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An Examination of the Relation between Strategic Interaction among Industry Firms and Firm Performance

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Abstract

This paper examines the relation between the degree and type of strategic interaction among industry firms and firm performance. As a measure of firm performance, we use data envelopment analysis (DEA) to estimate the efficiency of a firm relative to the 'best practice' firms in its industry. We find that firms in industries with higher levels of strategic interaction are less efficient and the negative relation is more pronounced in industries where firms compete in strategic substitutes. This finding is consistent with the idea that there is significantly more cooperation (tacit collusion) under strategic complements than strategic substitutes. We also find that frontier efficiency methodology outperforms other measures of firm performance in explaining the relation between strategic interaction and firm performance.

JEL Classification: G10, G30, L11, L22, L25
Keywords: Industry structure, strategic interaction, strategic complements, strategic substitutes, firm efficiency

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1. Introduction

An underlying assumption behind most studies on competition and performance is that the larger the number of existing rivals and new entrants in an industry, the higher the competition. These papers, however, do not consider strategic interaction among industry rivals. When there are numerous firms in an industry (as with perfect competition or monopolistic competition), there is no strategic interaction among firms. Yet, oligopoly is a common market structure (e.g., Coca-Cola and PepsiCo, Apple and Samsung, Nike and Adidas, Boeing and Airbus, Verizon and AT&T) and unique aspects of oligopolistic competition are mutual interdependence and repeated interaction. Game theory plays a central role in modeling the interactions between economic agents. According to the *Value Net* framework of Branderburger and Nalebuff (1996), firms interact vertically with customers and suppliers, and horizontally with substitutors and complementors. Along both vertical and horizontal dimensions, there is a mixture of cooperation and competition. Brandenburger and Nalebuff's concept of *co-opetition* is a recognition of the competitive and cooperative duality of business relationships.

This paper examines the relation between the extent and type of strategic interaction among industry firms and firm performance. We use the term "strategic interaction" to denote the entire array of firm behaviors in which there is some form of cooperation or coordination among industry players. Strategic interactions can range from tacit collusions (cooperative interactions) to non-cooperative interactions.[1] We capture the extent and type of strategic interaction in an industry by computing the competitive strategy measure (CSM) developed by Sundaram et al. (1996), Lyandres (2006), and Chod and Lyandres (2011). CSM is a measure of the slope of the

[1] In non-cooperative game theory, each economic agent in the game acts in his/her self-interest. In cooperative game theory, groups or subgroups of economic agents try to achieve certain outcomes among themselves through binding cooperative agreements. While most studies use the terms "collusion" and "cooperation" interchangeably, some differentiate between good and bad collusions. For example, Rey and Tirole (2013) characterize coordinated increase in price (bad collusion) as a "tacit collusion" and coordinated decrease in price (good collusion) as a "tacit cooperation."

firm's reaction (best-response) function. To examine how different types of strategic interactions affect the relation between the degree of strategic interaction and firm performance, we characterize markets by strategic complements or strategic substitutes following Fudenberg and Tirole (1984) and Bulow et al. (1985).[2] If the firm's reaction function is upward sloping, the firm is said to compete in strategic complements. When the reaction function is downward sloping, the firm is said to compete in strategic substitutes. Intuitively, the idea of strategic complements is that competitors match a firm's strategic move in the same direction. Examples of this strategy include lowering price in price competition, producing greater quantity in quantity competition, and increasing levels of advertising in response to greater advertising by rivals. With strategic substitutes, competitors move in the opposite direction (e.g., when one firm increases its output, competitors will lower their outputs in response). Whereas the sign of mean industry CSM indicates the type of strategic interaction among firms in the industry (strategic complements or strategic substitutes), its magnitude measures the intensity of this interaction.

To examine the relation between the extent and type of strategic interaction and firm performance, we evaluate firm performance using frontier efficiency methodology. Demerjian et al. (2012) argue that frontier efficiency methods outperform one-dimensional measures in two key aspects. First, this methodology provides an ordinal ranking of relative efficiency compared to the Pareto-efficient frontier—the best performance that can be practically achieved. Parametric methods (e.g., regression analysis, ratio comparisons) estimate performance relative to average performance, which is decreased disproportionately by underperforming industry peers. Second, frontier efficiency methods calculate performance without imposing an explicit, ad hoc weighting structure. Widely used performance measures assume that inputs and outputs

[2] Note that the term "strategic substitutes" ("strategic complements") refers to downward (upward) sloping reaction functions and therefore has a production perspective. The term "substitute products" ("complement products") refers to products with a positive (negative) cross price elasticity of demand, which therefore has a consumption perspective.

are equally valuable across firms and therefore are unable to control for differences among firms' input-output mix. Chen et al. (2015) argue that relative efficiency is closely tied to the concept of competitive advantage.[3] Thus, this paper provides firm managers with a way of looking at firm performance that controls for differences in input-output mix.

We find that firms operating in industries with a high level of strategic interaction (indicated by a high value of |CSM|) are less efficient. Further, we find that the negative relation between strategic interaction and firm efficiency is stronger (weaker) when firms compete in strategic substitutes (complements). The results are robust to alternative measures of strategic interaction in an industry: the total similarity (TSIMM) measure (Hoberg and Phillips, 2016), and industry concentration measures such as the Herfindahl-Hirschman Index and four-firm concentration ratio. The findings are consistent with the idea that there is significantly more cooperation when actions exhibit strategic complements than when they exhibit strategic substitutes (e.g., Haltiwanger and Waldman, 1991; Rotemberg, 1994; Bester and Güth, 1998).

A potential concern with our study design is that firm efficiency may be endogenous with strategic interaction. To address this concern, we conduct a quasi-natural experiment using tariff rate reductions as an exogenous competitive shock. We find that large reductions in import tariffs have a significant and negative effect on firm efficiency only in industries where firms compete in strategic complements. Given Potters and Suetens (2009) finding that there is significantly more cooperation when actions exhibit strategic complements, less efficient firms may survive longer despite the competitive shock. As a result, firm efficiency is lower after an import tariff reduction. In contrast, when actions exhibit strategic substitutes, non-cooperative

[3] Chen et al. (2015) showcase the relative superiority of the efficiency measure over financial performance measures by comparing American automotive companies with their Japanese counterparts. The major American automotive companies demonstrated relatively strong financial performance in the 1980s and 1990s, despite maintaining lower efficiency. This strategy backfired in the wake of increasing oil prices in that General Motors and Chrysler went bankrupt in 2009. Similarly, Zingales (1998) states that using return on assets (ROA) or sales (ROS) can be problematic as high ROA or ROS can indicate the presence of large monopoly rents, rather than high efficiency.

actions may result in less efficient firms exiting the industry, thus offsetting the negative effect of the shock on firm efficiency.

Our study confirms the importance of capturing multiple dimensions of industry structure and firm performance in empirical work and contributes to the growing literature that highlights the importance of competitive dynamics and strategic interaction for firm behavior (e.g., Fresard and Valta, 2016; Valta, 2012; Chod and Lyandres, 2011; Lyandres, 2006; Kedia, 2006; Sundaram et al., 1996). Further, while previous research commonly studies a single industry at a time, we examine firms in all industries with the exception of financials and utilities.

2. Related Literature and Hypotheses Development

2.1. Link between Competition and Performance

Holmes and Schmitz (2010) and Syverson (2011) provide a comprehensive review of the literature that links competition and firm performance. They review studies that look at the effect of increased competition on productivity, most of which report that increased competition increases performance. Increased competition is typically measured by a decrease in industry concentration, removal of a government-imposed entry-barrier, or trade liberalization (tariff reductions). They also review studies that examine mechanisms through which competition impacts performance. As stated in Syverson, there are two key mechanisms through which competition affects performance. First is the Darwinian selection effect where increased competition moves market share towards better performing firms through the exit of the worst performing firms. Second, heightened competition can induce firms to make performance increasing investments that they may otherwise not. Most empirical research on the link between competition and performance is based on industry studies, focusing on particular industries in great detail (e.g., Fabrizio et al., 2007; Schmitz, 2005; Syverson, 2004; Pavcnik, 2002; Nickell, 1996; Caves and Barton, 1990).

Caves and Barton (1990) use a frontier production function technique to estimate performance for 350 U.S. manufacturing industries and report that an increase in market concentration above a certain threshold tends to reduce technical efficiency. Nickell (1996) analyzes 670 U.K. manufacturing companies and presents evidence that competition, measured by increased numbers of competitors or by lower levels of rents, is associated with a significantly higher rate of total factor productivity growth. Fabrizio et al. (2007) examine regulatory restructurings of U.S. electric generating plants and suggest that there are medium-term technical efficiency gains from replacing a regulated monopoly with a market-based industry structure. In particular, publicly owned plants that are largely insulated from regulatory reforms experience the smallest efficiency gains, whereas investor-owned plants in states that restructure their wholesale electricity markets improve the most. Pavcnik (2002) shows that over a trade liberalization period in Chile, industry-level productivity of import competing industries grew relative to non-traded industries on the order of 25 percent. Part of this is attributable to the exit of inefficient plants and part is within plant efficiency gains.

2.2. Link between Strategic Interaction and Performance

An underlying assumption behind most of the studies mentioned in the previous section is that the larger the number of existing rivals and new entrants (domestic or foreign) in an industry, the higher the competition. These papers, however, do not consider strategic interaction among industry rivals. When there are numerous firms in an industry (as with perfect competition or monopolistic competition), there is no strategic interaction among firms. Yet, oligopoly is a common market structure and the strategic interaction among firms in such industries cannot be ignored. Additionally, duality between competitive and cooperative nature of the business relationships needs to be considered when evaluating interactions among industry rivals (e.g., Brandenburger and Nalebuff, 1996). Recognizing such duality, Dranove et al. (1998)

use the term strategic interactions to denote the entire array of firm behaviors that range from tacit collusions (cooperative interactions) to non-cooperative interactions.

Sundaram et al. (1996) first developed an empirical measure of strategic interactions in the finance literature. Their competitive strategy measure (CSM) captures the sensitivity of a firm's marginal profits with respect to changes in, both its own and, its competitors' output. Lyandres (2006) advances Sundaram et al.'s CSM measure by incorporating industrywide shocks and examining the relation between firms' capital structure and the intensity of strategic interaction, proxied by the absolute value of CSM. Intuitively, the strategic benefit of debt and optimal leverage should be monotonically decreasing as industries move from duopoly to perfect competition. Lyandres finds that firms' leverage is positively related to the extent of strategic interaction in the industry. Similarly, Chod and Lyandres (2011) find that the strategic benefit of being public, and thus, the proportion of public firms in an industry, is positively related to the level of strategic interaction among firms in the output market.

Since higher levels of strategic interaction exist in oligopolistic competition and not in perfect competition, and increased competition increases efficiency, we test the following:

<u>*Hypothesis 1*</u>*: High levels of strategic interaction among industry rivals are related to lower firm efficiency.*

2.2. Types of Strategic Interaction and Firm Performance

According to Fudenberg and Tirole (1984) and Bulow et al. (1985), strategic interactions among firms in their product markets are classified as strategic complements or strategic substitutes. Firms are said to compete in strategic complements whenever an aggressive move by a firm raises its rivals' marginal profits. Firms are said to compete in strategic substitutes when an aggressive strategy by a firm lowers its competitor's marginal profits. Specifically, if the correlation between the change in a firm's profit margin and the change in its rivals' combined sales is positive, the firm is classified as competing in strategic complements. When it is negative, the firm is classified as competing in strategic substitutes. While most studies treat Cournot-type quantity competition as competition in strategic substitutes and Bertrand-type price competition as competition in strategic complements, Bulow et al. (1985) point out that both types of strategic interaction are compatible with both price and quantity competition.[4]

Sundaram et al.'s (1996) CSM measure, the cross-partial derivative of a firm's value with respect to its own and rivals' operating strategies, captures strategic complements with positive CSM and strategic substitutes with negative CSM. Sundaram et al. use their CSM measure to examine the effect of R&D expenditure announcements on stock prices of announcing firms. They find that, while the average announcement effect of R&D expenditures is not significantly different from zero, it is significantly related to the type of strategic interaction. In particular, when the announcing firm competes in strategic substitutes, the announcement effect of R&D spending is positive; when the firm competes in strategic complements, the announcement effect is negative. Kedia (2006) finds that strategic substitutes decrease pay-for-performance incentives of CEOs, whereas strategic complements increase CEO pay for performance incentives. Fresard and Valta (2016) report that incumbents reduce capital expenditures in response to higher entry threat only in markets featuring competition in strategic substitutes. The change in investment is negligible in markets featuring competition in strategic complements. From these results, it appears that the type of strategic interaction among firms affects firm behavior, whether it is investments in R&D, capital expenditures, or managerial compensation schemes.

