Competition, Cost Analytics, and Offsetting Strategies:
Pressures and Opportunities on the Fraud Triangle

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ABSTRACT

This study introduces industry competition factors to fraud models to examine how competition associates with fraud risk. I argue that industry competition eclipses many firm-level determinants in their association with fraud risk, and that the cost of poor information elevates fraud risk as competition increases. I find that fraud risk is higher for firms in industries with 1) more substitutable products & services, 2) greater threats of new entry, and 3) larger incumbent pools of competitors, and that substitution exceeds every firm-level variable except size in its relevance with fraud risk. Cross-sectionally, I provide evidence that industry-wide non-adoption of advanced cost analytics (i.e. using obsolete, distortionary standard costing practices) may exacerbate the fraud-risk effects of competition, especially product substitution: a one standard deviation increase in substitution associates with over double the fraud risk for firms in industries typified by obsolete costing practices. I also find that different strategies vary in their fraud-offsetting associations dependent on the type of competition most prevalent in an industry. Together, these findings shed light on how the effects of industry competition may subsume or surpass most firm-level fraud determinants and provide evidence of previously unidentified drawbacks of obsolete cost accounting systems.

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GENERAL AUDIENCE ABSTRACT

Elements of industry competition help explain a firm's fraud risk. I find that bringing competition variables into firm-level fraud models helps explain a large portion of the firm's fraud risk, and that the effects of competition more strongly associate with fraud risk than most firm-level attributes. The results also indicate that the effects of competition on fraud risk may be even worse in industries where obsolete cost accounting practices remain widespread: the effects of price competition in such industries associates with significantly greater fraud risk than in other industries. Additional findings include the implied fraud-risk-reducing effects of different business strategies, depending on which type of competition is most intensive around a firm. Altogether, this study sheds light on the importance of including industry competition effects when assessing fraud risk, especially when a firm's or its peers' cost accounting system quality is poor and price competition is high.

DEDICATION

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CHAPTER ONE

INTRODUCTION

1.1 Introduction

Industry competition represents pressure to avoid adverse consequences and incentivizes managers to report positive firm outcomes. Fraud, the most egregious form of manipulated financial reporting, is susceptible to such competitive pressures. This study investigates whether industry competition surpasses firm-level attributes in their associations with fraud risk, and which specific dimension of competition is of foremost concern with fraud risk. It also builds upon the literature which examines the relationships between competition and management accounting quality (Krishnan et al. 2002; Krishnan 2005; Chen et al. 2015) by testing how the non-adoption of advanced cost analytics may influence the opportunity portion of the fraud triangle.

Empirical accounting research designs routinely control for industry fixed effects, tacitly acknowledging that 1) industry factors are important and 2) relevant industry factors are unidentified for that study. Compounding the problem of having excluded industry competition factors from financial reporting fraud (hereafter fraud) research is the practice of matching on industry when developing tested samples, thereby excluding industry factors from consideration. Research using industry-matched samples has identified several firm-level fraud-risk attributes. However, industry-matched samples inhibit the identification of relevant industry attributes which associate with fraud risk. We thus have not yet discovered whether industry competition has lesser or greater effects on firm-level fraud risk than firm-level determinants or how significantly a specific dimension of industry competition may effect fraud risk (AICPA 2002). This study seeks to address these questions.

The relation between industry competition and fraud is unclear: Karuna et al. (2015) provide evidence that competition increases industry-level fraud rates but Boone et al. (2019) find that competition decreases firm-level fraud risk. Both of these studies motivate this paper's research approach: Karuna et al. (2015) use the industry as the entity of interest regarding fraud rates, leaving for future researchers the question of how competition might contribute to firm-level models. Boone et al. (2019) utilize a specific type of competition, product similarity, in their firm-level fraud models, but leave for future research the obligation to assess other competition factors in firm-level models. Acknowledging the contributions of each of these studies, I seek to complement, extend, and refine our knowledge of competition and fraud risk by positing that three other fundamental dimensions of industry competition (Durnev and Mangen 2020) significantly associate with firm-level fraud risk.

I hypothesize that the elasticity of product substitution, entry threat, and market size significantly contribute to firm-level fraud models for two reasons. First, differentiating between the properties in substitution, entry threat, and market size has yielded insights in numerous studies, including with managerial incentives (Raith 2003; Karuna 2007; Chen et al. 2015), firm size (Subramanian 2013), competitive advantage (Peteraf and Bergen 2003), capital structure (Phillips 1995), and investment decisions (Durnev and Mangen 2020). Findings from this literature stream suggest likely associations with firm-level fraud risk despite the strong firm-level determinants which have been previously identified.

Second, these competition metrics have intuitive mechanisms for their influence on fraud risk. Managers in high substitution industries would have greater survival pressure, motivating the presentation superior financial results to win scarce capital resources and maintain market share. The enhanced exposure in high entry threat industries may increase fraud risk as managers seek to preemptively ensure access to external financing to defend their customer base from potential competitors. And the salience of larger pools of incumbent competitors in high market size industries may induce managers to present better results / prospects than their sundry peers.

The results indicate that substitution, entry threat, and market size all positively associate with firm-level fraud risk, and that they dominate most firm-level determinants of fraud, including the widely-used F-score (Dechow et al. 2011). These findings are economically significant since a one standard deviation increase in substitution, entry threat, and market size associates with increased probability of fraud by 44, 34, and 23 percent over the unconditional mean, respectively. Additional tests indicate that substitution and entry threat have the most robust associations with fraud.

In cross-sectional analyses, I examine how the internal information environment contextualizes the effects of competition. The purpose of these analyses is to examine whether the cost of poor internal information increases as competition increases. Advanced cost management theory suggests that new analytics approaches developed since the 1980's such as value-stream costing, lean accounting, and throughput accounting produce superior profitability insights and performance management (Goldratt 1984; Davis et al. 2020). Academic studies have also demonstrated numerous decision pitfalls related to the distortionary effects inherent in standard costing systems (Buchheit 2004; Gupta et al. 2010; Brüggen et al. 2011), particularly when making pricing and production decisions. Yet the majority of manufacturing firms have retained obsolete costing practices instead of using superior cost analytics (Clinton and White 2012; Lawson 2017). If obsolete standard costing's distortions 1) drive suboptimal product and pricing decisions , 2) create opportunities for concealment and deflection, 3) produce unexpected underperformance, and 4) pressure peers to match suboptimal pricing, then fraud risk would rise within obsolete costing industries as price competition rises. Testing these effects using substitution is appropriate since substitution associates directly with price competition (Nevo 2001).

The results indicate an exacerbating effect of obsolete costing practices on substitution and market size. A one-standard deviation increase in substitution and market size, respectively, associates with an 97 and 48 percent higher fraud probability above the unconditional mean for firms in obsolete-costing industries (versus a 35 and 11 percent increase in non-obsolete costing industries). Seemingly unrelated estimation tests indicate that the coefficients for substitution and market size are significantly larger in industries where obsolete standard costing practices are prevalent. The effects widen further when examining income statement fraud (hereafter IS fraud): a one-standard deviation increase in substitution and market size, respectively, associates with a 104 and 49 percent higher income statement fraud probability for firms in obsolete-costing industries (versus a 36 and 15 percent increase in non-obsolete costing industries). Interestingly, firms in industries with obsolete costing but very low substitution have *zero* instances of financial reporting fraud. I infer from these findings that obsolete costing systems might provide sufficient information quality if and only if cost information is inconsequential; otherwise, there is a strong detrimental effect on fraud risk, particularly income statement fraud. These results support the supposition that the cost of low-quality information increases as price competition increases and reemphasizes the value of internal information quality.

I also address the research gap on how fraud likelihood differs by competition type. I examine how non-fraud firms differ across industries by examining which strategies associate with reduced fraud risk by industry competition type. I find evidence that non-fraud firms in high-substitution and high-entry threat industries benefit from quality-differentiation strategies;

whereas non-fraud firms in high-market size industries benefit from cost leadership strategies (Kaplan and Norton 2000; Porter 1980). These findings imply that different strategies may have stronger fraud-offsetting properties under different competitive conditions.

This study makes three main contributions. First, it complements and extends prior studies regarding competition's effects on fraud risk. We know from prior research that competition influences fraud rates at the industry-level. However, the question has remained unanswered on whether firm-level fraud risk factors subsume or are surpassed by competition's effects. Whether firm-level or industry-level factors hold greater sway over firm-level fraud decisions has yet to be examined. It is important to address this question because fraud is fundamentally a firm-level, idiosyncratic incident, and so refining our understanding of how competition influences firm management's decisions to commit fraud helps us better understand how, given firm-level risk factors, external conditions may influence temptation to misreport. The finding that industry competition has more dominant associations with fraud risk than most firm-level determinants (including the F-score) is thus very important in comprehending the gravity of industry-level fraud factors.

Second, this study contributes to the information environment literature with evidence that the distortions inherent in obsolete costing practices may create opportunities for fraud, thereby intensifying the fraud risk effects from product market competition, especially price competition. It also illustrates how variance between competition types increases when contextualized by information quality. This extends the decision theory research in accounting (Gallemore and Labro 2015; Hemmer and Labro 2019) by providing evidence of a link between poor internal information quality and detrimental managerial decisions. This is relevant for regulators in detecting fraud and for executives seeking better monitoring tools.

Finally, this study contributes to the accounting strategy literature by demonstrating that different strategies may reduce fraud risk depending on the more prevalent form of competition which surrounds a firm. This is important to researchers, regulators, and managers since it demonstrates that fraud risk mitigation may be conditional upon previously unidentified industry factors.

This paper proceeds as follows. Chapter 2 motivates this study by reviewing relevant literature and developing hypotheses. Chapter 3 sets forth the research design. Chapter 4 presents the results and Chapter 5 concludes.

CHAPTER TWO

Literature Review & Hypothesis Development

2.1 Background: Research on Fraud

Amiram et al. (2018) recently called for research on financial misreporting examining factors outside a firm's boundaries. In their review of the fraud and corporate misconduct literature, they observe that although booming macroeconomic conditions can increase reporting risk due to decreased monitoring (Davidson 2011; Povel et al. 2007) there have been few studies researching large-scale fraud factors. Beasley et al. (2000) and Dechow et al. (2011) have previously called for industry-related research on financial reporting misstatements. Beasley et al. (2000) find that fraud techniques differ greatly across industries and Dechow et al. (2011) mention that their misreporting risk models might be modified by industry attributes. Other studies have documented that fraud can adversely influence a firm's industry peers (Beatty et al. 2013; Sadka 2006) by pressuring their decision-making toward suboptimal choices.

Theories of fraud treat pressures and incentives as important considerations. Industry competitive pressures mainly relate to the avoidance of negative consequences, while managerial performance incentives provide rewards for positive outcomes. The literature has found evidence that highly-incentivized managers resort to fraud to a) increase or maintain firm-based wealth (Armstrong et al. 2013), b) obtain more lucrative option exercises (Schrand and Zechman 2012), c) obtain a more dominant market position (Wang et al. 2010), or d) obtain excellent subsequent executive roles (Holmström 1999). Conversely, I theorize that executives at firms with intense industry competition might have more fraud risk to appear financially superior than reality/peers, and thus a) avoid surrendering excessive ownership in SEO's (Dechow et al. 1996), b) avoid higher interest on new debt (Dechow et al. 1996), c) avoid appearing surpassed by industry peers (Fernandes and Guedes 2010), and d) avoid involuntary turnover (Dasgupta et al. 2018).

The industrial organization literature provides consensus that intra-industry competition affects managerial decisions (Porter 1990; Nickell 1996; Raith 2003; Karuna 2007), but the particular industry traits that associate with fraud risk remain less substantiated. Karuna et al. (2015) provide evidence that competition *increases* industry-level earnings management activity, including industry-level fraud rates[1], whereas Boone et al. (2019) provide evidence that competition *reduces* fraud risk. They infer from their application of the Hoberg and Phillips (2010b, 2016) product similarity score that industry similarity enhances monitoring by external stakeholders, thereby decreasing fraud risk. Industry effects on fraud may be firm-dependent because there are varying types/degrees of cross-sectional heterogeneity within each industry. It may also be that the competition effects which associate with aggregate industry fraud rates are subsumed by the explanatory power of firm-level characteristics or that a particular industry factor may neutralize the significance of firm-level attributes. Thus, it remains unclear whether competition increases or decreases firm-level fraud risk and which competition type would have the strongest effects on fraud risk.

2.2 Competition

This study emphasizes three competitive measures which have more established findings: substitution, entry threat, and market size. The elasticity of substitution reflects the extent to which close substitutes exist for a firms' products, within or across industries. On the one hand, firms can compete on quality, customer service, or unique product attributes instead of price when substitution increases to improve their performance and thus reduce pressure to misreport.

[1] Karuna et al. (2015) design their tests and all variables at the industry level. I differ from their study by emphasizing firm-level fraud risk to examine the effects of competition in light of firm-level risk factors.

On the other hand, firms in high substitution industries might have higher fraud risk as elasticity increases. Because customers can easily switch between firms when product markets experience greater price competition, firms may strive to maintain operations by expending more on capacity or achieve cost leadership to counter declining prices. However, some economic theory suggests that, ceteris paribus, the elasticity of substitution increases within industries over time. Because profits might endogenously trend toward zero with greater substitution but cash flow needs increase from continued investment requirements, firms in high-substitution industries may more often need external financing to maintain market presence.

Diminishing profitability correlates with higher costs of capital, so managers could be pressured to present attractive financial statements to preserve current / future earnings while financing firm continuity (Dechow et al. 1996). Managers would also face pressure to report comparable or superior performance relative to peers (Fernandes and Guedes 2010). Solely from the 'appearances' perspective, when industry-wide margins shrink due to ample alternative offerings, managers would still desire to present comparable and superior results relative to their peers. Thus when substitution increases, firms would experience greater pressure to misstate performance. I therefore predict a positive relation between substitution and fraud risk.

It is important to note that substitution is the only competition proxy which associates directly with price competition (Nevo 2001), and is thus the sole proxy for price competition in this study. The rationale behind this is both theoretical and mechanical. Regarding theory, Lerner (1934) argue that as industry product market competition increases, firms are forced to reduced prices to the marginal cost. Thus when intense price competition exists, the difference between price (approximated by reported sales) and costs (approximated by reported expenses) diminishes to zero. Observed calculations of smaller price-cost margins, calculated as industry sales divided by industry expenses, or larger Lerner index values, calculated as industry expenses divided by industry sales, reasonably represent the reduction of prices to marginal costs. However, since downward pressure on prices influences only one variable used for calculating net earnings, it could be that managers facing intense price competition choose to manipulate reported costs to present desired profit margins. It would thus be reasonable to expect intense price competition to associate with higher income statement-related fraud risk. But because sales represent the results of aggregate realized prices, it could be tempting for managers to merely manipulate reported revenue in direct response to intensive price competition in their industry. Substitution might then exhibit a differential effect on revenue-related fraud risk alone.

The threat of new entrants represents the ease with which potential competitors can enter an industry. Incumbents in high-entry threat industries face pressure to sustain their financial health because influxes of new competitors put future profitability at risk. Thus entry threat represents a competitive pressure that may increase fraud risk as managers ensure access to external financing (Dechow et al. 1996). However, some high-barrier industries have low price competition (i.e. the mining industry) while other high-barrier industries have high price competition (i.e. the automotive industry). I predict that entry threat will significantly associate with fraud risk, even controlling for firm-level traits, since entry threat would create managerial decision conditions based on constant exposure to pending additional competitors. The resulting pressures for access to external financing to sustain product market share would prompt higher fraud likelihoods (Dechow et al. 1996).

Market size represents the core competitive landscape of an industry. Larger markets have more competing firms, and even with high aggregate demand the multitude of incumbents is a constant reminder that managers must fight for their firm's share of the product market.

Because larger markets denote actualized competition, they would be more salient to managers' desires to demonstrate superior performance. This would generate stronger peer effects for managers to misreport their performance as favorable as peers' performance (Fernandes and Guedes 2010). I predict that market size positively associates with fraud risk.

Boone et al. (2019) find that greater competition (product similarity) associates with decreased fraud risk. Hoberg and Phillips (2016)'s industry product similarity score might proxy for substitution instead of the price-cost margin and one minus the Lerner index, which comprise the factor score variable used in my study. The similarity score is based on textual analysis of firms' 10-K reports' product words. It calculates the similarity between a firm and all other firms by calculating pairwise word similarity scores of product offerings. Using these pairwise similarity scores, Hoberg and Phillips then group firms into industries dubbed text-based network industry classifications. Firms with larger similarity scores have competitors with more similar products (Hoberg and Phillips 2016) and have intense direct product market competition.

