CORPORATE ACTIONS AND OUTCOMES UNDER MULTIFACETED MARKET LANDSCAPE

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Contents

ABSTRACT

This thesis explores the multifaceted impact of competitive dynamics on firm performance and market behaviour across three empirical studies. The first study introduces a novel metric for labour market competitiveness, revealing its influence on stock prices. The second study examines how a firm's strategic orientation is shaped by CEO Industry Tournament Incentives. The final study shifts the lens to the broader Top Management Teams (TMT), examining the implications of psychological diversity, specifically confidence diversity, on a firm's innovation efficacy. Together, these studies provide insights into the influence of competitive pressures spanning the labour market, organizational, and individual dimensions on corporate actions and outcomes.

In the first study, I introduce a distinctive methodology to gauge labour market competitiveness, emphasizing the intensifying competition stemming from the surging demand for analogous occupations. This metric uncovers a correlation between escalating labour market competitiveness and a decline in aggregate market excess returns over the ensuing three to twelve months, reinforcing the 'war for talent' paradigm. The underlying mechanism reveals that amplified labour market competition leads to adverse cash flow shocks, evident through escalating personnel-related costs and dwindling cash reserves. Further exploration underscores that investors perceive an intensely competitive labour market as a risk factor, demanding higher returns for stocks that are more vulnerable to this particular risk.

The second study narrows its focus to the CEO labour market, highlighting the critical role of the relative pay disparity between a given CEO and the highest-earning CEO among a group of similar firms. This disparity is referred to as 'CEO industry tournament incentives.' Drawing from tournament theory, a larger pay gap intensifies the career-enhancement incentives for the focal CEO, subsequently steering the firm's strategic compass. CEOs with pronounced industry tournament incentives exhibit a propensity for distinctive strategies,

leading to increased strategic distinctiveness. A more detailed analysis indicates that tournament incentives enhance firm performance only when paired with strategic distinctiveness.

The last study of this thesis pivots to the broader TMT spectrum. It pioneers a construct that melds the Upper Echelons theory with group information-processing theory, subsequently scrutinizing the impact of TMT confidence diversity on corporate innovation paradigms. Empirical findings underscore a positive nexus between TMT confidence diversity and corporate innovation prowess, underscoring the benefits of diversity. Further, this association is moderated by task complexity, resonating with the group information-processing theory's assertion that complex decision-making landscapes necessitate collaborative information assimilation within groups.

Together, these three studies included in this thesis enriches the literature by shedding light on the multifaceted ways market and organizational dynamics influence corporate actions and outcomes. Diverse competitive pressures shape firms' investment decisions, strategic directions, and market valuations. This thesis endeavours to demystify the heterogeneity in corporate behaviours and the market's differential responses to these actions.

Declaration

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CHAPTER 1: GENERAL INTRODUCTION

In recent times, financial market environment has grown increasingly complex and dynamic. Firms face many factors that significantly influence their market valuation, strategic choices and operational performance. These factors can originate from market-level forces (see, e.g., Badertscher et al. 2019; Bolton & Kacperczyk 2023), organisation-specific strategies (see, e.g., Ketchen et al. 2004; Hitt et al. 2019), and managerial behaviour (see., e.g., Malmendier & Tate 2015; Steinbach, Holcomb, Holmes, et al. 2017). Inspired by the recent growing attention in the field of finance and my interests, in this thesis, I explore how labour market conditions, CEO incentives, and top management team diversity each play a role in shaping firm actions and outcomes.

The introductory chapter fulfills multiple objectives. Primarily, it establishes the central theme by reviewing relevant literature. Subsequently, it outlines the empirical methodologies used and summarizes the principal findings of the three studies that form the core of this thesis. The aim is to provide a comprehensive analytical framework that facilitates subsequent examination of how dynamics at multi-tiered levels—market, firm, and individual—affect firm actions and outcomes.

I first examine how market forces, i.e., labour market competition, can affect firm valuation. Labour markets are a cornerstone of an economy and play a pivotal role in shaping firm performance. Traditional labour economics has focused on wage levels, employment rates, and workplace policies and their impact (Postel–Vinay & Robin 2002; Cahuc et al. 2006; Belo et al. 2014; Agénor et al. 2021). Recent studies published in top-tier finance journals draw our attention to other aspects of the labour market and its consequential impact on firms. For instance, Kim (2020) shows that labour market size can affect firm capital structure. This is because a larger labour market makes filling a vacant job position less costly, and thus in turn reduce the indirect cost of financial distress and changing the optimal corporate capital structure. Kuehn et al. (2017) show that labour market frictions predict future stock returns in the cross-section.

Inspired by this stem of the literature, my first study in Chapter 2 explores the relationship between labour market competitiveness and aggregate stock market returns. This study is grounded in the idea that labour market conditions, as a market force, can significantly influence stock market dynamics. I present an innovative methodology for quantifying labour market conditions (i.e., job-specific competitiveness), utilising a unique dataset from Burning Glass Technologies (BGT) that comprises an extensive array of information gleaned from online job postings within the United States. Using this new metric of labour market conditions, I explore how labour market dynamics interact with firm valuation. My empirical analysis reveals a negative relationship between job-specific competitiveness and aggregate market excess returns over the subsequent three to twelve months. This relationship is more pronounced for portfolios of small stocks compared to large stocks, indicating that smaller firms are particularly susceptible to the impact of heightened levels of labour market competition.

My study in Chapter 2 broadens the scope of labour economics within financial studies and provides a detailed insight into the relationship between labour market dynamics and firm valuation. It first introduces a new metric for labour market competitiveness. This job-specific metric considers labour market linkages among firms even if they do not belong to the same industry and thus captures a broader picture of the competition in the market. Second, I use this new metric to demonstrate that the intensity of labour market competition has predictive power for future stock returns. Firms incur a higher cost of hiring when the labour market supply for vacant job positions is tight. Such a higher hiring cost transfers into cash flow shocks and thus affects firms' valuation.

Next, I turn my attention to a specific type of labour market, i.e., the executive labour market. The study in Chapter 3 aims to examine the determinants of organisation-specific strategies. According to the upper echelons theory (Hambrick & Mason 1984), top executives' interpretation of their strategic situation leads to different firm actions and outcomes. However, from an agency theory perspective (Ross 1973; Jensen & Meckling 1976), these executives may not pursue the strategies or investments that are value maximising. Due to the separation of ownership, it gives rise to the agency problem between shareholders and managers. One way to mitigate this agency problem is by designing compensation packages aligning managers' interests with their shareholders' (e.g., Jensen & Meckling 1976). Another way to minimise the conflicts between shareholders and managers is by utilising the competition in the executive labour market.

Top executives compete with each other within the labour market and thus give rise to promotion-based tournament incentives (i.e., the career-enhancing incentives of being promoted to a better position). Early studies on these tournament incentives find they can mitigate managerial risk aversion and help reduce the agency conflict between risk-averse executives and value-maximising shareholders (Kale et al. 2009; Kini & Williams 2012). These studies primarily focus on the effects of internal tournament incentives, measured by the pay gap between the CEO pay and the average or the median pay of non-CEO senior executives. The recent seminal paper of Coles et al. (2018) introduces another type of tournament incentive arising from the external labour market for managers, i.e., industry tournament incentives. Executives, especially CEOs, will likely be promoted to a more desirable position in the same or related industries if they can lead a company that delivers outstanding performance. Therefore, the highest-paid CEO compensation can serve as a prize to reward the best player in the executive market tournament, providing the industry tournament incentives. Furthermore, CEOs are arguably the most influential players of each firm, which is more likely to be true when it comes to formulating and implementing firm strategies (Finkelstein et al. 2009;

Quigley & Hambrick 2015). This raises the question of whether the amount of industry tournament incentives affects CEOs' strategic choices so that they can easily pursue the executive tournament prize. My study in Chapter 3 aims to address this question.

In Chapter 3, I investigate the impact of CEO Industry Tournament Incentives (CEO ITIs) on a firm's strategic distinctiveness (i.e., strategies that deviate from the industry's central tendencies). The study focuses on the CEO relative industry pay gap between focal CEO pay and the second-highest CEO pay in a similar sector as a measure of CEO ITIs. It argues that CEOs with lower relative pay have stronger incentives to adopt unique strategies to improve their standing in the labour market. Two perspectives are considered. These are the *differentiation proposition* and *conformity proposition*. The differentiation proposition suggests CEOs with lower relative pay are more likely to adopt unique strategies to create economic rent and increase long-term firm value, suggesting a positive association between CEO ITIs and corporate strategic distinctiveness. In contrast, the conformity proposition suggests that CEOs with lower relative pay may conform to industry norms to gain market legitimacy, leading to a negative association between CEO ITIs and strategic distinctiveness.

Empirical analysis using U.S. firm-year observations from 1992 to 2019 shows a positive association between CEO ITIs and corporate strategic distinctiveness, supporting the differentiation proposition. Furthermore, in the cross-sectional analysis, I find that the positive effect of CEO ITIs is more pronounced in firms with effective board structures, significant product-market competition, and CEOs with high managerial ability. Lastly, I confirm a positive and significant association between CEO ITIs and firm performance, similar to the findings of Coles et al. (2018). However, in a subsample analysis, I show that the positive association only exist for firms exhibiting high levels of strategic distinctiveness, not for firms conforming to industry-common strategies.

My study in Chapter 3 contributes to the literature by showing that CEO ITIs can significantly influence a firm’s strategic orientation, particularly in terms of its distinctiveness from industry norms. This study follows the steps of some management scholars (Crossland et al. 2014; Kang et al. 2020) who focus on finding the determinator of strategic distinctiveness. In addition, my study is also rooted in the upper echelons theory (Hambrick & Mason 1984). It aims to understand why some CEOs adopt unique strategies while others conform to industry norms. Second, my study built on the seminal work of Coles et al. (2018), where they find that CEO ITIs are positively associated with firm performance. My study indicates one possible channel through which CEO ITIs enhance firm performance. By differentiating from their peers, CEOs are likely to face less competition and deliver a strong performance, which can increase their likelihood of winning the industry tournament prize.

The last study in this thesis revisits the foundational elements of the upper echelons theory and examines managerial behaviour's impact on corporate outcomes. Unlike the study in Chapter 3, which only focuses on the effects of one executive, my study in Chapter 4 treats senior managers as a team and examines the diversity within the top management teams. This is inspired by the fact that the upper echelons theory was founded on the premise that the top management team (TMT) collectively shapes strategic outcomes (Hambrick and Mason, 1984; Hambrick, 2007). In line with this, some studies have examined the diversity within the TMT and show its importance (see Homberg & Bui 2013 for a systematic review). However, these studies primarily focus on the diversity of some demographic characteristics such as functional background (Cannella et al. 2008; Boone & Hendriks 2009), gender (Tang et al. 2021), and tenure (Hambrick et al. 1996). Some researchers have recognised the importance of executive’s psychological attributes (Finkelstein et al., 2009; Busenbark et al., 2016), but little attention has been given to the effects of the diversity of psychological attributes such as confidence within TMTs would affect firm outcomes (for exceptions, see Boone & Hendriks, 2009; Narayan et al., 2021). This literature gap inspired my third study, which is included in Chapter

4.

Many decisions are made based on cognitive attributes such as personal views on the likelihood of success. Similarly, the upper echelon theory states that firm outcomes reflect top managers' unique interpretations of the situation they face (Hambrick & Mason 1984; Hambrick 2007). Behaviour biases, however, can alter a person's cognitive base and affect the person's beliefs about future uncertain outcomes (Einhorn & Hogarth 1978). As one of the most prominent behaviour biases (Plous 1993), overconfidence has received much attention and shows its importance (Malmendier & Tate 2015). For example, in the seminal paper, Malmendier and Tate (2005) show that CEO overconfidence can result in investment distortions. Overconfident CEOs are prone to overinvest with internal funds but underinvest when a project requires external funding. This is because overconfident CEOs overestimate the performance of their firms with their management. As a result, they view external financing as costly and thus leave positive net present value (NPV) projects on the table. In contrast, when there are abundant internal funds, overconfident CEOs are likely to take on negative NPV projects because they overestimate these projects' returns. Later studies show that overconfidence has an explanatory power toward a firm's investment distortion (Malmendier & Tate 2005), valued-destroying mergers (Malmendier & Tate 2008), and the success of corporate innovation (Hirshleifer et al. 2012);

However, the abovementioned studies on overconfidence have solely focused on CEOs and ignored the interaction effects within the TMTs. One TMT may consist of high-confidence executives (i.e., overconfident) and low-confidence executives (i.e., underconfident) exhibiting high levels of confidence diversity. Another TMT may have little variation in confidence levels among executives, such as a TMT consisting of only one type of executives. How the two TMTs with different levels of diversity in the confidence levels of their members shape firm outcomes is unknown. In addition, Heavey et al. (2022) call our attention to confidence across the spectrum, including low, average, and high confidence levels.

My study in Chapter 4 answers the call of Heavey et al. (2022). It offers a pioneering examination of the role that confidence diversity plays within Top Management Teams (TMTs) and its consequent effect on firm innovation efficiency. Departing from traditional studies primarily focused on demographic diversity or individual managerial traits; this research introduces a novel construct—'TMT Confidence Diversity.' This term is defined as the variance in confidence levels among TMT members. I follow the literature (Malmendier & Tate 2005; Campbell et al. 2011; Hirshleifer et al. 2012) and use executives' behaviour of exercising their vested options to measure their confidence levels about future firm outcomes. Utilising a dataset of S&P 1500 firms between 1992 and 2017, the study empirically demonstrates that firms with higher TMT confidence diversity exhibit significantly greater innovation efficiency, as measured through the number of forward citations per spending on research and development expense. The findings are robust across various controls, including firm size, industry, and other governance mechanisms.

The contributions of my third study in this thesis are as follows. First, it introduces a new construct, TMT confidence diversity, and emphasises the influence of the entire TMT. Second, it moves beyond a static examination focused only on individual executives' overconfidence and examines confidence across different levels. Lastly, the study enriches the TMT diversity literature by emphasizing the significance of confidence diversity within Top Management Teams. It provides insight into how individual-level attributes and behaviours, when viewed from a team perspective, exert a pronounced influence on firm-level outcomes.

The thesis is organised into five chapters to provide a logical and comprehensive exploration of the central theme. Following this introductory chapter, Chapter 2 delves into the impact of labour market competitiveness on stock prices. Chapter 3 shifts the focus to the influence of CEO industry tournament incentives on a firm's strategic orientation. Chapter 4 rounds out the empirical studies by exploring the role of top management team confidence diversity in affecting a firm’s innovation efficiency. Finally, Chapter 5 serves as the capstone, summarising the key findings, synthesising the insights gained, and suggesting avenues for future research.

CHAPTER 2: THE IMPACT OF LABOUR MARKET COMPETITION ON STOCK RETURNS

1. INTRODUCTION

Previous studies on the time-series predictability of aggregate returns have identified a multitude of variables that can influence stock market forecasting, including valuation ratios (Campbell & Shiller 1988; Lewellen 2004), interest rates (Fama & Schwert 1977; Fama 1981), default and term premiums (Keim & Stambaugh 1986; Fama & French 1989), and inflation (Fama & Schwert 1977; Campbell & Vuolteenaho 2004). More recent work, however, has begun to underscore the importance of labour market conditions in predicting aggregate stock returns (Belo et al. 2023; Kothari & O'Doherty 2023).

In this chapter, I explore the predictive power of labour market competitiveness for aggregate return predictability. As a primary driver of economic growth and fluctuation, labour plays a pivotal role in any production process. Firms do not operate in a vacuum regarding labour-related activities such as hiring (e.g., Postel–Vinay & Robin 2002; Cahuc et al. 2006). In fact, firms often interact with each other within the labour market, particularly when they demand similar types of labour. This competition for talent can impact firms' operating costs and profitability, which can influence their stock prices. Consequently, the degree of competition in the labour market can offer valuable insights into stock market dynamics.

While there is reason to believe that an association exists between labour market competitiveness and expected market returns, the direction of this relationship remains uncertain. It is plausible that there is a positive association between labour market competitiveness and expected market returns. When firms share a demand for similar types of labour, they become more vulnerable to common economic shocks. For example, suppose multiple firms rely heavily on specific occupations. In that case, they will experience similar fluctuations in labour market conditions, such as expansions or contractions in the availability of those occupations (Topel 1986; Acemoglu & Autor 2011). During such periods, the average correlation between stock returns tends to rise, resulting in a positive risk premium as a higher correlation reduces the benefits of diversification (Krishnan et al. 2009; Pollet & Wilson 2010).

Conversely, it is also possible that the relationship between labour market competitiveness and expected market returns is negative. When competition for skilled employees intensifies, firms may find themselves allocating more resources towards attracting and retaining high-performing employees, often referred to as the 'war for talent' (Chambers et al. 1998). Kim (2022) provides evidence that firms in denser labour market networks tend to spend more on R&D and may face talent outflows when their labour market peers enhance their benefits for top employees. As a result, these firms may be compelled to increase their own employee benefits, leading to elevated costs and diminished firm valuations, resulting in lower stock prices. Kothari and O'Doherty (2023) find that higher staff turnover, as measured by the ratio of job postings to employed workers, can trigger increased adjustment costs, ultimately reducing the expected stock market return. Moreover, Belo et al. (2023) show that the aggregate hiring rate of publicly traded firms negatively predicts aggregate U.S. stock market excess returns and long-term cash flows, with a stronger relationship observed at longer horizons. These findings point toward the potential for labour market competitiveness to impact a firm's cash flows negatively and, consequently, its stock market returns.

In this chapter, I introduce a novel approach to measuring labour market competitiveness and investigate its relationship with aggregate stock market returns. I leverage a unique dataset provided by Burning Glass Technologies (BGT), which encompasses a vast majority of online job postings in the United States. As an employment data analytics firm, BGT collects data from online job boards and company websites daily, offering a wealth of information such as the employer's name, occupation title, job location, education, and skill requirements, among other data points. Such a granular dataset allows me to identify which occupations are currently in high demand and which ones are not. By utilizing BGT dataset, I can glean valuable insights into labour market competitiveness and its potential influence on stock market dynamics.

I adopt a methodology inspired by the information retrieval literature to measure labour market competitiveness, drawing upon works such as Sebastiani (2002) and Hoberg and Phillips (2016). My approach involves calculating the monthly cosine similarity score between two firms with similar labour demand profiles. This score is derived from comparing two vectors, each representing the occupations sought by the respective firms. A higher cosine similarity score indicates a higher competition intensity between the pair of firms in the labour market. To gain an overall assessment of labour market competition, I consider the cosine similarity scores across all possible firm pairs in the market and calculate the average value of these scores. As job postings are collected daily, the monthly competition measure is time-varying and reflects firms' labour demand changes. Therefore, the resulting value gives me a quantifiable measure of prevailing competition in the labour market.

My competition measure diverges from other labour market metrics employed in previous studies, such as the unemployment rate (Ludvigson & Ng 2007), the employment growth rate (Chen & Zhang 2011), the job openings-to-employment ratio (Kothari & O'Doherty 2023), and the aggregate hiring rate (Belo et al. 2023). While the unemployment rate reflects the proportion of individuals without employment in the labour force, and the employment growth rate represents the number of new jobs created, these metrics do not reflect the specific challenges that firms encounter when competing in the labour market, i.e., finding the right talent for a vacant position. Similarly, the job openings-to-employment ratio and the aggregate hiring rate primarily reflect employee turnover within firms but not the intensity of competition in hiring similar occupational categories. My metric, in contrast, offers a more nuanced perspective as it recognizes that certain occupations may be highly sought after, resulting in fierce competition among firms, while others may have lower demand, leading to reduced competition. Therefore, my aggregate metric provides a more accurate assessment of the level of competition firms can anticipate when seeking to hire labour since it considers the relative demand for different job categories.

To validate my labour market competitiveness measure, I perform several tests. First, I evaluate the correlation between my measure and the labour market concentration index derived in a similar fashion to the Herfindahl-Hirschman index, i.e., calculated based on the share of vacancies of all the firms that post vacancies in the market. My findings indicate a negative relationship between the two measures, i.e., as the labour market becomes concentrated, it becomes less competitive.[1] Second, I explore the link between my measure and the market average salary, uncovering a positive relationship. Higher levels of labour market competitiveness correspond to increased market average salaries, suggesting that individuals seeking employment possess greater market power when the labour market is more competitive.

For my formal analyses, I employ a predictive regression model and regress excess stock returns on lagged labour market competitiveness. My findings reveal a negative relationship: higher levels of competition in the labour market correspond to lower aggregate market excess returns over the subsequent three to twelve months. The observed negative coefficients for lagged labour market competitiveness remain statistically significant even when accounting for other well-established predictors documented in the literature. Thus, my findings indicate that labour market competitiveness carries its own distinct predictive power for future stock returns. Furthermore, my analysis reveals that the negative relationship

[1] In Section 4.1., I explain why my labour market competitiveness measure is superior to the labour market concentration index.

between labour market competitiveness and returns is more pronounced for a portfolio of small stocks than a portfolio of large stocks. This finding suggests that smaller firms are particularly vulnerable to the impact of heightened levels of labour market competition.

I investigate the impact of labour market competitiveness on aggregate stock returns through different transmission channels. I utilize the return decomposition approach proposed by Campbell and Shiller (1988) to separate asset returns into discount rate and cash flow shocks. I then regress these shocks on lagged labour market competitiveness. My findings indicate that labour market competitiveness primarily affects the expected cash flows rather than the discount rate shocks. The negative cash flow shocks manifest in higher selling, general, and administrative (SGA) as well as research and development (R&D) expenditures, two main proxies for personnel-related expenses, accompanied by a decrease in firms' cash holdings. These links are also found to be stronger in smaller firms. Together, these transmission channel results suggest that intensified labour market competition drives firms to allocate more resources toward hiring new employees or retaining high-calibre talents.

In the final part of this chapter, I delve into the economic implications of my finding that higher labour market competitiveness leads to lower returns. Specifically, I aim to determine whether investing in firms that are more responsive to labour market competition carries increased risk and commands a risk premium. To investigate this, I undertake analyses based on portfolio sorting. At the end of each year, I sort firms into double-sorted quintile portfolios based on their size and return sensitivity to my labour market competitiveness metric, which I refer to as the '*labour competition beta*.'

Following this, I track the performance of each portfolio over the following 12 months. I find that for the lower size quintile, firms with higher labour competition betas earn higher returns compared to firms with lower labour competition betas. The spread between the top and bottom quintiles of competition betas is 1.5% per month, equivalent to an annualized spread of 18%. I additionally evaluate the regression alphas across various asset pricing models, including the Fama and French (1996) three factors, Carhart (1997) momentum factor Fama and French (2015) five factors, and the Hou et al. (2015) q-factors. The results indicate that these alphas range between 1.1% and 1.5% per month. These results strongly support the hypothesis that my labour market competitiveness risk factor is indeed priced, particularly for the smaller firms who tend to be price-takers in the labour market. The positive and significant premium associated with this risk suggests that stocks with higher sensitivity to labour market competitiveness offer higher expected returns. This finding aligns with the notion that investors perceive a highly competitive labour market as undesirable and consequently demand compensation for holding stocks with greater exposure to this risk.

The main contribution of this chapter is twofold. First, it contributes to the growing field of literature that studies the interaction between labour and finance. Liu and Wu (2022) show that a firm's labour peers are vastly different from their industry peers. Returns of labour-linked firms strongly comove, and this comovement is larger when hiring is difficult. In contrast, the present study goes a step further by introducing a measure of aggregate labour market competition. I demonstrate that firm labour market linkages can be utilized to construct this measure, which provides insights into the overall level of competition within the labour market.

Second, this chapter introduces a novel labour market competition measure. It also differs from the concept of labour adjustment costs discussed in previous studies. For instance, Belo et al. (2014) examine the influence of labour market frictions on asset prices in the context of US firms. Their findings indicate that firms with high hiring rates experience lower future stock returns on average. These firms face higher search costs due to their expansion activities. Kothari and O'Doherty (2023) discover that the ratio of job postings to employment levels is a strong predictor of the aggregate equity premium. They show that job search activity is costly and associated with negative future market returns. Instead, the current research centres on labour market competition, which can fluctuate independently of staff turnover. I show that increased competition in the labour market compels firms to spend more to retain top talent. This heightened expenditure has implications for the firms' future stock returns.

I organize the remainder of the chapter 2 as follows. Section 2 discusses the theoretical motivation for hypothesizing a link between labour market competitiveness and stock returns. Section 3 discusses the data and explains the construction of my labour market competitiveness measure. Section 4 reports the empirical results. Section 5 concludes.

2. HYPOTHESES DEVELOPMENT

2.1. Labour Market Competitiveness and Stock Returns

Existing theories conflict on how labour market competitiveness affects firm value. On the one hand, the risk-return tradeoff suggests that security with a higher level of risk should earn a higher return. Based on the premise that a firm's business focus should be reflected by the people they hire, I hypothesize that commonality in the labour market leads to a greater correlation among stocks. For example, Darendeli et al. (2022) consider '*Green*' job postings as a reflection of a firm's environmental effort. When companies start to employ more employees with similar skill sets, the labour market becomes more concentrated and less diversified. Consequently, those companies will become more vulnerable to common market shocks. Therefore, I expect that greater labour market commonality leads to greater correlation among stocks. An increase in asset correlations can lower diversification benefits for investors and increase aggregate market risk. Therefore, the average correlation should forecast stock market returns. Indeed, several studies have documented that moderate correlation positively predicts future stock market returns (e.g., Krishnan et al. 2009; Pollet & Wilson 2010).

On the other hand, the labour market frictions literature suggests that in the presence of hiring frictions, replacing workers and adjusting employment levels in response to productivity changes are costly to firms. This is due to the resources required for searching and training new hires (Kuehn et al. 2017). Building upon this perspective, Kothari and O'Doherty (2023) assert that a measure reflecting firms' forward-looking intentions to hire new workers holds valuable information about expected aggregate stock market returns.