There exists some theoretical evidence for the hypothesis that cooperative preferences

[4] For example, quantity competition and constant elasticity demand may yield strategic complements, but a linear demand curve with the same elasticity around equilibrium will always yield strategic substitutes.

depend on whether actions are strategic substitutes or complements. For example, Haltiwanger and Waldman (1991) show that aggregate outcomes deviate more from the Nash equilibrium toward a cooperative outcome under strategic complements than under strategic substitutes. Rotemberg (1994) shows that rational players can choose to become cooperative in a first stage, if second-stage actions are strategic complements. Bester and Güth (1998) develop an evolutionary model and provide evidence for the hypothesis that some degree of cooperation is only evolutionarily stable when actions exhibit strategic complements.

On the basis of experimental data from oligopoly experiments with Cournot and Bertrand games, Suetens and Potters (2007) find statistical evidence that there seems to be more tacit collusion in Bertrand price-choice (strategic complements) than in Cournot quantity-choice (strategic substitutes) experiments. In a follow up study, Potters and Suetens (2009) conduct a laboratory experiment aimed at examining whether the type of strategic interaction has an impact on the tendency to cooperate in finitely repeated two-player games with a Pareto-inefficient Nash equilibrium. They confirm that there is significantly more cooperation (tacit collusion) when actions exhibit strategic complements than when they exhibit strategic substitutes. Consistent with these findings, Fehr and Tyran (2008) find that the adjustment of prices after an anticipated monetary shock is slower under strategic complements than under strategic substitutes. Given the theoretical and experimental evidence on the higher likelihood of tacit collusion under strategic complements, we hypothesize the following:

<u>Hypothesis 2</u>: *The negative relation between the degree of strategic interaction and firm efficiency is stronger (weaker) with strategic substitutes (strategic complements).*

3. Data and Methodology

3.1. Data

The sources of data used in the paper include Compustat Fundamentals (Annual and Quarterly) and the Census of Manufactures from the Census Bureau. The initial sample consists of all firms in Compustat, except financials and utilities, during the sample period 1988–2014. We classify product markets (industries) at the four-digit SIC code level. As pointed out by Clarke (1989), some four-digit SIC codes may fail to define sound economic markets. To minimize such concerns, we follow Clarke (1989) and Karuna (2007) and exclude four-digit SIC codes ending with zero and nine. Our final sample consists of 99,214 firm-year observations and 5,275 industry-year observations. We winsorize all variables at the first and ninety-ninth percentiles to reduce the effect of outliers.

3.2. Measure of Firm Performance

Studies that examine firm performance in a financial context most frequently use one-dimensional measures such as return on assets (ROA), return on sales (ROS), ratio of sales to employees, or regression based measures such as total factor productivity. While widely used in the economics literature (e.g., industrial organization, labor, trade) and the banking and insurance literature, frontier efficiency methodology is not as commonly used to measure firm performance in the finance literature (exceptions include Hunt-McCool et al., 1996; Habib and Ljungqvist, 2005; and Nguyen and Swanson, 2009).[5] Demerjian et al. (2012) show that the technical efficiency measure from frontier efficiency methodology outperforms one-dimensional

[5] Similarly, Chen et al. (2015) note that a search for studies using frontier efficiency methodology in three prestigious management journals (Strategic Management Journal, Academy of Management Journal, and Management Science) yields only 16 articles as compared to hundreds of articles using profit measures such ROA or ROS. In contrast, frontier efficiency methodology is widely used in the economics, banking, insurance, and operations research. For example, keyword search “efficiency, DEA” in ScienceDirect results in 117 articles in the *Journal of Banking and Finance* alone. Of these 117 articles, eleven appear in a 2010 special issue on “Performance measurement in the financial services sector: Frontier efficiency methodologies and other innovative techniques.” Six of the articles in this special issue focus on the banking industry and five on the insurance industry.

performance measures because it summarizes a firm’s financing, production, marketing, and innovation decisions in a single statistic that controls for differences among firms. Frontier efficiency methods control for differences in input usage and output production in multi-input, multi-output firms using a rigorous approach derived from micro-economic theory (e.g., Aigner et al., 1977; Charnes et al., 1978). Frontier efficiency methods measure a particular firm’s performance relative to a “best practice” frontier derived from the firms in the industry: those firms that produce the maximum output from a portfolio of inputs.

The best practice frontier also gauges efficiency as a measure of performance without imposing an explicit, ad hoc weighting structure on inputs and outputs. Firms can improve their efficiency in multiple ways. For example, a firm can change its input mix by reducing investments in capital expenditure, but increasing R&D investments. Alternatively, a firm can change its cost structure by investing more in advertising or more in employee/talent acquisition. Our measure of performance is based on a firm’s ability to fully (i.e., efficiently) utilize its resources. Ideally, two firms with similar characteristics and opportunity sets should have the same level of production, Y*. However, in reality some firms do not use their resources as efficiently as others. Thus, a firm may be at a production level Y, which is less than Y*. The difference between Y* and Y is firm inefficiency.

To measure efficiency as a firm’s deviation from Y*, we need a credible benchmark of Y*. In addition, to avoid an inequitable comparison of companies with different opportunities and characteristics, the benchmark needs to hold constant the firm’s opportunity set and characteristics. Frontier efficiency methods provide a mechanism to benchmark Y* and control for differences in input usage and output production. Output is measured by revenue and input is measured as costs. The difference between output and input for a firm is essentially the difference between revenue and costs, or in other words is profit. Therefore, efficiency, in the context of our inputs and outputs, is a measure of the firm's relative performance in maximizing firm profits (consistent with Alchian's (1950) idea that higher relative efficiency results in the survival of the fittest). The frontier function serves as the benchmark hypothetical value Y* that a firm could obtain if it were to match the production performance (e.g., profit or efficiency) of its best-performing peers. A firm's shortfall from the frontier is a measure of inefficiency.

Two prominent frontier efficiency methodologies exist: (i) parametric or stochastic frontier analysis (SFA), which generally makes assumptions about the functional form of the production function and error term distributions and estimates efficiency using econometric techniques; and (ii) non-parametric techniques such as data envelopment analysis (DEA), which do not make assumptions about functional form and estimate efficiency using mathematical (linear) programming.[6] In empirical studies, the DEA approach has been most frequently used (Eling and Luhnen, 2010). The DEA frontier is formed as the piecewise linear combinations that connect the set of the best-practice observations, yielding a convex production possibilities set. Banker and Natarajan (2008) show that DEA-based procedures generally outperform parametric methods since it is often the case that no *a priori* knowledge exists about the form of the production function.

In this paper, we employ the DEA approach with variable returns to scale (VRS) (Banker et al., 1984), as VRS is the most widely used assumption for DEA. VRS reflects the fact that production technology may exhibit increasing, constant, and decreasing returns to scale. Given a certain level of inputs and outputs, DEA compares each firm to its 'best practice' peers (by

[6] SFA was first proposed by Aigner et al. (1977) and DEA by Charnes et al. (1978). Although DEA was traditionally viewed as a strictly non-parametric methodology, research has shown that it can be interpreted as a maximum likelihood procedure (e.g., Banker, 1993). In addition, the DEA estimator is consistent and converges faster than other estimators (Grosskopf, 1996). As such, the asymptotic distribution of DEA estimators is identical to the true distribution of efficiency. DEA efficiency estimates, however, are biased upward in finite samples (e.g., Simar and Wilson, 1998). To correct the upward bias of our efficiency estimates, we implement the bootstrapping procedure of Simar and Wilson (1998) with 2,000 bootstrap replications by using rDEA, a package for frontier efficiency analysis in R (Simm and Besstremyannaya, 2016).

industry and year) and provides an efficiency score from zero to one. A firm is classified as fully efficient (Efficiency = 1.0) if it lies on the frontier and inefficient (0 < Efficiency < 1) if its outputs can be produced more efficiently by another set of firms. Details on estimating efficiency using DEA are available in Appendix A.

In most empirical studies that use DEA, input and output vectors are industry specific.[7] For example, in life insurance efficiency studies (e.g., Erhemjamts and Leverty, 2010), outputs include the real value of incurred benefits and additions to reserves for the five major lines of life insurance business – individual life insurance, individual annuities, group life insurance, group annuities, and accident and health insurance. In property and casualty insurance efficiency studies (e.g., Leverty and Grace, 2010), outputs include the present values of real losses incurred for the four major lines of property and casualty insurance business – short-tail personal lines, short-tail commercial lines, long-tail personal lines, and long-tail personal lines. The same inputs are used for each category of insurers – administrative labor, agent labor, materials and business services, financial equity capital, and policyholder-supplied debt capital. In bank efficiency studies (e.g., Berger and DeYoung, 1997), outputs are loans, deposits, and fee-based income; and inputs are labor, and physical capital.

Our efficiency measure extends across industries and does not require industry-specific regulatory filings (such as Call Reports filed by banks with the FFIEC and annual statements filed by insurers with the NAIC). Accordingly, we use measures of inputs and outputs that are applicable to all publicly-traded firms. For inputs, we follow Demerjian et al. (2012) by considering items that contribute to the production of revenue. The first input is net property, plant, and equipment (data item PPENT). The second input is capitalized operating leases,

[7] Berger and Humphrey (1997) survey 130 studies that apply frontier efficiency analysis to financial institutions in 21 countries. Eling and Luhnen (2010) survey 95 studies on efficiency measurement in the insurance industry.

calculated as the discounted (at 10 percent) present value of five years of lease payments. Compustat data items for the five lease obligations are MRC1, MRC2, MRC3, MRC4, and MRC5. The third input is the five-year capitalized value of R&D expense (data item XRD). The capitalized value is calculated as $RD_{cap} = \sum_{t=-4}^{0}(1 + 0.2t) * RD_{exp}$. The fourth input is purchased goodwill, calculated as the premium paid over the fair value of an acquisition (data item GDWL). The fifth input is other acquired and capitalized intangibles (data item INTAN – GDWL). The sixth input is cost of goods sold (data item COGS). The final input is selling, general, and administrative costs (data item XSGA). Demerjian et al. (2012) argue that the management team has a great deal of latitude in asset purchase and retirement decisions, therefore, these seven inputs capture choices managers make in generating revenue. Table 1 lists descriptive statistics for the input variables.

For output, also following Demerjian et al. (2012), we use revenue (Compustat data item SALE). Other papers (e.g., Habib and Ljungqvist, 2005; Nguyen and Swanson, 2009) have used Tobin's Q or net income as measures of output. Using Tobin's Q, however, may subject the efficiency measure to a potential misvaluation problem. That is, an irrational overvaluation of a firm's equity relative to its fundamentals may make the firm appear more efficient than it is in reality. In addition, Demerjian et al. (2012) argue against net income as an output since it is the aggregation of inputs and outputs (expenses and revenue). Lee and Choi (2010) show that the inclusion of a redundant output variable (e.g., net income) does not significantly change the DEA efficiency estimates. The DEA linear program measures a firm's ability to maximize output (revenue) given a certain level of inputs (costs). Therefore, firms that minimize costs for a given level of revenue are more profitable (i.e., more efficient).

