
	(-4.69)		
CashFlowVol	-0.143***		
	(-3.53)		
Z-score	-0.075***		
	(-6.24)		
ValueChange	0.053		
	(0.81)		
Leverage	0.090		
	(0.49)		

	(I) first stage ERM	(II) Invt_Turnover	(III) Invt_AdjTurn
InstOwnership	-0.082		
	(-0.96)		
ERM_IndRatio	**3.502*****		
	(14.74)		
Mills Ratio		-3.246**	-3.071**
		(-2.36)	(-2.23)
Constant	-4.653***	48.796***	43.125***
	(-10.79)	(9.22)	(8.12)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	4,237	4,237	4,237

Note: This table reports results of the treatment effect model of the impacts of ERM adoption (*ERM*) on inventory turnover (II) and industry-adjusted inventory turnover (III). First-stage (defined by equations (3)) results are reported in column (I). See the Appendix for variable definitions. All continuous variables are winsorized at the extreme 1 percent and 99 percent. The standard errors are heteroscedasticity-consistent and allow for clustering at the firm level. Test statistics are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 9: Propensity Score Matching

	(I) Invt_Turnover	(II) Invt_AdjTurn
Panel A: Nearest-neighbor Matching		
ERM = 1 vs. ERM = 0	**4.587*****	**4.057*****
	(4.02)	(3.78)
Controls	Yes	Yes
Industry & Year FE	Yes	Yes
Observations	4,902	4,902
Panel B: Kernel Matching		
ERM = 1 vs. ERM = 0	**4.801*****	**4.194*****
	(3.81)	(3.22)
Controls	Yes	Yes
Industry & Year FE	Yes	Yes
Observations	4,902	4,902
Panel C: Radius Matching		
ERM = 1 vs. ERM = 0	**4.685*****	**4.045*****
	(3.36)	(3.22)

	(I) Invt_Turnover	(II) Invt_AdjTurn
Panel C (con't)		
Controls	Yes	Yes
Industry & Year FE	Yes	Yes
Observations	4,902	4,902

Note: This table reports results of the estimates of differences in firms' inventory turnover (*Invt_Turnover*) and industry-adjusted inventory turnover (*Invt_AdjTurn*) between the treatment group (*ERM* = 1) and the control group (*ERM* = 0). The matched sample is constructed using nearest-neighbor (I), kernel (II), and radius (III) score matching given by a probit model in which *ERM* is the dependent variable. See the Appendix for variable definitions. All continuous variables are winsorized at the extreme 1 percent and 99 percent. The Standard errors are obtained using 200 bootstrap replications. Test statistics are reported in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 10: ERM Maturity Models

Panel A: OLS regression	(I) Invt_Turnover	(II) Invt_AdjTurn
ERM_Maturity-D1	**2.669****	**2.652****
	(2.41)	(2.35)
ERM_Maturity-D2	**4.023****	**3.773****
	(2.57)	(2.41)
ERM_Maturity-D3	**4.179****	**4.050****
	(2.11)	(2.06)
ERM_Ever	-2.152	-2.049
	(-1.06)	(-1.01)
GrossMargin	-0.417***	-0.417***
	(-5.35)	(-5.34)
CapitalIntensity	2.685**	2.677**
	(2.28)	(2.26)
Size	-4.365***	-4.358***
	(-3.09)	(-3.07)
Book-to-Market	-5.449**	-5.379*
	(-1.97)	(-1.95)
ROA	7.080	7.391
	(0.63)	(0.65)
Loss	-0.533	-0.474
	(-0.27)	(-0.24)