To capture this intention, I focus on measuring the level of competition within the labour market. Unlike approaches that only consider the number of hirings, my method accounts for broader labour market conditions. For instance, the labour market can become more competitive without an increase in total hiring. With increased labour market competitiveness, firms face higher costs associated with hiring new employees. Also, they must work more diligently to retain their existing workforce. This approach captures an additional dimension, offering a fresh perspective on comprehending the intricate relationship between labour market dynamics and expected aggregate stock market returns.

In summary, a highly correlated market is risky and thus demands higher returns. Alternatively, highly competitive labour markets pose greater challenges for firms, resulting in lower stock returns. Given that both perspectives hold validity, this issue becomes an empirical question. Consequently, I present the following hypothesis in its null form:

H1: *Higher labour market competitiveness impacts stock returns.*

2.2. Labour Market Competitiveness and Small Firms

The labour market dynamics present distinct challenges for large and small firms, impacting their ability to attract and retain talent. In this context, larger firms tend to hold a unique position as price makers in the labour market. Due to their size, established reputation, and resources, larger corporations are often able to set competitive compensation packages, offer attractive benefits, and provide robust career progression opportunities (see, e.g., Brown

& Medoff 1989; Brown et al. 1990; Troske 1999). These advantages, along with the perceived stability and growth potential of larger firms, make them attractive to job applicants.

In contrast, smaller firms typically operate as price-takers in the labour market, which means they have less bargaining power when it comes to attracting and retaining talent. Smaller firms must, therefore, differentiate themselves to attract talent. They may offer more accessible work opportunities, greater employee benefits tailored to individual preferences, or unique value propositions, such as a strong commitment to sustainable practices. In addition, small firms are often associated with new market entrants. Most new firms are short-lived (Geroski 1995; Shane 2009). Thus, accepting employment in a new venture carries inherent risk. These factors suggest that smaller firms face greater challenges when the labour market is competitive. I, therefore, hypothesize that:

H2: *Labour market competitiveness has a greater impact on small firms compared to larger firms.*

3. DATA

3.1. Burning Glass Technologies

I obtain job listings and their characteristics from Burning Glass Technologies (BGT), an analytics company that tracks online employment data. Starting in 2007, the company extracts job postings listed on more than 40,000 online job boards and company websites.[2] BGT parses and deduplicates (i.e., removes repeated postings that may concurrently appear on several job platforms) the postings into a machine-readable form, creating a comprehensive

[2] The database lacks postings from 2008 and 2009.

dataset for labour market analysis. I obtained these posting-level data for the years 2010 through 2021.

The BGT database captures nearly all online job postings, which presents a significant advantage over databases relying on a single source, such as CareerBuilder.com and Monster.com. An alternative popular database is the Job Openings and Labour Turnover Survey (JOLTS) by the U.S. Bureau of Labour Statistics. This database obtains labour market information by asking a nationally representative sample of employers for vacancies they wish to fill in the near term. However, JOLTS data is typically available only at an aggregated level and contains relatively limited information on the characteristics of the vacancies. In contrast, BGT data is rich in detail. It captures essential variables such as job text, posting date, employer, and location. Additionally, the data includes algorithmically derived metrics. These metrics encompass occupational classification, requisite skills, educational level, prior experience, and estimated wages, among over 70 standardized fields. Given this advantage, the BGT data have been used in recent studies, including Hershbein and Kahn (2018), Deming and Noray (2020), and Darendeli et al. (2022).

Despite its richness, the BGT data does have a few shortcomings. First, the dataset only covers postings on the internet. Although job postings have increasingly moved online, there could be concerns that the types of jobs posted online are not representative of all job openings. To assess this, Hershbein and Kahn (2018) compare the industry-occupation mix of vacancies in BGT relative to other sources such as JOLTS, the Current Population Survey, and the Occupational Employment and Wage Statistics. They find that while BGT postings tend to be skewed toward more highly-skilled occupations, the occupational and industry distributions remain stable over time and comparable to the aggregate trends in other sources. Second, job postings can remain unfilled. As a result, the number of job postings can be higher than the number of actual hires. While I do not have information on whether job postings are eventually filled, a recent study by Law and Shen (2021) validated BGT job postings data using employee resumes and H1B visa application data. They found the postings in BGT to be a reasonable proxy for firms' actual hiring.

While the BGT database provides occupation and employer names in job postings when available, about 40 percent of the postings lack the employer name. This is primarily due to the postings being listed on recruiting websites that often withhold the employer's name. I exclude these job posts from my study. A key step in my research involves matching the BGT dataset to the firm list from Compustat and subsequently linking it with the stock data from the Center for Research in Security Prices (CRSP). Since the employer name is the only identifier available in BGT, I employ machine- and manual-matching procedures to align the firm and its subsidiaries' names in Compustat. To ensure the accuracy of the match, I use a fuzzy matching approach with a 95% threshold. Any matches that raise doubts are manually verified for accuracy. From the sample period of January 2010 to December 2021, I successfully match 26,237,819 BGT job postings to publicly traded companies in Compustat. Following this, I use the identifier gvkey in Compustat to link my dataset with the stock price data from CRSP.

Appendix 2A compares the distribution of firms across industry sectors for my matched BGT sample and the Compustat universe. Comparable to the firms in Compustat, most of the industry sectors are fairly represented in my matched BGT dataset. The top four industry sectors are Durable goods, Non-durable goods, Finance and Insurance, and Information. Overall, I find that the matched BGT sample is representative of the publicly listed firms on major US stock exchanges.

3.2. Measuring Labour Market Competitiveness

To measure aggregate labour market competitiveness, I first calculate a labour demand similarity score between pairs of firms. My measure construction is underpinned by the assumption that firms competing in the same labour markets tend to seek employees within the same occupations. As more firms demand the same type of occupations, the labour market becomes more competitive. This approach thus enables each firm's competitors to be identified based on the similarity of the occupations they seek to hire[3]. I utilize the occupation name based on the O*NET code in each posting.[4] Each month I construct a set of unique occupations available in the BGT dataset. On average, there are 800 unique occupations every month in my dataset based on the O*NET code. Since I group the job postings by month, the set of unique occupations varies from month to month. Hence, the set of unique occupations always reflects the current occupation list demanded by U.S. firms.

To measure the labour demand similarity between two firms, I calculate the cosine similarity score between their labour demand profiles.[5] Specifically, I construct the labour demand profile as a vector $O_{i,t}$, corresponding to occupations demanded by firm i in month t. The length of the vector is the number of unique occupations demanded by all firms in month t. It is important to note that the information content of different occupations can vary. Occupations commonly demanded by a large number of firms (e.g., customer service representatives) contain less information about a specific company than unique occupations demanded by a small number of firms (e.g., business intelligence analysts). Therefore, using the raw count of job postings for each occupation does not adequately capture the information contained in the demand for a given occupation. This concern is echoed in the information

[3] I acknowledge that my methodology for assessing labor market competition primarily focuses on the demand side and may overlook fluctuations in labor market supply. This approach assumes a short-term stability in the supply of specific job roles. In Section 4.1, I conduct a verification test to ascertain the accuracy of this measure in reflecting true labor market competitiveness.

[4] O*NET is a classification of job titles widely used in labour economic studies. O*NET is the nation's primary source of occupational information, including worker attributes and job characteristics. It contains descriptions of over 1000 occupations, covering the entire U.S. economy. Just like the SIC codes for industry classifications, O*NET provides a common language for defining and describing occupations and job requirements. Website: https://www.onetcenter.org/.

[5] For a detailed review of related methods, see Sebastiani (2002). For a discussion on the empirical advantages of the cosine similarity method, see Hoberg and Phillips (2016).

retrieval literature, which suggests that common words are less informative than unique words. To address this, I apply weighing schemes to adjust the raw count of job postings for each occupation (see, e.g., Loughran & McDonald 2011). Specifically, I assign each element of $O_{i,t}$ to measure the weighted demand for the corresponding occupation. The k^{th} element of $O_{i,t}$ for firm i in month t is denoted as $o_{i,k,t}$ and is defined as follows:

$$o_{i,k,t} = \begin{cases} \frac{1+\log(p_{i,k,t})}{1+\log(P_{i,t})} \cdot \log\left(\frac{N_t}{n_{k,t}}\right), & if\ p_{i,k,t} \geq 1 \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where $p_{i,k,t}$ is the raw number of postings of the k^{th} occupation by firm i in month t, $P_{i,t}$ is the number of all job postings by firm i in month t, N_t is the total number of firms in the sample in month t, $n_{k,t}$ is the number of firms demanding at least one k^{th} occupation in month t. The term $\frac{1+\log(p_{i,k,t})}{1+\log(P_{i,t})}$ captures the weight of each occupation while the term $\log\left(\frac{N_t}{n_{k,t}}\right)$ gives greater weight for job postings that are unique, relative to job postings that are common across all firms.

I define the labour demand similarity between firm i and firm j as the cosine similarity of their vectors $O_{i,t}$ and $O_{j,t}$:

$$Labor_{i,j,t} = \frac{O_{i,t} \times O_{j,t}}{\|O_{i,t}\| \times \|O_{j,t}\|}. \tag{2}$$

$Labor_{i,j,t}$ is a value between zero and one. If the measure is close to one, then there is a large overlap between the occupations demanded by the two firms. If it is close to zero, then the two firms demand very different labour inputs.

Up to this point, I have developed a labour similarity measure that is continuous and varies with time, calculated between each pair of firms on a monthly basis. This forms a labour link network that changes over time. Each firm can have its own distinct set of labour-linked firms, with some closer and others distant. However, it is not possible for a single firm to dominate the labour market and be linked to all other firms in terms of labour. I, therefore, impose a minimum threshold requirement. That is, I define firm i's labour-linked firms as all firms j with $Labor_{i,j,t}$ above a pre-specified minimum threshold. A high threshold will result in fewer labour-linked firms. Following the approach of Liu and Wu (2022), I choose a threshold that ensures the number of labour-linked firms does not exceed the number of firms in the same industry as the firm in question. The number of firms in the industry is based on my sample and can be grouped using the three-digit SIC industries (SIC3)[6]. To mitigate the effect of firm size, for each firm, I compute the median similarity score of its pairwise similarity scores. I then subtract the median score from the firm's original pairwise similarity score before applying the minimum threshold. For each firm, I next compute the firm average similarity, $\overline{Labor_{i,t}}$. To calculate the aggregate labour market competition, I take the weighted average of firm-level similarities,

$$Competition_t = \sum_{i=1}^{N} w_{i,t} \cdot \overline{Labor_{i,t}}. \tag{3}$$

where N is the number of firms in my sample in month t, and $w_{i,t}$ is the ratio of market capitalization for firm i relative to the market total in month t. This value increases when there is a larger overlap in the occupations demanded by the overall market. In addition, it varies with time, as different firms may demand different occupations in different months.

Table Ch2-1 reports the summary statistics of my labour market competitiveness measure over the sample period. The measure ranges from a minimum of 0.211 to a maximum of 0.294, with a mean of 0.262. It is negatively skewed, with only a slight excess kurtosis. The first-order autocorrelation is 0.393, but the series is stationary, as shown by the p-value from Augmented Dickey-Fuller (ADF) test. On average, there are 203,736 job postings each month

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[6] Alternatively, I set the threshold for the number of firm pairs based on the sample firms utilized in Hoberg and Phillips (2016), obtained from https://hobergphillips.tuck.dartmouth.edu/. I cross-reference the firms employed in their study with the 3-digit SIC code obtained from Compustat and determine the number of firms representing each industry. Using this count as the threshold for calculating average similarity for each firm in our own sample, I obtain qualitatively similar findings.

from 1,614 unique firms. This leads to an average of 124 job postings per firm per month, spread across all states in the U.S.

Table Ch2-1. Summary statistics

This table reports monthly summary statistics for the labour market competitiveness, portfolio returns, and other stock market return predictors. *ACF* is the first-order autocorrelation function, and *ADF* is the Augmented Dickey-Fuller test p-value. The sample period is from January 2010 to December 2021.

Variables	*Mean*	*Median*	*Std. Dev.*	*Min*	*Max*	*Skew*	*Kurt*	*ACF*	*ADF*	*Correlation with Competition*
Labour market competitiveness (*Competition*)	0.262	0.262	0.010	0.211	0.294	-0.585	7.400	0.393	0.00	1.00
Total job postings monthly	203,736	213,780	69,964	15,188	389,605	0.029	2.753	0.816	0.00	0.38
Unique firms monthly	1,614	1,539	299	498	2105	-0.107	3.022	0.915	0.00	0.58
Average job postings	124	123	31	30	202	-0.030	2.499	0.734	0.06	0.18
Portfolio returns										
Portfolio market	0.0136	0.0172	0.054	-0.205	0.190	-0.275	5.327	-0.035	0.00	0.01
Portfolio small	0.0065	0.0090	0.054	-0.163	0.174	-0.255	3.730	-0.046	0.00	-0.03
Portfolio large	0.0147	0.0170	0.044	-0.112	0.145	-0.161	4.013	-0.091	0.00	0.05
Russell 2000	0.0074	0.0120	0.058	-0.249	0.194	-0.529	5.455	-0.046	0.00	0.01
Russell 1000	0.0087	0.0125	0.047	-0.216	0.167	-0.638	6.854	-0.077	0.00	0.04
Stock market predictors										
S&P500 Excess Return	0.011	0.017	0.040	-0.133	0.120	-0.530	4.199	-0.110	0.00	0.09
VIX	18.498	16.585	6.963	9.510	53.540	1.888	7.898	0.690	0.00	0.00
Average Correlation	0.244	0.225	0.111	0.063	0.630	0.977	3.898	0.447	0.00	-0.07
Realized Volatility	0.042	0.035	0.029	0.014	0.273	4.388	32.338	0.469	0.00	0.01
Dividend-Price Ratio	-3.960	-3.940	0.120	-4.370	-3.770	-1.769	6.142	0.898	0.85	-0.24
Dividend-Earnings Ratio	-0.920	-0.905	0.196	-1.240	-0.480	0.205	2.366	0.983	0.20	0.03
Labour market predictors										
Employment Growth Rate	0.063	0.058	0.022	0.035	0.147	0.782	3.350	0.900	0.08	-0.31
Unemployment Rate	0.003	0.004	0.021	-0.154	0.064	-5.368	40.032	0.597	0.00	0.04
Economic Policy Uncertainty	1.615	1.450	0.715	0.640	5.040	2.033	8.434	0.710	0.00	0.11
Economic predictors										
Chicago Fed National Activity Index	-0.051	-0.010	1.728	-17.960	6.120	-7.417	83.151	0.084	0.00	0.05
Industrial Production Growth	0.001	0.002	0.014	-0.132	0.063	-4.967	54.081	0.189	0.00	0.01
NBER Business Cycle	0.014	0.000	0.117	0.000	1.000	8.307	70.014	0.493	0.00	-0.05
Term Spread	0.021	0.020	0.012	0.000	0.040	-0.102	2.094	0.928	0.17	-0.38
Default Spread	0.025	0.026	0.005	0.017	0.036	0.125	2.046	0.931	0.10	-0.20

Figure Ch2-1. Labour market competitiveness over time

This figure shows the time series of the monthly value of the labour market competitiveness (left axis) and the unemployment rate (right axis). The unemployment rate is collected from the U.S. Bureau of Labour Statistics. The sample period is from January 2020 to December 2021.

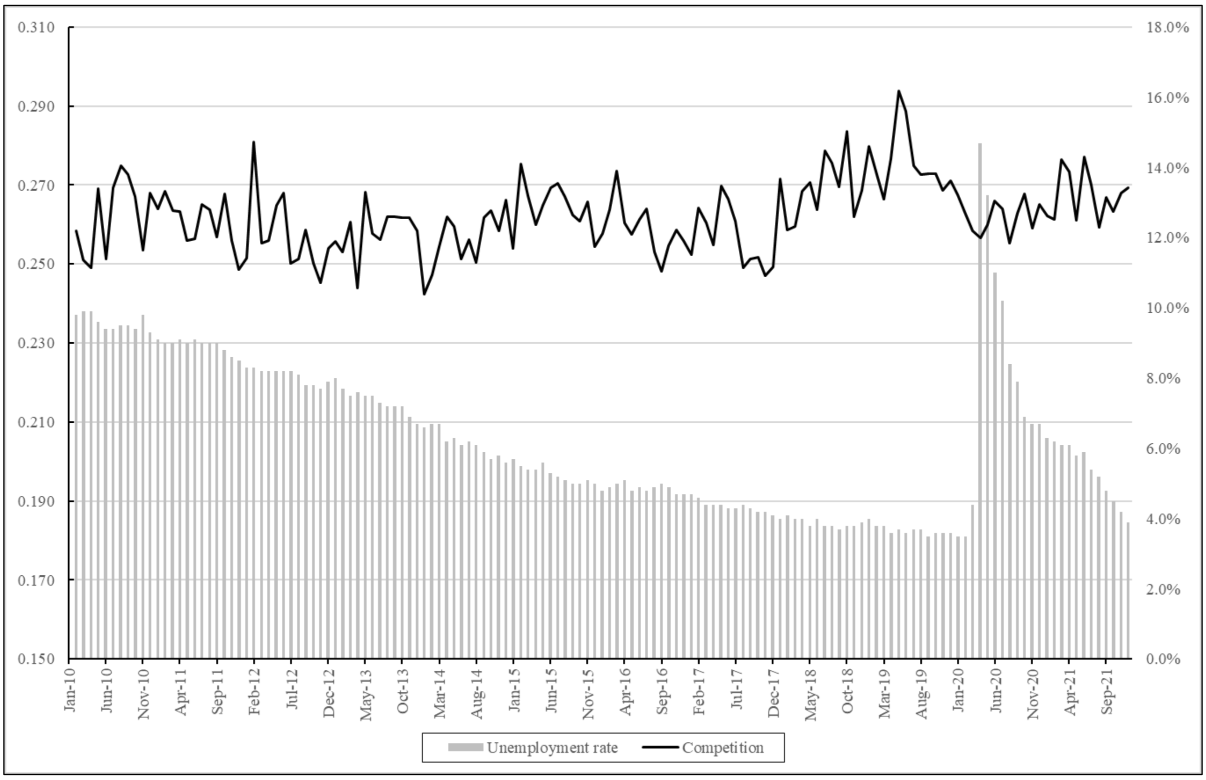


Figure Ch2-1 presents a plot of the monthly time series data for my Competition metric and the U.S. unemployment rate, spanning the period from January 2010 to December 2021. As the figure illustrates, my labour market competition metric captures market dynamics that are distinct from those captured by the unemployment indicator. Between 2010 and 2020, the unemployment rate declined while the labour market competitiveness fluctuated. However, during the first quarter of 2020, I observe a sudden jump in unemployment as businesses were forced to close due to the Covid-19 outbreak. This period was associated with a decrease in the overall labour market competition.

3.3. Stock Market Data

My stock data is obtained from the Center for Research in Security Prices (CRSP), which I access through the Wharton Research Data Services (WRDS). I collect daily data on closing price, volume, and market capitalization. This data later is linked to the sample firms that I matched between the BGT dataset and Compustat using the Compustat-CRSP match table provided by WRDS. From the daily stock price data and market capitalization obtained from CRSP, I compute the equal- and value-weighted stock returns, average return correlation, and realized volatility on a monthly basis. I construct the monthly excess return as the difference between the return for the stock portfolio and the U.S. 1-month Treasury Bill.

3.4. Other Predictor Variables

Throughout the paper, I compare the predictive power of $Competition$ for aggregate excess returns with other forecasting variables which have been documented in the literature. I focus on predictor variables introduced in previous studies that are available at a monthly frequency. I group them into three categories: (1) stock market predictors, (2) labour market predictors, and (3) economic predictors. The full list of predictors, definitions, and sources is provided in Appendix 2B.

The first group, the stock market predictors, consists of the S&P500 returns, the CBOE Implied Volatility Index (VIX), the market average (return) correlation, the market realized volatility, the dividend-price ratio, and the dividend-earnings ratio. To ensure that my results are not influenced by serial correlation in returns, I use the S&P 500 returns in excess of the risk-free rate. The VIX measures investors' expectations of market volatility over the next 30 days and reflects the near-term market sentiment of the stock market. Whaley (2009) documents that the VIX works reasonably well as a predictor of expected stock index movements. Pollet and Wilson (2010) show that the stock returns average correlation and average variance predicts subsequent stock market excess returns. This positive relationship is due to higher aggregate risk reflected by the higher correlation between stocks. Dividend-price ratios and dividend-earnings ratios are known predictors of stock returns (see, e.g., Fama & French 1988; Lettau & Ludvigson 2001; Chen & Zhang 2011).

The second group, labour market predictors, includes the average number of job postings, the employment growth rate, the unemployment rate, and economic policy uncertainty. According to Kothari and O'Doherty (2023), one of the most robust predictors of stock returns is the ratio of job postings to employment levels. They found that higher ratios indicate greater adjustment costs, which can lead to lower expected excess stock market returns. Unfortunately, the specific job openings-to-employment ratio used in their study is not publicly available. To address this limitation, I constructed a similar measure by dividing the total number of job postings by the number of firms posting those jobs. This approach provides a comparable proxy for the Kothari and O'Doherty ratio and enables me to investigate the relationship between job postings and stock returns. The employment growth rate is a negative predictor of stock market returns due to hiring frictions (Chen & Zhang 2011). Previous theoretical and empirical studies have also established a link between the unemployment rate and the aggregate expected returns (Ludvigson & Ng 2007; Hall 2017). High unemployment rates are commonly associated with a high discount rate, which prompts investors to demand higher returns on their investments. Furthermore, economic policy uncertainty can significantly impact the labour market, as it may lead firms to withhold hiring, thereby exacerbating unemployment levels (Baker et al. 2016).

The economic predictors' group includes various indicators, including the Chicago Fed National Activity Index, Industrial Production Growth, NBER business cycle, term spread, and default spread. In their study, Fama and French (1989) observed that expected returns include risk premiums that move inversely with business conditions. Consequently, stock returns tend to decrease (increase) following periods of economic expansion (contraction). Based on this, I can anticipate a negative correlation between market fundamentals such as the Chicago Fed National Activity Index and Industrial Production Growth, while a positive correlation with NBER business cycle indicators suggests recessionary periods. Finally, the relationship between term spread and stock returns, as well as between the default yield spread, can be explained by risk factors, as has been well documented in various studies (see, e.g., Campbell 1987; Fama 1990; Vassalou & Xing 2004).

As shown in Table Ch2-1, the average excess return from my equal-weighted stock market portfolio is approximately 1.36% per month (16.3% per annum) during the sample period from 2010 to 2021. This is primarily driven by the large stocks, where the average monthly return is 1.47%, while small stocks show an average monthly return of 0.65%. Contrary to the traditional convention, larger firms have yielded higher returns, particularly during the last two years from 2020 to 2021. For comparison, the Russell 1000 and Russell 2000 index returns are 0.87% and 0.74% per month, respectively.

The final column of Table Ch2-1 reports the correlations between my main measure of labour market competitiveness and the various predictors. The correlation coefficients indicate that my measure is not highly correlated with other predictors, ranging from -0.38 (with the term spread) to 0.18 (with the average job postings). The excess return of my market portfolio is highly correlated (0.95) with the excess return of the S&P 500, suggesting that my portfolio mimics the market very closely and is a good representation of the U.S. stock market.

4. RESULTS

4.1. Validation Tests

To ensure that my labour market competitiveness measure accurately captures the intensity of labour demand, I conduct two validation tests. The first test examines the association between the labour market competitiveness metric and the labour market concentration index, which is derived in a similar fashion to the Herfindahl-Hirschman index (HHI). The second test investigates the association between the labour market competitiveness metric and the market average wage. I now discuss each of these validation tests in turn.

The HHI is a widely employed metric to assess market concentration in product markets. Recently, Azar et al. (2022) construct HHI for the labour market, recognizing that product and labour markets are distinct from each other. The HHI for market m and month t can be calculated as

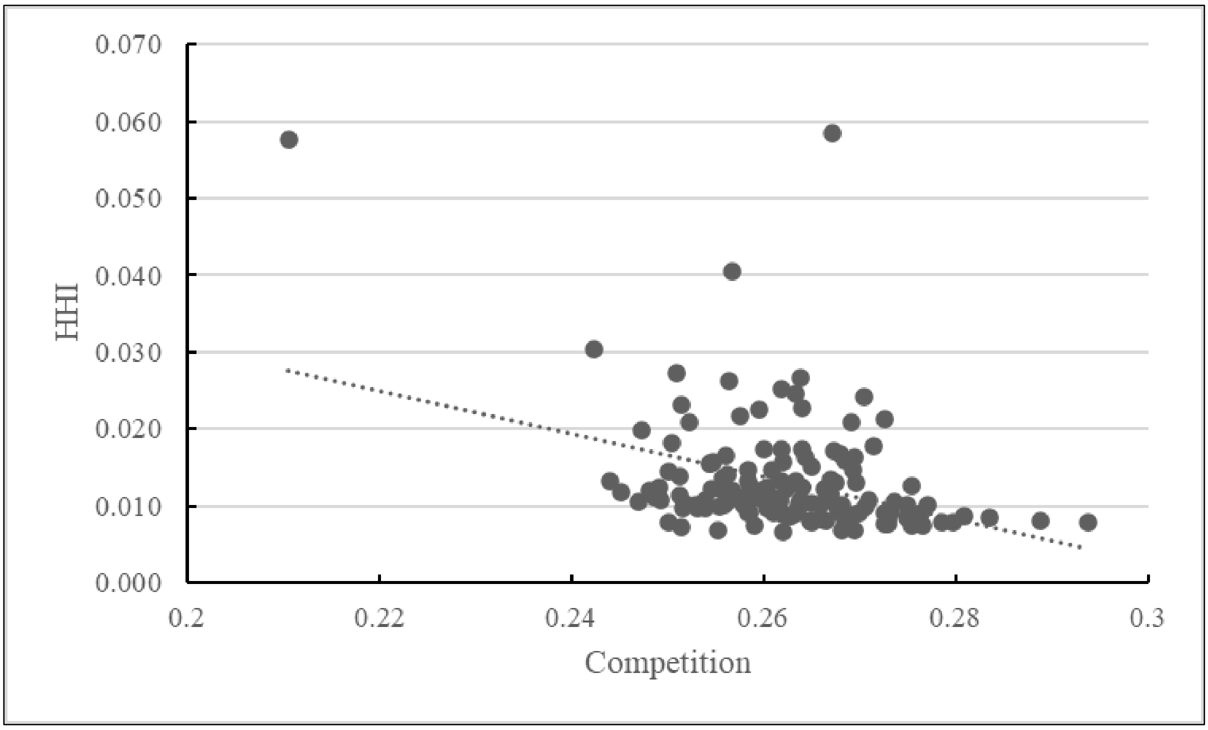
$$HHI_{m,t} = \sum_{i=1}^{N} s_{i,m,t}^{2} \tag{4}$$

where $s_{i,m,t}$ represents the market share of firm i in market m during month t. This market share is calculated as the sum of job postings by firm i in a given month divided by the total job postings in the market during that same period. A high HHI suggests that the firm fills the market with a large number of job vacancies, thereby dominating the demand-side of the labour market. This is contrary to a competitive labour market scenario where multiple firms vie for a talent pool. As such, I anticipate a negative correlation between my measure of labour market competitiveness and the labour market HHI index.