We measure efficiency for all firms in Compustat (except financials and utilities) during fiscal years 1988–2014. To be included in the final sample, firms must have no missing data for all input and output variables. Since we expect that firms in the same industry will have similar structures for converting capital into revenue, we estimate efficiency separately for each 2-digit SIC code industry and year. This allows cost functions to differ across industries. We obtain a measure of efficiency for 192,899 firm-years. Although our final sample is smaller due to additional data requirements (described below), we compute firm efficiency on as large a possible set of firms since it is the universe of firms that determines the 'best practice' frontier.

3.3. Measures of the Degree of Strategic Interaction

3.3.1. Absolute Value of CSM

Industry concentration can be used as a measure of the extent of strategic interaction since the fewer firms operating in an industry (i.e., higher concentration), the higher the extent of strategic interaction. However, Lyandres (2006) notes that high industry concentration could also be due to high variation in industry participants' sizes, which reduces the expected influence of firms' actions on their rivals. Similarly, industries with low concentration could consist of a large number of similarly sized firms, which cannot affect one another's actions, or a few large firms and numerous small firms, where large firms' choices can affect their large rivals' actions.

Shepherd (1972) argues that it is not appropriate to use industry concentration ratios to evaluate the degree of rivalry between firms within a given industry. For example, consider two firms, A and B, both of which operate in two industries. In the first industry, firm A has a dominant 80 percent market share, while B has a 20 percent market share. In the second industry, the situation is reversed: firm A has 20 percent market share, while B has 80 percent. Any measure of concentration would (correctly) indicate that both industries have the same degree of concentration. However, concentration measures do not reflect the radically different degree of rivalry that A and B face in each industry. Therefore, to assess the extent to which rivalry from other firms cut into a given firm's profits, one must exclude that firm's own market share from the traditional concentration measures.

As discussed earlier, Sundaram et al. (1996) develop a proxy (denoted competitive strategy measure or CSM) that measures strategic interaction among industry firms. Kedia (2006) and Lyandres (2006) modify this empirical proxy to control for the effect of industry shocks. Following Lyandres (2006), we estimate CSM for a given firm *i*, CSM_i as:

$$CSM_i = corr\left[\frac{\Delta\tilde{\pi}_i}{\Delta\tilde{S}_i}, \Delta S_R\right], \tag{1}$$

where $\Delta\tilde{\pi}_i$ and $\Delta\tilde{S}_i$ are the implied changes (between two consecutive quarters) in profits and sales of the i^{th} firm, respectively, and ΔS_R is the change in the firm's product market rivals' combined sales between two consecutive quarters. Lyandres (2006) shows that using implied changes (which takes into account changes in industry average profit margins), rather than actual changes in profits and sales (i.e., $\Delta\tilde{\pi}_i$ and $\Delta\tilde{S}_i$ rather than $\Delta\pi_i$ and ΔS_i), reduces the bias in CSM that can result from industry shocks.[8] CSM_i is used as a proxy for the cross-partial derivative of a firm's profit with respect to its own and its rivals' sales. We then define industry CSM as the mean CSM_i for all firms in a given four-digit SIC code industry.[9]

Finally, recognizing that a positive CSM corresponds to firms' strategies being strategic complements, while a negative CSM describes the case of competition in strategic substitutes, Lyandres uses the absolute value of CSM, |CSM|, to capture the extent of strategic interaction, regardless of the type of strategic interaction. A higher value of |CSM| reflects higher strategic interaction among industry competitors. We also measure the type of strategic interaction and

[8] Implied changes in profits and sales are estimated by following equations (8), (9), and (10) in Lyandres (2006), using the previous 20 quarters (requiring at least 10 observations for each regression). Since Compustat's quarterly files do not include historical SIC codes, we get industry classification from the annual files (data item SICH).
[9] A limitation of CSM is that it only captures within industry interactions and not between industry interactions.

classify firms into industries with a positive CSM (where firms compete in strategic complements) and industries with a negative CSM (where firms compete in strategic substitutes).

3.3.2. Total Similarity

As a second measure of strategic interaction, we use Hoberg and Phillips' (2016) total similarity measure (TSIMM), where total similarity is the sum of the pairwise similarities between a given firm and all other firms in their sample in a given year. They find that a manager of a firm with higher total similarity is more likely to disclose discussions noting higher levels of competition in the firm's Management's Discussion and Analysis section of its 10-K. This result suggests that information in the text-based network classification is informative regarding the presence of firms that managers perceive to be rivals. In particular, these rivals pose competitive threats that managers mention when interpreting their firm's performance and future prospects. The total similarity measure is downloaded from Hoberg and Phillips' data library: http://hoberg phillips.usc.edu/industryconcen.htm. Industry average levels of total similarity are calculated by 4-digit SIC code industry and year (similar to our measure of industry average CSM). Hoberg et al.'s (2016) sample period begins in 1997. Replicating this time period, our sample size drops from 99,214 to 67,818 firm-year observations.

3.4. Industry Concentration Measures

3.4.1 Herfindahl-Hirschman Index

Since industries with high concentration are typically assumed as having more strategic interaction, we use Compustat-based HHI (labeled as HHI) for the overall sample of firms and Census-based HHI (labeled as CHHI) for the subset of manufacturing industries, as an alternative measure of the degree of strategic interaction.[10] Census of Manufactures publications,

[10] Ali et al. (2009) show that measures of industry concentration that rely solely on Compustat firms may lead to incorrect conclusions due to omission of private firms from the computation of HHI.

provided by the U.S. Census Bureau, report concentration ratios for hundreds of industries in the manufacturing sector. We collect data on the U.S. Census-based HHI index from Census of Manufactures publications for the years 1987, 1992, 1997, 2002, and 2007. Data are for two-digit SIC industries (SIC codes between 20 and 39) for the years 1987 and 1992 and for six-digit North American Industry Classification System (NAICS) industries (NAICS codes between 311111 and 339999) for the years 1997, 2002, and 2007. Unlike Compustat-based industry concentration measures, U.S. Census-based measures are constructed using data from all public and private firms in an industry and hence should better capture actual industry concentration.

Census of Manufactures calculates the Herfindahl-Hirschman index of an industry as the sum of the squares of individual company market shares of all companies in an industry or the fifty largest companies in the industry, whichever is lower. Since the Census of Manufactures is published only once in every five years, we use the 1987, 1992, 1997, 2002, and 2007 Census-based concentration ratios for the periods 1988-1989, 1990-1994, 1995-1999, 2000-2004, and 2005-2014, respectively. This approach is similar to that used in several prior studies (e.g., Giroud and Mueller, 2011).

For the period 1995–2014, we use concentration ratios from the 1997, 2002, and 2007 Census of Manufactures publications in which industry is defined using six-digit NAICS codes. Census-based HHI for six-digit NAICS industries and total shipments for these industries reported in the Census of Manufactures can be used to calculate Census-based HHI for broader two-digit SIC industries. We do this by weighting Census HHI of component six-digit NAICS industries by the square of their share of shipments of the broader two-digit SIC industry.

3.4.2 Four-Firm Concentration Ratio

Another widely utilized measure of industry concentration is the four-firm concentration ratio (FFR). A high (low) value implies a more (less) concentrated industry with more (less) strategic interaction among fewer (many) firms. As we do with HHI, we compute a Compustat-based FFR as a measure of strategic interaction (higher concentration implies higher strategic interaction). Further, since this measure omits private firms, we also collect data on the U.S. Census-based FFR (CFFR) from Census of Manufactures publications for the years 1987, 1992, 1997, 2002, and 2007.

4. Empirical Analysis

4.1. Descriptive Statistics

Table 2 lists summary statistics for firm efficiency, strategic interaction, and our control variables. Panel A includes data on the overall sample of 99,214 firm-year observations, while Panel B includes data on manufacturing firms (45,983 firm-year observations) evaluated using the Census-based HHI and FFR.

The mean (median) efficiency for the sample firms is 0.781 (0.903), while the mean (median) bias-corrected efficiency is 0.610 (0.733). Because DEA efficiency estimates are biased upward in finite samples, we use bias-corrected efficiency throughout the analysis.[11] While the average efficiency is similar to the average value reported in Demerjian et al. (2012), the median value is higher.[12] There is a large variation in the values of efficiency scores across firms. Untabulated univariate analysis shows that 2-digit SIC code industries with the highest average efficiency score over the years include accommodation and food services (0.99), automotive dealers and gasoline service stations (0.98), heavy construction (0.98), and construction special trade contractors (0.98). The lowest average values of firm efficiency belong to the oil and gas

[11] Bias-corrected efficiency scores are estimated with a bootstrapping procedure of Simar and Wilson (1998). Due to this procedure, 4.5% of the sample firms have bias-corrected efficiency scores that are either less than 0 or greater than 1. Winsorizing those scores at the 1st and 99th percentiles, or restricting to scores between 0 and 1, does not change our results.

[12] Demerjian et al. (2012) report an average (median) efficiency score of 0.60 (0.59). However, we note that firm efficiency estimates of Demerjian et al. (2012) are not directly comparable to our estimates for two reasons. First, Demerjian et al. estimate efficiency by Fama-French industry, while we use 2-digit SIC code industry. Second, Demerjian et al. estimate efficiency by industry over their full sample period, while we measure efficiency by industry for each year of our sample.

extraction (0.21), chemicals and allied products (0.29), and metal mining (0.32) industries. The average efficiency score decreases over time from 0.78 in 1988 to 0.60 in 2014.

The sample mean (median) CSM is -0.025 (-0.023) and the minimum (maximum) is -0.988 (0.947), suggesting that within industries there is an almost even split between firms that compete as strategic substitutes and firms that compete as strategic complements. This is consistent with Sundaram et al. (1996) and Lyandres (2006). The mean (median) TSIMM for the sample industries is 4.721 (3.154). The mean (median) HHI for the sample industries is 0.201 (0.153). When we include just manufacturing firms, the mean (median) HHI is at 0.227 (0.181). However, both values are much higher than the Census-based HHI (CHHI) that includes public and private firms, where the mean (median) value is 0.072 (0.058) (the difference is statistically significant at 1% level). Similarly, the mean (median) FFR for the full sample is 0.655 (0.671). Including just manufacturing firms, the mean (median) FFR is at 0.695 (0.727). Both are again higher than the CFFR mean (median) value of 0.371 (0.345) (the difference is statistically significant at 1% level). These differences are not surprising given that CHHI and CFFR measures include private firms in the industry.

Data used to construct control variables come from Compustat. They include firm size (natural log of market value of assets; AT – CEQ + PRCC * CSHPRI), fixed asset ratio (PPENT/AT), market value leverage ratio (Total debt/Market value of assets; (DLTT + DLC) /(AT – CEQ + PRCC * CSHPRI), ROA (Operating income before depreciation /Book value of total assets; OIBDP/AT), and market-to-book ratio (Market value of total assets/Book value of total assets; (AT – CEQ + PRCC*CSHPRI)/AT).

We present correlations matrices in Table 3. Panel A reports correlations for the overall sample and Panel B reports correlations for the manufacturing industries only. Panel A of Table

3 shows a correlation between |CSM| and Efficiency of -0.103, while Panel B lists the correlation at -0.134 (both are significant at 1%). The correlation between TSIMM and Efficiency is -0.465 in Panel A and is -0.590 in Panel B (both significant at 1%). In contrast, the correlation between HHI (FFR) and Efficiency is 0.174 (0.243) in Panel A and the correlation between CHHI (CFFR) and Efficiency is 0.026 (-0.065). Thus, |CSM| and TSIMM might be similar and more consistent in their ability to explain firm efficiency, compared to HHI and FFR.

