ESSAYS IN FINANCE

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Abstract: Essay one examines multiple aspects of executive compensation using NCAA football head coach salaries. Our setting provides unique advantages to answering whether over- and under-paid salaries impact future performance. First, we observe the coaches' entire professional history, finding that firms non-myopically incorporate previous performance during contract negotiation. Second, all aspects of coach pay are explicitly outlined in the contract, allowing us to precisely value performance components of compensation. Additionally, we argue the managerial pay-performance nexus is more accurately estimated using the value of the entire contract versus annual compensation. We find that when a coach's total contract is excessively overpaid, future team performance suffers. Negative returns to overpaid contracts are the result of performance compensation, not guaranteed pay. Our results concur with the excess compensation literature, while being antithetical to tranches of conclusions made by the sports and managerial "pay-for-performance" research. Further investigations suggest this dichotomy is likely due to bias stemming from specification errors.

Essay two provides a literature review of academic research related to liquefied natural gas (LNG) hubs development and market integration. Studies show that Asian markets lack a transparent pricing benchmark which exists in North American and European markets. As a result, the formation of functional LNG market hubs in the Asia Pacific region will take time. Early research evidence suggests a strongly cointegrated relationship between LNG and crude oil. Concurring with more recent findings, we confirm that LNG's statistical relationship to both WTI and Brent ceases after the break dates of August 2008 and October 2015, respectively. Multiple initiatives are underway to facilitate development and price discovery for global LNG markets. However, the conclusions found within prior literature are dependent upon the sophistication of the estimation model and sample ranges employed.

Essay three documents a strong comovement between a firm's corporate social responsibility (CSR) score and the CSR scores of their social network. This result is strongest for the CEO's social network and when firms that have a high number of connections or more central positions within a network. Our results are robust within firm (firm fixed effect model) and cross sectional variation (industry fixed effect model). Furthermore, our results are robust to exogenous shocks to social networks including forced CEO turnover and the death of a director. Our research documents that social network-based peer effects have an important role in corporate CSR policy.

TABLE OF CONTENTS

Chapter Page

LIST OF TABLES

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

GRIDIRON CEOS: REVISING THE EXECUTIVE EXCESS PAY-FUTURE PERFORMANCE NEXUS

1. Introduction

"He didn't do nothin' but get paid a whole bunch of money."

- Ed Oliver referring to Texas A&M coach Jimbo Fisher[1]

Executive compensation has sparked an intense debate among academics and practitioners. In an ideal world, CEO incentives would be perfectly aligned with firm and investor objectives. Managerial self-interest and effort aversion necessitate the use of contracts to induce higher levels of performance. The theoretical literature has examined contract design through a variety of lenses such as informative signals (Holmström, 1979), private information disclosure (Diamond, 1985; Kyle, 1985), multi-period optimization (Indjejikian and Nanda, 1999), and non-performance measures (Bushman et al., 1996; Ittner et al., 1997). Supporting empirical studies have overwhelmingly tested these theories using a performance-by-year compensation structure. Such specifications run contrary to the multi-year design

[1]Source: Staples, A., 2018. Ed Oliver is college football's ultimate boss. Sports Illustrated. si.com/college/2018/08/14/ed-oliver-houston-cougars-heisman-nfl-draft

of contracts. While a few studies have attempted to address intertemporal concerns, they ultimately treat contract pay as being annually determined.

Using National Collegiate Athletic Association (NCAA) Football Bowl Subdivision (FBS) coaching contracts as a managerial setting, we examine the dynamic relationship between top managerial pay and firm performance at the contract level. Our unique empirical design has a number of key advantages over previous studies. By utilizing the full value of payouts over the contract's life, we are able to assess the manager's expected payoff at the exact point of signing. In practice, the compensation details are negotiated at the time of the initial contract signing, for which most extend over multi-year periods.[2] This is contrary to the majority of studies which consider CEO compensation negotiation as an annual occurrence determined by the same year's, or a few years' prior, performance (Joskow and Rose, 1994; Bertrand and Mullainathan, 2001; Banker et al., 2013). Although CEOs are in fact paid annually, the compensation structure (but not amount) will have already been previously determined at an earlier time of contract signing. Agents thereby maximize utility by optimizing their total payout (i.e., the sum of guaranteed and performance compensation) over the entire contract horizon.

In some cases, it may be more advantageous to chase one big annual performance based payout rather than a series of smaller guaranteed ones. Earnings management is a well-documented example of gaming performance indicators to reach a specific year's benchmark at the expense of current or future firm value (Degeorge et al., 2005; Matsumoto, 2002; Roychowdhury, 2006; Phillips et al., 2003). Studies using CEO pay-by-year specifications omit such possibilities by effectively arguing that the pay contract is being negotiated every year.[3] As performance bonuses would only payoff in a minority of observations, pay-by-

[2]Schwab and Thomas (2006) finds that almost all (>88%) CEO contract terms are two to five years, with the most common term (34.13%) being three years.

[3]For examples of annually renegotiated contract settings see: Antle and Smith (1986); Joskow and Rose (1994); Boschen and Smith (1995); and Sigler (2011).

year designs also have the downside of over-valuing guaranteed pay. This issue is further compounded by the use of rough approximations for valuing stock option compensation (Hall and Liebman, 1998; Ahn, 2015). Instead, we posit that managerial compensation is best described as the discounted present value of future expected payoffs over the life of a contract, measured at the date of contract signing. The nature of the NCAA contracts also allows us to observe exact values for both performance and guaranteed components of coach pay, which are then presented as an equivalent annual annuity. While utilizing contract level data reduces the size of the sample available, it comes with the advantage of accurately characterizing the contract process.

The above arguments beg the question of what pay level should be expected at the time of negotiation. In other words, does previous performance affect future pay? The predominant conclusion is that it does, although there is disagreement concerning how far back performance matters (Hall and Liebman, 1998; Banker et al., 2013). Introducing lagged firm or CEO performance variables for one to three years prior is the common practice (Hayes and Schaefer, 2000; Frydman and Saks, 2010; Ahn, 2015). A CEO's previous position is a probable factor when determining her compensation. However, defining the responsibilities of previous roles is often difficult, leading to bias when considering the relative value of personal performance to the current CEO position. Therefore, it is likely that significant error exists in determining a CEO's initial compensation. Since measures of individual managerial quality are relatively non-existent, it becomes increasingly important to determine how well the executive's previous firm faired. Such issues lead to a set of imperfect proxies for inferring firm performance. Accounting measures such as return on equity, profitability, and cash flows are often utilized. However, their measurement quality is significantly reduced if noisy (Lambert and Larcker, 1987). A number of authors suggest the use of stock prices to determine incentives (Jensen, 1989; Rappaport, 1999), even though they also sensitive to noise (Sloan, 1993) and measurement timing (Hall and Liebman, 1998). Further, value influencing factors such as economic conditions lie outside of the executives' control, thereby biasing value measures (Diamond and Verrecchia, 1982; Holmström and Tirole, 1993; Bertrand and Mullainathan, 2001). The use of relative performance evaluations (RPEs), which evaluate CEOs relative to their peer group, have been suggested (Dye, 1992; Gibbons and Murphy, 1990). However, it remains unclear how well this describes the CEO's personal quality relative to firm value (Gopalan et al., 2010; Liu and Sun, 2014).

NCAA sports is one setting that avoids performance measurement issues. Performance is readily explained through a variety of explicit factors including win/loss records, bowl wins, recruiting, and revenue generation (Leeds and Pham, 2020). Such measures are also readily available by season (one year period) across an array of public sources. Also, due to the purely competitive nature of sports, these are all relative measures. Relative performance evaluation is endogenous, and exogenous market factors are extraneous. While only forty percent of CEOs of S&P 500 firms are compensated using RPE measures (Tice, 2020), coaches are explicitly paid based on relative performance. Lastly, the structure of head coach pay is far less dependent on current performance compared to CEOs. DeVaro et al. (2018) samples all S&P 1500 firms from 1992-2014 and finds that salary accounts for an average 14.2% of total CEO compensation. In our sample we find that for head coaches, guaranteed pay comprises an average 73.3% of maximum compensation while the percentage of performance pay increases as maximum compensation increases. Therefore, coach compensation is highly dependent upon labor market incentives. Coaches' opportunities to increase future pay is markedly determined by the tier of university program they are coaching (Brook, 2021). A promotion to head coach or moving up to a better program does not occur without positive previous performance.

For these reasons our study presents a unique examination of executive compensation and excess pay and future firm performance. Using twenty years of NCAA football head coach contracts and a two-stage empirical design, we circumvent multiple recurring issues in the related empirical literature. In the first stage, we estimate an expected level of compensation for each contract. Due to the high specificity of sports data, we are able to track individual coaches' performance, relative to their position, across the majority of their career as well as test a wide array of corresponding specifications.[4] We show that coaches are positively paid relative to their historical career performance.

In the second stage, we test whether over- and under-paid contracts are associated with future team performance metrics. In the CEO literature, Core et al. (1999) find that overpaid CEOs are associated with future negative performance. They conjecture that this negative relation is possibly a manifestation of other contracting inefficiencies which led to the poor future performance. Brick et al. (2006) confirms these findings and suggests the negative relation is due to "mutual back scratching or cronyism." While we estimate similar regressions as those found in the CEO/managerial pay literature, we estimate over- and under-paid contracts at the contract level, a unique feature of this study. Thus, we ensure the results are not biased from utilizing a yearly performance specification. Our results suggest that overpaid contracts are associated with lower team performance in the future (fewer wins). The findings are driven by the highest quartile of overpaid coaches, an asymmetric effect. We also find that underpaid contracts are not associated with future performance. It appears that underpaid managers live up to their contracts, suggesting the underpaid coaches may have something to prove. Our results are robust to a wide variety of performance measures and lag order specifications.

Our findings run contrary to the prevailing sports compensation literature. This is likely a facet of two particular issues: the myopic view of aforementioned pay-by-year specifications, and bias issues stemming from omitted performance measurement. To illustrate our point, we conduct three additional tests. First, we conduct a univariate pay-for-performance

[4] Although our data begins in 2000, this creates a reasonably complete picture for coaches in our sample as we require at least two prior years of performance data for the contract to be included.

analysis and find that without controls, a positive and significant relation between pay and performance exists. Second, we re-estimate our model using the prevailing pay-by-year structure. We find performance has a positive and highly significant effect on compensation, which is unsurprising considering the results of similarly specified literature. The literature connotation is that this describes a positive relationship betwen pay and firm performance (Leeds et al., 2018; Grant et al., 2013). When taken in context, this dichotomy emphasizes the importance of accurately representing contract negotiation structures. We reinforce the conclusions of the corporate finance literature that excess compensation is associated with poorer firm performance (Core et al., 1999; Brick et al., 2006). Not only is a contract level setting necessary to accurately identify the pay-performance nexus, but also an excess pay structure.

We lastly revisit the recent study of Colbert and Eckard (2015), whose alternative approach estimates pay-performance relationships at the university level. Using a pay-by-year specification, and an array of controls common to the sports literature, they find positive but decreasing returns to compensation. Upon replication, we find their results only hold for the years used in their sample (2006-2011). Additionally, when the sample is extended to include the full range of years (2000-2020) and controls, no evidence of significant or non-linear effects exists. Such results are robust across multiple performance measures.

Our research concurrently informs the extant literatures concerning managerial performance measures, the managerial excess pay-performance nexus, and sports coaching contracts. Particularly, we provide evidence of four key developments. First, firms (i.e., universities) are non-myopic in past performance consideration. Second, the empirical research using a pay-by-year performance specification is likely misspecified. Third, negative performance effects of overpaid compensation are driven by the highest quartile of overpaid earners. Fourth, negative returns to overpay are the result of the performance components of compensation, and not a facet of guaranteed pay. The first and fourth developments represent extensions that would be quite difficult to reproduce outside of our NCAA setting. However, the second empirical implication (i.e., contract-level estimation) is readily adoptable across the wider corporate finance literature.

The remainder of the paper is organized as follows. In Section 2. we describe the data sample and performance measurement process. In Section 3, we optimize our first stage model and relative contract over- and under-pay estimations, using previous performance measures. We present second stage investigations of whether first stage mispricing is related to future performance in Section 4. In Section 5 we replicate the generalized methodologies of previous pay-by-year research and discusses the implications. Our conclusions and final remarks are provided in Section 6.

2. Data and Measurements

The NCAA Division I FBS is the highest level of college football. In 2006, the NCAA subdivisions were renamed the FBS and the Football Championship Subdivision (FCS).[5] While our sample covers pre-2006, our analysis is centered upon FBS head coaches. Key to the managerial pay-performance nexus is obtaining accurate determination of FBS head coach compensation. Maximum compensation is often sourced from USA Today. Performance dependent salary is proxied by combining USA Today data with revenue values from the Membership Financial Reporting System (MRFS) reports or Equity In Athletics Disclosure Act (EADA) to estimate a percentage of pay from outside sources. While MFRS includes salaries and provides the most extensive coverage of athletic department financials, the NCAA has not made it publicly available. Other studies have used other proxies such as athletic department ticket sales, fixed revenues, and expenses. Tatos (2018) notes that

[5] NCAA membership was divided into three legislative and competitive divisions, Division I, Division II and Division III. Division I was further subdivided into I-A and I-AA.

while individual sources are available through public request, they often come in the form of electronic pdf records. He states, "parties wishing to aggregate institutional data from these reports must expend significant time and resources re-creating a database..." Essentially, this is what we did. We obtain head coaching contracts from 2000-2020 through the Open Records and Freedom of Information Act (FOIA). We sent requests to each of the 130 current FBS universities. Contract information cannot be obtained for the private universities, those citing copyright infringement laws, or states with residency requirements for open access. Of the remaining universities, we obtain a final sample which includes 478 contracts across 228 coaches from 101 schools. These include base contracts, amendments, and extensions. We examine each contract for details of guaranteed compensation, maximum compensation, performance incentives, and non-perquisite incentives.

2.1. Coach Compensation

Our empirical analysis of head coach salary is primarily based on measures of maximum compensation, following the prevailing sports literature which utilizes USA Today salary measures.[6] Maximum compensation is the maximum available compensation a head football coach can receive under the current year contract and is the total of all guaranteed and performance-based salary. We also collect maximum guaranteed salary, maximum performance-based salary, and the percent of maximum compensation which is guaranteed. While NCAA football coach compensation has a maximum, the typical CEO pay does not. We will explore this unique feature in our tests.

As contracts extend over multiple years, annual compensation values are first put into parity by deflating them into 2021 dollars using the same years Consumer Price Index. Real annual salaries are summed to create a total contract salary, effectively the present value

[6] USA Today collects the maximum compensation from contracts. Studies using such data include: Leeds and Pham (2020); Berri et al. (2015); Fogarty et al. (2015); Colbert and Eckard (2015); Leeds et al. (2018); Brook (2021)

of the contract. We then calculate an equivalent annual annuity (EAA) for each year of the contract. Annual discount rates are determined by matching the starting month of the contract to Treasury Inflation-Protected Securities (TIPS) or Treasury Bond rates from the same month collected from the Federal Reserve of St. Louis FRED database. As annual compensation values are already deflated, we utilize monthly TIPS rates for 2003-2020. As TIPS data is unavailable prior to 2003, we use bond rates instead. Treasury security maturities are determined by matching the bonds maturity length to the corresponding contract term length. All available maturities are used. The number of annual periods is the length of the contract term. The final maximum compensation variable, *Max_comp*, is presented as an EAA occurring over the life of each contract. In Figure 1 we show a positive relation between a contract's *Max_comp* and the coaches winning percentage performance (*Win%*) over their contract term. Authors using USA Today data find similar preliminary results, implying a positive relationship between annual compensation and future performance.

2.2. Team and University Performance

Measuring performance has presented a number of difficulties for the managerial compensation literature. NCAA sports is an industry where collecting a coach's career performance is feasible. Kahn (2000) contends "There is no research setting other than sports where we know the name, face, and life history of every production worker and supervisor in the industry. Total compensation packages and performance statistics for each individual are widely available, and we have a complete data set of worker-employer matches over the career of each production worker and supervisor in the industry." However, to accomplish this we integrate data from many different sources.

For each of the head coaches in our sample, we determine his career from the "Coaching Career" section of their personal Wikipedia page. We collected not only their head coaching history, but also every other coaching position they held along with the corresponding school and covering years.[7] Coach positions were then matched to the school's annual season performance information. We obtain seasonal team and coach records from sports-reference.com.[8] Additional record data was collected from d3football.com and sports-football-results.com to fill in gaps.[9] NCAA coaches are often recruited from National Football League (NFL) teams and vice-versa. Therefore, we collect NFL team data when it is relevant to an FBS coach's history. A big part of a coach's duties is to recruit the best players for their team. Recruiting is also an important determinant of their compensation (Grant et al., 2013). We obtain annual FBS team recruiting data from rivals.com beginning in 2002. Recruiting data includes the total number of 3, 4, and 5-star recruits as well as total recruiting points and a relative recruiting rank for each season.

A common issue in the compensation literature is that previous managerial quality is difficult to determine. A CEO's hiring often comes from other company roles, thus muddling her individual contribution to firm performance. Similarly, a coach's historical performance may be ill-measured merely by his previous team's record. For example, a high scoring offensive coordinator may lose a game if the team's defense plays poorly. We control for this by collecting team level efficiency data from espn.com beginning in 2005. We record each team's annual efficiency score and ranking across the four categories of offense, defense, special teams, and team overall. These are matched to each coach's career coaching positions.[10] This ensures that coaches are measured only upon the efficiency rating of their previous roles.

We also record team performance across a variety of measures such as bowl appearances

[7] See Appendix 1 for the matching procedure.

[8] These include win/loss records, bowl history, and strength of schedule modifiers.

[9] Data from individual school football program websites were also used for a very small number of schools when data was still missing. These often include high school or community college results.

[10] Positions are matched as well as possible considering their sphere of influence. The full matching categorization can be seen in Appendix 1.

and outcomes. Bowl quality and supporting revenues are highly heterogeneous. Our sample covers a wide range of years during which a number of changes have occurred within the FBS. We endeavor to create a measure of parity in bowl quality across our sample. Therefore, we further separate these into three categories of New Years Six (NY6), Tier 1, and Tier 2. NY6 covers the top six most prestigious bowls (Rose Bowl, Sugar Bowl, Cotton Bowl, Orange Bowl, Peach Bowl, and Fiesta Bowl) along with Bowl Championship Series (BCS), College Football Playoffs, NFL Super Bowl, and NFL Divisional Playoff games. This provides a relative proxy for the premier football games. Beyond these, bowl quality becomes subjective and contentious. We examine many sources to create a plausible listing of Tier 1 and Tier 2 bowls, which can be found in Appendix 2.

University athletic programs annually report revenue and expense data to the U.S. Department of Education Equity In Athletics Data Analysis. We collect operating expenses, revenue, and expenses for the Men's Football Teams for 2002-2018. We further collect total, average, and year-over-year changes in football game attendance from NCAA National College Football Attendance reports beginning in 2003.[11] We report summary statistics for the full set of variables in Table 1.[12] Our compensation variables are broadly similar to those found in Colbert and Eckard (2015) and Leeds et al. (2018), albeit with greater variation due to our extended sample and since we value the entire contract. We find the average contract is worth $2.7 million annually, with a maximum of $11.9 million. The average coach wins 62.2% of his games, roughly 8 games per season, prior to contract signing, but only 55.4% post contract signing. We find slightly more coaching contracts are underpaid, 193 overpaid versus 183 underpaid. However, overpaid contracts exhibit higher means and more variation than those which are underpaid.

[11]Source: www.ncaa.org/championships/statistics/ncaa-football-attendance

[12]Select variable correlations are reported in Appendix 3.

3. Previous Performance and Contract Compensation

The primary goal of this research is to determine whether higher coach pay leads to improved team performance. Coaching contracts are universally multi-year agreements with negotiation only occurring prior to initial signing. Two key aspects determine how a contract's value is determined: the value of the coach's prior performance and expectations for a coach's future performance. This suggests the use of a two-stage approach requiring two separate calculations.

In the first stage, we estimate how much a coach should expect to be annually paid for his contract relative to previous performance. Expected compensation is calculated by regressing the maximum annual compensation (*Max_comp*) on key pay determinants, career performance measures, and coach and university level controls. We modify the specification across these variables to determine which are relevant to the analysis. The first stage model is as follows:

$$Comp_{i,t} = \beta_0 + \beta_1 X_{i,t-N} + \beta_2 Z_{i,t-N} + \beta_3 \Upsilon_{i,t-N} + \mathcal{E}_{i,t-N} \tag{1}$$

Comp, is either the EAA of maximum compensation for contract or the EAA of guaranteed compensation, for contract i. X_i is the corresponding performance variable including win percentage, annual wins, efficiency score, and efficiency rank. Z_i is the vector of compensation determinants including strength of schedule, average annual FBS program expenses, previous bowl performances, rival points, and average FBS program game attendance. Υ_i is the vector of coach characteristic controls. N denotes the number of prior years for calculating past performance. $\mathcal{E}_i$ is the residual expected annual compensation for the contract. These calculated residuals, overpaid and underpaid contracts, refer to a contract's mispricing relative to the coach's previous performance. These residuals do not account for future performance expectations. This regression, or a similar regression using changes, is often what is used to determine pay-for-performance in the extant literature. Our primary question, "Are over- and under-paid contracts related to future performance?," necessitates the residuals from Equation (1). We examine this question in Stage 2.

We present first stage results in Table 2. We find winning percentage (*Win%*) to be positive and significantly related to compensation in all specifications. Next, a series of coach level characteristic controls are added including previous NFL experience (*Prev_NFL*), previous head coach experience (*Hc_prev*), university tenure (*Yrs_uni*), and a dummy for membership in a Power Five conference (*Power5*).[13] All are shown to be significantly related to compensation and considerably improve the model's explanatory power. *Prev_NFL* is the sole exception, which becomes insignificant after including the university's average historical attendance. Previous performance controls are added sequentially. Model 7 is our preferred specification as it has the highest adjusted R-squared (0.602), the full set of controls, as well as a reasonably large number of observations. Sample size limitations are due to the large number of pay determining variables being used. We collected as much as was possible from publicly available sources. The preferred specification also performs best when using a coach's historical efficiency score as the main performance variable.[14] ESPN reports an efficiency score and rank for every NCAA football coach.

Strength of schedule (*SoS*) is the only variable negatively related to contract compensation, suggesting that universities do not fully account for the difficulty of a coach's previous opponents. A coach would be better served playing lower ranked opponents to inflate performance measures. All other variable coefficients are positive. Larger universities (*Attd Avg*) and larger FBS programs (*Expenses*) increase the value of a contract. Universities also pay a premium for previous head coach experience (*Hc_prev*), university tenure (*Yrs_uni*), and

[13]These are subsequently referred to as 'Coach Controls'.

[14]For results see Appendix 4.

more competitive conferences (*Power5*). Surprisingly, appearing in a previous year bowl is significant, while winning the bowl is not. Therefore, it is more important for a compensation maximizing coach to aim for a bowl invitation than on winning the game. Grant et al. (2013) suggests that recruiting ability (*Rival_points*) is a key determinant of compensation. However, we do not find a significant impact. Our assertion is this is likely due to it being highly correlated with other FBS program level variables such as revenue, expenses, average attendance, and bowl wins. Much of a team's recruiting ability may be tied to the historical quality of the university and the size of its football program as opposed to a coach's ability to attract talent.

We conduct similar robustness tests using *Win%* as well as alternative performance measures. In Table 3 we show that results are generally robust to these specifications. One additional win percentage is worth $15,701 in annual compensation. One point of efficiency score is valued approximately the same. Interestingly, win percentage carries a slight premium over average annual win rates. Using twelve average games per FBS season, a single win should be worth approximately $131,000.[15] However, when the performance measure is *Season Wins* (and not *Win%*), we find a single win is only worth $50,655. Some of this may be due to bowl games being included in total annual game calculation. Even so, this would not be enough to explain the gap. While the efficiency score is associated with higher pay, efficiency rank is negatively associated.

Before moving forward, we validate our preferred specification (Table 2: Model 7) in two ways. First, our preferred specification only includes bowls from the season prior to contract signing as well as a bowl win dummy. It is possible that the quality of bowl could affect a coach's compensation for the succeeding contract. We investigate this possibility by separately estimating whether a coach won a bowl previously (as opposed to the prior year) and separating the effects of individual bowl tiers. We report the results in Appendix 5. The

[15] The average FBS season is 12 games. 1/12=.0833, implies one additional win is equal to 8.33% win rate.

sharp increase in R^2 from including coach and contract controls, as seen from models (1) to (2), demonstrates the necessity of their inclusion. The R^2 further increases from model (3) to (4) when considering only the prior season as opposed to all prior seasons. When separately considering high prestige bowls in models 5 and 6, we find no significant effect on compensation. The final model which includes NY6, Tier 1 bowls, and a bowl win dummy lends additional support. The results suggest that a coach's next contract compensation only reflects whether his team appeared in a bowl, while not reflecting whether his team won the bowl nor the perceived quality of the bowl. Second, it is possible that a coach's compensation is only reflective of his recent performance. We examine how "backward-looking" universities are by estimating our preferred model under various lag orders (see Appendix 6). *Career* updates the bowl variables to include a coach's complete prior history. *Bowl* becomes insignificant and the R^2 decreases, suggesting these changes are not optimal. *Lag 1* and *Lag 3* consider only the coach's prior season performance and the average of the past three seasons, respectively. While the R^2 increases in both cases, the primary performance variables of *Win%* and *SoS* become insignificant. Due to these inconsistencies we rule them out as optimal models.

Next, we collect each contract's residual from Model 7 of Table 2. As previously discussed, a positive residual is interpreted as the coach being overpaid relative to their previous performance. A negative residual vis-à-vis implies being underpaid. In Figure 2, we present the number of contracts in each category by season, as well as the seasonal average magnitude. Prima facie evidence suggests that the number of overpaid contracts has increased over time. The average overpaid magnitude trend is positive as well. Underpaid contracts have been fairly flat or slightly decreasing. The steep decline in the number of contracts in 2018 is simply a facet of the data as we record fewer contracts with terms starting in this year.

An additional question is whether the rising number of overpaid contracts, shown in Figure 2, is due to the increasing value associated with college football programs. Essentially, some might argue that a general over-time trend exists above and beyond team income captured via revenue, expense, and attendance variables. We find this argument dubious as it suggests that coach compensation should increase regardless of any observable team value, risk premium, or inflationary factors.[16,17]

In Appendix 9, we then relate these residuals showing the top ten most over- and underpaid across three categories: individual contracts, net historical coach compensation, and net university FBS program compensation. Although these results are undoubtedly the biggest topic of conversation, we forgo discussion of these results as our intention is not to draw attention to individual parties and also to not be excluded from attendance at future games.

4. Can Future Performance Be Bought?

Our second stage examines whether the residuals from the first stage are relevant in predicting future performance. Our analysis is unique in three key ways.

First, a positive and statistically significant relationship between overpaid contracts and contract performance is evidence that performance can be bought. Similarly, we would expect a negative relationship between underpaid contracts and performance. The majority of the pay-by-year research takes an alternative approach by examining pay-performance sensitivity, investigating whether better firm performance leads to higher future pay. If a manager performs better, then their negotiating power may increase in the future, leading

[16] However, in Appendix 7 we test this possibility by including annual fixed effects across both specifications. In the second stage, we continue to find a negative performance effect for the top quintile of overpaid contracts, albeit significant at the 15% level. Given the low statistical power of a small observation count, and likely model overfit, our main conclusions are unaffected.

[17] In Appendix 8, we re-estimate our Table 4 results using a discount rate which accounts for risk. Recognizing that coaches may not discount at a risk free rate, we add a 40-year geometric average Fama-French historical risk premium to the risk free rate. Our results in the second stage are stronger than those in Table 4, consistent with our overall findings. Source: mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

to higher levels of performance pay. Abowd (1990) finds positive results when considering these issues under an annually renegotiated pay-by-year structure. The question still remains whether future firm performance is maximized across the life of the contract given an initially determined level of compensation.

Second, future firm performance is relative to how much is being paid to the manager. If a manager is being overpaid, then the contract principal should expect much better results compared to a fairly or underpaid manager. Conversely, an underpaid manager may retain their job despite not performing as well as expected. The secondary question is then, "Do firms get what they pay for?" For example, Nick Saban is often decried in the media for being the highest paid coach in the NCAA. Nick Saban has also won seven national titles, and his teams have rarely ranked outside the top 10. Jim Harbaugh is similarly decried and has yet to win a single national title. It is also possible to overpay even for great performance. How much should a team be willing to spend to win? While such questions are especially important when considering coach turnover, we leave these implications to future research. What we aim to answer is whether being relatively over or under-paid, based upon past performance, has any significant effect on future performance. Similar to the questions posed in Core et al. (1999) and Brick et al. (2006) regarding CEOs. By using the two stage structure we are able to improve upon the previous sports literature and derive more intuitive results.

Our second stage model is as follows:

$$Y_i = \beta_0 + \beta_1 \mathcal{E}_i + \beta_2 Z_i + \beta_3 \Upsilon_i + e_i \tag{2}$$

where Y_i is a performance measure taken over the life contract i, Z_i is the vector of compensation determinants including strength of schedule, average annual FBS program expenses, rival points, and average FBS program game attendance. Υ_i is the vector of coach characteristic controls. $\mathcal{E}_i$ is the residual contract mispricing, calculated from the first stage. We further separate the model into overpaid (i.e., positive residual) and underpaid (i.e., negative residual) contracts. We find that despite the attention placed on the high salaries of NCAA coaches, more contracts in our sample are underpaid than overpaid despite the rising number of overpaid contracts. We illustrate additional evidence in Figure 2.

In Table 4, we present our second stage results after separating overpaid (Panel A) and underpaid (Panel B) contracts. We use the absolute value of underpaid residuals for ease of interpretation. In Panel B, we find that underpaid coaches are associated with more future wins if we do not include controls. However, once we control for team spending, strength of schedule, and school size, the effect disappears. Additional coach level controls further reduce the significance. We show in Panel A that overpaid coaches are associated with lower future performance. All controls are also significant at the 1% level and improve the model's explanatory power as shown by the adjusted R-squared. Two potential explanations exist for this result. First, overpaid coaches have "already made it" and do not have to prove themselves as much as those that are underpaid. This seems quite unlikely, as top coaches obtain such roles by being extremely judicious and highly competitive. It seems improbable this would change once reaching the highest levels.

The second possibility is that the most overpaid coaches, while previously highly successful, overall do not perform well enough to justify their maximum compensation. While universities do not necessarily get a diminished performance from highly compensated coaches, they do receive diminishing performance returns to the salaries. If this is the case, it is likely the effect would be more observable in the most overpaid coaches relative to the least overpaid. We test this theory in Table 5, presenting quartile regression results for the overpaid sample. Consistent with this view, the first three quartiles exhibit no significant results. Only in the most overpaid quartile do we find a significant result. The coefficient is not only negative, but also sizable suggesting that the results are being driven by the most overpaid tier of coaches. The fourth quartile is also the only specification where strength of schedule is insignificant. It is unlikely our results are due to the most preeminent coaches having more competitive schedules.

As previously discussed, we find that recruiting has no significant effect on a coach's expected compensation (Table 2: Model 6). However, player quality may be still be an important determinant of future team performance. Therefore, we control for the possibility of player driven performance by additionally including a control for the quality of team recruitment (*Rival Points*) in both Table 2: Model 6 and Appendix 4: Model 6. We find *Rival Points* to be insignificant in both cases. This strongly suggests that the coach plays a significant role in future team performance beyond his current FBS program's ability to attract top player talent.

When we utilize win percentage as a performance measure, our results suggest that overpaid coaches do not tend to perform well enough to fully justify their maximum salaries. However, teams often hire coaches for reasons other than winning games alone. Teams may have alternative objectives such as reaching prestigious bowls, obtaining a perfect season, winning a national championship, or recruiting better players. It is not uncommon to hear phrases along the lines of "sure he wins games, but he's not winning you a national championship." In Appendix 10 we examine whether our results hold across a wider spectrum of potential performance measures. Beyond win percentage and annual wins, the only other significant effect is in the prestigious *NY6* bowl specification. The *NY6* coefficient is also negative, indicating that costs outweigh the benefits of overpaying a coach in hopes of reaching a prestigious bowl or the BCS championship. Performance variable coefficients for the remaining specifications are all insignificant. Overpaying a coach does not create marginal gains in efficiency, revenue, recruiting, or bowl attainment.