I expect that adding substitution to fraud risk models will add incremental explanatory power and will itself be positive and significant since substitution captures both within- and across-industry substitutability, whereas similarity represents only the substitutability of products that are more exactly alike. Substitution differs from similarity in its scope – a product need not be identical to be a substitute. For example, bicycles and public transit are dissimilar substitutes for automobiles. This rationale ties with Lerner (1934)'s argument: "we have rejected the criterion of physical similarity as a basis for the recognition or classification of commodities and have put in its place the principle of substitutability at the margin." Thus, greater substitution represents competitive substitutability across industries broadly, whereas similarity represents competitive substitutability within very narrow product markets. Additionally, it could be that firms with much higher similarity scores could be largely comprised of mechanized firms which also have high tangible barriers to entry (gold, petroleum, airplanes, etc.).

Including entry threat and market size would then also add incremental explanatory power to fraud risk models which include similarity. I predict that while similarity may retain the significance of its association with fraud risk, adding substitution, entry threat, and market size to firm-level fraud risk models 1) will significantly increase the model's explanatory power, 2) will demonstrate that these three variables have strong positive associations with fraud risk, and 3) will show that these variables of interest dominate nearly all of the firm-level determinants of fraud in their significance and magnitude.

The above reasons notwithstanding, whether industry competition increases firm-level fraud risk is not perfectly clear *ex ante*. It is possible that firm-level fraud determinants dominate managers' reporting decisions and that these determinants would override the explanatory power of industry-level factors. Nonetheless, I expect higher fraud risk when competition increases, especially from substitution since it associates directly with price competition (Nevo 2001) which is of utmost salience to managers. In sum, while competition may represent a fraud triangle pressure that influences fraud risk, existing theory and extant research does not provide for just one directional prediction. The association between industry-level competition and firm-level fraud remains an empirical question. This leads to my first hypothesis, stated in alternative form:

H1: Firm-level fraud risk increases as industry competition increases.

2.3 Obsolete Costing

The cost management literature provides additional motivation for examining the effects of industry competition. Increased substitution proxies for increased price competition (Nevo

2001), and increased price competition associates with greater focus on cost information and control (Krishnan 2005; Chen et al. 2015). This clear link between increased price competition and increased reliance on cost information illustrates the importance of sound accounting information. Managers must thoroughly understand the decision drivers and resource consumption drivers behind both price and cost to influence firm profitability. However, prior research has found that the distortions from standard costing systems can prompt irrational production and pricing decisions, harming firms' long-run viability (Buchheit 2004; Gupta et al. 2010; Brüggen et al. 2011).

Ernst & Young and the IMA reported survey results in 2003 and 2012, respectively, that managers had continued to conform with inferior standard costing conventions despite advances in cost analytics (Clinton and White 2012). More recent findings have demonstrated that most firms have continued to use obsolete costing systems (Lawson 2017). Given the non-adoption of advanced cost analytics over the sample period, I predict that the association between fraud risk and competition will be stronger in industries typified by obsolete costing.

Obsolete costing occurs when firms simultaneously 1) have multiple product lines (IMA 2019a, 2019b), 2) absorb distortionary labor and overhead cost allocations into product valuation estimates (Labro and Vanhoucke 2007; Gupta et al. 2010; Balakrishnan et al. 2011), 3) program these distortionary estimates into their ERPs for system-generated actual accounting debits and credits to inventories and cost/holding accounts, respectively, as operations advance during the reporting period (Roychowdhury 2006; Brüggen et al. 2011), and 4) clear end-of-period net credits in the cost/holding account with a credit reduction of COGS. These systems generate underperformance, but because controllers tend to view their local operating stewardship as more important than their chartered corporate responsibilities (Maas and Matejka 2009), this conflict tends to associate with greater internal misreporting. Indeed, as one automotive supplier plant controller expressed in 2015 when asked about his preference for obsolete standard costing, he replied “well, if we get rid of standard costs, then our actual expenses will come under much greater scrutiny by top management.” This implies that obsolete costing systems deflect and conceal costs from monitoring, whether accidentally or deliberately. Obsolete costing systems may thus represent a previously unexplored “opportunity” facet on the fraud triangle.

Poor costing systems lead to declining profits (Datar and Gupta 1994). I predict that distorted cost information prompts suboptimal decisions up to and including fraud since managers would not know the root causes of their decreasing performance, and when perceived “sound” cost/profit-based decisions failed, there would be increased temptation to resort to fraud. Additionally, I theorize that when firms use distorted cost information to offer prices below the levels that economic realities should allow, their intra-industry peer firms would be pressured to match those suboptimal prices to retain their presence in the market, causing a downward spiral of profitability from increased price competition. Compounding this issue is the overreliance managers place on multi-product costing systems when competition increases (Matsumura et al. 2018) and the opportunity to hide resource usage through distortionary allocations. Thus when obsolete costing is the industry norm, there would be an observable industry-wide increase in fraud risk as price competition also increases.

To summarize: when substitution is high then price competition is high, and greater price competition increases reliance on cost information. When costing systems distort the visibility of true costs, the combined price competition *pressure* and cost distortion *opportunity* may significantly increase fraud risk, especially with the income statement since this reports prices (sales) and most costs (expenses).

Obsolete costing would likely have stronger effects in high substitution industries since costs receive more immediate attention with price competition as opposed to with direct/indirect contests from incumbents (higher market size) or potential competitors (higher entry threat). However, because obsolete costing pervades manufacturing industries (Clinton and White 2012; Lawson 2017) and these industries require non-zero capital investment for entry, producers of physical goods would be more susceptible to fraud risk when entry threat is high (the investment threshold is low). Fraud risk would also increase with fiercer extant competition among manufacturers since physical products can be reverse-engineered and imitated with minor modifications, thereby threatening firms' future profitability. I thus expect that entry threat and market size would also have larger associations with income statement fraud risk in obsolete costing industries.

Opposing these theories and consulting / research findings is the phenomenon that the majority of firms with complex product offerings have not adopted advanced cost analytics (Clinton and White 2012; Lawson 2017). It is thus possible that "obsolete" costing practices are entirely sufficient for management's cost information needs and that the advocacy for better internal information lacks substance. If this were the case, then there would be no evidence of obsolete costing creating fraud opportunities, nor flawed decision-making arising therefrom that increase fraud risk. In sum, while obsolete costing practices may influence the relation between industry competition and fraud risk, the conflict between contemporary applied cost management theory and managers' non-implementation choices for cost analytics imply diverging predictions. The moderating effect of obsolete costing systems on the relation between competition and fraud risk is an empirical question. This leads to my second hypothesis, stated in alternative form:

H2: The fraud-risk effects of industry competition (substitution) are stronger in industries typified by obsolete costing practices, particularly with income statement fraud.

2.4 Industry Competition & Strategy

Strategy is the mechanism by which managers compete within industries (Kaplan and Norton 2000; Porter 1980). Firms with strategies similar to their peers compete directly, but firms with offsetting strategies compete less directly. It follows that some benefits of less-direct competition would be alleviated fraud risk. I examine this presumption in three industry competition settings: high-substitution, high-entry threat, and high-market size.

M&A's (*Acquisition Activity*) represent a firm's strategy to achieve synergies and create new products (Hoberg and Phillips 2010a). Physical capital intensity (*Capital Intense*) represents a firm's strategy to compete on quantity (Singh and Vives 1984; Hughes and Williams 2008) to achieve cost leadership (Banker and Ma 2019; Awate et al. 2020; Banker et al. 2020). R&D and advertising expenditures (*Intangible Exp)* represent a firm's strategy to focus on "non-price competition" (Symeonidis 2000b, 2000a; Chen et al. 2015), also termed "differentiation" from cost leadership (Porter 1980; Kaplan and Norton 2000; Banker and Ma 2019; Awate et al. 2020). I examine how these three strategies (synergy, cost leadership, and differentiation) may alter fraud risk in high-competition industries.

Firms in high-substitution industries have greater exposure to price competition (Nevo 2001). Their managers can choose to compete directly by yielding to downward-driving price forces from the market, but must subsequently preserve margins through cost leadership. Alternatively, they can enact the potentially offsetting strategies of differentiation or synergy. Since large acquisitions associate positively with fraud, I include synergy as an exploratory consideration but anticipate it will consistently tie to higher fraud risk across all competition types. However, differentiation entails focusing on actual quality (R&D) or perceived quality (marketing) and would theoretically reduce industry pressures arising from price competition since those firms might more easily convince customers of the value represented by their higher prices. I thus predict that firms in high-substitution industries will have significantly reduced fraud risk if they differentiate through greater commitments to non-price competition, proxied by higher R&D and advertising (Kaplan and Norton 2000; Symeonidis 2000b; Chen et al. 2015).

Firms in high-entry threat industries have low barriers to entry (Sutton 1991) and are thus exposed to new entrants which either imitate or provide unique alternative offerings. Incumbents facing greater entry threat may benefit from excellent differentiation, thereby helping preserve their market share from imitators and reduce the pressure of imminent new competitors. Higher R&D commitments would reduce the imitability of product offerings and more advertising would generate a greater customer base due to increased product awareness. I thus predict that firms in high-entry threat industries will experience significantly reduced fraud risk if they expend more on R&D and advertising as non-price competition (Symeonidis 2000b, 2000a; Stigler 1968).

Firms in high-market size industries experience constant risk of being crowded out, especially if they are the smallest in the competitive pool. Conversely, being a large competitor in a large pool could benefit the firm if the greater size comes from productive quantity capacities. The economics literature has identified that firms may choose quantity as their first strategic competitive variable (Shaked and Sutton 1982; Kreps and Scheinkman 1983; Singh and Vives 1984; Eaton and Lipsey 1989) and associates with economies of scale arising from capital intensity. Thus, firms in high-market size industries may mitigate fraud risk pressure if they compete on quantity. I thus predict that firms in high-market size industries will have reduced fraud risk if they focus on quantity competition. Together, these predictions lead to my third hypothesis, stated in alternative form:

H3: The fraud-risk effects of competition are mitigated for firms with offsetting strategies.

CHAPTER THREE

RESEARCH DESIGN

3.1 Sample Selection

My sample comes from the intersection of data between SEC Accounting and Auditing Enforcement Releases (AAERs), Compustat, CRSP, ExecuComp, IBES, and Thomson Reuters. There are 617 firms who received AAERs related to financial misreporting from the SEC which tie to Compustat data. This reduces to 555 treated firms after filtering on data available for variable calculations, resulting in 1,597 firm-years out of the 172,376 total observations from 1993 through 2016. This sample under study is from SEC AAERs issued through the end of 2019 since the SEC investigation announcement date differs from the violating years under the SEC's investigation, plus it generally takes more than three calendar years to discover/announce all frauds' periods investigated by the SEC.

I calculate industry competition variables using Fama-French 48 industry classifications for three reasons. First, these classifications group firms according to stock market risks (Fama and French 1997) and the literature has found evidence that fraud risk is related to managers' desire for favorable capital market perceptions, especially as motivation for obtaining lower-cost financing (Dechow et al. 1996; Kedia and Philippon 2009) and enrichment through equity incentives (Schrand and Zechman 2012; Armstrong et al. 2013). Second, the Fama-French 48 industry classification captures homogenous groups of firms that have comparable fundamental economic attributes (Chan et al. 2007). Third, the Fama-French 48 industry classification schema has a favorable tradeoff between granularity and fraud occurrence: each industry averages at least 10 firms and only 4 industries have zero AAERs over the time period examined. Contrarily, 4-digit SIC codes can range in membership from one to over one hundred firms and many of these industries have had zero AAERs issued to member firms; on the other extreme, Fama-French 17 and lower have no industries missing an AAER but have increasingly dissimilar member firms, which inhibits generalizability.

For each industry I use factor analysis to separately calculate 1) the elasticity of substitution (*Substitution*), 2) the threat of new entry (*Entry Threat*), 3) market size (*Market Size*), and 4) industry concentration (*Concentration*), each from two proxies used for that measure in prior literature. Each of these four competition concepts has been widely used in industrial organization, economics, finance, and accounting research (Alchian and Demsetz 1972; Demsetz 1973, 1982; Ali et al. 2009; Durnev and Mangen 2020) to represent different dimensions of industry competition.

3.2 Variable Measurement

I use SEC misstatement-based AAERs as a proxy for fraud because 1) fraud is frequently implied by the SEC's allegations in these AAERs, 2) these AAERs have the strongest overlap between alleged fraud and ultimate fraud convictions among the proxies examined by Karpoff et al. (2017), and 3) these AAERs have virtually no known false positives, which in a sample of 1,597 treated firm-year observations is more concerning than false negatives in a sample of 172,376 control firm-year observations. AAERs are highly utilized in fraud research (Erickson et al. 2006; Schrand and Zechman 2012; Armstrong et al. 2013; Davidson et al. 2015). The main dependent variable, *Fraud*, is a dummy equal to one during each misstated year if the SEC issued an AAER regarding the firm's financial reporting, zero otherwise. I also include *IS Fraud* and *Rev Fraud* as dummy variables equal to one if the firm's fraud included a misstatement related to the income statement or revenue, respectively; and zero otherwise.

For all competition metrics of interest, larger values represent increased competition. I use factor analysis[2] to calculate each competition metric, yielding the dual benefits of 1) using multiple proxies to capture each dimension of competition and 2) facilitating comparisons of competition types due to each construct being measured on the same 5-point continuous factor score scale. I follow prior literature using the industry price-cost margin to proxy for substitution (Domowitz et al. 1986; Karuna 2007; Subramanian 2013) and calculate it as industry-level sales divided by industry-level operating costs, multiplied by negative one so that higher values represent higher substitution. I also use one minus the Lerner index (Lerner 1934) as another widely-used proxy for substitution (Aghion et al. 2013; Aghion et al. 2005), where the Lerner index is the industry profit margin (Giroud and Mueller 2010). I then use factor analysis to create a reflective construct, *Substitution*, from these variables.

The threat of entry into an industry has an inverse relationship with barriers to entry (Sutton 1991). Prior research shows that tangible standing & spending costs represent greater barriers to entry. To determine the threat of entry into an industry I use the natural logarithm of the weighted average of industry-level PPE (Li 2010; Ali et al. 2014; Durnev and Mangen 2020) and the natural logarithm of the weighted average of industry-level capital expenditures (Li 2010; Chen et al. 2015). Weights are calculated by each within-industry firm's market share. PPE is the value of gross property, plant, and equipment, an exogenous sunk cost, whereas capital expenditures represent endogenous decisions to maintain, increase, or neglect tangible barriers (Chen et al. 2015). I multiply these values by negative one so that higher values

[2]I utilize factor analysis in this study's main tests since factor analysis assumes less variance is explained by the base variables than principal component analysis does. However, I also use principle component analysis, which produces similar results and significance.

represent lower barriers and thus greater entry threat. I then use factor analysis to create the formative construct *Entry Threat* from these two measures.

Prior research uses market size and firm count as proxies for industry competition. These represent aggregate demand for an industry's products but also the competitor pool which strives to provide them. Since prior literature considers market size to be exogenous, I use factor analysis to create a formative construct, *Market Size*, from the natural log of an industry's aggregate sales (Sutton 1991; Karuna 2007; Chen et al. 2015) and the natural log of incumbent firms (Li 2010).

Obsolete Costing is a dummy variable equal to one if the industry is typified by obsolete costing practices, zero otherwise (IMA 2014, 2019a, 2019b). I identify obsolete-costing industries based on whether they are typified by all four of the following factors: 1) their firms have multiple product lines (IMA 2019a, 2019b; Matsumura et al. 2018), 2) their firms' products absorb distortionary labor and overhead cost allocations for estimating cost of sales and inventory values (Gupta et al. 2010; Clinton and White 2012; Lawson 2017) , 3) their firms' ERP applications automatically generate these cost estimates as actual accounting debits and credits to inventories and cost/holding accounts, respectively, as production occurs (Roychowdhury 2006; Brüggen et al. 2011), and 4) the system clears end-of-period net credits in the cost/holding account with a credit reduction of COGS. Because this business scenario exists solely with firms involved in the production of tangible goods but not the process industries, I take all firms which are surveyed in the US Census' Annual Survey of Manufactures (ASM) and use a dummy variable equal to one if the majority of firms in a Fama-French 48 industry are sampled in the ASM[3]. These firms represent approximately thirty-nine percent of the sample's observations.