To examine this further, in Table 4 we tabulate average efficiency scores for industries categorized by |CSM| and TSIMM quartiles. Panel A reports efficiency scores for all industries, Panel B reports efficiency scores for industries with CSM>0, and Panel C for industries with CSM < 0. Efficiency scores are lowest (highest) when both |CSM| and TSIMM are higher (lower). For example, industries with |CSM| and TSIMM in the highest quartile have an average efficiency score of 0.164, while industries with |CSM| and TSIMM in the lowest quartile have an average efficiency score of 0.749 (Panel A). Thus, industries with more strategic interactions among firms are least efficient. Comparing Panels B and C, we see that positive CSM industries have higher efficiency scores than negative CSM industries. For example, positive CSM industries with |CSM| and TSIMM in the highest quartile have an average efficiency score of 0.172, while negative CSM industries with |CSM| and TSIMM in the highest quartile have an average efficiency score of 0.159 (the difference is significant at 5%). Likewise, positive CSM industries with |CSM| and TSIMM in the lowest quartile have an average efficiency score of 0.783, while negative CSM industries with |CSM| and TSIMM in the lowest quartile have an average efficiency score of 0.710 (difference is significant at 5%).

4.2. Empirical Strategy

To test the relation between the strategic interaction and firm efficiency in a multivariate setting, we estimate the following fixed effects regressions: [13]

$$\begin{aligned} Efficiency_{i,t} = {} & \beta_0 + \beta_1 Strategic\ Interaction_{j,t} + \\ & + \beta_2 Strategic\ Interaction_{j,t} \times Pos\_CSM + \\ & + \beta_3 Controls_{i,t} + \eta_i + u_j + v_t + \varepsilon_{i,t}, \end{aligned} \quad (2)$$

where *i*, *j*, and *t* are firm, industry, and time subscripts, respectively. We use |CSM| and TSIMM as measures of strategic interaction. To develop the assessment of whether the type of strategic interaction among firms in an industry is associated with the relation between strategic interaction and firm efficiency (Hypothesis 2), we interact these variables with Pos_CSM, equal to 1 for industries with positive mean CSM and 0 otherwise. A value of 1 for Pos_CSM indicates that the industry strategic interactions are in the form of strategic complements. The interaction allows us to identify the conditional impact of strategic interaction (strategic complements versus strategic substitutes) on firm efficiency. Control variables include firm characteristics size (Log (Assets)), fixed assets ratio (PP&E/Assets), Leverage, ROA, and Market-to-Book ratio.

Table 5 shows the results. Regressions (1) and (2) show the two measures of strategic interaction (|CSM| and TSIMM) individually. We see a negative sign for both measures: |CSM| and TSIMM (coefficients = -0.067 and -0.035, in regressions (1), and (2), respectively, both significant at 1%).[14] The results indicate that a higher level of strategic interaction is related to

[13] The sample includes 11,988 unique firms, out of which 1,113 (9.28%) change their 2-digit SIC code membership over time. Therefore, having both industry fixed effects and firm fixed effects is not redundant.

[14] We calculate a variable's economic significance as the difference in the efficiency score for firms with a |CSM| one standard deviation above the mean and one standard deviation below the mean. Focusing on regression 1 from Table 5, the economic significance of |CSM| is -0.0145 (i.e., the difference in efficiency scores for firms with a |CSM| one standard deviation above the mean and one standard deviation below the mean is -0.0145). While this value does not seem large, it is comparable to the effects of other variables on efficiency. For example, economic significance of Log(Assets) is -0.0142 (firms with Log(Assets) one standard deviation above the mean have an efficiency score that is 1.42% lower than firms with Log(Assets) one standard deviation below the mean) and the economic significance of Market-to-Book is 0.0206 (firms with Market-to-Book value one standard deviation above the mean have an efficiency score that is 2.06% higher than firms with Market-to-Book value one standard deviation below the mean). Overall, ROA has the highest economic significance among the predictor variables (0.0948) and Leverage has the lowest economic significance (0.0031). Similarly, focusing on regression 3 from Table 5 (for the

lower firm efficiency. Regressions (3) and (4) show results for the same regressions using the subsample of manufacturing industries (SIC codes 2000-3999). Consistent with Hypothesis 1, we again see the expected negative sign on strategic interaction terms in both regressions (coefficients = -0.042 and -0.036 in regressions (3) and (4), respectively, both significant at 1%). Thus, conclusions about the relation between efficiency and strategic interaction hold in a subsample of manufacturing industries.

4.2.2. Results Based on the Type of Strategic Interaction

Hypothesis 2 highlights the importance of examining how the type of strategic interaction in an industry, i.e., strategic complements versus strategic substitutes, are related to firm efficiency. We empirically investigate this by including the interaction term Pos_CSM in the regression analysis. In Table 5, this interaction term is positive and significant in three of the four regressions (coefficients = 0.050 and 0.004 in regressions 1 and 2, for example). Consistent with Hypothesis 2, we find that the negative relation between strategic interaction and firm efficiency is more pronounced in industries where firms compete in strategic substitutes. This is consistent with previous research (e.g., Potters and Suetens, 2009) that shows there is significantly more cooperation (collusion) when firms compete in strategic complements. When interactions are non-cooperative (i.e., under strategic substitutes), reacting constantly to competitors' actions reduces firm efficiency. The results are also consistent with Fresard and Valta (2016) who show that firms reduce capital expenditures in response to higher entry threat only in markets with competition in strategic substitutes. The change in investment is negligible in markets with competition in strategic complements.

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subsample of manufacturing firms), firms with a |CSM| one standard deviation above the mean have an efficiency score that is 0.0096 lower than firms with a |CSM| one standard deviation below the mean. This is again comparable to the effects of other variables on efficiency. Overall, ROA has the highest economic significance among the predictor variables (0.0948) and Leverage has the lowest economic significance (0.0031). Our findings on the economic significance of |CSM| and ROA are similar to those in Lyandres (2006).

4.2.3. Industry Concentration Ratios as Measures of Strategic Interaction

As mentioned above, the most commonly used measures of industry competition are Herfindahl-Hirschman Index (HHI) and four-firm concentration ratio (FFR), where a higher HHI or FFR implies concentrated industries, with more strategic interaction among the fewer firms. To test for differences in the relation between strategic interaction and firm efficiency using these traditional measures versus |CSM| and TSIMM, we estimate fixed effects regressions using HHI (Compustat-based), CHHI (Census), FFR (Compustat-based), and CFFR (Census). Results are presented in Table 6.

In contrast to Table 5, HHI and FFR show a positive relation with efficiency (coefficients = 0.250 and 0.347 in regressions (1) and (2), respectively, both significant at 1%). That is, high strategic interaction/high concentration industries with fewer firms lead to higher efficiency. The analysis in regressions (1) and (2) uses Compustat-based HHI and FFR as the measure of strategic interaction. However, as mentioned above, Compustat-based HHI and FFR may lead to incorrect conclusions due to the omission of private firms from the computation of HHI. To see if that is the case, we narrow our sample to include just manufacturing industries (SIC codes 2000-3999) and use Census-based HHI (CHHI) and FFR (CFFR) as measures of industry concentration. Results are reported in regressions (3) and (4) of Table 6. Consistent with Hypothesis 1, we now see the expected negative sign on strategic interaction terms (coefficients = -0.101 and -0.063, respectively, both significant at 5% or better). Thus, as found by Ali et al. (2009), the inclusion of both public and private firms in an industry appears to make Census-based industry concentration measure superior to Compustat-based concentration measure.

4.3. Endogeneity of Strategic Interaction

It is quite possible that strategic interaction among firms does not drive behavior and performance, but the contrary: performance leads to very specific behaviors that shape strategic interaction. To alleviate potential concerns about the endogeneity of strategic interaction, we conduct a quasi-natural experiment. Specifically, we examine the response of firm efficiency to unexpected reductions of industry-level import tariffs.[15] According to the literature on barriers to trade, globalization of economic activities and trade openness brings major changes in the competitive configuration of industries (Tybout, 2003).[16] In particular, the lessening of trade barriers triggers significant intensification of competitive pressures from foreign rivals (Bernard et al., 2006). Recently, several papers use tariff reductions to measure exogenous shocks to the competitive environment (e.g., Fresard, 2010; Valta, 2012).

To measure reductions in import tariffs at the four-digit SIC industry level, we follow Fresard and Valta (2016) and Valta (2012) and use industry-year ad valorem tariff rate as duties collected at U.S. customs divided by Free-on-Board custom value of imports. More specifically, tariff data for manufacturing industries is downloaded from Laurent Fresard's website: http://terpconnect.umd.edu/~lfresard/. These data span the period 1989-2005[17] and include 113 of the 126 manufacturing industries in our sample. To ensure that tariff cuts truly reflect non-transitory changes in the competitive environment, we exclude tariff cuts that are followed by equivalently large tariff rate increases. Further, we limit the sample to those industries that have three years of data before and after the rate reduction. Using these filters, we identify 51 large tariff rate

[15] The trade literature finds that export-oriented firms tend to be more efficient (e.g., Bernard and Jensen 1995, 1999, 2004). As a result, firm efficiency is not randomly distributed across industries. We check the robustness of our main results in Table 5 by incorporating a measure of foreign sales exposure in the main regressions. In particular, we measure foreign sales exposure using an indicator variable, Export-Oriented Dummy. This variable takes value of 1 when a firm has non-zero foreign sales (sum of sales from non-domestic segments of the firm and export sales from its domestic segments) and 0 otherwise. Since we use segment level data from Compustat Segments database, our sample size drops significantly due to the requirement that the sum of all segment sales should not deviate from the firm-level sales from Compustat Industrial Annual by more than 1%. Despite the drop in sample size, our main results hold and the Export-Oriented Dummy is positive and significant at the 1% level.

[16] Since tariff reductions result in increased competition from foreign rivals, firm efficiency should increase following such changes. Consistent with this intuition, Bernard et al. (2006) find an inverse relation between change in industry trade costs and industry total factor productivity (TFP) growth. Similarly, Amato and McNees (2014) find an inverse relation between industry tariff rates and firm-level TFP. In untabulated results, we also see that change in industry tariff rates is inversely related to firm efficiency for manufacturing firms in our sample.

[17] While tariff data is available for 1974-2005, coding of imports changed in 1989. Therefore, Fresard and Valta (2016) recommend ignoring tariff changes that occurr between 1988 and 1989.

reductions between 1989 and 2005: 14 of the 51 reductions (28%) occur in 1995, which coincides with the creation of the North American Free Trade Agreement (NAFTA). Over the period 1989-2005, we see a decreasing trend in tariff rates for all manufacturing industries in our sample. However, the rate of change for industries that do not experience large reductions is much slower. Specifically, the average tariff rate for industries that do not experience large tariff reductions decreases from 4.25% in 1990 to 2.65% in 2005 (a 16-year period). In contrast, the average tariff rate for industries that experience large tariff reductions see the same level of reduction within six years (from t = -3 to t = +3).

We consider changes in import tariffs as shocks to the competitive environment to see if the relation between efficiency and the type of strategic interaction is stronger or weaker after tariff changes. To investigate the effect of large shifts of import tariff rates on firm efficiency in a multivariate setting, similar to Fresard and Valta (2015) and Valta (2012), we estimate the following regression model:

$$\begin{aligned} Efficiency_{i,t} = \beta_0 + \beta_1 Post\_Reduction_{j,t} + \beta_2 Post\_reduction_{j,t} \times Pos\_CSM + \\ + \beta_3 Controls_{i,t} + \eta_i + u_j + v_t + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

As in equation (2), i, j, and t are firm, industry, and time subscripts, respectively. Post_Reduction is a dummy variable equal to one if industry j has experienced a significant tariff rate reduction by year t and zero otherwise (Valta, 2012). We compare tariff reductions in a given industry-year to the industry's median change over the period of 1989-2005. We define a significant tariff reduction for a specific industry-year as one in which the negative change in the tariff is three times, and separately, two times, the median tariff rate reduction in industry j.[18] We include two versions of Pos_CSM: Pos_CSM1 and Pos_CSM2. Pos_CSM1 takes value of 1 if

[18] Following Valta (2012), if an industry experiences more than one tariff rate reduction larger than three times the median rate reduction in that industry, we identify the largest tariff rate reduction as the event. In our sample, there are 62 industries that never experience a large tariff rate reduction. These industries serve as "control" industries.

mean industry CSM is positive. Pos_CSM2 takes value of 1 if *median* industry CSM is positive. Control variables are the same as in equation (2).