Due to the unique nature of our setting, we are able to disctinctly identify guaranteed and maximum compensation. The prior corporate finance compensation literature has utilized total compensation, received annually, by the manager (Joskow and Rose, 1994; Hayes and Schaefer, 2000; Ahn, 2015). Presumably, this is due to large portions of CEO performance compensation being stock option based. Such measures do not describe the total potential value of performance compensation or its relation to guaranteed compensation. Additionally, annual-return specifications price the value of stock options using the Black-Scholes model, thereby imposing a hard annual cutoff-date for the value of firm stock value (Hall and Liebman, 1998; Ahn, 2015). Because of the specificity of our NCAA contract details, we observe the exact value maximum value of the coaches' performance-based pay. Our use of maximum compensation allows us to "price the option." In Table 6, we investigate whether over- and under-paid guaranteed salary is associated with better future firm performance. In the first stage, we find positive prior coaching performance is associated with higher contract guaranteed salary. Our second stage results find no relation between guaranteed compensation and future team performance. This suggests that paying coaches a higher base salary would not meaningfully improve firm performance.

5. Robustness and Alternative Specifications

Heretofore, our results support the prevailing findings of the excess compensation literature (Core et al., 1999; Brick et al., 2006; Basu et al., 2007; Dah and Frye, 2017). The empirical sports literature appears to have found opposing results. We investigate three bias areas which result in such differences.

5.1. Determinant selection

The first potential bias stems from omitting important pay determinants. Prior evidence for which determinants should be included is no less mixed as well. Berri et al. (2015) utilize a 'fixed revenue' model, finding wins, lagged wins, market size, and stadium capacity to be significant. Brook (2021) uses a similar approach to find significance for marginal program revenues, experience, and assistant coach salaries. Grant et al. (2013) refrain from distinguishing between fixed and variable revenues, finding determinants of BCS rank, lifetime win percent, revenue, enrollment, and graduation rate. Leeds and Pham (2020) make the compelling argument that coach salaries are a function of the rents they can extract from improving revenues. Their model finds lagged win percentage, career win percentage, bowl history, and FBS conference to be important.

We verify our results by taking the contra approach of a univariate perspective. If determinants are unimportant, then univariate specifications across both the first and second stages should yield concurring results. We report these results in Table 7. First stage performance is significant across all variables. That is, prior performance is positively related to future compensation. In our second stage, overpaid is also positive and significant. Underpaid is only significant when using win rates as the performance variable. Interestingly, second stage signs are all opposite of the main results. However, the models are not explaining very much of the variation as noted by the low R-squared statistics. In our main analysis establishing an optimal model required trying a wide variety of potential specifications. Many of these permuted across variables common to previous research.[18] The stark contrast between univariate and multivariate results reveals a potential for omitted variable bias. Unreliable variables would do little to alleviate such issues and may lead to distorted conclusions (Diamond and Verrecchia, 1982; Lambert and Larcker, 1987).

[18] Due to sheer size limitations we do not report all the results here. Additional evidence is available upon request.

5.2. Pay-by-year specifications

The managerial pay-performance nexus is more accurately described by employing specifications which incorporate the manager's entire contract term. We consider the implications of using an annualized pay-performance structure within our sample. While such specifications are predominantly utilized by the literature, the extended nature of our dataset supports a more comprehensive estimation. Further, we shed light on previous excess pay results by estimating future performance effects over multiple outlooks. The distinct differences we find are key to demonstrating the value of contract level specification.

In Table 8, we report the results of applying the pay-by-year structure to our sample. We employ our preferred specification from the main methodology. The first stage shows that performance has a positive and significant effect on compensation. Much like the aforementioned studies, most variables are also highly significant at the 1% level. Bowl appearance and bowl wins do not generate additional compensation. In stage two, neither overpaid nor underpaid contracts have an effect on future wins. These results hold when considered for the next season and as an average over the next three seasons. Overpaid and underpaid coefficients are relatively smaller than those we found in Table 4. They also sharply decline the greater the number of future seasons we examine. While not reported, the decrease and corresponding insignificance is even larger when considering a 5 year ($T+5$) outlook. The pay-by-year setting underestimates performance effects while additionally prompting a more myopic empirical outlook.[19]

Previous managerial research has argued that variables such as underpaid and overpaid exhibit non-linear effects. It is possible that our previous specifications have not captured this possibility. Testing non-linear theories usually takes the form of interaction variables

[19] The prevalent connotation of the pay-by-year literature is that current pay results in better future performance. We provide further evidence against this in Appendix 11 when regressing future *Win%* on current compensation. *Max_comp* is only significant when relevant controls, indicated by much larger R^2 and prior results, are omitted

(Dah and Frye, 2017; Cooper et al., 2016) or squared terms (Colbert and Eckard, 2015) within a pay-by-year setting. Given our two-stage setting, interacting additional variables on pay is dubious. In Table 9 we opt for the latter option and include squared terms of pay variables. For brevity, we only report the second stage results. We find only overpaid squared to be significant, and also negative, in the three-year equation.

5.3. University level estimation and sample bias

Colbert and Eckard (2015) provides the strongest evidence of positive non-linear "diminishing" returns to coach pay. Their performance and pay regressions are at the university level as opposed to the individual coach or contract. In effect, they conclude that universities "get what they pay for" albeit with less "bang for their buck" at the highest compensation levels. This is especially interesting for universities and administrators seeking to maximize budget spending over the long run.

We broadly revisit Colbert and Eckard (2015) results with two additional extensions. First, the authors use compensation data from USA Today along with annual performance metrics. Although USA Today encompasses data from all publicly available schools, the authors only include five years of data.[20] Despite having fewer universities overall, our sample updates and extends theirs by 13 years covering 2002-2019. Second, we apply our contract level setting at the university level to match their methodology.

We collect Annual Sagarin Ratings from USA Today. Sagarin ratings are an Elo type system used to assign a power rating to each team based upon final game scores, win-loss records, and the relative ratings of their opponents.[21] AP (Associated Press) Poll Points are from collegepollarchive.com. AP Rank provides an end of season ranking of the top

[20]Their data is from 2006-2011. 2008 is excluded as USA Today did not publish data that year. However, we include 2008 in our replication.

[21]Elo type ratings are widely used in chess and other sports to form direct comparisons between players and teams.

NCAA teams by sports writers and broadcasters. The team with the fewest votes on the list, meaning the fewest non-zero vote count, scores the team one point. Conversely, the first place receives a value equal to the maximum number of annually ranked teams listed. Therefore, higher points reflect a better ranked standing. We collect total *AP_Points* for each team across every year of the sample, which is then aggregated into a historical *AP_RankPoints* value for each university. Colbert and Eckard (2015) only considers the top 25 teams when calculating their version of *AP_Points*. We include the maximum number of teams possible in each year, with 48 being the highest number. These scores have a long history of being utilized in sports media. Due to difficulty in finding sufficient historical data, we use proxies for two of their commitment variables. *'AQ BCS'* is a dummy for whether the university was a member of AQ BCS conferences including the Big East, SEC, Big 12, Big 10, ACC, or Pac 10/12. Our *Power 5* variable is quite similar covering all but the Big East. Second, we proxy for stadium seating capacity (Colbert and Eckard (2015) Capacity variable), replacing it with average game attendance *(Attd Avg)* as both capture that schools with more success accommodate increased ticket demand. We further transform the maximum compensation variable into millions USD by dividing by $1,000,000 (*Compmax_mil*) and add a squared compensation term ($Compmax_mil^2$) for consistency with their methodology.

We present results across both sample ranges in Table 10.[22] The USA Today data covers all of publicly reported universities annually. Some univiersities, however, decline reporting. Nonetheless, our sample from 2006-2011 covers the vast majority.[23] In the Sagarin Rating regression's restricted sample (2006-2011), we find results quite similar to Colbert and Eckard

[22]We report summary statistics for relevant variables in Appendix 12. Our data is quite similar in the restricted sample. Minimal discrepancy exists, likely due to methodological differences in calculating maximum compensation versus USA Today's approach. The use of equivalent annual annuity calculations in lieu of nominal values is also a probable reason. The full 'All Seasons' sample is slightly different by design.

[23]There are a number of reasons this occurred. Federal FOIA and public records requirements, such as residency requirements and excessive document fees, are variable by school policy and from state-to-state. Covid-19 also limited reporting in a few cases during the collection period. Additionally, individual responders may waive reporting restrictions on a case-by-case basis.

(2015). We find *Compmax_mil* is positively associated with rating, but the squarted variable (*Compmax_mil*^{2}) is negative, indicating diminishing returns. However, these results do not hold when we apply the same specification to the full sample. In both equations the coefficient on *Compmax_mil* is positively significant when controls are excluded. These results suggest the findings of Colbert and Eckard (2015) are a facet of their sample range. This result is robust across the two additional performance measures, *Eff. Score* and *Win%*. The improved R^2 of the full sample further supports this conclusion.

6. Conclusion

In this study we present a unique view of the managerial excess compensation and performance nexus literature. Using compensation and performance data collected for NCAA FBS coaches, we circumvent a wide array of measurement errors common to the managerial literature. Additonally, our two-stage contract level approach enhances previous research by calculating an equivalent annual annuity over the life of the contract for both guaranteed and total components of compensation. This is in contrast to the conventional pay-by-year compensation structures of prior research. Our results imply three principal conclusions.

First, firms are non-myopic in their incorporation of a manager's historical performance. Due to the clear distinction of coaching roles and specificity of sports data, we are able to closely map the coach's individual contribution to the performances of his prior firms. Stage one results show universities review a coach's full history when determining pay relative to past performance, although bowl appearances and wins only matter for the previous season. We also incorporate the difficulty of obtaining performance results through measures such as strength of schedule.

Second, we show that overpaid coaches do not generate better performance. However, we confirm this result only among the upper quartile of overpaid earners, and when using win rate performance as well as prestigious bowl appearances. Interestingly, guaranteed compensation has no significant positive or negative effect on future performance. We find no evidence of non-linear dynamics when using contract level estimation. A number of our supplementary empirical investigations, such as univariate and temporal outlook specifications, demonstrate potential areas for bias. Determinant selection in the first stage pay-for-performance equation is another root of bias. Our results suggest that excessively overpaid coaches do not live up to their maximum compensation.

Lastly, this research provides evidence that annualized pay-by-year specifications, common to the prevailing literature, are misspecified. While annualized approaches ensure a large number of "manager-year" observations, they do not accurately describe the multi-year design of contracts. Additionally, a contract level design reflects multi-year compensation optimization. We find support for this in the robustness of our results across a wide variety of alternative specifications, verifying that intertemporal management issues are best examined by adopting a contract level approach.

Overall, our findings are similar to those found in the excess compensation literature. However, our second stage results advocate different conclusions to some of the sports research. Examples of this dichotomy suggest that empirical investigations of principal-agent theories may benefit from incorporating multi-period dynamics. Solutions which optimize over the contract term, as opposed to a single or set number of periods, provide an unambiguous and more accurate framework across practical settings. Our research sheds light on many prior works and has important implications for future analysis in their respective areas.

APPENDICES

APPENDIX A: Figures

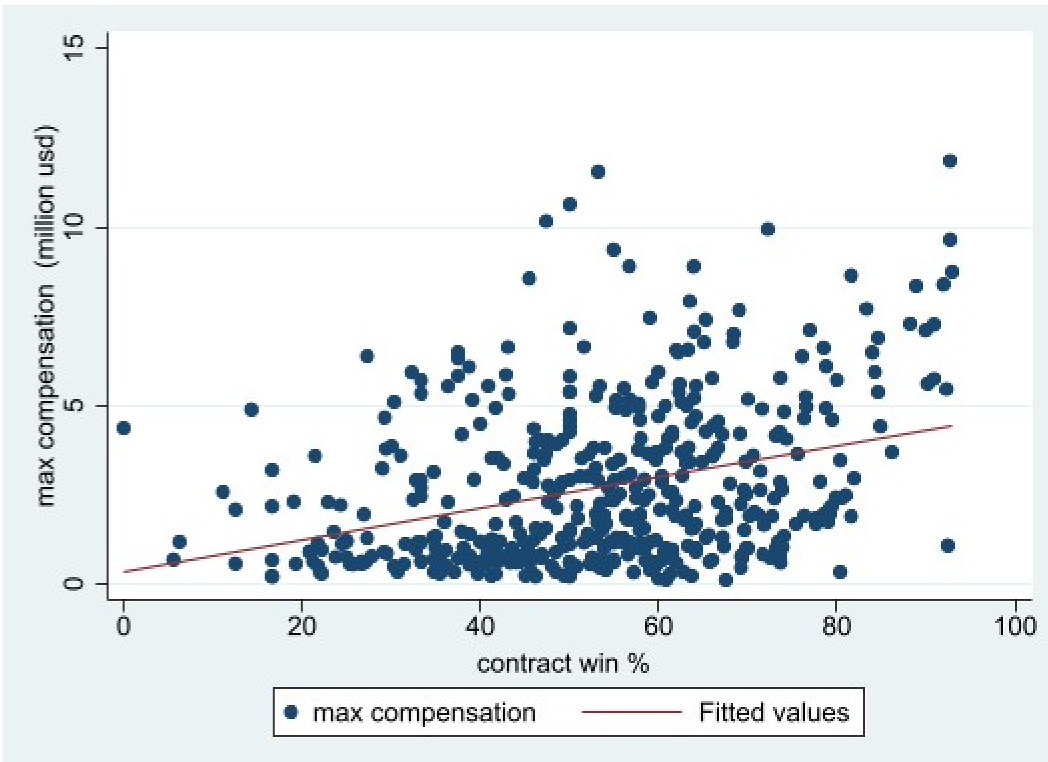

Figure 1. Shows all contracts maximum compensation relative to win percentage. Total compensation is an equivialent annual annuity in 2021 US dollars. Linear trendline displays a positive relationship.

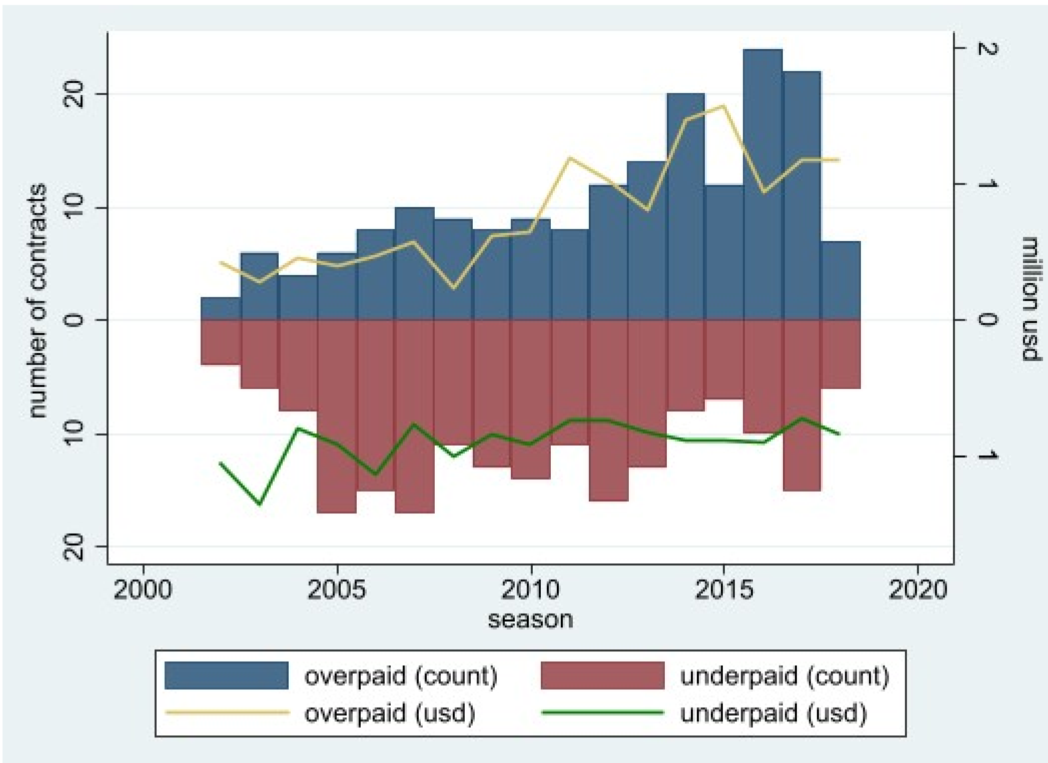

Figure 2. Chart lines and right y-axis shows the average level of over- and under-paid contracts. Bars and left y-axis show the seasonal count of over- and under-paid contracts. The analysis covers the 2002-18 seasons. All values are presented in 2021 US dollars.

APPENDIX B: Tables

Table 1. Summary Statistics

Variable	Obs.	Mean	St. Dev	Min	p25	p75	Max
Contract Compensation							
Max_comp ($Million)	478	2.70	2.25	0.11	0.90	4.03	11.90
Guar_comp ($Million)	478	1.98	1.76	0.11	0.60	2.79	10.60
Overpaid	183	0.93	1.13	0.00	0.28	1.12	7.47
Underpaid	193	0.89	0.69	0.00	0.38	1.29	3.81
Prior Performance							
Win %	478	62.23	11.79	6.67	54.08	70.00	92.31
Season Wins	478	8.00	3.00	0.00	6.00	10.00	15.00
SoS	471	0.86	2.66	-7.77	-0.93	2.88	6.63
Revenue ($Million)	467	24.50	17.10	0.24	9.68	36.70	79.40
Attd Avg	465	302.83	182.73	34.78	137.78	412.61	842.22
Bowl Dummy	465	0.55	0.50	0.00	0.00	1.00	1.00
Bowl Win Dum	465	0.27	0.44	0.00	0.00	1.00	1.00
Rival Points	473	1,082.87	613.61	39.00	602.86	1,520.83	2,804.75
Eff. Score	441	55.46	15.16	8.70	45.43	66.25	88.58
Eff. Rank	426	51.79	26.57	2.00	30.75	70.33	128.00
Expenses ($Million)	385	13.00	6.59	1.69	7.74	16.90	39.50
Contract Performance							
Win %	478	55.43	17.25	0.00	41.67	64.10	92.94
Season Wins	477	6.06	2.39	0.50	5.00	8.20	13.17
SoS	474	0.32	3.98	-8.94	-3.31	3.61	8.18
Revenue ($Million)	402	33.00	27.90	0.89	9.08	48.10	156.00
Attd Avg	466	302.83	182.73	34.78	137.78	412.61	842.22
Attd Chg	466	-451.00	7,261.00	-32,032.00	-3,832.00	2,376.00	26,250.00
Bowls	478	2.33	1.93	0.00	1.00	4.00	9.00
Bowl Wins	478	1.49	1.36	0.00	0.00	2.00	7.00
NY6 Bowl	478	0.54	1.12	0.00	0.00	1.00	6.00
Tier 1 Bowl	478	0.95	1.18	0.00	0.00	2.00	7.00
Rival Points	416	1,260.84	732.67	39.00	832.45	1,716.30	3,193.00
Eff. Score	468	51.47	17.97	3.30	37.55	64.31	95.33
Eff. Rank	468	60.54	31.60	1.50	36.00	86.50	127.50
Expenses ($Million)	402	18.20	11.50	0.84	8.58	24.90	69.70

This table presents summary statistics at the coach-contract level. Contract compensation measures are presented in millions of US dollars, deflated into 2021 values. Over- and underpaid contracts are derived from positive and negative first stage residuals, respectively. Prior Performance measures are presented as averages occurring before a contracts term begins. Contract Performance measures are presented as averages occurring over the contract's term. Sample range includes the years 2000-2020.

Table 2. Previous Performance Results (Stage 1)

	Dependent Variable = Max_comp						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Win %	56,692***	43,656***	37,501***	24,891***	23,346***	22,195***	15,701**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
SoS			124,815***	-53,844*	-47,520	-62,697*	-70,129**
			(0.00)	(0.09)	(0.13)	(0.10)	(0.02)
Expenses				0.12***	0.12***	0.11***	0.10***
				(0.00)	(0.00)	(0.00)	(0.00)
Bowl.L1					609,742***	604,023***	475,996***
					(0.00)	(0.00)	(0.01)
BowlWin.L1					221,796	223,036	78,660
					(0.23)	(0.25)	(0.67)
Rival Points						121.15	
						(0.56)	
Attd Avg							2.64***
							(0.00)
Prev_NFL		1,270,027***	1,137,579***	376,319*	387,385*	361552*	244421
		(0.00)	(0.00)	(0.07)	(0.06)	(0.09)	(0.23)
Hc_prev		934,785***	1,006,905***	654,473***	695,536***	696,332***	453,362**
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)
Yrs_uni		97,095***	97,195***	57,952***	49,598**	51940**	50483***
		(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)
Power5		1,740,013***	1,524,723***	1,760,411***	1,788,428***	1,821,569***	1,404,978***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-817,552	-2,231,603***	-1,865,093***	-2,281,507***	-2,409,515***	-2,389,699***	-2,051,183***
	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Adj. R^2	0.086	0.359	0.372	0.567	0.578	0.569	0.602
Obs.	473	464	457	374	374	362	374

This table presents *Max_comp* regressed on performance variables prior to contract signing. *Max_comp* is a contract's EAA. *L1* refers to the first lag for a variable. All values are in 2021 dollars. P-values are in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Table 3. Alternative Performance Measures (Stage 1)

	Dependent Variable = Max_comp							
	Win %		Season Wins		Eff. Score		Eff. Rank	
Performance	62,408***	15,701**	149,931***	50,655*	62,408***	15,524**	-33,417***	-7162*
	(0.00)	(0.02)	(0.00)	(0.09)	(0.00)	(0.03)	(0.00)	(0.07)
SoS		-70,128**		-57,921*		-68,809**		-69,981**
		(0.03)		(0.07)		(0.05)		(0.05)
Expenses		0.106***		0.108***		0.093***		0.096***
		(0.00)		(0.00)		(0.00)		(0.00)
Bowl L1		475,996***		396,058**		46,647**		484,906**
		(0.01)		(0.04)		(0.02)		(0.02)
Bowl Win L1		78,659		-10,921		80,238		102,593
		(0.67)		(0.96)		(0.69)		(0.61)
Attd Avg		2.63***		2.74***		2.66***		2.76***
		(0.00)		(0.00)		(0.00)		(0.00)
Constant	-817,552	-2,051,183***	-777,399**	-1,491,264***	-1768507***	-1,696,218***	2,677,358***	-563,744
	(0.13)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.23)
Coach Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.086	0.602	0.349	0.598	0.308	0.601	0.423	0.599
Obs.	473	374	464	374	426	346	426	346

This table presents *Max_comp* regressed on performance variables prior to contract signing. *Max_comp* is a contracts EAA. *L1* refers to the first lag of a variable. All values are in 2021 dollars. Coach Controls: Prev_NFL, Hc_prev, Yrs_uni, Power5. P-values are in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Table 4. Pay and Future Performance (Stage 2)

Panel A: Overpaid Contracts	Dependent Variable = Contract Win %						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Overpaid	9.19e-07	1.34e-08	-2.25e-06**	-2.52e-06***	-2.07e-06*	-1.66e-06	-1.37e-06
	(0.37)	(0.99)	(0.02)	(0.01)	(0.02)	(0.07)	(0.12)
Expenses			7.45e-07***	9.66e-07***	9.87e-07***	5.18e-07***	5.58e-07***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SoS				-0.938**	-0.512	1.749***	1.3908***
				(0.02)	(0.23)	(0.00)	(0.00)
Attd Avg						5.20e-05***	4.65e-05***
						(0.00)	(0.00)
Constant	53.975***	41.951***	40.725***	36.991***	34.173***	30.118***	27.932***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Coach Controls	No	Yes	No	No	Yes	No	Yes
Adj. R^2	0.004	0.187	0.327	0.345	0.408	0.411	0.460
Obs.	183	183	183	183	183	183	183
Panel B: Underpaid Contracts	Dependent Variable = Contract Win %						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Underpaid	5.13e-06***	6.38e-06***	1.41e-06	1.38e-06	4.94e-06***	2.42e-06	9.55e-07
	(0.00)	(0.00)	(0.44)	(0.45)	(0.01)	(0.15)	(0.57)
Expenses			6.52e-07***	6.82e-07***	4.49e-07***	3.55e-07**	1.72e-07
			(0.00)	(0.00)	(0.01)	(0.02)	(0.23)
SoS				-0.122	-1.028**	-2.375***	-1.210***
				(0.74)	(0.02)	(0.00)	(0.01)
Attd Avg						7.59e-05***	7.14e-05***
						(0.00)	(0.00)
Constant	48.687***	42.403***	41.355***	40.881***	43.334***	26.513***	30.34893***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Coach Controls	No	Yes	No	No	Yes	No	Yes
Adj. R^2	0.039	0.145	0.137	0.133	0.247	0.347	0.438
Obs.	191	191	191	191	191	191	191

This table presents contract *Win%* regressed on performance variables residuals from the preferred specification of Stage 1 (i.e. Table 2: Model 7). Panel A presents *Overpaid*, i.e. positive contract residuals. Panel B presents *Underpaid*, i.e. negative contract residuals. All values are in 2021 dollars. Coach Controls: Prev_NFL, Hc_prev, Yrs_uni, Power5. P-values are in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Table 5. Overpaid Contract Quartiles (Stage 2)

	Dependent Variable = Contract Win %			
	Q1	Q2	Q3	Q4
Overpaid	-3.85e-05	-9.52e-06	-1.24e-05	-2.54e-06***
	(0.20)	(0.69)	(0.34)	(0.00)
Expenses	5.27e-07	-1.37e-07	9.69e-07***	3.86e-07**
	(0.14)	(0.78)	(0.00)	(0.05)
SoS	-1.963**	-1.955**	-1.874**	-0.892
	(0.05)	(0.03)	(0.05)	(0.18)
Attd Avg	5.23e-05**	1.01e-04***	2.11e-05	5.03e-05***
	(0.04)	(0.00)	(0.40)	(0.00)
Constant	34.895***	33.495***	36.12595***	36.651***
	(0.00)	(0.00)	(0.01)	(0.00)
Coach Controls	No	No	No	No
Adj. R^2	0.279	0.278	0.426	0.653
Obs.	46	46	46	45

This table presents contract *Win%* regressed on performance variables over the contract term. *Overpaid* quartiles (i.e. negative stage 1 residuals) are from the preferred specification of Stage 1 (i.e. Table 2: Model 7). All values are in 2021 dollars. Coach Controls: Prev_NFL, Hc_prev, Yrs_uni, Power5. P-values are in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Table 6. Guaranteed Compensation Results

Stage 1	Dep Var = Guar_comp	Stage 2: Dep Var = Contract Win %	Q1	Q2	Q3	Q4
Win %	17,538***	Overpaid	6.94e-06	-4.10e-06	-1.32e-06	-1.60e-06
	(0.00)		(0.83)	(0.87)	(0.94)	(0.31)
SoS	-30,969	Expenses	-7.33e-08	3.69e-07	6.25e-07*	5.60e-07***
	(0.18)		(0.87)	(0.347)	(0.06)	(0.01)
Expenses	0.08***	SoS	-1.561	-2.057**	-1.526**	-0.537
	(0.00)		(0.175)	(0.04)	(0.05)	(0.50)
Bowl.L1	251,867*	Attd Avg	6.81e-05*	7.1e-05***	3.59e-05**	4.07e-05**
	(0.07)		(0.10)	(0.01)	(0.05)	(0.02)
BowlWin.L1	-41,934					
	(0.76)					
Attd Avg	2.80					
	(0.00)					
Prev_NFL	386,773					
	(0.01)					
Hc_prev	360,915					
	(0.02)					
Yrs_uni	44,200					
	(0.00)					
Power5	713,547					
	(0.00)					
Constant	-2,024,109***	Constant	34.237***	28.550**	29.167***	30.784***
	(0.00)		(0.00)	(0.02)	(0.01)	(0.00)
Adj. R^2	0.623	Adj. R^2	0.09	0.24	0.36	0.58
Obs.	374	Obs.	46	46	46	46

This table presents *Guar_comp* regressed on performance variables prior to contract signing. *Guar_comp* is a contract's guaranteed compensation expressed as an EAA. *L1* refers to the first lag for a variable. All values are in 2021 dollars. P-values are in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Table 7. Alternative Performance Measures (Stage 2)

	Stage 1: Dependent Variable = Max_comp			
	(1)	(2)	(3)	(4)
Performance	56,692***	206,211***	83,944***	-45,788***
	(0.00)	(0.00)	(0.00)	(0.00)
Adj. R^2	0.088	0.075	0.309	0.283
Obs.	473	467	426	426
	Stage 2: Dependent Variable = Contract Win %			
	(1)	(2)	(3)	(4)
Overpaid	2.29e-06***	2.23e-06***	2.53e-06***	-2.84e-06***
	(0.00)	(0.00)	(0.00)	(0.00)
Adj. R^2	0.054	0.050	0.004	0.057
Obs.	193	180	189	187
Underpaid	-5.93e-07	-1.81e-06	-2.95e-06**	2.85e-06**
	(0.63)	(0.17)	(0.02)	(0.02)
Adj. R^2	0.001	0.007	0.024	0.023
Obs.	280	287	237	239

This table presents both Stage 1 and Stage 2 results using a univariate specification. In Stage 1, the *Performance* variable employed is as follows: Model (1): *Win%*, Model (2): *Season Wins*, Model (3): *Eff. Score*, and Model (4): *Eff. Rank*. Stage 1 and Stage 2 specifications correspond to the same numbered column. *Overpaid* and *Underpaid* refer to positive and negative Stage 1 residuals, respectively. All values are in 2021 dollars. P-values are in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Table 8. Pay-by-year Results

	Stage 1: Dep Var = Max_comp		Stage 2: Dep Var = Contract Win %			
			$T+1$	$T+3$	$T+1$	$T+3$
Win%	12,081***	Overpaid	-1.30e-06	-6.44e-07		
	(0.00)		(0.11)	(0.23)		
SoS	-58,768***	Underpaid			9.84e-08	6.69e-08
	(0.00)				(0.94)	(0.94)
Expenses	0.099***	SoS	-1.006***	-0.987***	-1.467***	-1.397***
	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)
Bowl.L1	134,657	Expenses	4.55e-07***	4.83e-07***	3.83e-07***	3.72e-07***
	(0.12)		(0.00)	(0.00)	(0.00)	(0.00)
BowlWin.L1	-93,568					
	(0.30)					
Attd Avg	1.305***	Attd Avg	4.55e-05***	4.03e-05***	5.14e-05***	5.07e-05***
	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)
Constant	-1,288,994***	Constant	32.461***	32.148***	32.046***	31.943***
	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)
Coach Controls	Yes	Coach Controls	No	No	No	No
Adj. R^2	0.582	Adj. R^2	0.247	0.347	0.194	0.275
Obs.	1,495	Obs.	566	697	696	798

This table presents both Stage 1 and Stage 2 results using pay-by-year specifications. *Overpaid* and *Underpaid* refer to positive and negative Stage 1 residuals, respectively. *T+1* and *T+3* refer to next season performance and next three season average performance, respectively. Coach Controls: Prev. NFL, Prev. Head Coach, Years University, Power5. All values are in 2021 dollars. P-values are in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Table 9. Nonlinear Compensation Effects

	Pay-By-Year: Dep Var = Win %				Contract: Dep Var = Win %	
	$T+1$	$T+3$	$T+1$	$T+3$	Overpaid	Underpaid
Overpaid	1.18e-06	1.21e-06			-1.33e-06	-5.66e-07
	(0.52)	(0.31)			(0.55)	(0.88)
Overpaid^2	-5.01e-13	-3.61e-13*			-5.64e-14	-7.22e-13
	(0.13)	(0.08)			(0.87)	(0.59)
Underpaid			4.44e-06	2.65e-06		
			(0.16)	(0.25)		
Underpaid^2			-1.85e-12	-1.11e-12		
			(0.14)	(0.22)		
SoS	-1.030***	-1.016***	-1.543***	-1.463***	-1.749***	-2.417***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Expenses	4.32e-07***	4.66e-07***	4.01e-07***	3.86e-07 ***	5.14e-07***	3.57e-07**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
Attd Avg	4.58e-05***	4.06e-05***	5.16e-05***	5.10e-05***	5.20e-05***	7.66e-05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	31.613***	31.490***	30.312***	30.799***	30.001***	25.512***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Coach Controls	No	No	No	No	No	No
Adj. R^2	0.25	0.35	0.20	0.28	0.41	0.35
Obs.	566	697	696	798	183	191

This table presents Stage 2 results using pay-by-year and contract level specifications. *T+1* and *T+3* refer to next season performance and next three season average performance, respectively. All values are in 2021 dollars. P-values are in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Table 10. University Level Replication