[3] The type of obsolete costing examined in this study, where all 4 factors are present, exists only in the manufacturing industries. Brüggen et al. (2011) interview managers with such costing systems, i.e. "traditional

3.3 Control Variables

I make no predictions for the effects of concentration on firm level fraud risk since there are reasons to expect either a positive or negative association between concentration and fraud risk (Bresnahan 1989; Ali et al. 2014). I follow prior literature by including it as a baseline competition control variable (Sutton 1991; Raith 2003; Vives 2008) and use factor analysis to create a reflective construct, *Concentration*, from 1) the natural log of the Herfindahl-Hirschman Index (HHI) at the Fama French 48 level and 2) the four-firm concentration ratio. HHI is a measure of industry concentration calculated by taking each firm's percentage of its industry's market value in sales, squaring that product, and then summing all of the squared percentages; the four-firm concentration ratio is the sum of market shares of an industry's four largest firms (Li 2010).

To compare the fraud risk effects of my competition variables of interest and product similarity (Boone et al. 2019), I include Hoberg and Phillips (2016)'s TNIC product similarity score as *Similarity*. I transform their score into decile rankings and then re-scale by tenths from zero to one, with one representing the highest product similarity. When including equity incentive variables *Vega* and *Delta* (Armstrong et al. 2013), there are fewer than one-fifth the observations (31,534) due to limited ExecuComp data by firm; I include them to assess competition's robustness in initial tests. *Vega* is the expected dollar change in CEO wealth for a 0.01 change in stock return volatility computed as in Core and Guay (1999) and Coles et al.

absorption cost accounting and performance measurement systems". They find that "managers are aware that overproduction can have potential adverse consequences", yet managers state that "basically we talk ourselves into overproduction", and Brüggen et al. observe that "the result [of such systems] is a distorted incentive to increase production". These systems thus distort 1) pricing decisions (Buchheit 2004) and 2) production decisions, which also lead to price declines (Brüggen et al. 2011).

(2013, 2006). *Delta* is the expected dollar change in CEO wealth for a 0.01 change in stock price computed as in Core and Guay (2002) and Coles et al. (2013, 2006).

I control for firm-specific attributes that have established or likely influences on fraud risk to assess the incremental effects of industry competition on firm-level fraud risk. For general firm attribute variables I include firm size as the natural log of assets (*Size*) and firm age as the number of years included in Compustat (*Age*). For firm performance/outlook variables I include Tobin's Q as the firm's market value divided by its book value (*Tobin's Q*), return on assets as earnings scaled by average assets (*RoA*), and sales growth as the difference in sales from year t-1 to year t divided by sales in year t-1 (*Sales Growth*). Other firm attributes associated with fraud include inventory (*Inventory*) and accounts receivable (*Receivables*), which are both scaled by assets.

Dechow et al. (2011) find that firms with an F-score over 1.85 have a greater chance of receiving an AAER related to misreporting, so I include *F Score* as a dummy variable equaling one if the original score exceeds 1.85, zero otherwise. I also include Altman's Z-score , the Whited Wu Index (Whited and Wu 2006), whether the firm has a credit rating, and long term debt scaled by assets to control for potential financial distress as *Z Score*, *Constrained*, *Credit Rated*, and *Leverage*, respectively.

I control for external financing amount as the dollar value of debt and equity issuances (*Financing Amount*) due to the model set forth by Povel et al. (2007) and empirical evidence from Dechow et al. (1996) and Wang et al. (2010). These studies have established that firms commit fraud to raise less expensive external capital. For strategy related variables I include *Acquisition* as a dummy variable equal to one for firm-years wherein M&A activity transpired to represent a product market synergy strategy (Hoberg and Phillips 2010a), physical capital intensity as industry-median-adjusted gross property, plant, and equipment scaled by assets (*Capital Intense*) to represent a cost leadership strategy (Banker and Ma 2019), and industry-median-adjusted intangible expenditures as the ratio of R&D and advertising expense to sales (*Intangible Exp*) to represent differentiation strategies (Symeonidis 2000b, 2000a; Chen et al. 2015; Porter 1980).

I also control for institutional ownership (*Inst Ownership*) and analyst coverage (*Analyst Coverage*) to incorporate the fraud risk effects of external monitoring. Finally, I control for risks inherent in a firm's internal structure using the fragmentation of geographic segments (*Geographic Dispersion*) and fragmentation of operating segments (*Organizational Complexity*) (Bushman et al. 2004). To remove the effects of outliers, I winsorize all continuous variables at the 1% and 99% levels. All independent variables, including variables of interest, are lagged one year. Variable definitions are in the Appendix.

3.4 Descriptive Statistics

I identify my sample's fraud firms from all AAERs issued through 2019 that have firm-year violations from 1993 through 2016. SEC announcement dates are naturally later than offending firms' misreported years since it historically requires more than three years to identify all misstated reporting periods during/after a fraud. The sample (Table 1, Panel A) includes only those AAER firms for which the SEC investigation involved material financial reporting misstatements. Matching to Compustat data results in 617 fraud firms. After calculating (lagged) variables of interest and control variables, 555 firms remain from 1993 through 2016. This sample has 172,376 firm year observations.

Table 1, Panel B presents fraud rates by industry, average number of firms by industry, and total fraud firms per industry. Prior studies on fraud often list frequency of fraud by industry, but Panel B demonstrates ranking by fraud rates, which I present as an industry's fraud firm years divided by an industry's total firm years, multiplied by 100. The automotive industry is thus revealed as the worst offender of the fraud-perpetrating industries. It is followed by Computers, Recreation (Toys), Apparel, and Healthcare as the five most fraudulent industries. The five least fraudulent industries where at least one fraud occurred from 1993 through 2016 are Non-Metallic/Industrial Metal Mining, Precious Metals Mining, Aircraft, and Business Supplies. Industries with fraud rates of zero include Beer & Liquor, Tobacco Products, Shipbuilding & Railroad Equipment, Defense, and Shipping Containers. Notably, the fraud rate of the most fraudulent industry (Automotive and Trucks) is 2,098 percent larger than the least fraudulent, non-zero industry (Non-Metallic and Industrial Metal Mining) and 331 percent larger than the median fraud rate industries (Banking and Other). This wide range of industry fraud rates reinforces the motivation for considering industry factors in fraud analyses.

Table 2 presents descriptive statistics and comparison data. It reports T-tests of differences in means and Wilcoxon/Chi-square tests of differences in medians for fraud firms versus non-fraud firms. The results of these tests imply that fraud firms are more often in industries with higher product substitutability (*Substitution*), greater threat of new entry (*Entry Threat*), and larger competitor pools (*Market Size*). These tests also indicate that industry concentration/fragmentation has no meaningful difference from fraud firms to non-fraud firms, whether at the mean or at the median. These statistics also indicate that fraud firms have stronger equity incentives (*Vega* and *Delta*), are bigger, have higher Tobin's Q, have higher return on assets, have higher sales growth, have larger inventories, have larger receivables, have higher F scores and Z scores, are less financially constrained or leveraged, make larger acquisitions, are less capital intensive, spend less on R&D and advertising, have higher institutional ownership and analyst coverage, are more geographically dispersed, and have more complex organizations.

3.5 Empirical Tests of Hypotheses

To begin testing competition's associations with managerial fraud risk, I begin by calculating and importing lagged industry-level variables into firm-level data. I predict that *Substitution*, *Entry Threat*, and *Market Size* will remain significantly associated with fraud risk when controlling for firm-level attributes and the baseline competition variable *Concentration*. *Substitution* associates directly with price competition (Nevo 2001), which would be more salient for managers; *Entry Threat* would create a managerial environment based on constant exposure to immediately-pending increased competition; and *Market Size* would stand as the constant reminder of actual competitors. The resulting pressures to appear superior to peers and be able to access external financing to sustain product market share would prompt higher likelihoods for misstated financial performance (Dechow et al. 1996). Thus substitution, entry threat, and market size would increase the 'pressure' factor of the fraud triangle. For firm *i* and industry *j*, I estimate the following Model (1) for firm-level logit regressions with year fixed effects:

$$\begin{aligned}
Fraud, IS|Rev_{i,t} &= \alpha + \beta_1 Substitution_{j,t-1} + \beta_2 Entry\ Threat_{j,t-1} + \beta_3 Market\ Size_{j,t-1} \\
&+ \beta_4 Concentration_{j,t-1} + \beta_5 Size_{i,t-1} + \beta_6 Age_{i,t-1} + \beta_7 Tobin's\ Q_{i,t-1} \\
&+ \beta_8 RoA_{i,t-1} + \beta_9 Sales\ Growth_{i,t-1} + \beta_{10} Inventories_{i,t-1} \\
&+ \beta_{11} Receivables_{i,t-1} + \beta_{12} F\ Score_{i,t-1} + \beta_{13} Z\ Score_{i,t-1} \\
&+ \beta_{14} Financial\ Constraint_{i,t-1} + \beta_{15} Credit\ Rated_{i,t-1} + \beta_{16} Leverage_{i,t-1} \\
&+ \beta_{17} Financing\ Amount_{i,t-1} + \beta_{18} Acquisition_{i,t-1} \\
&+ \beta_{19} Capital\ Intense_{i,t-1} + \beta_{20} Intangible\ Exp_{i,t-1} \\
&+ \beta_{21} Inst\ Ownership_{i,t-1} + \beta_{22} Analyst\ Coverage_{i,t-1} \\
&+ \beta_{23} Geographic\ Dispersion_{i,t-1} + \beta_{24} Organizational\ Complexity_{i,t-1} \\
&+ YearFE + \varepsilon_{i,t} \qquad (1)
\end{aligned}$$

Substitution, *Entry Threat*, *Market Size*, and *Concentration* are all calculated at the industry level. All other variables in Model (1) are calculated at the firm level. To test whether the association between *Substitution* and *Fraud* is stronger for firms in obsolete costing industries, I interact *Substitution*, *Entry Threat*, *Market Size*, and *Concentration* each with *Obsolete Costing* to see the effects on *Fraud* but also on *IS Fraud* and *Rev Fraud*. I expect that the associations between *Substitution* and *Fraud* are stronger in obsolete costing industries due to increasing both the pressure and opportunity factors of the fraud triangle. Also, because *Substitution* directly associates with price competition pressure (Nevo 2001) and obsolete costing would provide managerial opportunities to conceal expense information, I predict that the effects of substitution in obsolete costing industries will be greater for *IS Fraud* than for *Fraud* or *Rev Fraud*. I estimate the following Model (2) for logit regressions with year fixed effects:

$$\begin{aligned} Fraud, IS|Rev_{i,t} &= \alpha + \beta_1 Substitution_{j,t-1} + \beta_2 Substitution_{j,t-1} * Obsolete\ Costing_{j,t-1} \\ &+ \beta_3 Entry\ Threat_{j,t-1} + \beta_4 Entry\ Threat_{j,t-1} * Obsolete\ Costing_{j,t-1} \\ &+ \beta_5 Market\ Size_{j,t-1} + \beta_6 Market\ Size_{j,t-1} * Obsolete\ Costing_{j,t-1} \\ &+ \beta_7 Concentration_{j,t-1} + \beta_8 Concentration_{j,t-1} * Obsolete\ Costing_{j,t-1} \\ &+ \beta_9 Obsolete\ Costing_{j,t-1} + \sum \beta_k controls_{i,t-1} + YearFE + \varepsilon_{i,t} \end{aligned} \quad (2)$$

The dependent variable is either *Fraud*, *IS Fraud*, or *Rev Fraud.* I am interested in coefficients *β1*, *β3*, *β5*, and *β7*, which represent the associations between competition and fraud risk in firms operating in non-obsolete costing industries; the summation of coefficients *β1* with *β2*, *β3* with *β4*, *β5* with *β6*, and *β7* with *β8*, which represent the associations between competition and fraud risk in firms operating in obsolete costing industries; and coefficients *β2*, *β4*, *β6*, and *β8*, which represent the differences in the association between competition and fraud risk between non-obsolete and obsolete costing industries' firms.

I next estimate how firms' strategic positioning interacts with competitive pressures to determine fraud risk. The motivation behind these analyses is to determine how fraud firms (or fraud-resistant firms) differ from one another in succumbing to (or reducing) fraud risk by competition type. I examine the industry effects high-substitution, high-entry threat, and high-market size. I estimate the following Model (3) OLS regression:

$$\begin{aligned} Fraud_{i,t} = \alpha &+ \beta_1 Acquisition_{i,t-1} + \beta_2 Capital\ Intense_{i,t-1} + \beta_3 Intangible\ Exp_{i,t-1} \\ &+ \beta_4 High\ Industry_{j,t-1} + \beta_5 Acquisition_{i,t-1} * High\ Industry_{j,t-1} \\ &+ \beta_6 Capital\ Intense_{i,t-1} * High\ Industry_{j,t-1} \\ &+ \beta_7 Intangible\ Exp_{i,t-1} * High\ Industry_{j,t-1} + \sum \beta_k controls_{i,t-1} \\ &+ YearFE + \varepsilon_{i,t} \end{aligned} \tag{3}$$

The dependent variable is fraud. *High Industry* is a dummy variable equal to one if the firm is in a high-competition industry, zero otherwise. I estimate Model (3) using three main proxies for strategy: *Acquisition Activity* for synergy, *Intangible Exp* for differentiation, and *Capital Intense* for cost leadership. For these tests, I am interested in coefficients *β1*, *β2*, and *β3*, which represent the associations between strategy and fraud risk in firms operating in low-competition industries; the summation of coefficients *β1*, *β2*, and *β3* with *β5*, *β6*, and *β7*, respectively, which represent the associations between strategy and fraud risk in firms operating in high-competition industries; and coefficients *β5*, *β6*, and *β7*, which represent the differences in the associations between strategy and fraud risk in firms operating in low- and high-competition industries.

CHAPTER FOUR

RESULTS

4.1 Main Results

Table 3 presents Pearson and Spearman correlation coefficients between fraud and various competition pressure and incentive variables. Panel A reports results for the full sample from 1993 through 2016, Panel B reports results from the subsample including *Similarity* from 1997 through 2016 (due to variable availability limitations), and Panel C reports results from the incrementally smaller subsample including both *Similarity* and managerial incentives *Delta* and *Vega* from 1997 through 2016 (due to data limitations of inputs required to calculate *Delta* and *Vega* while still including *Similarity*). As predicted, the competition variables of interest are significantly and highly positively correlated with the fraud variables and with each other[4], although *Concentration* lacks significance in its correlation with *Fraud* and *IS Fraud*. *Similarity* has a negative significant association with all types of fraud risk (Panel B) but once *Delta* and *Vega* are also included in the model (Panel C), *Similarity* only has a significant negative correlation with *Rev Fraud*. This provides some initial evidence that managerial decisions to commit fraud may be influenced by the competitive environment represented by industry substitution, entry threat, and market size, and that their effects are robust to sample selection changes.

Table 4, Panel A presents the regression results of Model (1) while including *Similarity* to test whether the competition metrics of interest provide incremental explanatory power. Columns 1 and 2 report the results with *Fraud* as the dependent variable while controlling for *Similarity* (Column 1) and then adding the competition variables of interest in Column 2

[4] Variance inflation factor tests run with regressions of Models (1) and (2) suggest there is no multicollinearity between *Substitution*, *Entry Threat*, *Market Size*, and *Concentration*.

(*Substitution*, *Entry Threat*, and *Market Size*, plus including/controlling for *Concentration*). As predicted, the coefficient on *Substitution*, 3.960 is positive and highly significant with z-stat 4.27. The coefficient on *Entry Threat*, 2.659, is positive and highly significant with z-stat 4.05. Finally, the coefficient on *Market Size*, 2.623, is positive and highly significant with z-stat 3.03. Control variable *Concentration* also has a positive significant association with *Fraud*: its coefficient of 2.049 is significant at $p<0.05$, supporting the idea that unethical anti-competitive conduct in concentrated industries may associate with greater fraud risk (Bresnahan 1989). Importantly, the Vuong Z-statistic (6.317, $p<0.01$) signals significant incremental explanatory power of the *Fraud* model when including the competition variables of interest. These findings point to the importance and significance of this study's competition metrics of interest.

Table 4, Panel A, Columns 3 and 4 report the results with *IS Fraud* as the dependent variable while controlling for *Similarity* (Column 3) and then adding the competition variables of interest in Column 4 (*Substitution*, *Entry Threat*, and *Market Size*, plus including/controlling for *Concentration*). As predicted, the coefficient on *Substitution*, 4.676, is positive and highly significant with z-stat 6.14; the coefficient on *Entry Threat*, 3.647, is positive and highly significant with z-stat 6.60; and the coefficient on *Market Size*, 2.357, is positive and highly significant with z-stat 3.26. Control variable *Concentration* has a positive significant association with *IS Fraud*: its coefficient of 2.427 is also significant at $p<0.01$. Again, the Vuong Z-statistic (6.552, $p<0.01$) suggests significant incremental explanatory power of the *IS Fraud* model when including the competition variables of interest. The effects of competition are more pronounced for *Rev Fraud* as presented in Columns 5 and 6, respectively. As predicted, the coefficient on *Substitution*, 4.246, is positive and highly significant with z-stat 3.58. The coefficient on *Entry Threat*, 3.027, is positive and highly significant with z-stat 4.51. The coefficient on *Market Size*, 2.978, is positive and highly significant with z-stat 3.36. Interestingly, the coefficient on *Concentration*, 3.729, is positive and highly significant with z-stat 4.52. Again, the Vuong Z-statistic (6.050, p<0.01) suggests significant incremental explanatory power of the *Rev Fraud* model when including the competition variables of interest.