Table 7 presents the results. In regressions (1) and (2), large tariff reductions are defined as those that are 3 times larger than the industry median change, while in regressions 3 and 4 large tariff reductions are those that are 2 times larger than the industry median change. The coefficient on Post_Reduction*Pos_CSM is negative and statistically significant in all regressions (e.g., the coefficient is -0.030 in regression 1 (significant at 1%)). The result indicates that a large reduction in import tariffs has a significant and negative effect on firm efficiency in industries where firms compete in strategic complements. Given Potters and Suetens (2009) finding that there is significantly more cooperation when actions exhibit strategic complements, less efficient firms may survive longer despite the competitive shock. As a result, post-tariff firm efficiency is lower. In contrast, when actions exhibit strategic substitutes, non-cooperative actions may result in less efficient firms exiting the industry, thus offsetting the negative effect of the shock on firm efficiency.

4.4. Corporate Governance

Our analysis so far has excluded any role of corporate governance in influencing the relation between product market competition and firm efficiency. There is a substantial amount of research which shows that corporate governance affects firm performance. The classic hypothesis that competition mitigates managerial slack suggests that the inclusion of corporate governance measures could provide insight into when improving corporate governance is more beneficial: when competition is weak and the intensity of strategic interaction is high or when competition is fierce and the intensity of strategic interaction is low. Accordingly, we collect corporate governance data on the sample firms from RiskMetrics. RiskMetrics data is available only for S&P1500 firms. Thus, when we merge our full sample with RiskMetrics governance data, we have a smaller sample: 15,230 observations, averaging 609 firms a year.

Bebchuk et al.'s (2009) Entrenchment Index, or E-Index, is used to measure corporate governance. Of the twenty-four provisions followed by the Investor Responsibility Research Center (IRRC), they find that the entrenchment index (E-index) based on six provisions (staggered boards, limits to shareholder bylaw amendments, poison pills, golden parachutes, supermajority requirements for mergers, and charter amendments) drive the relation between IRRC provisions and firm valuation. The other eighteen IRRC provisions not in their entrenchment index are uncorrelated with firm valuation. The level of the E-index for any given firm is calculated by giving one point for each of the six components of the index that the firm has. RiskMetrics changed the definitions of some of the provisions (e.g., limits to shareholder bylaw amendments, charter amendments) after acquiring IRRC in 2007. So, we use a subset of the six provisions as E-Index4, which includes staggered boards (CBOARD), poison pills (PPILL), golden parachutes (GPARACHUTE), and supermajority requirements for mergers (SUPERMAJOR_PCNT greater than 51%). Using this measure, the sample is separated into firms with weak governance (E-index4 > 1) and firms with strong governance (E-index4 ≤ 1).[19] We then add an interactive term, Weak_Gov, to evaluate efficiency of firms in industries with weak corporate governance relative to efficiency of firms in industries with strong governance.

Results of regressions incorporating corporate governance are reported in Table 8. From these regressions, we first see that results from Table 5 remain. Consistent with Hypothesis 1, using |CSM| and TSIMM, higher levels of strategic interactions are associated with lower efficiency, e.g., the coefficient on |CSM| in regression (1) is -0.258 (significant at 1%). Also, consistent with Hypothesis 2, we again find that the relation between strategic interaction and

[19] An *E-index4* value of 1 represents the 25th percentile in our sample.

firm efficiency is weaker when firms compete in strategic complements, e.g., the coefficient on |CSM|*Pos_CSM in regression (1) is 0.373, significant at 1%. The coefficient of |CSM|*Weak_Gov is positive and significant in all regressions (e.g., the coefficient is 0.226 in regression (1), significant at 1%), and the coefficient on |CSM|*Pos_CSM *Weak_Gov is negative and significant in all regressions (e.g., the coefficient is -0.336 in regression (1), significant at 1%). Thus, as corporate governance improves (e.g., lower E-index4), the negative relation between strategic interaction and efficiency disappears in industries where firms compete in strategic complements. Thus, improvement in corporate governance is positively related to firm efficiency in industries where strategic interactions exhibit strategic complements. These results are consistent with recent papers showing that firms in non-competitive industries benefit relatively more from good governance (e.g., Giroud and Mueller, 2011).

4.5. Robustness Tests

4.5.1. Efficiency Measure versus More Traditional Measures of Firm Performance

As mentioned, a unique aspect of this paper is that we evaluate firm performance using frontier efficiency methodology. Frontier efficiency methodology calculates performance without imposing an explicit, ad hoc weighting structure, unlike widely used performance measures such as ROA, which often assume that all inputs and outputs are equally valuable across firms. To examine the value of the frontier efficiency measure versus more traditional measures, we incorporate some of these measures into the analysis as a robustness test. The alternate measures of firm performance we use include total factor productivity, revenue per employee, and ROA. Total factor productivity (TFP) is a measure of productivity that looks at the change in total outputs net of the change in total inputs. Following Faleye et al. (2006), we calculate TFP using a regression-based approach assuming a Cobb–Douglas production function:

$$Y_{it} = AL_{it}^{\beta} K_{it}^{\alpha} . \qquad (4)$$

where, Y_{it} is net sales for firm i in period t, L_{it} is the number of employees, K_{it}, is net property, plant, and equipment, and A, α , and β are parameters. All variables are adjusted for inflation using CPI. We employ residuals from our estimation of the natural log transformation of equation (4) over all Compustat firms as a measure of firm-level TFP, controlling for industry factors by estimating a separate equation for each two-digit SIC industry group. By construction, the average TFP (i.e., the average of residuals) in any two-digit SIC code industry is zero.

Revenue per employee (Sales/Employee) is a firm's total revenue divided by the number of employees. It measures performance as revenue produced relative to a specific input (number of employees). ROA is operating income before depreciation divided by book value of total assets and is an often used measure of firm performance. The measure of strategic interaction we use in all regressions is |CSM|. Further, because ROA is now used as a measure of performance, we remove it as an independent variable.

Results, shown in Table 9, confirm those from Table 5. Consistent with Hypothesis 1, higher levels of strategic interaction are associated with lower performance whether it be measured using frontier efficiency methodology, total factor productivity, revenue per employee, or ROA. However, of the four measures, Efficiency produces the strongest results. For example, the coefficient on |CSM| in regression 1 is -0.069 (significant at 1%), while the coefficients in regressions 2 (using TFP) and 3 (using Sales/Employee) are both -0.074 (both significant at 5%) and the coefficient in regression 4 is insignificant. Also, consistent with Hypothesis 2, when firms compete in strategic complements (where there tends to be more cooperation), the relation between strategic interaction and firm performance is weaker. However, firm performance measured using Efficiency again produces the strongest results (e.g., the coefficient on |CSM|*Pos_CSM in regression 1 is 0.046 (significant at 1%) and in regressions 2 and 3 are 0.075 and 0.092, respectively (significant at 5%)), and the sign is reversed using ROA (the coefficient is -0.039, significant at 5%). Thus, it appears that, consistent with Chen et al. (2015) and Demerjian et al. (2012), frontier efficiency methodology outperforms other measures of firm performance in explaining the relation between strategic interaction and firm performance.

4.5.2. Firm Survival and Performance

As a second robustness test of the use of frontier efficiency methodology over other performance measures, we compare the likelihood of being delisted using the various performance measures. Consistent with Alchian's (1950) idea that higher relative performance results in the survival of the fittest, Syverson (2011) suggests that heightened competition moves market share towards the best performing firms through the exit of the worst performing firms, leaving remaining firms to perform better. Thus, various performance measures are compared by their ability to predict whether the best performing firms survive.

We run Cox proportional hazard regressions in which the dependent variable is survival time. For delisted firms this is defined as year of delisting minus the first year the firm appears in the sample. For the remaining firms, we use the last year in the sample minus the first year in the sample (these are considered right censored).[20] Cox regressions estimate the hazard ratio as a function of explanatory variables. Expectations are that the higher the performance measure, the lower the hazard ratio (i.e., there is a lower likelihood of being delisted). In addition to control variables used in earlier regressions, we include firm age and modified Z-score. Previous studies (e.g., Syverson, 2011) have shown that learning-by-doing, i.e., experience, allows firms to improve efficiency. Firm age is included to control for this possibility. Modified Z-score is a measure of ex-ante bankruptcy risk from Graham et al. (2008) and is a modified version of Altman's (1968) Z-score, which does not include the ratio of market value of equity to book value of total debt because a similar term, market-to-book, is included as a separate variable. A higher modified Z-score indicates better financial health and thus lower default risk.

Results are reported in Table 10, where we find only two of the performance measures produce the expected results. The coefficient on Efficiency in regression 1 is -1.832 (significant at 1%) and on ROA in regression 2 is -0.717 (both are significant at 1%). Coefficients in regressions 3 (using TFP) and 4 (using Log(Sales/Employee*)* are both insignificant. Looking at the Akaike's Information Criteria (AIC, lower AIC means a better fit), regression 1 (using Efficiency) does a better job at explaining failure rates (i.e., between Efficiency and ROA,

[20] This type of censoring makes logistic regression an inappropriate way to analyze the data due to censoring bias (Kalbfleisch and Prentice, 2002; Hosmer et al., 2008).

Efficiency has bigger impact on the hazard ratio). Thus, firms that have the highest Efficiency are those that survive.

5. Conclusions

This paper empirically examines the relation between the extent and type of strategic interaction among industry firms and firm performance. We capture the extent of strategic interaction in an industry by computing the competitive strategy measure (CSM) developed by Sundaram et al. (1996) and Lyandres (2006). The absolute value of CSM is used to capture the extent of strategic interaction. Recognizing that a positive CSM corresponds to firms' strategies being complements, while a negative CSM describes the case of competition in strategic substitutes, the signed CSM is used to evaluate the impact of the type of strategic interaction. Further, firm performance is evaluated using frontier efficiency methodology.

We find that the relation between the degree of strategic interaction and firm efficiency is negative and significant. In addition, the negative relation is more pronounced when firms compete in strategic substitutes. This finding is consistent with the idea that there is significantly more cooperation when actions exhibit strategic complements than when they exhibit strategic substitutes. Results are robust under alternate measures of strategic interaction. Using tariff rate reductions as an exogenous competitive shock in a quasi-natural experiment setting, we confirm that the type of strategic interaction impacts the effect of a competitive shock on firm efficiency. In particular, we find that large reductions in import tariffs have a significant and negative effect on firm efficiency only in industries where firms compete in strategic complements. Finally, we find that frontier efficiency methodology outperforms other measures of firm performance in explaining the relation between strategic interaction and firm performance.

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Table 1

Descriptive Statistics: Input and Output Variables

This table reports descriptive statistics of the firm-level variables used to calculate DEA firm efficiency for sample firms in Compustat during fiscal years 1988-2014. All input and output quantities are in millions of dollars and are constructed as in Demerjian et al. (2012). Seven inputs are used: (1) net property, plant and equipment (PP&E); (2) capitalized operating leases, which is calculated as the discounted (at 10%) present value of five years of lease payments (Leases); (3) five-year capitalized value of research and development expenses (R&D); (4) purchased goodwill, which is calculated as the premium paid over the fair value of an acquisition (Goodwill); (5) other acquired and capitalized intangibles (Intangibles); (6) cost of goods sold (COGS); and (7) selling, general, and administrative costs (SG&A). Output is net sales of the firm (Revenue). A firm is classified as fully efficient if it lies on the production best-practice frontier of firms (Efficiency = 1) and inefficient if its outputs can be produced more efficiently by another set of firms (0 < Efficiency < 1). Efficiency is measured separately by year and industry. Panel A reports data for the full sample, while Panel B reports results for the subsample of manufacturing firms.