Panel A: OLS regression		
	(I) Invt_Turnover	**(II) Invt_AdjTurn**
SalesGrowth	0.077**	0.073**
	(2.43)	(2.33)
SalesVolatility	-3.701	-3.933
	(-0.80)	(-0.85)
Age	-0.963	-0.982
	(-0.74)	(-0.76)
ForeignSales	-1.346	-1.270
	(-0.75)	(-0.70)
Segments	-7.999**	-7.903**
	(-2.19)	(-2.17)
Auditor	-0.788	-0.752
	(-0.39)	(-0.38)
Invt_MWIC	-3.605	-3.535
	(-1.23)	(-1.22)
Rev_MWIC	-1.759	-1.686
	(-0.53)	(-0.54)
Other_MWIC	-0.868	-0.830
	(-0.85)	(-0.79)
Constant	57.064***	51.554***
	(5.26)	(4.73)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	4,915	4,915
Clusters	513	513
Adj. R-squared	0.345	0.172

Panel B: 2SLS regression			
	(I) first stage ERM_Maturity	**(II) Invt_Turnover**	**(III) Invt_AdjTurn**
ERM_Maturity		**7.310****	**7.212****
		(2.17)	(2.13)
ERM_Ever	1.171***	-8.934**	-8.783*
	(24.15)	(-2.00)	(-1.96)

Panel B: 2SLS regression			
	(I) first stage ERM_Maturity	**(II) Invt_Turnover**	**(III) Invt_AdjTurn**
GrossMargin	0.001	-0.421***	-0.421***
	(0.74)	(-5.50)	(-5.49)
CapitalIntensity	0.117***	1.944	1.942
	(3.07)	(1.46)	(1.45)
Size	-0.001	-4.352***	-4.346***
	(-0.03)	(-3.08)	(-3.07)
Book-to-Market	-0.009	-5.363*	-5.296*
	(-0.12)	(-1.93)	(-1.91)
ROA	-0.302	9.047	9.351
	(-0.79)	(0.80)	(0.83)
Loss	0.039	-0.787	-0.724
	(0.51)	(-0.39)	(-0.35)
SalesGrowth	-0.01	0.086***	0.082***
	(-1.29)	(2.75)	(2.63)
SalesVolatility	0.04	-3.783	-4.019
	(0.23)	(-0.81)	(-0.86)
Age	0.009	-1.028	-1.047
	(0.25)	(-0.79)	(-0.81)
ForeignSales	-0.059	-1.061	-0.987
	(-1.09)	(-0.59)	(-0.54)
Segments	-0.015	-7.606**	-7.514**
	(-0.15)	(-2.12)	(-2.09)
Auditor	0.049	-0.918	-0.884
	(0.34)	(-0.41)	(-0.40)
Invt_MWIC	0.084	-4.349	-4.273
	(0.53)	(-1.46)	(-1.45)
Rev_MWIC	0.17	-2.676	-2.586
	(0.96)	(-0.77)	(-0.78)
Other_MWIC	-0.009	-0.800	-0.765
	(-0.17)	(-0.79)	(-0.73)
ERM_IndRatio	**1.497*** **		
	(7.73)		

Panel B: 2SLS regression			
	(I) first stage ERM_Maturity	(II) Invt_Turnover	(III) Invt_AdjTurn
Constant	-1.804	66.360***	60.783***
	(-5.51)	(5.24)	(4.78)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	4,915	4,915	4,915
Clusters	513	513	513
Adj. R-squared	0.140	0.311	0.130

Note: Panel A (Panel B) reports results of the ERM maturity baseline (2SLS) regression of the effects of ERM maturity, proxied by three dummy variables (one categorical variable), on inventory turnover and industry-adjusted inventory turnover. See the Appendix for variable definitions. All continuous variables are winsorized at the extreme 1 percent and 99 percent. Standard errors are heteroscedasticity-consistent and allow for clustering at the firm level. T-statistics are presented in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 11: Effects of ERM Adoption on Inventory Impairment

Panel A: OLS regression			
	(I) Impair_Magn	(II) Impair_AdjMagn	(III) Impair_Dum
ERM	**-3.030*****	**-0.702*****	**-0.327****
	(-2.94)	(-2.84)	(-2.56)
ERM_Ever	-1.920*	-0.497	-0.269*
	(-1.75)	(-1.42)	(-1.81)
GrossMargin	0.088***	0.033***	0.009**
	(2.75)	(3.10)	(2.48)
CapitalIntensity	-1.904**	-0.396	-0.282***
	(-2.50)	(-1.54)	(-3.19)
Size	0.975	0.282	0.132
	(1.16)	(1.06)	(1.39)
Book-to-Market	3.312**	0.737*	0.454**
	(2.26)	(1.82)	(2.29)
ROA	-0.792	-1.484	0.107
	(-0.14)	(-0.79)	(0.15)
Loss	3.582***	1.247***	0.338**
	(2.82)	(3.21)	(2.12)