Table 4, Panel B presents the regression results of Model (1) with a sample that is limited by the data availability of inputs required for calculating equity incentives *Delta* and *Vega*, and serves to illustrate the robustness of my competition variables of interest. Columns 1 and 2 report the results with *Fraud* as the dependent variable while controlling for *Similarity*, *Delta*, and *Vega* (Column 1) and then adding the competition variables of interest in Column 2 (*Substitution*, *Entry Threat*, and *Market Size*, plus including/controlling for *Concentration*). As predicted, the coefficient on *Substitution*, 5.219, is positive and highly significant with z-stat 3.36; the coefficient on *Entry Threat*, 2.554, is positive and highly significant with z-stat 2.53; the coefficient on *Market Size*, 3.995, is positive and highly significant with z-stat 3.38; and the coefficient on *Concentration*, 2.964, is positive and highly significant with z-stat 2.62. The Vuong Z-statistic (4.950, p<0.01) signals significant incremental explanatory power of the *Fraud* model when including the competition variables of interest.

Table 4, Panel B, Columns 3 and 4 report the results with *IS Fraud* as the dependent variable while controlling for *Similarity*, *Delta*, and *Vega* (Column 3) and then adding the competition variables of interest in Column 4 (*Substitution*, *Entry Threat*, and *Market Size*, plus including/controlling for *Concentration*). As predicted, the coefficient on *Substitution*, 5.070, is positive and highly significant with z-stat 3.24; the coefficient on *Entry Threat*, 2.845, is positive and highly significant with z-stat 2.74; and the coefficient on *Market Size*, 4.497, is positive and highly significant with z-stat 3.69. Control variable *Concentration* has a positive significant association with *IS Fraud*: its coefficient of 3.682 is also significant at $p<0.01$. Again, the Vuong Z-statistic (5.073, $p<0.01$) suggests significant incremental explanatory power of the *IS Fraud* model when including the competition variables of interest. The associations between competition and *Rev Fraud* are presented in Columns 5 and 6, respectively. As predicted, the coefficient on *Substitution*, 5.885, is positive and highly significant with z-stat 2.68; the coefficient on *Entry Threat*, 3.351, is positive and highly significant with z-stat 2.65; the coefficient on *Market Size*, 4.814, is positive and highly significant with z-stat 3.44. Interestingly, the coefficient on *Concentration*, 5.075, is positive and highly significant with z-stat 4.74. Again, the Vuong Z-statistic (5.008, $p<0.01$) suggests significant incremental explanatory power of the *Rev Fraud* model when including the competition variables of interest.

Together, Table 4's results support the justification for adding industry competition metrics to firm-level fraud models and yield positive, highly significant results regardless of sample selection/size and controlling for alternative metrics of competition (*Similarity*) and managerial equity incentives (*Delta* and *Vega*). This supports H1's supposition that *Substitution*, *Entry Threat*, and *Market Size* have robust competitive environment effects on *Fraud*, *IS Fraud*, and *Rev Fraud*. However, for the remaining analyses I exclude *Similarity* (*Delta* and *Vega*) since their inclusion reduces the treated sample of fraud firm-years by 27 percent (64 percent). By preserving the sample size of fraud observations in the remaining tests, this study helps establish the generalizability of competition's associations with fraud risk.

Table 5, Panel A presents the results the regression results of Model (1) with *Fraud* as the dependent variable. Column 1 presents logit coefficients and the statistical significance of the differences between coefficients. For ease of interpretation, Column 2 presents the marginal effects of each variable. Columns 3 and 4 present the relative impacts of each variable on fraud risk with its standardized coefficient and standardized coefficient ranking, respectively. As predicted, the coefficient on (marginal effects of) *Substitution*, 4.581 (0.041), is positive and highly significant with z-stat 6.31 (5.89); the coefficient on (marginal effects of) *Entry Threat*, 3.448 (0.031), is positive and highly significant with z-stat 6.60 (6.20); and the coefficient on (marginal effects of) *Market Size*, 2.229 (0.020), is positive and highly significant with z-stat 3.26 (3.19). The coefficient on *Substitution* is significantly larger than the coefficients on *Market Size* and *Concentration* at $p<0.05$. The standardized coefficients signal that *Substitution*, *Entry Threat*, and *Market Size* have the 2^{nd}, 4^{th}, and 5^{th} most significant associations with *Fraud*. Notably, each of these are more significant than the *F Score*.

These findings have economic significance: a one standard deviation increase in *Substitution*, *Entry Threat*, and *Market Size* associates with a 44, 34, and 23 percent increase in fraud risk over the unconditional fraud probability of 0.0093, respectively. Together, these results support H1, that firm-level fraud risk increases as industry competition increases. They also suggest that industry competition has more dominant associations with fraud risk than most firm-level determinants, especially *Substitution*.

Table 5, Panel B presents the regression results of Model (1) with *IS Fraud* as the dependent variable. Column 1 presents logit coefficients and the statistical significance of the differences between coefficients. For ease of interpretation, Column 2 presents the marginal effects of each variable. Columns 3 and 4 present the relative impacts of each variable on fraud risk with its standardized coefficient and standardized coefficient ranking, respectively. As predicted, the coefficient on (marginal effects of) *Substitution*, 4.676 (0.039), is positive and highly significant with z-stat 6.14 (5.75); the coefficient on (marginal effects of) *Entry Threat*, 3.647 (0.031), is positive and highly significant with z-stat 6.60 (6.17); and the coefficient on (marginal effects of) *Market Size*, 2.357 (0.020), is positive and highly significant with z-stat 3.26 (3.22). The coefficient on *Substitution* is significantly larger than the coefficients on *Market Size* and *Concentration* at $p<0.05$. Again, the standardized coefficients signal that *Substitution*, *Entry Threat*, and *Market Size* have the 2nd, 4th, and 5th most significant associations with *Fraud* and that each of these rank higher in their associations than the *F Score*.

Table 5, Panel C presents the regression results of Model (1) with *Rev Fraud* as the dependent variable. Column 1 presents logit coefficients and the statistical significance of the differences between coefficients. For ease of interpretation, Column 2 presents the marginal effects of each variable. Columns 3 and 4 present the relative impacts of each variable on fraud risk with its standardized coefficient and standardized coefficient ranking, respectively. As predicted, the coefficient on (marginal effects of) *Substitution*, 5.055 (0.029), is positive and highly significant with z-stat 5.28 (4.98); the coefficient on (marginal effects of) *Entry Threat*, 4.435 (0.026), is positive and highly significant with z-stat 6.79 (6.16); and the coefficient on (marginal effects of) *Market Size*, 2.387 (0.014), is positive and highly significant with z-stat 2.86 (2.82). The coefficient on *Substitution* is significantly larger than the coefficient on *Market Size* at $p<0.05$. The standardized coefficients signal that *Substitution*, *Entry Threat*, and *Market Size* have the 3rd, 4th, and 6th most significant associations with *Fraud*, with *Tobin's Q* surpassing *Substitution* and *Concentration* surpassing *Market Size*. Each of these rank higher in their associations than the *F Score*.

These findings have economic significance. Regressing *IS Fraud* (*Rev Fraud*) on competition, a one standard deviation increase in *Substitution*, *Entry Threat*, and *Market Size* associates with a 45 (49), 36 (44), and 24 (24) percent increase in fraud risk over the unconditional fraud probability 0.0086 (0.0059) for that fraud type, respectively. Taken together, these results support H1, suggesting that industry competition may increase fraud risk. Importantly, they also suggest that industry competition has more dominant associations with fraud risk than most firm-level determinants. They also signal that, among the dimensions of competition being tested, *Substitution* has the largest, most significant association with fraud risk generally and income statement fraud especially, but not necessarily for revenue fraud.

Although I control for Dechow et al. (2011)'s *F Score*, another question is which metrics of competition have incremental explanatory power for fraud likelihood when the treatment and control firms have identical fraud risk as derived from firm-level determinants. Since traditional matching could eliminate the industry variation under study, I use entropy balancing to address this question. I balance firms with high fraud risk (*F Score* dummy equal to one) against low fraud risk (*F Score* dummy equal to zero) on all control variables and years – the sample of firms that had high calculated fraud risk (Dechow et al. (2011)'s F-score value greater than 1.85) against those that did not. Achieving entropy balancing convergence, I run the same tests as presented in Table 5 on this fraud-risk-balanced sample. Table 6 presents the regression results. Notably, the coefficients on *Substitution* and *Entry Threat* remain positive and significant for each type of fraud, whereas *Market Size* loses its significance and *Concentration* loses its significance for *Fraud* and *IS Fraud*, but not for *Rev Fraud*. The difference between *Substitution* and *Concentration* ($\beta 1$ - $\beta 4$) is significant when regressing either *Fraud* or *IS Fraud* on competition ($p<0.05$, Columns 1 through 2) but not when regressing *Rev Fraud* on competition (Column 3). These results suggest that fraud's foremost competition metrics may be *Substitution* and *Entry Threat*.

4.2 Competition & Obsolete Costing

I next examine how competition associates with fraud as contextualized by obsolete costing. Figure 1 plots how the linear probability of *Fraud* gradually increases as *Substitution* increases[5]. However, Figure 2 presents side-by-side plots for non-obsolete, non-distortionary costing industries in blue on the left and obsolete, distortionary costing industries in red on the right. The difference is striking wherein the non-obsolete subsample has a gradual upward slope with each sample bin denoting steadily increasing fraud probabilities; the obsolete costing subsample on the right signifies very low probability of fraud for its low-substitution firms but a strong upward slope toward very high fraud probability as substitution increases. These visuals provide preliminary motivating insights about *Substitution*'s possible greater influence on fraud risk as contextualized by *Obsolete Costing*.

Table 7, Panel A presents the results of Model (2) with *Fraud* as the dependent variable in Column 1 and marginal effects of each dimension of competition for the obsolete costing (OC) group versus non-obsolete costing (NOC) in columns 2 and 3, respectively. When regressing *Fraud* on the variables of interest, the coefficient on *Substitution* (3.873) is positive and significant at $p<0.01$ (z-stat 5.02) for non-obsolete costing industries, suggesting a positive relationship between substitution and fraud risk. The association increases significantly from non-obsolete to obsolete costing industries as denoted by the coefficient on *Substitution*Obsolete Costing* (4.926, z-stat 2.57). The coefficient summation ($\beta 1 + \beta 2$) of these two variables, 8.799, represents the logit coefficient on *Substitution* for firms in obsolete costing industries and is significant at $p<0.01$ (z-stat 4.87). *Market Size* has an insignificant association with fraud in non-obsolete costing industries, but its coefficient in obsolete costing industries (3.160, $p<0.01$) is significantly larger (difference of 2.956, $p<0.05$). Although *Entry Threat* has a

[5] As discussed, *Substitution* is also a proxy for price competition; *Entry Threat* and *Market Size* are not.

significant effect on fraud for both obsolete and non-obsolete costing industries, there is not a statistically significant difference between coefficients across groups. Regarding economic significance, a single standard deviation increase in *Substitution* (*Market Size*) increases the probability of fraud by 35 (11) percent for non-obsolete costing industries but by 97 (48) percent for obsolete costing firms. These findings support H2, that the fraud-risk associations of industry competition (especially *Substitution*) are stronger in industries typified by obsolete costing practices.

Table 7, Panel B presents the results of Model (2) with *IS Fraud* as the dependent variable in Column 1 and marginal effects of each dimension of competition for the obsolete costing (OC) group versus non-obsolete costing (NOC) in columns 2 and 3, respectively. When regressing *IS Fraud* on the variables of interest, the coefficient on *Substitution* (4.029) is positive and significant at $p<0.01$ (z-stat 4.88) for non-obsolete costing industries, suggesting a positive relationship between substitution and income statement fraud risk. The association increases significantly from non-obsolete to obsolete costing industries as denoted by the coefficient on *Substitution*Obsolete Costing* (5.052, z-stat 2.56). The coefficient summation ($\beta 1 + \beta 2$) of these two variables, 9.081, represents the logit coefficient on *Substitution* for firms in obsolete costing industries and is significant at $p<0.01$ (z-stat 4.93). *Market Size* has an insignificant association with *IS Fraud* in non-obsolete costing industries, but its coefficient in obsolete costing industries (4.003, $p<0.01$) is significantly larger (difference of 2.400, $p<0.1$). Although *Entry Threat* has a significant effect on *IS Fraud* for both obsolete and non-obsolete costing industries, there is not a statistically significant difference between coefficients across groups. Regarding economic significance, a single standard deviation increase in *Substitution* (*Market Size*) increases the probability of fraud by 36 (15) percent for non-obsolete costing industries but by 104 (49) percent for obsolete costing firms. These findings support H2, that the fraud-risk associations of industry competition (especially *Substitution*) are stronger in industries typified by obsolete costing practices, especially for income statement fraud.

Table 7, Panel C presents the results of Model (2) with *Rev Fraud* as the dependent variable in Column 1 and marginal effects of each dimension of competition for the obsolete costing (OC) group versus non-obsolete costing (NOC) in columns 2 and 3, respectively. The difference in coefficients' associations with *Rev Fraud* does not differ significantly from non-obsolete to obsolete costing industries. Table 7, Panel D presents the results of comparing coefficients for obsolete costing industries. Although there appear to be no significant differences in coefficients' associations with *Rev Fraud* among obsolete costing industries, the results indicate that *Substitution* has significantly larger associations with *Fraud* than *Entry Threat* [($\beta 1 + \beta 2$) - ($\beta 3 + \beta 4$) is 5.639, significant at $p<0.01$)], *Market Size* [($\beta 1 + \beta 2$) - ($\beta 3 + \beta 4$) is 4.733, significant at $p<0.05$)], and *Concentration* [($\beta 1 + \beta 2$) - ($\beta 7 + \beta 8$) is 6.980, significant at $p<0.01$)]. Similarly, the results indicate that *Substitution* has significantly larger associations with *IS Fraud* than *Entry Threat* [($\beta 1 + \beta 2$) - ($\beta 3 + \beta 4$) is 5.889, significant at $p<0.01$)], *Market Size* [($\beta 1 + \beta 2$) - ($\beta 3 + \beta 4$) is 5.078, significant at $p<0.05$)], and *Concentration* [($\beta 1 + \beta 2$) - ($\beta 7 + \beta 8$) is 7.572, significant at $p<0.01$)]. These results provide additional evidence for H2, that the fraud-risk associations of *Substitution* are stronger in industries typified by obsolete costing practices, especially for income statement fraud.

In Table 8, I report subsample tests based on whether the firm is in an *Obsolete Costing* industry using seemingly unrelated estimation. This approach has the dual benefit of examining whether there is a difference across subsamples and testing whether competition remains significant within a given subsample by fraud risk type, holding within-group firm characteristics more constant. The results suggest that the effects of *Substitution* and *Market Size* are significantly stronger in obsolete costing industries than in non-obsolete costing industries. The evidence for significantly higher effects is more pronounced with *Fraud* and *IS Fraud*, although the significance is somewhat smaller for *Substitution* with respect to *Rev Fraud*. These findings complement earlier results with cross-sectional evidence that supports H2, that the obsolete costing practices may have an exacerbating effect on fraud risk, particularly with income statement fraud.

4.3 Competition & Offsetting Strategies

In additional cross sectional analysis, I test whether offsetting strategies are associated with lower fraud risk when competition is higher. Table 9 presents the OLS results of Model (3). In Column 1, *Acquisition* is positive and significant for both low-substitution (0.010, $p<0.01$) and high-substitution industries (0.008, $p<0.05$), but there is no significant difference in its effects between groups. The coefficient on *Capital Intense* is negative and insignificant for firms in low-substitution industries (-0.002, t-stat -1.07) but negative and significant for high-substitution industries (-0.008, t-stat -2.17). The coefficient on *Intangible Exp* is negative and significant for low-substitution industries (-.007, t-stat -3.41), suggesting a strong negative relationship between a highly-committed quality-based strategy and fraud risk. Its negative coefficient is larger and more significant in high-substitution industries (-.015, t-stat -3.79). The economic effects of course differ between for low- and high-substitution industries as well. A one standard deviation increase in industry-adjusted *Intangible Exp* associates with a 7 percent decrease in fraud probability in low-substitution industries but a 15 percent drop for high-substitution industries. The difference in *Intangible Exp*'s coefficients between groups has a significant chi-square value ($p<0.05$, again using seemingly unrelated estimation), providing evidence that differentiation has a stronger fraud-mitigating effect in high-substitution industries than in low-substitution industries.