Figure Ch2-2 presents the scatter plot between *Competition* and *HHI*. The correlation between the two metrics is negative. Greater labour market competitiveness is associated with lower labour market concentration. While the HHI may serve as an inverse indicator of labour market competitiveness, it is not an ideal proxy. The HHI gauges the participation rate of a firm in the labour market but does not take into account the overlap of job postings among firms in the market. As such, a firm may post many job vacancies, but only a few of these vacancies are also in demand by other firms. My measure of competitiveness, on the other hand, is more nuanced than the HHI. I posit that considering the interconnectedness among firms is essential to better capture the true nature of competition in the labour market.

Figure Ch2-2. Labour market competition and labour market concentration index (HHI)

This figure shows the scatter plots between labour market competitiveness and the labour market concentration index (HHI). The sample period is from January 2020 to December 2021. Trendline is dashed.



For the second validation test, I consider the market average of wages. Studies have documented that labour market concentration is associated with lower average wages. The Monopsony Theory proposes that as the labour market becomes more concentrated around fewer firms, job seekers will face diminished bargaining power, resulting in lower average wages (see, e.g., Boal & Ransom 1997; Ashenfelter et al. 2010, among others). Consequently, I expect that higher labour market competitiveness to be positively correlated with the market average wage. To calculate the average wage, I utilize the salary information associated with each job posting in BGT. Wages are reported as a range rather than a single value. As such, I take the midpoint of the two values and use it as estimated wages. I calculate the average wage for a given market and month by taking the simple average across all job postings from the firms in my sample.

Figure Ch2-3. Labour market competition and market average wage

This figure shows the scatter plots between labour market competitiveness and the (log) market average wage. The sample period is from January 2020 to December 2021. Trendline is dashed.

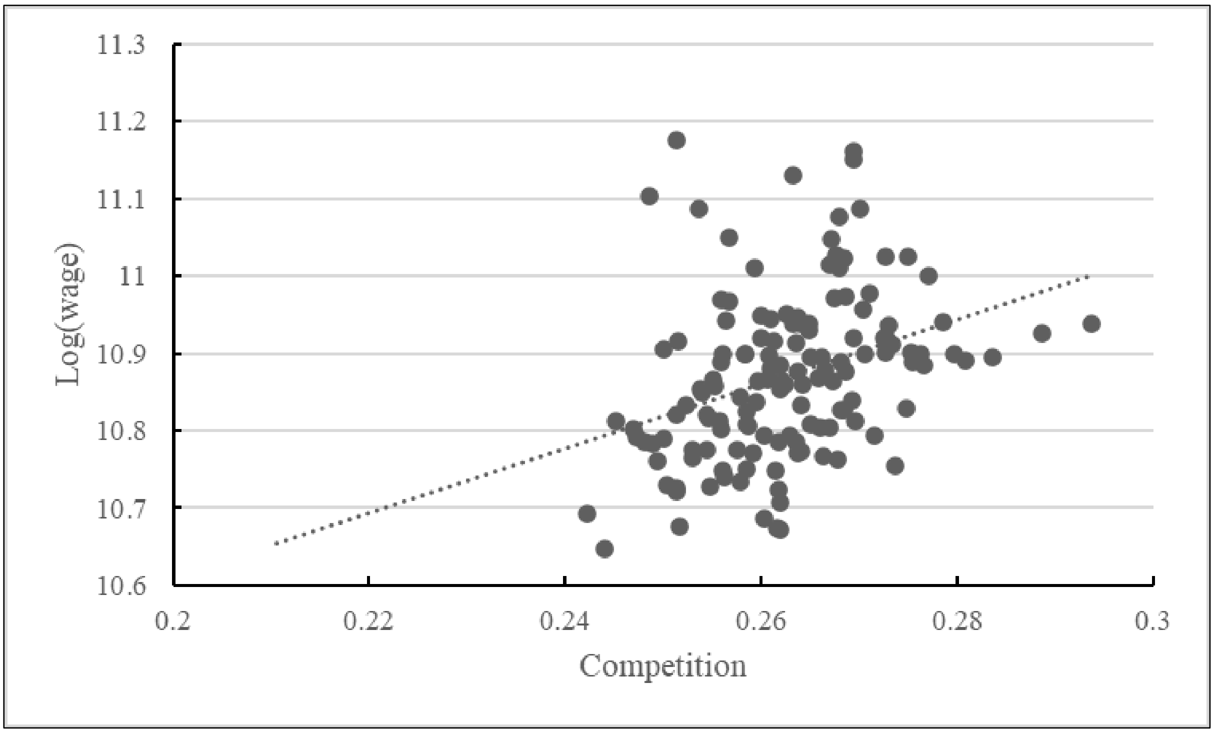


Figure Ch2-3 shows that higher labour market competitiveness is associated with higher average wages. This implies that as more firms compete for a limited pool of resources, job seekers become more valuable. This is reflected in higher average salaries.

4.2. Aggregate Risk Premium

To assess the predictive power of labour market competitiveness for aggregate stock returns, I consider the realized future excess market returns. More specifically, I regress the future excess returns of the market portfolio on my measure of labour market competitiveness:

$$R_{t+1:t+h} = \alpha + \beta \cdot Competition_t + \varepsilon_{t+1:t+h} \quad (5)$$

Here, $R_{t+1:t+h}$ is the cumulative excess return for the stock market portfolio from my sample over months $t+1$ through $t+h$, after subtracting the cumulative return on the one-month

Treasury Bill. I consider h = 1, 3, 6, 9, 12, 15, and 18 months, representing the time horizons over which I calculate the future excess returns, spanning from one month to six quarters. To assist with the interpretation and economic significance of the predictability, I normalize the variable $Competition_t$. Specifically, from each month t observation, I subtract the sample mean and divide this difference by the series standard deviation. The main coefficient of interest is β, as it captures the average response of market returns to competition in the labour market.

Table Ch2-2 reports the OLS estimates, the associated t-statistics, and the regression adjusted R^2 values. Panel A shows the result based on equal-weighted returns. The first set of columns shows that, for the market portfolio, the slope coefficient is negative and statistically significant. For instance, the coefficient for the first quarter ($h = 3$) is -0.022, suggesting that a one standard deviation increase in labour market competitiveness leads to a 2.2% decrease in stock excess return over the next quarter. The coefficients remain significant until the fourth quarter ($h = 12$), indicating that the stock market adjusts to changes in labour market competitiveness within less than a year. These results support my hypothesis H1, which states that labour market competition affects aggregate stock market return.

Table Ch2-2. Univariate regression results

This table reports the univariate regression results of stock market excess returns (returns in excess of the 1-month Treasury Bill) on the lagged labour market competitiveness. The dependent variable $Ret_{(t+1:t+h)}$ is the cumulative excess returns from month $t+1$ to month $t+h$, where h = *1, 3, 6, 9, 12, 15, 18*. Panels A and B report the results based on equal-weighted and value-weighted returns, respectively. *Portfolio market* is the returns of a portfolio constructed from the firms in my sample. *Portfolio small* is returns based on small stocks in the sample (lower than the size median). *Portfolio large* is returns based on large stocks in the sample (higher than the size median). *Russell 2000* is the returns of a portfolio from the smallest 2000 stocks in the Russell 3000 index. *Russell 1000* is the returns of a portfolio from the largest 1000 stocks in the Russell 3000 index. The sample period is from January 2010 to December 2021. Regression coefficients for the constant are not reported for brevity. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

		Portfolio market			*Portfolio small*			*Portfolio large*			*Russell 2000*			*Russell 1000*		
	Obs	*Competition*	*t-stat*	*Adj. R2*	*Competition*	*t-stat*	*Adj. R2*	*Competition*	*t-stat*	*Adj. R2*	*Competition*	*t-stat*	*Adj. R2*	*Competition*	*t-stat*	*Adj. R2*
Panel A: Equal-weighted returns																
h=1	143	-0.005*	(-1.83)	0.00	-0.007**	(-2.40)	0.01	-0.003	(-1.25)	0.00	-0.005*	(-1.72)	0.00	-0.004	(-1.44)	0.00
h=3	141	-0.022***	(-3.25)	0.05	-0.027***	(-3.83)	0.08	-0.015***	(-2.74)	0.04	-0.022***	(-2.83)	0.04	-0.016***	(-2.82)	0.04
h=6	138	-0.023**	(-2.32)	0.03	-0.032***	(-2.86)	0.06	-0.014*	(-1.73)	0.01	-0.027**	(-2.23)	0.03	-0.018**	(-1.96)	0.03
h=9	135	-0.040***	(-3.10)	0.06	-0.054***	(-3.68)	0.12	-0.027***	(-2.84)	0.05	-0.051***	(-3.15)	0.09	-0.036***	(-2.95)	0.09
h=12	132	-0.038***	(-2.63)	0.04	-0.057***	(-3.49)	0.10	-0.025**	(-2.36)	0.03	-0.055***	(-3.32)	0.08	-0.040***	(-3.74)	0.08
h=15	129	-0.024	(-1.19)	0.01	-0.048**	(-2.40)	0.06	-0.015	(-0.98)	0.00	-0.045**	(-2.24)	0.05	-0.036***	(-2.90)	0.06
h=18	126	0.005	(0.20)	-0.01	-0.022	(-0.87)	0.01	0.007	(0.33)	-0.01	-0.017	(-0.62)	0.00	-0.019	(-1.13)	0.01
Panel B: Value-weighted returns																
h=1	143	-0.002	(-0.75)	-0.01	-0.001***	(-4.13)	0.05	-0.002	(-0.72)	-0.01	-0.004	(-1.40)	0.00	-0.001	(-0.63)	-0.01
h=3	141	-0.010**	(-2.11)	0.02	-0.002***	(-3.81)	0.15	-0.009**	(-2.09)	0.02	-0.019***	(-2.62)	0.04	-0.010**	(-2.03)	0.02
h=6	138	-0.006	(-0.86)	0.00	-0.002***	(-2.81)	0.11	-0.005	(-0.77)	0.00	-0.023**	(-2.02)	0.03	-0.008	(-1.05)	0.00
h=9	135	-0.016**	(-2.04)	0.02	-0.003***	(-3.07)	0.14	-0.014**	(-1.97)	0.02	-0.045***	(-3.24)	0.09	-0.020**	(-2.52)	0.04
h=12	132	-0.013	(-1.42)	0.00	-0.004***	(-2.75)	0.11	-0.011	(-1.27)	0.00	-0.050***	(-3.77)	0.09	-0.021***	(-2.95)	0.04
h=15	129	-0.002	(-0.11)	-0.01	-0.003**	(-2.07)	0.07	-0.001	(-0.06)	-0.01	-0.040***	(-2.60)	0.06	-0.014	(-1.44)	0.01
h=18	126	0.019	(1.04)	0.01	-0.002	(-1.23)	0.02	-0.011	(-1.27)	0.00	-0.017	(-0.82)	0.00	0.000	(0.02)	-0.01

In the next two sets of columns, I consider portfolios constructed using the small and large firms in my sample, i.e., those with market capitalization lower and higher than the full sample median, respectively. I observe that return predictability is stronger for the small compared to the large portfolio. Comparing the coefficients for one year (h = 12), one standard deviation increases in the *competition* lead to 5.7% decrease in stock excess return for the small portfolio, while it is 2.5% for the large portfolio. In addition, I find the predictive power of labour market competitiveness lasts longer in the small portfolio than the larger portfolio, where the predictability lasts up until the fifth quarter ($h = 15$) for the smaller portfolio, but it become insignificant for the large portfolio. Further, I find similar results when examining the predictive power of labour market competitiveness on stock market indices, the Russell 2000 and Russell 1000, representing the smallest 2000 stocks and the largest 1000 stocks in the US, respectively. This indicates that the predictive power of labour market competitiveness on stock returns is stronger for smaller firms compared to larger ones, support my hypothesis H2.

Panel B of Table Ch2-2 presents the results based on value-weighted returns. While the results show fewer significant coefficients, they are consistently negative across various time horizons. More importantly, the predictability is stronger for the small market portfolio and the Russell 2000 returns, indicating that smaller firms are more responsive to labour market competitiveness.

Strong labour market conditions have the potentials to heighten inflation and diminish the actual returns on investments. In such a case, it is plausible that the impact of labour market competitiveness on stock returns becomes negligible when adjusted for inflation. I control for this potential effect by employing real returns, i.e., monthly returns in excess of the monthly inflation rate, as the dependent variable in Eq. (5). Real returns are also used in similar context in studies such as Hsu (2009) and Belo et al. (2023). I present these results in Appendix 2C. I do not observe qualitatively different results from those reported in Table Ch2-2, implying that the linkage between labour market competitiveness and aggregate stock returns is not through inflation.

Next, I conduct pairwise horseraces in a multiple regression framework to compare the predictive power of labour market competitiveness with other known predictors of stock returns. I assess the incremental effects using the following multivariate regression specification,

$$R_{t+1:t+h} = \alpha + \gamma \cdot Predictor_t + \beta \cdot Competition_t + \varepsilon_{t+1:t+h} \quad (6)$$

where $Predictor_t$ is one of the predictor variables discussed in Section 3.

Table Ch2-3 reports the results of the regression analyses based on the next quarter's equal-weighted stock returns ($h = 3$).[7] In Panel A, each of the predictor variables are added separately into the predictive regressions. The second column presents the expected sign based on the findings in extant literature. Many of the known predictors are significant in predicting future stock excess returns in my regression model. For example, in terms of stock market predictors, I find the S&P 500 excess returns, VIX, average correlation, and realized volatility significantly predict stock returns over the next quarter. An increase in the VIX leads to a risk premium as investors expect higher compensation for holding riskier stocks. Similarly, average correlation leads to higher returns as it reflects an increase in aggregate risk (Pollet & Wilson 2010). In terms of labour market predictors, log (average posts), unemployment rate, and economic policy uncertainty are significant factors affecting stock returns. Additionally, the NBER business cycle and the default spread are significant economic predictors.

[7] Results based on value-weighted stock returns are reported in Appendix 2D.

Table Ch2-3. Multivariate regression results (next quarter returns)

This table reports the multivariate regression results of equal-weighted stock market excess returns on labour market competitiveness and other predictors. I use $Ret_{(t+1:t+3)}$ as the dependent variable. Panel A reports the results based on a univariate regression on known predictors (*Predictor*). Panel B reports the coefficients for *Competition* in addition to other known predictors. Panels C and D report the coefficients for *Competition* from the multivariate regressions based on small and large market portfolio returns, respectively. *sign* is the expected relation between predictor and stock returns (based on the literature). The sample period is from January 2010 to December 2021. Details on each of these variables can be found in Appendix B. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent: $Ret_{(t+1:t+3)}$		Panel A: Univariate regression			Panel B: Multivariate regression					Panel C: Portfolio small		Panel D: Portfolio large	
	sign	*Predictor*	*t-stat*	*Adj. R^2*	*Predictor*	*t-stat*	*Competition*	*t-stat*	*Adj. R^2*	*Competition*	*t-stat*	*Competition*	*t-stat*
Stock market predictors													
S&P500 Excess Return	-	-0.330*	(-1.82)	0.01	-0.283	(-1.61)	-0.021***	(-3.14)	0.06	-0.026***	(-3.73)	-0.014***	(-2.55)
VIX	+	0.007***	(5.37)	0.24	0.007***	(5.47)	-0.022***	(-3.65)	0.30	-0.027***	(-4.29)	-0.015***	(-2.86)
Average Correlation	+	0.270***	(2.65)	0.10	0.257***	(2.71)	-0.020***	(-3.60)	0.14	-0.025***	(-4.21)	-0.013***	(-2.90)
Realized Volatility	+	1.357***	(6.31)	0.17	1.366***	(6.68)	-0.022***	(-3.84)	0.23	-0.027***	(-4.30)	-0.015***	(-3.13)
Dividend-Price Ratio	+	0.158	(1.31)	0.03	0.117	(0.97)	-0.019***	(-2.91)	0.06	-0.023***	(-3.31)	-0.013**	(-2.36)
Dividend-Earnings Ratio	+	0.107	(1.43)	0.04	0.113	(1.49)	-0.023***	(-3.23)	0.10	-0.028***	(-3.82)	-0.015***	(-2.72)
Labour market predictors													
log(average posts)	-	-0.087***	(-3.02)	0.06	-0.072**	(-2.28)	-0.017***	(-2.59)	0.09	-0.023***	(-3.16)	-0.011**	(-2.10)
Employment Growth Rate	-	-0.501	(-1.11)	0.01	-0.461	(-1.05)	-0.022***	(-3.26)	0.05	-0.027***	(-3.83)	-0.015***	(-2.72)
Unemployment Rate	+	1.104**	(2.47)	0.06	0.885*	(1.92)	-0.016***	(-2.70)	0.08	-0.023***	(-3.38)	-0.010**	(-2.10)
Economic Policy Uncertainty	+	0.058***	(5.04)	0.19	0.062***	(5.29)	-0.027***	(-4.77)	0.27	-0.031***	(-5.03)	-0.018***	(-3.94)
Economic predictors													
Chicago Fed National Activity Index	-	-0.005	(-1.40)	0.00	-0.005	(-1.26)	-0.022***	(-3.26)	0.05	-0.027***	(-3.82)	-0.015***	(-2.73)
Industrial Production Growth	-	-0.564	(-0.98)	0.00	-0.543	(-1.01)	-0.022***	(-3.26)	0.05	-0.027***	(-3.82)	-0.015***	(-2.74)
NBER Economic Cycle	+	0.228***	(8.00)	0.08	0.219***	(7.70)	-0.021***	(-3.21)	0.12	-0.026***	(-3.79)	-0.014***	(-2.65)
Term Spread	+	-0.303	(-0.28)	-0.01	-1.153	(-1.01)	-0.027***	(-3.32)	0.06	-0.031***	(-3.73)	-0.019***	(-2.77)
Default Spread	+	6.086**	(2.52)	0.08	5.381**	(2.30)	-0.017***	(-2.97)	0.11	-0.023***	(-3.62)	-0.011**	(-2.34)

In Panel B of Table Ch2-3, I include labour market competitiveness in the regression model. The coefficients for labour market competitiveness remain negative and highly significant, with Newey-West t-statistics above 2.0 and, in many cases, over 3.0 in absolute terms. The coefficients range from -0.016 (in the model with the unemployment rate) to -0.027 (in the model with term spread and economic policy uncertainty), indicating that increased competition leads to lower stock returns by 1.6% to 2.7% over the next quarter. More importantly, my finding suggests that the explanatory power of labour market competitiveness for aggregate market returns is unaffected by the presence of other predictors. The adjusted R^2 is larger after the inclusion of my competitiveness measure (an average of 0.072 in Panel A and 0.118 in Panel B), suggesting that the competition metric contributes to the power of the predictive model. The findings again strongly support my hypothesis H1, that is, increased labour market competitiveness has a significant impact on stock returns.

In Panels C and D, I estimate Eq. (6) for the portfolios of small and large stocks, respectively. The coefficients for labour market competitiveness are significantly negative in both panels. However, the magnitude is noticeably larger for the small stock portfolio. This observation further shows that small firms are more affected by the level of competition in the labour markets, supporting hypothesis H2.

Table Ch2-4. Multivariate regression results (next four-quarter returns)

This table reports the multivariate regression results of equal-weighted stock market excess returns on labour market competitiveness and other predictors. I use $Ret_{(t+1:t+12)}$ as the dependent variable. Panel A reports the results based on a univariate regression on known predictors (*Predictor*). Panel B reports the coefficients for *Competition* in addition to other known predictors. Panels C and D report the coefficients for *Competition* from the multivariate regressions based on small and large market portfolio returns, respectively. *sign* is the expected relation between predictor and stock returns (based on the literature). The sample period is from January 2010 to December 2021. Details on each of these variables can be found in Appendix B. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent: $Ret_{(t+1:t+12)}$		Panel A: Univariate regression			Panel B: Multivariate regression					Panel C: Portfolio small		Panel D: Portfolio large	
	sign	*Predictor*	*t-stat*	*Adj.* R^2	*Predictor*	*t-stat*	*Competition*	*t-stat*	*Adj.* R^2	*Competition*	*t-stat*	*Competition*	*t-stat*
Stock market predictors													
S&P500 Excess Return	-	-0.641	(-1.39)	0.013	-0.573	(-1.23)	-0.036**	(-2.41)	0.048	-0.056***	(-3.28)	-0.023**	(-2.14)
VIX	+	0.015***	(4.27)	0.351	0.015***	(4.33)	-0.037***	(-2.74)	0.391	-0.057***	(-3.61)	-0.024**	(-2.51)
Average Correlation	+	0.544***	(2.64)	0.115	0.525***	(2.59)	-0.034***	(-2.62)	0.146	-0.054***	(-3.70)	-0.022**	(-2.26)
Realized Volatility	+	3.081***	(5.30)	0.254	3.104***	(5.53)	-0.039***	(-2.92)	0.299	-0.059***	(-3.81)	-0.026***	(-2.61)
Dividend-Price Ratio	+	0.740	(1.57)	0.069	0.654	(1.41)	-0.030**	(-2.17)	0.089	-0.045***	(-3.07)	-0.018*	(-1.83)
Dividend-Earnings Ratio	+	0.261	(1.62)	0.074	0.272*	(1.70)	-0.040***	(-2.62)	0.120	-0.060***	(-3.43)	-0.026**	(-2.36)
Labour market predictors													
log(average posts)	-	-0.160**	(-2.54)	0.050	-0.136**	(-2.15)	-0.030**	(-1.99)	0.071	-0.052***	(-3.04)	-0.017	(-1.63)
Employment Growth Rate	-	-2.407**	(-2.19)	0.077	-2.368**	(-2.19)	-0.037***	(-2.58)	0.113	-0.056***	(-3.45)	-0.024**	(-2.31)
Unemployment Rate	+	3.095***	(2.55)	0.149	2.849**	(2.22)	-0.018	(-1.33)	0.153	-0.039***	(-2.61)	-0.009	(-0.91)
Economic Policy Uncertainty	+	0.153***	(6.31)	0.390	0.160***	(7.82)	-0.051***	(-4.55)	0.468	-0.068***	(-4.63)	-0.034***	(-4.28)
Economic predictors													
Chicago Fed National Activity Index	-	-0.014	(-0.95)	0.012	-0.014	(-0.91)	-0.037***	(-2.59)	0.049	-0.057***	(-3.47)	-0.024**	(-2.32)
Industrial Production Growth	-	-1.299	(-0.58)	0.003	-1.322	(-0.60)	-0.038***	(-2.65)	0.042	-0.057***	(-3.50)	-0.025**	(-2.37)
NBER Business Cycle	+	0.629***	(16.15)	0.178	0.615***	(15.76)	-0.034**	(-2.39)	0.210	-0.055***	(-3.38)	-0.022**	(-2.10)
Term Spread	+	-2.083	(-0.75)	0.013	-3.773	(-1.33)	-0.055***	(-2.75)	0.089	-0.066***	(-3.28)	-0.036**	(-2.39)
Default Spread	+	17.446***	(3.74)	0.187	16.547***	(3.62)	-0.027**	(-2.43)	0.203	-0.044***	(-4.32)	-0.017*	(-1.86)

Table Ch2-4 presents the results for the regression analyses based on a longer horizon, i.e., over the next one year.[8] Consistent with the previous results, labour market competitiveness remains predictive of market excess returns. Except for the model with the Unemployment rate, the coefficient for labour market competitiveness is negative and statistically significant in predicting stock returns. The coefficients range from -0.018 (unemployment rate) to -0.055 (term spread), implying that an increase in labour market competition leads to a lower return from 1.8% to 5.5% over the next 12 months. Splitting the sample into small and large market portfolios, I again observe that the negative predictive power of labour market competitiveness on stock returns is stronger for the portfolio consisting of small stocks.

4.3. Transmission Channel

The above results show that labour market competitiveness can predict aggregate stock market return. In this subsection, I examine where such a predictability comes from and what mechanism predominantly influences the stock market's response to labour market competition. There are two possible channels that labour market competitiveness affects aggregate stock market return. On the one hand, heightened labour market competitiveness can result in increased stock correlation, thereby eroding the benefits of diversification (risk channel). On the other hand, intensified labour market competition can also prompt companies to allocate additional resources toward attracting new workers and retaining high-performing employees (cash flow channel). Drawing from Campbell and Shiller (1988), unexpected asset returns can be decomposed into two components: 1) shocks pertaining to cash flows, which

[8] Results based on value-weighted stock returns are reported in Appendix 2E.

reflect changes in firm fundamentals, and 2) shocks related to discount rates, which indicate varying levels of risk aversion or investor sentiment over time.