	Sagarin Rating				Eff. Score				Win %			
Seasons	All	All	2006-11	2006-11	All	All	2006-11	2006-11	All	All	2006-11	2006-11
Compmax_mil	4.983***	1.830	13.532***	9.554***	7.603***	2.4461	18.040***	11.189***	1.423	0.615	9.786**	10.336**
	(0.00)	(0.22)	(0.00)	(0.00)	(0.00)	(0.25)	(0.00)	(0.01)	(0.53)	(0.81)	(0.02)	(0.03)
Compmax_mil ^{2}	-0.037	-0.156	-1.653***	-1.408***	-0.191	-0.254	-2.014**	-1.619**	0.3720	-0.140	-0.821001	-1.523*
	(0.87)	(0.42)	(0.00)	(0.00)	(0.54)	(0.34)	(0.02)	(0.03)	(0.30)	(0.67)	(0.38)	(0.08)
Power5		1.081		-1.318		0.501		-3.718		-6.829*		-10.260***
		(0.62)		(0.50)		(0.87)		(0.28)		(0.07)		(0.01)
Attd		2.84e-05***		1.21e-05**		4.08e-05***		2.27e-05**		2.95e-05***		1.14e-05
		(0.00)		(0.05)		(0.00)		(0.03)		(0.00)		(0.36)
Opex		5.36e-09		1.48e-09		4.65e-08		1.48e-08		8.39e-08*		9.24e-09
		(0.83)		(0.95)		(0.20)		(0.71)		(0.06)		(0.19)
AP_Points		0.0091***		0.038***		0.012***		0.067***		0.016***		0.081***
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Constant	57.021***	54.493***	53.681***	53.346***	32.614***	28.330***	27.262***	26.421***	44.376***	37.847***	37.671***	34.753***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R^2	0.625	0.807	0.590	0.773	0.596	0.797	0.486	0.717	0.268	0.578	0.234	0.539
Obs.	96	93	88	85	100	96	91	88	101	97	94	91

This table replicates and extends the specifications of Eckard and Colbert (2015). Results are aggregated by university. *Compmax_mil* is the historical university average of *Comp_max* divided by 1,000,000. *Compmax_mil* ^{2} is the same variable squared. *Opex* is the FBS programs operating expenditures minus coaches maximum compensation. *Attd* is the universities historical average FBS game attendance. *AP_Rank* was collected as end of season rankings and are only available for the top 40 ranked teams annually. All values are in 2021 dollars. P-values are in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Appendix 1: Coach Position Index

Position	Index Dummy	
Overall Team Efficiency	1	
Offensive Efficiency	2	
Defensive Efficiency	3	
Special Teams Efficiency	4	
Position Shorthand	Position Title	Index
A	Assistant	1
GA	Grad Assistant	1
HC	Head Coach	1
IHC	Interim Head Coach	1
QC	Quality Control	1
RC	Reserve Coach	1
Scout	Scout	1
OA	Offensive Assistant	2
OC	Offensive Coordinator	2
OL	Offensive Line	2
OLB	Offensive Linebacker	2
PGC	Passing Game Coordinator	2
QB	Quarterbacks Coach	2
RB	Runningbacks Coach	2
SB	Slotbacks Coach	2
TE	Tight Ends	2
WR	Wide Receivers	2
CB	Cornerbacks Coach	3
DA	Defensive Assistant	3
DB	Defensive Backs	3
DC	Defensive Coordinator	3
DE	Defensive Ends	3
DL	Defensive Line	3
DT	Defensive Tackles	3
LB	Linebacker Coach	3
S	Secondary/Safeties	3
ST	Special Teams	4

Appendix 2: Bowl Tier List

New Years Six (NY6)	Tier 1	Tier 2	
Chik-fil-Al	AdvoCare V100	Arizona	Lending Tree
Cotton	Alamo	Bahamas	Little Caesars
Fiesta	Armed Forces	BBVA Compass	Meineke
Orange	Camping World	Beef O'Brady's	Miami Beach
Peach	Capital One	Brimingham	Micron PC
Rose	Champs Sports	Boca Raton	Mobile Alabama
Sugar	Citrus	Buffalo Wild Wings	Montgomery
NFL Super Bowl	Famous Idaho Potato	Cactus	Motor City
NFL Divisional	Frisco	Camellia	MPC Computers
	Gator	Continental	Myrtle Beach
	Hawaii	Tire	New Mexico
	Holiday	Dollar General	New Orleans
	Insight	Duke's Mayo	Oahu Classic
	Liberty	Eagle Bank	PapaJohns.com
	Maaco	Emerald	Quick Lane
	Military	Fight Hunger	Redbox
	Music City	First Responder	Russell Athletic
	Outback	Fort Worth	San Francisco
	Pinstripe	Foster Farms	Seattle
	Poinsettia	Gallery Furniture	Silicon Valley
	Popeyes Bahamas	GMAC	St. Petersburg
	Sun	GoDaddy	Tangerine
	Belk	Heart of Dallas	Tax Slayer
	Cheez-It	Houston	Texas
	Aloha Classic	Humanitarian	Union Home
	Cure	Independence	Mortgage
	NFL Divisional	International	Ticket City
	NFL Wildcard	Las Vegas	Gasparilla

Appendix 3: Select Variable Correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Max_comp	(1)	1															
Win %	(2)	0.33	1														
Wins/season	(3)	0.29	0.46	1													
SoS	(4)	0.29	0.21	0.06	1												
Revenue	(5)	0.48	0.40	0.20	0.56	1											
Attd Avg	(6)	0.63	0.36	0.31	0.38	0.52	1										
Bowl Dum.	(7)	0.28	0.25	0.26	0.05	0.14	0.35	1									
Bowl Win Dum.	(8)	0.12	0.22	0.26	0.01	0.06	0.20	0.56	1								
Rival Points	(9)	0.43	0.36	0.18	0.67	0.77	0.47	0.09	0.05	1							
Eff. Score	(10)	0.55	0.58	0.42	0.33	0.53	0.58	0.46	0.31	0.53	1						
Eff. Rank	(11)	-0.52	-0.57	-0.41	-0.33	- 0.51	-0.57	-0.46	-0.31	- 0.52	-0.99	1					
Expenses	(12)	0.56	0.30	0.20	0.49	0.90	0.47	0.15	0.04	0.72	0.54	-0.51	1				
Prev_NFL	(13)	0.15	-0.21	0.01	0.16	0.22	0.19	-0.08	-0.03	0.24	0.00	0.01	0.02	1			
Hc_prev	(14)	0.21	0.01	-0.07	-0.13	- 0.01	0.20	0.14	0.05	-0.05	0.10	-0.09	0.01	0.02	1		
Yrs_uni	(15)	0.21	0.23	0.19	0.02	0.04	0.14	0.34	0.31	-0.08	0.28	-0.28	0.05	-0.22	0.2	1	
Power5	(16)	0.61	0.17	0.13	0.36	0.35	0.58	0.12	0.00	0.34	0.36	-0.36	0.39	0.13	0.14	0.12	1

Appendix 4: Previous Performance Regressions (Eff. Score)

	Dependent Variable = Max_comp						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Eff. Score	83,944***	62,408***	59,510***	30,306***	27,049***	29,108***	15,524**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)
SoS			-60,643	-60,954*	-50,375	-56,988	-68,809**
			(0.11)	(0.09)	(0.16)	(0.18)	(0.05)
Expenses				0.10***	0.10***	0.09***	0.09***
				(0.00)	(0.00)	(0.00)	(0.00)
Bowl.L1					533,794***	544,213***	466,477**
					(0.01)	(0.01)	(0.02)
BowlWin.L1					143,159	148,338	80,238
					(0.49)	(0.48)	(0.69)
Rival Points						41.86	
						(0.85)	
Attd Avg							2.66***
							(0.00)
Prev_NFL		783,012***	732,921***	222,075	224,750	232,643	102,402
		(0.00)	(0.00)	(0.28)	(0.27)	(0.27)	(0.61)
Hc_prev		993,037***	946,024***	630,338***	662,978***	641,593***	481,910**
		(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.03)
Yrs_uni		48,481**	49,445**	40,374**	36,071*	36,213	39,472*
		(0.03)	(0.02)	(0.05)	(0.09)	(0.11)	(0.06)
Power5		1,345,738***	1,281,542***	1,755,079***	1,786,490***	1,795,106***	1,429,676***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-1,768,507***	-2,455,232***	-2,253,878***	-1,927,613***	-1,965,856***	-2,107,631***	-1,696,218***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Adj.R^2$	0.308	0.440	0.442	0.571	0.578	0.568	0.601
Obs.	426	425	421	346	346	336	346

This table presents *Max_comp* regressed on performance variables prior to contract signing. A coaches historical efficiency score (*Eff. Score*) is used in place of winning percentage (*Win %*). *Max_comp* is a contract's EAA. 'L1' refers to the first lag of a variable. All values are in 2021 dollars. P-values are in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Appendix 5: Bowls and Coach Compensation (Stage 1)

	Dependent Variable = Max_comp						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Win %	48,827***	15,439**	16,112**	15,701**	15,466**	15,705**	16,478**
	(0.00)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Bowl.prev	948,649***	186,293	263,574				
	(0.00)	(0.24)	(0.14)				
BowlWin.prev			97,115				
			(0.60)				
Bowl.L1				475,996***			
				(0.01)			
BowlWin.L1				78,659			
				(0.67)			
NY6.L1					101,500		148,393
					(0.68)		(0.51)
NY6Win.L1					-6,479		
					(0.98)		
Tier1.L1						119,661	142,750
						(0.51)	(0.44)
Tier1Win.L1						-176,314	
						(0.51)	
Win.L1							-233,138
							(0.15)
Constant	-844,156	-1,937,295***	-1,969,676***	-2,051,183 ***	-1,920,782***	-1,965,129***	-1,937,947 ***
	(0.11)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Contract Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Coach Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.126	0.595	0.595	0.602	0.593	0.593	0.594
Obs.	471	374	374	374	374	374	374

This table presents *Max_comp* regressed on career win percentage and bowl tier types prior to contract signing. *Max_comp* is a contract's EAA. *L1* refers to the first lag of a variable. *.prev* means the variable includes reference to the coach's entire prior career. *Win.L1* refers to the coach winning any tier bowl in the previous season. See Appendix 2 for bowl tier categorization. All values are in 2021 dollars. Contract Controls: SoS, Attd Avg, Expenses. Coach Controls: Prev_NFL, Hc_prev, Yrs_uni, Power5. P-values are in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Appendix 6: Lag Order Testing (Stage 1)

	Dependent Variable = Max_comp			
	Best	Career	Lag 1	Lag 3
Win%	15,701**	16,112**	4,038	7,273
	(0.02)	(0.02)	(0.39)	(0.15)
SoS	-70,128**	-75,798**	-19,582	112,932***
	(0.03)	(0.02)	(0.39)	(0.00)
Expenses	0.106***	0.108***	0.064***	0.056***
	(0.00)	(0.00)	(0.00)	(0.00)
Attd Avg	2.64***	2.60***	4.74***	4.28 ***
	(0.00)	(0.00)	(0.00)	(0.00)
Bowl	475,996***	263,574	417,837**	201,266
	(0.01)	(0.14)	(0.05)	(0.42)
BowlWin	78,659	97,115	86,763	56,807
	(0.67)	(0.60)	(0.71)	(0.81)
Prev_NFL	244,420	261,721	86,878	-95,350
	(0.23)	(0.20)	(0.68)	(0.61)
Hc_prev	453,361**	414,939**	734,264***	680,448***
	(0.03)	(0.05)	(0.00)	(0.00)
Yrs_uni	50,482***	50,392***	30,115	46,930***
	(0.01)	(0.01)	(0.15)	(0.01)
Power5	1,404,978***	1,374,369***	857,721***	361,718**
	(0.00)	(0.00)	(0.00)	(0.04)
Constant	-2,051,183***	-1,969,676***	-1,416,812***	-912,526**
	(0.00)	(0.00)	(0.00)	(0.02)
Adj. R^2	0.602	0.595	0.617	0.649
Obs.	374	374	358	358

This table presents *Max_comp* regressed on performance variables prior to contract signing. Various preceeding outlooks are utilized. *Best* refers to the preferred specification of Stage 1 (i.e. Table 2: Model 7). *Career* modifies the Bowl variables from the *Best* model to instead include the coach's entire bowl history. *Lag 1* only includes prior season performance for all variables. *Lag 3* is all performance variables average over the prior three seasons. *Max_comp* is a contracts EAA. All values are in 2021 dollars. P-values are in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Appendix 7: Annual Fixed Effects Results

Stage 1		Stage 2: Dep Var = Contract Win %				
Dep Var = Max_comp			Q1	Q2	Q3	Q4
Win %	12,490**	Overpaid	1.11e-05	1.62e-05	-1.65e-05	-1.73e-06
	(0.05)		(0.70)	(0.46)	(0.24)	(0.15)†
SoS	-48,739***	Expenses	5.34e-07	6.82e-08	-1.32e-07	2.93e-07
	(0.10)		(0.18)	(0.84)	(0.65)	(0.21)
Expenses	0.06 ***	SoS	-3.24***	-0.79	-2.25***	-0.84
	(0.00)		(0.00)	(0.45)	(0.00)	(0.23)
Bowl.L1	510,494***	Attd Avg	9.35e-05***	3.09e-05	1.13e-05***	6.33e-05***
	(0.00)		(0.01)	(0.18)	(0.00)	(0.00)
BowlWin.L1	114,954					
	(0.51)					
Attd Avg	3.50***					
	(0.00)					
Prev_NFL	127,291					
	(0.51)					
Hc_prev	374,760					
	(0.22)					
Yrs_uni	23,369					
	(0.22)					
Power5	1,333,755***					
	(0.00)					
Season FE	Yes	Season FE	No	No	No	No
Constant	-2,302,467***	Constant	17.716*	38.297***	31.320***	31.415***
	(0.00)		(0.06)	(0.00)	(0.00)	(0.00)
Adj. R^2	0.651	Adj. R^2	0.27	0.06	0.37	0.39
Obs.	374	Obs.	46	46	46	46

This table presents *Max_comp* regressions including annual fixed effects. *Max_comp* is a contract's maximum compensation as an EAA. *L1* refers to the first lag for a variable. All values are in 2021 dollars. P-values are in parentheses. Significance levels 15%, 10%, 5%, and 1% are denoted by †, *, **, and ***, respectively.

Appendix 8: Risk Premium Compensation Results

Stage 1		Stage 2: Dep Var = Contract Win %				
Dep Var = RP_CompMax			Q1	Q2	Q3	Q4
Win %	18,279***	Overpaid	-9.02e-06	-1.49e-05	-2.19e-05**	-2.66e-06***
	(0.01)		(0.67)	(0.47)	(0.02)	(0.00)
SoS	-75,699**	Expenses	3.02e-07	2.57e-07	7.89e-07***	3.71e-07*
	(0.03)		(0.44)	(0.49)	(0.01)	(0.08)
Expenses	0.12	SoS	-1.49	-1.92**	-1.45	-0.92
	(0.00)		(0.11)	(0.02)	(0.13)	(0.21)
Bowl.L1	522,759***	Attd Avg	4.89e-05**	7.2e-05**	3.4e-05	5.63e-05***
	(0.01)		(0.03)	(0.01)	(0.17)	(0.00)
BowlWin.L1	64,168					
	(0.76)					
Attd Avg	3.07***					
	(0.00)					
Prev_NFL	262,466					
	(0.25)					
Hc_prev	544,778**					
	(0.02)					
Yrs_uni	68,827***					
	(0.00)					
Power5	1,634,334***					
	(0.00)					
Constant	-2,390,240***	Constant	36.695***	34.552***	49.765***	35.515***
	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)
Adj. R^2	0.617	Adj. R^2	0.20	0.37	0.32	0.63
Obs.	374	Obs.	46	46	46	46

This table presents *RP_CompMax* regression results. *RP_CompMax* is a contract's maximum compensation as an EAA when an annual risk premium is included in the calculation. *L1* refers to the first lag for a variable. All values are in 2021 dollars. P-values are in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Appendix 9: Excess Compensation Rankings

Panel A: Coach Contracts

Most Overpaid Contracts				Most Underpaid Contracts			
Rank	Coach	University	Season	Rank	Coach	University	Season
1	Charlie Strong	UT Austin	2014	1	Ed Orgeron	Louisiana State	2016
2	Todd Graham	Arizona State	2015	2	Frank Solich	Ohio U	2010
3	Todd Graham	Arizona State	2012	3	Frank Solich	Ohio U	2015
4	Jim Harbaugh	U of Michigan	2015	4	Jim Tressel	Ohio U	2003
5	Kliff Kingsbury	Texas Tech	2014	5	Mike Shula	Alabama – Tusc.	2006
6	Paul Pasqualoni	UConn	2011	6	Chuck Martin	Miami U of Ohio	2014
7	Tom Herman	UT Austin	2017	7	DeWayne Walker	New Mexico State	2009
8	Kirk Ferentz	U of Iowa	2012	8	Brad Lambert	UNC - Charlotte	2017
9	Bobby Petrino	U of Louisville	2016	9	Luke Fickell	U of Cincinnati	2017
10	Kevin Sumlin	Texas A&M	2015	10	Darrell Hazell	Kent State	2011

Panel B: Coaches

Rank	Most Overpaid	Most Underpaid
1	Todd Graham	Mike Shula
2	Jim Harbaugh	Chuck Martin
3	Paul Pasqualoni	DeWayne Walker
4	Tom Herman	Brad Lambert
5	Charlie Strong	Frank Solich
6	Kliff Kingsbury	Joe Tiller
7	Kevin Sumlin	Luke Fickell
8	Justin Wilcox	Paul Haynes
9	George O'Leary	Will Muschamp
10	Nick Saban	Kyle Flood

Panel C: FBS Universities

Rank	Most Overpaying	Most Underpaying
1	UT Austin	UNC - Charlotte
2	Arizona State	Ohio U
3	U of Louisville	Middle Tennessee
4	U of Michigan	Utah State
5	U of Oregon	Florida Atlantic
6	U of Colorado	Virginia Tech
7	U of Oklahoma	Wisconsin - Madison
8	Alabama - Tusc.	Kent State
9	Nebraska - Lincoln	Clemson
10	Texas A&M	Kansas State

This table presents the top ten most over- and under-paid rankings within our sample range of 2000-2020. *Panel A: Coach Contracts* refers to individual contracts within our sample. *Panel B: Coaches* refers to coach's average compensation over their entire career. *Panel C: FBS University* refers to average compensation for all head football coaches across the university's history. Due to data and reporting limitations, we make no comments as to whether these rankings hold across the entire FBS or in an extended sample.

Appendix 10: Alternative Performance Measures (Stage 2)

	Dependent Variable								
	Win%	Season Wins	Eff. Score	Revenue	Rival Points	Bowl	Bowl Win	NY6	Tier 1
Overpaid	-1.66e-06*	-2.58e-07**	-1.02e-06	0.744	-2.79e-06	-1.52e-08	-1.41e-07	-2.17e-07***	7.99e-08
	(0.07)	(0.05)	(0.22)	(0.40)	(0.92)	(0.89)	(0.12)	(0.00)	(0.38)
Expenses	5.18e-07***	6.81e-08***	4.60e-07***	1.409***	2.68e-05***	1.25e-08	2.45e-08	3.14e-08***	-1.68e-08
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.52)	(0.11)	(0.01)	(0.27)
SoS	1.749***	-0.257***	0.0478	-174737	8.579	-0.165***	-0.115***	-0.085***	0.0513907
	(0.00)	(0.00)	(0.90)	(0.66)	(0.50)	(0.00)	(0.01)	(0.01)	(0.21)
Attd Avg	5.21e-05***	7.84e-06***	4.74e-05***	70.406***	0.002***	7.90e-06***	4.38e-06***	4.37e-06***	2.14e-06*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)
Constant	30.118***	3.3607***	28.922***	-1.30e+07***	168.518**	0.198	-0.318	-1.109***	0.743***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.57)	(0.25)	(0.00)	(0.01)
Adj. R^2	0.411	0.396	0.599	0.863	0.751	0.321	0.249	0.438	0.078
Obs.	183	183	183	183	183	183	183	183	183

This table presents contract term performance variables regressed on Stage 1 residuals and relevant controls. *Overpaid* refers to positive Stage 1 contract residuals. All values are in 2021 dollars. P-values are in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Appendix 11: Pay-by-year and Future Performance

	Dependent Variable = Win %					
	T+1			T+3		
Max_comp	2.59e-06***	1.60e-06***	4.88e-08	2.61e-06***	1.82e-06***	2.71e-07
	(0.00)	(0.00)	(0.90)	(0.00)	(0.00)	(0.35)
Constant	48.21***	40.02***	30.58***	47.41***	39.35***	28.08***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Contract Controls	No	No	Yes	No	No	Yes
Coach Controls	No	Yes	Yes	No	Yes	Yes
Adj. R^2	0.060	0.094	0.224	0.094	0.147	0.359
Obs.	1,869	1,862	1,450	2,066	2,058	1,495

This table regresses future *Win%* on current *Max_comp* using pay-by-year specifications. *T+1* and *T+3* refer to next season performance and next three season average performance, respectively. Contract Controls: SoS, Attd Avg, Bowl.L1, BowlWin.L1, and Expenses. Coach Controls: Prev. NFL, Prev. Head Coach, Years University, Power5. All values are in 2021 dollars. P-values are in parentheses. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Appendix 12: Summary Statistics

	Obs.	Mean	St. Dev	Max	Min	p25	p75
All Seasons							
Sagarin	96	68.650	47.988	98.655	10.977	60.298	75.956
Eff. Score	100	49.449	17.42	90.769	15.524	37.468	60.823
Win%	101	51.308	22.121	87.121	13.456	41.414	58.831
Compmax_mil	101	2.430	0.134	7.630	1.860	0.736	3.845
Power5	101	0.475	0	1	0.502	0	1
Attd	101	293,137	62,443	750,732	179,334	129,971	397,906
Opex	97	5.44E+07	1.22E+07	1.46E+08	3.19E+07	2.99E+07	7.52E+07
AP_Rank	49	400	42	811	201	218	559
2006-2011							
Sagarin	88	69.652	42.655	94.4	10.971	60.636	77.629
Eff. Score	91	49.574	19.575	87	17.206	34.614	63
Win%	94	50.667	18.429	92.308	16.421	37.5	61.538
Compmax_mil	95	1.684	0.166	5.171	1.246	0.588	2.545
Power5	95	0.463	0	1	0.501	0	1
Attd	93	302,411	53,506	804,746	192,258	121,636	425,250
Opex	93	5.89E+07	2208227	1.73E+08	3.86E+07	3.21E+07	7.86E+07
AP_Points	47	401	42	811	201	218	560

This table presents summary statistics for variables utilized in Table 10. Such variables are derived similar to those found in Colbert and Eckard (2015), with relevant deviations noted within our text. *All Seasons* refers to our full sample range of 2000-2020.

Appendix 13: Variable Descriptions

Variable	
Contract Compensation	
Max_comp	Total compensation possible for the coach. Calculated as the sum of guaranteed and performance components. Presented as an equivalent annual annuity over the life of their contract.
Guar_comp	Guaranteed compensation for the coach. Presented as an equivalent annual annuity over the life of their contract.
Overpaid	Positive residuals from the optimal first stage estimation (Table 2: model 7).
Underpaid	Negative residuals from the optimal first stage estimation (Table 2: model 7).
Prior Performance	
Win %	Percentage win rate. Calculated as $\frac{Wins+0.5*Ties}{Games}$.
Season Wins	Total wins per season. Calculated as $Wins + 0.5 * Ties$.
SoS	Team strength of schedule.
Revenue	Dollar value of average annual team revenue.
Attd Avg	Average annual attendance at home games.
Bowl Dummy	Dummy variable indicating a bowl appearance. Equal to 1 if true.
Bowl Win Dum	Dummy variable indicating a bowl win. Equal to 1 if true.
Rival Points	Recruting rating from *rivals.com*.
Eff. Score	Team or coach position specific efficiency rating. Collected from *espn.com*.
Eff. Rank	Team or coach position specific efficiency ranking. Collected from *espn.com*.
Expenses	Dollar value of average annual team expenses.
Hc_prev	Dummy variable indicating a coach's prior head coaching experience. Equal to 1 if true.
Power 5	Dummy variable indicating team membership to the SEC, Big 12, Big 10, ACC, or Pac 10/12.. Equal to 1 if true.
Prev_NFL	Dummy variable indicating a coach's prior NFL coaching experience. Equal to 1 if true.
Yrs_uni	Coach's current university tenure.
Sagarin Rating	Elo type rating indicating annual team performance.
Expenses	Dollar value of average annual team operating expenses.
Unreported	
Age	Variable indicating the coach's age. Collected from the coach's Wikipedia page.
Race	Variable indicating the coach's racial demographic. Collected from the coach's Wikipedia page as 'White', 'Black', 'Hispanic', or 'Other'.
Attd Total	Total annual attendance at home games.
Attd Change	Change in average annual attendance at home games.

In this table, we present definitions for each of the variables utilized in the analysis. 'Unreported' variables were collecte and employed during the optimization process. However, they are absent from the final models and, for brevity, were unreported. See *rivals.com/news/rivals-com-football-team-recruiting-rankings-formula* for in-depth explanations of Rival Points calculation.

CHAPTER II

A REVIEW OF THE LITERATURE ON LNG HUBS DEVELOPMENT, MARKET INTEGRATION, AND PRICE DISCOVERY

1. Introduction

The growth of U.S. liquefied natural gas (LNG) exports is transforming natural gas (NG) markets from a collection of segmented regional markets into an integrated global market. The first-ever export of domestically produced LNG from the lower-48 states occurred in February 2016 with a shipment from Cheniere Energy's Sabine Pass Terminal in Louisiana to Brazil. As of the end of 2021, the U.S. ranks first in the world for LNG export capacity of 92.5 million metric tons per year, ahead of Australia (87.6) and Qatar (77.4). The development of U.S. LNG becoming a major global player has implications for global NG prices and the behavior of those prices. By the end of 2022, the EIA forecasts U.S. nominal capacity to increase to 11.4 billion cubic feet per day (Bcf/d), and peak capacity to increase to 13.9 Bcf/d, exceeding estimated capacities of the two largest LNG exporters, Australia (peak capacity of 11.4 Bcf/d) and Qatar (peak capacity of 10.4 Bcf/d).[1]

[1]See https://www.eia.gov/todayinenergy/detail.php?id=50598 and https://www.eia.gov/naturalgas/U.S.liquefactioncapacity.xlsx.

On March 25, 2022, President Biden announced the U.S. will supply an incremental 15 billion cubic meters (bcm) in addition to the current volumes that have been flowing to Europe. As Europe imports 16 Bcf/d of LNG in peak months, this will account for an additional 10% of LNG supplies. During the winter of 2022, European LNG infrastructure will be tested to its maximum and will not likely be able to absorb more than the volumes during the 2021 winter. This is primarily due to pipeline constraints between the south and north. Europe imported 36 Bcf/d of natural gas in 2020 and 16 Bcf/d of these imports came from Russia. Therefore, the proposed additional 1.5 Bcf/d of U.S. LNG volumes comprise only 4% of the total NG imports or 9% of total imports from Russia. However, this is a significant step in helping Europe reduce its dependence on Russian gas and underscores LNG's role as one of the most important energy resources in the world.

Understanding the drivers of LNG prices is paramount for our global energy future. Academic research on topics related to NG, LNG hubs development, pricing relationships, market integration, etc., can be found in top finance and economics journals from 1994-present (2022). However, many of the LNG specific works are more recently published, after 2010. While earlier works explore LNG, we find the analysis to often be conducted in a secondary or tangential context. This is one likely reason for the general dearth of systematic reviews for LNG related literature. Our study is primarily motivated to fill this literary gap by providing a comprehensive review of the academic and industry publications related to LNG hub development and market integration. In this way, we contribute to both the areas of energy economics and climate finance

Secondly, our paper seeks to promote additional LNG focused research. LNG markets are unique and vary by global region. Therefore, the issues we have explored characterize only a tranche of the greater dynamics exhibited across the global LNG markets. However, we find a few noteworthy results broadly hold across the literature. First, most U.S. purchase agreements are free of take-or-pay and destination restrictions while most global LNG trade occurs under long-term contracts (GIIGNL, 2020). At the same time, Europe and the U.S. have mature hub market development with strong levels of intra-regional integration. The higher number of importing terminals has additionally lead to an increase in LNG spot trading. In the Asia Pacific region, a lack of transparent pricing benchmarks has inhibited the formation of functional NG hubs, although initiatives are underway to promote price discovery and market expansion in these markets (Shi, 2016). We also find the correlations to be high between regasification capacity and the number of terminals, and between the number of terminals and volume of spot trading.

Second, gas-on-gas pricing, increasing market financialization, and lower transaction costs have led to more integrated global gas markets. Overall, LNG price convergence has been found to be increasing, although it is unclear if or for how long such convergence will last. Prior research has shown structural changes can often occur quickly and for a wide variety of reasons. An example of this is in the oil to NG relationship. Early evidence pointed to a strong cointegrating relationship (Asche et al., 2006; Bachmeier and Griffin, 2006; Brown and Yücel, 2008), whereas recent evidence suggests diverging price paths (Erdos, 2012; Aruga, 2016). The broad research consensus is that North American gas prices decoupled from their global counterparts in Europe and Asia around 2009. We find preliminary evidence of cointegrating relationship break dates of August 2008 for West Texas Intermediate (WTI)/LNG and October 2015 for Brent/LNG. Both intra- and inter-regional gas markets are becoming more integrated, due in significant part to increasing LNG trade (Bastianin et al., 2019; Garaffa et al., 2019; Oglend et al., 2020). Exploring the fundamental factors of LNG market dynamics has become increasingly important to understanding the long- and short-run nature of gas pricing relationships. Further, structural changes can occur rapidly, highlighting the need for continuing research. Therefore, we lastly propose a few key areas for future research into the challenges for global market integration and price discovery for policy-makers and practitioners to employ.

This paper proceeds as follows. Section 2 provides an overview of the published research to date. Section 3 describes LNG contracting terms and regional differences in term application. Section 4 discusses the dynamics of LNG hub and market development, as well as the developmental trends across Europe and Asia. We also bring special attention to the roles of spot trading and regasification capacity, which have become increasingly important in recent years. In Section 5, we investigate whether the prevailing research has found gas markets to be globally integrated. Two specific areas of price integration are explored, the oil-to-gas relationship and the interregional gas relationships. Additionally, we briefly discuss the prevalent econometric methodologies used to study integration, as well as their relative strengths. Section 6 concludes the paper.

2. Overview of Published Research

In this section, we provide a brief overview of the published academic research. More detailed and comprehensive analysis of the included research is provided in later sections. We sample sixty-two publications including academic research articles, industry reports, and studies by research centers relevant to this study. Of these works fifty-three (85.4%) are academic studies related to LNG or natural gas, five (8.1%) are publications by the government, industry centers, or research centers, and four (6.5%) are academic articles proposing commonly used econometric methodologies. Table 1 identifies key characteristics of these works. The research papers are subcategorized in a similar manner with the main topics and sections they refer to. Also included are the ABDC journal ranking, number of citations to show the paper's relative influence, and the frequency of the data utilized by the author.

The top ranked journals for research on NG, LNG hubs development, pricing relationships, market integration, etc., are: Energy Economics, A*; Journal of Commodity Markets, A; The Energy Journal, A; Energy Policy, A; and Applied Energy, A. In the top panel of Figure 1, we present the number of articles published across the most frequently selected journals for research in the area. As shown, The Energy Journal, Energy Economics, and Energy Policy have published thirty-eight out of the fifty-eight surveyed articles. A well noted difficulty of conducting empirical LNG research is the scarcity of LNG specific data, which stems from two key issues. First, most LNG contracts are between private parties and not publicly filed. Second, of the limited LNG based or LNG tangential data that is available, much of it is quite expensive to procure. In the bottom panel of Figure 1, we show the number and shares of surveyed empirical works which utilize data from each fuel source type in the empirical analysis. Natural gas data is by far the most commonly used. Typically, this refers to WTI, Brent, or other European prices, although regional and global price series are occasionally employed. Oil is the second most common source, due to the plethora of research concerning price spillovers and statistical relationships between global crude and gas prices. Unfortunately, LNG specific data including transportation costs and pricing, such as Japan-Korea Market (JKM) and netback, is only utilized in less than one-third of the research papers. This is surprising considering the articles surveyed quite often make inferences or draw conclusions concerning LNG markets, and highlights the need for expanding LNG data availability and corresponding empirical research.

Figure 2 presents evidence of the sample ranges used in empirical LNG studies cited throughout the following sections. As LNG and natural gas research continues to develop, we observe that relatively few have utilized data from post-shale periods occurring in the later 2000s and onward. Much of the literature has found structural breaks occurring in such periods, which changes the nature of the crude and natural gas relationship. Similar structural breaks are also found for LNG, for which we find concurring evidence. Therefore, we would also like to emphasize the call for LNG research utilizing up-to-date data to both expand our understanding of current dynamics and re-evaluate prior conclusions.

3. LNG Contract Specifications

Most LNG contracts are long-term with maturities greater than four years. Sale and purchase agreements (SPAs) contain several provisions that set the obligations of the parties. Usually, the basic obligations are to sell and purchase certain quantities of NG, with specified volumes and prices. There are other commitments such as take-or-pay provisions, extraction, marketing obligations, restrictions on the destination, allocation of liability in the event of accidents, most favored nation provisions, and force majeure provisions.