Panel A: OLS regression			
	(I) Impair_Magn	**(II) Impair_AdjMagn**	**(III) Impair_Dum**
SalesGrowth	-0.020	-0.002	-0.003*
	(-1.23)	(-0.30)	(-1.66)
SalesVolatility	-2.986	0.187	-0.604
	(-0.97)	(0.23)	(-1.52)
Age	-0.130	-0.047	-0.034
	(-0.17)	(-0.27)	(-0.34)
ForeignSales	1.759**	0.403*	0.275***
	(2.28)	(1.66)	(2.61)
Segments	-0.580	-0.507	0.085
	(-0.32)	(-1.04)	(0.38)
Auditor	-0.181	0.676	-0.401
	(-0.06)	(0.58)	(-0.95)
Invt_MWIC	5.638*	1.358	0.867**
	(1.93)	(0.92)	(2.10)
Rev_MWIC	0.546	1.523	-0.019
	(0.20)	(0.99)	(-0.05)
Other_MWIC	0.154	0.034	0.045
	(0.16)	(0.09)	(0.38)
Constant	-3.341	0.186	0.300
	(-0.47)	(0.10)	(0.34)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	3,545	3,545	3,545
Clusters	415	415	407
Pseudo/Adj. R-squared	0.088	0.143	0.185

Panel B: 2SLS regression				
	(I) first stage ERM	**(II) Impair_Magn**	**(III) Impair_AdjMagn**	**(IV) Impair_Dum**
ERM_		**-1.708***	**-1.912****	**-0.262***
		(-1.79)	(-2.04)	(-1.94)
ERM_Ever	0.455***	-0.014	0.077	0.005
	(22.01)	(-0.02)	(0.14)	(0.07)

Panel B: 2SLS regression				
	(I) first stage ERM	(II) Impair_Magn	(III) Impair_AdjMagn	(IV) Impair_Dum
GrossMargin	0.001	0.033***	0.033***	0.003***
	(0.83)	(3.16)	(3.16)	(2.83)
CapitalIntensity	0.053***	-0.326	-0.328	-0.072***
	(3.73)	(-1.20)	(-1.21)	(-2.87)
Size	-0.014	0.247	0.265	0.037
	(-0.87)	(0.92)	(0.98)	(1.48)
Book-to-Market	0.005	0.770*	0.737*	0.130**
	(0.16)	(1.88)	(1.83)	(2.36)
ROA	-0.035	-1.554	-1.541	-0.038
	(-0.19)	(-0.84)	(-0.84)	(-0.19)
Loss	0.008	1.283***	1.259***	0.089**
	(0.25)	(3.19)	(3.26)	(2.00)
SalesGrowth	0.001	-0.001	-0.002	-0.001
	(0.10)	(-0.20)	(-0.32)	(-1.59)
SalesVolatility	0.041	0.290	0.202	-0.156
	(0.54)	(0.36)	(0.25)	(-1.55)
Age	0.001	-0.045	-0.044	-0.015
	(0.01)	(-0.26)	(-0.26)	(-0.65)
ForeignSales	-0.019	0.447*	0.385	0.086***
	(-0.84)	(1.82)	(1.59)	(2.81)
Segments	0.022	-0.516	-0.509	0.021
	(0.51)	(-1.07)	(-1.05)	(0.37)
Auditor	0.095	0.687	0.774	-0.127
	(0.92)	(0.67)	(0.74)	(-0.99)
Invt_MWIC	0.056	1.260	1.420	0.243*
	(0.86)	(0.86)	(0.98)	(1.80)
Rev_MWIC	0.143*	1.607	1.708	0.051
	(1.88)	(1.04)	(1.13)	(0.38)
Other_MWIC	-0.026	0.037	-0.006	0.013
	(-0.96)	(0.09)	(-0.02)	(0.36)
ERM_IndRatio	**0.767*** **			
	(9.37)			