Using Campbell and Shiller (1988) return decomposition, I estimate the monthly cash flow and discount rate shocks. The model decomposes the unexpected stock returns into shocks about future dividends, which reflect changes in firm fundamentals, and future discount rates, which indicate varying levels of risk aversion or investor sentiment over time:

$$
\begin{aligned}
r_{t+1} - E_t r_{t+1} &= (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j r_{t+1+j} \\
&= N_{CF,t+1} - N_{DR,t+1} \qquad (7)
\end{aligned}
$$

where r_{t+1} is a log stock return, E_t and E_{t+1} are expectations at time t and $t+1$, Δd_{t+1} is a one-period change in log dividends, ρ is a constant discount factor, $N_{CF,t+1}$ is shocks about future cash flows, and $N_{DR,t+1}$ is shocks about future discount rates. To implement this decomposition, I follow Campbell and Vuolteenaho (2004) and estimate the series of cash flow and discount rate shocks using a first-order vector autoregression (VAR) model, which captures the linear interdependencies among the time series:

$$z_{t+1} = c + \Gamma z_t + u_{t+1} \qquad (8)$$

where z_{t+1} is an m-by-1 state vector with r_{t+1} as its first element, c and Γ are m-by-1 vectors and m-by-m matrix of constant parameters, and u_{t+1} is an i.i.d. m-by-1 vector of shocks. Subsequently, the cash flow and discount rate shocks are linear functions of the shock vector:

$$
\begin{aligned}
N_{CF,t+1} &= (e1' + e1'\lambda) u_{t+1} \\
N_{DR,t+1} &= e1'\lambda u_{t+1} \qquad (9)
\end{aligned}
$$

where $\lambda \equiv \rho\Gamma(I - \rho\Gamma)^{-1}$, and $e1$ is a vector whose first element is equal to one and zero otherwise. ρ is a constant close to but lower than 1.[9] Following Campbell and Vuolteenaho (2004), I select four state variables: (1) the excess market return, (2) the term spread, (3) the market's smoothed price-earnings ratio (measured as the log ratio of the S&P500 price index to a ten-year moving average of S&P 500 earnings), and (4) the small-stock value spread (measured as the difference between the log book-to-market ratios of small value and small growth stocks).[10]

Once I have obtained the time series of the cash flow shocks ($N_{CF,t+1}$), and discount rate shocks ($N_{DR,t+1}$), I regress each series on the lagged labour market competitiveness variable, i.e., $Competition_t$, to examine how these shocks respond to changes in labour market competitiveness. The results of these regressions are reported in Table Ch2-5.

[9] Campbell and Vuolteenaho (2004) recommend a ρ of $0.95^{\frac{1}{12}}$ for monthly data as it corresponds to an annual average dividend-price or consumption-wealth ratio of 5.2 percent, which is reasonable for a long-term investor.

[10] Data on the term spread and smoothed price-earnings ratio are obtained from Robert Shiller's online repository. The small-stock value spread is constructed using the size and book-to-market sorted portfolio data from Kenneth French's website.

Table Ch2-5. The impact of labour market competitiveness on cash flows and discount rate shocks

This table reports the regression results of cash flow shocks, $N_{CF,t+1}$, and discount rate shocks, $N_{DR,t+1}$, on labour market competitiveness, $Competition_t$. The cash flow and discount rate shocks used in Panel A are derived from a VAR using the following state variables: excess market returns, term spread, smoothened price-earnings ratio, and value spread. The shocks in Panel B are derived from a VAR using the following state variables: excess market returns, term spread, dividend yield, credit default spread, and detrended risk-free rate. The sample period is from January 2010 to December 2021. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Portfolio market		*Portfolio small*		*Portfolio large*		*Russell 2000*		*Russell 1000*	
	$N_{CF,t+1}$	$N_{DR,t+1}$	$N_{CF,t+1}$	$N_{DR,t+1}$	$N_{CF,t+1}$	$N_{DR,t+1}$	$N_{CF,t+1}$	$N_{DR,t+1}$	$N_{CF,t+1}$	$N_{DR,t+1}$
Panel A: VAR based on Campbell and Vuolteenaho (2004)										
$Constant$	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.000	0.000
	(0.20)	(0.34)	(0.18)	(0.16)	(0.20)	(0.22)	(0.14)	(0.12)	(0.14)	(0.02)
$Competition_t$	-0.005**	0.000	-0.008***	-0.002	-0.003	0.000	-0.005**	-0.001	-0.004*	-0.001
	(-2.01)	(-0.38)	(-2.78)	(-1.13)	(-1.30)	(-0.24)	(-2.01)	(-1.21)	(-1.83)	(-1.26)
Obs.	143	143	143	143	143	143	143	143	143	143
Adj. R^2	0.004	-0.006	0.018	-0.002	-0.002	-0.007	0.003	-0.001	0.003	-0.001
Panel B: VAR based on Atilgan et al. (2015)										
$Constant$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(-0.01)	(0.00)	(-0.01)	(0.00)	(-0.01)	(0.00)	(-0.01)	(0.00)	(-0.01)	(0.00)
$Competition_t$	-0.004**	0.000	-0.008***	-0.003	-0.004	-0.002	-0.003*	0.001	-0.006*	-0.003
	(-2.36)	(0.04)	(-2.98)	(-0.65)	(-1.17)	(-0.34)	(-1.73)	(0.41)	(-1.67)	(-0.60)
Obs.	143	143	143	143	143	143	143	143	143	143
Adj. R^2	0.004	-0.007	0.013	-0.006	0.001	-0.007	0.000	-0.007	0.010	-0.005

Panel A shows that cash flow shocks respond negatively to a one standard deviation increase in the competition variable. The coefficient estimate is -0.005 for the market portfolio, -0.008 for the small market portfolio, -0.003 for the large market portfolio, -0.005 for the Russell 2000 index, and -0.004 for the Russell 1000 index. Apart from the large market portfolio, all the above coefficients are significant at the 10% level or better. The discount rate shocks, on the other hand, are not responsive to labour market competition as none of the coefficients are statistically significant. These findings suggest that the expected cash flows decrease in response to an increase in labour market competitiveness, and such a relationship is more pronounced for small market portfolio (and Russell 2000 index). This indicates that the negative relationship between labour market competitiveness and aggregate market return are more likely to be driven by the negative cash flow shock, and the shock is more influential for small firms.

One concern regarding the above approach is that the results may be sensitive to the choice of state variables in the VAR (Chen & Zhao 2009). Since the true model is unknown, discount rate shocks cannot be perfectly measured. Inevitably, the cash flow shocks, which are obtained as the residuals, inherit the misspecification error of the discount rate shocks. To alleviate this concern, I employ an alternative set of state variables that have been employed in various studies, such as Petkova (2006) and Atilgan et al. (2015). In particular, I employ the following five state variables: (1) the excess market return, (2) the term spread, (3) dividend yield, (4) credit default spread, and (5) stochastically detrended risk-free rate (measured as the yield on the one-month Treasury bill minus its one-year backward moving average).

Panel B presents the findings from an alternative VAR model. The analysis reveals a negative impact of labour market competitiveness on cash flow shocks. The coefficient estimates consistently demonstrate negative effects across all portfolios, except for the large market portfolio, where the significance is not statistically significant. Nonetheless, these results align with my previous findings, indicating that an increase in labour market competitiveness leads to a decrease in expected cash flows.

A decrease in cash flow can be driven by multiple factors, and my proposition suggests that intensified labour market competition drives firms to allocate more resources toward hiring new employees or retaining high-calibre talent. This prompts me to investigate whether labour market competitiveness corresponds to an upsurge in firms' expenditures, as this would provide further evidence of firms allocating more resources to compete for talent. Specifically, I analyze firms' SGA expenses as a proxy for workforce expenses and firms' R&D spending, which often aligns with salaries for skilled employees. Additionally, I evaluate the level of cash holding, recognizing its significance in gauging firms' ability to generate revenue.

I perform a panel regression analysis at a firm-year level, and the model specifications are as follows:

$$Y_{i,k} = c + \beta_1 \cdot Competition_k + \Gamma \cdot Controls_{i,k} + Firm\ FE + \varepsilon_{i,k} \quad (10)$$

$$Y_{i,k} = c + \beta_1 \cdot Competition_k + \beta_2 \cdot Small_{i,k} + \beta_3 \cdot Competition_k \times Small_{i,k}$$
$$+ \Gamma \cdot Controls_{i,k} + Firm\ FE + \varepsilon_{i,k} \quad (11)$$

where $Y_{i,k}$ is either the log of SGA expenses, R&D expenditure, or cash holding for firm *i* in year k. $Controls_{i,k}$ includes a set of control variables which follows Hirshleifer et al. (2012) and Huang et al. (2019). There variables are firm market capitalization (*Size*), leverage ratio (*Leverage*), return on assets (*ROA*), Tobin's Q ratio (*TQ*), and (log) capital expenditure (*Capex*). To further mitigating firm-specific effects, I include firm-fixed effects in the regressions, and cluster standard error at the firm and year level. My analysis below focuses on firms' fiscal year ending in December each year. Doing so can avoid having different fiscal ending months and the labour market competitiveness are measured by different time periods.

I construct $Competition_k$ as the past one-year average labour market competitiveness 3 months prior to December, i.e., from October year *k-1* to September year *k*. In so doing allows me to assess the predictive power of labour market competitiveness on firms' expenses in the next quarter at each fiscal year-end. To further improve the robustness of my result, I construct $Competition_k$ as the past one-year average labour market competitiveness 6 and 9 months prior to December. Moreover, in Eq. (11), I introduce $Small_{i,k}$ as an indicator variable if the market capitalization of firm i is lower than the sample median. I interact $Competition_k$ and $Small_{i,k}$ to test my proposition that small firms are more likely to be adversely influenced by labour market competitiveness.

In Panel A of Table Ch2-6, I present the findings regarding the predictive power of labour market competitiveness on firm expenditures for the subsequent quarter. The first column reveals that higher competition leads to increased firms' SGA expenses, consistent with my earlier finding that the increased expenditure acts as a negative shock to cash flow. I also find that higher competition leads to higher R&D expenditure in the second column, suggesting increased compensation for R&D personnel. Additionally, I find a decrease in cash holdings following an increase in labour market competitiveness. The last three columns further show that smaller firms are more significantly impacted by the increase in labour market competition, as evidenced by the significant coefficients for the interaction term. The coefficients for the control variables corroborate previous literature (Hirshleifer et al. 2012; Huang et al. 2019). In particular, larger firms tend to have higher expenses and cash holdings, and more leveraged firms have lower cash reserves. Firms with higher ROA tend to have lower expenses and higher cash. Finally, firms with high capital expenditure tend to also have larger SGA and R&D expenses.

Table Ch2-6. The impact of labour market competitiveness on firm cash flows

This table presents the panel regression results of firms' selling, general and administrative expenses (*SGA*), R&D expenses (*R&D*), and cash holding (*Cash*) on labour market competitiveness (*Competition*). All dependent variables are in natural log form. In Panels A, B, and C, *Competition* is lagged by 3-, 6- and 9-month from the dependent variable, respectively. *Small* is an indicator variable for firms whose market capitalization is below the sample median. The control variables include firm market capitalization (*Size*), leverage ratio (*Leverage*), return on assets (*ROA*), Tobin's Q ratio (*TQ*), and (log) capital expenditure (*Capex*). All dependent and explanatory variables are winsorized at the 1% level each tail. I include firm-fixed effect. Standard errors are clustered by firm and year. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	[1]	[2]	[3]	[4]	[5]	[6]
VARIABLES	R&D	SGA	Cash	R&D	SGA	Cash
Panel A: *Competition* is lagged by 3-month						
Competition	3.871***	4.772***	-6.043**	3.047***	2.401**	-4.876
	(3.36)	(3.39)	(-2.19)	(3.12)	(2.06)	(-1.62)
Small				-0.525***	-1.127***	0.736
				(-2.73)	(-2.83)	(1.31)
*Competition*Small*				1.724***	3.820***	-2.362
				(2.33)	(2.45)	(-1.11)
Size	0.562***	0.562***	0.749***	0.551***	0.545***	0.766***
	(31.92)	(23.89)	(16.89)	(31.31)	(21.29)	(17.43)
Leverage	0.016	-0.033	-0.188***	0.013	-0.038*	-0.184***
	(1.68)	(-1.60)	(-7.25)	(1.36)	(-1.84)	(-7.12)
ROA	-0.106***	-0.126***	0.026**	-0.104***	-0.124***	0.024*
	(-14.96)	(-8.82)	(2.13)	(-14.85)	(-8.75)	(1.96)
TQ	0.000	0.002	0.004**	0.000	0.001	0.004***
	(0.58)	(1.79)	(3.14)	(0.45)	(1.67)	(3.20)
Capex	0.048***	0.087***	0.007	0.048***	0.087***	0.007
	(12.53)	(10.45)	(0.59)	(12.52)	(10.39)	(0.58)
Constant	-0.437	-1.750***	0.453	-0.112	-0.943**	-0.023
	(-1.40)	(-4.26)	(0.57)	(-0.40)	(-2.70)	(-0.03)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	37,010	18,125	43,198	37,010	18,125	43,198
Adj. R^2	0.561	0.351	0.192	0.562	0.352	0.193
Panel B: *Competition* is lagged by 6-month						
Competition	3.714***	4.696***	-2.206	2.895**	2.706**	-0.216
	(2.97)	(3.12)	(-0.56)	(2.48)	(2.25)	(-0.05)
Small				-0.501***	-0.938**	1.198**
				(-3.30)	(-2.41)	(2.46)
*Competition*Small*				1.640***	3.113**	-4.125**
				(2.81)	(2.03)	(-2.21)
Panel C: *Competition* is lagged by 9-month						
Competition	3.072***	3.660**	0.623	2.437**	2.365**	2.490
	(2.83)	(2.50)	(0.16)	(2.23)	(2.25)	(0.59)
Small				-0.385***	-0.628*	1.102***
				(-2.88)	(-1.82)	(2.71)
*Competition*Small*				1.199**	1.934	-3.754**
				(2.40)	(1.41)	(-2.44)

Panels B and C present the results on the predictive power of labour market competitiveness on firms' expenses and cash holdings for the subsequent two and three quarters. The findings remain consistent with the previous panel, as higher competition continues to correlate with increased SGA and R&D expenditures. This trend is stronger for the smaller firms, although the significance of the interaction term coefficient in the fifth column of Panel C diminishes. Notably, I observe that cash holdings for smaller firms decrease following intensified labour market competition, but this effect becomes significant only after the second quarter. This is evidenced by the significant negative coefficients for the interaction term in the last column of Panels B and C.

In summary, my findings indicate that heightened labour market competitiveness has a detrimental impact on cash flows, as reflected by negative shocks to firms' cash flows due to increased expenditures. This is manifested in increased expenses, specifically in terms of selling, general and administrative, and research and development expenditures, which serve as proxies for personnel-related costs. Additionally, my results highlight that higher expenditures are associated with decreased cash holdings for firms, with smaller firms being particularly vulnerable to this effect.

4.4. Is Labour Market Competitiveness Priced?

My previous evidence suggests that stronger labour market competition leads to lower stock returns. For my next analysis, I explore whether a stock's expected return is related to the sensitivity of its return to movements in labour market competitiveness, referred to as its 'competition beta.' Arguably, stocks that are more sensitive to labour market competition have more variable returns compared to stocks that are less sensitive. This suggests that stocks with high competition beta are riskier relative to stocks with low competition beta. Therefore, they should command higher expected returns. Based on this, I should observe that a strategy exploiting competition beta generates positive and significant excess returns.

My analysis covers all common stocks traded on the NYSE, NYSE MKT, and NASDAQ. All data is collected from CRSP (exchange codes 1, 2, and 3, and share codes 10 and 11). I exclude stocks with prices below $5 and above $1,000. For each stock, I estimate its historical competition beta by regressing stock excess returns on *Competition* using the most recent five years of monthly data. To ensure more precise estimates of beta, I require firms to have 60 monthly observations. Based on these filters, I ended up with 2,859 unique stocks over the period from 2010 to 2022.

I adopt a regression specification similar to the one used by Pástor and Stambaugh (2003),

$$r_{i,t} = c + \beta_i^{Comp} \cdot Competition_t + \beta_i^{MKT} \cdot MKT_t + \beta_i^{SMB} \cdot SMB_t + \beta_i^{HML} \cdot HML_t + \epsilon_{i,t} \quad (11)$$

$r_{i,t}$ denotes stock i's excess return in month t, MKT, SMB, and HML, represent the market risk premium, the size factor, and the value factor, respectively, as defined by Fama and French (1996). Of particular interest is the coefficient β_i^{Comp}, which captures the stock's sensitivity to labour market competitiveness. Given my focus on this sensitivity, I take the absolute value of β_i^{Comp} to isolate its magnitude regardless of the direction of the relationship.

Building upon my previous findings that labour market competitiveness has a more significant impact on portfolios of small stocks compared to large stocks, I also take into account the cross-sectional variation across firms. More specifically, at the end of each year, I sort stocks into five size quintiles based on their market capitalization. Within each size quintile, I further sort stocks based on their (absolute) competition betas. By doing so, I create 5×5 distinct portfolios. To track the performance of these portfolios, I calculate the returns over the next 12 months across multiple years, forming a single return series for each of the 25 portfolios. To examine the return premium associated with competition beta, I also form a high-minus-low portfolio that takes a long position in the portfolio of stocks with high competition beta and a short position in the portfolio of stocks with low competition beta, and I calculate the returns on this portfolio.

Table Ch2-7 presents the results of the portfolio sorting. Panel A corresponds to the small stocks (size quintile 1), while Panel E corresponds to the large stocks (size quintile 5). Within each panel, the stocks are further split into those with low competition beta (beta quintile 1) up to those with high competition beta (beta quintile 5).[11]

The table shows that competition betas serve as a predictor of future stock returns, particularly for the smaller firms, i.e., those with an average market capitalization of $140 million. Panel A, in particular, shows that the average competition beta ranges from 0.17 for Q1 to 4.12 for Q5. The monthly excess returns are lowest for Q1 (1.22%) and highest for Q5 (2.74%). More importantly, the high-minus-low (Q5-Q1) portfolio provides an excess return of 1.52% per month (18% per annum) with a t-statistic of 2.01. The Sharpe ratio ranges from 0.21 for Q1 to 0.28 for Q5, and that of the Q5-Q1 portfolio is 0.23. I do not observe such a pattern across the other size quintiles.

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[11] Results based on value-weighted stock returns are reported in Appendix 2F.

Table Ch2-7. Portfolio sorting

This table reports the average returns for portfolios double-sorted by firm size, followed by (absolute) competition beta. Panel A shows the results for the small stocks (size Q1), and Panel E shows the results for the large stocks (size Q5). The sample period is from January 2015 to December 2022. I report the monthly equal-weighted portfolio returns. I also present the Sharpe ratio, average competition beta, average market capitalization, and the number of firms in each portfolio. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Panel A: Size Q1						
Return	0.012**	0.014***	0.010*	0.016**	0.027**	0.015**
t-stat	(2.25)	(2.63)	(1.75)	(2.36)	(2.35)	(2.01)
Sharpe Ratio	0.21	0.25	0.17	0.24	0.28	0.23
Competition beta	0.17	0.53	0.96	1.67	4.12	
Average size (‘000)	137,369	141,836	145,348	135,776	132,271	
Firms	86	85	86	85	86	
Panel B: Size Q2						
Return	0.011*	0.010*	0.011*	0.012*	0.010	-0.001
t-stat	(1.76)	(1.67)	(1.69)	(1.81)	1.22	-0.16
Sharpe Ratio	0.16	0.15	0.15	0.17	0.11	-0.02
Competition beta	0.17	0.50	0.91	1.52	3.34	
Average size (‘000)	609,573	611,072	626,050	603,955	583,260	
Firms	86	85	85	85	86	
Panel C: Size Q3						
Return	0.010*	0.009	0.010	0.010*	0.010	0.000
t-stat	(1.82)	1.58	1.60	(1.76)	1.16	-0.07
Sharpe Ratio	0.15	0.13	0.13	0.14	0.11	-0.01
Competition beta	0.17	0.48	0.84	1.36	2.93	
Average size (‘000)	1,760,266	1,750,317	1,759,275	1,734,632	1,704,006	
Firms	86	85	85	85	86	
Panel D: Size Q4						
Return	0.009*	0.008	0.007	0.009*	0.008	-0.001
t-stat	(1.77)	1.56	1.40	(1.69)	1.38	-0.52
Sharpe Ratio	0.14	0.13	0.11	0.13	0.11	-0.05
Competition beta	0.13	0.41	0.72	1.16	2.30	
Average size (‘000)	4,981,108	4,956,824	5,018,690	5,062,311	4,771,297	
Firms	86	85	85	85	86	
Panel E: Size Q5						
Return	0.008**	0.010***	0.011***	0.008*	0.009*	0.000
t-stat	(2.14)	(2.63)	(2.69)	(1.93)	(1.88)	0.22
Sharpe Ratio	0.16	0.19	0.20	0.14	0.14	0.02
Competition beta	0.11	0.34	0.59	0.92	1.80	
Average size (‘000)	63,063,005	64,728,338	50,346,940	41,917,296	39,242,397	
Firms	86	85	86	85	86	

These findings suggest that labour market competitiveness possesses a significant predictive ability for stock returns, particularly for small firms. In my subsequent analysis, I will direct my attention toward the competition beta premium, specifically within the small stock portfolios.

Next, I perform formal asset pricing regressions to assess the extent to which the variation in the average returns of the competition beta-sorted portfolios can be explained by existing risk factors. I conduct regression analysis on the excess returns of my portfolios, incorporating various risk factors commonly used in empirical asset pricing studies, including the Fama and French (1996) three-factor model, the Carhart (1997) four-factor model, the Fama and French (2015) five-factor model, and the Hou et al. (2015) q-factor model. The alpha derived from this analysis represents the portion of a portfolio's expected returns that cannot be explained by its exposure to the risk factors included in the model.

Table Ch2-8 reports the alphas from existing risk factor models. My findings across all five beta quintiles indicate that the cross-sectional return spread across portfolios sorted on competition beta cannot be explained by other known risk factors. More importantly, the alphas in the long-short portfolio (Q5-Q1) remain statistically significant, indicating that the positive risk premium that I document cannot be simply attributed to common risk factors.[12]

[12] Results based on value-weighted stock returns are reported in Appendix 2G.

Table Ch2-8. Asset pricing factor tests

This table reports the results from asset pricing factor tests for portfolios sorted on competition beta. In Panel A, I use Fama and French (1996) three factors (MKT, SMB, and HML). In Panel B, I use the Fama and French three factors and the Carhart (1997) momentum factor (UMD). In Panel C, I use Fama and French (2015) five factors (MKT, SMB, HML, RMW, and CMA). In Panel D, I use Hou, Xue, and Zhang (2015) q-factors (MKT, SMB, IA, and ROE). The sample period is from January 2015 to December 2022. All coefficients are monthly. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Panel A: FF3						
alpha	0.007***	0.009***	0.004***	0.009***	0.020***	0.014**
	(3.88)	(5.78)	(2.86)	(3.42)	(3.09)	(2.14)
MKT	0.008***	0.007***	0.008***	0.009***	0.010***	0.003*
	(9.35)	(15.07)	(17.58)	(13.56)	(6.56)	(1.77)
SMB	0.007***	0.008***	0.007***	0.008***	0.015***	0.009*
	(8.54)	(10.22)	(9.67)	(9.51)	(3.21)	(1.71)
HML	0.003***	0.003***	0.003***	0.002***	0.001	-0.002**
	(5.10)	(4.98)	(4.70)	(3.58)	(1.43)	(-2.31)
Panel B: FF4						
alpha	0.007***	0.009***	0.005***	0.009***	0.018***	0.011**
	(4.12)	(5.97)	(3.31)	(3.79)	(3.38)	(2.04)
MKT	0.007***	0.006***	0.007***	0.009***	0.011***	0.004***
	(8.74)	(12.95)	(16.59)	(11.89)	(7.92)	(3.37)
SMB	0.006***	0.007***	0.007***	0.008***	0.016***	0.010*
	(8.30)	(10.09)	(9.04)	(9.24)	(3.02)	(1.76)
HML	0.003***	0.003***	0.002***	0.002***	0.002*	0.000
	(4.12)	(4.08)	(4.14)	(3.12)	(1.71)	(-0.34)
UMD	-0.001***	-0.001	-0.002***	-0.001	0.004	0.005
	(-2.40)	(-1.34)	(-2.77)	(-1.50)	(1.11)	(1.41)
Panel C: FF5						
alpha	0.006***	0.009***	0.004***	0.009***	0.020***	0.015**
	(3.29)	(5.83)	(2.78)	(3.59)	(3.47)	(2.52)
MKT	0.007***	0.006***	0.008***	0.009***	0.012***	0.005***
	(10.78)	(16.54)	(15.67)	(13.40)	(8.54)	(3.80)
SMB	0.008***	0.008***	0.008***	0.009***	0.013***	0.005
	(8.66)	(9.08)	(8.55)	(9.32)	(3.24)	(1.30)
HML	0.003***	0.004***	0.003***	0.002**	-0.001	-0.004
	(2.82)	(4.33)	(3.01)	(2.20)	(-0.35)	(-1.49)
RMW	0.003**	0.000	0.000	0.000	-0.007**	-0.010***
	(2.39)	(0.49)	(0.13)	(0.46)	(-2.48)	(-3.54)
CMA	0.000	-0.001	0.001	0.000	0.008	0.008
	(-0.08)	(-1.08)	(0.44)	(0.00)	(1.22)	(1.23)
Panel D: HXZ						
alpha	0.006***	0.009***	0.005***	0.009***	0.021***	0.015***
	(3.29)	(4.58)	(2.63)	(3.67)	(3.93)	(2.75)
MKT	0.008***	0.007***	0.008***	0.009***	0.010***	0.002
	(8.97)	(12.74)	(20.10)	(12.77)	(7.44)	(1.62)
SMB	0.007***	0.008***	0.006***	0.008***	0.015***	0.008
	(5.23)	(6.42)	(6.11)	(7.08)	(3.01)	(1.41)
I/A	0.003***	0.002*	0.003***	0.001	0.004	0.001
	(3.55)	(1.80)	(3.64)	(1.59)	(1.33)	(0.36)
ROE	-0.002*	-0.002***	-0.003***	-0.002***	-0.005***	-0.003
	(-1.77)	(-2.81)	(-3.70)	(-2.57)	(-2.56)	(-1.33)

Overall, my evidence strongly supports the hypothesis that labour market competitiveness exerts a more pronounced impact on smaller firms. The presence of a positive risk premium suggests that stocks with higher sensitivity to competition beta exhibit higher expected returns. This outcome aligns with my second hypothesis that, compared to larger firms, smaller firms face greater challenges in hiring workers under competitive market conditions.