There are two types of LNG loading and delivery terms: Free On Board (FOB) and Delivered Ex-Ship (DES). These terms determine the point of transfer of the title, where the risk and ownership of LNG will be passed on from seller to the buyer. FOB contract transfers occur at the loading point and the buyer provides a vessel in a ready to load condition. The buyer has the freedom to divert cargoes, for example, if there is a better price at a different receiving terminal. However, as the seller is responsible for delivering the LNG, the buyer may not have destination freedom unless there is a diversion provision. DES contract transfers occur at the destination port. In general, buyers prefer FOB over DES contract structures.

The take-or-pay provisions require the buyer to purchase a minimum annual quantity, which is defined as annual contract quantity (ACQ). A take-or-pay provision ensures that the buyer bears the full quantity risk, while providing comfort to investors that they can recover the amount of capital invested for the construction and operation of gas production facilities. Destination restrictions exist because the seller does not want the buyer to compete with their other buyers. Therefore, the seller aims to prevent a buyer from being able to deliver cargoes to other destinations.

In general, most U.S. purchase agreements are free of take-or-pay and destination restrictions, with pricing on the Henry Hub basis. The EU also does not allow destination restrictions, whereas Asian markets have destination restrictions. Recently, the Japanese Fair-Trade Commission announced that they may restrict the use of destination clauses. South Korea is following Japan on this issue as well. The diversion provisions provide buyers with the flexibility to divert gas to more profitable destinations and are more prevalent since they allow for profit sharing agreements.

As of 2020, most global LNG traded was under long-term contracts (GIIGNL, 2020). Creti and Villeneuve (2004) review the literature on long-term NG contracts. In particular, they analyze the take-or-pay clauses and price indexation rules, questioning whether regulation is in the way of having optimal contract duration. Christie et al. (2020) describe LNG contract terms and emphasize the issues surrounding the force majeure clauses following the Covid-19 crisis. They conclude that price review clauses will become more detailed and include more flexible terms. It is also likely that Asian markets will evolve and require shorter price review periods. Additionally, the Covid-19 crisis may be a trigger for new efforts for the development of a local hub.

4. LNG Hubs Development

4.1. European hubs development

Europe is often seen as a benchmark on hub development. Researchers investigate the main factors that led to efficient pricing hubs. Miriello and Polo (2015) and Dickx et al. (2014) investigate the creation of wholesale markets for NG, viewed as a consequence of balancing needs following market liberalization. The authors identify four stages in gas hub development: market liberalization, balancing platforms, wholesale trading, and financial operations. They analyze the stage development for eight European countries: Austria, Belgium, France, Germany, Italy, Netherlands, Spain, and U.K. In their research, they specify two important questions: What determines the emergence of gas hubs? Is there a predictable pattern of development? Additionally, for every country, they document several parameters that are key to market liquidity: bid-ask spread, churn ratio, volume, existence of futures markets, and internal production demand. Based on the four stages of market development they conclude that the U.K. National Balancing Point (NBP) is at the highest level of development. The Dutch Title Transfer Facility (TTF) follows closely. NetConnect Germany (NCG) and Belgian Zeebrugge follow in terms of volumes traded. These two papers are a useful starting point to analyze the hub development in Asia.

Recently, Heather (2021) argues that the vision set 20 years ago of a fully liberalized traded gas market on the wider European level is almost fulfilled. Heather points to a merger of hubs in Germany scheduled to be completed in October 2021.[2] The expectations are that this hub will become one of the most attractive and liquid gas trading hubs in Europe. However, Heather does not see a real potential for such transformation. The TTF and NBP are important benchmarks, and it is very likely that TTF will continue to be the European gas price benchmark.

Shi (2016) identified several key factors for successful hub development such as market liberalization and competition. They concluded that market liberalization is necessary to create a competitive environment. Additionally, market liberalization is a necessary measure to create demand for wholesale trade, which is the key incentive and fundamental role of a hub. They identified key factors needed for successful hub development. Factors include:

[2] Two hubs, Gaspool and NetConnect Germany (NCG) merged to create a new gas trading platform, Trading Hub Europe (THE). For more information, see (Afanasley, 2021).

pricing transition for long-term contracts; political will; natural factors, domestic production and culture. Authors used those factors to compare hubs development in Europe and East Asia. They conclude that lack of indigenous production and inter-connectivity, vertically integrated industrial structure, the traditional preference of supply security and unclear political signals, will make LNG hub development in East Asia more difficult than in Europe. Their forecast is that even if some East Asian countries are determined to develop their hubs, there is a very small chance to have one by 2030.

4.2. Asian hubs development

Recent hub development research focuses on hubs in Asia. Tong et al. (2014) argue that China has more advantages in establishing an Asian NG trading hub than other countries like Singapore, Japan, and Malaysia. Their analysis was based on internal strength/weakness and external competitiveness. The authors argue that there are many factors that favor China such as supporting policies on the NG sector, initiation of spot and futures markets, rapid growth of NG production, improved infrastructure, and Shanghai's strategic location. Shi and Variam (2018) identify the key elements for having a fully functional NG hub applicable to East Asia. Their framework establishes nine key elements. Since these factors are relevant to this research, in Table 2, we replicate key elements of functional gas hubs from the findings of Shi and Variam (2018).

Shi and Variam (2016) use the Nexant World Gas Model to study hub competition.[3] They find that both price benchmark change and contract flexibility improvements will create an overall benefit for the world and East Asia importers. Vivoda (2014a) evaluates the impact of Japan's LNG strategy on regional pricing. Japan implemented several measures to challenge oil indexation with the objective to reduce transaction costs. The author argues

[3] Nexant World Gas Model is a simulation engine that allows exploring different scenarios. https://www.nexanteca.com/program/world-gas-model.

that despite all the initiatives started by Japan, the LNG pricing will only partially shift away from oil-indexation by year 2020. Vivoda (2014b) extends this analysis to analyze the role of import diversification on hub and market development across the five largest Asian importers: China, India, Japan, South Korea, and Taiwan. The author finds that more diversified import portfolios are correlated to a larger share of spot and short-term contracts. However, no evidence is found that lower prices were a result. Shi (2016) summarizes four papers on LNG and trading hubs in East Asia. He finds that a liquid futures market is the key to formulate benchmark prices while a well-developed spot market is the foundation. Additionally, political will and strong leadership are required to restructure the NG market and to overcome the power of incumbents that impede the development of completive markets. The hub development requires governments to go through tough domestic market reforms, including liberalization and cooperation with each other and with gas exporters.

Kim (2017) studies the LNG market changes under low oil prices observed in 2014. His overall conclusion is that the evolution of an Asian gas hub will be highly influenced by decisions made by both China and Russia. Kim (2019) argues that the Asian gas hub pricing dynamics in 2014-2017 look similar to that of Europe in 2009-2012; however, the path to an Asian hub will be very different from Europe. Citing challenges and complexities, he concludes that it makes more sense to expect a virtual LNG hub and not a NG trading hub.

Stern (2014) describes the time series of events leading to transition to hub pricing in Europe. He calls the situation in Asia a "crisis of fundamentals" and concludes that a hub is still a distant prospect. Zhang et al. (2018) use a structure vector auto-regression model and monthly LNG prices of four East Asian importers to study if markets are integrated. They find that the LNG markets are fragmented and recommend multiple LNG benchmark trading hubs so that each can reflect different fundamentals. Palti-Guzman (2018) examines how the LNG market functions in Asia and argues that an opportunity exists for Asia to develop a regional trading hub. The author points to several policy implications, such as access to LNG will have an environmental benefit, a trusted Asian hub will make regional gas markets more efficient, and a regional LNG hub will foster intraregional trade and synergies.

del Valle et al. (2017) develop a model to analyze the different stages of the implementation and development of a virtual hub. The virtual hub is set up as an entry-exit framework. Assumptions regarding shippers, businesses and industries participating in the electricity market, and other players, are made to set up the virtual hub. They make a few conclusions. First, with the introduction of the virtual hub, the marginal cost of all shippers reaches a unique value, i.e., the transparent gas hub price. Second, the aggregated profit of the shippers is increasing even when anticompetitive behavior is not explicitly represented, due to the flexibility gained by shippers with the hub. Accordingly, and third, the hub is a necessary, but not sufficient condition to increase competition. The entry of new players is critical and discouraging market regulations or the anticompetitive behavior of a highly concentrated market may not facilitate it.

The research report, "Perspectives on the Development of LNG Market Hubs in the Asia Pacific Region", by EIA (2017) analyzes the state of LNG hubs in the Asia Pacific Region. It makes the following conclusions. Global liquefaction capacity is projected to increase by one-third by 2020. U.S. LNG exports will increase liquidity in global LNG trade and enhance supply security. Asian markets lack a transparent pricing benchmark and multiple initiatives are underway to facilitate price discovery in Asian LNG markets. As a result, the formation of functional NG market hubs in the Asia Pacific region will take time. In Figure 2, we summarize the stages of development for hubs in Europe and Asia.

4.3. Spot trading and regasification capacity

Annual reports by GIIGNL provide key data on LNG markets.[4] Using data from their annual reports for the years 2004-2020, the following tables and charts are constructed to gain insights on developments in the LNG markets over time. Figure 4 shows the time series of regasification capacity and spot trading, including short-term contracts. Table 3 shows the correlations between regasification capacity, number of terminals and spot trading. Note that as the total number of terminals and regasification capacity increases, so does spot trading. The correlations are high, with 99.57% between regasification capacity and number of terminals, and 78.08% between number of terminals and spot trading.

5. Market Integration

While there is a plethora of academic studies examining NG, few studies focus on LNG. Likely, this is because large-scale international LNG market development and intercontinental arbitrage has only taken place over the last couple of decades. In response, many early works interchangeably consider NG and LNG. With the growth of LNG hub development and transportation in recent years, research specific to LNG is becoming more common.

Additionally, NG and petroleum products have historically been viewed as close substitutes. In North America, power generators often alternated between fuel oil and NG depending on whichever was least expensive. Price movements between the two fuels were therefore closely related. An early NG price rule-of-thumb ratio was 10:1, meaning that one barrel of WTI crude oil was priced at roughly ten times one million British thermal units (MMBtu) of NG. It was not until the late 1990s that this rule-of-thumb was changed to a

[4]For examples see, GIIGNL (2013; 2015; 2016; 2017; 2018; 2019; 2020).

6:1 ratio, which more accurately reflected the Btu energy conversions. Figure 4 we provide a brief summary of the key findings found within the following section.

5.1. Pricing systems and empirical methodology

Over the last decades, regulatory changes, infrastructural changes, and trading developments have curtailed the ability to substitute fuels easily. This has led to alternative pricing mechanisms, each with its own set of advantages and disadvantages. Generally speaking, NG has faced three main pricing mechanisms:

- Hub pricing known as 'gas-on-gas' competition;
- Government regulated prices; and
- Oil-indexation.

Gas-on-gas (GOG) pricing indexes the NG price to market spot prices, which are determined by supply and demand factors. These factors often widely vary across hubs, with each exhibiting its own set of dynamics. Therefore, GOG pricing reflects the prevailing market equilibrium occurring at an individual hub location. Historically, oil-indexed (OI) pricing has been the most widely used. Under OI, contractual NG prices are set in relation to netback values, using a formula to calculate the point of sale value minus transportation costs and profit margin. Such formulas are contract specific. These contracts are traditionally viewed as 'long-term', lasting upwards of 20-25 years. OI pricing relies upon a number of suppositions such as crude oil and NG are near perfectly substitutable fuels, the oil market is too big to be manipulated, and international oil prices provide a 'price-anchor' to limit substantial regional price gaps. These suppositions are quite strong. Determining which pricing mechanism is most efficient, GOG or OI, requires additional investigation into each. Nonetheless, the global trend has strongly favored a movement toward GOG pricing. International Gas Union (2020) finds that from 2005 to 2019, the number of countries using

GOG pricing has increased from seven to twenty-nine while the number of countries using OI pricing has decreased from thirty-three to twenty-two. They also find that the proportion of LNG spot trading has increased nearly thirty percent over the same time.

The strongest supposition is the substitutability principle. Contractual OI efficiency requires a long-term relationship between crude and NG prices. Without a strong relationship, a hub-based pricing mechanism would more closely reflect NG market fundamentals. Prices would also be able to respond more quickly to gas market specific changes and disruptions. Most of the academic articles on NG/LNG are focused on testing this relationship. Next section presents a summary of the most influential ones.

5.2. Key econometric models

Academics have employed a wide variety of methods for determining the strength of fuel pricing relationships. Such methods include:

- Cointegration;
- Ordinary least squares (OLS) and simple regression;
- Vector auto regressive (VAR);
- Generalized auto-regressive conditional heteroskedasticity (GARCH);
- Time-series smoothing models; and
- Various alternative approaches.

Each of these methods presumes a time-series relationship between NG and oil prices, consistent with the long-run nature of contracts. Each method also presents a different framework for how the long-run pricing relationship is formed. As these methods all have their own set of characteristic benefits and drawbacks, it is impractical to consider which is optimal. Nonetheless, the most widely used methodology is cointegration which tests for a long-run correlating relationships between time series processes. Engle and Granger (1987) formalized the multiple cointegrated vector approach. Most macroeconomic data exhibit stochastic trends and drifts over time and are referred to as 'non-stationary'. Non-stationary variables are 'unstable', making long-term characteristics difficult to define. To aid in interpretation, researchers often convert such variables into stable 'stationary' forms by differencing the data into higher orders, where the mean, variance, and autocorrelation does not change over time. Generally, differencing is conducted until the data is stationary. Cointegration exploits statistical relationships by creating a linear combination of the differenced series. This combination essentially 'cancels out' their individual stochastic elements, leaving only their shared long-run trends. When this occurs, the two variables are referred to as being cointegrated. Many advancements have been made since, such as those by Phillips and Ouliaris (1990) and Hansen (1991). However, the Engle and Granger (1987) approach remains the foundation for much of the prevailing energy market research.

In Figure 5, we plot the monthly spot prices for WTI crude oil, Brent crude oil, LNG, and Henry Hub natural gas from January 2001 to June 2021. We first transform each of the variables into logarithms, and then into their stationary forms via differencing. We find all price level series are of order I(1), reflecting that they are stationary when first-differenced. The differenced price series plots are shown in the bottom panel of Figure 5. Lastly, we apply the tests of Engle and Granger (1987) to log series of the LNG and WTI data. In Figure 6, we present the implied price of LNG given the long-run cointegration relationship with WTI.

Essentially, a cointegration path is the mean long-run relationship left after filtering out the cyclical components and short-run deviations. This implies that although short-run deviations may occur, there always tends to be a reversal to the mean relationship. The short-run corrections back to the mean (i.e., mean reversion), known as an adjustment path, is of considerable importance to practitioners and researchers alike. Vector Error Correction Models (VECM or ECM) estimate the adjustment path by representing each series deviations in an auto-regressive vector form. Within the literature, VECM estimation often follows once a cointegrated relationship is confirmed and estimated.

5.3. The early gas-oil relationship

Due to the scarcity of LNG specific research and its' synonymous consideration with NG, it is necessary to address the prevailing literature across all NG prices. The authors Brown and Yücel provide seminal studies of the cointegration relationships between oil and NG prices. They also interchangeably utilize the terminology. Brown and Yücel (2008), their most widely cited study, examines weekly HH and WTI prices from June 1997 through June 2007. Additionally, they include heating and cooling degree days to account for demand changes due to weather and seasonality, gas storage to account for supply constraints, and a series of control variables in the cointegration equation. They find strong evidence of oil and NG cointegration, both with and without the use of control variables. Further, the relationships causality implies that oil is the determining factor of NG prices, and not vice-versa. ECM results indicate that deviations from the long-run path are corrected at a rate of 6% to 12% per week, with 90% adjustment occurring within 12 weeks.

Brown and Yücel (2009), expand their work to include European markets. They find evidence that the NBP and Brent crude prices are cointegrated. Integrated relationships are also found between HH and NBP prices, suggesting that North American and European markets are integrated. Price determination is shown to run from North America to Europe, with WTI being the driving factor of both HH and NBP. Additionally, HH prices are a determining factor of NBP, with mean adjustment occurring at 4.8% to 14.1% per week, respectively. Conversely, Brent exhibits no such causal relationship on HH prices. They also find strong evidence of Cross-Atlantic GOG arbitrage opportunities; such that coordination of NG prices could be facilitated through movements with crude-oil prices.

The early literature evidence points to a strongly cointegrated relationship between NG and crude oil prices, which widely holds throughout the 1980s, 1990s, and early 2000s. However, the exact reasons for the relationship's strength are widely debated. Yucel and Guo (1994) provide one of the earliest cointegration studies, finding North American oil and NG prices to be strongly integrated over the years 1975-1990. They suggest this is mainly due to the perceived substitutability of gas and oil in energy markets. Asche et al. (2006) find evidence of energy price cointegration within the U.K. market during the years of 1995-1998. This period exhibited heavy deregulation. After the opening of the Interconnector in 1998, the U.K. market became integrated with global oil prices. In each case, oil prices were the leading factor for NG price determination. In addition, they conclude that changes in regulatory structures and capacity constraints can make prices appear to be more or less cointegrated. These results are broadly supported by the work of Panagiotidis and Rutledge (2007).

Bachmeier and Griffin (2006) come to similar conclusions for U.S. regional markets. Using daily prices, they find HH and WTI prices to be strongly integrated in the long-run and suggesting strong evidence of market integration. They find global oil prices to be integrated as well, with WTI being a leading factor across four global oil markets of Brent, ANS, Dubai, and Arun (Indonesia). Their results show that oil price shocks quickly reverberate around the world while NG prices, although integrated, respond much slower. Serletis and Herbert (1999) show the North American market NG integration extends to NYMEX fuel oil. However, the integration was strongest in U.S. North American Electric Reliability Council (NERC) regions where fuel-switching capability was greater (Hartley et al., 2008).

Villar and Joutz (2006) support the presence of a significant and stable long-run cointegration relationship between the WTI and HH when using a time trend. Although they find evidence of short periods of price decoupling, the adjustment speed parameter is 0.19, indicating 19% of the difference is recovered in the following period. Further, the effect of oil prices on NG demand is dominant in the short-run with every 10% increase in oil prices leading to a 2.6% increase in NG price. They conclude that short-run supply and demand factors are the driving force for cross-commodity price changes. Presumably, technological changes also played a role in the early formation of integrated relationships. Hartley et al. (2008) show the emergence of combined cycle NG power plant reduced costs, increasing the demand for NG. They determine that technological factors explain the trend (drift) in the long-run gas-oil relationship. Therefore, disequilibria in long-run gas-oil prices were driven not only by random shocks to the international crude oil market but also technological factors influencing the relationships drift. Variables such as weather, inventories, and seasonal factors had, and continue to have, significant influence on short-run price adjustment dynamics, with extended periods counteracting adjustment back to long-run equilibrium.

5.4. Dating the structural break

Even in the early literature, evidence was building that the strong relationship between NG and oil prices was beginning to decay. Serletis and Rangel-Ruiz (2004) examine the impact of a series of North American regulatory changes on HH and WTI prices using daily data from January 1991 to April 2001. Particularly, they focus upon the U.S. Natural Gas Policy Act of 1978, Natural Gas Decontrol Act of 1989, FERC Orders 486 and 636, the Free Trade Agreement (FTA) of 1988, and the North American Free Trade Agreement (NAFTA) signed in 1993. These policies fundamentally changed the environment of the North American energy industry by promoting efficiency through deregulation. Their analysis finds that although a common oil-gas nexus could not be rejected, the strength of the relationship had significantly weakened in post-policy periods of deregulation.

It is important to note that energy price decoupling was reasonably unexpected, both regionally and globally. Using the cointegrated relationship from 1989-2005, Ghouri (2006) predicted regional gas and oil prices would continue to be linked in the long-run. He suggested the linkages were primarily due to gas trade contract price formulas being oil based. Further, he forecasted that limited gas production and growing demand would push prices higher. The highest prices were expected to be in Asia Pacific regions, such as Japan and Korea, where long-distance transportation would cause increased trade frictions.

While technological advancement, gas infrastructure development, and deregulation were clearly factors driving decoupling, it was seemingly that shale had the greatest impact. Asche et al. (2012) was one of the earliest papers to consider the shale impact. Although they find evidence of a stable long-run oil-gas relationship, their Chow test results do not find evidence of a structural break. However, the model employed is not robust and the data is quite limited, ending in 2010. In all likelihood, such a sample would not have ample observations to statistically find post-shale changes; an issue they themselves note when discussing significant future supply changes stemming from increasing U.S. production.

Erdos (2012) expands upon the work of Brown and Yücel (2009) by testing the regional and global gas-to-gas and oil-to-gas relationships. He considers changes in NBP, WTI, and HH equilibrium relationship over time, by restricting subsamples and re-estimating the relationship. Controls for exogenous demand and supply shocks are additionally included in the vector error correction model. Interestingly, his results for the 1997 to 2008 period find strong short- and long-term integration, aligning with findings of previous authors. He attributes this to higher U.S. prices attracting LNG exports to the U.S. on a netback basis, lowering the potential supply in Europe thereby triggering cross Atlantic price adjustment and integration. Atlantic arbitrage flows from the U.S. to Europe, due to shale oversupply, should have led to a stable price relationship of relatively lower U.S. gas prices. However, this arbitrage did not 'work' due to a lack of liquefying and export capacity in the U.S. Therefore, North American gas prices decoupled from their global counterparts in Europe and Asia around 2009.

The overwhelming consensus of the literature is that ‘shale gas revolution’ occurred between 2008 and 2009. Caporin and Fontini (2017) specifically test for the presence of structural breaks in the cointegration equation. They utilize an expanded dataset from 1997 to 2013, which results in two major implications. First, they show HH and WTI prices to be non-stationary. As stationarity is a pre-requisite of a cointegration relationship, this result suggests an end to linearly related prices. Secondly, although initial Philips-Perron tests find changes in the oil-gas relationship around 2007, with the impact of oil prices on gas prices more than doubling. They attribute such inter-period effects to transitory factors including market anticipation, tight oil production, and delayed global market impacts. Most importantly, they cease to find a long-run relationship from 2009 onward and refrain from making generalized claims due to the shortness of the monthly post-2009 subsample. Additional vector error correction research by Lin and Li (2015) offers additional support.

5.5. Alternative model evidence

A number of authors have investigated the decoupling result using a variety of alternative (non-cointegration) models. Geng et al. (2016) analyze the impact of the shale gas revolution using a Markov switching model, showing that HH prices decoupled from oil after 2008. They suggest that a relative lack of LNG infrastructure limited early NG exports from North America, while in the future large quantities of North American shale gas were apt to be exported to other countries. Additionally, they believe the European gas market to be vulnerable to external supply shocks due to its heavy reliance on imported gas.

Wakamatsu and Aruga (2013) estimate the impact of shale on the Japanese NG market. Using a Bai-Perron test, they find two structural breaks in the Japanese market to have occurred in 2005 and 2009. The first break is attributed to gas consumption changes, while the second break is due to price and income shocks. Market impacts are also estimated using a vector auto regressive (VAR) impulse response model. VAR results show a one-sided influence of gas prices from the United States toward Japan prior to 2005, after which the influence ceases. Aruga (2016) extends this work to include shale impacts across both Japanese and European markets. These findings are qualitatively similar, with a key difference of determining the break date to have been in August 2006. Again, U.S. NG prices are shown to decouple and no longer influence international markets.

Similar results are found across a variety of other models including long-memory ordinary least squares (Zhang & Ji, 2018), Philips-Sul and Kalman Filters (Li et al., 2014), multi-variate threshold testing (Potts & Yerger, 2016), and global multi-sector general equilibrium models (Arora & Cai, 2014). Considered together, the North American shale revolution is the primary factor for U.S. LNG and NG prices decoupling from global oil prices. At the same time, global NG prices have not yet fully decoupled from global oil. While there is minor variation in the exact date by region, the North American break is strongly suggested to have occurred in late 2008/early 2009 while global breaks, when present, range between 2005-2009. Two key empirical issues prevail throughout much of the literature. First, there is a shortage of recent evidence utilizing updated data. Most gas research, especially the most highly cited research, uses data from the 1990s or 2000s. A notable exception is Scarcioffolo and Etienne (2019) who investigate the dynamic spatial integration between U.S. natural gas markets. Using daily spot prices from eight hubs, they find long-run cointegrating equilibrium relationships present in each as well as a high level of price-spillovers across the regional price sequences. This suggests that the North American natural gas market is not only highly integrated, but also that price shocks quickly flow across regions. However, they also find the level of connectedness and spillovers has decreased since peaking in 2012, which they attribute to increasing gas abundance outpacing pipeline capacity expansion.

Second, empirical examinations predominantly consider only the NG to oil relationship and not the specific LNG to oil relationship. We briefly address this by employing the structural break tests of Gregory and Hansen (1996) on the Engle-Granger cointegration relationship between LNG and WTI prices. We also utilize the most current data (January 2001 to June 2021) taken from EIA. In Figure 7, we show the structural break in the LNG-WTI cointegrated relationship occurs in August 2008. For LNG-Brent the break date is October 2015. Across both crude to LNG relationships, all test statistics conclude a strongly cointegrated relationship prior to the break date and no relationship after. Although these results are from a simplified model and require significant further examination, they fall well within the generalized findings of the literature.

5.6. Convergence toward a no-arbitrage relationship

Natural gas has become a key fossil fuel for power, industrial, and residential sectors. Natural gas demand has also seen an increase in all regions of the world. Such trends have not only created upward pressure on prices, but also triggered competition between formerly segmented regions. Traditionally, pipeline NG has supplied nearby regional markets, which have historically had their own supply-demand balances, contractual structures, and gas price formation mechanisms. Historical price series analysis suggests that both inter-market and inter-hub price differentials have created opportunities for LNG arbitrage. The growth of LNG supply to regional markets, and improved destination flexibility from hub development, have increased LNG trade to the point of playing an important role in interconnecting markets.

Historically, LNG prices have been indexed to crude oil. The plethora of cointegration literature has measured whether LNG and crude oil markets were linked, a signal for arbitrage. Overall, the cointegration research has found that early gas-oil relationships were strong and arbitraged, while after the shale revolution, such relationships waned. Similar results have been found for regional oil markets as well (Kleit, 2001).

A separate literature has examined whether regional gas markets are linked and arbitraged across regions. While early cointegration methods were able to estimate whether long-run relationships existed, the methodology had not developed enough to estimate the strength of the relationship. Therefore, early papers modeled the speed and degree of convergence using a variety of time series filters. King and Cuc (1996) apply a Kalman Filter to analyze price convergence in North American NG markets. Their results suggested that regional gas markets were not only becoming increasingly connected, but also that regional market price convergence was becoming stronger. Increasing convergence was particularly occurring within larger North American regions, with an 'east-west' split characterized by western basins being more strongly linked with each other than eastern ones. They attribute the growing convergence to the development of pipelines and interconnectors driven by price deregulation.

Not long after North America experienced major changes to HH integration, international NG markets went through similarly substantial periods of deregulation and infrastructure during the early 2000s. Neumann (2008) examines the integration between U.K. NBP, Zeebrugge, and HH pricing. The authors argue that the U.K. followed a similar path to the U.S., with a delay of around half a decade. For example, in 1986 the U.K. ended the British gas monopoly, opening competition and a truly competitive European gas market. Although trailing behind, continental Europe similarly opened market competition with the EU Acceleration Directive and the Dutch TTF hub. The newly restructured global LNG market featured a high proportion of spot trading and generally shorter contracts. Using the Kalman Filter methodology, he finds evidence of convergence to the law of one price, independent of fuel oil prices. The strength of the convergence is shown to be increasing over time, and to be seasonally stronger in winter months. Further, cross Atlantic LNG arbitrage, in response to short-term supply and demand imbalance, is theorized to be the driving force behind the convergence. Renou-Maissant (2012) similarly utilizes the Kalman-Filter and cointegration methodologies to test the degree of integration and convergence between six western European industrial gas markets. Cointegration results are varied and not robust, finding differing results depending on the technique and unit root relationship specified. However, the Kalman-Filter methodology finds the links between the European gas markets strengthened over the sample while also exhibiting increasing convergence for the country-pairs since 2001.

Neumann and Cullmann (2012) continue this line of research, testing for convergence across 26 European hub pairs. Interestingly, within region convergence is found in only 12 of the pairs. They speculate that introducing spread contracts and reducing the number of European market areas would 'harmonize' services, providing control over short-term trade incumbents and pricing structures. Importantly, they note that capacity allocation and congestion management mechanisms would have to be efficiently managed for such benefits to take place. Considering events surrounding recent European NG crises, additional investigations are needed to see if such conclusions hold. A key drawback of the Kalman Filter methodology is that it 'smooths out' long-term relationships between prices. Therefore, it omits potential for discrete changes, such as global events, which structurally change the prior relationship. Additionally, Kalman Filter research tends to come from earlier decades. While contemporary works occasionally employ filter methods, more often than not it is to contextualize the results of more robust methodologies. Many newer methodologies not only allow for structural breaks, but also incorporate robust time-variant dynamics such as asymmetric positive and negative responses, regime shifts, and non-linearity.

Agerton (2017) examines the convergence of gas prices across 16 global import-export pairs, allowing for structural breaks in the equation. Although a co-integration framework is employed, the allowance of multiple in-model structural breaks circumvents the issue of not being able to examine convergent relationship magnitudes. He finds that although LNG prices appear strongly oil-linked, LNG-oil relationships are asymmetric within importing countries. Moreover, structural breaks are found to be quite common in Asian markets, occurring in two out of four Korean series and both of the two Taiwanese series, due to heterogeneous portfolios of long-term contracts. However, there are fewer breaks per relationship as only one (South Korea-Indonesia) has more than a single break. While import-export prices would be expected to normally correspond to single contracts, changes to portfolios that include large numbers of contracts are shown to induce structural breaks. It is unsurprising that global markets exhibit such changes as contract terms have become more flexible over time (Hartley, 2015; Ikkonikova et al., 2009). While increased flexibility is not new to global markets, Asian markets have featured relatively more contract pricing changes. The analysis finds that Japan has had the most contract term revisions, followed by South Korea, Spain, Malaysia, and Taiwan. A mismatch of LNG pricing is also found following the mid-2000s, due to tightening of LNG markets. While a variety of region-specific convergence breaks exists, two periods stand out. The first is 2008-2009, where a cluster of structural breaks corresponds to oil price volatility and the global financial crisis. The second is the Fukushima disaster of 2011, where Japanese LNG import prices markedly increased in response. However, the LNG-oil relationship did not respond, consistent with long-term contracts providing a form of insurance against unexpected energy shocks. Interestingly, after 2011 fewer structural breaks are found. In general, Asian markets have been less prone to convergence than their global counterparts have, likely due to the continuing ubiquity of long-term oil-linked contracts.

There is some dissent to the global convergence argument. Ritz (2014) builds a theoretical model of LNG market arbitrage. He finds that price differentials arise due to exporter market power. He concludes that this assures that global LNG prices will never converge, even after considering transportation costs. However, no corresponding empirical examination is provided to support the model results. However, his work highlights the importance of contextualizing convergence trends under prevailing production and transportation infrastructure factors. Oglend et al. (2016) and Oglend et al. (2020) concur that transportation costs provide a missing link to determining price convergence. Using a more recent sample, these studies find that shipping costs are endogenous to regional LNG price spreads. However, they also find initial evidence of increasing price spreads, a hallmark of divergence, once capacity and transport limitations are included the spreads become negligible. Garaffa et al. (2019) find the German, Dutch, and Belgium gas markets to be strongly integrated, with prices quickly converging toward long-run equilibrium. However, asymmetrically adjusting prices reflect transaction costs across the markets. They note these transaction costs are not only transportation expenditure based, but also financial market liquidity and storage capacity based.

Convergence has been found to be increasing between city-gate and residential prices as well. Using a sample of 50 U.S. state level data from 1989 to 2007, Arano and Velikova (2009) find evidence that residential and city-gate prices were increasingly cointegrated, implying that various industry segments have moved toward a long-run competitive equilibrium over the last few decades. They argue that increasing retail unbundling, market liberalization, and customer choice have provided benefits both down the supply chain and to residential customers. Avalos et al. (2016) find evidence that regional deviations of city-gate prices from the greater equilibrium are in large part due to region-specific pipeline capacity congestions and constraints. Overall, the global LNG price convergence has been found to be increasing. However, it must be noted that this conclusion is highly heterogeneous across region, import export pairs, and subsample analysis. A key dissention is Chai et al. (2019), which finds a low degree of integration between global gas markets, especially in connection to gas prices in China. However, they find that Japan, United States, and Europe are highly representative of the international market. Further, the fluctuations of these three regions have significant, albeit asymmetric, impacts on the fluctuations of Chinese market prices.

In other words, although China's gas prices remain independent in the short-run, due to the natural of the contract pricing, Chinese gas prices are affected by other global regions in the long-run.