Variable	N	Mean	Median	Stdev	Min	Max
Panel A – Full Sample						
PP&E	99,214	397.28	11.60	1,419.16	0.00	10,329.85
Leases	99,214	43.02	2.88	127.51	0.00	803.49
R&D	99,214	88.40	0.37	606.36	0.00	15,682.87
Goodwill	99,214	81.42	0.00	319.61	0.00	2,266.26
Intangibles	99,214	48.53	0.00	208.87	0.00	1,581.10
COGS	99,214	596.85	35.19	1,873.33	0.03	12,531.34
SG&A	99,214	109.89	8.15	353.96	0.00	2,382.94
Revenue	99,214	916.82	62.02	2,791.21	0.02	18,329.70
Panel B – Manufacturing Subsample						
PP&E	45,983	345.46	8.25	1,309.53	0.00	10,329.85
Leases	45,983	27.91	1.93	96.37	0.00	803.49
R&D	45,983	150.86	5.35	810.37	0.00	15,682.87
Goodwill	45,983	81.36	0.00	315.93	0.00	2,266.26
Intangibles	45,983	45.31	0.00	199.61	0.00	1,581.10
COGS	45,983	587.21	29.44	1,889.51	0.03	12,531.34
SG&A	45,983	116.62	8.75	369.59	0.00	2,382.94
Revenue	45,983	927.96	48.45	2,877.30	0.02	18,329.70

Table 2

Descriptive Statistics

This table reports descriptive statistics for industry-level variables for 1988-2014. Panel A reports statistics on variables for the overall sample, which includes all industries except financials and utilities. Panel B reports results for the subsample of manufacturing firms. Data come from Compustat and Census of Manufactures. Efficiency is the DEA firm efficiency measure. Efficiency Bias-Corrected are bias-corrected efficiency scores that are estimated with bootstrapping procedure of Simar and Wilson (1998). CSM is a competitive strategy measure adapted from Lyandres (2006). It is the cross-partial derivative of a firm's profit with respect to its strategy and its rivals' strategy computed using quarterly data from Compustat. |CSM| is the absolute value of the competitive strategy measure, proxying for the type of strategic interaction. TSIMM is the total similarity measure of product market competition from Hoberg and Phillips (2016). HHI is the Herfindahl-Hirschman index of an industry, calculated by adding the squares of the sales market shares of all the firms in an industry that have sales data on Compustat. FFR is the concentration ratio for the four largest firms in the industry. CHHI is the Herfindahl-Hirschman index of an industry calculated by the Census of Manufactures as the sum of the squares of individual company market shares of all companies in an industry or the fifty largest companies in the industry, whichever is lower. *CFFR* is the concentration ratio of an industry calculated using the Census of Manufactures as the sum of the squares of individual company market shares for the four largest firms in an industry. Firm-level control variables include market value of total assets, fixed asset ratio (PP&E/Book value of total assets), market value leverage ratio (Total debt/Market value of assets), ROA (Operating income before depreciation /Book value of total assets), and market-to-book ratio (Market value of total assets/Book value of total assets).

Panel A – Full Sample	N	Mean	Median	Stdev	Min	Max
Efficiency	99,214	0.781	0.903	0.278	0.000	1.000
Efficiency Bias-Corrected	99,214	0.610	0.733	0.414	-1.606	1.514
CSM	99,214	-0.025	-0.023	0.162	-0.988	0.947
|CSM|	99,214	0.124	0.095	0.107	0.000	0.988
TSIMM	67,818	4.721	3.154	4.319	1.000	24.196
HHI	99,214	0.201	0.153	0.163	0.034	1.000
FFR	99,214	0.655	0.671	0.207	0.266	1.000
Assets (millions of $)	99,214	4,518.53	198.94	22,145.20	0.027	733,413.40
PP&E/Assets (%)	99,214	0.273	0.187	0.248	0.001	0.921
Leverage (%)	99,214	0.166	0.104	0.184	0.000	0.992
ROA (%)	99,214	-0.057	0.091	0.557	-3.912	0.438
Market-to-Book (X)	99,214	2.630	1.526	3.912	0.519	31.534
Panel B – Manufacturing Subsample						
Efficiency	45,983	0.780	0.893	0.279	0.000	1.000
Efficiency Bias-Corrected	45,983	0.611	0.730	0.392	-1.606	1.000
CSM	45,983	-0.004	-0.002	0.177	-0.988	0.827
|CSM|	45,983	0.136	0.115	0.114	0.000	0.988
TSIMM	30,915	5.591	3.130	5.654	1.000	24.196
HHI	45,983	0.227	0.181	0.172	0.048	1.000
FFR	45,983	0.695	0.727	0.206	0.321	1.000
CHHI	45,983	0.072	0.058	0.048	0.001	0.300
CFFR	45,983	0.371	0.345	0.148	0.035	0.911
Assets (millions of $)	45,983	4,997.76	172.27	25,554.13	0.031	733,413.40
PP&E/Assets (%)	45,983	0.215	0.170	0.176	0.001	0.921
Leverage (%)	45,983	0.143	0.083	0.165	0.000	0.929
ROA (%)	45,983	-0.096	0.083	0.586	-3.912	0.438
Market-to-Book (X)	45,983	2.817	1.612	4.059	0.519	31.534

Table 3

Correlation Matrices

The table presents correlation matrices for industry-level variables for 1988-2014. Panel A reports correlations between firm- and industry-level variables for the overall sample, which includes all industries except financials and utilities. Panel B reports correlations between firm- and industry-level variables for the manufacturing subsample (SIC codes 2000-3999). Data come from Compustat and Census of Manufactures. Efficiency is the DEA firm efficiency measure. CSM is a competitive strategy measure adapted from Lyandres (2006). It is the cross-partial derivative of a firm's profit with respect to its strategy and its rivals' strategy computed using quarterly data from Compustat. |CSM| is the absolute value of the competitive strategy measure, proxying for the type of strategic interaction. TSIMM is the total similarity measure of product market competition from Hoberg and Phillips (2016). HHI is the Herfindahl-Hirschman index of an industry, calculated by adding the squares of the sales market shares of all firms in an industry that have sales data on Compustat. FFR is the concentration ratio for the four largest firms in the industry. CHHI is the Herfindahl-Hirschman index of an industry calculated by the Census of Manufactures as the sum of the squares of individual company market shares of all companies in an industry or the fifty largest companies in the industry, whichever is lower. CFFR is the concentration ratio of an industry calculated using the Census of Manufactures as the sum of the squares of the individual company market shares for the four largest firms in an industry.

Panel A: Full Sample	Efficiency	CSM	|CSM|	TSIMM	HHI	FFR	Assets	PPE/A	Leverage	ROA	Market-to-Book
Efficiency	1.000										
CSM	0.054	1.000									
|CSM|	**-0.103**	-0.183	1.000								
TSIMM	**-0.465**	0.062	0.092	1.000							
HHI	**0.174**	0.142	-0.021	-0.330	1.000						
FFR	**0.234**	0.176	-0.037	-0.396	0.830	1.000					
Assets	-0.028	0.013	-0.008	-0.015	-0.040	-0.059	1.000				
PP&E/Assets	-0.021	-0.025	-0.163	-0.023	-0.165	-0.212	0.060	1.000			
Leverage	0.107	0.004	-0.084	-0.158	0.002	0.018	0.010	0.322	1.000		
ROA	0.213	0.010	-0.090	-0.174	0.021	0.028	0.077	0.132	0.063	1.000	
Market-to-Book	-0.155	-0.019	0.081	0.143	-0.035	-0.040	-0.020	-0.131	-0.190	-0.636	1.000

Panel B: Manufacturing Subsample	Efficiency	CSM	|CSM|	TSIMM	CHHI	CFFR	Assets	PPE/A	Leverage	ROA	Market-to-Book
Efficiency	1.000										
CSM	-0.039	1.000									
|CSM|	**-0.134**	-0.131	1.000								
TSIMM	**-0.590**	0.119	0.099	1.000							
CHHI	**0.026**	-0.044	-0.055	-0.080	1.000						
CFFR	**-0.065**	0.010	-0.065	0.160	0.809	1.000					
Assets	0.008	0.005	0.006	-0.011	0.097	0.086	1.000				
PP&E/Assets	0.259	-0.036	-0.116	-0.235	-0.049	-0.024	0.104	1.000			
Leverage	0.193	-0.027	-0.064	-0.208	0.003	-0.023	0.024	0.317	1.000		
ROA	0.301	-0.017	-0.083	-0.241	0.003	-0.010	0.084	0.147	0.055	1.000	
Market-to-Book	-0.233	0.003	0.071	0.194	-0.008	0.005	-0.026	-0.140	-0.179	-0.649	1.000

Table 4

Average Efficiency Scores by |CSM| and TSIMM Quartiles

This table reports average efficiency scores for industries categorized by |CSM| and TSIMM quartiles (Q1 being the lowest and Q4 the highest quartile). Efficiency is the bias-corrected DEA firm efficiency measure. CSM is a competitive strategy measure adapted from Lyandres (2006). |CSM| is the absolute value of the competitive strategy measure, proxying for the extent of strategic interaction. TSIMM is the total similarity measure of product market competition from Hoberg and Phillips (2016). Panel A reports efficiency scores for all industries, Panel B for industries with CSM>0, and Panel C for industries with CSM<0.

Panel A: All Industries

	TSIMM_Q1	TSIMM_Q2	TSIMM_Q3	TSIMM_Q4
|CSM|_Q1	0.749	0.713	0.688	0.281
|CSM|_Q2	0.737	0.650	0.607	0.259
|CSM|_Q3	0.723	0.647	0.598	0.282
|CSM|_Q4	0.742	0.632	0.532	0.164

Panel B: CSM>0 Industries

	TSIMM_Q1	TSIMM_Q2	TSIMM_Q3	TSIMM_Q4
|CSM|_Q1	0.783	0.731	0.660	0.376
|CSM|_Q2	0.750	0.732	0.614	0.278
|CSM|_Q3	0.757	0.636	0.607	0.250
|CSM|_Q4	0.787	0.637	0.587	0.172

Panel C: CSM<0 Industries

	TSIMM_Q1	TSIMM_Q2	TSIMM_Q3	TSIMM_Q4
|CSM|_Q1	0.710	0.702	0.705	0.223
|CSM|_Q2	0.725	0.607	0.603	0.237
|CSM|_Q3	0.700	0.655	0.592	0.297
|CSM|_Q4	0.713	0.628	0.505	0.159

Table 5

Regressions of Firm Efficiency on Strategic Interaction

This table reports results for fixed effects regressions showing the impact of various strategic interaction measures on firm efficiency for 1988-2014. Data come from Compustat Industrial Annual database. Efficiency is the bias-corrected DEA firm efficiency measure. CSM is a competitive strategy measure adapted from Lyandres (2006). Pos_CSM is a dummy variable equal to 1 when CSM is positive and 0 otherwise. TSIMM is the total similarity measure of product market competition from Hoberg and Phillips (2016). Log(Assets) is the natural logarithm of market value of assets, PP&E/Assets is the ratio of net property, plant, and equipment to book value of total assets, Leverage is ratio of total debt to market value of assets, ROA is operating income before depreciation divided by book value of total assets, and Market-to-Book is market value of assets divided by book value of assets. Estimations (1) and (2) report results for all industries and (3) and (4) report results for manufacturing industries (SIC codes 2000-3999). In addition to firm fixed effects, year dummies and 2-digit SIC code industry dummies are included in the regressions, but are not reported. Robust standard errors are reported in brackets. * p<0.10, ** p<0.05, *** p<0.01.