5. CONCLUSION

This study contributes to the existing literature by introducing a novel measure of labour market competitiveness, which captures the intensity of demand for specific occupations. This measure provides a more nuanced understanding of labour market dynamics, as it recognizes that competitiveness can increase even without a rise in total hiring. This approach offers a significant departure from previous studies that primarily rely on the total number of hires as a proxy for labour market competitiveness.

My empirical analysis reveals a significant negative relationship between labour market competitiveness and future aggregate stock returns, even after controlling for other known predictors. This finding underscores the importance of labour market conditions in influencing stock market performance. I also find that heightened labour market competition leads to negative cash flow shocks, reflected in increased firm expenditures and decreased cash holdings. These effects are particularly pronounced for smaller firms, which often have less bargaining power in the labour market. Furthermore, my results provide evidence of a risk premium associated with labour market competitiveness. Specifically, smaller firms with higher sensitivity to labour market competition tend to yield higher returns, suggesting that investors require compensation for the increased risk associated with these stocks.

Overall, my study provides evidence that heightened competition in the labour market has detrimental impacts on firms' future stock returns. My study also highlights the significant role of labour market competitiveness in shaping stock market returns and firm financial performance. My findings emphasize the need for investors and firms’ management to pay close attention to labour market dynamics when making decision.

CHAPTER 3: CEO INDUSTRY TOURNAMENT INCENTIVES AND STRATEGIC DISTINCTIVENESS

1. INTRODUCTION

Why do some CEOs develop unique strategies while others are more inertial and committed to the common strategies in an industry? Since formulating and implementing distinctive strategies (i.e., strategies that deviate from the industry's central tendencies) is key to success (Miller & Chen 1996; Finkelstein et al. 2009), finding their antecedents is critical. Studies following the upper echelons tradition (Hambrick & Mason 1984) show that CEOs' backgrounds and characteristics can affect their willingness to follow versus deviate from those common strategies in the industry (Crossland et al. 2014; Wowak et al. 2016; Kang et al. 2020). These studies have greatly enhanced my understanding of how CEOs affect their firms' pursuit of novel strategies. However, a firm's shareholders and the board of directors have little control over these factors without replacing the incumbent CEO. Furthermore, little work has examined one of the most controllable factors for shareholders and the board of directors in explaining corporate strategic distinctiveness: CEO compensation.

Although CEO total pay is important, this study focuses on CEO relative pay. This is inspired by the survey results from Graham et al. (2005), which suggests that U.S. CEOs assert their relative pay in the industry is more important than the compensation scheme at their current employing firms when making managerial decisions. In addition, CEO relative pay captures the tournament incentives that arise from the CEO labor market tournament. Many prior works have indicated the importance of tournament incentives in different areas, including professional golfers (Brown 2011), race-car drivers (Becker & Huselid 1992), and mutual fund managers (Brown et al. 1996).

CEOs compete within the CEO labour market. The highest-paid CEO compensation in a CEO labour market signal the potential that one CEO can receive if the CEO eventually becomes the leader in the labour market. Therefore, the highest-paid CEO compensation is the prize that will reward the best player in the labour market tournament. Further, the size of the tournament prize is the difference between a CEO’s current pay and the highest CEO pay within a group of similar firms (i.e., in the same industry). Based on tournament theory (Lazear & Rosen 1981), recent studies on CEO industry tournament incentives show its importance regarding firm performance (Coles et al. 2018), corporate innovation (Nguyen & Zhao 2021), and hedge policies (Lonare et al. 2022). However, how CEO industry tournament incentives (hereafter CEO ITIs) can impact the adoption of unique strategies in firms is unclear. The current study aims to fill in this literature gap.

CEO ITIs can affect the tension for CEOs to be differential or to conform the common strategies in two competing ways. CEOs with relatively lower pay in the labour market have stronger incentives to move up and increase their compensation by delivering outstanding performance. However, both differentiation and conformity propositions in strategies have been suggested that can import firm performance. On the one hand, adopting unique strategies can create economic rent and consequently increase a firm's long-term value (Barney 1986; Deephouse 1999; Litov et al. 2012; Zhao et al. 2017; Oehmichen et al. 2021). With private information about the optimal combination of assets and resources, top managers use their strategic foresight to acquire assets and resources that can bring synergies to the firm. If such a strategy is uncommon, they are likely to acquire assets at discounted prices (Litov et al. 2012). In addition, organizational ecology discusses how a lack of strategic distinctiveness can have higher competitive intensity and thus affect survival rates (Hannan et al. 1990; Baum & Singh

1994). Conforming to the strategies of others would tap on the same resources so that intensifies the competition of resources (Baum & Singh 1994). Lack of strategic distinctiveness also limits the performance of a firm because of higher market competition (Hannan et al. 1990). Eventually, such a market would approach to perfect economic competition with the economic rents equaling zero (Deephouse 1999). Therefore, the differentiation proposition predicts a positive association between CEO ITIs with corporate strategic distinctiveness.

On the other hand, CEOs with lower pay ranks receive institutional pressures to conform to common strategies based on institutional theory. Conforming to norms and beliefs can gain legitimacy from the market, which affects firm performance by avoiding legitimacy challenges that can hinder resource acquisition (DiMaggio & Powell 1983). This alternative perspective thus suggests a negative association between CEO ITIs with corporate strategic distinctiveness.

In this chapter, I empirically examine which perspective low-pay-rank CEOs are likely to take to compete with others within the labour market. I begin by documenting a positive association between CEO ITIs and corporate strategic distinctiveness. Using U.S. 27, 646 firm-year observations from 1992 to 2019, I find CEO ITIs positively relate to firms' strategic distinctiveness using ordinary least square (OLS) regression models. However, the matches between each firm and its CEO may not be random, raising potential endogeneity concerns. I thus utilise the staggered adoption of the Inevitable Disclosure Doctrine (IDD) by U.S. state courts to get around such identification concerns. Using a staggered difference-in-difference approach, I find that firms headquartered in IDD adopting states decrease their strategic distinctiveness relative to firms headquartered in non-adopting states. Whether CEOs can freely move in the labour market is a critical criterion for participating in an industry-wide labour market tournament. The IDD suddenly reduces treated CEOs' chance of winning the industry tournament prize and makes it less attractive to them. Therefore, the negative coefficient of the DiD estimator shows a consistent result with the result from OLS estimation.

Next, I show the effects of CEO ITIs on strategic distinctiveness have cross-sectional variation. A given level of ITIs could provide different incentives to CEOs, thus affecting firms' strategic distinctiveness differently. In cross-sectional analysis, I find that the positive effect of CEO ITIs on corporate strategic distinctiveness is more pronounced in firms with effective board structures, in firms facing significant product-market competition, and in firms with CEOs having a high managerial ability. Overall, these results are consistent with the notion that the importance of ITIs differs for firms and CEOs. Thereby the effects of CEO ITIs on firms' strategic distinctiveness change cross-sectionally.

I further test the channel that CEO ITIs are more likely to go through to affect strategic distinctiveness. Since ITIs can provide CEOs with performance-enhanced and risk-taking incentives, both incentives can potentially lead to a higher level of corporate strategic distinctiveness. In the subsample analysis designed to uncover the channel, I find the positive effect of CEO ITIs is more pronounced in firms where their CEOs have been provided with a lower level of pay-performance incentives. In contrast, using two subsamples partitioned by the sample median CEO risk-taking incentives, I find the estimated effects of CEO ITIs are similar. Together, these results suggest CEO ITIs affect corporate strategic distinctiveness by providing CEOs with performance-related incentives and perhaps encouraging them to exert more effort, nor providing them with risk-taking incentives.

In the final part of the paper, I evaluate whether strategic distinctiveness plays a role in the positive relationship between CEO ITIs and firm performance, as documented by Coles et al. (2018). My analysis, however, finds that the positive relation only exists for firms with a higher level of strategic distinctiveness. Using the whole sample, I can find a positive association between CEO ITIs and firm performance, as in Coles et al. (2018). Further, in a subsample analysis, I find the coefficient of CEO ITIs is positively significant when regressing CEO ITIs on firm performance using that sample that consists of firms with high strategic distinctiveness. On the other hand, the coefficient of CEO ITIs is insignificant when using the sample contains firms with low strategic distinctiveness. This result sheds light on the moderating role that strategic distinctiveness plays in the relation between CEO ITIs and firm performance.

My study contributes to two main strands of research: strategic management and industry tournament theory. First, it shows CEO ITIs as an important determinator of strategic distinctiveness, contributing to management literature. Strategic management scholars have given much attention to the consequences of being different (Porter 1991; Miller & Chen 1996; Finkelstein et al. 2009). However, less attention has been given to why some firms purse greater strategic distinctiveness while others conform to those strategic norms in the industries. A few exceptions are the studies focused on CEO characteristics (Crossland et al. 2014; Wowak et al. 2016; Kang et al. 2020). In contrast to these studies, my study focuses on CEO compensation design, in which the board of directors has more control over CEO characteristics. My findings suggest a more accessible way to increase corporate strategic distinctiveness, that is, decreasing the current CEO pay and thus increasing the external pay gap.

Second, this study is closely related to the growing literature on CEO tournament incentives (Kale et al. 2009; Kini & Williams 2012; Coles et al. 2018; Islam et al. 2022). Previous studies on tournament incentives suggest that incentives, either from internal competition (Kale et al. 2009) or external competition in the labour market (Coles et al. 2018), can encourage CEOs to exert more effort and thus enhance firm performance. My finding shows that the increased effort can lead to more adoption of distinctive strategies in firms.

Given the benefits of being strategically distinct, my study suggests a possible channel that CEO ITIs go through and thus lead to higher firm performance. This complements the work by Coles et al. (2018), who document a positive relation between CEO ITIs and firm performance.

The reminder of the chapter 3 is organised as follows. Section 2 discusses the related literature and develops the main hypotheses. Section 3 discusses data and research design. The main findings are present in section 4 with discussion, and section 5 concludes this paper.

2. Literature review and hypotheses development

The strategic management literature has long recognised that pursuing greater strategic distinctiveness—the degree to which a firm's strategy differs from the strategies of other firms in the same industry, is vital for firms to obtain and sustain competitive advantages (Miller & Chen 1996; Porter 1996; Finkelstein et al. 2009). Total market share is often assumed to be finite at any point in time, divided among competing firms (Deephouse 1999). By entering a market with many similar competitors, a firm's performance is limited as such a place will eventually form perfect economic competition and drive economic rents to approach zero (Deephouse 1999). On the other hand, with less competition, firms can earn higher rents and may even be a local monopoly (Baum & Singh, 1994). Porter (1991) emphasises that being strategically unique is crucial because adopting common strategies almost ensures a lack of competitive advantage and hence mediocre performance.

While pursuing distinctive strategies is important and potentially creates value, some factors hinder firms from doing so. The question of why some firms are structurally inertial while others exhibit much more novelty has received much attention from scholars (Kelly &

Amburgey 1991; Crossland et al. 2014). The traditional view on this question is that companies are constrained by pre-existing resource allocations, such that the default tendency is to continue along the same path (Hannan & Freeman 1977; DiMaggio & Powell 1983). It arguably requires extra managerial effort from a firm's top executives to defy this inertial pull from the firm itself. Moreover, adopting strategies not prevailing in an industry is seen as risky and less legitimate (Deephouse 1999), which can cause many firms to shy away from novel strategies. This view is drawn from the institutional theory (DiMaggio & Powell 1983) that focuses on legitimacy and suggests it affects many aspects of a firm, such as resource acquisition and survival. Over time, top executives within an industry develop a cognitive consensus about successful strategies, called "industry recipes" (Spender 1989). Selecting strategies outside the receipt can lead to legitimacy challenges (Porac et al. 1989), which can diminish a firm's ability to acquire resources from potential exchange partners (DiMaggio & Powell 1983). For example, a supplier may offer less favourable terms for a firm whose legitimacy is challenged. Part of the reason is that less legitimate firms are more likely to fail (Baum & Oliver 1991). Reger and Huff (1993) label firms that received legitimacy challenges as "idiosyncratic firms", suggesting high risks involved in these firms' operation.

In practice, CEOs are arguably the more influential person in the firm when it comes to formulating and implementing firm strategies (Finkelstein et al., 2009), and their impacts have increased over time (Quigley & Hambrick 2015). Some previous studies have examined what affects CEOs' tendency to pursue strategic distinctiveness (Crossland et al. 2014; Wowak et al. 2016; Kang et al. 2020). This literature was built on the upper echelons theory (Hambrick & Mason 1984) and has consistently shown that CEO personal characteristics influence the strategic choices of their firms. For instance, Kang et al. (2020) document that CEOs with uncommon names tend to develop a conception of being different from their peers and pursue distinct strategies within the industry. Together, the literature indicates that pursuing strategic distinctiveness can enhance value. Still, it is not an easy task in many firms and may require support from their top executives, especially the CEO.

However, from an agency perspective, CEOs may not be willing to pursue strategic distinctiveness because their interests are misaligned with those of shareholders. Formulating and implementing unique strategies costs managerial effort for CEOs because they cannot imitate uncommon strategies from their industry peers (Haveman 1993). CEOs may, on the other hand, prefer a quiet life by avoiding difficult decisions and costly efforts (Bertrand & Mullainathan 2003). Moreover, CEOs may not prefer to adopt uncommon strategies because it involves higher risk. This implies that the pursuit of strategic distinctiveness is not aligned with the risk preference of CEOs, who have non-diversifiable financial and human capital bounded with their firms (Gormley & Matsa 2011). Therefore, the pursuit of strategic distinctiveness in firms may thus hinder by a classic agency problem arising from the separation of ownership and management.

A large body of literature documents how firms can use compensation contracts to mitigate agency problems (e.g. Jensen & Meckling 1976; Coles et al. 2006; Gormley 2013). In addition, the literature on tournament incentives suggests that promotion-based incentives can also be used to provide CEO firm-performance-related incentives (Lazear & Rosen 1981; Kale et al. 2009; Coles et al. 2018). Lazear and Rosen (1981) first illustrate the effects of promotion-based incentives and provides the theoretical foundation for later studies on tournament incentives. In their two-player tournament setup with the effort being the only choice variable, each player will exert more effort when the size of the tournament prize is greater. Coles et al. (2020) later extend this internal tournament game by allowing one player to start the contest with a lead. In so doing, it allows the tournament incentives theory to be extended to the managerial labour market (i.e., industry tournament incentives). The size of this external labour market tournament prize is the initial pay gap between the aspirant and the leader. Empirical studies that focus both the intra-firm and industry tournament confirm the performance-enhancing effects of tournament incentives. Kale et al. (2009) find that within-firm tournament incentives, as measured by the pay disparity between the CEO and other top executives, relate positively to firm performance. Coles et al. (2018) show that firm performance is positively associated with the size of the industry tournament prize.

Promotion-based incentives can also motivate players in a tournament to undertake higher risks. Hvide (2002) extends tournament theory by adding *risk-taking* as another choice variable into Lazear and Rosen's (1981) tournament model. His model illustrates that tournament incentives also encourage them to take more risks besides encouraging more players' effort. Higher risk-taking activities can lead to widespread outcomes, which implies potentially better outcomes on the right tail and worse results on the left tail. However, a tournament prize will be rewarded for the best performance. This reward mechanism disregards the left-tail consequences and incentivises players to take more risks. Later empirical studies confirm that such risk-encouraging effects are present both in the internal corporate tournament and the external industry tournament. Kini and Williams (2012) document that higher tournament incentives can result in greater risk-taking by top executives. Coles et al. (2018) show that industry tournament incentives are positively associated with firm risk.

In a survey study, Graham et al. (2005) show that most US CEOs assert that outside opportunity in the labour market is more important than the current firm's compensation scheme in impacting their own managerial decisions. This survey result highlights the potential impacts of the external labour market on corporate decisions. Empirical studies on ITIs echo the notion that the external labour market can provide CEO incentives and affect managerial decisions and corporate polices. For example, Chowdhury et al. (2020) show that ITIs induce CEOs to implement strategies that are less prone to future stock price crash risk. ITIs incentivise CEOs to brand themselves according to the sustained visibility concept. Therefore, they use fewer accounting techniques, such as accrual manipulation and earning management, to facilitate information flow to maximise their labour market visibility. Auditors also perceive less risk and agency costs involved in the auditing service for firms whose CEO received higher ITIs. Tan (2020) shows that auditors incorporate the negative relation between ITIs and audit risk into pricing decisions and charge fewer audit fees for firms managed by CEO with higher ITIs. He also suggests that ITIs dominate CEOs' working appetites and corporate policies compared with intra-firm tournament incentives. This is because the major competition that shapes compensation is from the industry rather than the firm. In relation to this argument, Islam et al. (2022) document that firms act to adjust their CEOs' compensation contracts to accommodate the sudden decrease in ITIs because of mobility shocks. Regarding resource allocation, Huang et al. (2019) find that ITIs encourage CEOs to hold a higher level of cash. Also, ITIs motivate CEOs to treat cash as a riskier "strategic weapon" rather than a conservative asset to implement value-maximising strategies, which leads to a higher marginal value of cash holdings. These prior studies on ITIs together emphasise the importance of external labour marking in influencing corporate policies and strategic choices.

Drawing from the above literature, I hypothesise that CEO ITIs positively correlate with firm strategic distinctiveness. First, adopting distinct strategies can bring competitive advantages to firms and increase firms' propensity to deliver outstanding performance (Baum & Singh 1994; Porter 1997). In addition, CEOs' labour market visibility is closely tied to the firm performance under their management. A CEO is more likely to be a strong candidate for the industry prize if the CEO can lead a company to deliver outstanding performance (Coles et al. 2018). Therefore, pursuing strategic distinctiveness is aligned with CEOs' career goals. This alignment is tightened when the industry tournament prize is larger, which implies a positive relation between CEO ITIs and firm strategic distinctiveness. Second, CEO ITIs can help with the agency's issues of pursuing strategic distinctiveness. While adopting uncommon strategies is in shareholders' interests because of the benefits it can bring, it may not be in their CEOs' interests because of the effort and risk involved. ITIs can encourage costly CEO effort and risk-taking (Coles et al. 2018) and reduce agency costs (Tan 2020). Therefore, ITIs are expected to alleviate shareholder and CEO conflicts in pursuing strategic distinctiveness, leading to more distinct strategies being adopted at firms. Hence, my first hypothesis is:

Hypothesis 1: *CEO ITIs is positively related to firm strategic distinctiveness.*

The effects of CEO ITIs on corporate strategic distinctiveness can vary cross-sectionally. For example, CEO ITIs is expected to affect corporate strategic distinctiveness because of the potential rewards a CEO can receive after leading a firm that delivers outstanding performance. Firms' reward mechanisms may thus moderate or mitigate the positive effect of CEO ITIs on strategic distinctiveness. CEOs can obtain part of the industry tournament prize through increased compensation (Coles et al. 2018). How effective a CEO's compensation is adjusted according to the CEO's shown talent or effort might thus affect the relation between CEO ITIs and corporate strategic distinctiveness. In many public corporations, the board of directors as a key internal control mechanism for overseeing CEO compensation (Boyd 1994; Chhaochharia & Grinstein 2009). This suggests the board structure can affect the relationship between CEO ITIs and corporate strategic distinctiveness. With a more effective board that is able to react quickly to the demand for higher CEO pay, CEO compensation can be timely adjusted, moderating the relationship between CEO ITIs and strategic distinctiveness. Hence, my second hypothesis is:

Hypothesis 2: *The positive association between CEO ITIs and firm strategic distinctiveness is stronger in firms with more effective boards.*

Next, the product market competition in an industry can play an important role in the relation between CEO ITIs and firms' strategic distinctiveness. CEO ITIs are expected to provide CEOs performance-related incentives because aspirant CEOs earn the tournament prize by showing outstanding firm performance under their management (Coles et al. 2018). A distinct position from its rivals enables a firm to enjoy less competition, leading to better performance through perhaps charging higher market rents (Porter 1991; Baum & Singh 1994). These together suggest that firms and their CEOs in a highly competitive market are more eager to stake out a distinct position from their rivals to increase firms' performance and the chances of their CEOs winning the tournament prize. Hence, the relation between CEO ITIs and corporate strategic distinctiveness can be stronger for firms in industries with higher product market competition. This leads to my third hypothesis, that is:

Hypothesis 3: *The positive association between CEO ITIs and firm strategic distinctiveness is stronger for firms facing higher industry competition.*

Lastly, CEOs' outside opportunities depend on their ability (Fee & Hadlock 2003; Rajgopal et al. 2006). Moreover, CEOs' managerial ability is central to understanding their influence on firm performance (Tan 2020). These imply that the effects of CEO ITIs on firm strategic distinctiveness can vary with CEO managerial ability. Fee and Hadlock (2003) show that past superior firm performance led by a CEO enhances the CEO's opportunities in the external labour market. Furthermore, Kaplan et al. (2012) find that CEOs' managerial ability is positively related to subsequent their firms' performance. Therefore, CEOs may enjoy more external employment opportunities with higher managerial abilities because they are more prone to show outstanding firm performance and signal their talents to the market. In addition, CEOs with higher abilities are more knowledgeable about the business operation (Demerjian et al. 2012), so they are more capable to implement distinctive strategies in response to the ITIs. Hence, I expect that:

Hypothesis 4: *The positive association between CEO ITIs and firm strategic distinctiveness is stronger for firms run by CEOs with better managerial ability.*

The above hypotheses are designed to uncover a relationship between CEO ITIs and corporate strategic distinctiveness, and if any, whether such a relationship has cross-sectional variation regarding firms' internal corporate governance efficiency, firms' product market competition, and firms' CEOs' managerial ability. These hypotheses will be rigorously tested in the later empirical section. In addition, some subsample analyses are performed without proposing formal hypotheses. These aim to shed light on the channel that CEO ITIs may go through to affect strategic distinctiveness and the role that strategic distinctiveness may play in the relation between CEO ITIs and firm performance.

3. DATA AND METHODOLOGY

3.1 Data and Sample Selection

My initial sample consists of all firms covered by the Standard and Poor's (S&P) ExecuComp database from 1992 to 2020. The ExecuComp database provides compensation data, such as salary, bonus, option grants and total compensation for named executive officers. Firm-year observations that do not have an identifiable CEO (using CEOANN) or in regulated financial and utility industries (Standard Industrial Classification (SIC) codes 6000-6999 and 4900-4999, respectively) are excluded. I further append these data with monthly stock return data from the Center for Research in Security Prices (CRSP) database and firm fundamentals data from the Compustat database. After the merging process, the final sample of this study contains 2,461 unique firms and 28,166 observations.

3.2 Description of Main Variables

This section describes the main dependent, independent, and control variables used in my study. Notice that both the Fama-French 48 (FF48) and 2-digit standard Industry Code (SIC2) industry classification schemes are used when calculating industry-related variables in this study. These variables include such as the primary dependent and independent variables, *strategic distinctiveness* and *ITIs*, and industry-wide control variable, *firm ranks*.

3.2.1 Measure of strategic distinctiveness

The main dependent variable of interest is *strategic distinctiveness*. It analyses firm resource allocation along seven dimensions (Crossland et al. 2014; Kang et al. 2020): (1) advertising intensity (advertising expense/sales), (2) inventory level (inventories/sales), (3) plant and equipment newness (net plant and equipment/gross plant and equipment), (4) research and development (R&D) intensity (R&D expense/sales), (5) nonproduction overhead (selling, general, and administrative expense/sales), (6) financial leverage (total debt/equity), and (7) capital intensity (fixed assets/total employees). Along with each dimension, I first calculate the standardised absolute differences between each firm's score and the average industry's score. Then, I sum up the seven standardised scores to measure strategic distinctiveness. A higher value of *strategic distinctiveness* indicates that a firm allocates its resource more distinctly than its industry peer firms.

3.2.2 Measure of industry tournament incentives

Following Coles et al. (2018), industry tournament incentives (*ITIs*) are measured by the pay gap between a firm's CEO pay and the industry's second-highest-paid CEO's pay[13]. Using a potential increase in a CEO's pay when winning a tournament has been used as a popular proxy for tournament incentives (see e.g., Kale et al. 2009; Kini & Williams 2012; Shen & Zhang 2018). The measure of industry tournament incentives in Coles et al. (2018) is built on the premise that every aspirant CEO except the leader CEO has an incentive to compete for the maximal CEO pay in the industry. The more significant the pay gap, the more potential increase in pay a CEO will receive, thus providing stronger tournament incentives. Therefore, a higher value of *ITIs* indicates a CEO receives stronger industry tournament incentives[14].

3.2.3 Other variables

In my regression analysis, I also include a set of firm and industry-wide controls. To ensure my set of control variables align with the literature examining industry tournament

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[13] The reason for using the second-highest-paid CEO pay rather than the highest-paid CEO pay is to minimise the potential effects from outliers, suggested by Coles et al (2018).