Panel B: 2SLS regression				
	(I) first stage ERM	**(II) Impair_Magn**	**(III) Impair_AdjMagn**	**(IV) Impair_Dum**
Constant	-0.801***	0.705	0.675	0.587**
	(-4.98)	(0.39)	(0.37)	(2.43)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	3,545	3,545	3,545	3,545
Clusters	415	415	415	415
Adj. R-squared	0.177	0.159	0.131	0.164

Panel C: Treatment effect model				
	(I) first stage ERM	**(II) Impair_Magn**	**(III) Impair_AdjMagn**	**(IV) Impair_Dum**
ERM		**-1.970*** **	**-2.161*** **	**-0.190*** **
		(-3.84)	(-4.24)	(-3.38)
ERM_Ever		-0.426**	-0.442**	-0.079***
		(-2.41)	(-2.52)	(-4.05)
GrossMargin		0.026***	0.026***	0.002***
		(6.09)	(6.13)	(4.37)
CapitalIntensity		-0.317***	-0.327***	-0.078***
		(-3.19)	(-3.31)	(-7.17)
Size		0.236**	0.254**	0.043***
		(2.21)	(2.39)	(3.65)
Book-to-Market		0.708***	0.648**	0.134***
		(2.78)	(2.57)	(4.81)
ROA		-1.377	-1.603	0.016
		(-1.06)	(-1.24)	(0.11)
Loss		1.313***	1.257***	0.093***
		(4.73)	(4.56)	(3.04)
SalesGrowth		-0.002	-0.003	-0.001***
		(-0.62)	(-0.79)	(-2.80)
SalesVolatility		-0.074	-0.156	-0.215***
		(-0.13)	(-0.28)	(-3.45)
Age		-0.132	-0.128	-0.028**
		(-1.26)	(-1.23)	(-2.45)

Panel C: Treatment effect model				
	(I) first stage ERM	**(II) Impair_Magn**	**(III) Impair_AdjMagn**	**(IV) Impair_Dum**
ForeignSales		0.584***	0.526***	0.111***
		(3.34)	(3.03)	(5.78)
Segments		-0.686***	-0.703***	-0.001
		(-2.74)	(-2.83)	(-0.04)
Auditor		0.593	0.596	-0.204**
		(0.72)	(0.73)	(-2.25)
Invt_MWIC		1.462	1.629	0.267*
		(1.13)	(1.26)	(1.88)
Rev_MWIC		-1.377	-1.222	-0.151
		(-0.99)	(-0.88)	(-1.00)
Other_MWIC		-0.081	-0.136	0.014
		(-0.26)	(-0.43)	(0.39)
DailyRtnVol	-0.503***			
	(-6.21)			
CashRatio	-0.768***			
	(-2.98)			
Opacity	-0.790***			
	(-4.69)			
CashFlowVol	-0.143***			
	(-3.53)			
Z-score	-0.075***			
	(-6.24)			
ValueChange	0.053			
	(0.81)			
Leverage	0.090			
	(0.49)			
InstOwnership	-0.082			
	(-0.96)			
ERM_IndRatio	**3.502*** **			
	(14.74)			
Mills Ratio		0.785**	0.894***	0.067**
		(2.56)	(2.93)	(1.99)

Panel C: Treatment effect model				
	(I) first stage ERM	**(II) Impair_Magn**	**(III) Impair_AdjMagn**	**(IV) Impair_Dum**
Constant	-4.653***	1.633	1.226	0.733***
	(-10.79)	(1.42)	(1.07)	(5.81)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	3,054	3,054	3,054	3,054