In Table 9 Column 2, *Acquisition* is positive and significant for both low-entry threat (coefficient 0.006, $p<0.05$) and high-entry threat industries (coefficient 0.016, $p<0.01$). However, the difference in coefficients between groups is not significant. The coefficient on *Intangible Exp* (-0.006, t-stat -2.50) is negative and significant for low-threat industries which, mechanically, have members with high production capacities, suggesting a negative relationship between a differentiation strategy and fraud risk. However, the coefficient on industry-adjusted *Intangible Exp* for high-threat industries is larger (-0.018) and more significant ($p<0.01$, t-stat -6.37). A one standard deviation increase in *Intangible Exp* associates with a 6 percent reduction from baseline fraud probability for firms competing in industries that have low-entry threat, but has an even greater reduction (17 percent) for firms in industries with high entry threat. This suggests that firms facing high threat of new entrants can especially mitigate fraud risk by differentiating with non-price competition. Chi-square tests of coefficients between models are highly significant ($p<0.01$). Together, these results provide support for H3 that offsetting strategies, i.e. non-price differentiation, may considerably reduce fraud risk in high-entry threat industries.

Column 3 of Table 9 presents the results for high- versus low-market size industries. The coefficient on *Acquisition* is positive and significant for both low-market size (0.005, $p<0.05$) and high-market size industries (0.017, $p<0.01$). The difference between groups is significant, ($p<0.05$), suggesting that pursuing acquisitive strategies in large markets actually increases fraud risk. The coefficient on *Capital Intense* is negative (-0.002) but not significant (t-stat -0.99) for low-market size industries. However, its negative coefficient (-0.011) is much more significant (t-stat -2.84) for high-market size industries. A one standard deviation increase in *Capital Intense* reduces fraud risk from the unconditional probability by 4 percent for low-market size industries but by 20 percent for high-market size industries. This suggests that firms competing in industries with large competitor pools can reduce the fraud risk by focusing more on quantity competition. The chi-square test of coefficients between models reinforces that there is a significant difference ($p<0.05$) in fraud risk when firms differentiate through quantity competition (*Capital Intense*) in industries typified by higher market size.

The results in Table 9 provides some evidence that offsetting strategies may reduce the effects that competition exhibits with fraud risk. These findings are important to researchers of fraud since they demonstrate that the attributes of fraud firms vary across industries and that, given differing industry competition types, different strategies may reduce fraud pressures in different ways. However, the pursuit of acquisitive strategies when industries have higher entry threat tend to be positively related to fraud risk despite the competition type and its intensity. This is notable since managers differentiate to favorably alter competitive landscapes, thereby reducing the influence of the mainstream competition types; however, acquisitive strategies seem to increase fraud-risk regardless of industry conditions.

4.4 Additional Analyses

To address the concern that my results are specific to Fama-French 48, I run the analyses using various Fama-French, SIC, and NAICS classifications. The main results hold regardless of industry schema. In addition to the tests run using an entropy-balanced sample, I utilize a propensity score matched sample which yields qualitatively similar results.

Another concern might be whether the enhanced effect of *Substitution* would exist in industries with different types of costing systems. To contrast the distortionary effects of obsolete standard costing I interact the competition variables with process costing, service costing, and “other” costing. These untabulated analyses yield insignificant results, supporting the idea that traditional standard costs distort information inputs for pricing and production decisions (Buchheit 2004; Gupta et al. 2010; Brüggen et al. 2011) and create fraud opportunities by concealing real cost information and producing unexpected underperformance.

Another question which arises involves the internal validity of the proxy for obsolete costing. While survey evidence has established that most firms have not transitioned from inferior costing systems (Clinton and White 2012; Lawson 2017) and the firms which would be most impacted by such cost accounting systems are manufacturers (IMA 2019a, 2019b), it might be wondered whether the distortionary effects of cost accounting systems are the most natural explanation for the increased fraud risk when firms have higher price competition. To address these questions, I run untabulated identification tests which produce evidence of significantly inferior information quality in manufacturing firms (Gallemore and Labro 2015; Heitzman and Huang 2019). I also find evidence of a link between a firm’s idiosyncratic fraud risk and its peer firms’ having inferior accounting systems. While these findings will be developed further in subsequent research studies, they support the position that when most of an industry’s firms have retained obsolete costing systems, there is a corresponding decrease in accounting information quality and increase in fraud risk for its member firms.

CHAPTER FIVE

CONCLUSION

5.1 Conclusion

I provide evidence that competition associates with greater firm-level fraud risk and that these industry effects tend to dominate most firm-level determinants of fraud, including the F-Score. This paper empirically examines the effects of three major types of industry competition on fraud risk: substitution, entry threat, and market size. Using factor analysis to aid with comparisons, I predict and find that these competition types have significant positive associations with financial reporting fraud risk. Robustness tests indicate that substitution and entry threat have the foremost associations with fraud risk. I also predict and find evidence that the non-adoption of advanced cost analytics exacerbates substitution’s effects on fraud risk, especially income statement fraud. Additional findings imply that managers may reduce fraud risk by embracing competitive strategies dependent upon prevailing competition types.

This study extends the product market competition and fraud risk literature with evidence that industry competition not only influences firm-level fraud risk as a pressure factor of the fraud triangle, but that competition surpasses most firm-level determinants of fraud. Results from this study also highlight the importance of distinguishing between competition types since they have varying associations with fraud risk, with substitution seeming to have the strongest effects on fraud risk. It also extends the information environment literature by illuminating the heightened fraud risk in industries typified by obsolete costing practices, a previously unstudied opportunity factor of the fraud triangle. These findings support the idea that the cost of poor information increases as competition also increases, particularly with respect to fraud risk.

Limitations of this study provide future research opportunities. Researchers could develop new constructs for other facets of industry competition to further academics' understanding of how pressures influence fraud. Researchers could mitigate database overlap limitations through additional data collection to expand sample data sets in research on fraud. Finally, I focus on the single managerial decision of fraud commission. Future research could apply competition concepts to motivate other important decision-making questions.

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TABLES & FIGURES

FIGURES

Figure 1. Regression plot of fraud on substitution. This figure presents the linear probability of fraud as a function of the firm's industry's elasticity of substitution. The y-axis is the linear probability of *Fraud*. The x-axis is the elasticity of substitution (*Substitution*) which increases in elasticity from left to right. *Substitution* is calculated using factor analysis from the industry price/cost margin multiplied by negative one & one minus the industry Lerner index, & directly associates with price competition (Nevo, 2001).

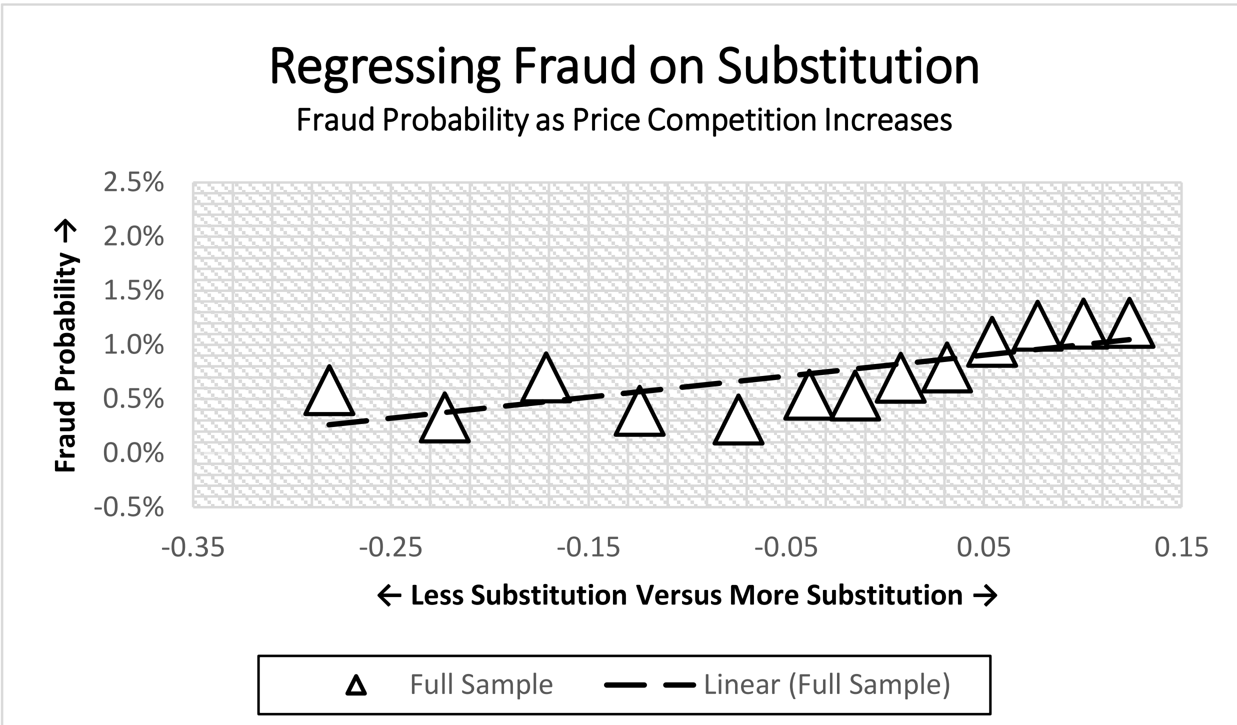
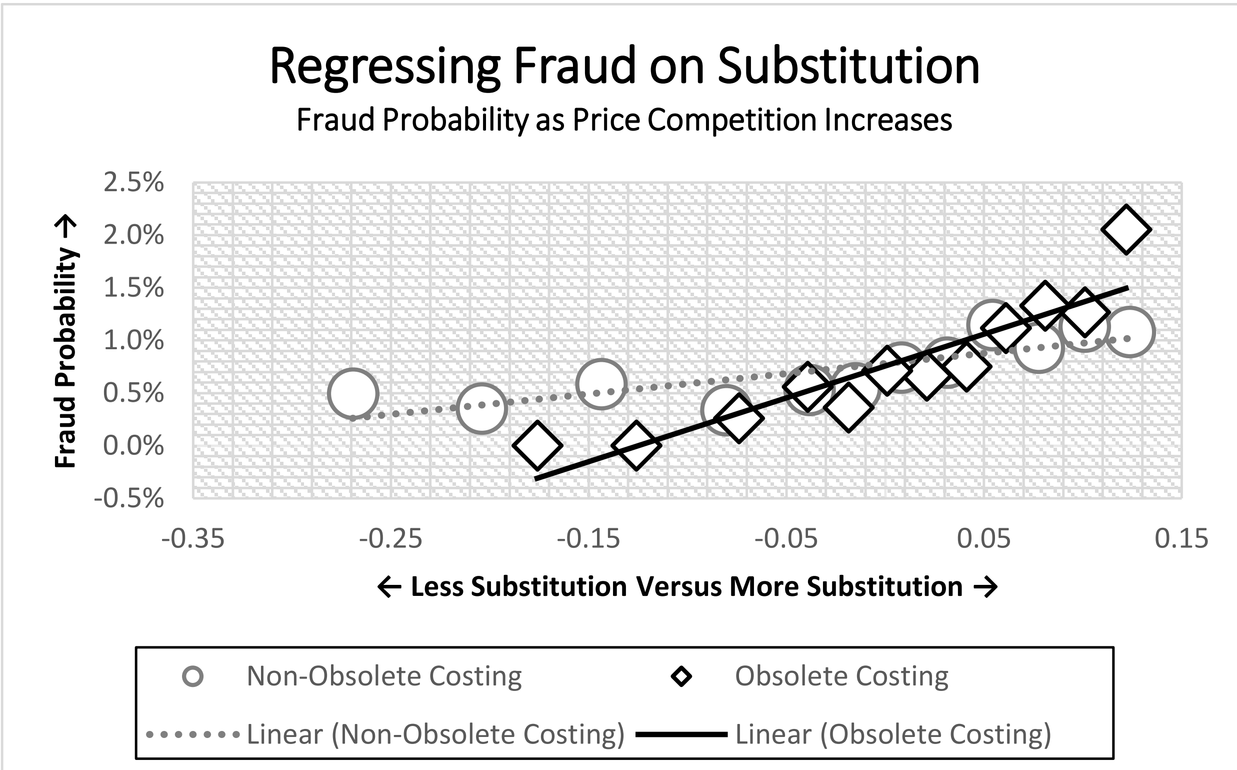


Figure 2. Regression plot of fraud on substitution by cost-practice subsamples. This figure presents the linear probability of fraud as a function of the firm's industry's elasticity of substitution. The y-axis is the linear probability of *Fraud*. The x-axis is the elasticity of substitution (*Substitution*) which increases in elasticity from left to right. *Substitution* is the elasticity of substitution, calculated using factor analysis from the industry price/cost margin multiplied by negative one & one minus the industry Lerner index, & directly associates with price competition (Nevo, 2001). Subsamples are non-obsolete costing industries (blue circles) & industries which use obsolete, distortionary standard costing (red diamonds).



TABLES

Table 1. Sample construction and fraud data

Panel A: Sample construction

Compustat Annual data, 1992-2016	233,931
Less: missing data for (lagged) variable calculations	61,555
Main sample, 1993-2016	172,376
Number of AAER firms matched to Compustat	617
Firms without required data	62
Final sample	555
Final treated firm years	1,597
Average duration of fraud	2.8 years
Median duration of fraud	2 years
Shortest case	1 quarter
Longest case	13 years

Table 1, continued.

Panel B: Fraud Rates by Industry.

This table reports the mean *Fraud Rate* by Fama French 48 industry from 1993 through 2016. 'Fraud Rate' is fraud firm years divided by total firm years, multiplied by 100; it is the rate in the industry over the sample period. 'Average No. of Firms' is the average number of firms per industry-year. 'Total Fraud Firms' is the total number of AAER firms in that industry over the sample period.

Fama-French 48 Industry Name	Fraud Rate	Avg. No. of Firms	Total Fraud Firms
Automobiles and Trucks	1.930	117	14
Computers	1.715	321	46
Recreation, Toys	1.511	64	11
Apparel	1.457	90	12
Healthcare	1.386	133	14
Machinery	1.362	243	22
Personal Services	1.333	90	10
Food Products	1.231	129	14
Business Services	1.207	1053	112
Electronic Equipment	1.198	461	46
Agriculture	1.183	30	3
Wholesale	1.160	298	34
Construction	1.085	89	10
Retail	1.022	366	35
Insurance	0.914	251	19
Transportation	0.753	228	12
Electrical Equipment	0.715	113	9
Fabricated Products	0.677	26	3
Printing and Publishing	0.673	62	4
Medical Equipment	0.672	264	19
Entertainment	0.650	147	9
Coal	0.639	20	2
Rubber and Plastic Products	0.633	67	4
Other	0.585	203	9
Banking	0.580	961	51
Measuring and Control Equipment	0.576	148	7
Steel Works Etc.	0.470	109	4
Real Estate	0.457	114	4
Consumer Goods	0.454	117	7
Financial Trading	0.443	527	23
Chemicals	0.428	150	8
Textiles	0.425	30	2
Candy & Soda	0.389	24	1
Utilities	0.380	324	9
Pharmaceutical Products	0.362	570	20
Petroleum and Natural Gas	0.293	503	10
Communication	0.277	316	11
Construction Materials	0.276	147	6
Restaurants, Hotels, Motels	0.270	151	3
Business Supplies	0.178	97	3
Aircraft	0.144	34	1
Precious Metals	0.114	212	3
Non-Metallic and Industrial Metal Mining	0.092	263	1
Beer & Liquor	0.000	33	0
Tobacco Products	0.000	10	0
Shipbuilding, Railroad Equipment	0.000	15	0
Defense	0.000	11	0
Shipping Containers	0.000	20	0

Table 2. Data summary.