[14] It is recognized that CEO compensation encompasses various forms. Central to tournament theory is the notion that incentives are primarily driven by the size of the 'winner's prize,' regardless of its composition. Therefore, to be consistent with prior literature, when calculating CEO industry tournament incentives, this study utilizes 'Total CEO Compensation' (denoted as TDC1 in the ExecuComp database), as it represents a comprehensive measure of this 'prize'.

incentives, I follow the most recent published paper, Islam et al. (2022), in selecting the set of control variables. In particular, I control for financial leverage (*Leverage*) measured as total long-term and short-term debt divided by total assets, firms' investment in research and development calculated as R&D expense scaled by the total asset (*R&D exp.*), firms' growth opportunities measured as the total value of share outstanding scaled by the total book value of equity (*MB ratio*), capital expenditure measured as total capital expenditure scaled by total assets (*CAPX*), firm size measured as the natural logarithm of the book value of total assets (*Size*), and cashflow volatility measured as the standard deviation of a firm's return on assets over the previous five years (*Cashflow vol.*). I also control firms' rankings in the industry (*Firm rank*). Specifically, in each year and industry, I sort firms into deciles on the basis of their annual sales within their belonging industries. Firms with higher yearly sales in an industry are sorted into the higher deciles, whereas firms with lower sales are placed in the lower deciles.

3.3 Econometric models

3.3.1 The baseline model

I use panel Ordinary Least Squares (OLS) regression analysis to examine the impact of CEO ITIs on corporate strategic distinctiveness. Specifically, I estimate the following model:

$$Strategic\ Distinctiveness_{i,t+1} = \beta_0 + \beta_1 ITIs_{i,t} + \delta \boldsymbol{X}_{i,t} + YearFE + FirmFE + \varepsilon_{i,t} \quad \textbf{(1)}$$

where *i* and *t* denote firm and year, respectively. β_0 is the intercept, and $\varepsilon_{i,t}$ is the error term. The dependent variable in equation (1), *Strategic Distinctiveness*, measures the extent that firms' strategic choices deviate from the industry central tendency. The coefficient $\beta_1$is the main coefficient of interest for this study as it measures the effect of CEO ITIs on firms' strategic distinctiveness. Hypothesis 1 predicts $\beta_1$will be positive. That is, the higher CEO ITIs, the more distinct strategies are selected by the firm. The vector $\boldsymbol{X}_{i,t}$ includes the set of controls as mentioned above. Worth to note that my baseline regression includes both firm ($FirmFE$) and year fixed-effects ($YearFE$) to control for omitted time-invariant firm characteristics and unobservable time-trend effects. In addition, to mitigate reverse causation in the relation between CEO ITIs and strategic distinctiveness, I employ lag one-year explanatory variables, suggested by Coles et al. (2018). All continuous variables are winsorised at their 1% and 99% values to minimise the impact of outliers, and standard errors are clustered by firm.

3.3.2 The DiD approach

Although regression model (1) includes firm and year fixed-effects to capture common characteristics in particular firms and time trends, there may be time-varying firm characteristics that correlate with both CEO ITIS and strategic distinctiveness but have not been included. This implies the omitted variable bias that can affect the results from OLS regression. My attempt to mitigate this endogeneity concern is to use a quasi-natural experiment that generates plausibly exogenous variation in CEOs' mobility. For example, to participate in an industry tournament, CEOs should be able to move freely from one firm to another. Thus, a mobility shock that restraints CEO mobility may exogenously trigger changes in CEO ITIs and help with the identification problem.

Following Klasa et al. (2018) and Islam et al. (2022), I use the staggered adoption of the Inevitable Disclosure Doctrine (IDD) by several US state courts as unexpected mobility shocks. Under IDD, firms can sue their former employees for leaking trade secrets to rival firms simply because they are currently employed by a rival firm. This potential litigation risk can distort CEOs' mobility, so CEOs in IDD-adopted states are unlikely to move. If CEO ITIs are the driving forces of firms' strategic distinctiveness, one should expect a reduction of strategic distinctiveness for firms headquartered in IDD-adopted states. Therefore, I estimate the following DiD model:

$$Strategic\ Distinctiveness_{i,t} = \beta_0 + \beta_1 IDD_{i,t} + \delta \boldsymbol{X}_{i,t} + Industry \times Year\ FE + Firm\ FE + \varepsilon_{i,t} \quad (\mathbf{2})$$

In regression model (2), *IDD* is a state-wide treatment indicator that equals one for firms headquartered in IDD adopting states, and zero otherwise. *IDD* is reverted back to zero in the year when a state court rejects IDD after its adopted IDD in the past. Thus, the treatment group comprises firms headquartered in IDD-adopted states. In contrast, the control group includes firms headquartered in states that are not affected by the IDD (i.e., either not yet adopted IDD or already rejected IDD after the previous adoption). β_1 is the DiD estimator, which estimates the difference between the pre-to-post change in strategic distinctiveness of treated firms relative to the change in untreated firms. I include industry × year fixed-effects to control common trends in industries and firm fixed-effects to control time-unvarying firm characteristics, following Klasa et al. (2018).

4. EMPIRICAL RESULTS

4.1. Descriptive Statistics and Correlation

Table Ch3-1. Summary statistics

This table report summary statistics of the variables used in the main analysis. After merging the Compustat, CRSP, and Execucomp databases, the final sample contains 2,461 unique firms and 28,166 observations, covering S&P 1500 firm from 1992 to 2020. All continuous variables are winsorised at the 1% level.

	N	Mean	Std. Dev.	p25	Median	p75	min	max
SD (ff48)	27646	-1.032	1.44	-1.985	-1.34	-.449	-3.328	8.315
SD (sic2)	25949	-1.002	1.511	-1.988	-1.327	-.402	-3.453	9.121
ITIs(ff48)	28166	9.457	.898	8.932	9.527	9.997	6.446	11.773
ITIs(sic2)	26843	9.458	.977	8.885	9.573	10.06	6.125	11.779
Leverage	28166	.224	.216	.047	.2	.332	0	4.077
R&D expenditure	28166	.034	.063	0	.004	.044	0	1.022
MB ratio	28166	2.093	1.704	1.236	1.637	2.367	.53	75.67
CAPX	28166	.056	.056	.021	.039	.07	0	.442
Firm size	28166	7.186	1.549	6.09	7.073	8.171	-.625	11.517
Cashflow vol.	28166	.07	.19	.018	.035	.072	.001	11.672
Firm ranks(ff48)	28166	7.906	1.861	7	8	9	1	10
Firm ranks(sic2)	28166	7.938	1.885	7	8	9	1	10

Table Ch3-1 presents descriptive statistics for the sample used in the primary analysis. The mean of strategic distinctiveness based on FF48 (i.e., *SD_ff48*) and SIC2 (i.e., *SD_sic2*) industry classification is -1.032 and -1.002, respectively. As these means are less than zero, it highlights the fact that firms, on average, allocate their resources conforming to the industry strategic norm. Using the second-highest CEO pay in the industry as the benchmark, the mean industry-wide pay gap is 9.457 and 9.458, respectively, based on FF48 (i.e., *ITIs_ff48*) and SIC2 (i.e., *ITIs_sic2*) industry classification schemes. In dollar terms (i.e., without taking the natural logarithm), these pay gaps are $12.80 million (based on FF48) and $12.81 million (based on SIC2), similar to the statistics in previous studies on industry tournament incentives (Coles et al. 2018; Huang et al. 2019).

Table Ch3-2 reports the correlation coefficients of the main variables. As predicted, the correlation between strategic distinctiveness and CEO ITIs is positive and significant at the 1% confidence level. This preliminary result is consistent with hypothesis H1. It is also interesting to note that financial leave and firm growth opportunities positively relate to corporate strategic distinctiveness. In contrast, firm size and ranks negatively correlate to strategic distinctiveness, suggesting that larger firms tend to adopt more common strategies in the industry. These correlation coefficients are expected because large firms are likely to be the players who set each industry’s strategic norms, followed by other firms in the industry.

Table Ch3-2. Matrix of correlations

This table presents the correlation coefficient among the main variables of the study. Industry-level variables are measured based on either Fama-French 48 (ff48) industries or SIC 2-digi industries (sic2). Correlations are measured based on consistent industry classification which leave some rows blank.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) SD (ff48)	1.000											
(2) SD (sic2)	0.787	1.000										
(3) ITIs (ff48)	0.018		1.000									
(4) ITIs (sic2)		0.005	0.641	1.000								
(5) Leverage	0.174	0.166	-0.113	-0.092	1.000							
(6) R&D expenditure	0.027	0.020	0.136	0.249	-0.173	1.000						
(7) MB ratio	0.043	0.025	0.107	0.132	-0.064	0.265	1.000					
(8) CAPX	0.087	0.095	0.021	-0.049	0.062	-0.112	0.023	1.000				
(9) Firm size	-0.058	-0.034	-0.151	-0.102	0.251	-0.224	-0.119	-0.012	1.000			
(10) Cashflow vol.	0.108	0.102	0.100	0.103	0.034	0.200	0.077	-0.017	-0.169	1.000		
(11) Firm ranks (ff48)	-0.136		-0.088	-0.064	0.075	-0.025	0.032	-0.020	0.601	-0.126	1.000	
(12) Firm ranks (sic2)		-0.119	-0.118	-0.016	0.087	-0.062	0.006	-0.005	0.612	-0.144	0.862	1.000

4.2 Baseline Regression

Table Ch3-3 presents the main results of my study. Initially, in Columns (1) and (3), I estimate regression model (1) with only firm and year fixed-effects based on FF48 and SIC2 industries, respectively. Without adding control variables, it mitigates the concern that the results are driven by endogenous control variables (Gormley & Matsa 2013). Columns (2) and (4) report regression results with control variables (described earlier). The coefficients of *ITIs* are always positive and significant to at least the 5% level across all the regressions in Table 3 (Column 1: $\beta = 0.041$, p-value = 0.007; Column 2: $\beta = 0.031$, p-value = 0.034; Column 3: $\beta = 0.040$, p-value = 0.012; Column 4: $\beta = 0.031$, p-value = 0.047). These findings support hypothesis H1: CEO ITIs are positively related to firms' strategic distinctiveness[15]. Based on Column (4), one standard deviation rise in *ITIs* increases firms' forward strategic distinctiveness by 0.03. Given that the mean strategic distinctiveness in the sample for SIC2 industries is -1.002, the amount of increase is economically significant.

[15] An alternative hypothesis posits that CEOs receiving comparatively lower compensation might be inclined to exert less effort. While plausible, this suggests a negative correlation between CEO industry tournament incentives and firm strategic distinctiveness, as developing a unique strategy demands significant time and effort. My findings appear to reject this hypothesis, demonstrating a positive impact of CEO industry tournament incentives on firm strategic distinctiveness.

Table Ch3-3. Baseline

This table present the baseline regressions of firm strategic distinctiveness on CEO industry tournament incentives. The dependent variable Strategic distinctiveness indicates how far a firm's strategic outlook is away from the industry norm. The main independent variable, CEO industry tournament incentives (*ITI*), measures the difference between a focal CEO's pay to the second highest-paid CEO's pay in the industries. Columns (1) and (2) present the results based on Fama-French 48 industries while columns (3) and (4) show the results based on 2-digit SIC code industries. All regressions control for firm-fixed effects and year effect. *t-Statistics* based on robust standard errors and clustered at the firm level. *p-values* are within parentheses. ***, **, and * denote significant level at 1%, 5% and 10%, respectively.

	Strategic distinctiveness			
Industry classification	FF48		SIC 2-digit	
VARIABLES	(1)	(2)	(3)	(4)
ITIs	0.041***	0.031**	0.040**	0.031**
	(0.007)	(0.034)	(0.012)	(0.047)
Leverage		1.012***		1.096***
		(0.000)		(0.000)
R&D expenditure		-0.507		-0.100
		(0.300)		(0.830)
MB Ratio		0.009		0.015
		(0.340)		(0.103)
CAPX		0.690**		1.007***
		(0.046)		(0.009)
Firm size		-0.123***		-0.103***
		(0.001)		(0.005)
Cashflow vol.		0.066		0.115
		(0.394)		(0.156)
Firm ranks		-0.087***		-0.054**
		(0.000)		(0.027)
Constant	-1.400***	-0.025	-1.363***	-0.468*
	(0.000)	(0.925)	(0.000)	(0.094)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	29,386	28,166	27,592	26,448
R-squared	0.580	0.596	0.585	0.597

In Table Ch3-3, other estimated coefficients, such as the positive coefficients of *Leverage* and *CAPX*, and the negative coefficients of *Firm size* and *Firm rank,* are as expected. For example, financial leverage is one of the strategic dimensions considered by the measure of strategic distinctiveness. Not surprisingly, it is positively related to the levels of strategic distinctiveness in firms. Likewise, capital expenditure includes firm expenses that can be capitalised and thus relate to plant and equipment newness, which is one of the dimensions included in strategic distinctiveness. This can explain the positive coefficients of *CAPX*. Furthermore, larger firms in an industry or firms with higher ranks within an industry can be the firms in the industry setting the industry norm. This implies negative relations between firm size and industry sales rank with strategic distinctiveness, explaining the negative coefficients of *firm size* and *firm ranks*.

4.3 IDD Adoption

Next, I utilise the staggered adoption of IDD to mitigate potential endogeneity concerns with the OLS regression analysis above. Table Ch3-4 presents the DiD regression results using FF48 industries (in Column (1)) and SIC2 industries (in Column (2)). The dummy indicator, *IDD adoption*, equals one for firms headquartered in IDD adopting states in a fiscal year, and zero for firms headquartered in states not affected by IDD that year. The coefficients of *IDD adoption* are negative and significant in both columns (Column 1: β = -0.062, p-value = 0.017; Column 2: β = -0.056, p-value = 0.010). These negative coefficients suggest that firms headquartered in IDD adoption states decrease their strategic distinctiveness more than firms outside those IDD adoption states. Because participating in the industry tournament required free movement in the labour market, a shock on CEO mobility decreases treated CEOs' ITIs. Therefore, the negative coefficients of *IDD adoption* show consistent results to the results of OLS regression and mitigate potential endogeneity concerns.

To ensure DiD analysis is robust, I also check whether the parallel trend assumption is satisfied. This assumption states that the difference in the dependent variable between the treatment and control firms should be stable in the absence of treatment. In other words, the coefficients of a DiD estimator should be zero in the periods without treatment effects in place.

Table Ch3-4. IDD adoption

This table shows the staggered difference-in-difference regression results around IDD adoption events. IDD adoption serves as a shock to CEOs mobility and thus reduce these CEOs willingness to join the industry tournament competition. Therefore, the coefficients of *IDD adoption* show the effect of reduced CEO industry tournament incentives on corporate strategic distinctiveness. The dummy, *IDD adoption*, equals to 1 if a operate in the state has adopted the inevitable disclosure doctrine, and 0 otherwise. Following Klasa et al. (2018) and Islam et al. (2022), all regressions control for Firm-fixed effects and the interaction effects of industry and year. Industries are defined by Fama-French 48 industries in column (1) and 2-digit SIC code in column (2). *t-Statistics* based on robust standard errors and clustered at the firm level. *p-values* are within parentheses. ***, **, and * denote significant level at 1%, 5% and 10%, respectively.

	Strategic distinctiveness	
	FF48	SIC 2-digit
VARIABLES	(1)	(2)
IDD adoption	-0.062**	-0.056***
	(0.017)	(0.010)
Leverage	0.717***	0.725***
	(0.000)	(0.000)
R&D expenditure	-0.072	-0.090
	(0.647)	(0.530)
MB Ratio	-0.004	-0.005
	(0.416)	(0.260)
CAPX	-0.091	-0.145
	(0.708)	(0.472)
Firm size	-0.067**	-0.078**
	(0.017)	(0.019)
Cashflow vol.	0.026	0.026
	(0.192)	(0.167)
Firm ranks	-0.218***	-0.203***
	(0.000)	(0.000)
Constant	0.926***	0.884***
	(0.000)	(0.000)
Firm FE.	Y	Y
Industry & Year FE.	Y	Y
Observations	69,880	67,219
R-squared	0.618	0.625

To examine the parallel trend assumption, I first generate three time-dummy indicators: *IDD adoption (t-5, t-1)*, *IDD adoption (t)*, and *IDD adoption (t>=1)*. Then, I re-estimate the regression Model (2) by replacing *IDD adoption* with these three time-dummy indicators. *IDD adoption (t-5, t-1)*, *IDD adoption (t)*, and *IDD adoption (t>=1)* equal one if a firm is in the treated state and years from t-5 to t-1, t, and t>=1, with year t denoting the IDD adoption year, and zero otherwise. For example, in the year 1997, Arkansas adopted the IDD. Therefore, the IDD adoption affected firms headquartered in Arkansas in 1997. Accordingly, *IDD adoption (t-5, t-1)* is set to one for 1992 – 1996 for these firms. In addition, *IDD adoption (t)* and *IDD adoption (t>=1)* are set to one for the year 1997 and the periods after the year 1997. Other firms not affected by the IDD have these three time-dummy equaling zero.

Table Ch3-5 reports the result of the trend analysis. In both Columns (1) and (2), the coefficients of *IDD adoption (t-5, t-1)* are statistically zero, but the coefficients of *IDD adoption (t>=1)* are negative and significant at the 1% confidence level. These results suggest no statistical difference in strategic distinctiveness between the treated and untreated firms in the five years leading up to an IDD adoption, and the difference only emerges one year after the IDD adoption. This evidence shows that the parallel trend assumption is likely to be satisfied.

Table Ch3-5. Trend analysis

This table aims to show the staggered difference-in-difference regression in table Ch3-4 satisfied the parallel trend assumption. The coefficients of *IDD adoption (t-5, t-1)* represent the effects of IDD adoption on strategic distinctiveness before the actual IDD adoption in each state. Both of the coefficients in columns (1) and (2) are insignificant suggesting that there is no effect of IDD adoption on strategic distinctiveness prior to IDD adoption. This suggests the parallel trend assumption is satisfied. The coefficients of *IDD adoption (t)* and *IDD adoption (t≥1)* show the effects of IDD adoption at the adopting year and the years after the adoption. Industries are defined by Fama-French 48 industries in column (1) and 2-digit SIC code in column (2). *t-Statistics* based on robust standard errors and clustered at the firm level. *p-values* are within parentheses. ***, **, and * denote significant level at 1%, 5% and 10%, respectively.

	Strategic distinctiveness	
	FF48	SIC 2-digit
VARIABLES	(1)	(2)
IDD adoption (t-5, t-1)	-0.067	-0.049
	(0.168)	(0.183)
IDD adoption (t)	-0.106*	-0.063
	(0.098)	(0.221)
IDD adoption(t≥1)	-0.081***	-0.077***
	(0.001)	(0.004)
Leverage	0.728***	0.735***
	(0.000)	(0.000)
R&D expenditure	-0.018	-0.013
	(0.916)	(0.937)
MB Ratio	-0.004	-0.005
	(0.332)	(0.204)
CAPX	-0.040	-0.152
	(0.865)	(0.466)
Firm size	-0.061**	-0.073**
	(0.030)	(0.029)
Cashflow vol.	0.022	0.021
	(0.264)	(0.246)
Firm ranks	-0.217***	-0.202***
	(0.000)	(0.000)
Constant	0.910***	0.893***
	(0.000)	(0.000)
Firm FE.	Y	Y
Industry & Year FE.	Y	Y
Observations	69,880	67,219
R-squared	0.620	0.634

Figures Ch3-1 and Ch3-2 visually present the results from Columns (1) and (2) in Table Ch3-5. Each dot point in blue is the point estimated coefficients for the time dummies, *IDD adoption (t-5, t-1)*, *IDD adoption (t),* and *IDD adoption (t>=1)*. The whiskers above and below each dot point are the 95% confidence intervals of each estimated coefficient. The horizontal red line represents the zero coefficient. When a whisker crosses the red line, it indicates that the estimated coefficient is statistically indifferent to zero at the 95% confidence levels. In both Figures, I show that the whiskers of *IDD adoption (t-5, t-1)* and *IDD adoption (t)* come across the horizontal red line, suggesting the coefficients of both dummies are statistically zero. In contrast, the whiskers of *IDD adoption (t>=1)* never come across the red line, suggesting the point estimated coefficients are statistically different from zero.

Figure Ch3-1. Trend Analysis based on FF48 industries

Figure Ch3-1 present the effect of *IDD Adoption* on corporate strategic distinctiveness based on Fama-French 48 industries. Each dot on the graph represents a point estimation of the effects that *IDD Adoption* on strategic distinctiveness in different periods, i.e., before (t-5 to t-1), current(t), and after (t>=1). The whiskers above and below each dot point are the 95% confidence intervals of each estimated effects. The horizontal red line is the zero-coefficient line, and any whisker across this line indicates the effect is insignificant at the 95% confidence level.

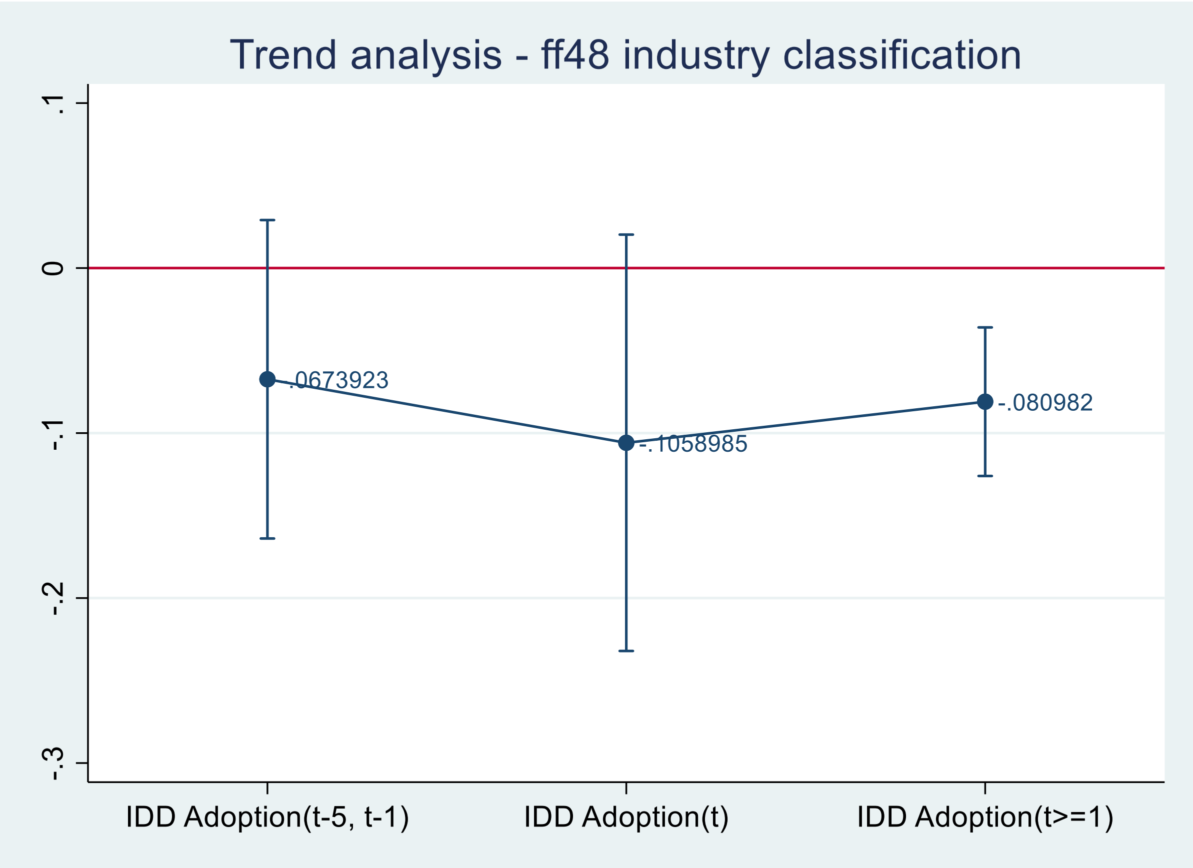
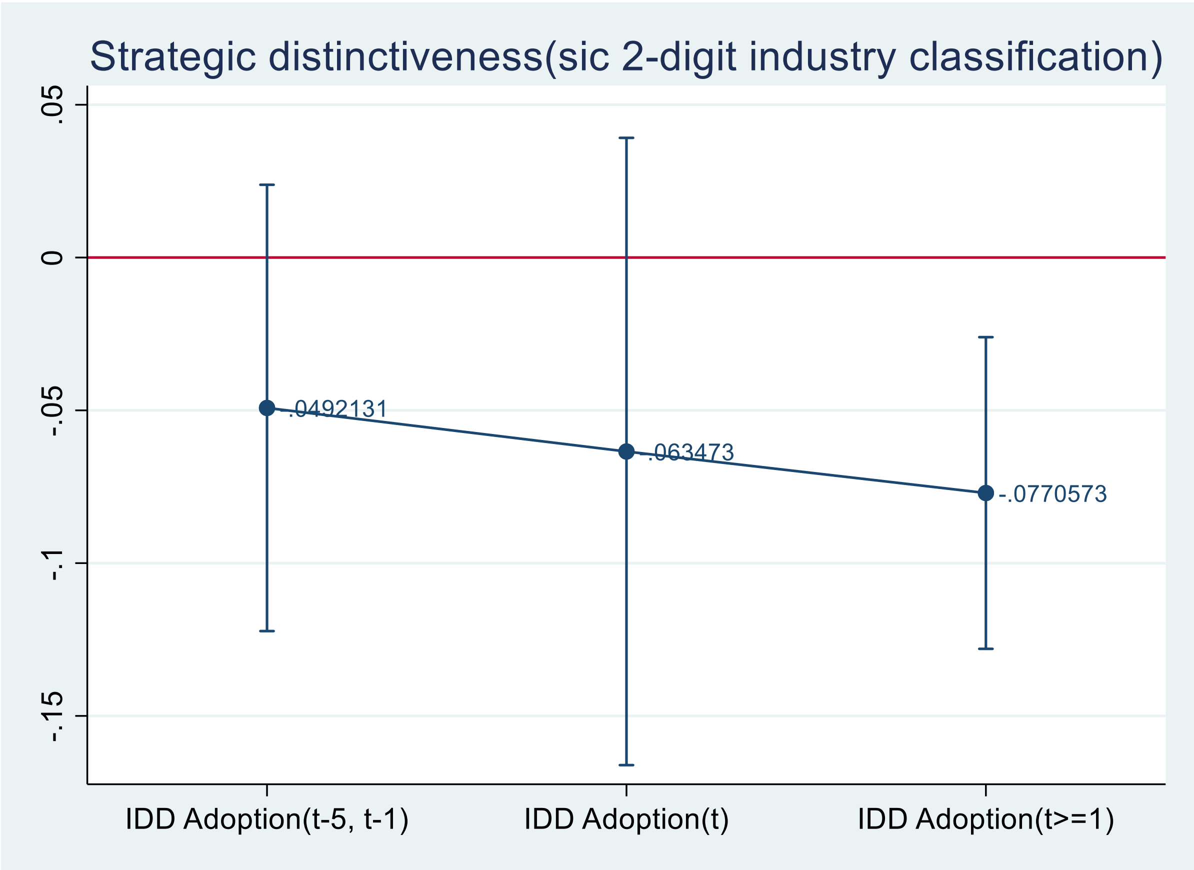


Figure Ch3-2. Trend Analysis based on SIC 2-digit industries

Figure Ch3-2 present the effect of *IDD Adoption* on corporate strategic distinctiveness based on SIC 2-digit indutries. Each dot point indicates the point estimated coefficient of *IDD Adoption* on strategic distinctiveness in different periods, i.e., before (t-5 to t-1), current(t), and after (t>=1). The whiskers above and below each dot point are the 95% confidence intervals of each estimated effects. The horizontal red line is the zero-coefficient line, and any whisker across this line indicates the effect is insignificant at the 95% confidence level.