	(I) Impair_Magn	**(II) Impair_AdjMagn**	**(III) Impair_Dum**
Panel D1: Nearest-neighbor Matching			
ERM = 1 vs. ERM = 0	**-1.121*****	**-1.093*****	**-0.156*****
	(-9.15)	(-9.06)	(-10.99)
Controls	Yes	Yes	Yes
Industry & Year FE	Yes	Yes	Yes
Observations	3,534	3,534	3,534
Panel D2: Kernel Matching			
ERM = 1 vs. ERM = 0	**-1.120*****	**-1.127*****	**-0.148*****
	(-9.30)	(-8.46)	(-9.02)
Controls	Yes	Yes	Yes
Industry & Year FE	Yes	Yes	Yes
Observations	3,534	3,534	3,534
Panel D3: Radius Matching			
ERM = 1 vs. ERM = 0	**-1.113*****	**-1.060*****	**-0.154*****
	(-8.94)	(-8.75)	(-9.20)
Controls	Yes	Yes	Yes
Industry & Year FE	Yes	Yes	Yes
Observations	3,534	3,534	3,534

Panel E: OLS regression using ERM maturity dummies			
	(I) Impair_Magn	**(II) Impair_AdjMagn**	**(III) Impair_Dum**
ERM_Maturity-D1	**-2.341*****	**-0.553****	**-0.301*****
	(-2.63)	(-2.32)	(-2.80)

Panel E: OLS regression using ERM maturity dummies			
	(I) Impair_Magn	**(II) Impair_AdjMagn**	**(III) Impair_Dum**
ERM_Maturity-D2	**-2.704****	**-0.618****	**-0.320****
	(-2.49)	(-2.21)	(-2.39)
ERM_Maturity-D3	**-4.327*****	**-0.898*****	**-0.497*****
	(-2.94)	(-2.70)	(-2.68)
ERM_Ever	-1.539	-0.426	-0.209
	(-1.35)	(-1.17)	(-1.37)
GrossMargin	0.087***	0.033***	0.009**
	(2.74)	(3.10)	(2.47)
CapitalIntensity	-1.851**	-0.387	-0.275***
	(-2.43)	(-1.50)	(-3.12)
Size	0.946	0.280	0.129
	(1.13)	(1.05)	(1.36)
Book-to-Market	3.357**	0.741*	0.461**
	(2.28)	(1.83)	(2.31)
ROA	-0.518	-1.428	0.138
	(-0.09)	(-0.76)	(0.20)
Loss	3.592***	1.256***	0.338**
	(2.83)	(3.23)	(2.13)
SalesGrowth	-0.020	-0.002	-0.003*
	(-1.25)	(-0.33)	(-1.70)
SalesVolatility	-2.921	0.166	-0.601
	(-0.95)	(0.20)	(-1.52)
Age	-0.100	-0.046	-0.030
	(-0.13)	(-0.27)	(-0.31)
ForeignSales	1.742**	0.405*	0.272**
	(2.22)	(1.65)	(2.56)
Segments	-0.595	-0.507	0.082
	(-0.33)	(-1.04)	(0.37)
Auditor	0.019	0.710	-0.377
	(0.01)	(0.61)	(-0.90)
Invt_MWIC	5.695*	1.361	0.876**
	(1.95)	(0.92)	(2.13)

Panel E: OLS regression using ERM maturity dummies			
	(I) Impair_Magn	**(II) Impair_AdjMagn**	**(III) Impair_Dum**
Rev_MWIC	0.614	1.545	-0.003
	(0.23)	(1.00)	(-0.01)
Other_MWIC	0.150	0.028	0.041
	(0.16)	(0.07)	(0.36)
Constant	-3.940	0.078	0.219
	(-0.56)	(0.04)	(0.24)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	3,545	3,545	3,545
Clusters	415	415	407
Adj. R-squared	0.089	0.143	0.188