Descriptive statistics for fraud and non-fraud firms

This table presents the mean, median, & standard deviations of industry-level & firm-level variables for the fraud/non-fraud samples. There are 1,597 (170,779) firm-years in the Fraud (Non-Fraud) sample. The subsample of firms for which *Similarity* is calculated from 1997-2016 are 1,163 (88,344) firm years in the Fraud (Non-Fraud) sample. The subsample of firms for which *Delta* & *Vega* are calculated from 1993-2016 are 573 (31,534) firm years in the Fraud (Non-Fraud) sample. The significance of t-tests of differences in means & Wilcoxon/Chi-square tests of differences in medians are presented with the corresponding variables in the non-fraud subsample, where ***p<0.01, **p<0.05, *p<0.1. See the Appendix for full variable definitions.

	Fraud Firms			Non-Fraud Firms		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
IS Fraud	0.932	1.000	0.251	0.000***	0.000***	0.000
Rev Fraud	0.633	1.000	0.482	0.000***	0.000***	0.000
Substitution	0.036	0.053	0.080	0.005***	0.038***	0.098
Entry Threat	0.016	0.010	0.089	0.001***	-0.003***	0.101
Market Size	0.015	0.026	0.097	0.003***	0.014***	0.104
Concentration	-0.006	-0.018	0.093	-0.008	-0.008	0.098
Similarity	0.515	0.500	0.244	0.506	0.500	0.258
Delta	5.189	5.103	1.491	4.467***	4.458***	1.420
Vega	3.633	3.731	1.529	2.965***	3.067***	1.549
Size	6.444	6.349	2.497	5.518***	5.503***	2.480
Age	14.755	11.000	11.736	14.627	11.000	11.720
Tobin's Q	1.839	1.426	1.176	1.666***	1.249***	1.221
RoA	-0.029	0.026	0.326	-0.129***	0.017***	0.692
Sales Growth	0.424	0.171	0.909	0.262***	0.082***	0.870
Inventories	0.124	0.070	0.148	0.101***	0.036***	0.135
Receivables	0.212	0.175	0.168	0.200**	0.139***	0.199
F Score	0.158	0.000	0.365	0.075***	0.000***	0.263
Z Score	1.167	1.191	1.925	0.298***	0.897***	4.929
Financial Constraint	-0.243	-0.256	0.171	-0.185***	-0.213***	0.200
Credit Rated	0.339	0.000	0.474	0.224***	0.000***	0.417
Leverage	0.549	0.543	0.327	0.651***	0.557***	0.745
Financing Amount	0.206	0.072	0.350	0.185**	0.037***	0.379
Acquisition	0.084	0.000	0.277	0.034***	0.000***	0.182
Capital Intense	0.001	-0.007	0.149	0.025***	0.002***	0.177
Intangible Exp	0.004	0.000	0.038	0.015***	0.000	0.091
Inst Ownership	0.157	0.000	0.300	0.138***	0.000	0.277
Analyst Coverage	1.533	0.000	1.724	1.096***	0.000***	1.579
Geographic Dispersion	1.228	1.029	0.264	1.141***	1.000***	0.236
Organizational Complexity	1.170	1.000	0.247	1.122***	1.000***	0.220

Table 3. Pearson and Spearman Correlations.

Panel A: Correlation coefficients, fraud and competition metrics. This presents results from the full sample with 172,376 observations and 1,597 *Fraud* firm-years. Pearson (Spearman) coefficients are presented below (above) the diagonal. ***p<0.01, **p<0.05, *p<0.1. See the Appendix for full variable definitions.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fraud	(1)		0.965***	0.794***	0.035***	0.018***	0.010***	0.002
IS Fraud	(2)	0.965***		0.823***	0.035***	0.020***	0.011***	0.003
Rev Fraud	(3)	0.794***	0.823***		0.032***	0.018***	0.007***	0.008***
Substitution	(4)	0.030***	0.030***	0.029***		-0.210***	-0.382***	0.303***
Entry Threat	(5)	0.015***	0.016***	0.014***	-0.394***		0.496***	-0.361***
Market Size	(6)	0.011***	0.012***	0.008***	-0.404***	0.500***		-0.610***
Concentration	(7)	0.002	0.002	0.007***	0.302***	-0.378***	-0.637***	

Panel B: Correlation coefficients, fraud and competition metrics. This presents results from the subsample including *Similarity*, with 89,507 observations and 1,163 *Fraud* firm-years. Pearson (Spearman) coefficients are presented below (above) the diagonal. ***p<0.01, **p<0.05, *p<0.1. See the Appendix for full variable definitions.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fraud	(1)		0.975***	0.802***	0.042***	0.012***	0.010***	0.003	-0.010***
IS Fraud	(2)	0.975***		0.823***	0.043***	0.013***	0.011***	0.005	-0.010***
Rev Fraud	(3)	0.802***	0.823***		0.039***	0.012***	0.005	0.014***	-0.014***
Substitution	(4)	0.037***	0.037***	0.035***		-0.289***	-0.411***	0.316***	-0.412***
Entry Threat	(5)	0.008**	0.010***	0.007**	-0.460***		0.547***	-0.464***	0.280***
Market Size	(6)	0.012***	0.013***	0.006*	-0.435***	0.533***		-0.658***	0.477***
Concentration	(7)	0.002	0.004	0.013***	0.341***	-0.457***	-0.672***		-0.375***
Similarity	(8)	-0.010***	-0.010***	-0.014***	-0.472***	0.325***	0.464***	-0.371***	

Panel C: Correlation coefficients, fraud and competition metrics. This presents results from the subsample including *Similarity* and managerial incentives *Delta* and *Vega*, with 31,534 observations and 573 *Fraud* firm-years. Pearson (Spearman) coefficients are presented below (above) the diagonal. ***p<0.01, **p<0.05, *p<0.1. See the Appendix for full variable definitions.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Fraud	(1)		0.973***	0.799***	0.043***	0.029***	0.038***	0.001	0.005	0.062***	0.058***
IS Fraud	(2)	0.973***		0.821***	0.044***	0.031***	0.039***	0.006	0.002	0.063***	0.059***
Rev Fraud	(3)	0.799***	0.821***		0.041***	0.026***	0.025***	0.019***	-0.011*	0.050***	0.045***
Substitution	(4)	0.030***	0.031***	0.032***		-0.154***	-0.345***	0.233***	-0.304***	-0.017***	0.000
Entry Threat	(5)	0.026***	0.028***	0.022***	-0.362***		0.440***	-0.325***	0.182***	0.062***	0.010*
Market Size	(6)	0.039***	0.039***	0.027***	-0.381***	0.465***		-0.615***	0.418***	0.051***	0.010*
Concentration	(7)	-0.001	0.003	0.015***	0.269***	-0.335***	-0.648***		-0.330***	0.027***	0.038***
Similarity	(8)	0.005	0.001	-0.011**	-0.402***	0.241***	0.413***	-0.339***		0.060***	0.029***
Delta	(9)	0.068***	0.068***	0.055***	-0.022***	0.050***	0.039***	0.040***	0.056***		0.636***
Vega	(10)	0.058***	0.059***	0.045***	0.016***	0.009*	0.017***	0.040***	0.023***	0.610***	

Table 4. Competition and Firm-level Fraud Risk.

Panel A: Regression of fraud on *Similarity*, with/without additional competition metrics. This table presents the results of Model (1) for logit regressions of fraud variables on competition & control variables. It includes Vuong tests of differences in the models' explanatory power when *Substitution*, *Entry Threat*, *Market Size*, and *Concentration* are excluded (included) in linear probability models with *Similarity*. *Fraud* is a dummy variable equal to one for all misstated firm-years identified in AAERs, zero otherwise. *IS Fraud* (*Rev Fraud*) is a dummy variable equal to one if the fraud included an income statement (revenue) misstatement, zero otherwise. *Substitution* is the elasticity of substitution, calculated using factor analysis from the industry price/cost margin multiplied by negative one & one minus the industry Lerner index. *Entry Threat* is the threat of new entrants, calculated using factor analysis from the natural log of the size-weighted average gross PPE by industry & multiplied by negative one and from the natural log of the size-weighted average gross capex by industry & multiplied by negative one. *Market Size* is the size of the competitive landscape, calculated using factor analysis from the log of industry sales & the log of an industry's firm count. *Concentration* is industry concentration calculated using factor analysis from the Herfindahl-Hirschman Index & the 4-firm concentration ratio. *Similarity* is the decile-ranked product similarity score from Hoberg & Philips (2016) scaled by 10. See the Appendix for full variable definitions. All independent variables are lagged one year & winsorized at the 1st & 99th percentiles. Robust z-statistics are in parentheses (standard errors clustered at the firm level). ***p<0.01, **p<0.05, *p<0.1.

	(1) DV = *Fraud*	(2) DV = *Fraud*	(3) DV = *IS Fraud*	(4) DV = *IS Fraud*	(5) DV = *Rev Fraud*	(6) DV = *Rev Fraud*
Similarity	-0.448*	-0.450	-0.484*	-0.479*	-0.747**	-0.640*
	(-1.71)	(-1.59)	(-1.81)	(-1.67)	(-2.41)	(-1.93)
Substitution		3.960***		4.028***		4.246***
		(4.27)		(4.31)		(3.58)
Entry Threat		2.659***		3.027***		3.683***
		(4.05)		(4.51)		(4.64)
Market Size		2.623***		2.978***		2.795***
		(3.03)		(3.36)		(2.70)
Concentration		2.049**		2.648***		3.729***
		(2.44)		(3.21)		(4.52)
Size	0.399***	0.409***	0.405***	0.416***	0.375***	0.388***
	(9.10)	(9.26)	(8.96)	(9.13)	(6.99)	(7.12)
Age	-0.017***	-0.014**	-0.019***	-0.016***	-0.021***	-0.018**
	(-2.93)	(-2.39)	(-3.26)	(-2.67)	(-3.01)	(-2.47)
Tobin's Q	0.233***	0.213***	0.251***	0.226***	0.274***	0.253***
	(5.43)	(4.94)	(5.85)	(5.21)	(5.89)	(5.39)
RoA	-0.373***	-0.091	-0.386***	-0.113	-0.467***	-0.231
	(-2.80)	(-0.52)	(-2.98)	(-0.69)	(-3.58)	(-1.45)
Sales Growth	0.045	0.045	0.047	0.049	0.084*	0.086*
	(1.07)	(1.04)	(1.10)	(1.11)	(1.69)	(1.69)
Inventories	1.576***	1.483***	1.773***	1.671***	1.902***	1.685***
	(3.28)	(3.13)	(3.69)	(3.56)	(3.25)	(2.93)
Receivables	0.488*	0.311	0.580**	0.327	0.751**	0.468
	(1.67)	(0.89)	(1.96)	(0.91)	(2.13)	(1.07)
F Score	0.586***	0.433***	0.597***	0.428***	0.719***	0.533***
	(5.09)	(3.68)	(5.11)	(3.58)	(5.11)	(3.71)
Z Score	0.087*	0.011	0.072	-0.002	0.070	0.001
	(1.88)	(0.24)	(1.57)	(-0.04)	(1.31)	(0.01)
Financial Constraint	-0.106	-0.104	-0.088	-0.089	-0.052	-0.062
	(-0.31)	(-0.33)	(-0.26)	(-0.27)	(-0.13)	(-0.17)
Credit Rated	-0.029	0.010	-0.025	0.018	0.217	0.251
	(-0.18)	(0.07)	(-0.16)	(0.11)	(1.18)	(1.35)
Leverage	-0.935***	-0.705***	-0.997***	-0.749***	-1.147***	-0.891***
	(-4.20)	(-3.18)	(-4.29)	(-3.27)	(-4.11)	(-3.23)
Financing Amount	0.277**	0.240*	0.313**	0.273**	0.112	0.064
	(2.20)	(1.94)	(2.49)	(2.20)	(0.68)	(0.39)
Acquisition	0.481***	0.463***	0.517***	0.499***	0.340**	0.327**
	(3.57)	(3.48)	(3.83)	(3.75)	(2.16)	(2.11)
Capital Intense	-0.325	-0.817**	-0.414	-0.992**	0.017	-0.591
	(-0.94)	(-2.07)	(-1.16)	(-2.44)	(0.04)	(-1.25)
Intangible Exp	-2.213	-2.791	-3.822***	-5.044**	-3.437**	-4.775**

	(-1.58)	(-1.50)	(-2.58)	(-2.53)	(-2.06)	(-2.03)
Inst Ownership	-0.286	-0.249	-0.293	-0.260	-0.486	-0.471
	(-1.18)	(-1.04)	(-1.17)	(-1.05)	(-1.54)	(-1.51)
Analyst Coverage	-0.075*	-0.088**	-0.061	-0.073*	-0.056	-0.065
	(-1.76)	(-2.07)	(-1.37)	(-1.66)	(-1.04)	(-1.22)
Geographic Dispersion	0.800***	0.657***	0.813***	0.662***	0.641**	0.465
	(3.24)	(2.73)	(3.19)	(2.65)	(2.13)	(1.60)
Organizational Complexity	0.132	0.143	0.146	0.159	0.347	0.346
	(0.56)	(0.61)	(0.59)	(0.65)	(1.19)	(1.19)
Constant	-7.661***	-7.667***	-7.753***	-7.762***	-7.996***	-8.036***
	(-16.49)	(-16.41)	(-16.25)	(-16.17)	(-14.43)	(-14.46)
Observations	89,507	89,507	89,507	89,507	89,507	89,507
Year FE	YES	YES	YES	YES	YES	YES
Pseudo R-squared	0.087	0.099	0.093	0.107	0.093	0.109
Model comparison with/without *Substitution*, *Entry Threat*, *Market Size*, and *Concentration*						
Vuong Z-Statistic from LPM		6.317***		6.552***		6.050***
p-value		0.000		0.000		0.000

Table 4, continued. Competition and firm-level fraud risk.

Panel B: Regression of fraud on *Similarity*, *Delta*, and *Vega*, with/without additional competition metrics, with managerial equity incentives included. This table presents the results of Model (1) for logit regressions of fraud variables on competition & control variables. It includes Vuong tests of differences in the models' explanatory power when *Substitution*, *Entry Threat*, *Market Size*, and *Concentration* are excluded (included) in linear probability models with *Similarity*, *Delta*, and *Vega*. *Fraud* is a dummy variable equal to one for all misstated firm-years identified in AAERs, zero otherwise. *IS Fraud* (*Rev Fraud*) is a dummy variable equal to one if the fraud included an income statement (revenue) misstatement, zero otherwise. *Substitution* is the elasticity of substitution, calculated using factor analysis from the industry price/cost margin multiplied by negative one & one minus the industry Lerner index. *Entry Threat* is the threat of new entrants, calculated using factor analysis from the natural log of the size-weighted average gross PPE by industry & multiplied by negative one and from the natural log of the size-weighted average gross capex by industry & multiplied by negative one. *Market Size* is the size of the competitive landscape, calculated using factor analysis from the log of industry sales & the log of an industry's firm count. *Concentration* is industry concentration calculated using factor analysis from the Herfindahl-Hirschman Index & the 4-firm concentration ratio. *Similarity* is the decile-ranked product similarity score from Hoberg & Philips (2016) scaled by 10. *Vega* is the volatility of managerial equity incentives. *Delta* is the magnitude of managerial equity incentives. See the Appendix for full variable definitions. All independent variables are lagged one year & winsorized at the 1st & 99th percentiles. Robust z-statistics are in parentheses (standard errors clustered at the firm level). ***p<0.01, **p<0.05, *p<0.1.

	(1) DV = *Fraud*	(2) DV = *Fraud*	(3) DV = *IS Fraud*	(4) DV = *IS Fraud*	(5) DV = *Rev Fraud*	(6) DV = *Rev Fraud*
Similarity	-0.319	-0.299	-0.475	-0.464	-1.053**	-0.932*
	(-0.81)	(-0.74)	(-1.19)	(-1.13)	(-2.19)	(-1.89)
Delta	0.185**	0.179**	0.179**	0.174**	0.163*	0.154
	(2.53)	(2.43)	(2.30)	(2.21)	(1.74)	(1.61)
Vega	0.094	0.067	0.114	0.082	0.067	0.035
	(1.32)	(0.98)	(1.48)	(1.11)	(0.76)	(0.41)
Substitution		5.219***		5.070***		5.885***
		(3.36)		(3.24)		(2.68)
Entry Threat		2.554**		2.845***		3.351***
		(2.53)		(2.74)		(2.65)
Market Size		3.995***		4.497***		4.814***
		(3.38)		(3.69)		(3.44)
Concentration		2.964***		3.682***		5.075***
		(2.62)		(3.45)		(4.74)
Constant	-7.133***	-7.196***	-7.370***	-7.419***	-7.871***	-7.852***
	(-9.36)	(-9.75)	(-9.48)	(-9.72)	(-8.16)	(-8.44)
Observations	31,534	31,534	31,534	31,534	31,534	31,534
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Pseudo R-squared	0.102	0.121	0.111	0.132	0.110	0.136
Model comparison with/without *Substitution, Entry Threat, Market Size,* and *Concentration*						
Vuong Z-statistic from LPM		4.950***		5.073***		5.008***
p-value		0.000		0.000		0.000

Table 5: Competition and firm-level fraud risk.