Recent dynamic models, which take into account key trade frictions and regional pricing determinants, ostensibly agree on the presence of a general trend toward long-run LNG market convergence. However, Bastianin et al. (2019) suggests this may be limited to price-growth convergence as opposed to price-level convergence. Bastianin et al.'s results additionally predict an inevitable tightening of cross-country LNG prices. Particularly due to existence of trading hubs and rising degree of interconnection. Improved convergence implies benefits for both consumers and producers. The ability for consumers to access energy at the lowest prices while producers obtain the best prices, regardless of their respective locations, improves overall market welfare. Increasing price integration also implies that the markets have become more competitive due to a growing number of participants. As a result, the potential for a few players to dominate the market is reduced. However, regional variation and corresponding arbitrage opportunities remain across regional markets. Conversely, within-region long-run price convergence has become increasingly omnipresent.

It is unclear if or for how long such convergence will last, especially when considering regional price differences. Aune et al. (2009) predicts that global gas markets will continue to become more integrated, driven substantially by falling LNG transport costs. However, not only have transport costs proven to be volatile in recent years, changes to prior dynamics have become increasingly important as well. The literature has shown structural changes can often occur quickly and for a wide variety of reasons. Contracts, infrastructural development, transportation technological advances, global political volatilities, and changing regulatory settings have all shown to be important factors of both long and short-run price relationships. Hossain and Serletis (2017) show that fuel substitutability and relative price have also been key historical drivers of individual fuel source demand. If anything, the prevailing literature emphasizes the need for timely and informed analysis to provide a robust picture of current global LNG market.

6. Conclusion

According to many experts, NG via LNG is expected to be the next energy tsunami and the bridging fuel of the future. Studying these markets are an important area of energy finance, climate finance, and price discovery. Natural gas has the lowest CO2 output of all fossil fuels and many sources include it as key to helping with climate change and more renewables are employed in the energy mix.

This study provides a literature review of academic research related to LNG hubs development, market integration, and price discovery. Current studies show that Asian markets lack a transparent pricing benchmark and multiple initiatives are underway to facilitate price discovery in LNG markets. However, our main findings suggest there are numerous gaps in the literature specific to LNG. A primary example is how early research publications show strong evidence of a cointegrated relationship between LNG and crude oil. Later works, which use updated data and evolved methodologies, find that this relationship has ceased after a series of structural breaks. Using a simple version of similar methodology, we confirm the latter results. Therefore, we find the conclusions found within prior LNG literature are highly dependent upon the sophistication of the estimation model and sample ranges employed. In Table 4, we identify important gaps in the literature and suggest key areas which we hope future authors address to further the prevailing knowledge of LNG markets.

APPENDICES

APPENDIX A: Figures

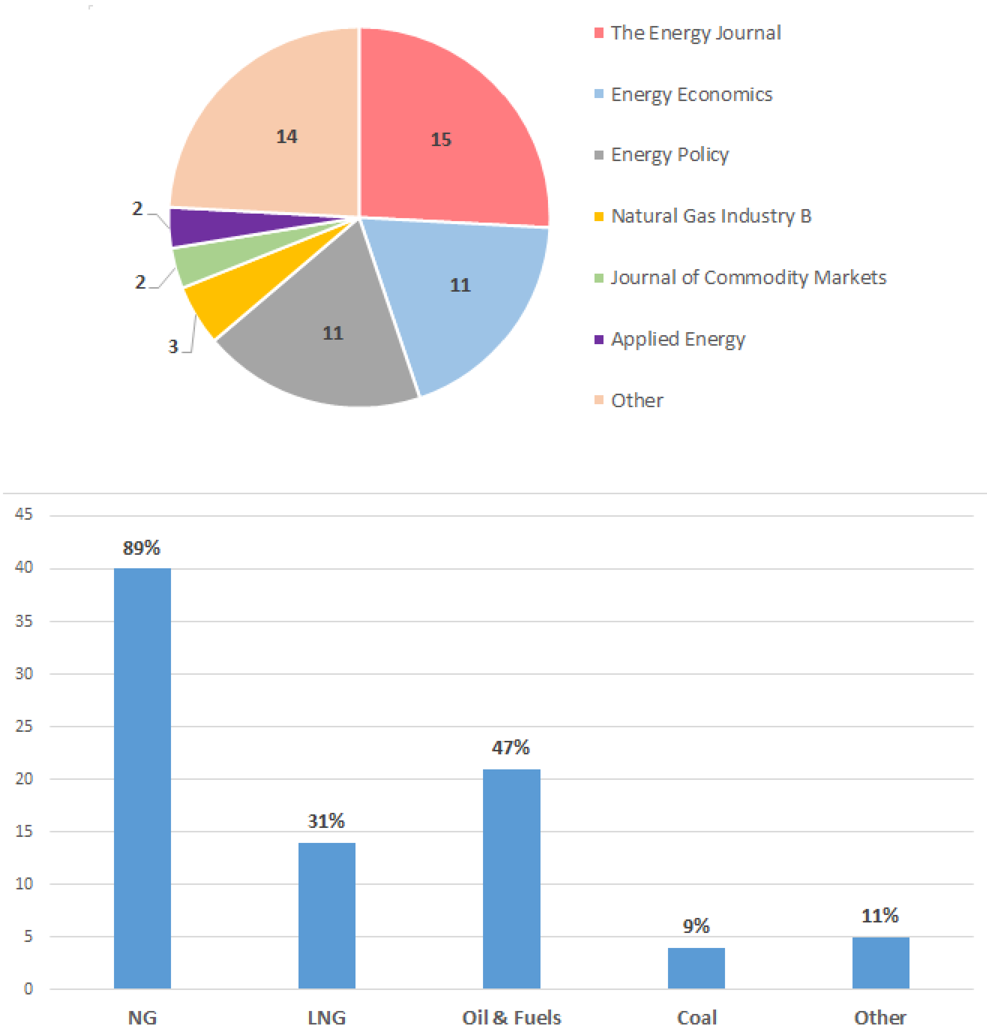

Figure 1. Overview of Included Research
This figure provides visual representations of characteristics from the literature surveyed. The top panel presents the number of articles surveyed from the academic journals. For the top panel, 'Other' refers to all journals not explicitly outlined in the legend. The bottom panel shows the frequency of empirical utilization for data stemming from individual energy sources. For the bottom panel, 'Other' refers to all sources not prior outlined including, but not limited to, power markets, pipeline costs, shipping costs, import/exports volumes, and city-gate prices. Bold numerical values, above each bar, represent the share of data-utilization across the sampled empirical literature.

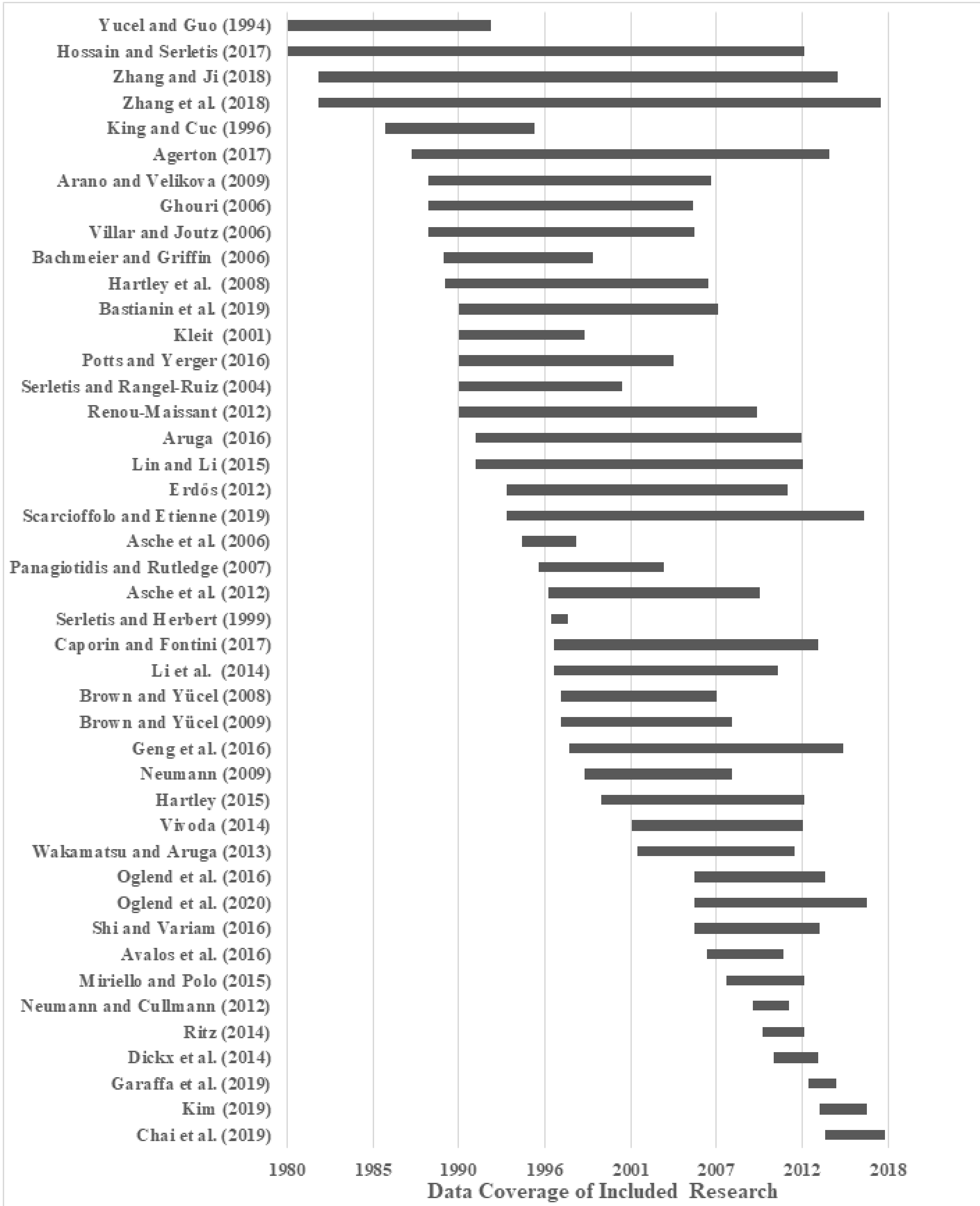

Figure 2. Data sample coverage of included research
This figure presents a visual representation of the data sample ranges included in the LNG research. When multiple samples are used within the research, the range is based on the key results. Samples beginning prior to 1980 have been truncated for brevity.

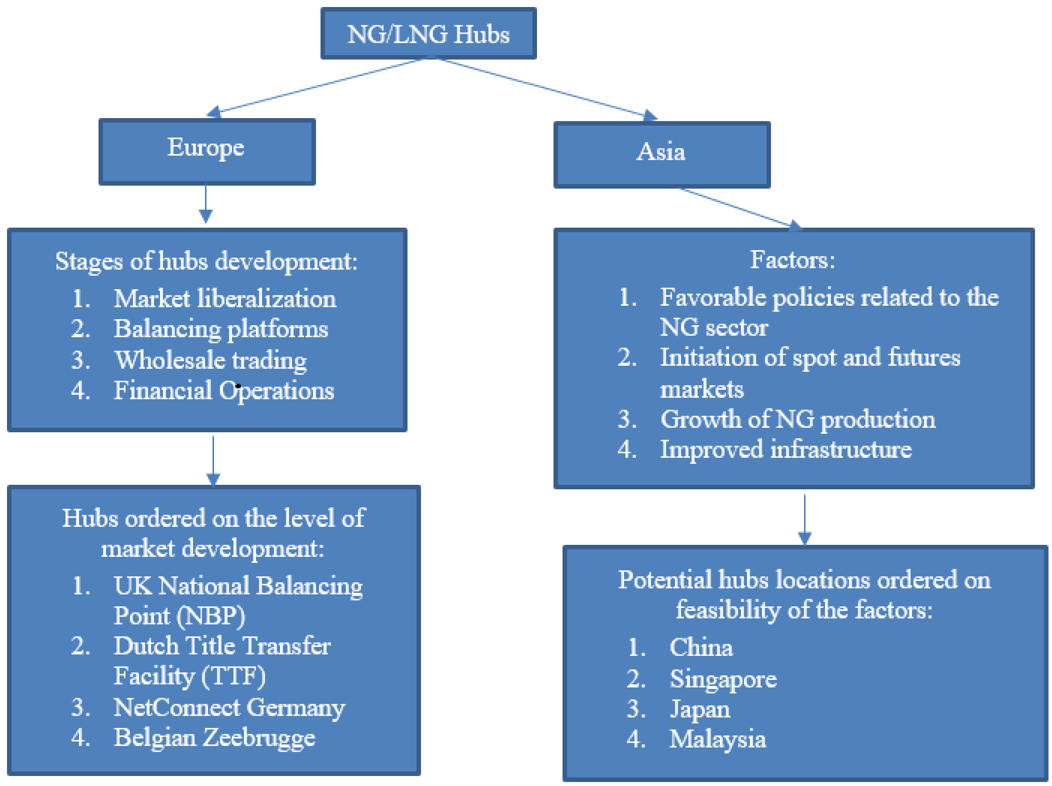

Figure 3. Stages of development of LNG hubs

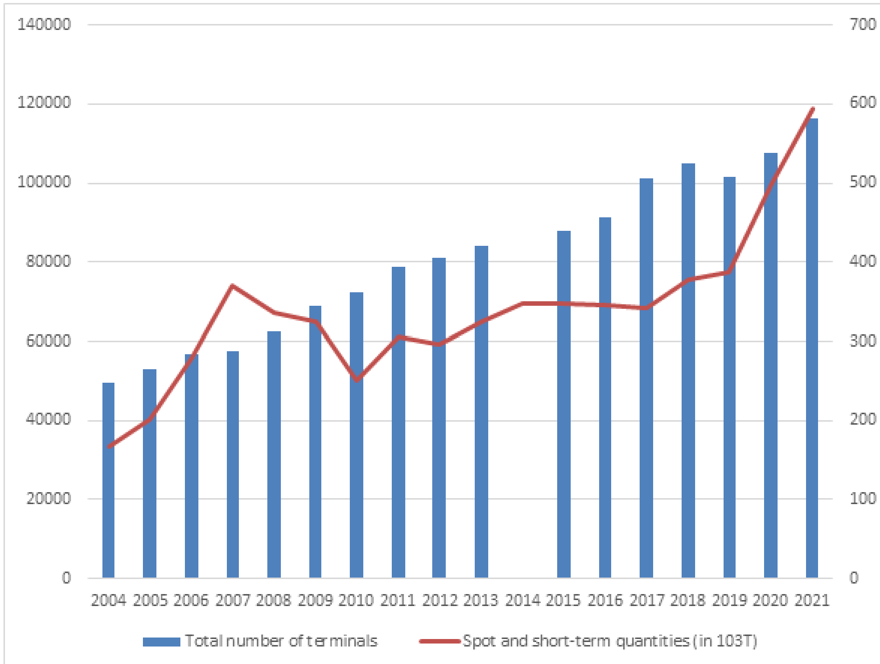

Figure 4. Time Series of Regasification Capacity and Spot Trading
This figure plots the time series of regasification capacity measured as total number of LNG terminals (left-hand axis) versus spot trading. Spot trading is measured as Short-term trading, defined as any contract that is less than four years. We obtain our data from GIIGNL annual reports over the period 2004-2021.

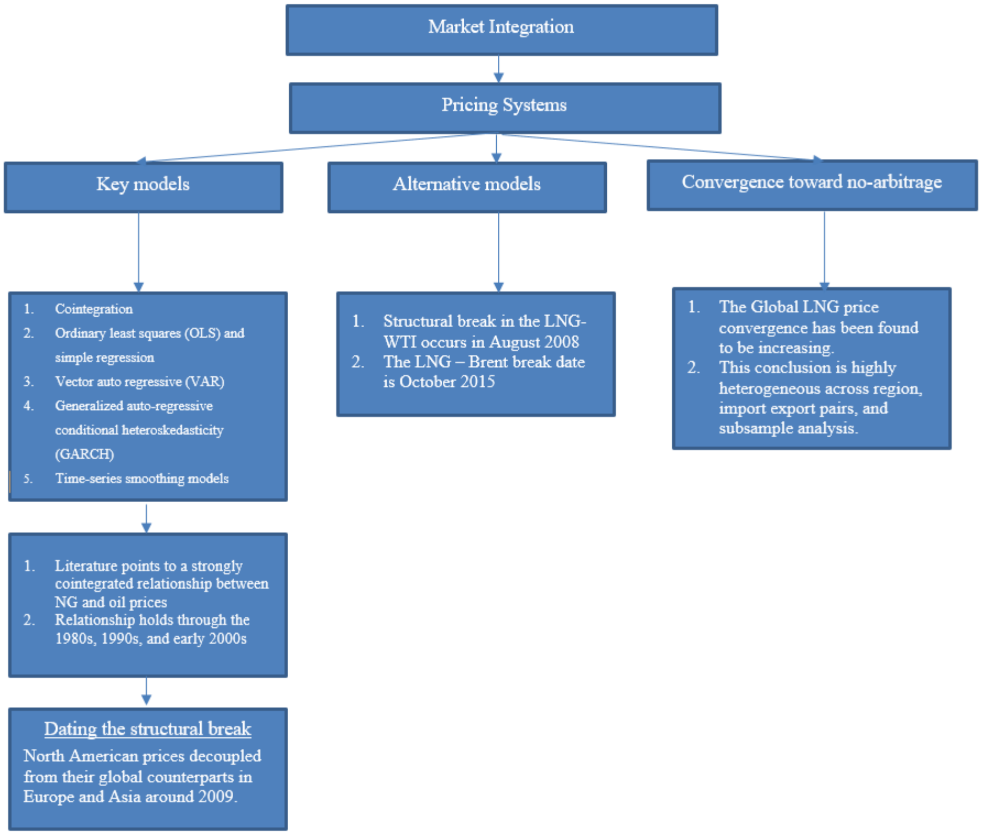

Figure 5. Market integration summary

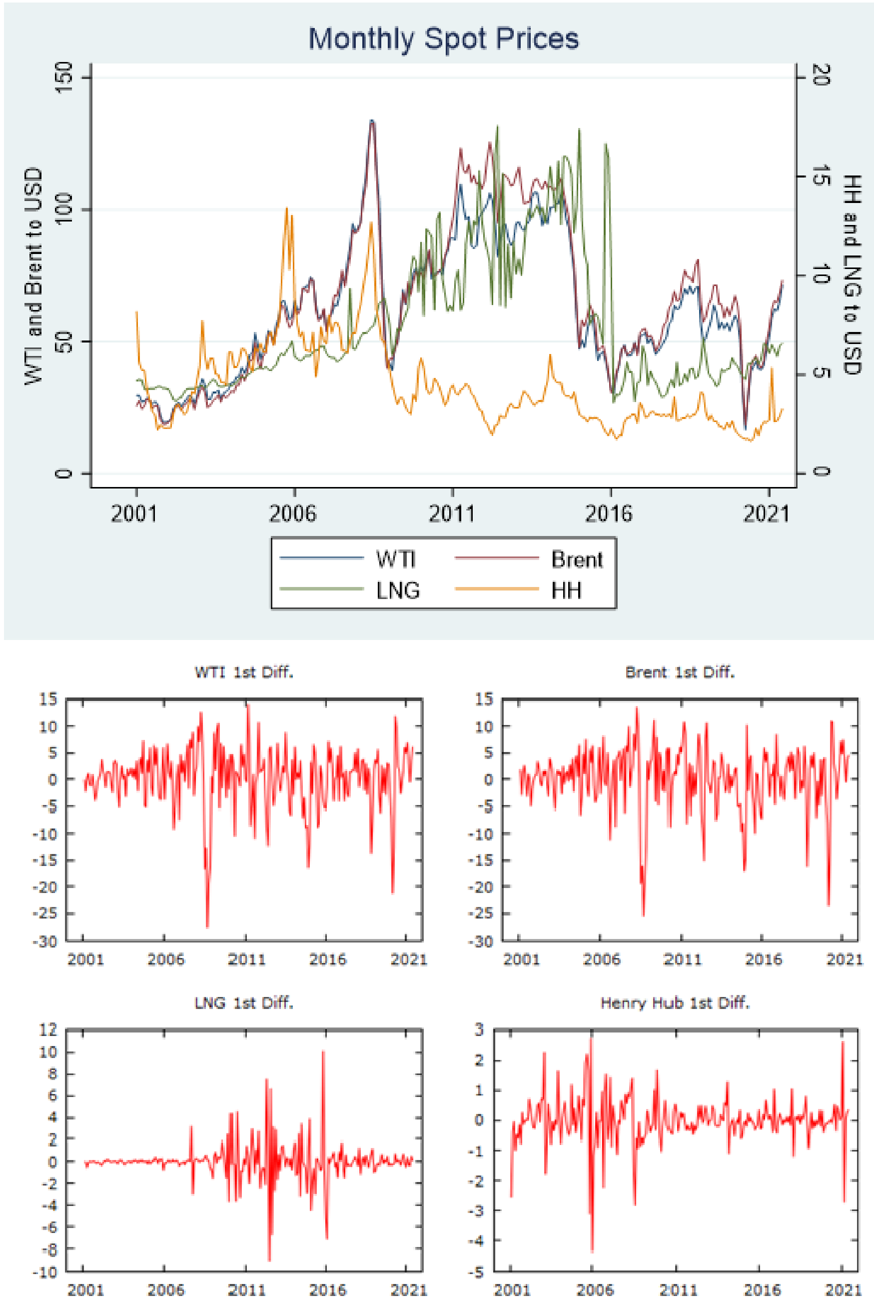

Figure 6. Monthly spot prices and first-differenced series
The top panel represents the monthly spot prices for WTI, Brent, LNG, and Henry Hub NG over 2001 to 2021. WTI and Brent are plotted on the left-hand axis and LNG and Henry Hub NG are plotted on the right-hand axis. The lower panel represents the first-differenced prices for WTI, Brent, LNG, and Henry Hub NG over the same sample period.

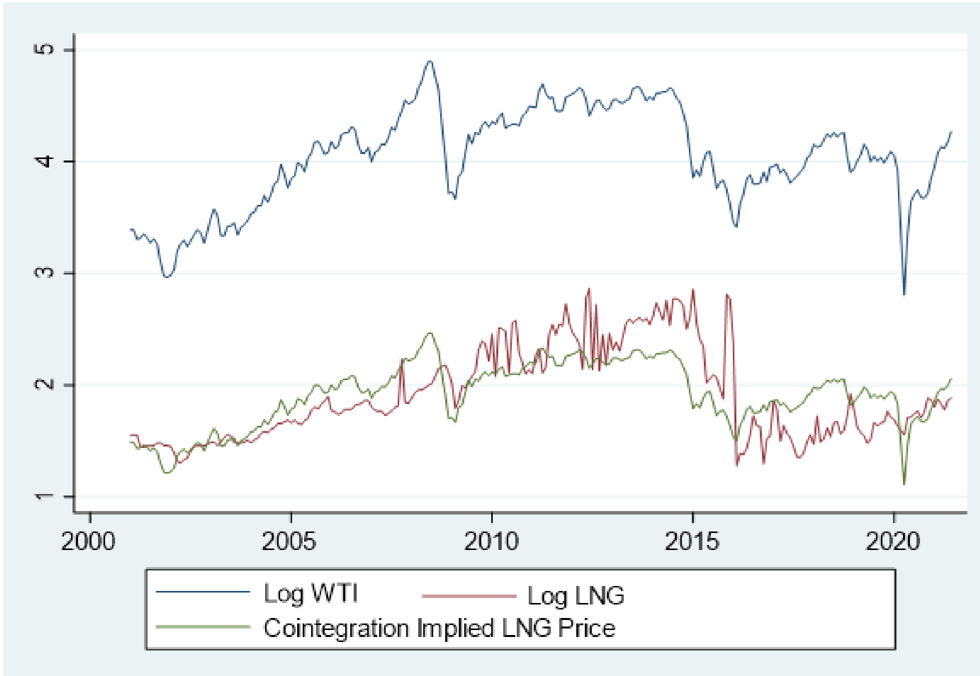

Figure 7. Cointegration relationship of log LNG and log WTI
This figure illustrates the log monthly price series from 2001 to 2021 for WTI and LNG, as well as the implied price of LNG given the long-run cointegration relationship with WTI.

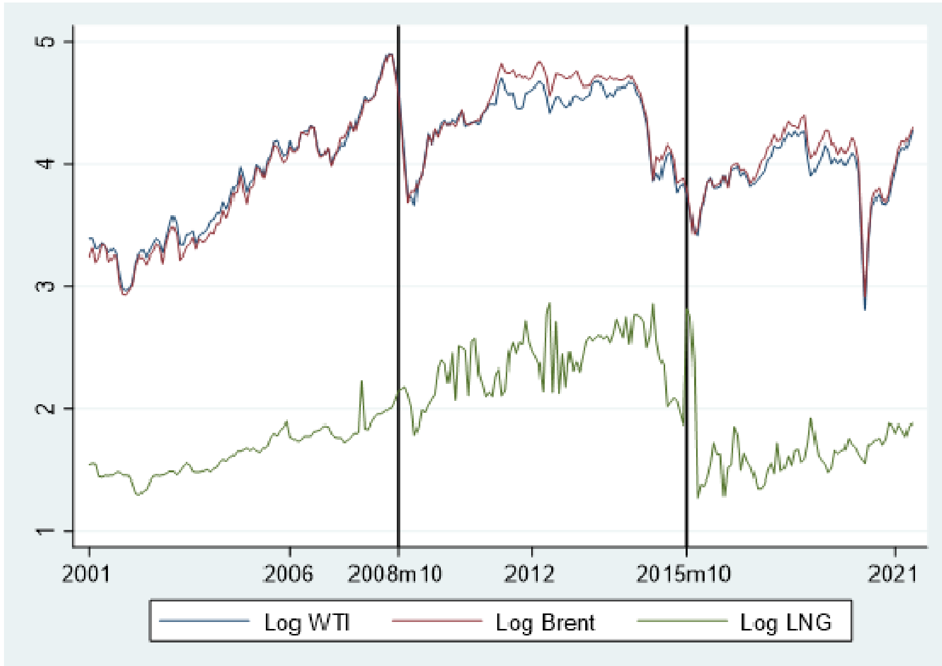

Figure 8. Crude oil and LNG cointegration relationship break tests
This figure presents the results of Gregory-Hansen tests for dating breaks in the cointegration relationships of monthly price series. Breaks for WTI/LNG and Brent/LNG are found in August 2008 and October 2015, respectively. After these dates, the cointegrated relationship is no longer found to hold.

APPENDIX B: Tables

Table 1: Characteristics of included research

Note: The quality of the journal is indicated using the Australian Business Deans Council (ABDC) list. ABDC's highest rank is A*, followed by A, B, and C. The ABDC list only ranks academic business journals so a dash (-) indicates the rank is not available. A dash in the 'Data Frequency' column indicates it is not relevant or the research is non-quantitative. Google Scholar Citations are provided as of March 24, 2022. Refer to the Bibliography section for full article citations.

Paper	Name	Author(s)	Year	Journal	ABDC	Citations	Data Frequency
LNG contracts							
1	Long-term contracts and take-or-pay clauses in natural gas markets	Creti and Villeneuve	2004	Energy Studies Review	C	97	-
2	LNG contract adjustments in difficult times: The interplay between force majeure, change of circumstances, hardship, and price review clauses	Christie et al.	2020	Oil, Gas & Energy Law	-	1	-
Hubs development							
3	Balancing systems and flexibility tools in European gas markets	Dickx et al.	2014	IEFE - Cent. Res. Energy Environ. Econ. Policy Bocconi Univ.	-	8	Monthly
4	International gas pricing in Europe and Asia: A crisis of fundamentals	Stern	2014	Energy Policy	A	98	-
5	Strategic analysis on establishing a natural gas trading hub in China	Tong et al.	2014	Natural Gas Industry B	-	38	-
6	Natural gas in Asia: trade, markets, and regional institutions	Vivoda	2014a	Energy Policy	A	56	-
7	LNG import diversification in Asia	Vivoda	2014b	Energy Strategy Reviews	-	69	Annual
8	The development of gas hubs in Europe	Miriello and Polo	2015	Energy Policy	A	46	Annual
9	Development of Europe's gas hubs: Implications for East Asia	Shi	2016	Natural Gas Industry B	-	22	-
10	Gas and LNG trading hubs, hub indexation and destination flexibility in East Asia	Shi and Variam	2016	Energy Policy	A	71	Annual
11	Asian LNG market changes under low oil prices: prospects for trading hubs and a new price index	Kim	2017	Geosystem Engineering	-	16	-

12	A fundamental analysis on the implementation and development of virtual natural gas hubs	del Valle et al.	2017	Energy Economics	A*	8	-
13	The future of Asia's natural gas market: the need for a regional LNG hub	Palti-Guzman	2018	Asia Policy	C	1	-
14	Key elements for functioning gas hubs: A case study of East Asia	Shi and Variam	2018	Natural Gas Industry B	-	14	-
15	Oil indexation, market fundamentals, and natural gas prices: an investigation of the Asian premium in natural gas trade	Zhang et al.	2018	Energy Economics	A*	91	Monthly
16	Obstacles to the creation of gas trading hubs and a price index in Northeast Asia	Kim	2019	Geosystem Engineering	-	5	Monthly
17	European traded gas hubs: German hubs about to merge	Heather	2021	Oxford Inst. Energy Stud.	-	2	-
Common econometric methodologies							
18	Co-integration and error correction: Representation, estimation, and testing	Engle and Granger	1987	Econometrica	A*	46,101	-
19	Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models	Johansen	1991	Econometrica	A*	14,699	-
20	Asymptotic properties of residual based tests for cointegration	Phillips and Ouliaris	1990	Econometrica	A*	2,588	-
21	Residual-based tests for cointegration in models with regime shifts	Gregory and Hansen	1996	Journal of Econometrics	A	3231	-
Early gas-oil relationships							
22	Fuel taxes and cointegration of energy prices	Yucel and Guo	1994	Contemporary Economic Policy	B	45	Annual
23	The message in North American energy prices	Serletis and Herbert	1999	Energy Economics	A*	182	Daily
24	The UK market for natural gas, oil and electricity: Are the prices decoupled?	Asche et al.	2006	The Energy Journal	A	245	Monthly
25	Testing for market integration crude oil, coal, and natural gas	Bachmeier and Griffin	2006	The Energy Journal	A	302	Daily

26	Oil and gas markets in the UK: Evidence from a cointegrating approach	Panagiotidis and Rutledge	2007	Energy Economics	A*	226	Monthly
27	What drives natural gas prices?	Brown and Yücel	2008	The Energy Journal	A	386	Weekly
28	The relationship of natural gas to oil prices	Hartley et al.	2008	The Energy Journal	A	240	Monthly
29	Market arbitrage: European and North American natural gas prices	Brown and Yücel	2009	The Energy Journal	A	90	Weekly
Structural break dating							
30	Testing for common features in North American energy markets	Serletis and Rangel-Ruiz	2004	Energy Economics	A*	150	Daily
31	Forecasting natural gas prices using cointegration technique	Ghouri	2006	OPEC Review	C	16	Annual
32	The relationship between crude oil and natural gas prices	Villar and Joutz	2006	EIA: Office of Oil and Gas	-	277	Monthly
33	Gas versus oil prices the impact of shale gas	Asche et al.	2012	Energy Policy	A	143	Monthly
34	Have oil and gas prices got separated?	Erdős	2012	Energy Policy	A	118	Weekly
35	The impact of the shale gas revolution on the U.S. and Japanese natural gas markets	Wakamatsu and Aruga	2013	Energy Policy	A	70	Monthly
36	U.S. natural gas exports and their global impacts	Arora and Cai	2014	Applied Energy	A	67	-
37	International natural gas market integration	Li et al.	2014	The Energy Journal	A	54	Monthly
38	The spillover effects across natural gas and oil markets: Based on the VEC-MGARCH framework	Lin and Li	2015	Applied Energy	A	97	Monthly
39	The U.S. shale gas revolution and its effect on international gas markets	Aruga	2016	Journal of Unconventional Oil and Gas Resources	-	57	Monthly
40	The impact of the North American shale gas revolution on regional natural gas markets: Evidence from the regime-switching model	Geng et al.	2016	Energy Policy	A	56	Daily

41	Marcellus shale and structural breaks in oil and gas markets: The case of Pennsylvania	Potts and Yerger	2016	Energy Economics	A*	10	Monthly
42	The long-run oil-natural gas price relationship and the shale gas revolution	Caporin and Fontini	2017	Energy Economics	A*	57	Monthly
43	Further evidence on the debate of oil-gas price decoupling: A long memory approach	Zhang and Ji	2018	Energy Policy	A	42	Monthly
44	How connected are the U.S. regional natural gas markets in the post-deregulation era? Evidence from time-varying connectedness analysis	Scarcioffolo and Etienne	2019	Journal of Commodity Markets	A	13	Daily
LNG arbitrage and market price convergence							
45	Price convergence in North American natural gas spot markets	King and Cuc	1996	The Energy Journal	A	132	Monthly
46	Are regional oil markets growing closer together?: An arbitrage cost approach	Kleit	2001	The Energy Journal	A	82	Weekly
47	Linking natural gas markets - Is LNG doing its job?	Neumann	2009	The Energy Journal	A	127	Daily
48	Globalisation of Natural Gas Markets – Effects on Price and Trade Patterns	Aune et al.	2009	The Energy Journal	A	48	-
49	Linking natural gas markets - Is LNG doing its job?	Neumann	2009	The Energy Journal	A	127	Daily
50	Strategic model of LNG arbitrage: Analysis of LNG trade in Atlantic Basin	Ikonnikova et al.	2009	Association for Energy	-	5	-
51	What's the story with natural gas markets in Europe? Empirical evidence from spot trade data	Neumann and Cullmann	2012	9th International Conference	-	25	Daily
52	Toward the integration of European natural gas markets: A time-varying approach	Renou-Maissant	2012	Energy Policy	A	9	Bi-Annual
53	Price discrimination and limits to arbitrage: An analysis of global LNG markets	Ritz	2014	Energy Economics	A*	38	Monthly
54	The future of long-term LNG contracts	Hartley	2015	The Energy Journal	A	72	Annual

55	Measuring the effects of natural gas pipeline constraints on regional pricing and market integration	Avalos et al.	2016	Energy Economics	A*	29	Daily
56	Trade with endogenous transportation costs: The case of liquified natural gas	Oglend et al.	2016	Energy Economics	A*	25	Monthly
57	Global LNG pricing terms and revisions: An empirical analysis	Agerton	2017	The Energy Journal	A	11	Monthly
58	A century of interfuel substitution	Hossain and Serletis	2017	Journal of Commodity Markets	A	15	Annual
59	Convergence of European natural gas prices	Bastianin et al.	2019	Energy Economics	A*	20	Annual
60	Is China's natural gas market globally connected?	Chai et al.	2019	Energy Policy	A	19	Daily
61	Price adjustments and transaction costs in the European natural gas market	Garaffa et al.	2019	The Energy Journal	A	9	Daily
62	Time commitments in LNG shipping and natural gas price convergence	Oglend et al.	2020	The Energy Journal	A	30	Monthly

Table 2: Key elements for gas hubs

This table lists the key elements for having a fully functional NG hub and is replicated from Table 1 of Shi and Variam (2018).