4.4 Subsample Analysis

So far, my findings suggest a positive relationship between CEO ITIs and firm strategic distinctiveness. Next, I examine whether the strength of such a positive relation varies across firms, industries, and CEOs with different characteristics.

4.4.1 Effective boards

According to Hypothesis 2, if potential pay increases motivate a CEO to adopt more distinct strategies at the firm, the relation between CEO ITIs and strategic distinctiveness should be stronger in firms with effective internal control mechanisms that oversee CEO compensation. I test this conjecture by performing a subsample test based on the board size since corporate governance literature has long suggested that smaller boards are more effective than larger boards (Jensen 1993; Yermack 1996).

Table Ch3-6. Subsample analysis – Effective boards

This table shows the effects of CEO industry tournament incentives (*ITIs*) on strategic distinctiveness under different corporate governance environments. Columns (1) and (3) show the effect of CEO *ITIs* with the board size less than the sample median board size, whereas columns (2) and (4) show the effect with the board size greater than the sample median. The row, Diff. in Coefficient, show the Chi^2 tests for the difference in the coefficient of *ITIs* between column (1) and (2) and between column (3) and (4). Industries are defined by Fama-French 48 industries in column (1) and 2-digit SIC code in column (2). *t-Statistics* based on robust standard errors and clustered at the firm level. *p-values* are within parentheses. ***, **, and * denote significant level at 1%, 5% and 10%, respectively.

	Strategic distinctiveness			
Industry classification	FF48		SIC 2-digit	
	Small board	Large board	Small board	Large board
VARIABLES	(1)	(2)	(3)	(4)
ITIs	0.047**	0.009	0.050*	-0.010
	(0.044)	(0.681)	(0.051)	(0.679)
Leverage	0.947***	0.866***	0.985***	1.047***
	(0.000)	(0.001)	(0.000)	(0.001)
R&D expenditure	-0.563	-1.041	-0.182	-1.913
	(0.486)	(0.572)	(0.817)	(0.210)
MB Ratio	0.033**	0.002	0.034**	0.022
	(0.032)	(0.943)	(0.032)	(0.431)
CAPX	1.164**	0.590	1.377**	1.509
	(0.032)	(0.494)	(0.020)	(0.149)
Firm size	-0.090	-0.308***	-0.085	-0.170*
	(0.151)	(0.000)	(0.203)	(0.057)
Cashflow vol.	0.281	0.559	0.278	0.598
	(0.186)	(0.240)	(0.167)	(0.240)
Firm ranks	-0.062*	-0.124**	-0.045	-0.066
	(0.071)	(0.050)	(0.226)	(0.379)
Constant	-0.747*	2.087***	-0.974**	0.544
	(0.094)	(0.006)	(0.041)	(0.524)
Diff. in Coefficient	0.038		0.060*	
(*p-value*)	(0.231)		(0.100)	
Firm FE.	Y	Y	Y	Y
Year FE.	Y	Y	Y	Y
Observations	10,901	6,206	10,208	5,741
R-squared	0.655	0.684	0.650	0.698

Table Ch3-6 presents the subsample analysis results. In there, I show the results by re-estimating my baseline regression with two subsamples formed by splitting my firm-year observations. One sample contains firms with a board size higher than the sample median board size, whereas another sample consists of firms with a board size lower than the median. Consistent with Hypothesis 2, the results in Table Ch3-6 reveal that CEO ITIs' positive effect is significant in firms governed by smaller boards. In particular, in columns (1) and (3), I find positive and significant coefficient results for *ITIs* in the subsample of firms with smaller board size (Column 1: β = 0.047, p-value = 0.044; Column 3: β = 0.050, p-value = 0.051). In contracts, with the subsample containing firms with larger board sizes, I find the coefficients for *ITIs* are statistically insignificant. Further, I employ the seemingly unrelated regression methodology (e.g., Hoetker 2007; Lee et al. 2020) to check whether the coefficients of *ITIs* between these two subgroups differ, as shown at the bottom of Table Ch3-6. The test shows that the magnitude of the positive effect of CEO ITIs is more pronounced in the subsample of firms with smaller board sizes. Specifically, comparing the coefficients of *ITIs* in Columns (3) and (4), the difference is 0.060 and significant at the 10% confidence level.

4.4.2 Market competition

Next, I examine whether the positive effect of CEO ITIs on strategic distinctiveness changes with the market competition that firms face. The main argument that CEO ITIs positively affect corporate strategic distinctiveness is premised on the notion that adopting uncommon strategies can reduce product market competition. The lower market competition allows a firm to extract higher rents from the market, thus leading to higher firm performance and increasing the chance for a CEO to win the industry tournament. Therefore, the positive effect of CEO ITIs is expected to be stronger where firms face higher market competition (or lower market concentration).

To test hypothesis 3, I perform a subsample analysis based on industry-wide product market concentration and present the results in Table Ch3-7. Industry-wide market concentration is measured by the Herfindahl–Hirschman Index (HHI). It uses the annual sales of firms belonging to each industry to calculate industry-wide HHIs per fiscal year (Hou & Robinson 2006; Luo et al. 2015). Columns (1) and (3) present the regression results when I re-run my baseline regression with the low HHI (i.e., high market competition) subsample. It consists of firms in industries with an HHI lower than the sample median of HHI. The results in there show positive and significant effect of CEO ITIs on corporate strategic distinctiveness (Column 1: $\beta = 0.081$, p-value = 0.000; Column 3: $\beta = 0.078$, p-value = 0.000). In contrast, when using the high HHI subsample that consists of firms in industries where their HHI is higher than the sample mean of HHI, I find the coefficients of *ITIs* are insignificant (in Columns (2) and (4)). Further, the Chi-square tests reported at the bottom of Ch3-7 confirm that there are significant differences of the coefficient for *ITIs* between the two subsamples (Column (1) and (2): *difference = 0.075*, *p*-value = 0.087; and Column (3) and (4): *difference = 0.075*, *p*-value = 0.031). This result support Hypothesis 3, which states that the positive effect of CEO ITIs is stronger for firms that face higher market competition than firms with less market competition.

Table Ch3-7. Subsample analysis – Industry competitiveness

This table shows the effects of CEO industry tournament incentives (*ITIs*) on strategic distinctiveness under different industry competitiveness environments. Industry concentration is measured by the Herfindahl–Hirschman Index (HHI). Low (High) HHI indicates low (high) industry concentration, i.e., high (low) industry competitiveness. Columns (1) and (3) show the effect of CEO *ITIs* in firms operated in industries with higher than sample median competitiveness, whereas columns (2) and (4) show the effect in firms operated in industries with lower than sample median competitiveness. The row, Diff. in Coefficient, show the Chi^2 tests for the difference in the coefficient of *ITIs* between column (1) and (2) and between column (3) and (4). Industries are defined by Fama-French 48 industries in column (1) and 2-digit SIC code in column (2). *t-Statistics* based on robust standard errors and clustered at the firm level. *p-values* are within parentheses. ***, **, and * denote significant level at 1%, 5% and 10%, respectively.

	Strategic distinctiveness			
Industry classification	FF48		SIC 2-digit	
	Low HHI	High HHI	Low HHI	High HHI
VARIABLES	(1)	(2)	(3)	(4)
ITIs	0.081***	0.006	0.078***	0.003
	(0.000)	(0.782)	(0.000)	(0.905)
Leverage	1.035***	0.914***	0.863***	1.094***
	(0.000)	(0.000)	(0.000)	(0.000)
R&D expenditure	-0.781	-0.611	-0.101	-0.961
	(0.374)	(0.295)	(0.863)	(0.196)
MB Ratio	0.006	0.009	0.017	0.001
	(0.541)	(0.589)	(0.117)	(0.961)
CAPX	0.839	0.351	0.731	1.149***
	(0.104)	(0.380)	(0.240)	(0.007)
Firm size	-0.180***	-0.117**	-0.138**	-0.116**
	(0.000)	(0.016)	(0.010)	(0.039)
Cashflow vol.	0.156	-0.131	0.129	0.101
	(0.125)	(0.462)	(0.289)	(0.313)
Firm ranks	-0.043	-0.099***	-0.049	-0.026
	(0.166)	(0.001)	(0.127)	(0.432)
Constant	-0.477	0.331	-0.618	-0.332
	(0.213)	(0.372)	(0.170)	(0.414)
Diff. in Coefficient	0.075*		0.075**	
(*p-value*)	(0.087)		(0.031)	
Firm FE.	Y	Y	Y	Y
Year FE.	Y	Y	Y	Y
Observations	11,659	16,313	11,678	14,620

R-squared	0.632	0.628	0.618	0.642

4.4.3 Managerial ability

In the last subsample analysis, I examine whether CEO managerial ability can affect the relation between CEO ITIs and firms' strategic distinctiveness. As stated in Hypothesis 4, high-ability CEOs are more likely to win the industry labour market tournament because the labour market demands talent, suggesting that high-ability CEOs are more incentivised by the industry pay gap than low-ability CEOs. Therefore, the relationship between CEO ITIs and strategic distinctiveness may be more pronounced in firms with high-ability CEOs. I test this prediction by performing a subsample analysis based on CEO ability.

Table Ch3-8 presents the results. CEO ability is proxied by the widely accepted managerial ability score from Demerjian et al. (2012) [16]. Based on this measure, I partition my sample into high- and low-ability subsamples. Specifically, the high-ability sample contains firms managed by CEOs with an ability score higher than the sample median managerial ability score. In contrast, the low ability sample includes firms with a CEO with a lower managerial ability score than the sample median. Using the high-ability sample, I find positive and significant coefficients of *ITIs* (Column 1: β = 0.045, p-value = 0.013; Column 3: β = 0.033, p-value = 0.084). In comparison, the coefficients of *ITIs* are insignificant in Columns (2) and (4) when estimating the regression based on the low-ability sample. Looking at the coefficients of *ITIs* in Columns (1) and (2), the difference equals 0.043 and is significant at the 5% confidence level. This suggests that the positive effect of CEO ITIs is more pronounced in firms with high-ability CEOs, supporting Hypothesis 4.

[16] See more detailed calculation in Demerjian et al., (2012)

Table Ch3-8. Subsample analysis - Managerial ability

This table shows the effects of CEO industry tournament incentives (*ITIs*) on strategic distinctiveness when the managerial team with different ability levels. The measure, managerial ability, is sourced from Demerjian et al. (2012). Columns (1) and (3) show the effect of CEO *ITIs* in firms with high ability managerial team, whereas columns (2) and (4) show the effect in firms operated in industries with low ability managerial team. The row, Diff. in Coefficient, show the Chi^2 tests for the difference in the coefficient of *ITIs* between column (1) and (2) and between column (3) and (4). Industries are defined by Fama-French 48 industries in column (1) and 2-digit SIC code in column (2). *t-Statistics* based on robust standard errors and clustered at the firm level. *p-values* are within parentheses. ***, **, and * denote significant level at 1%, 5% and 10%, respectively.

	Strategic distinctiveness			
Industry classification	FF48		SIC 2-digit	
	High ability	Low ability	High ability	Low ability
VARIABLES	(1)	(2)	(3)	(4)
ITIs	0.045**	0.002	0.033*	0.004
	(0.013)	(0.937)	(0.084)	(0.863)
Leverage	0.887***	1.069***	0.964***	1.184***
	(0.000)	(0.000)	(0.000)	(0.000)
R&D expenditure	-0.324	-1.416	-0.159	-0.334
	(0.616)	(0.136)	(0.791)	(0.706)
MB Ratio	0.016*	-0.051	0.017*	-0.010
	(0.054)	(0.121)	(0.063)	(0.698)
CAPX	0.629	0.875*	0.671	1.565***
	(0.193)	(0.065)	(0.226)	(0.004)
Firm size	-0.117***	-0.173***	-0.079*	-0.144***
	(0.010)	(0.001)	(0.085)	(0.007)
Cashflow vol.	0.046	0.014	0.074	0.077
	(0.823)	(0.863)	(0.694)	(0.432)
Firm ranks	-0.057*	-0.062**	-0.061**	-0.009
	(0.071)	(0.045)	(0.048)	(0.801)
Constant	-0.362	0.422	-0.506	-0.324
	(0.282)	(0.269)	(0.142)	(0.438)
Diff. in Coefficient	0.043**		0.029	
(*p-value*)	(0.029)		(0.475)	
Firm FE.	Y	Y	Y	Y
Year FE.	Y	Y	Y	Y
Observations	16,313	11,659	14,620	11,678
R-squared	0.628	0.632	0.642	0.618

Taken together, the above results in Tables 6-8 show that the strength of the positive effect of CEO ITIs on strategic distinctiveness has cross-sectional variation. CEO ITIs encourage more distinct strategies adoption in situations where boards are more effective, product market competition is higher, and CEOs have higher managerial ability.

4.5 Channel Analysis

In this subsection, I further distinguish the two possible channels that CEO ITIs go through to affect corporate strategic distinctiveness. According to Hypothesis 1, CEO ITIs can affect firms' strategic distinctiveness through either CEOs' increased performance-based incentives or risk-taking incentives. If the former channel is more likely, the positive effect of CEO ITIs on strategic distinctiveness should be more pronounced when a firm provides insufficient pay-performance incentives to its CEO. Whereas, if the latter channel is more likely, the positive effect of CEO ITIs should be more pronounced where CEOs are received insufficient risk-taking incentives from their compensation package. Three sets of subsample analysis thus are performed to provide suggestive evidence.

Table Ch3-9 presents the channel analysis results[17]. Columns (1) to (4) report the results examining the first possible channel. That is, ITIs provide CEOs with higher performance-related incentives, thereby pursuing strategic distinctiveness in their firms. Specifically, I present the results in each column when I re-run my baseline regression with one of the following four subsamples. These are: (1) high delta sample that includes firms that are managed by CEOs who receive pay-performance incentives higher than half of the CEOs in the sample; (2) low delta sample which contains firms that provide lower than the sample

[17] Industries are defined based on Fama-French 48 industry classification. Similar results are found if industries are defined by using the 2-digit SIC code.

median pay-performance incentives to their CEO; (3) high firm-specific wealth sample that contains firms managed by CEOs who have firm-specific wealth higher than the half of other CEOs in the sample; and (4) low firm-specific wealth sample that consists of firms managed by CEOs who have firm-specific wealth lower than the half of other CEOs in the sample[18]. In subsamples (1) and (3), CEOs may receive sufficient performance-related incentives, whereas, in subsamples (2) and (4), the performance-related incentives may be insufficient. Using these subsamples and estimating the baseline regression, I find the coefficients of *ITIs* are insignificant in Columns (1) and (3) but positive and significant in Columns (2) and (4) (Column 2: β = 0.092, p-value = 0.000; Column 4: β = 0.075, p-value = 0.005). Further, the chi-square tests on the coefficients between each subsample set find statistically significant differences at the 5% confidence levels. Between Columns (1) and (2), the difference between the coefficients of *ITIs* is 0.062 (p-value = 0.011), and between Columns (3) and (4), the difference in coefficients is 0.063 (p-value = 0.040). This result indicates the positive effect of CEO ITIs on strategic distinctiveness is prone to show in firms that provide insufficient performance-related incentives to their CEOs.

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[18] CEO delta is measured as dollar change in CEOs' wealth associated with a 1% change in their managed firm's stock price, whereas CEO firm-specific wealth is the total value of a CEO's stock and option. These two measurers are calculated following the methodology described in Coles et al (2013), which their seminal work Coles et al (2006) is based on. I thank the authors making the calculation SAS code publicly available.

Table Ch3-9. Channel analysis

This table analyses the channels that CEO industry tournament incentives (*ITIs*) go through to affect corporate strategic distinctiveness with different CEO compensation structures. High delta (in column 1) and high firm-specific wealth (in column 3) sample contain firms' CEOs' having the delta and firm-specific wealth higher than the sample median. In contrast, low delta (in column 2) and low firm-specific wealth (in column 4) sample contain firms' CEOs' having the delta and firm-specific wealth lower than the sample median. Columns (5) and (6) contains firms with their CEOs' vega is higher and lower than the sample median CEO vega, respectively. CEO delta, firm-specific wealth, and vega are calculated following the methodology proposed by Coles et al. (2013). Industries are defined by Fama-French 48 industries across all regression models. *t-Statistics* based on robust standard errors and clustered at the firm level. *p-values* are within parentheses. ***, **, and * denote significant level at 1%, 5% and 10%, respectively.

	Strategic distinctiveness					
	High delta	Low delta	High firm-specific wealth	Low firm-specific wealth	High vega	Low vega
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
ITIs	0.010	0.092***	0.012	0.075***	0.028	0.049*
	(0.498)	(0.000)	(0.518)	(0.005)	(0.134)	(0.059)
Leverage	0.950***	1.204***	0.943***	1.213***	1.325***	1.026***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D expenditure	-1.321***	-0.055	-1.250**	-0.073	-1.620***	0.685
	(0.001)	(0.870)	(0.044)	(0.908)	(0.007)	(0.282)
MB Ratio	0.034***	-0.024*	0.032***	-0.019	0.038**	-0.004
	(0.000)	(0.095)	(0.005)	(0.616)	(0.014)	(0.826)
CAPX	2.696***	0.008	2.643***	0.068	1.922***	0.472
	(0.000)	(0.979)	(0.000)	(0.892)	(0.005)	(0.328)
Firm size	-0.017	-0.213***	-0.014	-0.219***	-0.079	-0.148**
	(0.524)	(0.000)	(0.788)	(0.001)	(0.102)	(0.012)

Cashflow vol.	0.286**	0.030	0.374*	-0.012	0.164	-0.042
	(0.020)	(0.701)	(0.073)	(0.901)	(0.408)	(0.715)
Firm ranks	-0.019	-0.038**	-0.036	-0.027	-0.029	-0.051
	(0.376)	(0.039)	(0.369)	(0.384)	(0.412)	(0.113)
Constant	-1.249***	-0.467*	-1.187***	-0.265	-0.942**	-0.346
	(0.000)	(0.090)	(0.004)	(0.566)	(0.032)	(0.387)
Diff. in Coefficient	0.062**		0.063**		0.45	
(*p-value*)	(0.011)		(0.040)		(0.504)	
Firm FE.	Y	Y	Y	Y	Y	Y
Year FE.	Y	Y	Y	Y	Y	Y
Observations	11,496	12,255	11,211	11,966	11,628	12,097
R-squared	0.030	0.037	0.642	0.645	0.642	0.641

Columns (5) and (6) of Table Ch-9 show the third set of the subsample analysis results for identifying the channel. In Column (5), I present the results by re-estimating my baseline regression with the high vega sample, which consists of firms that provide higher than the sample median risk-taking incentives value (i.e., CEO vega)[19] to their CEOs. This finds an insignificant coefficient of *ITIs*. In contracts, Column (6) presents the baseline regression results using the low vega sample, which consists of firms managed by CEOs with lower than the sample median risk-taking incentives. The coefficient of *ITIs* is positive and significant (β = 0.049, p-value = 0.059). However, the chi-square test result suggests the difference is statistically zero when comparing the two coefficients of ITIs between Columns (5) and (6), implying the effect of CEO ITIs is similar in firms managed by CEOs either with higher or lower risk-taking incentives.

Taken together, the results in Table Ch3-9 suggest that CEO ITIs are likely providing CEOs with higher performance-based incentives rather than risk-taking incentives and thus affect corporate strategic distinctiveness.

4.6 The Role of Strategic Distinctiveness

Coles et al. (2018) show that firm performance is positively associated with CEO ITIs. I further examine the intermediate role of strategic distinctiveness may play in the relationship. To do so, I replicate their baseline regression result in my setting. First, I split my sample into two based on the sample median strategic distinctiveness value. Specifically, firms with an above-median strategic distinctiveness are assigned to one sample (i.e., high SD sample). Another sample includes firms with a below-median strategic distinctiveness (i.e., low SD

[19] CEO vega or risk-taking incentives is estimated by the dollar change in CEOs' wealth associated with a 1% change in the standard deviation of their firms' returns following Coles et al (2013).

sample). Then, I re-estimate my baseline regression model by replacing the dependent variable with a measure of firm performance. Instead of using Tobin's Q as in Coles et al. (2018), I use the CEO skill-related firm performance measure from Daniel et al. (2020). Doing so allows me focus on the performance related to CEO managerial skills since the measure only considers the firm performance driven by CEO skill-related factors and disregards the performance caused by the co-movement in the industry.

Table Ch3-10 presents the results. First, in Columns (1) and (4), I reconcile my results with the main findings in Coles et al. (2018) using the FF48 and SIC2 industry classification schemes, respectively. Consistent with their findings, I find CEO ITIs are positively associated with firm performance in both columns when estimating the modified baseline regression with the whole sample (Column 1: β = 0.023, p-value = 0.000; Column 4: β = 0.018, p-value = 0.005). Next, I show the modified baseline regression results using a smaller sample in the remaining Columns of Table 10. In both Columns (2) and (5), I find the estimated coefficients of *ITIs* are positive and significant using the high SD sample (Column 2: β = 0.040, p-value = 0.031; Column 5: β = 0.045, p-value = 0.007). In contrast, in Columns (3) and (6), I show that the estimated coefficients of *ITIs* are statistically indifferent to zero. Furthermore, the Chi-square tests on the coefficients of *ITIs* between Columns (2) and (3) and between Columns (5) and (6) both confirm the differences in coefficients are statistically significant (Column (2) and (3): *difference = 0.035*, *p*-value = 0.031; and Column (5) and (6): *difference = 0.047*, *p*-value = 0.013). These results in Table 10 show that the positive relation between CEO ITIs and firm performance (related to CEO managerial skills) is more pronounced in firms with higher levels of strategic distinctiveness. Therefore, implementing distinctive strategies can be one avenue through which CEO ITIs positively affect firm performance, complimenting the results in Coles et al. (2018).

Table Ch3-10. The role of strategic distinctiveness

This table shows the impact of CEO industry tournament incentives on CEO skill-related firm performance. Columns (1) and (4) show the results based on the full sample, while columns (2), (3), (5), and (6) show the results based on subsample analysis. Columns (2) and (5) show the subsample analysis for firms with strategies are distinctive to their industry peers (i.e., high strategic distinctiveness), whereas columns (3) and (6) show the results based on the subsample with firms' strategies are similar to their industry peers (i.e., Low strategic distinctiveness). Industries are defined by Fama-French 48 industries (in columns (1) to (3)) and 2-digit SIC code (in columns (4) to (6)). *t-Statistics* based on robust standard errors and clustered at the firm level. *p-values* are within parentheses. ***, **, and * denote significant level at 1%, 5% and 10%, respectively.

	Firm performance (CEO skill related)					
Industry classification	FF48			SIC 2-digits		
	All	High SD	Low SD	All	High SD	Low SD
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
ITIs	0.023***	0.040**	0.005	0.018***	0.045***	-0.002
	(0.000)	(0.031)	(0.578)	(0.000)	(0.007)	(0.766)
Leverage	0.053*	0.221***	0.067	0.049*	0.227**	0.053
	(0.064)	(0.010)	(0.333)	(0.097)	(0.012)	(0.438)
R&D expenditure	0.363***	-0.330	0.496	0.349***	-0.264	0.427
	(0.002)	(0.429)	(0.185)	(0.003)	(0.550)	(0.250)
MB Ratio	-0.034***	-0.022**	-0.043***	-0.033***	-0.023**	-0.042***
	(0.000)	(0.031)	(0.004)	(0.000)	(0.024)	(0.005)
CAPX	-0.392***	-0.328	-0.762***	-0.401***	-0.396	-0.673***
	(0.000)	(0.199)	(0.000)	(0.000)	(0.121)	(0.001)
Firm size	-0.153***	-0.209***	-0.157***	-0.154***	-0.226***	-0.148***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cashflow vol.	-0.040	0.071	-0.195	-0.040	0.052	-0.186
	(0.258)	(0.567)	(0.195)	(0.259)	(0.675)	(0.213)
Sale Rank	-0.001	0.027	0.002	-0.001	0.030	-0.005
	(0.888)	(0.197)	(0.842)	(0.859)	(0.172)	(0.695)
Constant	0.947***	0.923***	1.184***	1.000***	0.985***	1.241***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Diff. in Coefficient		0.035**			0.031**	
(*p-value*)		(0.013)			(0.013)	
Firm FE.	Y	Y	Y	Y	Y	Y
Year FE.	Y	Y	Y	Y	Y	Y
Observations	15,711	1,486	4,953	15,480	1,484	4,868
R-squared	0.231	0.364	0.313	0.234	0.362	0.322

4.6. Robustness Checks

I perform a battery of robustness tests to ensure my main finding is robust and presented in Table Ch3-11. First, I check whether my results are robust to a different regression estimation method. A firm's strategic distinctiveness may be sticky. This suggests a positive correlation between a firm's current and past strategic distinctiveness. To deal with this issue, I follow Kang et al. (2020) and use the feasible generalised least squares (FGLS) regression estimation method. This method can consider heteroscedasticity and firm-specific AR1 autocorrelation in the dependent variable of a regression model. Columns (1) and (2) of Table Ch3-11 present the results estimated by FGLS. Consistent with the results from OLS (i.e., in Columns (2) and (4) of Table Ch3-3), the coefficients of *ITIs* are positive and significant in both columns (Column 1: β = 0.008, p-value = 0.051; Column 2: β = 0.010, p-value = 0.032), showing the robustness of my main findings to an alternative regression estimation method.