Panel A: Regression *Fraud* on competition. This table presents the results of Model (1) for logit regressions of fraud on competition & control variables. It includes marginal effects and standardized coefficient tests, with rankings of variables' association with fraud by standardized coefficient. *Fraud* is a dummy variable equal to one for all misstated firm-years identified in AAERs, zero otherwise. *IS Fraud* (*Rev Fraud*) is a dummy variable equal to one if the fraud included an income statement (revenue) misstatement, zero otherwise. *Substitution* is the elasticity of substitution, calculated using factor analysis from the industry price/cost margin multiplied by negative one & one minus the industry Lerner index. *Entry Threat* is the threat of new entrants, calculated using factor analysis from the natural log of the size-weighted average gross PPE by industry & multiplied by negative one and from the natural log of the size-weighted average gross capex by industry & multiplied by negative one. *Market Size* is the size of the competitive landscape, calculated using factor analysis from the log of industry sales & the log of an industry's firm count. *Concentration* is industry concentration calculated using factor analysis from the Herfindahl-Hirschman Index & the 4-firm concentration ratio. See the Appendix for full variable definitions. All independent variables are lagged one year & winsorized at the 1^{st} & 99^{th} percentiles. Robust z-statistics & t-statistics are in parentheses (standard errors clustered at the firm level). ***p<0.01, **p<0.05, *p<0.1.

		(1) DV = *Fraud* Logit	(2) Marginal Effects	(3) Standardized Coefficient	(4) Standardized Coefficient Ranking
β1	*Substitution*	4.581***	0.041***	0.037***	2
		(6.31)	(5.89)	(11.88)	
β2	*Entry Threat*	3.448***	0.031***	0.031***	4
		(6.57)	(6.20)	(9.73)	
β3	*Market Size*	2.229***	0.020***	0.028***	5
		(3.22)	(3.19)	(7.74)	
β4	*Concentration*	2.246***	0.020***	0.024***	6
		(3.34)	(3.31)	(7.16)	
	Size	0.245***	0.002***	0.055***	1
		(7.39)	(6.86)	(12.66)	
	Tobin's Q	0.226***	0.002***	0.035***	3
		(6.78)	(6.46)	(10.97)	
	F Score	0.414***	0.004***	0.020***	7
		(4.09)	(4.02)	(7.81)	
	Constant	-7.410***			
		(-21.27)			
	Coeff. Differences				
	β1 - β2	1.133			
		(1.26)			
	β1 - β3	2.352**			
		(2.46)			
	β1 - β4	2.335**			
		(2.30)			
	β2 - β3	1.219			
		(1.35)			
	β2 - β4	1.201			
		(1.58)			
	β3 - β4	-0.018			
		(-0.03)			
	Observations	172,376			
	Controls	YES			
	Year FE	YES			
	Pseudo R-squared	0.086			

Table 5, continued: Competition and firm-level fraud risk.

Panel B: Regression *IS Fraud* on competition. This table presents the results of Model (1) for logit regressions of income statement fraud on competition & control variables. It includes marginal effects and standardized coefficient tests, with rankings of variables' association with fraud by standardized coefficient. *Fraud* is a dummy variable equal to one for all misstated firm-years identified in AAERs, zero otherwise. *IS Fraud* (*Rev Fraud*) is a dummy variable equal to one if the fraud included an income statement (revenue) misstatement, zero otherwise. *Substitution* is the elasticity of substitution, calculated using factor analysis from the industry price/cost margin multiplied by negative one & one minus the industry Lerner index. *Entry Threat* is the threat of new entrants, calculated using factor analysis from the natural log of the size-weighted average gross PPE by industry & multiplied by negative one and from the natural log of the size-weighted average gross capex by industry & multiplied by negative one. *Market Size* is the size of the competitive landscape, calculated using factor analysis from the log of industry sales & the log of an industry's firm count. *Concentration* is industry concentration calculated using factor analysis from the Herfindahl-Hirschman Index & the 4-firm concentration ratio. See the Appendix for full variable definitions. All independent variables are lagged one year & winsorized at the 1st & 99th percentiles. Robust z-statistics & t-statistics are in parentheses (standard errors clustered at the firm level). ***p<0.01, **p<0.05, *p<0.1.

		(1) DV = *IS Fraud* Logit	(2) Marginal Effects	(3) Standardized Coefficient	(4) Standardized Coefficient Ranking
β1	*Substitution*	4.676***	0.039***	0.036***	2
		(6.14)	(5.75)	(11.56)	
β2	*Entry Threat*	3.647***	0.031***	0.031***	4
		(6.60)	(6.17)	(9.65)	
β3	*Market Size*	2.357***	0.020***	0.029***	5
		(3.26)	(3.22)	(8.02)	
β4	*Concentration*	2.427***	0.020***	0.025***	6
		(3.56)	(3.50)	(7.37)	
	Size	0.261***	0.002***	0.056***	1
		(7.45)	(6.87)	(12.78)	
	Tobin's Q	0.237***	0.002***	0.036***	3
		(7.10)	(6.68)	(11.24)	
	F Score	0.425***	0.004***	0.021***	7
		(4.09)	(4.03)	(8.26)	
	Constant	-7.760***			
		(-21.43)			
	Coeff. Differences				
	β1 - β2	1.028			
		(1.10)			
	β1 - β3	2.318**			
		(2.34)			
	β1 - β4	2.249**			
		(2.18)			
	β2 - β3	1.290			
		(1.36)			
	β2 - β4	1.220			
		(1.55)			
	β3 - β4	-0.070			
		(-0.10)			
	Observations	172,376			
	Controls	YES			
	Year FE	YES			
	Pseudo R-squared	0.095			

Table 5, continued: Competition and firm-level fraud risk.

Panel C: Regressing Revenue Fraud on Competition. This table presents the results of Model (1) for logit regressions of revenue fraud on competition & control variables. It includes tests of differences in coefficients within models. *Fraud* is a dummy variable equal to one for all misstated firm-years identified in AAERs, zero otherwise. *IS Fraud* (*Rev Fraud*) is a dummy variable equal to one if the fraud included an income statement (revenue) misstatement, zero otherwise. *Substitution* is the elasticity of substitution, calculated using factor analysis from the industry price/cost margin multiplied by negative one & one minus the industry Lerner index. *Entry Threat* is the threat of new entrants, calculated using factor analysis from the natural log of the size-weighted average gross PPE by industry & multiplied by negative one and from the natural log of the size-weighted average gross capex by industry & multiplied by negative one. *Market Size* is the size of the competitive landscape, calculated using factor analysis from the log of industry sales & the log of an industry's firm count. *Concentration* is industry concentration calculated using factor analysis from the Herfindahl-Hirschman Index & the 4-firm concentration ratio. See the Appendix for full variable definitions. All independent variables are lagged one year & winsorized at the 1^{st} & 99^{th} percentiles. Robust z-statistics & t-statistics are in parentheses (standard errors clustered at the firm level). ***p<0.01, **p<0.05, *p<0.1.

		(1) DV = *Rev Fraud* Logit	(2) Marginal Effects	(3) Standardized Coefficient	(4) Standardized Coefficient Ranking
β1	*Substitution*	5.055***	0.029***	0.032***	3
		(5.28)	(4.98)	(10.28)	
β2	*Entry Threat*	4.435***	0.026***	0.031***	4
		(6.79)	(6.16)	(9.68)	
β3	*Market Size*	2.387***	0.014***	0.025***	6
		(2.86)	(2.82)	(6.80)	
β4	*Concentration*	3.242***	0.019***	0.026***	5
		(4.54)	(4.40)	(7.66)	
	Size	0.220***	0.001***	0.041***	1
		(5.40)	(5.07)	(9.38)	
	Tobin's Q	0.273***	0.002***	0.035***	2
		(7.65)	(6.93)	(11.15)	
	F Score	0.530***	0.003***	0.022***	7
		(4.39)	(4.33)	(8.45)	
	Constant	-8.096***			
		(-20.09)			
	Coeff. Differences				
	β1 - β2	0.620			
		(0.54)			
	β1 - β3	2.668**			
		(2.21)			
	β1 - β4	1.813			
		(1.51)			
	β2 - β3	2.048*			
		(1.83)			
	β2 - β4	1.193			
		(1.32)			
	β3 - β4	-0.855			
		(-1.19)			
	Observations	172,376			
	Controls	YES			
	Year FE	YES			
	Pseudo R-squared	0.095			

Table 6. Competition and firm-level fraud risk: entropy-balanced sample.

This table presents the results of Model (1) for regressions of fraud variables on competition & controls in an entropy balanced sample. I show the results of balancing firms with high fraud risk (*F Score* dummy equal to one) against low fraud risk (*F Score* dummy equal to zero) on all control variables and years – the sample of firms that had high calculated fraud risk (Dechow et al. 2011's F-score value greater than 1.85) against those that did not. Entropy balancing convergence was achieved. *Fraud* is a dummy variable equal to one for all misstated firm-years identified in AAERs, zero otherwise. *IS Fraud* (*Rev Fraud*) is a dummy variable equal to one if the fraud included an income statement (revenue) misstatement, zero otherwise. *Substitution* is the elasticity of substitution, calculated using factor analysis from the industry price/cost margin multiplied by negative one & one minus the industry Lerner index. *Entry Threat* is the threat of new entrants, calculated using factor analysis from the natural log of the size-weighted average gross PPE by industry & multiplied by negative one and from the natural log of the size-weighted average gross capex by industry & multiplied by negative one. *Market Size* is the size of the competitive landscape, calculated using factor analysis from the log of industry sales & the log of an industry's firm count. *Concentration* is industry concentration calculated using factor analysis from the Herfindahl-Hirschman Index & the 4-firm concentration ratio. Chi-squared results of seemingly unrelated estimations are in columns 4-6. See the Appendix for full variable definitions. All independent variables are lagged one year & winsorized at the 1st & 99th percentiles. Robust z-statistics are in parentheses (standard errors clustered at the firm level). The significance of the coefficients & chi-squared tests are based on two-tailed tests. ***p<0.01, **p<0.05, *p<0.1.

		(1) DV = *Fraud* Logit	(2) DV = *IS Fraud* Logit	(3) DV = *Rev Fraud* Logit
β1	*Substitution*	4.125***	4.196***	4.828***
		(4.14)	(4.13)	(3.98)
β2	*Entry Threat*	3.360***	3.419***	4.679***
		(4.27)	(4.25)	(4.76)
β3	*Market Size*	1.576	1.268	2.109
		(1.52)	(1.20)	(1.62)
β4	*Concentration*	0.796	0.717	2.816**
		(0.73)	(0.65)	(2.35)
	Constant	-7.517***	-7.800***	-7.905***
		(-13.96)	(-14.17)	(-12.88)
	Coeff. Differences			
	β1 - β2	0.765	0.777	0.149
		(0.62)	(0.62)	(0.10)
	β1 - β3	2.549*	2.928**	2.719
		(1.84)	(2.07)	(1.53)
	β1 - β4	3.329**	3.479**	2.012
		(2.21)	(2.25)	(1.12)
	β2 - β3	1.784	2.151	2.570
		(1.32)	(1.56)	(1.47)
	β2 - β4	2.564**	2.702**	1.863
		(2.16)	(2.21)	(1.29)
	β3 - β4	0.780	0.551	-0.707
		(0.84)	(0.58)	(-0.68)
	Observations	172,376	172,376	172,376
	Industry FE	YES	YES	YES
	Year FE	YES	YES	YES
	Pseudo R-squared	0.110	0.118	0.114

Table 7. Competition, obsolete costing, and firm-level fraud risk.

Panel A: Regressing fraud on competition. This table presents the results of Model (2) for logit regressions of fraud on competition & control variables. It includes tests of coefficients within & across models. The sample period is from 1993 through 2016. *Fraud* is a dummy variable equal to one for all misstated firm-years identified in AAERs, zero otherwise. *Obsolete Costing* is a dummy variable equal to one for industries typified by obsolete costing practices. *Substitution* is the elasticity of substitution, calculated using factor analysis from the industry price/cost margin multiplied by negative one & one minus the industry Lerner index. *Entry Threat* is the threat of new entrants, calculated using factor analysis from the natural log of the size-weighted average gross PPE by industry & multiplied by negative one and from the natural log of the size-weighted average gross capex by industry & multiplied by negative one. *Market Size* is the size of the competitive landscape, calculated using factor analysis from the log of industry sales & the log of an industry's firm count. *Concentration* is industry concentration calculated using factor analysis from the Herfindahl-Hirschman Index & the 4-firm concentration ratio. See the Appendix for full variable definitions. All independent variables are lagged one year & winsorized at the 1st & 99th percentiles. Robust z-statistics are in parentheses (standard errors are clustered at the firm level). ***p<0.01, **p<0.05, *p<0.1.

		(1)	(2)	(3)
		DV =	Marginal Effects	
		Fraud	*Obsolete Costing*	*Obsolete Costing*
		Logit	= 0	= 1
β1	*Substitution*	3.873***	0.033***	0.092***
		(5.02)	(4.75)	(4.16)
β2	*Substitution*Obsolete Costing*	4.926**		
		(2.57)		
β3	*Entry Threat*	4.346***	0.038***	0.033***
		(6.52)	(6.09)	(3.28)
β4	*Entry Threat*Obsolete Costing*	-1.186		
		(-1.12)		
β5	*Market Size*	1.110	0.010	0.042***
		(1.09)	(1.11)	(3.65)
β6	*Market Size*Obsolete Costing*	2.956**		
		(2.24)		
β7	*Concentration*	2.168**	0.019**	0.019**
		(2.30)	(2.27)	(2.03)
β8	*Concentration*Obsolete Costing*	-0.349		
		(-0.26)		
	Constant	-7.367***		
		(-21.13)		
	Coeff. Summation:			
	β1 + β2	8.799***		
		(4.87)		
	β3 + β4	3.160***		
		(3.76)		
	β5 + β6	4.066***		
		(4.25)		
	β7 + β8	1.818*		
		(1.96)		
	Observations	172,376		
	Controls	YES		
	Year FE	YES		
	Pseudo R-squared	0.089		

Table 7, continued. Competition, obsolete costing, and firm-level fraud risk.

Panel B: Regressing income statement fraud on competition. This table presents the results of Model (2) for logit regressions of fraud on competition & control variables. It includes tests of coefficients within & across models. The sample period is from 1993 through 2016. *IS Fraud* is a dummy variable equal to one if the fraud included an income statement misstatement, zero otherwise. *Obsolete Costing* is a dummy variable equal to one for industries typified by obsolete costing practices. *Substitution* is the elasticity of substitution, calculated using factor analysis from the industry price/cost margin multiplied by negative one & one minus the industry Lerner index. *Entry Threat* is the threat of new entrants, calculated using factor analysis from the natural log of the size-weighted average gross PPE by industry & multiplied by negative one and from the natural log of the size-weighted average gross capex by industry & multiplied by negative one. *Market Size* is the size of the competitive landscape, calculated using factor analysis from the log of industry sales & the log of an industry's firm count. *Concentration* is industry concentration calculated using factor analysis from the Herfindahl-Hirschman Index & the 4-firm concentration ratio. See the Appendix for full variable definitions. All independent variables are lagged one year & winsorized at the 1st & 99th percentiles. Robust z-statistics are in parentheses (standard errors are clustered at the firm level). ***p<0.01, **p<0.05, *p<0.1.

		(1)	(2)	(3)
		DV =	Marginal Effects	
		IS Fraud	*Obsolete Costing*	*Obsolete Costing*
		Logit	= 0	= 1
β1	*Substitution*	4.029***	0.031***	0.092***
		(4.88)	(4.65)	(4.15)
β2	*Substitution*Obsolete Costing*	5.052**		
		(2.56)		
β3	*Entry Threat*	4.805***	0.037***	0.032***
		(6.80)	(6.15)	(3.24)
β4	*Entry Threat*Obsolete Costing*	-1.614		
		(-1.48)		
β5	*Market Size*	1.603	0.013	0.041***
		(1.48)	(1.53)	(3.47)
β6	*Market Size*Obsolete Costing*	2.400*		
		(1.74)		
β7	*Concentration*	2.752***	0.021***	0.015*
		(2.82)	(2.73)	(1.65)
β8	*Concentration*Obsolete Costing*	-1.244		
		(-0.91)		
	Obsolete Costing	0.040		
		(0.24)		
	Constant	-7.680***		
		(-21.13)		
	Coeff. Summation:			
	β1 + β2	9.081***		
		(4.93)		
	β3 + β4	3.192***		
		(3.73)		
	β5 + β6	4.003***		
		(4.04)		
	β7 + β8	1.509		
		(1.60)		
	Observations	172,376		
	Controls	YES		
	Year FE	YES		
	Pseudo R-squared	0.099		

Table 7, continued. Competition, obsolete costing, and firm-level fraud risk.