European Federation of Energy Traders hub element	Basic elements for all hubs	Additional elements for benchmark hubs
Entry-exit system established	A trading point; could be a virtual trading point or a physical network interconnection. The trading point is operated by the TSO.	In the case of a benchmark pricing hub, one trading point needs to be designated as the benchmark hub.
Defined role of hub operator	Provides some services in addition to the infrastructure under the trading point. Could be undertaken by TSOs or exchanges.	
Establishment of exchange	Trading platform, often an exchange.	
Standardized contract	Specification of contract and products including but not limited to standardization.	Derivatives products and market to be developed.
Price reporting agencies (PRAs)		PRA published assessment of traded prices and price indexes for various kinds of contracts.
Market makers, brokers, and access to non-physical traders	Right mix of market players including participation of financial players.	The number of players and the market liquidity have to be sufficient to allow for competition. Financial market participants.

Table 3: Correlations between capacity and short-term contracts

This table shows the correlations between regasification capacity, number of terminals and spot trading. As shown, th correlations are high, with 99.57% between regasification capacity and number of terminals, and 78.08% between number of terminals and spot trading.

	Total Regasification Capacity (MTPA)	Total number of terminals	Spot and short-term quantities (in 103T)
Total Regasification Capacity (MTPA)	1		
Total number of terminals	0.9957	1	
Spot and short-term quantities (in 103T)	0.7808	0.7884	1

CHAPTER III

SOCIALLY RESPONSIBLE CORPORATE NETWORKS

1. Introduction

Corporate social responsibility (CSR) has been a highly researched topic over the past decade and is an increasingly important part of corporate policy. Researchers find that higher CSR ratings are associated with greater and more accurate analyst coverage (Dhaliwal et al., 2011; Dhaliwal et al., 2012), cheaper financing costs (El Ghoul et al., 2011; Dhaliwal et al., 2011), greater investor attention (Nofsinger et al., 2019), risk mitigation (Godfrey, 2005; Dhaliwal et al., 2011), improved employee productivity (Valentine and Fleischman, 2008), and enhanced firm reputation (Borghesi, Houston, and Naranjo, 2014). Further, in many cases there are also positive valuation effects related to greater social responsibility. For example, Servaes and Tamayo (2013) find a positive relation between firm value and CSR for firms with high customer awareness while Deng et al. (2013) find that mergers by high CSR firms take less time complete and are less likely to fail. Further, they find greater merger announcement returns for high CSR firms, as well as larger increases in post-merger operating performance, as compared to low CSR firms. Finally, Edmans (2011) finds a positive relation between employee satisfaction and firm stock returns. Given the benefits of

CSR, we seek to better understand nonperformance based factors involved with the setting of CSR policies.

In this paper, we propose that social, educational, and professional networks between board members and managers (i.e., CEOs) influence the CSR policies of other firms in their network. Amin et al. (2020) examine a similar research question and find that when the firm's board of directors has more connections, the firm typically has higher CSR scores. On the other hand, Chahine et al. (2019) find that CEOs with high network centrality are negatively associated with firm value, which are mitigated by strong governance and areas of high social capital. This suggests competing agency tradeoffs to the strength of a CEO's network. For example, if a firm's CEO has a large network of connections that engage in low CSR, would the firm itself have high CSR because the CEO has a larger and more diverse network, which imparts informational advantages consistent with Amin et al. (2020)? Or would the firm have a low CSR because it is managerially rent-seeking at the expense of responsible policy? Fracassi (2017) documents that managers tend to have similar capital investment as their social peers. Therefore, we argue that if a firm has many network connections to firms with high (low) CSR scores, it follows that the firm itself will have higher (lower) CSR scores. In other words, the CSR policy of a firm 'spills-over' to other firms in its' board and CEO network.

We find that a firm's CSR policy is highly sensitive to the CSR policy of the firm's network connections after controlling for geography, network size, and other known determinants of CSR policy while including firm fixed effects to examine within firm variation and control for time invariant factors. As such, we conclude that there is a strong positive relation between a firm's CSR policy and the CSR policy of its network connections. Furthermore, we show this is robust to examining a total CSR composite as well as its individual components of Employee CSR, Diversity CSR, Human Rights CSR, and Environmental CSR. We also document that our results are robust to including industry times year fixed effects rather than firm fixed effects to examine the cross sectional variation of our research question.

We then perform a series of robustness tests to address additional potential concerns. First, We re-estimate our main regressions using the CSR changes of firms' networks to examine whether policy spillover is driven by cross-sectional differences or investment accumulations, instead of the CSR developments of connected firms and control for our results are potentially confounded by the persistence exhibited by firm and industry CSR scores (Di Giuli and Kostovetsky, 2014; Kim et al., 2014; Krüger, 2015). We find that firms respond positively to the policy peers in their network by increasing their CSR scores when their network's CSR scores increase. This result is strongest for Employee, Human Rights, and Environmental CSR.

A second possibility is that network spillovers are enhanced when the intra-firm connection stems from a CEO, rather than being merely between board members as a great deal of research suggests that CEOs are strongly influence by their peers and the strength of the CEO's related connections have a similarly strong influence on corporate policies (Hwang and Kim, 2009; Fracassi and Tate, 2012; Nguyen, 2012; Fracassi, 2017). Our analysis allows us to address two key questions: "Do CEO connections matter more than the board's?" and "Does firm policy respond more to direct CEO to CEO connections?" to investigate these questions, we employ three subsamples: (1) firm linkages that include connections originating from a CEO in the focal firm; (2) firm linkages which originating from a CEO in the connecting firm; and (3) firm linkages which include a direct CEO to CEO connection. While we find positive spillover in all cases, the strongest spillover effects exist for the latter group. This suggests that direct CEO connections have the largest influence on corporate CSR policy.

Third, we explore the importance of board connectedness as Amin et al. (2020) document that firms with larger networks have higher CSR. We address whether well-connected firms have a stronger CSR transmission, by separating our sample by above (high) and below

(low) the median of the number of total connections within our sample. We find that the CSR policies of highly connected firms (i.e., above the median) are much more influenced by their peers. We also explore the quality of these connects as research shows that the quality of connections, rather than the nominal number, drives network information flows and corporate policy determination (El-Khatib et al., 2015; Skousen et al., 2018; Miranda-Lopez et al., 2019; Bouchet et al., 2022). We conduct a similar high/low analysis using firm level network centrality measures of closeness, betweenness, and eigenvector following Shahgolian et al. (2015). In all cases, we find that more centrally connected boards exhibit larger incoming CSR policy spillovers, suggesting that the quality of the connection plays an important role.

Fourth, we employ a framework similar to that used by Li and Wang (2022) and Nofsinger et al. (2022) to further control for geographic spillover and industry peer effects, by creating three portfolios: 1) The average CSR of connected firms headquartered in the same state; 2) The average CSR of non-connected firms headquartered in the same state; 3) The average CSR of connected firms headquartered in different states.[1] Our results show a strong relation between firm network's CSR from different states and the CSR policy of the firm showing that our results are not driven by geography. Furthermore, our results are strongest for connected firms within the same state. Finally, we exploit forced CEO turnover and the death of a director as an exogenous shock to the firm's network to explore how this affects CSR comovement. Our research contributes to the literature in several ways. First, our study extends to the determination of CSR policy determinants (Fabrizi et al., 2014, Flammer, 2015; Dyck, 2019; Nofsinger et al., 2019). Second, we compliment and extend prior studies of CSR policy spillovers and corporate herding behavior, by introducing the channel of network-based spillovers (Amin et al., 2020; Cao et al., 2019; Li & Wang, 2022; Nofsinger et al., 2022). Third, we contribute to studies examining the importance

[1]Both papers acknowledge that their methodology is based on Dougal et al. (2015)

of board and CEO social networks in corporate governance on firm policy and decisions (Chhaochharia & Grinstein, 2009; Masulis & Guo, 2015; Pathan, 2009; Cai & Sevilir, 2012; Chang & Wu, 2022).

The remainder of our paper is organized as follows. In Section 2, we describe our data and procedures, peer network construction, and the formation of CSR portfolios. We report the results and discuss our findings in Section 3. Section 4 concludes.

2. Sample and Variable Construction

We collect yearly data on firm CSR scores from MSCI (formerly KLD and GMI) for the 2000 – 2018 period. We follow the methodology of Lins et al. (2017) in the following ways to construct our CSR variables. First, we focus our analysis on the five categories: community, diversity, employee relations, environmental, and human rights.[2] Second, for each measure, a firm receives a positive strength (+1) or negative concern (-1) if they exhibit an activity, while zero indicates a neutral (0). We then standardize the net strengths and concerns for each CSR category by taking the summation and dividing it by the number possible in year. This results in a scale of -1 to 1 given to firms for each individual category. To create a composite CSR score (*Total CSR*), we add up the five CSR components which provides a possible range from -5 to 5. Third, controversial industries including tobacco, gambling, alcohol, and oil are omitted as it difficult to improve their CSR scores due to the business practices of their industries.[3] Finally, financial and utility firms are excluded due to heavy regulation.

We obtain social and professional network data for firm directors and executives from

[2]The rest of categories are omitted from our analysis.

[3]Controversial industries include this with SIC codes between 2100-2199, 2080-2285, 3760-3769,3795,3480-3489,2832-2835,1310-1339,1370-1382,2900-2912,2990-2999, 7132, 71312, 313120, 71329, 713290, 72112, 721120, 1300, and 1389.

the BoardEx database. From BoardEx, we collect biographical information including the directors name, date of birth, gender, professional title, and the beginning and end dates for current and past positions. We also collect educational (i.e., degree obtained and the granting institution) and social activity backgrounds, along with dates of death.[4] For each focal firm, we are interested if it is connected to any of the other firms in our sample (*Network Connected*). Two firms are considered connected if the CEO or a member of the board has at least one connection joining it to a similar board member or top executive from another firm.[5] Connections between two individuals are constructed using employment, social, and educational connections. An employment connection is formed if they are concurrently employed by the same firm, other than the focal firm, in the current or a prior year. Social connections are formed if both individuals belong to the same charity, club, sporting, or medical association in the current or prior year. Following Engelberg et al. (2013) and Chang and Wu (2022), we require both individuals to hold active positions in the organization by omitting connections where one of the individuals holds merely a "member" role.[6] Governmental and Armed Forces connections are also omitted. Educational connections are formed when two individuals attended the same educational institution in the same year.[7] Similar to Chang and Wu (2021), we do not confine networks to only connections among directors as connections between a director and a top non-director executive in another firm can also be an avenue for informational exchange. While our main analysis focuses upon the existence of any connection between firms each year, we additionally aggregate the number of connections for each focal board (*Network Size*). An important factor for informational

[4]Our BoardEx sample begins in 2000, due to BoardEx's reliability issues as noted by Chang and Wu (2022). However, our results are robust to the inclusion of additional prior years.

[5]Our results are robust to alternative cutoffs of 2,5, and 10 minimum connections.

[6]We extend the "member" omission to state legal associations (i.e., state bars) as well. It would be a stretch to consider simply being a lawyer in the same state as a connection. Further, when we do not omit such connections, states such as New York and California create extreme numbers of additional connections.

[7]Fracassi (2012) considers attendance and graduation up to one-year apart. Similar specification has trivial effect on the number of educational connections for individuals in our sample. Further, we are primarily interested in the existence of a connection at the firm level and not the individual connection type.

transmission to a firm, is how well it is connected within the network (El-Khatib et al., 2015; Shahgolian et al., 2015; Amin et al., 2020). Therefore, we conduct additional analysis using annual measures of a board's centrality including weighted degree, eigenvector, closeness, and betweenness, which are constructed following Freeman (1979).

Prior research finds that CEO and board characteristics influence CSR measures (Amin et al., 2020; Fabrizi et al., 2014; Oh et al., 2016; Meier and Scheir, 2021; Chen et al., 2020). Motivated by this literature, in our main specification we include the variables of whether the CEO holds the concurrent position of chairman of the board (*CEO Duality*), if the CEO holds an academic degree from an Ivy League university (*CEO Ivy League*), the age of the CEO, calculated from the date of birth provided by BoardEx (*CEO Age*), and the *Network Size*.[8]

CSR and BoardEx data are then matched with Compustat on Global Company ID (GVKEY) and the firm's New York Stock Exchange ticker. A fuzzy string match is applied by firm name if these two identifiers are not available. From Compustat we collect the control variables of firm size (*Size*); leverage ratio (*Leverage*); asset tangibility (*Tangibility*); cash to total asset ratio (*Cash*); growth opportunity (*Tobin's Q*); profitability (*ROA*); and cash dividend to total asset ratio (*Dividend*). We also collect institutional ownership percentage (Institutional Ownership) from Thomson-Reuters 13-F filings.[9] Appendix 1 details the definitions and calculations of the variables used in the analysis.

Geographic herding and industry effects have also been shown to affect firms CSR scores (Nofsinger et al., 2022; Li and Wang, 2022). Our goal is to ensure our estimates capture firm connection effects beyond concurrent location-based effects. To parse these out from our estimates, we include the state headquarters location for firms in our sample

[8]Ivy League universities include Brown University, Columbia University, Cornell University, Dartmouth College, Harvard University, Princeton University, the University of Pennsylvania, and Yale University.

[9]We utilize the natural log of firm size (Size). All other Compustat variables and institutional ownership are winsorized at the 1% and 99%.

and include a corresponding state-level fixed effect and perform additional analysis which incorporates the state a firm is headquartered within.[10]

Our final sample includes 22,296 firm-year observations across 4,127 firms. We report our summary statistics in Table 1. The average focal firm has a Total CSR score of -0.31 and is connected to 18.4 other firms. Of the firm-to-firm connections, 82.2% include a connection originating from the CEO of the focal firm, 87.2% include a CEO in the connected firm, and 75.3% include a CEO-to-CEO connection. The average board has 1,659 total network connections, whereas the vast majority of these are employment based. In 51.4% of the sample, the CEO is also the chair of the board, 13.7% of CEOs have an Ivy League education, and the average incumbent CEO age is approximately 55 years old. Firms in our sample have an average institutional ownership of 63.2%, a leverage ratio of 21.8%, ROA of 2.3% and Tobin's Q of 2.03.

3. Methodology and Results

3.1. The impact of firm connections on CSR spillovers

Our primary question is whether firms CSR policies spill over through manager social connections of corporate leadership. We broadly adopt the methodologies of Dougal et al. (2015), Li and Wang (2022), and Nofsinger et al. (2022). Our first test examines this question for Total CSR using the following model:

$$\begin{aligned} CSR_{j,t} = \alpha + \beta_1 CSR^c_{-j,t} + \beta_2 X_{j,t} + \beta_3 Z_{j,t} + StateFE_t + YearFE_t \\ + FirmFE_t + \varepsilon_t \end{aligned} \tag{1}$$

[10]Our results are robust to using regional fixed effects following the specifications of Li and Wang (2022) rather than state fixed effects.

Where $CSR^c_{-j,t}$ represents the equal-weighted CSR portfolio of all connected firms, c, excluding firm j, in year t. X is the set of board and Z is the set of firm controls. Consistent with prior studies, we include state-, firm-, and year-level fixed effects (Dougal et al., 2015; Nofsinger et al., 2022). State-fixed effects account for potential area-based differences in CSR policy. Year- and firm-fixed effects account for CSR variation over time. Year fixed effects account for unobserved time invariant differences across firm. Lastly, ε denotes the error term which we present as robust standard errors.

In our analysis, β_1 measures the sensitivity of the focal firm, j's, Total CSR to the average Total CSR of connected firms. We present our results in Table 2. In each specification, our results show a positive relation between the CSR scores of connected firms and the focal firm's CSR score. In column 3, the Network Connected coefficient implies that a one standard deviation increase (0.48) in the CSR of connected firms is associated with a 0.084 increase in the *Total CSR* of the focal firm. This result is similar in size across all three specifications and significant at the 1% level. While not the focus of our study, we find statistically significant coefficients for *Size* (positive) and *Tobin's Q* (negative), suggesting that larger and less valuable firms have greater CSR scores. For board controls, the only significant result is a significant negative coefficient estimate for CEOs age.[11] This supports the notion that younger CEOs are more socially conscious, which follows the conclusions of Borghesi et al. (2014) and Meier and Schier (2021).

In Table 3, we extend this analysis to the five CSR component scores. For *Total CSR* and most of the component CSR scores we find positive coefficients that are statistically significant at the 1% level. The most impacted policies are environmental and human rights, where a one standard deviation increase in connected firms scores is related to focal firm score increases of 0.252 and 0.229, respectively. The lone exception is community CSR, for which

[11] We do not find Network Size to be significant in our main analysis, likely due to including connection effects via connected firm portfolio scores. However, in Table 7 we do find centrality measures, including degree, to be positive and significant similar to Amin et al. (2020).

is highly influenced by local events and interactions than corporate networks. Therefore, a firm's component CSR scores, are positively associated with those of socially connected firms. When taken together, the results of Table 2 and Table 3 concur with research finding policy similarities among managerial social networks (Fracassi, 2017; Nandy et al., 2020; Amin et al., 2020).

3.2. Network changes and CSR

One concern for our analysis is the potential persistence of CSR policies. Kim et al. (2014) describe CSR scores as being 'sticky' across years, while also finding that CSR scores in early sample years (i.e., pre-2004) are consistently smaller than later scores. Using seven years of data, Di Giuli and Kostovetsky (2014) also find strong persistence in CSR scores. While they find a positive relation between the political environment and CSR, they argue that the insignificance of the result stems from both the persistence and low power. Krüger (2015) argues that persistence, and subsequent auto-correlation, could be a facet of measurement, as scores are tabulated annually and therefore only account for information different from the prior year. While our 18-year sample is long enough that we are unconcerned with low power, CSR relationships between firms could be affected by the accretion of effects from prior implemented policies.

CSR scores reflect both a firm's current and accumulated prior policies. Following Li and Wang (2022), we re-estimate our model from Equation 1, replacing the CSR variables with CSR score changes (δCSR) which is a better proxy for policy developments. Therefore, the dependent variable becomes the change in a firm's CSR score from the prior to the current year, while the independent variable of interest is the similar change in the equally weighted portfolio of connected firms with the results provided in Table 4. For socially connected firm policy changes, we find significant positive spillovers, significant at the 1%

level, for total CSR along with the employee, diversity, and environmental scores. This suggests that firm CSR policies positively associated with the policies of socially networked firms. In other words, firms change CSR when their peers do. Further, this provides evidence that the relationship is not emanating from prior policies that happen to influence current CSR scores.[12]

3.3. Connection type

The literature suggests that the characteristics of management play an important role in firm policy, for which CSR is no different. Davidson et al. (2019) show that CEO-fixed effects explain over half of the variation in a firm's CSR score, whereas firm-fixed effects explain less than one-quarter. Many studies examine the aspects of a CEO's background which drive their CSR strategies. Borghesi et al. (2014) find that female CEOs have more socially responsible corporate practices and have higher CSR scores, while older CEOs exhibit the opposite effect. Hedge and Mishra (2019) find that married CEOs exhibit values aimed at enhancing the combination of financial and social returns, leading to pro-CSR managing. Di Giuli and Kostovetsky (2014) show that having a Democrat leaning CEO is associated with higher firm CSR scores.

Socially responsible decision-making can sometimes make its way past a board's purview. For example, institutional investors can drive environmental and social performance, even if the board has been historically underinvesting in those areas. Powerful CEOs can similarly leverage their influence to effect critical firm decisions such as technology policy (Lefebvre et al., 1997), wage and incentive structure (Morse et al., 2011), and accounting decisions (Dejong and Ling, 2013). Ultimately, influential CEOs decisions will affect firm financial performance (Adams et al., 2005). Due to CEOs being integral to a firms' corpo-

[12]In Appendix 2, we conduct analysis using first difference transformations of all control variables, along with transformation of the CSR variables, which yields consistent findings.

rate strategy and the complex nature of CEO-board dynamics, it is also plausible that a sufficiently powerful CEO could circumvent a board, and derive advice directly from their social circle, regarding these decisions as well.

We test whether intra-firm CSR transmission is stronger for firm connections which include a CEO. For this analysis, we create three subsamples of our firms: (1) firm linkages which include connections originating from a CEO in the focal firm, (2) firm linkages which originating from a CEO in the connecting firm, and (3) firm linkages which include a direct CEO to CEO connection. Of the firm-to-firm connections, 82.2% fall under the first category, 87.2% the second, and 75.3% the latter. We then employ our original empirical model from Equation 1, reporting results in Table 5. Our results are statistically and economically similar to those of Table 2. Positive relations are found for all connected firm subsamples, with the exception of community CSR. The largest spillovers are for direct CEO-to-CEO connections.

In the prior analyses we explore the CSR policy spillovers stemming from a firm's social network connections. However, not all firms are equally connected. Social media sites such as Twitter, Facebook, and Instagram, with more connections and reach (i.e., followers, friends, etc.), are better at disseminating information and more influential (Al Guindy, 2022). Prior research has also shows that firms with larger networks innovate more (Chang and Wu, 2021), have better financial reporting (Intintoli et al., 2018), and exhibit more similar capital investment levels to their peers (Fracassi, 2017). Our next question is whether firms with more social connections are more influenced by their peers.

There are two primary aspects of social network strength, the number of total connections and the quality of those connections. We address the former facet first by creating a dummy variable for whether a firm's number of connections is above the median (*High*) and interacting it with our connected firm CSR portfolio (*Network Connected*High*) to test whether firms with more connections exhibit greater spillovers. We present these results in

Table 6. We find that the coefficients on *Network Connected*High* are positive and statistically significant. The exception is for Diversity. As such, we conclude that large numbers of connections provide greater spillover effects. [13]

Stemming from the seminal work of Freeman (1979) and early psychology authors, researchers have begun studying the quality of social connectedness through centrality variables. A wide array of finance research has picked up on network centrality. Information dissemination stemming from highly central firms can be positive (Larcker et al., 2013; Chuluun et al., 2017). CSR policies for highly connected firms, can also have value-enhancing effects through social performance (Amin et al., 2020). There may also be a negative side to centrality if high quality social connections are leveraged at the expense of the firm. For example, El-Khatib et al. (2015) find that CEOs with high centrality conduct more M&A deals that have lower acquirer abnormal returns, while at the same time increasing their own compensation. Miranda-Lopez et al. (2019) come to similar conclusions about CEO centrality, showing that firms with high centrality CEOs have lower cash holdings. Managers may also over-invest in CSR policies if it gains them more social capital or and private benefits (Barnea and Rubin, 2010; Masulis and Reza, 2015).

Following the prior centrality literature, we utilize four primary centrality variables of weighted degree, eigenvector, closeness, and betweenness, with each capturing a particular network dynamic. Following Shahgolian et al. (2015), centrality measures are calculated at the board (or firm) level, with each board representing a node (or vertices). Therefore, each board-node's network is a sum of its total social connections, and the subsequent connections to other firms.

The individual *Weighted Degree* represents a node's strength and is calculated as the sum of weights assigned to the node's direct connections. A tuning parameter is then used

[13]In unreported results, we observe these findings are robust to specifying the *High* variable using the upper quartile of total connections.

to set the relative importance of the number of ties compared to tie weights.[14] *Eigenvector* incorporates both how many links a node has, as well as the degree of the nodes to which it is connected. Eigenvector weights the links according to their eigenvector values, as opposed to equally weighting each link. Therefore, *Eigenvector* considers how well connected the firms connected to the focal firm are. The more influential a firm's links, the more influential it will be as well. *Closeness* measures the distance between each node and the other nodes within the network. The shorter the number of pathways between the node and others, the easier it is for information to transfer between them. *Closeness* can be viewed as a measure of influence rather than information flow, with high values indicating that a firm is readily able to independently access other firms without going through social intermediaries. *Betweenness* measures how often a firm lies between the paths of other firms within the network. In other words, it measures the firm's position within the network between other firms and, therefore, how much of an intermediary role the firm plays within the entire networks' information transmission. A high *Betweenness* score indicates a firm collects large amounts of information and is a key facilitator of information flows.

Similar to our prior analysis, and for each centrality measure, we create a dummy variable equal to 1 for firms than the median (High).[15] We then interact this dummy with our *Connected* firm portfolio. Table 7 reports that all above-median centrality interactions exhibit a positive effect that is significant at the 1% level. Therefore, the more important a firm is within the social network the more policy spillovers it experiences. The largest effect is found for *Closeness*, suggesting that the most important aspect of centrality for CSR policy flows is having easy social access to other firms within the network. Such results concur not only with our previous analysis, but also the positive CSR centrality effects found by Amin et al. (2020) and Nandy et al. (2020).

[14] For additional description of the weighting procedure see Opsahl et al. (2010).

[15] Our results are robust to specifying *High* as the upper quartile of each centrality measure.

3.4. Changes to networks

CEOs are also heavily influenced by the policies of the peers in their network (Fracassi and Tate, 2012; Nguyen, 2012; Fracassi, 2017). We further examine whether our results are driven primarily driven by the connections of an incumbent CEO, those of the board, or persistent policy inertia. A common strategy to parse out CEO effects from the firm dynamics is to focus on changes surrounding CEO succession. We construct our sample as follows by identifying each year that a firm's CEO changes in BoardEx. We then create a separate observation for each individual CEO-firm combination and sort them by historical order. The policy of each preceding CEO is then tested against changes that occur with the succeeding (Post) CEO. This design allows us to examine whether firm CSR policy changes when a CEO succession, and corresponding change to the firm's social network, occurs. Additionally, CEO turnover may create changes to the firm's network as the old CEO's connections leave the firm and the new CEO brings in new connects.

We report our results in Table 8. The coefficients on Post provide mixed evidence on changes to CSR policy following a CEO succession. Only Diversity (positive) and Environmental (negative) show any change following a new CEO. One potential explanation is that new CEOs are not hired for their total CSR impact, but instead to focus on the specific areas of increasing diversity and creating new projects, which would conceivably result in a lower environmental score. However, the positive coefficients of *Network Connected*Post*, for *Total CSR* and nearly all the component scores, suggest that the positive association of a focal firm's CSR, to that of connecting firms, significantly increases following a succession event. Therefore, the combined effect of a new CEOs and their network, is related to stronger CSR scores overall.

One limitation of our previous analysis is that CEO successions, including voluntary changes, are not necessarily an exogenous shock. To further control for possible endogeneity, we provide evidence from two quasi-natural experiments characterized by exogenous social network shocks: (1) the death of a focal firm board member (Carter et al., 2023; Fracassi & Tate, 2012; Intintoli et al., 2018) and (2) a forced CEO turnover (Farrell & Whidbee, 2002; Parrino et al., 2003). The events not only alter the social network of the board, but also may affect a firm's CEO policy (Amin et al. 2020).

Board member death events are collected from BoardEx, while forced CEO turnover events are from an open-source dataset provided by Gentry et al. (2021). In our sample, there are 1,088 board member deaths across 833 (29.2%) firms, whereas there are 384 forced CEO turnovers across 277 (13.4%) firms. We define Post as a dummy variable equal to one for the three years following the event. Using a similar post-methodology to prior analyses, we then examine our findings for Total firm CSR. We present the results in Table 9. The Connected coefficient results are both positive and significant, while their magnitudes are comparable to prior analyses. Neither board member death nor forced CEO turnover shows any significant effect on firm CSR. However, the interaction of *Connected*Post* is negative and significant across both specifications. This suggests that a board death event decreases the positive relation of a focal firm's CSR to its social network. However, the similar effect of a forced CEO turnover only occurs within a three-year event window. These results follow prior literature, which finds a positive relation between exogenous deaths of connected directors and idiosyncratic CSR policy (Fracassi, 2017; Alves, 2021).

3.5. Complementary peer effects

A firm's peer group can take many forms, and each group has its own network effects. We can think of a firm's policy as being influenced by multiple networks, similar to a secondary school student. A student may interact with one peer group while in class, another peer group during after-school sports. In some cases, they have little choice in choosing these peers. However, they can choose their social peers, whom they may sit with during lunch or associate with outside of school. Similarly, a firm may have relatively less control over its regional and industry peer groups than the board members' ability to choose whom to share information with on a social level. Prior works find strong evidence of positive CSR policy spillovers from both regional peers (Li and Wang, 2022; Nofsinger et al., 2022) and industry peers (Nofsinger et al. 2019). Our next examination is two-fold, whether information transmission from a social network is stronger or weaker than region and industry peer transmission and whether the contemporaneous effects are complementary or reductive.

Our analysis requires separating a firms' peers into network peer effects and an additional level of regional/industry effects. We first re-categorize each firms' peers across these two dimensions, resulting in three peer groupings similar to previous research (Dougal et al. 2015; Li & Wang, 2022; Nofsinger et al., 2022): Same State and Network Connected, Same State and Not Network Connected, Different State and Network Connected.[16] We then utilize the following empirical model:

$$\begin{aligned} CSR_{j,t} = \alpha + \beta_1 CSR^{s,-c}_{-j,t} + \beta_2 CSR^{-s,c}_{-j,t} + \beta_3 CSR^{s,c}_{-j,t} + \beta_4 X_{j,t} \\ + \beta_5 Z_{j,t} + StateFE_t + YearFE_t + FirmFE_t + \varepsilon_t \end{aligned} \tag{2}$$

Where $CSR^{s,-c}_{-j,t}$ (i.e., Same State Not Network Connected) represents the equal-weighted CSR portfolio of all non-connected firms in the same industry i, in year t. $CSR^{-s,c}_{-j,t}$ (i.e., Different State Network Connected) represents the equal-weighted CSR portfolio of all connected firms not in the same industry i, in year t. $CSR^{s,c}_{-j,t}$ (i.e., Same State Network Connected) represents the equal-weighted CSR portfolio of all connected firms in the same state i, excluding firm j, in year t. Similar to Equation (1), X is the set of board controls and

[16] Alternatively, Li and Wang (2022) define spatial peer groups by nine North American regions. It is conceivable that a firm on the edge of a region could headquarter in a city closer to a firm in a nearby region, but be categorized as not in the same peer group. Therefore, we believe this to be too broad for our analysis. Nonetheless, our results are robust to the nine-realm specification rather than state level.

Z is the set of firm controls. Following our prior analysis, state-, year, and firm-level fixed effects are included. Lastly, ε denotes the error term which we present as robust standard errors. Our main coefficient of interest, β_1, captures the CSR policy behavior of firms in the same state and connected to the focal firm, while β_2 and β_3 capture the CSR sensitivity of a firm's CSR policy to state and network peers, respectively. As we have already controlled for state, via β_2, and social network effects, via β_3, β_1 can be interpreted as the interaction between industry and social network effects (Dougal et al., 2015).