Panel F: 2SLS regression using categorical ERM maturity				
	(I) first stage ERM_Maturity	**(II) Impair_Magn**	**(III) Impair_AdjMagn**	**(IV) Impair_Dum**
ERM_Maturity		**-0.926***	**-1.040****	**-0.142***
		(-1.77)	(-2.00)	(-1.91)
ERM_Ever	1.182***	0.302	0.432	0.054
	(20.53)	(0.41)	(0.60)	(0.53)
GrossMargin	0.001	0.033***	0.033***	0.003***
	(0.38)	(3.11)	(3.10)	(2.76)
CapitalIntensity	0.156***	-0.272	-0.267	-0.063**
	(3.78)	(-0.96)	(-0.94)	(-2.34)
Size	-0.043	0.232	0.247	0.035
	(-0.93)	(0.85)	(0.91)	(1.36)
Book-to-Market	0.012	0.773*	0.739*	0.130**
	(0.13)	(1.89)	(1.83)	(2.37)
ROA	0.143	-1.362	-1.324	-0.009
	(0.29)	(-0.73)	(-0.71)	(-0.04)
Loss	0.067	1.331***	1.312***	0.096**
	(0.74)	(3.27)	(3.35)	(2.15)

Panel F: 2SLS regression using categorical ERM maturity				
	(I) first stage ERM_Maturity	**(II) Impair_Magn**	**(III) Impair_AdjMagn**	**(IV) Impair_Dum**
SalesGrowth	-0.001	-0.001	-0.002	-0.001*
	(-0.27)	(-0.26)	(-0.38)	(-1.66)
SalesVolatility	0.015	0.234	0.139	-0.165
	(0.08)	(0.29)	(0.17)	(-1.62)
Age	0.005	-0.040	-0.039	-0.014
	(0.11)	(-0.24)	(-0.23)	(-0.62)
ForeignSales	-0.012	0.468*	0.409*	0.089***
	(-0.19)	(1.89)	(1.66)	(2.88)
Segments	0.046	-0.511	-0.502	0.022
	(0.37)	(-1.05)	(-1.02)	(0.38)
Auditor	0.323	0.823	0.928	-0.106
	(1.59)	(0.79)	(0.88)	(-0.81)
Invt_MWIC	0.163	1.315	1.482	0.252*
	(0.96)	(0.89)	(1.02)	(1.84)
Rev_MWIC	0.416**	1.748	1.866	0.072
	(2.16)	(1.13)	(1.22)	(0.53)
Other_MWIC	-0.082	0.006	-0.040	0.008
	(-1.34)	(0.02)	(-0.11)	(0.22)
ERM_IndRatio	**1.415*** **			
	(6.43)			
Constant	-2.14***	-0.573	-1.336	0.365
	(-5.30)	(-0.29)	(-0.66)	(1.31)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	3,545	3,545	3,545	3,545
Clusters	415	415	415	415
Adj. R-squared	0.570	0.148	0.116	0.144

Note: This table reports the results of the tests on the association between ERM adoption/maturity and inventory impairment measured by impairment magnitude (*Impair_Magn*), industry adjusted impairment magnitude (*Impair_AdjMagn*), and impairment dummy (*Impair_Dum*). Panel A reports results of the baseline model using tobit (Column (I)), OLS (Column (II)), and probit (Column (III)) regression. Panels B, C, and D, report results of the two-stage least squares model, the treatment effect model, and propensity score matching. Panel E reports results of ERM maturity baseline model where ERM maturity dummies are used in tobit (Column I), OLS (Column II), and probit (Column III) regressions. Panel F reports results of ERM maturity 2SLS regression.