	(1) Efficiency	(2) Efficiency	(3) Efficiency	(4) Efficiency
|CSM|	-0.067***		-0.042***	
	[0.011]		[0.014]	
|CSM|*Pos_CSM	0.050***		0.023	
	[0.013]		[0.015]	
TSIMM		-0.035***		-0.036***
		[0.001]		[0.002]
TSIMM*Pos_CSM		0.004***		0.002***
		[0.000]		[0.000]
Log(Assets)	-0.003***	-0.004***	0.006***	0.005***
	[0.000]	[0.001]	[0.001]	[0.001]
PP&E/Assets	0.010	0.003	0.050***	0.040***
	[0.006]	[0.008]	[0.010]	[0.013]
Leverage	-0.007	0.021***	0.009	0.034***
	[0.006]	[0.008]	[0.009]	[0.012]
ROA	0.090***	0.076***	0.081***	0.058***
	[0.002]	[0.003]	[0.003]	[0.004]
Market-to-Book	0.003***	0.002***	0.001*	-0.001
	[0.000]	[0.000]	[0.000]	[0.001]
Constant	0.623***	0.786***	0.570***	0.819***
	[0.014]	[0.018]	[0.009]	[0.015]
Adjusted R2	0.07	0.05	0.09	0.06
No. observations	99214	67818	45983	30915

Table 6

Regressions of Firm Efficiency on Strategic Interaction – Alternate Measures

This table reports results of fixed effects regressions showing the impact of alternate measures of strategic interaction on firm efficiency for 1988-2014. Data come from Compustat and Census of Manufactures. Efficiency is the bias-corrected DEA firm efficiency measure. CSM is a competitive strategy measure adapted from Lyandres (2006). Pos_CSM is a dummy variable equal to 1 when CSM is positive and 0 otherwise. HHI is the Herfindahl-Hirschman index of an industry, calculated by adding the squares of sales market shares of all firms in an industry that have sales data on Compustat. FFR is the concentration ratio for the four largest firms in the industry. CHHI is the Herfindahl-Hirschman index of an industry calculated by the Census of Manufactures as the sum of the squares of individual company market shares of all companies in an industry or the fifty largest companies in the industry, whichever is lower. CFFR is the concentration ratio of an industry calculated using the Census of Manufactures as the sum of the squares of individual company market shares for the four largest firms in an industry. Log(Assets) is the natural logarithm of market value of assets, PP&E/Assets is the ratio of net property, plant, and equipment to book value of total assets, Leverage is ratio of total debt to market value of assets, ROA is operating income before depreciation divided by book value of total assets, and Market-to-Book is market value of assets divided by book value of assets. In addition to firm fixed effects, year dummies and 2-digit SIC code industry dummies are included in the regressions, but are not reported. Robust standard errors are reported in brackets. * p<0.10, ** p<0.05, *** p<0.01.

	(1) Efficiency	(2) Efficiency	(3) Efficiency	(4) Efficiency
HHI	0.250***			
	[0.011]			
HHI*Pos_CSM	0.003			
	[0.008]			
FFR		0.347***		
		[0.010]		
FFR*Pos_CSM		0.007**		
		[0.003]		
CHHI			-0.101**	
			[0.050]	
CHHI*Pos_CSM			0.128***	
			[0.031]	
CFFR				-0.063***
				[0.017]
CFFR*Pos_CSM				0.022***
				[0.007]
Log(Assets)	-0.003***	-0.002***	0.006***	0.006***
	[0.000]	[0.000]	[0.001]	[0.001]
PP&E/Assets	0.011	0.011*	0.051***	0.050***
	[0.006]	[0.006]	[0.010]	[0.010]
Leverage	-0.004	-0.005	0.009	0.009
	[0.006]	[0.006]	[0.009]	[0.009]
ROA	0.090***	0.090***	0.081***	0.081***
	[0.002]	[0.002]	[0.003]	[0.003]
Market-to-Book	0.003***	0.003***	0.001*	0.001*
	[0.000]	[0.000]	[0.000]	[0.000]
Constant	0.558***	0.371***	0.571***	0.588***
	[0.014]	[0.015]	[0.009]	[0.011]
Adjusted R2	0.08	0.08	0.09	0.09
No. observations	99214	99214	45983	45983

Table 7

Reduction of Import Tariff Rates and Firm Efficiency

This table reports results of fixed effects regressions on firm efficiency for 1989-2005 using a subsample that consists of manufacturing industries (SIC codes 2000-3999) with import tariff data available. Tariff data is downloaded from http://terpconnect.umd.edu/~lfresard/. Efficiency is the bias-corrected DEA firm efficiency measure. CSM is a competitive strategy measure adapted from Lyandres (2006). Pos_CSM1 takes value of 1 if *mean* industry CSM is positive. Pos_CSM2 takes value of 1 if *median* industry CSM is positive. Post_Reduction$_{j,t}$ equals one if industry j has experienced a tariff rate reduction by time t that is larger than three times the median tariff rate reduction in that industry, and zero otherwise. Log(Assets) is the natural logarithm of market value of assets, PP&E/Assets is the ratio of net property, plant, and equipment to book value of total assets, Leverage is ratio of total debt to market value of assets, ROA is operating income before depreciation divided by book value of total assets, and Market-to-Book is market value of assets divided by book value of assets. In addition to firm fixed effects, year dummies and 2-digit SIC code industry dummies are included in the regressions, but are not reported. Robust standard errors are reported in brackets. * p<0.10, ** p<0.05, *** p<0.01.

	Efficiency: $\lvert\Delta$Tariff$\rvert$ > 3*median (1)	Efficiency: $\lvert\Delta$Tariff$\rvert$ > 3*median (2)	Efficiency: $\lvert\Delta$Tariff$\rvert$ > 2*median (3)	Efficiency: $\lvert\Delta$Tariff$\rvert$ > 2*median (4)
Post_Reduction	0.011	0.014**	0.003	0.008
	[0.007]	[0.007]	[0.007]	[0.007]
Post_Reduction*Pos_CSM1	-0.030***		-0.027***	
	[0.008]		[0.008]	
Post_Reduction*Pos_CSM2		-0.039***		-0.038***
		[0.009]		[0.008]
Log(Assets)	0.003***	0.003***	0.002***	0.002***
	[0.001]	[0.001]	[0.001]	[0.001]
PP&E/Assets	0.032***	0.032***	0.031***	0.031***
	[0.011]	[0.011]	[0.011]	[0.011]
Leverage	0.025**	0.025**	0.027***	0.027***
	[0.010]	[0.010]	[0.010]	[0.010]
ROA	0.120***	0.120***	0.120***	0.119***
	[0.004]	[0.004]	[0.004]	[0.004]
Market-to-Book	0.001**	0.001**	0.001**	0.001**
	[0.001]	[0.001]	[0.001]	[0.001]
Constant	0.555***	0.555***	0.560***	0.560***
	[0.010]	[0.010]	[0.010]	[0.010]
Adjusted R2	0.12	0.12	0.12	0.12
No. observations	24086	24086	23812	23812

Table 8

Impact of Corporate Governance on the Relation between Efficiency and Strategic Interaction

This table reports results of fixed effects regressions on firm efficiency for 1997-2014. Regressions are run on the sample firms for which corporate governance data is available. Corporate governance data comes from Risk Metrics. Remaining data come from Compustat and Census of Manufactures. Bebchuk et al.'s (2009) Entrenchment Index, or E-Index, is used to measure corporate governance. We use a subset of the six provisions in the E-Index as E-Index4, which includes staggered boards (CBOARD), poison pills (PPILL), golden parachutes (GPARACHUTE), and supermajority requirements for mergers (SUPERMAJOR_PCNT greater than 51%). Using this measure, the sample is separated into those firms with weak governance (E-index4 > 1) and those with strong governance (E-index4 ≤ 1). We then add an interactive term, Weak_Gov, to evaluate efficiency of firms with weak corporate governance relative to efficiency of firms in industries with strong corporate governance. Efficiency is the bias-corrected DEA firm efficiency measure. CSM is a competitive strategy measure adapted from Lyandres (2006). |CSM| is the absolute value of the competitive strategy measure, proxying for the extent of strategic interaction. Pos_CSM is a dummy variable equal to 1 when CSM is positive, and 0 otherwise. TSIMM is the total similarity measure of product market competition from Hoberg and Phillips (2016). Log(Assets) is the natural logarithm of market value of assets, PP&E/Assets is the ratio of net property, plant, and equipment to book value of total assets, Leverage is ratio of total debt to market value of assets, ROA is operating income before depreciation divided by book value of total assets, and Market-to-Book is market value of assets divided by book value of assets. In addition to firm fixed effects, year dummies and 2-digit SIC code industry dummies are included in the regressions, but are not reported. Robust standard errors are reported in brackets. * p<0.10, ** p<0.05, *** p<0.01.

	(1) Efficiency	(2) Efficiency
|CSM|	-0.258***	
	[0.040]	
|CSM|*Pos_CSM	0.373***	
	[0.055]	
|CSM|*Weak_Gov	0.226***	
	[0.042]	
|CSM|*Pos_CSM*Weak_Gov	-0.336***	
	[0.067]	
TSIMM		-0.042***
		[0.003]
TSIMM*Pos_CSM		0.016***
		[0.002]
TSIMM*Weak_Gov		0.007***
		[0.002]
TSIMM*Pos_CSM*Weak_Gov		-0.009***
		[0.002]
Log(Assets)	-0.017***	-0.023***
	[0.002]	[0.002]
PP&E/Assets	-0.021	-0.013
	[0.023]	[0.029]
Leverage	0.066***	0.116***
	[0.022]	[0.027]
ROA	0.217***	0.208***
	[0.024]	[0.028]
Market-to-Book	-0.009***	-0.007***
	[0.002]	[0.002]
Constant	0.841***	1.002***
	[0.022]	[0.028]
Adjusted R2	0.04	0.04
No. observations	15230	11474

Table 9

Regressions of the Relation between Alternate Measures of Performance and Strategic interaction

This table reports results of fixed effects regressions on firm efficiency for 1988-2014. Firm data come from Compustat and Census of Manufactures. Efficiency is the bias-corrected DEA firm efficiency measure. TFP is total factor productivity, a measure of productivity that looks at the change in total outputs net of the change in total inputs. Sales/Employee is revenue per employee, a firm's total revenue divided by the number of employees. ROA is operating income before depreciation divided by book value of total assets. CSM is a competitive strategy measure adapted from Lyandres (2006). |CSM| is the absolute value of the competitive strategy measure, proxying for the extent of strategic interaction. Pos_CSM is a dummy variable equal to 1 when CSM is positive, and 0 otherwise. Log(Assets) is the natural logarithm of market value of assets, PP&E/Assets is the ratio of net property, plant, and equipment to book value of total assets, Leverage is ratio of total debt to market value of assets, and Market-to-Book is market value of assets divided by book value of assets. In addition to firm fixed effects, year dummies and 2-digit SIC code industry dummies are included in the regressions, but are not reported. Robust standard errors are reported in brackets. * p<0.10, ** p<0.05, *** p<0.01.