Panel C: Regressing revenue fraud on competition. This table presents the results of Model (2) for logit regressions of fraud on competition & control variables. It includes tests of coefficients within & across models. The sample period is from 1993 through 2016. *Rev Fraud* is a dummy variable equal to one if the fraud included revenue misstatement, zero otherwise. *Obsolete Costing* is a dummy variable equal to one for industries typified by obsolete costing practices. *Substitution* is the elasticity of substitution, calculated using factor analysis from the industry price/cost margin multiplied by negative one & one minus the industry Lerner index. *Entry Threat* is the threat of new entrants, calculated using factor analysis from the natural log of the size-weighted average gross PPE by industry & multiplied by negative one and from the natural log of the size-weighted average gross capex by industry & multiplied by negative one. *Market Size* is the size of the competitive landscape, calculated using factor analysis from the log of industry sales & the log of an industry's firm count. *Concentration* is industry concentration calculated using factor analysis from the Herfindahl-Hirschman Index & the 4-firm concentration ratio. See the Appendix for full variable definitions. All independent variables are lagged one year & winsorized at the 1st & 99th percentiles. Robust z-statistics are in parentheses (standard errors are clustered at the firm level). ***p<0.01, **p<0.05, *p<0.1.

		(1) Logit DV = *Rev Fraud*	(2) Marginal Effects *Obsolete Costing* = 0	(3) *Obsolete Costing* = 1
β1	*Substitution*	4.827***	0.026***	0.047***
		(4.41)	(4.30)	(3.01)
β2	*Substitution*Obsolete Costing*	2.186		
		(0.95)		
β3	*Entry Threat*	5.632***	0.030***	0.025***
		(6.63)	(5.73)	(3.22)
β4	*Entry Threat*Obsolete Costing*	-1.860		
		(-1.44)		
β5	*Market Size*	1.493	0.008	0.027***
		(1.17)	(1.21)	(2.96)
β6	*Market Size*Obsolete Costing*	2.482		
		(1.52)		
β7	*Concentration*	3.113***	0.017***	0.020***
		(3.08)	(2.98)	(2.91)
β8	*Concentration*Obsolete Costing*	-0.169		
		(-0.11)		
	Obsolete Costing	0.152		
		(0.76)		
	Constant	-8.050***		
		(-19.86)		
	Coeff. Summation:			
	β1 + β2	7.012***		
		(3.37)		
	β3 + β4	3.772***		
		(3.84)		
	β5 + β6	3.975***		
		(3.43)		
	β7 + β8	2.944***		
		(2.83)		
	Observations	172,376		
	Controls	YES		
	Year FE	YES		
	Pseudo R-squared	0.097		

Table 7, continued. Competition, obsolete costing, and firm-level fraud risk.

Panel D: Differences in coefficients for obsolete costing industries. This table presents the coefficient results from *Obsolete Costing* (OC) industries of Model (2) logit regressions of fraud on competition & control variables, as presented in Table 7 Panels A, B, and C. The sample period is from 1993 through 2016. *Fraud* is a dummy variable equal to one for all misstated firm-years identified in AAERs, zero otherwise. *IS Fraud* is a dummy variable equal to one if the fraud included an income statement misstatement, zero otherwise. *Rev Fraud* is a dummy variable equal to one if the fraud included revenue misstatement, zero otherwise. *Obsolete Costing* is a dummy variable equal to one for industries typified by obsolete costing practices. *Substitution* is the elasticity of substitution, calculated using factor analysis from the industry price/cost margin multiplied by negative one & one minus the industry Lerner index. *Entry Threat* is the threat of new entrants, calculated using factor analysis from the natural log of the size-weighted average gross PPE by industry & multiplied by negative one and from the natural log of the size-weighted average gross capex by industry & multiplied by negative one. *Market Size* is the size of the competitive landscape, calculated using factor analysis from the log of industry sales & the log of an industry's firm count. *Concentration* is industry concentration calculated using factor analysis from the Herfindahl-Hirschman Index & the 4-firm concentration ratio. See the Appendix for full variable definitions. All independent variables are lagged one year & winsorized at the 1st & 99th percentiles. Robust z-statistics are in parentheses (standard errors are clustered at the firm level). ***p<0.01, **p<0.05, *p<0.1.

OC Variables	Coefficient Differences	(1) From Panel A DV = *Fraud* Logit	(2) From Panel B DV = *IS Fraud* Logit	(3) From Panel C DV = *Rev Fraud* Logit
Substitution vs Entry Threat	*(β1 + β2) - (β3 + β4)*	5.639***	5.889***	3.240
		(2.96)	(3.01)	(1.45)
Substitution vs Market Size	*(β1 + β2) - (β5 + β6)*	4.733**	5.078**	3.037
		(2.28)	(2.41)	(1.27)
Substitution vs Concentration	*(β1 + β2) - (β7 + β8)*	6.980***	7.572***	4.068
		(3.22)	(3.47)	(1.64)
Entry Threat vs Market Size	*(β3 + β4) - (β5 + β6)*	-0.906	-0.812	-0.203
		(-0.66)	(-0.57)	(-0.12)
Entry Threat vs Concentration	*(β3 + β4) - (β7 + β8)*	1.342	1.683	0.828
		(1.08)	(1.35)	(0.59)
Market Size vs Concentration	*(β5 + β6) - (β7 + β8)*	2.247**	2.495**	1.031
		(2.30)	(2.45)	(0.92)

Table 8. Competition, obsolete costing, and fraud risk: seemingly unrelated estimation.

This table presents the results of Model (2) as *Obsolete Costing* (OC) versus non-obsolete costing (NOC) subsample logit regressions for the association between competition and fraud risk. Chi-squared results of seemingly unrelated estimations are presented at the bottom of each grouping. The sample period is from 1993 through 2016. *Fraud* is a dummy variable equal to one for all misstated firm-years identified in AAERs, zero otherwise. *IS Fraud* (*Rev Fraud*) is a dummy variable equal to one if the fraud included an income statement (revenue) misstatement, zero otherwise. *Obsolete Costing* is a dummy variable equal to one for industries typified by obsolete costing practices. *Substitution* is the elasticity of substitution, calculated using factor analysis from the industry price/cost margin multiplied by negative one & one minus the industry Lerner index. *Entry Threat* is the threat of new entrants, calculated using factor analysis from the natural log of the size-weighted average gross PPE by industry & multiplied by negative one and from the natural log of the size-weighted average gross capex by industry & multiplied by negative one. *Market Size* is the size of the competitive landscape, calculated using factor analysis from the log of industry sales & the log of an industry's firm count. *Concentration* is industry concentration calculated using factor analysis from the Herfindahl-Hirschman Index & the 4-firm concentration ratio. See the Appendix for full variable definitions. All independent variables are lagged one year & winsorized at the 1st & 99th percentiles. Robust z-statistics are in parentheses (standard errors are clustered at the firm level). The significance of the coefficients & chi-squared tests are based on two-tailed tests. ***p<0.01, **p<0.05, *p<0.1.

	(1)		(2)		(3)	
Dependent Variable:	*Fraud*		*IS Fraud*		*Rev Fraud*	
Substitution	9.895***	3.273***	10.080***	3.368***	8.055***	3.717***
	(4.88)	(4.22)	(4.99)	(4.08)	(3.60)	(3.36)
Entry Threat	3.352***	4.342***	3.454***	4.808***	4.226***	5.743***
	(3.84)	(6.27)	(3.88)	(6.46)	(4.10)	(6.36)
Market Size	4.903***	0.461	4.991***	0.826	5.311***	0.276
	(4.62)	(0.45)	(4.54)	(0.76)	(4.07)	(0.22)
Concentration	1.846*	1.580	1.602	2.131**	3.149***	2.281**
	(1.87)	(1.58)	(1.60)	(2.01)	(2.85)	(2.14)
Model	Logit	Logit	Logit	Logit	Logit	Logit
Subsample	OC	NOC	OC	NOC	OC	NOC
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	66,533	105,843	66,533	105,843	66,533	105,843
Pseudo R-squared	0.084	0.104	0.092	0.117	0.082	0.132
χ2 Test of Coeff. Diff. between OC and NOC:						
Substitution	9.29***		9.44***		3.02*	
Entry Threat	0.79		1.37		1.23	
Market Size	9.11***		7.26***		7.90***	
Concentration	0.04		0.13		0.31	

Table 9. Offsetting strategies and fraud risk.

This table presents results of Model (3) for OLS regressions with industry high-competition pressure terms interacted with firm-level competition activities: *Acquisition*, *Capital Intense*, & *Intangible Exp*. *Acquisition* is a dummy variable equal to one if the firm reported M&A where at least 20% of sales came from acquired firms, zero otherwise. *Capital Intense* is the industry-median adjusted gross PPE scaled by assets. *Intangible Exp* is the industry-median adjusted sum of R&D & advertising scaled by sales. *High Industry* is a dummy variable equal to one if the firm is in the top tercile of competitive industries, zero otherwise. The sample period is from 1993 through 2016. *Fraud* is a dummy variable equal to one for all misstated firm-years identified in AAERs, zero otherwise. The significance of Chi-squared results of seemingly unrelated estimations are presented at the bottom of each column. See the Appendix for full variable definitions. All independent variables are lagged one year & winsorized at the 1st & 99th percentiles. Robust t-statistics are in parentheses (standard errors clustered at the firm level). The significance of the coefficients & chi-squared tests are based on two-tailed tests. ***p<0.01, **p<0.05, *p<0.1.

		(1) *High Industry* *= Substitution*	(2) *High Industry* *= Entry Threat*	(3) *High Industry* *= Market Size*
			DV = *Fraud*	
		OLS	OLS	OLS
β1	*Acquisition*	0.010***	0.006**	0.005**
		(3.40)	(2.19)	(1.99)
β2	*Capital Intense*	-0.002	-0.004*	-0.002
		(-1.07)	(-1.90)	(-0.99)
β3	*Intangible Exp*	-0.007***	-0.006**	-0.007
		(-3.41)	(-2.50)	(-1.50)
β4	*High Industry*	0.004***	0.003***	0.002*
		(3.85)	(2.96)	(1.82)
β5	*Acquisition*High Industry*	-0.002	0.010*	0.012**
		(-0.35)	(1.85)	(2.07)
β6	*Capital Intense*High Industry*	-0.005	-0.002	-0.008*
		(-1.33)	(-0.56)	(-1.95)
β7	*Intangible Exp*High Industry*	-0.007*	-0.012***	-0.004
		(-1.80)	(-3.81)	(-0.85)
	Constant	-0.020***	-0.021***	-0.021***
		(-5.77)	(-6.00)	(-5.84)
	Coeff. Summation			
	β1 + β5	0.008**	0.016***	0.017***
		(2.06)	(3.29)	(3.43)
	β2 + β6	-0.008**	-0.006	-0.011***
		(-2.17)	(-1.63)	(-2.84)
	β3 + β7	-0.015***	-0.018***	-0.011***
		(-3.79)	(-6.37)	(-5.30)
	Observations	172,376	172,376	172,376
	Controls	YES	YES	YES
	Year FE	YES	YES	YES
	Adj. R-squared	0.008	0.008	0.008

χ2 Cross model difference comparisons	p-value	p-value	p-value
Acquisition, High Industry - Acquisition, Low Industry	0.530	0.268	0.093
Capital Intense, High Industry - Capital Intense, Low Industry	0.257	0.425	0.013
Intangible Exp, High Industry - Intangible Exp, Low Industry	0.016	0.002	0.526

APPENDIX

VARIABLE DEFINITIONS

Variable	Definition	Source
Fraud	A dummy variable equal to one during each misstated year if the SEC issued an AAER regarding the firm's financial reporting, zero otherwise.	SEC
IS Fraud	A dummy variable equal to one if the firm's fraud included a misstatement on the income statement, zero otherwise.	SEC
Rev Fraud	A dummy variable equal to one if the firm's fraud included a misstatement of revenue, zero otherwise.	SEC
Industry-Level Variables:		
Substitution	Product substitutability. Calculated using factor analysis from 1) the industry price/cost margin following Karuna (2007), multiplied by negative one; and 2) one minus the Lerner index (Lerner, 1934) following Giroud and Mueller (2010).	Compustat
Entry Threat	The threat of entry. Calculated using factor analysis from 1) the natural log of the size-weighted average gross PPE by industry and multiplied by negative one and 2) the natural log of the size-weighted average capex by industry and multiplied by negative one.	Compustat
Market Size	Competitive landscape. Calculated using factor analysis from the natural log of aggregate industry sales and the natural log of an industry's incumbent firm count.	Compustat
Concentration	Industry concentration. Calculated using factor analysis from 1) the natural log of the Herfindahl-Hirschman Index and 2) the 4-firm concentration ratio.	Compustat
Similarity	A firm's decile-ranked text-based product similarity score from Hoberg & Phillips (2010, 2016), scaled from zero to one.	Hoberg & Phillips
Obsolete Costing	A dummy variable equal to one if the industry’s typical costing practices have remained obsolete from 1993 through 2016, combining 1) estimating per-unit distortionary labor & overhead allocations for multiple products, 2) programming these estimates into a standard costing system, 3) using these programmed estimates for work-system generated debits to inventory & credits to cost/holding accounts as production occurs, and 4) clearing end-of-period net credits in the cost/holding account with a credit to COGS. Inclusive of all industries where the majority of firms are ASM Census takers.	Compustat, ASM Survey, EY/IMA Surveys
High-substitution	A dummy variable equal to one if the industry's elasticity of substitution is in the top 3rd, zero otherwise; used for cross-sectional analysis.	Compustat

High-entry threat	A dummy variable equal to one if the industry's entry threat is in the top 3rd, zero otherwise; used for cross-sectional analysis.	Compustat
High-market size	A dummy variable equal to one if the industry's market size is in the top 3rd, zero otherwise; used for cross-sectional analysis.	
Firm-Level Variables:		
Vega	Expected dollar change in the average of the top 5 executives' wealth for a 0.01 change in stock return volatility (using entire portfolio of options) computed as in Guay (1999) and Coles et al. (2006, 2013).	Compustat, ExecuComp, CRSP
Delta	Expected dollar change in the average of the top 5 executives' wealth for a 1% change in stock price (using entire portfolio of stocks and options) computed as in Core and Guay (2002) and Coles et al. (2006, 2013).	Compustat, ExecuComp, CRSP
Size	The natural log of firm assets.	Compustat
Age	Firm age as the number of years listed in Compustat.	Compustat
Tobin's Q	Tobin's Q following Ozbas and Scharfstein (2010).	Compustat
RoA	Return on assets.	Compustat
Sales Growth	Sales growth proxied by the difference in sales divided by lagged sales.	Compustat
Inventories	Inventory scaled by total assets.	Compustat
Receivables	Accounts receivable scaled by total assets.	Compustat
F Score	A dummy variable equal to one if the firm's F-score (Dechow et al. 2011, Model 1) is greater than or equal to 1.85, zero otherwise.	Compustat
Z Score	Altman's Z-score (1968).	Compustat
Constrained	Financial constraints index (Whited & Wu, 2006).	Compustat
Credit Rated	A dummy variable equal to 1 if the firm held a credit rating, zero otherwise.	Compustat
Leverage	Long term debt scaled by assets.	Compustat
Financing Amount	The dollar value of debt and equity issued.	Compustat
Acquisition	A dummy variable equal to one if the firm's M&As contributed to at least 20% of sales, zero otherwise.	Compustat
Capital Intense	Firm-level capital intensity proxied by gross property, plant, and equipment scaled by assets adjusted by the industry median.	Compustat
Intangible Exp	The ratio of R&D and advertising expense to sales adjusted by the industry median.	Compustat
Inst Ownership	The percentage of firm ownership held by institutional investors.	Thomson Reuters
Analyst Coverage	The natural log of the number of analysts following a firm each year.	IBES
Geographic Dispersion	The dispersion of geographic segments using HHI following Bushman et al. 2004; single-geography firms equal one and multi-segment firms are 2 minus their geoseg HHI.	Compustat
Organizational Complexity	The complexity of business segments using HHI following Bushman et al. 2004; single-industry-segment firms equal one and multi-segment firms are 2 minus their busseg HHI.	Compustat