APPENDIX

VARIABLE DESCRIPTION

Variable Name	Description
ERM	A dummy variable that takes the value of 1 if the firm has an active ERM program in that year, and 0 otherwise.
ERM_Ever	A dummy variable that equals 1 if the firm has ever adopted ERM, and 0 otherwise.
ERM_IndRatio	The ratio of ERM adoption for the firm's industry-year, computed as total number of ERM adopters for the firm's industry-year, divided by the total number of firms in that industry-year.
ERM_Maturity	A categorical variable that takes the value of 0, 1, 2, and 3, before the adoption of ERM, within the first and second years of ERM adoption, within the third and fourth years of ERM adoption, and after the fourth year of ERM adoption, respectively.
ERM_Maturity-D1	A dummy variable that takes the value of 1 within the first and second year of ERM adoption, and zero otherwise.
ERM_Maturity-D2	A dummy variable that takes the value of 1 within the third and fourth year of ERM adoption, and zero otherwise.
ERM_Maturity-D3	A dummy variable that takes the value of 1 after the fourth year of ERM adoption, and zero otherwise.
Invt_Turnover	Inventory turnover ratio measured as annual cost of sales (Compustat COGS), divided by average annual inventory (Compustat INVT) over the same year, where inventory is averaged using the beginning and ending inventory of that year. (on a FIFO basis).
Invt_AdjTurn	The firm-specific *Invt_Turnover* less the median *Invt_Turnover* for the firm's industry-year, where industry is defined using Fama and French 30-industry classification.
Impair_Magn	The amount of inventory impaired throughout the year, divided by average annual FIFO inventory, times 100, where annual impairments of less than 1% of average annual FIFO inventory are considered zero.
Impair_AdjMagn	The firm-specific *Impair_Magn* less the median *Impair_Magn* for the firm's industry-year, where industry is defined using Fama and French 30-industry classification.
Impair_Dum	A dummy variable that takes the value of 1 if *Impair_Magn is* greater than 1, and 0 otherwise.
GrossMargin	Percentage of gross profit, measured as sales (Compustat REVT) less cost of sales (Compustat COGS) divided by sales (Compustat REVT), times 100 (on a FIFO basis).
CapitalIntensity	End of year natural logarithm of gross property, plant, and equipment (Compustat PPEGT).
Size	Natural logarithm of total annual sales (Compustat REVT).
Book-to-Market	End of year book value of equity divided by end of year market value of equity.

Variable Name	Description
ROA	Annual earnings before extraordinary items (Compustat IB), divided by average annual total assets (Compustat AT) over the same year, where total assets are averaged using the beginning and ending total assets of that year.
Loss	A dummy variable that takes the value of 1 if annual net income (Compustat NI) is less than zero, and 0 otherwise.
SaleGrowth	Percentage of growth in annual sales (Compustat REVT) from year t-1 to year t.
SaleVolatility	The standard deviation of annual sales (Compustat REVT) divided by average total assets (Compustat AT) over the prior seven years (requiring at least three non-missing observations), where total assets are averaged using the beginning and ending total assets of that year.
Age	Natural logarithm of the number of years that a company is covered by CRSP.
ForeignSale	A dummy variable that takes the value of 1 if the firm reports foreign sales (Compustat FCA) in that year, and 0 otherwise.
Segments	Natural logarithm of the total number of geographic and operating segments.
Auditor	A dummy variable that takes the value of 1 if the firm hires one of the four largest audit firms (Audit Analytics AUDITOR_FKEY < 5), and 0 otherwise.
Inventory-MW	A dummy variable that takes the value of 1 if the firm reports an inventory-related material weakness in internal control in year t, and 0 otherwise. (The dummy's value is 1 if any of NOTEFF_ACC_REAS_KEYS, NOTEFF_ FINFRAUD_KEYS, or NOTEFF_OTHER_REAS_KEYS equal 32).
Revenue-MW	A dummy variable that takes the value of 1 if the firm reports a revenue-related material weakness in internal control in year t, and 0 otherwise. (The dummy's value is 1 if any of NOTEFF_ACC_REAS_KEYS, NOTEFF_ FINFRAUD_KEYS, or NOTEFF_OTHER_REAS_KEYS equal 39).
Other-MW	Natural logarithm of the number of material weaknesses in internal control excluding those related to inventory or revenue. (That is, excluding material weaknesses incidents where NOTEFF_ ACC_REAS_KEYS and NOTEFF_FINFRAUD_KEYS and NOTEFF_OTHER_REAS_KEYS are all not equal to 32 or 39).
O-Score	Ohlson O-score (Ohlson 1980)
R&DExpnd	Annual research and development expense (Compustat XRD) divided by annual sales (Compustat REVT)
ForecastDispersion	Standard deviation of one-year-ahead forecasts of all analysts divided by fiscal year end stock price (Compustat PRCC_F)

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