Table 10 presents the results corresponding to equation (2). As expected, geographically close firms have similar CSR scores even if they do not share a social network, particularly when it comes to diversity, human rights, and environmental CSR. Furthermore, due to the interaction effect of the same state network connected variable the local social network effect on total CSR is greater than 50% ((0.027+0.051)/0.152) of the pure geographic effect. Moreover, the social network effect is greater than the geographic spillover for community, employee, and human rights CSR and has a near equal effect for diversity and environmental. Overall, this suggests that social network peer effects have a complementary transmission mechanism to state peer group effects. Interestingly, social network effects, generally, have more impact on firms outside of their own state. CSR policies have an inherent political context (Di Giuli and Kostovetsky, 2014; Borghesi et al., 2014). Li and Wang (2022) show that firms within a state exhibit herding effects, and ostensibly similar political and policy outlooks. Therefore, it is sensible that any social network spillovers would have greater effects on firms that begin with different policy viewpoints, and thus are more likely to be located elsewhere.

We also conduct a similar analysis on the interaction of industry and network peer effects. We re-categorize each firms' peers across the dimensions of social connection and the industry the firm operates in. This results in three peer groupings: Same Industry and Network Connected, Same Industry and Not Network Connected, Different Industry and

Network Connected.[17] We then utilize the following empirical model:

$$CSR_{j,t} = \alpha + \beta_1 CSR^{i,-c}_{-j,t} + \beta_2 CSR^{-i,c}_{-j,t} + \beta_3 CSR^{i,c}_{-j,t} + \beta_4 X_{j,t} + \beta_5 Z_{j,t} + StateFE_t + YearFE_t + FirmFE_t + \varepsilon_t \tag{3}$$

Where $CSR^{i,-c}_{-j,t}$ (i.e., Same Industry Not Network Connected) represents the equal-weighted CSR portfolio of all non-connected firms in the same industry i, in year t. $CSR^{-i,c}_{-j,t}$ (i.e., Different Industry Network Connected) represents the equal-weighted CSR portfolio of all connected firms not in the same industry i, in year t. $CSR^{i,c}_{-j,t}$ (i.e., Same Industry Network Connected) represents the equal-weighted CSR portfolio of all connected firms in the same industry i, excluding firm j, in year t.

We report the results from our industry and social network analysis in Table 11. As expected, being in the same industry has a large spillover effect on CSR policy even with non-connected firms (Nofsinger, et al. 2022). For same-industry firms, the social network effect leads to and, approximately, 86% increase in the CSR spillover. However, the interaction effect of the same state network connected variable the local social network effect on total CSR is difficult to parse. Moreover, the social network effect is greater than the geographic spillover for community, employee, and human rights CSR and has a near equal effect for diversity and environmental. However, we find social networks stemming from different industries only have a significant and positive relation for employee, human rights, and environmental CSR. In our sample, we find firms to have far more connections within their own industry, 242 on average, than to firms outside of their own industry, 74 on average. Considering the evidence that numbers of network connections tend to drive CSR policy similarities (Amin et al., 2020; Alves, 2021; Li and Wang, 2022), it may be that there is simply not enough network strength to lead to a meaningful impact across total CSR and

[17] This methodology follows Dougal et al. (2015), Nofsinger et al. (2019), and Li and Wang (2022), who also form peer groups across two dimensions.

all the components. However, we do find a positive different-industry social network effect for employee, environmental, and human rights scores. Nonetheless, our overall findings suggest that social networks between firms in the same industry have the greatest spillover on CSR policy.

4. Conclusion

Recently, there has been increasing pressure for companies to become more socially responsible. We examine whether CSR policies spillover between firms through the social networks of board members, CEOs, and top executives. We find strong evidence of positive policy transmission between socially connected firms. Further, this effect is robust across *Total CSR* as well as the individual components of the CSR composite. This result is robust to looking at CSR in levels and taking the first difference to look at the year over year change in CSR scores.

We further document that not all social connections are created equal. We find an increased positive effect when firms are connected by a CEOs network, as opposed to only by board member's networks. We also find the strongest CSR spillovers occur when two CEOs are directly network connected. We split our sample into firms with high (above median) and low (below median) number of social connections. Firms with high network connections exhibit stronger CSR policy herding with their peers. To alternatively examine network quality, we split our sample into high and low groups according to each of the commonly used centrality variables. Again, our results suggest that firms with high centrality positions in a network display more CSR transmission. Further, we find *Closeness* to be the most impactful measure, suggesting that firm CSR information flows best between social connections that are either directly connected or have fewer connections to travel between.

To examine shocks to the firm's social network we investigate whether the policy spillovers effects continue after a CEO sucession. While our results suggest that CSR policy spillovers are primarily connected to the firm, we find that the relationship between peer firms becomes stronger with a new CEO.

Clearly, social networks are not the only channel for inter-firm information diffusion. Prior research shows policies spread through many types of networks, including spatial, industry, and similar firm peer-networks. Our results do not disagree that CSR spillovers stem from many these channels. Specifically, we test for industry- and geographic-network effects, which we find to be larger than the social network effect. Therefore, we find that social networks play a concurrent and complementary role.

Overall, our findings provide additional evidence that executive social connectedness is an important determinant of firm policy. We explore only a few potential dimensions of the relationship between social connection and firm CSR policy, leaving further inquiries to future research.

APPENDIX A: Tables

Table 1: Summary Statistics

Variables	Mean	SD	Min	p25	Median	p75	Max
Panel A: Focal Firm CSR							
Total	-0.031	0.487	-2.983	-0.333	0	0.125	3.5
Human Rights	0	0.087	-0.5	0	0	0	1
Environmental	0.013	0.097	-0.714	0	0	0	0.833
Diversity	-0.048	0.319	-1	-0.333	0	0.042	1
Community	0.007	0.176	-1	0	0	0	1
Employee	-0.003	0.152	-1	0	0	0	0.889
Panel B: Link Types							
Number of Connected Firms	18.409	19.483	0	4.2	11.9	26.5	142.7
Focal Firm CEO	0.822	0.383	0	1	1	1	1
Connected Firm CEO	0.872	0.334	0	1	1	1	1
CEO to CEO	0.753	0.431	0	1	1	1	1
Panel C: Board Controls							
Network Size	1638	2081	1	318	834	1994	8438
CEO Duality	0.514	0.500	0	0	1	1	1
CEO Ivy League	0.137	0.344	0	0	0	0	1
CEO Age	54.792	7.598	24	50	55	60	86
Panel D: Firm Controls							
Size	7.488	1.727	3.759	6.223	7.404	8.592	12.182
Leverage	0.218	0.204	0	0.039	0.182	0.336	0.908
Tangibility	0.212	0.222	0.001	0.040	0.128	0.316	0.878
Cash	0.120	0.136	0.001	0.023	0.071	0.167	0.709
Tobin's Q	2.030	1.423	0.787	1.135	1.530	2.322	9.099
ROA	0.023	0.118	-0.511	0.007	0.035	0.076	0.277
Dividend	0.012	0.023	0	0	0.002	0.015	0.148
Institutional Ownership	0.632	0.325	0	0.445	0.721	0.877	3.847

Table 2: Connected Firm Total CSR Spillover

This table presents estimates of how the Total CSR of board-connected firms are related to the Total CSR score of the focal firm. Sample includes the years 2000 to 2018. State, firm, and year fixed effects are included in all models. Robust t-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% level is shown by ***, **, and *, respectively.

	Total CSR	Total CSR	Total CSR
Network Connected	0.086***	0.084***	0.084***
	(3.23)	(3.16)	(3.14)
Size		0.017**	0.017**
		(2.41)	(2.37)
Leverage		0.030	0.031
		(1.26)	(1.30)
Tangibility		-0.044	-0.044
		(-0.97)	(-0.97)
Cash		0.018	0.018
		(0.58)	(0.58)
Tobin's Q		-0.012***	-0.012***
		(-4.29)	(-4.28)
ROA		0.038	0.038
		(1.24)	(1.27)
Dividend		0.107	0.106
		(0.70)	(0.70)
Institutional Ownership		0.010	0.009
		(0.80)	(0.76)
Network Size			0.001
			(0.32)
CEO Duality			0.008
			(1.03)
CEO Ivy League			-0.008
			(-0.70)
CEO Age			-0.001*
			(-1.92)
Constant	-0.054***	-0.154***	-0.110*
	(-14.19)	(-2.84)	(-1.74)
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	21,695	21,695	21,695
R-squared	0.593	0.594	0.594

Table 3: Individual CSR Component Spillover

This table presents estimates for how the individual CSR components for connected firms are related to the component scores of the focal firm. Sample includes the years 2000 to 2018. State, firm, and year fixed effects are included in all models. Robust t-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% level is shown by ***, **, and *, respectively.

	Community	Employee	Diversity	Human Rights	Environmental
Network Connected	0.006	0.166***	0.148***	0.229***	0.252***
	(0.20)	(5.33)	(5.09)	(7.41)	(9.10)
Size	-0.008**	-0.004	0.036***	-0.002	-0.006***
	(-2.50)	(-1.45)	(7.87)	(-1.11)	(-3.65)
Leverage	0.028***	0.011	-0.022	0.003	0.011**
	(2.69)	(1.27)	(-1.42)	(0.53)	(2.04)
Tangibility	-0.018	-0.000	-0.031	0.015	-0.009
	(-0.89)	(-0.02)	(-1.05)	(1.47)	(-0.90)
Cash	0.011	-0.010	0.007	0.009	0.002
	(0.83)	(-0.89)	(0.33)	(1.34)	(0.25)
Tobin's Q	-0.005***	-0.002**	-0.003	-0.001	-0.001
	(-3.88)	(-2.37)	(-1.47)	(-1.56)	(-1.63)
ROA	-0.008	0.046***	0.018	-0.017**	0.000
	(-0.59)	(4.22)	(0.92)	(-2.49)	(0.01)
Dividend	-0.027	0.149***	0.054	-0.072**	0.004
	(-0.41)	(2.72)	(0.55)	(-2.10)	(0.12)
Institutional Ownership	-0.005	-0.010**	0.020**	-0.007**	0.011***
	(-0.99)	(-2.12)	(2.46)	(-2.40)	(3.94)
Network Size	-0.002	-0.003**	0.013***	-0.001	0.006***
	(-1.05)	(-2.03)	(4.39)	(-0.85)	(5.72)
CEO Duality	-0.003	-0.005*	0.012**	0.000	0.004**
	(-0.94)	(-1.83)	(2.38)	(0.08)	(2.23)
CEO Ivy League	-0.005	0.003	-0.010	-0.001	0.005*
	(-1.00)	(0.77)	(-1.25)	(-0.51)	(1.70)
CEO Age	-0.000	0.000	-0.001	-0.000	-0.000
	(-1.60)	(0.44)	(-1.50)	(-0.88)	(-0.80)
Constant	0.111***	0.042*	-0.379***	0.026*	0.089***
	(3.96)	(1.83)	(-9.22)	(1.80)	(6.00)
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	21,695	21,695	21,695	21,695	21,695
R-squared	0.329	0.501	0.610	0.370	0.469

Table 4: Network Peer Effects of ΔCSR

This table presents estimates of how the changes in CSR component scores of connected firms are related to changes in the total and component CSR scores of the focal firm. Sample includes the years 2000 to 2018. State, firm, and year fixed effects are included in all models. Robust t-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% level is shown by ***, **, and *, respectively.

	ΔTotal	ΔCommunity	ΔEmployee	ΔDiversity	ΔHuman Rights	ΔEnvironmental
ΔNetwork Connected	0.095***	-0.019	0.098***	0.160***	0.031	0.149***
	(3.54)	(-0.57)	(3.41)	(5.28)	(1.02)	(5.91)
Size	0.008	0.005	-0.006**	0.003	0.004**	0.002
	(0.95)	(1.21)	(-2.10)	(0.55)	(2.14)	(1.28)
Leverage	-0.015	0.011	-0.000	-0.020	-0.002	-0.004
	(-0.53)	(0.86)	(-0.01)	(-1.05)	(-0.37)	(-0.65)
Tangibility	0.060	0.052**	-0.013	0.003	-0.001	0.018
	(1.10)	(2.03)	(-0.69)	(0.08)	(-0.08)	(1.56)
Cash	-0.023	0.003	-0.009	-0.009	-0.006	-0.002
	(-0.61)	(0.15)	(-0.71)	(-0.35)	(-0.75)	(-0.26)
Tobin's Q	0.000	-0.001	0.002	-0.001	0.000	0.001
	(0.03)	(-0.78)	(1.26)	(-0.58)	(0.36)	(1.29)
ROA	0.064*	0.020	0.032**	0.016	-0.004	0.001
	(1.74)	(1.15)	(2.56)	(0.64)	(-0.48)	(0.11)
Dividend	-0.288	-0.071	-0.129**	-0.129	0.025	0.017
	(-1.51)	(-0.80)	(-2.01)	(-1.00)	(0.64)	(0.41)
Institutional Ownership	-0.002	-0.006	0.007	-0.010	0.002	0.005
	(-0.15)	(-0.92)	(1.40)	(-0.99)	(0.64)	(1.59)
Network Size	0.007	0.001	0.000	0.007*	-0.001	-0.001
	(1.32)	(0.55)	(0.26)	(1.92)	(-0.97)	(-0.87)
CEO Duality	0.003	0.001	0.003	0.004	-0.004**	-0.001
	(0.33)	(0.21)	(0.89)	(0.61)	(-1.99)	(-0.44)
CEO Ivy League	-0.007	-0.009	0.001	-0.003	0.003	0.001
	(-0.48)	(-1.35)	(0.29)	(-0.28)	(0.98)	(0.18)
CEO Age	-0.000	-0.000	-0.000	-0.000	0.000	0.000
	(-0.60)	(-0.84)	(-0.68)	(-0.37)	(0.90)	(0.46)
Constant	-0.060	-0.037	0.050*	-0.026	-0.025	-0.021
	(-0.76)	(-1.00)	(1.89)	(-0.49)	(-1.53)	(-1.25)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,367	18,367	18,367	18,367	18,367	18,367
R-squared	0.145	0.052	0.086	0.267	0.050	0.105

Table 5: CSR and CEO Link Type

This table presents estimates of how individual CSR components of board connected firms are related to the component scores of the focal firm, when the connection includes a CEO in the focal firm, a CEO in the connected firm, and a CEO in both firms. Sample includes the years 2000 to 2018. State, firm, and year fixed effects are included in all models. Robust t-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% level is shown by ***, **, and *, respectively.

	Total			Community			Employee		
	Focal CEO	Linked CEO	CEO to CEO	Focal CEO	Linked CEO	CEO to CEO	Focal CEO	Linked CEO	CEO to CEO
Network	0.106***	0.105***	0.139***	0.010	0.002	0.004	0.253***	0.216***	0.303***
Connected	(2.95)	(3.10)	(3.43)	(0.22)	(0.05)	(0.08)	(5.79)	(5.37)	(6.12)
Constant	-0.094	-0.124*	-0.127	0.114***	0.107***	0.113***	0.058**	0.049*	0.048
	(-1.26)	(-1.76)	(-1.56)	(3.38)	(3.38)	(3.02)	(2.16)	(1.92)	(1.63)
Board Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,881	19,951	17,475	18,881	19,951	17,475	18,881	19,951	17,475
R-squared	0.590	0.593	0.588	0.330	0.333	0.334	0.505	0.504	0.505
	Diversity			Human Rights			Environmental		
	Focal CEO	Linked CEO	CEO to CEO	Focal CEO	Linked CEO	CEO to CEO	Focal CEO	Linked CEO	CEO to CEO
Network	0.228***	0.181***	0.279***	0.282***	0.374***	0.363***	0.319***	0.294***	0.357***
Connected	(5.99)	(5.01)	(6.60)	(6.95)	(9.61)	(7.61)	(8.30)	(8.23)	(8.21)
Constant	-0.403***	-0.405***	-0.419***	0.036**	0.026*	0.034*	0.101***	0.092***	0.098***
	(-8.49)	(-8.96)	(-8.21)	(2.19)	(1.66)	(1.91)	(5.67)	(5.52)	(5.01)
Board Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,881	19,951	17,475	18,881	19,951	17,475	18,881	19,951	17,475
R-squared	0.604	0.608	0.602	0.368	0.370	0.367	0.476	0.473	0.481

Table 6: CSR Spillover and Number of Network Connections

This table presents estimates of how the CSR component scores of connected firms are related to the component score of the focal firms with a high number of total network connections. High is a categorical variable equaling 1 if the firms total board network connections are equal to or above the median, and 0 otherwise. Sample includes the years 2000 to 2018. State, firm, and year fixed effects are included in all models. Robust t-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% level is shown by ***, **, and *, respectively.

	Total	Community	Employee	Diversity	Human Rights	Environmental
Network Connected	0.238***	0.459***	0.382***	-0.147***	0.348***	0.881***
* High	(10.00)	(13.26)	(13.49)	(-5.67)	(7.63)	(37.14)
Connected	0.053**	-0.075**	0.123***	0.175***	0.172***	0.046*
	(1.99)	(-2.32)	(3.94)	(6.02)	(5.44)	(1.69)
High	-0.039***	-0.021***	-0.014***	0.028***	-0.004**	-0.032***
	(-4.57)	(-5.66)	(-4.86)	(5.20)	(-2.27)	(-16.85)
Size	0.021***	-0.006**	-0.002	0.036***	-0.001	-0.006***
	(3.06)	(-2.11)	(-0.80)	(8.04)	(-0.62)	(-3.95)
Leverage	0.020	0.027**	0.005	-0.020	0.001	0.010*
	(0.85)	(2.58)	(0.62)	(-1.33)	(0.18)	(1.85)
Tangibility	-0.026	-0.015	0.010	-0.033	0.018*	-0.003
	(-0.57)	(-0.74)	(0.60)	(-1.11)	(1.78)	(-0.26)
Cash	0.020	0.011	-0.009	0.005	0.009	-0.002
	(0.65)	(0.85)	(-0.78)	(0.24)	(1.30)	(-0.28)
Tobin's Q	-0.012***	-0.004***	-0.002**	-0.003	-0.001	-0.001**
	(-4.08)	(-3.50)	(-1.97)	(-1.58)	(-1.40)	(-1.99)
ROA	0.031	-0.009	0.043***	0.016	-0.018***	0.000
	(1.01)	(-0.71)	(4.00)	(0.84)	(-2.63)	(0.01)
Dividend	0.089	-0.027	0.136**	0.064	-0.076**	0.005
	(0.59)	(-0.40)	(2.49)	(0.64)	(-2.23)	(0.14)
Institutional Ownership	0.015	-0.005	-0.007	0.019**	-0.006**	0.012***
	(1.17)	(-0.84)	(-1.61)	(2.35)	(-2.24)	(4.22)
CEO Duality	0.006	-0.004	-0.005**	0.012**	-0.000	0.003
	(0.75)	(-1.13)	(-2.00)	(2.50)	(-0.25)	(1.58)
CEO Ivy League	-0.007	-0.005	0.004	-0.010	-0.001	0.004
	(-0.58)	(-0.97)	(0.84)	(-1.28)	(-0.46)	(1.47)
CEO Age	-0.001	-0.000	0.000	-0.001	-0.000	0.000
	(-1.63)	(-1.51)	(0.65)	(-1.60)	(-0.44)	(0.13)
Constant	-0.144**	0.090***	0.005	-0.308***	0.012	0.053***
	(-2.40)	(3.41)	(0.24)	(-7.94)	(0.92)	(3.92)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,695	21,695	21,695	21,695	21,695	21,695
R-squared	0.596	0.336	0.505	0.611	0.372	0.504

Table 7: Total CSR Spillover and Centrality Measures

This table presents estimates of how the total CSR scores of connected firms are related to the total CSR score of the focal firms with a high levels of network centrality. High is a categorical variable equaling 1 if the focal firms' centrality score is equal to or above the median, and 0 otherwise. Sample includes the years 2000 to 2018. State, firm, and year fixed effects are included in all models. Robust t-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% level is shown by ***, **, and *, respectively.

	Degree	Eigenvector	Closeness	Betweenness
Network Connected	0.082***	0.151***	0.291***	0.121***
* High	(3.60)	(6.84)	(11.39)	(5.96)
Connected	0.066**	0.055**	0.360***	0.052*
	(2.43)	(2.02)	(10.02)	(1.89)
High	-0.010	-0.015*	-0.016*	-0.008
	(-1.20)	(-1.81)	(-1.94)	(-1.00)
Size	0.008	0.008	0.007	0.008
	(1.01)	(1.06)	(0.91)	(0.99)
Leverage	-0.008	-0.006	-0.008	-0.007
	(-0.68)	(-0.55)	(-0.69)	(-0.63)
Tangibility	-0.001*	-0.001*	-0.001*	-0.001**
	(-1.91)	(-1.88)	(-1.88)	(-1.98)
Cash	0.018***	0.019***	0.018**	0.018***
	(2.59)	(2.78)	(2.54)	(2.65)
Tobin's Q	0.028	0.023	0.020	0.026
	(1.18)	(0.96)	(0.87)	(1.11)
ROA	-0.043	-0.034	-0.039	-0.041
	(-0.94)	(-0.75)	(-0.86)	(-0.92)
Dividend	0.017	0.017	0.015	0.017
	(0.55)	(0.55)	(0.48)	(0.55)
Institutional Ownership	-0.012***	-0.012***	-0.011***	-0.012***
	(-4.21)	(-4.19)	(-3.95)	(-4.24)
CEO Duality	0.036	0.034	0.033	0.037
	(1.18)	(1.12)	(1.09)	(1.22)
CEO Ivy League	0.108	0.099	0.112	0.115
	(0.71)	(0.66)	(0.74)	(0.76)
CEO Age	0.006	0.008	-0.003	0.007
	(0.49)	(0.65)	(-0.28)	(0.58)
Constant	-0.110*	-0.124**	-0.108*	-0.112*
	(-1.83)	(-2.07)	(-1.82)	(-1.87)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	21,695	21,695	21,695	21,695
R-squared	0.594	0.595	0.597	0.595

Table 8: CSR Policy Changes Surrounding CEO Succession

This table presents estimates of how the CSR component scores of board-connected firms are related to the component score of the focal firm, both before and after a change in the focal firms' incumbent CEO. Post is a categorical variable equaling 1 for a firms' incumbent CEO, and 0 for the prior CEO. Sample includes the years 2000 to 2018. State, firm, and year fixed effects are included in all models. Robust t-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% level is shown by ***, **, and *, respectively.

	Total	Community	Employee	Diversity	Human Rights	Environmental
Network Connected	0.031*	0.083***	0.056***	-0.007	0.065**	0.101***
*Post	(1.93)	(3.32)	(2.88)	(-0.40)	(2.16)	(5.28)
Connected	0.092***	-0.017	0.155***	0.185***	0.234***	0.241***
	(4.06)	(-0.63)	(5.81)	(7.51)	(8.48)	(9.87)
Post	0.001	-0.002	-0.002	0.005*	-0.000	-0.003**
	(0.15)	(-1.18)	(-1.19)	(1.83)	(-0.34)	(-2.23)
Size	0.015***	-0.009***	-0.007***	0.037***	-0.002	-0.004***
	(2.68)	(-3.48)	(-3.32)	(10.02)	(-1.30)	(-3.24)
Leverage	0.019	0.021**	0.009	-0.028**	0.003	0.014***
	(1.00)	(2.45)	(1.31)	(-2.31)	(0.77)	(3.18)
Tangibility	-0.012	-0.008	-0.006	-0.020	0.020**	0.003
	(-0.32)	(-0.45)	(-0.44)	(-0.85)	(2.42)	(0.29)
Cash	0.002	0.008	-0.019**	0.009	0.008	-0.003
	(0.08)	(0.70)	(-2.07)	(0.52)	(1.39)	(-0.52)
Tobin's Q	-0.014***	-0.006***	-0.002***	-0.002	-0.002***	-0.001*
	(-5.72)	(-5.67)	(-2.92)	(-1.26)	(-3.54)	(-1.89)
ROA	0.025	-0.007	0.043***	0.007	-0.014**	-0.004
	(1.01)	(-0.63)	(5.04)	(0.46)	(-2.53)	(-0.67)
Dividend	0.033	-0.060	0.138***	0.028	-0.065**	-0.006
	(0.27)	(-1.06)	(3.12)	(0.35)	(-2.30)	(-0.20)
Institutional	0.014	-0.004	-0.010***	0.020***	-0.006***	0.013***
Ownership	(1.37)	(-0.78)	(-2.78)	(3.10)	(-2.65)	(5.56)
Network Size	0.007**	-0.001	-0.002*	0.016***	-0.001	-0.006***
	(1.98)	(-0.31)	(-1.91)	(6.92)	(-1.08)	(-7.15)
CEO Duality	0.012**	-0.003	-0.003	0.013***	0.001	0.004***
	(1.97)	(-1.11)	(-1.59)	(3.47)	(0.52)	(2.74)
CEO Ivy League	-0.013	-0.007*	-0.001	-0.007	-0.000	0.003
	(-1.39)	(-1.73)	(-0.40)	(-1.22)	(-0.17)	(1.48)
CEO Age	-0.001**	-0.000**	0.000	-0.000*	-0.000	-0.000
	(-2.24)	(-2.06)	(0.40)	(-1.81)	(-0.64)	(-0.42)
Constant	-0.132**	0.115***	0.066***	-0.415***	0.024**	0.076***
	(-2.53)	(4.86)	(3.57)	(-12.31)	(2.03)	(6.20)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,215	34,215	34,215	34,215	34,215	34,215
R-squared	0.600	0.335	0.505	0.609	0.378	0.482

Table 9: CSR Policy Changes Surrounding Network Shocks

This table presents estimates of how the CSR component scores of board-connected firms are related to the component score of the focal firm, both before and after a network shock to the focal firm. Post is a categorical variable equaling 1 for three years after a board member death or CEO turnover event. Restricted samples only include firm-years pre- and post-event, whereas Unrestricted includes all firm years. Sample includes the years 2000 to 2018. State, firm, and year fixed effects are included in all models. Robust t-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% level is shown by ***, **, and *, respectively.

	Board Member Death	CEO Forced Turnover
Connected * Post	-0.014*	-0.014**
	(-1.77)	(-2.12)
Connected	0.162*	0.099***
	(1.90)	(2.70)
Post	0.016	0.000
	(0.89)	(0.11)
Size	0.011	0.022
	(0.76)	(1.04)
Leverage	-0.012	0.088
	(-0.53)	-1.12
Tangibility	0.139***	0.021
	(3.57)	(0.60)
Cash	-0.000	-0.002
	(-0.31)	(-0.88)
Tobin's Q	0.005	-0.020
	(0.18)	(-0.52)
ROA	-0.131	0.071
	(-1.47)	(0.61)
Dividend	-0.001	-0.634***
	(-0.01)	(-2.90)
Institutional Ownership	-0.082	-0.211
	(-0.73)	(-1.39)
Network Size	-0.027**	-0.017
	(-2.45)	(-1.04)
CEO Duality	0.043	0.154
	(0.42)	(1.30)
CEO Ivy League	-1.111*	0.132
	(-1.81)	(0.17)
CEO Age	0.105**	0.033
	(2.19)	(0.55)
Constant	-0.156	0.221
	(-0.63)	(0.62)
State FE	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	2,735	1,589
R-squared	0.694	0.714

Table 10: CSR Spillovers by State and Board Link

This table presents estimates for how the CSR scores for connected and same-state headquartered firms are related to the scores of the focal firm. Sample includes the years 2000 to 2018. State, firm, and year fixed effects are included in all models. Robust t-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% level is shown by ***, **, and *, respectively.

	Total	Community	Employee	Diversity	Human Rights	Environmental
Same State	0.152***	0.027	0.019	0.129***	0.103***	0.221***
Not Network Connected	(5.44)	(0.98)	(0.57)	(4.63)	(4.46)	(6.61)
Different State	0.051**	0.020	0.106***	0.109***	0.142***	0.167***
Network Connected	(2.14)	(0.75)	(3.90)	(4.22)	(5.19)	(6.86)
Same State	0.027**	0.059***	0.054***	0.008	0.027**	0.056***
Network Connected	(2.36)	(4.68)	(4.05)	(0.59)	(2.05)	(4.67)
Board Network Size	0.015**	-0.009***	-0.005*	0.038***	-0.002	-0.007***
	(2.19)	(-2.85)	(-1.93)	(8.48)	(-1.19)	(-4.52)
Size	0.023	0.027***	0.006	-0.022	0.003	0.012**
	(1.00)	(2.68)	(0.66)	(-1.44)	(0.64)	(2.14)
Leverage	-0.043	-0.015	-0.005	-0.029	0.014	-0.007
	(-0.98)	(-0.77)	(-0.30)	(-1.02)	(1.43)	(-0.71)
Tangibility	0.020	0.011	-0.011	0.008	0.010	0.002
	(0.67)	(0.81)	(-0.99)	(0.42)	(1.44)	(0.35)
Cash	-0.013***	-0.005***	-0.003***	-0.003	-0.001*	-0.001
	(-4.48)	(-4.05)	(-2.68)	(-1.39)	(-1.67)	(-1.60)
Tobin's Q	0.032	-0.008	0.047***	0.009	-0.018***	0.002
	(1.08)	(-0.62)	(4.37)	(0.49)	(-2.71)	(0.27)
ROA	0.149	-0.030	0.163***	0.097	-0.068**	-0.008
	(0.99)	(-0.45)	(3.01)	(1.00)	(-2.00)	(-0.23)
Dividend	0.005	-0.006	-0.010**	0.020**	-0.010***	0.011***
	(0.43)	(-1.16)	(-2.19)	(2.52)	(-3.53)	(3.76)
Institutional Ownership	0.003	-0.001	-0.002*	0.010***	-0.001	-0.003***
	(0.97)	(-0.76)	(-1.66)	(4.38)	(-1.25)	(-3.31)
CEO Duality	0.008	-0.003	-0.004	0.010**	0.001	0.004**
	(1.03)	(-0.93)	(-1.53)	(2.09)	(0.43)	(2.25)
CEO Ivy League	-0.009	-0.006	0.003	-0.010	-0.001	0.005*
	(-0.73)	(-1.07)	(0.70)	(-1.30)	(-0.49)	(1.70)
CEO Age	-0.001**	-0.000	0.000	-0.001	-0.000	-0.000
	(-2.10)	(-1.63)	(0.25)	(-1.49)	(-1.41)	(-0.79)
Constant	-0.113*	0.110***	0.046**	-0.387***	0.032**	0.079***
	(-1.86)	(4.11)	(2.10)	(-9.75)	(2.33)	(5.58)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,296	22,296	22,296	22,296	22,296	22,296
R-squared	0.594	0.335	0.503	0.610	0.366	0.473

Table 11: CSR Spillovers by Industry and Board Connection

This table presents estimates for how the CSR scores for connected and same-industry firms are related to the scores of the focal firm. Sample includes the years 2000 to 2018. State, firm, and year fixed effects are included in all models. Robust t-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% level is shown by ***, **, and *, respectively.