	(1) Efficiency	(2) TFP	(3) Sales/Employee	(4) ROA
|CSM|	-0.069***	-0.074**	-0.074**	-0.022
	[0.011]	[0.031]	[0.034]	[0.015]
|CSM|*Pos_CSM	0.046***	0.075**	0.092**	-0.039**
	[0.013]	[0.037]	[0.040]	[0.017]
Log(Assets)	0.004***	0.035***	0.121***	0.079***
	[0.000]	[0.001]	[0.001]	[0.001]
PP&E/Assets	0.004	-1.592***	-0.475***	-0.064***
	[0.006]	[0.019]	[0.021]	[0.008]
Leverage	-0.032***	-0.017	0.076***	-0.271***
	[0.006]	[0.017]	[0.019]	[0.008]
Market-to-Book	-0.005***	-0.035***	-0.056***	-0.084***
	[0.000]	[0.001]	[0.001]	[0.000]
Constant	0.594***	0.385***	4.176***	-0.323***
	[0.014]	[0.034]	[0.037]	[0.018]
Adjusted R2	0.06	0.11	0.13	0.48
No. observations	99214	92038	92546	99214

Table 10

A Comparison of Performance Measures and Default/Delisting Probabilities

This table presents results of Cox proportional hazard regressions. The dependent variable is survival time. For delisted firms this is defined as year of delisting minus the first year the firm appears in the sample. For the remaining firms we use the last year in the sample minus the first year in the sample. Cox regressions estimate the log-hazard ratio as a function of explanatory variables. Efficiency is the bias-corrected DEA firm efficiency measure. TFP is total factor productivity, a measure of productivity that looks at the change in total outputs net of the change in total input usage. Sales/Employee is revenue per employee, a firm's total revenue divided by the number of employees. ROA is operating income before depreciation divided by book value of total assets. Log(Assets) is the natural logarithm of market value of assets. Leverage is ratio of total debt to market value of assets, and Market-to-Book is market value of assets divided by book value of assets. Firm Age is the age of the firm. Modified Z-score is a modified version of Altman's (1968) Z-score which does not include the ratio of market value of equity to book value of total debt. Robust standard errors are reported in brackets. * p<0.10, ** p<0.05, *** p<0.01.

	(1)	(2)	(3)	(4)
	Log Hazard Ratio	Log Hazard Ratio	Log Hazard Ratio	Log Hazard Ratio
Efficiency	-1.832***			
	[0.372]			
ROA		-0.717***		
		[0.167]		
TFP			0.111	
			[0.106]	
Log(Sales/Employee)				0.081
				[0.094]
Log(Assets)	-0.665***	-0.634***	-0.649***	-0.653***
	[0.058]	[0.057]	[0.058]	[0.059]
Firm Age	-0.026**	-0.030***	-0.030***	-0.029***
	[0.011]	[0.011]	[0.011]	[0.011]
Leverage	4.113***	4.084***	4.216***	4.104***
	[0.362]	[0.360]	[0.378]	[0.371]
Market-to-Book	0.011	-0.016	0.002	-0.001
	[0.038]	[0.041]	[0.031]	[0.031]
Modified Z-Score	-0.024***	-0.004	-0.033***	-0.033***
	[0.005]	[0.010]	[0.005]	[0.005]
Observations	70300	70300	68327	68398
Pseudo R^2	0.169	0.167	0.163	0.163
AIC	2731.6	2736.3	2370.3	2400.0

Appendix A – Frontier Efficiency Methodology

The concept of economic efficiency flows directly from the microeconomic theory of the firm. The efficiency of a firm is defined by comparing the observed value with the optimal value of its vector of inputs and outputs. Efficiency can be characterized by either output shortage for a given level of input or input excess for a given level of output. Both yield identical values. Conditioning on a specific output vector, a firm is considered fully efficient if its actual input usage equals optimal input usage and inefficient if its actual input usage exceeds optimal input usage. A production frontier indicates the minimum inputs required to produce any given level of output for a firm operating with full efficiency. Figure A.1 shows a production frontier, V, for a firm with one input and one output. Firm *i* is operating at point (x_i, y_i). This firm could operate more efficiently by moving to the frontier, i.e., by reducing its input usage. The firm's level of technical efficiency, TE(x,y), is given by the ratio Oa/Ob.

To measure technical efficiency, we estimate a "best-practice" frontier for each firm. Specifically, we use Data Envelopment Analysis (DEA), which uses a standard linear programming technique to pinpoint a peer group of efficient firms for each firm being evaluated. There are several different ways to present DEA technical efficiency problems, but the simplest representation for firm *i* is the following:

$$TE(x_i,y_i)= \min \theta_i$$

$$\text{subject to: } Y\lambda_i \geq y_i,\ X\lambda_i \leq \theta_i x_i \text{, and } \sum_{i=1}^{S} \lambda_i = 1.$$

(A.1)

where firm subscript i=1,2,…,S. Y is an N x S output matrix and X is a M x S input matrix for all firms' in the sample; y_i is an N x 1 output vector and x_i is an M x 1 input vector for firm i; and λ_i is an S x 1 intensity vector for firm i. The constraint $\sum_{i=1}^{S} \lambda_i$ =1 imposes variable returns to scale (VRS). Firms with elements of λ_i that are non-zero are the set of "best-practice" reference firms for the firm under analysis. Efficiency, θ_i, is between zero and one.

Below we provide a numerical example to illustrate what this measure represents and how it is computed. Suppose there are four firms and each firm uses two inputs, labor and capital, to generate sales:

Firm	Labor (X_1)	Capital (X_2)	Sales
1	1000	5000	20000
2	2000	2000	20000
3	4000	1000	20000
4	4000	3000	20000

Figure A.2 presents the four firms and piece-wise linear best-practice frontier, i.e., the isoquant for a firm with one output and two inputs. The isoquant represents various combinations of the two inputs required to produce a fixed amount of the single output using the best available technology. Firms operating on the isoquant are considered to be technically efficient. Firms 1, 2, and 3 are on the best-practice frontier and are thereby technically efficient. Firm 4 is not. It could reduce its input usage by adopting the best technology. Using DEA, we can show that Firm 4 is only 60 percent efficient relative to its peers, implying the firm could produce the same level of output with 60 percent of the inputs actually utilized.

For Firm 4, the DEA linear programming problem is:

$\max_{\lambda i}(-\theta)$ subject to:

$20000\lambda_1 + 20000\,\lambda_2 + 20000\,\lambda_3 + 20000\,\lambda_4 \geq 20000$

$1000\,\lambda_1 + 2000\,\lambda_2 + 4000\,\lambda_3 + 4000\,\lambda_4 \leq 4000\theta$

$5000\,\lambda_1 + 2000\,\lambda_2 + 1000\,\lambda_3 + 3000\,\lambda_4 \leq 3000\theta$

$\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 = 1$

$\lambda_1 \geq 0, \lambda_2 \geq 0, \lambda_3 \geq 0, \lambda_4 \geq 0$

The lambdas (λ) are the weights on each input or output of the firm. In this simplified example, the first constraint is equivalent to the fourth constraint, so the Lagrangian of the objective function and constraints is: $L = -\theta - \gamma_1 (\lambda_1 + 2\lambda_2 + 4\lambda_3 + 4\lambda_4 - 4\theta)$

$- \gamma_2 (5\lambda_1 + 2\lambda_2 + \lambda_3 + 3\lambda_4 - 3\theta)$

$- \gamma_3 (1 - \lambda_1 - \lambda_2 - \lambda_3 - \lambda_4)$

$+ \gamma_4\lambda_1 + \gamma_5\lambda_1 + \gamma_6\lambda_1 + \gamma 7\lambda_1$

Taking the first-order conditions:

$$\frac{\partial L}{\partial \theta} = 0 \Rightarrow -1 + 4\gamma_1 + 3\gamma_2 = 0 \qquad (FOC\ 1)$$

$$\frac{\partial L}{\partial \lambda_1} = 0 \Rightarrow -\gamma_1 - 5\gamma_2 + \gamma_3 + \gamma_4 = 0 \qquad (FOC\ 2)$$

$$\frac{\partial L}{\partial \lambda_2} = 0 \Rightarrow -2\gamma_1 - 2\gamma_2 + \gamma_3 + \gamma_5 = 0 \qquad (FOC\ 3)$$

$$\frac{\partial L}{\partial \lambda_3} = 0 \Rightarrow -4\gamma_1 - \gamma_2 + \gamma_3 + \gamma_6 = 0 \qquad (FOC\ 4)$$

$$\frac{\partial L}{\partial \lambda_4} = 0 \Rightarrow -4\gamma_1 - 3\gamma_2 + \gamma_3 + \gamma_7 = 0 \qquad (FOC\ 5)$$

$$\gamma_1(\lambda_1 + 2\lambda_2 + 4\lambda_3 + 4\lambda_4 - 4\theta) = 0 \qquad (FOC\ 6)$$

$$\gamma_2(5\lambda_1 + 2\lambda_2 + \lambda_3 + 3\lambda_4 - 3\theta) = 0 \qquad (FOC\ 7)$$

$$\gamma_3(1 - \lambda_1 - \lambda_2 - \lambda_3 - \lambda_4) = 0 \qquad (FOC\ 8)$$

$$\gamma_4\lambda_1 = \gamma_5\lambda_2 = \gamma_6\lambda_3 = \gamma_7\lambda_4 = 0 \qquad (FOC\ 9-12)$$

To solve the system of equations, we iteratively examine different values for the γ 's. Take the case where $\gamma_5 = \gamma_6 = 0$. From FOC 3 and FOC 4, we find $\gamma_2 = 2\gamma_1$, which yields the following:

$$-1 + 4\gamma_1 + 6\gamma_1 = 0 \qquad (FOC\ 1)$$

Therefore, $\gamma_1 = \frac{1}{10}$ and $\gamma_2 = \frac{1}{5}$, which using FOC 3 implies $\gamma_3 = \frac{3}{5}$. Substituting these values into FOC 2 and FOC 5 yields $\gamma_4 = \frac{1}{2}$ and $\gamma_7 = \frac{2}{5}$. The feasible set of multipliers ($\gamma_1 - \gamma_7$) is $\left(\frac{1}{10}, \frac{1}{5}, \frac{3}{5}, \frac{1}{2}, 0, 0, \frac{2}{5}\right)$. Since $\gamma_4 \neq 0$and $\gamma_7 \neq 0$, then FOC 9-12 indicate that $\lambda_1 = \lambda_4 = 0$. Using these values, *FOC* 6-8 become:

$$2\lambda_2 + 4\lambda_3 = 4\theta$$

$$2\lambda_2 + \lambda_3 = 3\theta$$

$$\lambda_2 + \lambda_3 = 1$$

Solving these equations shows that $\theta = 0.6$, $\lambda_2 = 0.8$, and $\lambda_3 = 0.2$. Hence Firm 4 is only 60 percent efficient relative to its peers. Since λ_2 and λ_3 are non-zero they represent the set of “best-practice” reference firms for Firm 4. Firms 1, 2, and 3 can be shown to have 100% efficiency through similar procedures.

Figure A.1

Firm Efficiency – One Input and One Output

This figure shows a production frontier for a firm with one input and one output. A production frontier indicates the minimum inputs required to produce any given level of output for a firm operating with full efficiency. Firm *i* is operating at point (x_i, y_i). The firm's level of technical efficiency, TE(x,y), is given by the ratio Oa/Ob.

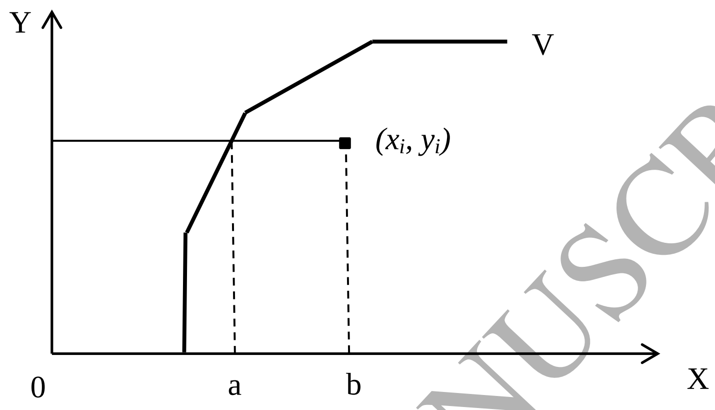

Figure A.2

Firm Efficiency – Two Inputs and One Output

This figure shows the piece-wise linear best-practice frontier for four firms, each of which uses two inputs, labor and capital to generate sales. The isoquant represents the various combinations of the two inputs required to produce a fixed amount of the single output using the best available technology. Firms operating on the isoquant are considered to be technically efficient.