	Total	Community	Employee	Diversity	Human Rights	Environmental
Same Industry	0.137***	0.245***	0.333***	0.076*	0.616***	0.234***
Not Network Connected	(3.14)	(4.46)	(6.99)	(1.83)	(16.01)	(6.10)
Different Industry	0.004	0.018	0.076***	0.008	0.106***	0.167***
Network Connected	(0.16)	(0.67)	(2.78)	(0.31)	(3.96)	(6.85)
Same Industry	0.118***	0.070***	0.100***	0.144***	0.099***	0.109***
Network Connected	(8.41)	(4.31)	(7.02)	(9.29)	(5.80)	(8.37)
Size	0.015**	-0.009***	-0.004*	0.036***	-0.001	-0.007***
	(2.17)	(-3.00)	(-1.76)	(8.17)	(-0.58)	(-4.35)
Leverage	0.026	0.028***	0.005	-0.023	0.006	0.014**
	(1.11)	(2.72)	(0.63)	(-1.54)	(1.21)	(2.54)
Tangibility	-0.055	-0.015	-0.007	-0.035	0.015	-0.007
	(-1.24)	(-0.76)	(-0.46)	(-1.23)	(1.53)	(-0.67)
Cash	0.019	0.010	-0.012	0.008	0.010	0.001
	(0.63)	(0.77)	(-1.08)	(0.42)	(1.50)	(0.09)
Tobin's Q	-0.013***	-0.005***	-0.002**	-0.003	-0.001	-0.001**
	(-4.49)	(-4.07)	(-2.20)	(-1.64)	(-1.24)	(-1.96)
ROA	0.029	-0.008	0.043***	0.011	-0.015**	0.003
	(0.99)	(-0.63)	(4.05)	(0.56)	(-2.31)	(0.46)
Dividend	0.155	-0.039	0.151***	0.115	-0.056*	0.010
	(1.03)	(-0.59)	(2.79)	(1.18)	(-1.65)	(0.30)
Institutional Ownership	0.004	-0.006	-0.010**	0.020**	-0.009***	0.010***
	(0.36)	(-1.15)	(-2.19)	(2.54)	(-3.35)	(3.69)
Network Size	0.003	-0.001	-0.002	0.011***	-0.001	-0.003***
	(0.92)	(-0.76)	(-1.58)	(4.61)	(-1.06)	(-3.33)
CEO Duality	0.007	-0.003	-0.003	0.010**	0.001	0.004**
	(0.95)	(-0.88)	(-1.24)	(2.01)	(0.56)	(2.05)
CEO Ivy League	-0.008	-0.005	0.003	-0.010	-0.002	0.005*
	(-0.67)	(-0.95)	(0.61)	(-1.29)	(-0.71)	(1.81)
CEO Age	-0.001**	-0.000*	0.000	-0.001	-0.000	-0.000
	(-2.20)	(-1.82)	(0.00)	(-1.59)	(-1.42)	(-0.55)
Constant	-0.105*	0.116***	0.049**	-0.358***	0.023*	0.069***
	(-1.73)	(4.35)	(2.23)	(-8.99)	(1.68)	(4.87)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,296	22,296	22,296	22,296	22,296	22,296
R-squared	0.595	0.335	0.505	0.612	0.376	0.474

Appendix 1: Variable Descriptions

CSR Variables	Definition
Community	Community strengths - community concerns
Diversity	Diversity strengths - diversity concerns
Employee	Employee strengths – employee concerns
Environmental	Environmental strengths - environmental concerns
Human Rights	Human rights strengths – human rights concerns
Total	Sum of community, diversity, employee, environmental, and human rights scores
Board Controls	Definition
Network Size	Total of employment, education, and social network connections.
CEO Duality	Dummy variable equaling 1 if the CEO is a chairman of the board and 0 otherwise.
CEO Ivy League	Dummy variable equaling 1 if the CEO went to Brown, Columbia, Dartmouth, Harvar
CEO Age	CEO age in years.
Firm Controls	Definition
Size	Natural log of total assets.
Leverage	Total debt (DLTT + DLC) divided by total assets.
Tangibility	Property, plant, and equipment (PPENT) divided by total assets.
Cash	Cash balances divided by total assets.
Tobin's Q	Market Capitalization value of equity plus total debt, divided by total assets.
ROA	Net income divided by total assets.
Dividend	Total cash dividends divided by total assets.
Institutional Ownership	The percentage of the common share held by institutional ownership.

Appendix 2: Variable Descriptions

This table presents estimates of how the changes in CSR component scores of board-connected firms are related to changes in the component score of the focal firm. Sample includes the years 2000 to 2018. State, firm, and year fixed effects are included in all models. Robust t-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% level is shown by ***, **, and *, respectively.

	ΔTotal CSR	Δ Community	Δ Employee	Δ Diversity	ΔHuman Rights	Δ Environmental
ΔNetwork Connected	0.097***	-0.020	0.097***	0.160***	0.029	0.153***
	(3.60)	(-0.61)	(3.35)	(5.26)	(0.96)	(6.08)
ΔSize	-0.016	-0.006	0.002	-0.005	-0.000	-0.007**
	(-1.06)	(-0.81)	(0.33)	(-0.48)	(-0.09)	(-2.09)
ΔLeverage	-0.043	0.003	-0.017	-0.035	-0.001	0.009
	(-1.20)	(0.17)	(-1.45)	(-1.46)	(-0.20)	(1.14)
ΔTangibility	-0.041	0.004	-0.013	0.007	-0.008	-0.032**
	(-0.55)	(0.12)	(-0.50)	(0.13)	(-0.51)	(-1.98)
ΔCash	0.012	0.006	-0.003	0.019	-0.002	-0.007
	(0.35)	(0.36)	(-0.27)	(0.80)	(-0.31)	(-0.94)
ΔTobin's Q	-0.009***	-0.004**	0.000	-0.005**	-0.000	0.000
	(-2.60)	(-2.50)	(0.20)	(-2.12)	(-0.25)	(0.02)
ΔROA	0.011	0.013	0.013	-0.000	-0.015**	0.002
	(0.36)	(0.87)	(1.25)	(-0.01)	(-2.40)	(0.33)
ΔDividend	-0.099	-0.022	-0.047	-0.035	-0.006	0.011
	(-0.63)	(-0.31)	(-0.89)	(-0.33)	(-0.18)	(0.32)
ΔInstitutional Ownership	-0.013	-0.015*	0.004	-0.004	-0.003	0.005
	(-0.77)	(-1.84)	(0.67)	(-0.31)	(-0.91)	(1.26)
ΔNetwork Size	-0.001	-0.000	0.001	0.003	-0.002	-0.004***
	(-0.10)	(-0.02)	(0.58)	(0.73)	(-1.29)	(-2.89)
ΔCEO Duality	-0.004	-0.005	0.002	0.003	-0.003	-0.002
	(-0.42)	(-1.07)	(0.72)	(0.41)	(-1.45)	(-0.79)
ΔCEO Ivy League	-0.011	-0.013	-0.002	0.003	-0.003	0.005
	(-0.60)	(-1.51)	(-0.38)	(0.23)	(-0.87)	(1.21)
ΔCEO Age	0.002**	0.000	0.000	0.001	0.000*	0.000
	(2.17)	(1.28)	(0.58)	(1.12)	(1.89)	(1.22)
Constant	0.033***	0.002	0.005***	0.022***	0.001**	0.002***
	(10.87)	(1.19)	(5.64)	(10.88)	(2.19)	(3.17)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,367	18,367	18,367	18,367	18,367	18,367
R-squared	0.145	0.052	0.085	0.267	0.050	0.106

Appendix 3: CSR Spillovers: Using Industry-by-year Fixed Effects

This table presents estimates of how the changes in CSR component scores of connected firms are related to changes in the total and component CSR scores of the focal firm. Sample includes the years 2000 to 2018. State, firm, and year fixed effects are included in all models. Robust t-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% level is shown by ***, **, and *, respectively.

Panel A: Nominal CSR scores						
	Total	Community	Employee	Diversity	Human Rights	Environmental
Network	0.044*	-0.032	0.111***	0.076***	0.191***	0.199***
Connected	(1.79)	(-0.99)	(3.57)	(2.60)	(6.13)	(7.23)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Board Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,694	21,694	21,694	21,694	21,694	21,694
R-squared	0.604	0.342	0.515	0.620	0.385	0.489
Panel B: Change in CSR scores						
	Δ Total	Δ Community	Δ Employee	Δ Diversity	Δ Human Rights	Δ Environmental
Δ Network	0.061**	-0.047	0.073**	0.126***	0.008	0.133***
Connected	(2.34)	(-1.39)	(2.52)	(4.15)	(0.27)	(5.32)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Board Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,367	18,367	18,367	18,367	18,367	18,367
R-squared	0.161	0.066	0.104	0.280	0.065	0.129

References

Abowd, J. M. (1990). Does performance-based managerial compensation affect corporate performance? *ILR Review 43*(3), 52–S.

Agerton, M. (2017). Global LNG pricing terms and revisions: An empirical analysis. *The Energy Journal 38*(1).

Ahn, J.-Y. (2015). CEO pay for long-run performance: A dynamic view. *Journal of Applied Business Research 31*(1), 317–330.

Al Guindy, M. (2022). Fear and hope in financial social networks: Evidence from COVID-19. *Finance Research Letters 46*, 102271.

Alves, R. (2021). Social Networks and Corporate Social Responsibility. *Available at SSRN 3710868*.

Amin, A., L. Chourou, S. Kamal, M. Malik, and Y. Zhao (2020). It's who you know that counts: Board connectedness and CSR performance. *Journal of Corporate Finance 64*, 101662.

Antle, R. and A. Smith (1986). An empirical investigation of the relative performance evaluation of corporate executives. *Journal of Accounting Research*, 1–39.

Arano, K. and M. Velikova (2009). Price convergence in natural gas markets: city-gate and residential prices. *The Energy Journal 30*(3).

Arora, V. and Y. Cai (2014). US natural gas exports and their global impacts. *Applied Energy 120*, 95–103.

Aruga, K. (2016). The US shale gas revolution and its effect on international gas markets. *Journal of Unconventional Oil and Gas Resources 14*, 1–5.

Asche, F., A. Oglend, and P. Osmundsen (2012). Gas versus oil prices the impact of shale gas. *Energy Policy 47*, 117–124.

Aune, F. R., K. E. Rosendahl, and E. L. Sagen (2009). Globalisation of natural gas markets-effects on prices and trade patterns. *The Energy Journal 30*(Special Issue).

Avalos, R., T. Fitzgerald, and R. R. Rucker (2016). Measuring the effects of natural gas pipeline constraints on regional pricing and market integration. *Energy Economics 60*, 217–231.

Bachmeier, L. J. and J. M. Griffin (2006). Testing for market integration: crude oil, coal, and natural gas. *The Energy Journal 27*(2).

Banker, R. D., M. N. Darrough, R. Huang, and J. M. Plehn-Dujowich (2013). The relation between CEO compensation and past performance. *The Accounting Review 88*(1), 1–30.

Barnea, A. and A. Rubin (2010). Corporate social responsibility as a conflict between shareholders. *Journal of Business Ethics 97*, 71–86.

Bastianin, A., M. Galeotti, and M. Polo (2019). Convergence of European natural gas prices. *Energy Economics 81*, 793–811.

Basu, S., L.-S. Hwang, T. Mitsudome, and J. Weintrop (2007). Corporate governance, top executive compensation and firm performance in Japan. *Pacific-Basin Finance Journal 15*(1), 56–79.

Berri, D. J., M. A. Leeds, and P. von Allmen (2015). Salary determination in the presence of fixed revenues. *International Journal of Sport Finance 10*(1), 5.

Bertrand, M. and S. Mullainathan (2001). Are CEOs rewarded for luck? The ones without principals are. *The Quarterly Journal of Economics 116*(3), 901–932.

Bills, K. L., L. L. Lisic, and T. A. Seidel (2017). Do CEO succession and succession planning affect stakeholders' perceptions of financial reporting risk? Evidence from audit fees. *The Accounting Review 92*(4), 27–52.

Borghesi, R., J. F. Houston, and A. Naranjo. Corporate socially responsible investments: CEO altruism, reputation, and shareholder interests.

Boschen, J. F. and K. J. Smith (1995). You can pay me now and you can pay me later: The dynamic response of executive compensation to firm performance. *Journal of Business*, 577–608.

Bouchet, A., X. Song, and L. Sun (2022). CEO network centrality and corporate social responsibility. *Social Responsibility Journal 18*(1), 106–127.

Brick, I. E., O. Palmon, and J. K. Wald (2006). CEO compensation, director compensation, and firm performance: Evidence of cronyism? *Journal of Corporate Finance 12*(3), 403–423.

Brook, S. L. (2021). A Comparison of NCAA FBS Head Coaches Salary Determination From New and Modified Contracts. *Journal of Sports Economics 22*(5), 491–513.

Brown, S. P. and M. K. Yucel (2008). What drives natural gas prices? *The Energy Journal 29*(2).

Bugeja, M., Z. Matolcsy, and H. Spiropoulos (2017). The CEO pay slice: Managerial power or efficient contracting? Some indirect evidence. *Journal of Contemporary Accounting & Economics 13*(1), 69–87.

Bushman, R. M., R. J. Indjejikian, and A. Smith (1996). CEO compensation: The role of individual performance evaluation. *Journal of Accounting and Economics 21*(2), 161–193.

Cai, Y. and M. Sevilir (2012). Board connections and M&A transactions. *Journal of Financial Economics 103*(2), 327–349.

Cao, J., H. Liang, and X. Zhan (2019). Peer effects of corporate social responsibility. *Management Science 65*(12), 5487–5503.

Caporin, M. and F. Fontini (2017). The long-run oil–natural gas price relationship and the shale gas revolution. *Energy Economics 64*, 511–519.

Carter, D., C. Shank, and M. Wynter (2023). Do female directors decrease corporate misconduct? *Working Paper*.

Cavaco, S. and P. Crifo (2014). CSR and financial performance: Complementarity between environmental, social and business behaviours. *Applied Economics 46*(27), 3323–3338.

Chahine, S., Y. Fang, I. Hasan, and M. Mazboudi (2019). Entrenchment through corporate social responsibility: Evidence from CEO network centrality. *International Review of Financial Analysis 66*, 101347.

Chai, J., Z. Wei, Y. Hu, S. Su, and Z. G. Zhang (2019). Is China's natural gas market globally connected? *Energy Policy 132*, 940–949.

Chen, J., X. Liu, W. Song, and S. Zhou (2020). General managerial skills and corporate social responsibility. *Journal of Empirical Finance 55*, 43–59.

Chhaochharia, V. and Y. Grinstein (2009). CEO compensation and board structure. *The Journal of Finance 64*(1), 231–261.

Chuluun, T., A. Prevost, and A. Upadhyay (2017). Firm network structure and innovation. *Journal of Corporate Finance 44*, 193–214.

Colbert, G. J. and E. W. Eckard (2015). Do colleges get what they pay for? Evidence on football coach pay and team performance. *Journal of Sports Economics 16*(4), 335–352.

Cooper, M. J., H. Gulen, and P. R. Rau (2016). Performance for pay? The relation between CEO incentive compensation and future stock price performance. *The Relation Between CEO Incentive Compensation and Future Stock Price Performance (November 1, 2016)*.

Core, J. E., R. W. Holthausen, and D. F. Larcker (1999). Corporate governance, chief executive officer compensation, and firm performance. *Journal of Financial Economics 51*(3), 371–406.

Creti, A. and B. Villeneuve (2005). Longterm contracts and take-or-pay clauses in natural gas markets. *Energy Studies Review 13*(1).

Dah, M. A. and M. B. Frye (2017). Is board compensation excessive? *Journal of Corporate Finance 45*, 566–585.

Degeorge, F., J. Patel, and R. Zeckhauser (2005). *Earnings management to exceed thresholds*. Princeton University Press.

Dejong, D. and Z. Ling (2013). Managers: Their effects on accruals and firm policies. *Journal of Business Finance & Accounting 40*(1-2), 82–114.

del Valle, A., P. Dueñas, S. Wogrin, and J. Reneses (2017). A fundamental analysis on the implementation and development of virtual natural gas hubs. *Energy Economics 67*, 520–532.

Deng, X., J.-k. Kang, and B. S. Low (2013). Corporate social responsibility and stakeholder value maximization: Evidence from mergers. *Journal of Financial Economics 110*(1), 87–109.

DeVaro, J., J.-H. Kim, and N. Vikander (2018). Non-performance Pay and Relational Contracting: Evidence from CEO Compensation. *The Economic Journal 128*(613), 1923–1951.

Dhaliwal, D. S., O. Z. Li, A. Tsang, and Y. G. Yang (2011). Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting. *The Accounting Review 86*(1), 59–100.

Dhaliwal, D. S., S. Radhakrishnan, A. Tsang, and Y. G. Yang (2012). Nonfinancial disclosure and analyst forecast accuracy: International evidence on corporate social responsibility disclosure. *The Accounting Review 87*(3), 723–759.

Di Giuli, A. and L. Kostovetsky (2014). Are red or blue companies more likely to go green? Politics and corporate social responsibility. *Journal of Financial Economics 111*(1), 158–180.

Diamond, D. W. (1985). Optimal release of information by firms. *The Journal of Finance 40*(4), 1071–1094.

Diamond, D. W. and R. E. Verrecchia (1982). Optimal managerial contracts and equilibrium security prices. *The Journal of Finance 37*(2), 275–287.

Dickx, L., C. Miriello, M. Polo, et al. (2014). Balancing systems and flexibility tools In European gas markets. *IEFE Centre for Research on Energy and Environmental Economics and Policy at Bocconi University*.

Dougal, C., C. A. Parsons, and S. Titman (2015). Urban vibrancy and corporate growth. *The Journal of Finance 70*(1), 163–210.

Dyck, A., K. V. Lins, L. Roth, and H. F. Wagner (2019). Do institutional investors drive corporate social responsibility? International evidence. *Journal of Financial Economics 131*(3), 693–714.

Dye, R. A. (1992). Relative performance evaluation and project selection. *Journal of Accounting Research 30*(1), 27–52.

Edmans, A. (2011). Does the stock market fully value intangibles? Employee satisfaction and equity prices. *Journal of Financial Economics 101*(3), 621–640.

EIA (2017). Perspectives on the Development of LNG Market Hubs in the Asia Pacific Region. *U.S. Energy Information Administration*.

El Ghoul, S., O. Guedhami, C. C. Kwok, and D. R. Mishra (2011). Does corporate social responsibility affect the cost of capital? *Journal of Banking & Finance 35*(9), 2388–2406.

El-Khatib, R., K. Fogel, and T. Jandik (2015). CEO network centrality and merger performance. *Journal of Financial Economics 116*(2), 349–382.

Engle, R. F. and C. W. Granger (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica*, 251–276.

Fabrizi, M., C. Mallin, and G. Michelon (2014). The role of CEO's personal incentives in driving corporate social responsibility. *Journal of Business Ethics 124*, 311–326.

Farrell, K. A. and D. A. Whidbee (2002). Monitoring by the financial press and forced CEO turnover. *Journal of Banking & Finance 26*(12), 2249–2276.

Flammer, C. (2015). Does product market competition foster corporate social responsibility? Evidence from trade liberalization. *Strategic Management Journal 36*(10), 1469–1485.

Fogarty, K., B. P. Soebbing, K. J. Agyemang, et al. (2015). NCAA Division I-FBS salary determinants: A look at new and amended contracts. *Journal of Issues in Intercollegiate Athletics 8*(1), 123–138.

Fracassi, C. (2017). Corporate finance policies and social networks. *Management Science 63*(8), 2420–2438.

Fracassi, C. and G. Tate (2012). External networking and internal firm governance. *The Journal of Finance 67*(1), 153–194.

Freeman, L. C. et al. (2002). Centrality in social networks: Conceptual clarification. *Social Network 1*, 238–263.

Frydman, C. and R. E. Saks (2010). Executive compensation: A new view from a long-term perspective, 1936–2005. *The Review of Financial Studies 23*(5), 2099–2138.

Garaffa, R., A. Szklo, A. F. Lucena, and J. G. Féres (2019). Price adjustments and transaction costs in the European natural gas market. *The Energy Journal 40*(1).

Geng, J.-B., Q. Ji, and Y. Fan (2016). The impact of the North American shale gas revolution on regional natural gas markets: Evidence from the regime-switching model. *Energy Policy 96*, 167–178.

Gentry, R. J., J. S. Harrison, T. J. Quigley, and S. Boivie (2021). A database of CEO turnover and dismissal in S&P 1500 firms, 2000–2018. *Strategic Management Journal 42*(5), 968–991.

Ghouri, S. S. (2006). Forecasting natural gas prices using cointegration technique. *OPEC Review 30*(4), 249–269.

Gibbons, R. and K. J. Murphy (1990). Relative performance evaluation for chief executive officers. *ILR Review 43*(3), 30–S.

GIIGNL (2013). LNG Annual Report 2013.

GIIGNL (2014). LNG Annual Report 2014.

GIIGNL (2015). LNG Annual Report 2015.

GIIGNL (2016). LNG Annual Report 2016.

GIIGNL (2017). LNG Annual Report 2017.

GIIGNL (2018). LNG Annual Report 2018.

GIIGNL (2019). LNG Annual Report 2019.

GIIGNL (2020). LNG Annual Report 2020.

Godfrey, P. C. (2005). The relationship between corporate philanthropy and shareholder wealth: A risk management perspective. *Academy of Management Review 30*(4), 777–798.

Gopalan, R., T. Milbourn, and F. Song (2010). Strategic flexibility and the optimality of pay for sector performance. *The Review of Financial Studies 23*(5), 2060–2098.

Grant, R. R., J. C. Leadley, and Z. X. Zygmont (2013). Just win baby? Determinants of NCAA Football Bowl Subdivision coaching compensation. *International Journal of Sport Finance 8*(1), 61.

Gregory, A. W. and B. E. Hansen (1996). Residual-based tests for cointegration in models with regime shifts. *Journal of Econometrics 70*(1), 99–126.

Guo, L. and R. W. Masulis (2015). Board structure and monitoring: New evidence from CEO turnovers. *The Review of Financial Studies 28*(10), 2770–2811.

Hall, B. J. and J. B. Liebman (1998). Are CEOs really paid like bureaucrats? *The Quarterly Journal of Economics 113*(3), 653–691.

Hartley, P. R., K. B. Medlock III, and J. E. Rosthal (2008). The relationship of natural gas to oil prices. *The Energy Journal 29*(3).

Hayes, R. M. and S. Schaefer (2000). Implicit contracts and the explanatory power of top executive compensation for future performance. *The RAND Journal of Economics*, 273–293.

Heather, P. (2021). *European traded gas hubs: German hubs about to merge*. Number 170.

Hegde, S. P. and D. R. Mishra (2019). Married CEOs and corporate social responsibility. *Journal of Corporate Finance 58*, 226–246.

Holmström, B. (1979). Moral hazard and observability. *The Bell Journal of Economics*, 74–91.

Holmström, B. and J. Tirole (1993). Market liquidity and performance monitoring. *Journal of Political Economy 101*(4), 678–709.

Hong, H., J. D. Kubik, and J. C. Stein (2008). The only game in town: Stock-price consequences of local bias. *Journal of Financial Economics 90*(1), 20–37.

Huson, M. R., P. H. Malatesta, and R. Parrino (2004). Managerial succession and firm performance. *Journal of Financial Economics 74*(2), 237–275.

Hwang, B.-H. and S. Kim (2009). It pays to have friends. *Journal of Financial Economics 93*(1), 138–158.

Iliev, P. and L. Roth (2022). Directors and corporate sustainability. *Available at SSRN 3575501*.

Indjejikian, R. and D. Nanda (1999). Dynamic incentives and responsibility accounting. *Journal of Accounting and Economics 27*(2), 177–201.

International Gas Union (2020). Wholesale Price Survey.

Intintoli, V. J., K. M. Kahle, and W. Zhao (2018). Director connectedness: Monitoring efficacy and career prospects. *Journal of Financial and Quantitative Analysis 53*(1), 65–108.

Ittner, C. D., D. F. Larcker, and M. V. Rajan (1997). The choice of performance measures in annual bonus contracts. *Accounting Review*, 231–255.

Jensen, M. C. (1989). Active investors, LBOs, and the privatization of bankruptcy. *Journal of Applied Corporate Finance 2*(1), 35–44.

Joskow, P. L. and N. L. Rose (1994). CEO pay and firm performance: dynamics, asymmetries, and alternative performance measures. *NBER working paper* (w4976).

Kahn, L. M. (2000). The sports business as a labor market laboratory. *Journal of Economic Perspectives 14*(3), 75–94.

Kim, Y. (2017). Asian LNG market changes under low oil prices: Prospects for trading hubs and a new price index. *Geosystem Engineering 20*(3), 129–141.

Kim, Y. (2019). Obstacles to the creation of gas trading hubs and a price index in Northeast Asia. *Geosystem Engineering 22*(2), 59–71.

Kim, Y., H. Li, and S. Li (2014). Corporate social responsibility and stock price crash risk. *Journal of Banking & Finance 43*, 1–13.

King, M. and M. Cuc (1996). Price convergence in North American natural gas spot markets. *The Energy Journal 17*(2).

Kleit, A. N. (2001). Are regional oil markets growing closer together?: An arbitrage cost approach. *The Energy Journal 22*(2).

Krüger, P. (2015). Corporate goodness and shareholder wealth. *Journal of Financial Economics 115*(2), 304–329.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, 1315–1335.

Lambert, R. A. and D. F. Larcker (1987). An analysis of the use of accounting and market measures of performance in executive compensation contracts. *Journal of Accounting Research*, 85–125.

Leeds, M. A., E. M. Leeds, and A. Harris (2018). Rent sharing and the compensation of head coaches in power five college football. *Review of Industrial Organization 52*(2), 253–267.

Leeds, M. A. and N. T. N. Pham (2020). Productivity, rents, and the salaries of group of five football coaches. *Journal of Sports Economics 21*(1), 3–19.

Lefebvre, L. A., R. Mason, and E. Lefebvre (1997). The influence prism in SMEs: The power of CEOs' perceptions on technology policy and its organizational impacts. *Management Science 43*(6), 856–878.

Li, C. and X. Wang (2022). Local peer effects of corporate social responsibility. *Journal of Corporate Finance 73*, 102187.

Li, R., R. Joyeux, and R. D. Ripple (2014). International natural gas market integration. *The Energy Journal 35*(4).

Lin, B. and J. Li (2015). The spillover effects across natural gas and oil markets: Based on the VEC–MGARCH framework. *Applied Energy 155*, 229–241.

Liu, Q. and B. Sun (2014). Relative wealth concerns, executive compensation, and risk taking. *Executive Compensation, and Risk Taking (October 6, 2014).*

Masulis, R. W. and S. W. Reza (2015). Agency problems of corporate philanthropy. *The Review of Financial Studies 28*(2), 592–636.

Matsumoto, D. A. (2002). Management's incentives to avoid negative earnings surprises. *The Accounting Review 77*(3), 483–514.

Meier, O. and G. Schier (2021). CSR and family CEO: The moderating role of CEO's age. *Journal of Business Ethics 174*, 595–612.

Miranda-Lopez, J., S. Orlova, and L. Sun (2019). CEO network centrality and corporate cash holdings. *Review of Quantitative Finance and Accounting 53*, 967–1003.

Miriello, C. and M. Polo (2015). The development of gas hubs in Europe. *Energy Policy 84*, 177–190.

Morse, A., V. Nanda, and A. Seru (2011). Are incentive contracts rigged by powerful CEOs? *The Journal of Finance 66*(5), 1779–1821.

Nandy, M., S. Lodh, J. Kaur, and J. Wang (2020). Impact of directors' networks on corporate social responsibility: A cross country study. *International Review of Financial Analysis 72*, 101601.

Neumann, A. (2009). Linking natural gas markets-is LNG doing its job? *The Energy Journal 30*(Special Issue).

Neumann, A. and A. Cullmann (2012). What's the story with natural gas markets in Europe? Empirical evidence from spot trade data. In *2012 9th international conference on the European energy market*, pp. 1–6. IEEE.

Nguyen, B. D. (2012). Does the Rolodex matter? Corporate elite's small world and the effectiveness of boards of directors. *Management Science 58*(2), 236–252.

Oglend, A., T. S. Kleppe, and P. Osmundsen (2016). Trade with endogenous transportation costs: The case of liquefied natural gas. *Energy Economics 59*, 138–148.

Oglend, A., P. Osmundsen, and T. S. Kleppe (2020). Time commitments in LNG shipping and natural gas price convergence. *The Energy Journal 41*(2).

Oh, W.-Y., Y. K. Chang, and Z. Cheng (2016). When CEO career horizon problems matter for corporate social responsibility: The moderating roles of industry-level discretion and blockholder ownership. *Journal of Business Ethics 133*, 279–291.

Opsahl, T., F. Agneessens, and J. Skvoretz (2010). Node centrality in weighted networks: Generalizing degree and shortest paths. *Social Networks 32*(3), 245–251.

Palti-Guzman, L. (2018). The future of Asia's natural gas market: The need for a regional LNG hub. *Asia Policy 13*(3), 101–126.

Panagiotidis, T. and E. Rutledge (2007). Oil and gas markets in the UK: Evidence from a cointegrating approach. *Energy Economics 29*(2), 329–347.

Parrino, R., R. W. Sias, and L. T. Starks (2003). Voting with their feet: Institutional ownership changes around forced CEO turnover. *Journal of Financial Economics 68*(1), 3–46.

Parsons, C. A., J. Sulaeman, and S. Titman (2018). The geography of financial misconduct. *The Journal of Finance 73*(5), 2087–2137.

Pathan, S. (2009). Strong boards, CEO power and bank risk-taking. *Journal of Banking & Finance 33*(7), 1340–1350.

Phillips, J., M. Pincus, and S. O. Rego (2003). Earnings management: New evidence based on deferred tax expense. *The Accounting Review 78*(2), 491–521.

Phillips, P. C. and S. Ouliaris (1990). Asymptotic properties of residual based tests for cointegration. *Econometrica*, 165–193.

Potts, T. B. and D. B. Yerger (2016). Marcellus Shale and structural breaks in oil and gas markets: the case of Pennsylvania. *Energy Economics 57*, 50–58.

Rappaport, A. (1999). New thinking on how to link executive pay with performance. *Harvard Business Review 77*(2), 91–92.

Renou-Maissant, P. (2012). Toward the integration of European natural gas markets: A time-varying approach. *Energy Policy 51*, 779–790.

Ritz, R. A. (2014). Price discrimination and limits to arbitrage: An analysis of global LNG markets. *Energy Economics 45*, 324–332.

Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics 42*(3), 335–370.

Schwab, S. J. and R. S. Thomas (2006). An empirical analysis of CEO employment contracts: What do top executives bargain for. *Washington & Lee Law Review 63*, 231.

Serletis, A. and J. Herbert (1999). The message in North American energy prices. *Energy Economics 21*(5), 471–483.

Serletis, A. and R. Rangel-Ruiz (2004). Testing for common features in North American energy markets. *Energy Economics 26*(3), 401–414.

Servaes, H. and A. Tamayo (2013). The impact of corporate social responsibility on firm value: The role of customer awareness. *Management Science 59*(5), 1045–1061.

Shahgholian, A., B. Theodoulidis, and D. Diaz (2015). Social Network Metrics: The BoardEx case study. *Available at SSRN 2613156*.

Shi, X. (2016a). Development of Europe's gas hubs: Implications for East Asia. *Natural Gas Industry B 3*(4), 357–366.

Shi, X. (2016b). Gas and LNG pricing and trading hub in East Asia: An introduction. *Natural Gas Industry B 3*(4), 352–356.

Shi, X., Y. Shen, and Y. Wu (2019). Energy market financialization: Empirical evidence and implications from East Asian LNG markets. *Finance Research Letters 30*, 414–419.

Shi, X. and H. M. Variam (2018). Key elements for functioning gas hubs: A case study of East Asia. *Natural Gas Industry B 5*(2), 167–176.

Shmatenko, L., K. Christie, and M. Han (2020). LNG contract adjustments in difficult times: The interplay between force majeure, change of circumstances, hardship, and price review clauses. *Oil, Gas & Energy Law 18*(3).

Sigler, K. J. (2011). CEO compensation and company performance. *Business and Economics Journal 31*(1), 1–8.

Skousen, C. J., X. J. Song, and L. Sun (2018). CEO network centrality and bond ratings. *Advances in Accounting 40*, 42–60.

Sloan, R. G. (1993). Accounting earnings and top executive compensation. *Journal of Accounting and Economics 16*(1-3), 55–100.

Stern, J. (2014). International gas pricing in Europe and Asia: A crisis of fundamentals. *Energy Policy 64*, 43–48.

Tatos, T. (2018). An empirical evaluation of EADA and NCAA college sports financial data: Applications for research and litigation. *Marquette Sports Law Review 29*, 411.

Tice, F. M. (2020). Explicit Relative Performance Evaluation and Managerial Decision-Making: Evidence from Firm Performance and Risk-Taking Behavior. *Available at SSRN: https://ssrn.com/abstract=2645956*.

Tong, X., J. Zheng, and B. Fang (2014). Strategic analysis on establishing a natural gas trading hub in China. *Natural Gas Industry B 1*(2), 210–220.

Valentine, S. and G. Fleischman (2008). Ethics programs, perceived corporate social responsibility and job satisfaction. *Journal of Business Ethics 77*, 159–172.

Villar, J. A. and F. L. Joutz (2006). The relationship between crude oil and natural gas prices. *Energy Information Administration, Office of Oil and Gas 1*, 1–43.

Vivoda, V. (2014a). LNG import diversification in Asia. *Energy Strategy Reviews 2*(3-4), 289–297.

Vivoda, V. (2014b). Natural gas in Asia: trade, markets and regional institutions. *Energy Policy 74*, 80–90.

Vücel, M. K. and S. Guo (1994). Fuel taxes and cointegration of energy prices. *Contemporary Economic Policy 12*(3), 33–41.

Wakamatsu, H. and K. Aruga (2013). The impact of the shale gas revolution on the US and Japanese natural gas markets. *Energy Policy 62*, 1002–1009.

Yorucu, V. and P. Bahramian (2015). Price modelling of natural gas for the EU-12 countries: evidence from panel cointegration. *Journal of Natural Gas Science and Engineering 24*, 464–472.

Zhang, D. and Q. Ji (2018). Further evidence on the debate of oil-gas price decoupling: A long memory approach. *Energy Policy 113*, 68–75.

Zimbalist, A. (2010). CEOs with Headsets. *Harvard Business Review 88*(9), 21–23.

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