Next, I check whether my results are sensitive to the measurement of firm strategic distinctiveness. In the primary analysis, I calculate strategic distinctiveness by analysing seven dimensions that CEOs have the most impact on suggested by the previous literature (Crossland et al. 2014; Kang et al. 2020). For the robustness test, I follow Crossland et al. (2014) and analyse firms' strategic distinctiveness along the six dimensions[20]. Columns (3) and (4) of Table Ch3-11 show the results using this alternative measure of strategic distinctiveness. The coefficients of *ITIs* are positive and significant at the 1% confidence level in both Columns (3) and (4) (Column 3: β = 0.030, p-value = 0.002; Column 4: β = 0.031, p-value = 0.002). These results show the main findings in the current are robust and not sensitive to a different measure

[20] The six dimensions are advertising intensity, R&D intensity, overhead efficiency, capital intensity, plant and equipment newness, and financial leverage.

of the dependent variable.

Furthermore, I include multiple CEO- and board-level variables into the baseline regression model (1) to control other potential factors from CEO characteristics or the board structure that can bias my main findings. Specifically, I control for CEO age because, on average, younger CEOs have less career variety and experience, limiting their strategic choices. I also include CEO delta, CEO vega, and CEO total pay to control for potential influence from CEOs' compensation packages. At the board level, I control board size, board independence, and board gender diversity. These variables are used to control for corporate governance and the heterogeneity among the board members. Columns (5) and (6) of Table Ch3-11 present regression results, including these additional CEO- and board-level controls. Again, I find the coefficients of *ITIs* are positive and significant (Column 5: $\beta = 0.038$, p-value = 0.010; Column 6: $\beta = 0.050$, p-value = 0.000), mitigating further potential omitted variable concerns involved in the main finding of this study.

Lastly, in Columns (7) and (8), I show my baseline regression results still hold with spell fixed-effects (Graham et al. 2012; Islam et al. 2022). It is possible that the positive association between CEO ITIs and firm strategic distinctiveness is driven by the endogenous matching between CEOs' and firms' preferences. I include the spell fixed-effects to my baseline regression model (1) to address this concern since Islam et al. (2022) suggest that using spell fixed-effects can control for any confounding effects from the endogenous matching between CEOs and firms. Once again, I find the coefficients of *ITIs* are positive and significant at least at the 5% confidence levels (Column 7: $\beta = 0.037$, p-value = 0.024; Column 8: $\beta = 0.042$, p-value = 0.004), suggesting the endogenous matching between CEOs' and firms' preference is a less severe concern in this study.

Table Ch3-11. Robustness

This table present additional tests to ensure the main findings in the current study is robust. Columns (1) and (2) re-run the baseline regression using feasible generalised least squares approach. Columns (3) and (4) use an alternative measure of strategic distinctiveness. Columns (5) to (8) include a larger set of control variables and show the results of baseline regression with different fixed-effects. The regressions in columns (5) and (6) include CEO fixed-effects, whereas the regressions in columns (7) and (8) include CEO-firm pair effects (Spell fixed effects). Industries are defined by Fama-French 48 industries (in columns (2), (4), (6) and (8)) and 2-digit SIC code (in columns (1), (3), (5), and (7)). *t-Statistics* based on robust standard errors and clustered at the firm level. *p-values* are within parentheses. ***, **, and * denote significant level at 1%, 5% and 10%, respectively.

			Strategic distinctiveness (SD.)					
	FGLS		Alternative SD measures		Additional controls		CEO-firm paired FE.	
Industry classification:	Sic 2-digt	FF48	SIC-2 Digit	FF48	SIC-2 Digit	FF48	SIC-2 Digit	FF48
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ITIs	0.008*	0.010**	0.030***	0.031***	0.038***	0.050***	0.037**	0.042***
	(0.051)	(0.032)	(0.002)	(0.002)	(0.010)	(0.000)	(0.024)	(0.004)
Leverage	0.163***	0.181***	0.309***	0.269***	0.449***	0.359***	0.481***	0.313**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.022)
R&D expenditure	0.259***	0.411***	-0.293	-0.246	0.046	-0.230	0.249	0.027
	(0.000)	(0.000)	(0.285)	(0.403)	(0.910)	(0.601)	(0.457)	(0.942)
MB Ratio	0.006***	0.012***	0.008	0.003	0.015	0.006	0.013	0.008
	(0.010)	(0.000)	(0.154)	(0.585)	(0.255)	(0.604)	(0.295)	(0.517)
CAPX	0.435***	0.199***	0.222	0.023	0.301	-0.086	0.372	-0.145
	(0.000)	(0.010)	(0.343)	(0.912)	(0.440)	(0.788)	(0.393)	(0.681)
Firm size	0.015***	0.007*	-0.092***	-0.072***	-0.084**	-0.108***	-0.086**	-0.093**
	(0.000)	(0.058)	(0.000)	(0.000)	(0.011)	(0.001)	(0.029)	(0.018)
Cashflow vol.	0.070**	-0.003	0.014	-0.023	-0.012	-0.026	-0.059	-0.086
	(0.026)	(0.924)	(0.844)	(0.640)	(0.880)	(0.738)	(0.451)	(0.425)
Sale Rank	-0.027***	-0.027***	0.007	-0.019	-0.014	-0.038*	-0.012	-0.051**

	(0.000)	(0.000)	(0.598)	(0.150)	(0.532)	(0.056)	(0.614)	(0.028)
Lagged SD	0.803***	0.798***	0.560***	0.554***	0.489***	0.492***	0.367***	0.375***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CEO age					0.003	0.003*	0.024	-0.023
					(0.174)	(0.078)	(0.583)	(0.512)
CEO Delta					-0.014	-0.017	-0.029	-0.036*
					(0.242)	(0.141)	(0.133)	(0.075)
CEO Vega					0.004	0.001	0.002	0.006
					(0.627)	(0.922)	(0.821)	(0.583)
CEO total pay					0.015	0.033**	0.041**	0.053***
					(0.383)	(0.045)	(0.029)	(0.003)
Board size					-0.002	-0.004	-0.003	-0.010
					(0.728)	(0.528)	(0.691)	(0.170)
Board independence					0.065	-0.010	0.015	-0.171
					(0.547)	(0.921)	(0.913)	(0.203)
Board gender div.					-0.156	-0.042	-0.232	-0.172
					(0.359)	(0.779)	(0.221)	(0.350)
Constant	-0.241***	-0.225***	-0.123	-0.055	-0.394	-0.277	-1.715	1.328
	(0.000)	(0.000)	(0.431)	(0.716)	(0.237)	(0.361)	(0.483)	(0.493)
Year & Firm FE.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CEO FE	No	No	No	No	Yes	Yes	No	No
Spell FE.	No	No	No	No	No	No	Yes	Yes
Observations	26,856	28,718	27,065	28,957	15,309	16,346	14,815	15,810

5. CONCLUSIONS

In this study, I investigate whether the CEO industry pay gap affects corporate strategic distinctiveness. Based on tournament incentives theory (Lazear & Rosen 1981; Coles et al. 2018), I argue and show that CEO industry tournament incentives encourage more distinct strategies being adopted at firms. This relationship is robust to a DiD analysis, which utilises the stagged adoption of the Inevitable Disclosure Doctrine in the US as exogenous shocks to CEOs' mobility. Furthermore, further analysis shows such a positive effect of CEO ITIs is more likely driven by increased CEO efforts rather than more risk-taking activities. Lastly, I find the positive impact of CEO ITIs varies within firms and industries. It is more pronounced in firms where the board structure is more effective, the product-market competition is higher, and the CEO has a higher managerial ability. These indicate the critical role that corporate governance effectiveness, market competition, and CEO talents play in the relation between CEO ITIs and strategic distinctiveness.

My study relates to the management and tournament incentive literature and provides some important implications. First, it highlights a possible and more accessible venue for helping firms to pursue strategic distinctiveness. Previous studies document that CEO characteristics such as career variety (Crossland et al. 2014), charisma (Wowak et al. 2016), and name uniqueness (Kang et al. 2020) are important antecedents to strategic distinctiveness. However, these characteristics are CEO specific and can only be changed if a firm replaces its current CEO. In contrast to these studies, my study offers a solution that the board of directors has more control over. I find a higher value of CEO ITIs can lead to higher strategic distinctiveness. Therefore, rather than replacing the current CEO, the board of directors can redesign the CEO's compensation package to pursue strategic distinctiveness at the firm.

Second, my study contributes to the tournament incentives theory (Lazear & Rosen 1981; Kale et al. 2009; Coles et al. 2018) by showing ITIs can help to combat the costly efforts of CEOs and thus affect corporate strategic distinctiveness. The literature on tournament incentives has suggested the internal corporate tournament is important in influencing firm performance (Kale et al. 2009), firm innovation (Shen & Zhang 2018), and firm risk (Kini & Williams 2012). However, less attention has been given to the external labour market tournament. Following the lead of Coles et al. (2018), this study shed light on the importance of the external labour market tournament and the incentives it can provide to CEOs. Therefore, investors and compensation designers should not ignore such incentives when making investment decisions or designing CEO contracts.

CHAPTER 4: TMT CONFIDENCE DIVERSITY AND INNOVATION EFFICIENCY

1. INTRODUCTION

Core to upper echelons (UE) theory (Hambrick & Mason 1984) is the premise that differences among top executives shape their "personalized interpretations of the strategic situations they face" (Hambrick 2007: 334) and thus lead to different firm actions and outcomes. Although initial UE research focused on distal demographic characteristics (such as age, tenure, and educational background; Wiersema & Bantel 1992; Tihanyi et al. 2000; Henderson et al. 2006), recent scholarship has turned to executives' psychological attributes. These studies have explored aspects of executives' personalities (e.g., the Big Five personality traits; Harrison et al. 2019), their motivational orientation (e.g., temporal focus and regulatory focus; Nadkarni & Chen 2014; Gamache et al. 2015), and their self-concept (e.g., narcissism, hubris, and overconfidence; Hayward & Hambrick 1997; Chatterjee & Hambrick 2007; Galasso & Simcoe 2011).

Although most research on the psychological attributes of executives has understandably focused on the CEO due to their significant influence on firm outcomes (e.g., Quigley & Hambrick 2015), UE theory was founded on the premise that the top management team (TMT) collectively shapes strategic outcomes (Hambrick & Mason 1984; Hambrick 2007). In line with this, another significant research stream has developed that studies diversity within the TMT (e.g., Boone et al. 2019; Tang et al. 2021). This work, however, has focused almost exclusively on the diversity of demographic characteristics such as functional background, gender, tenure, and others (see Homberg & Bui 2013). In this vein, the lack of research on the diversity of psychological attributes is a glaring omission. While substantial research has recognized the importance of executive's psychological attributes (Finkelstein et al. 2009; Busenbark et al. 2016), I know little about how TMT diversity among these attributes shapes firm outcomes (for exceptions, see Boone & Hendriks 2009; Narayan et al. 2021).

In this chapter, I focus on confidence diversity within TMTs. Drawing on a recent review, I define executive confidence as their generalized "conviction in their capability to complete tasks, influence events, and/or achieve outcomes" (Heavey et al. 2022). Further, I define TMT confidence diversity as the degree to which confidence levels vary throughout the top management team. While some TMTs are likely to exhibit high levels of confidence diversity, others may have much greater conformity. A TMT with high confidence diversity will have some highly overconfident members and some with much lower levels of confidence. In contrast, a TMT with low confidence diversity will have little variety in confidence levels among members. In these teams, all members may be highly overconfident, all have a similar mid-level of confidence, or all have lower confidence levels.

Examining the diversity of confidence levels within the TMT is critical for several reasons. First, most prior research on overconfidence has focused on the CEO. However, Hambrick (2007a: 334) argues that focusing on the team rather than on one individual often "yields better explanations of organizational outcomes." This is especially likely to be true when I move beyond individual decisions that are directly under the purview of the CEO (such as the decision to acquire a company; Meyer-Doyle et al. 2019) and into broader outcomes that involve the organization as a whole—such as efficiently managing innovations.

Second, scholars recognize that executive overconfidence may deliver both costs and benefits to the organization (Malmendier & Tate 2005; Galasso & Simcoe 2011). Thus, when TMT confidence diversity is high, the highly confident executives will be balanced out by low confident executives. When this happens, it is unclear whether the costs or the benefits of overconfidence might win out. In this vein, it is crucial to understand whether TMT confidence diversity will shape organizational outcomes.

Third, self-concept variables such as confidence are likely to have greater variance in TMTs than other psychological attributes. Indeed, some psychological attributes are likely to be somewhat homogonous on TMTs due to similarity-attraction effects in selection and turnover decisions (Nielsen 2010; Westphal & Zajac 2013) and the tendency of motivational attributes to spillover or be entrained from leaders to followers (Bluedorn & Jaussi 2008; Johnson et al. 2017). However, this homogeneity is less likely with self-concept variables. Indeed, recent research suggests that overconfident CEOs seldom make changes to their TMTs (Kowalzick & Appels 2022), which suggests that attraction-selection processes are less likely to occur. Thus, it is possible for a CEO to be highly overconfident but for other top management team members to have much loIr levels of confidence (or vice versa), thus creating the potential for substantial diversity in confidence levels among members of the TMT.

Finally, as noted above, TMT scholars have studied the strategic implications of diversity on demographic characteristics such as gender, tenure, functional background, and education (see Homberg & Bui 2013). Studying TMT confidence diversity allows me to examine the diversity of a psychological attribute that differs among executives. Whereas diversity of demographic attributes allows for social categorization based on visible qualities (e.g., Boone et al., 2019), diversity of psychological attributes is often harder to ascertain and, therefore, less likely to trigger social categorization to harm the team process (Olson et al. 2007). In this vein, I argue that TMT confidence diversity will shape how the team processes information, thus influencing their effectiveness in implementing strategic decisions.

In this study, therefore, I integrate UE theory (Hambrick & Mason 1984) and information processing theory on diversity (Mayo et al. 2017; Tasheva & Hillman 2019) to examine the effect of TMT confidence diversity on firm innovation efficiency. Innovation efficiency is defined as the degree to which a firm can maximize the innovation output value associated with a given level of inputs (Hambrick & MacMillan 1985; Hirshleifer et al. 2012).

Innovation is critical for a business to attain competitive advantage and long-term firm survival (Ahuja & Morris Lampert 2001; Boone et al., 2019). However, not all firms effectively convert innovation investments in research and development (R&D) into valuable innovation outcomes such as highly cited patents (Hambrick & MacMillan 1985; Hirschleifer et al., 2012). While a simple increase in R&D spending can increase innovation development, a more critical challenge for firms is "how to improve the efficiency of transforming R&D input into innovation output" (Zhou et al. 2017: 397).

Thus, I develop a hypothesis, that is, TMT confidence diversity will be positively related to firm innovation efficiency due to information processing benefits when making decisions about innovation. Further, I examine two decision-making contexts that are likely to affect the frequency and intensity of TMT decision-making—industry competitive intensity and the firm's level of financial maturity. I test my hypotheses using a broad panel dataset of S&P 1500 firms between 1992 and 2017, finding strong support for all hypotheses.

My study makes several contributions to the corporate finance literature of TMTs. First, it reveals the critical role of TMT confidence diversity. In this way, this study is consistent with the roots of UE theory, which emphasizes the importance of studying the entire TMT (Hambrick & Mason 1984). However, my focus on TMT confidence diversity suggests that when it comes to strategy implementation, the diversity of confidence levels within the team may be more important than the team's average or overall confidence level. Second, my study moves beyond a static examination focused only on individual executives' overconfidence. In this way, I answer the call to examine confidence across the spectrum, including low, average, and high levels of confidence (Heavy et al., 2022). My findings show that confidence levels vary within TMTs and that when TMT confidence diversity is high, it can provide substantial benefits for the firm—in terms of higher innovation efficiency.

Additionally, my study contributes to research on TMT diversity by focusing on the diversity of a psychological attribute, which, unlike demographic factors, is less likely to create categorization effects within the team. This is an important extension for upper echelon research, which has primarily focused on demographic characteristic diversity (e.g., Boone et al., 2019; Chen et al. 2016) and only begun to examine the psychological attributes of executives (e.g., Narayan et al., 2021). Finally, I contribute to research on corporate innovation. The findings in this study show that TMT confidence diversity is positively associated with innovation efficiency. By focusing on innovation efficiency rather than overall levels of innovation, I show how executive attributes not only shape the degree to which firms pursue innovation strategies (Nadkarni & Chen 2014; Kashmiri et al. 2017; Tuncdogan et al. 2017) but also shape how effective the firms are at implementing those strategies.

The reminder of chapter 4 is organised as follows. Section 2 discusses the related literature and develops the three hypotheses. Section 3 includes illustration of the data and methodology. The main findings are present in section 4 with discussion, and section 5 concludes this paper.

2. LITERATURE REVIEW & HYPOTHESES DEVELOPMENT

2.1. Executive Confidence

Although UE Theory initially focused on the importance of the entire TMT, research over the past two decades has emphasized the role of the CEO (Hambrick 2007; Finkelstein et al., 2009). This is especially true in the studies of psychological attributes, with much research now focusing on CEO attributes such as their personality, self-concept, and motivational orientation (for a review, see Busenbark et al. 2016).

Along these lines, substantial work has focused on the self-concept of the CEO, examining constructs such as narcissism, hubris, and humility (e.g., Hayward & Hambrick 1997; Chatterjee & Hambrick 2007; Petrenko et al. 2019). A key aspect of executive self-concept is their confidence level. As I defined earlier, this refers to the level of their conviction in their ability to complete tasks and achieve desired outcomes (Heavey et al., 2022). Executive confidence, therefore, is a continuum ranging from low confidence (underconfidence) to high confidence (overconfidence) (Heavey et al., 2022).

Despite this, research has almost exclusively focused on studying “overconfidence” (Heavey et al., 2022). This research has been fruitful, with a wide range of strategic outcomes being attributed to overconfidence. Overconfident executives tend to overestimate the returns they will receive from a given project and thus overinvest in specific strategies, for example, by engaging in more acquisitions and paying higher premiums for them (Malmendier & Tate 2008; Liu et al. 2009). Overconfident CEOs tend to fund their investments using cash or debt rather than equity financing, viewing the latter as unnecessarily expensive due to their confidence in future growth (Malmendier & Tate 2005). Additionally, CEO overconfidence has often been tied to ethically questionable practices. For example, overconfident CEOs are more likely to intentionally misstate financial earnings (Schrand & Zechman 2012), engage in aggressive accounting practices (Ahmed & Duellman 2013), and backdate stock option dates (Bianchi & Mohliver 2016).

Notwithstanding these adverse outcomes, the research on overconfidence is not all bleak. For instance, based on the logic that overconfident executives underestimate the risks and overestimate the potential success of their initiatives, scholars have demonstrated that overconfident executives are more likely to pursue and introduce pioneering products (Simon & Houghton 2003). Similarly, Hirshleifer et al. (2012) find that overconfident CEOs invest more heavily in R&D and achieve a greater quantity of innovation in terms of patent and citation counts. Although most of this research is ambivalent to the performance implications of these innovation efforts—indeed, Simon and Houghton (2003) show that performance among these pioneering products was less likely to be successful—recent meta-analytic research suggests CEO overconfidence is, on average, beneficial for firm performance because it encourages valuable strategic risk taking (Burkhard et al., in press).

Despite this research, and as mentioned earlier, very little research has extended my understanding of executive confidence to the TMT level[21]. Therefore, I seek to advance this research by examining the impact of confidence diversity within the TMT, drawing on substantial research on TMT diversity.

2.2. Top Management Team Diversity

Even though there has been a trend in recent decades for UE scholars to focus on the CEO, one stream of research continues to focus on the team as a whole—that work focused on TMT diversity. Indeed, one benefit of studying the entire TMT is that it recognizes the role of "dispersion characteristics" that reflect how similar or different members are to one another (Hambrick & Mason 1984: 197). This research, however, almost completely focuses on TMT demographic characteristics such as education, tenure, national diversity, and functional background (e.g., Boone et al., 2019; Hambrick et al. 1996; Cannella Jr et al. 2008), and has only begun to examine the diversity of psychological attributes (Boone & Hendriks 2009; Narayan et al., 2021).

Even with its limited focus on demographic characteristics, TMT diversity research has provided a valuable understanding of the role of TMT diversity on critical firm outcomes. For example, TMT gender diversity is associated with fewer acquisitions and smaller acquisitions (Chen et al., 2016) but more significant investments in R&D (Post et al. 2022). Perhaps the most studied form of TMT diversity is functional background diversity (Nielsen 2010). TMT functional diversity is associated with an increased ability to gain venture capital funding (Beckman et al. 2007) but is also with ineffective communication and information sharing (Glick et al. 1993; Bunderson & Sutcliffe 2002). Consistent throughout this research, therefore,

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is that TMT diversity can have both beneficial and detrimental effects on organizational outcomes.

Although it is beyond the scope of the current study to summarize every study on TMT diversity—other scholars have provided excellent reviews of this literature (Nielsen 2010; Homberg & Bui 2013)—it is important for me to discuss the major theoretical perspectives undergirding this research. Most importantly, research from social psychology has informed the UE perspective through two theoretical lenses. The first theoretical perspective argues for the detrimental effects of diversity due to conflicts resulting from the social categorization of individuals. This work argues that diversity among team members tends to increase fear and uncertainty, while similarity among team members increases identification and cohesion within the team to improve decision quality (Van Knippenberg & Schippers 2007). The second theoretical perspective argues for the beneficial effects of diversity on teams' decision-making and is known as the information-decision-making perspective (Bantel & Jackson 1989). The fundamental premise is that high levels of team diversity create a more comprehensive range of perspectives and increased information exchange, thus enhancing decision-making quality (Brockmann & Anthony 2002).

Many studies have demonstrated that both social categorization and information processing benefits can exist, and scholars have argued that information processing benefits are likely to be more prominent in three situations. These are 1)when the diverse attribute specifically impacts the focal task, 2) when the diverse attribute is less visible (such as one's education), and 3) when team members frequently interact over time, such as in TMTs (Schubert & Tavassoli 2020; Tang et al., 2021). Consistent with this, I argue that TMT confidence diversity will lead to information processing benefits for innovation decisions because 1) executive confidence levels are directly relevant to innovation decisions (Simon & Houghton 2003; Galasso & Simcoe 2011), 2) confidence levels, like other executive psychological attributes, are less visible, and 3) TMTs often interact frequently over a more extended period than most other teams (Jackson et al. 2003; Tang et al., 2021).

2.3. Innovation Efficiency

To test the impact of TMT confidence diversity in firms, I focus on the firms' innovation efficiency. I define innovation efficiency as the ability of a firm to achieve the most innovation outputs relative to a given level of inputs (Hirshleifer et al. 2013). Firms high in innovation efficiency can maximize the value of their R&D budgets to patent and develop novel and valuable ideas. Thus, innovation efficiency is not simply about the quantity of innovation-related outputs (i.e., patents) but rather how well firms utilize their limited resources to develop these outputs (Duran et al. 2016). Indeed, while innovation spending has the potential to create a valuable source of competitive advantage (Mount et al. 2021), it also has the potential to result in substantial waste (Duran et al., 2016). As a result, firms can have high (low) levels of investments but low (high) levels of innovation outputs (Duran et al., 2016). Unsurprisingly, firms that can efficiently manage their innovation efforts outperform those that are less efficient (Hirschleifer et al., 2013).

I argue that innovation efficiency is an ideal first outcome to study the effects of TMT confidence diversity for two primary reasons. First, the TMT plays a critical role in driving innovation outcomes, and as a result, many executive attributes have been shown to influence firm innovation outcomes. For example, research has shown that attributes such as executive narcissism and hubris spur innovation by propelling executives to take significant risks and make bold investments in innovation (Gerstner et al. 2013; Tang et al. 2015), while executive prevention focus leads to loIr investments in innovation (Scoresby et al. 2021). Although, on the surface, innovation outcomes may appear relatively distal from the TMT, top managers shape the firm's innovation through allocating and investing resources, inspiring and establishing a culture of innovation, and setting the overall corporate vision (Elenkov et al.

2005; Elenkov & Manev 2005; Watts et al. 2020). Inspired by this stem of the literature, substantial research provides evidence that even those at the very top of the organization can shape innovation (for a review of the role of strategic leadership in innovation, see Kurzhals et al. 2020).

Second, innovation is among the most studied outcomes of executive overconfidence (Heavey et al., 2022). This research suggests that firms led by overconfident CEOs are willing to take higher risks and, as a result, produce more innovation outcomes in terms of more frequent patenting and new product introductions (Simon & Houghton 2003; Galasso & Simcoe 2011; Tang et al. 2015). However, overconfident CEOs may invest more resources in innovation efforts without necessarily seeing positive performance benefits. Indeed, overconfident CEOs may overestimate the potential outcomes from innovation investments and underestimate the risks of failure (Galasso & Simcoe 2011; Heavey et al., 2022). As I argue below, confidence diversity in the TMT may serve as an antidote for reckless spending and provide for more efficient innovation investment decisions.

2.4. Hypotheses Development

2.4.1 The main Hypothesis

As discussed above, my primary hypothesis is that TMT confidence diversity will be associated with greater innovation efficiency. While I acknowledge that some types of diversity can create increased distrust and conflict due to social categorization (Williams & O'Reilly, 1998), theory suggests that diversity along less visible attributes within long-standing teams and those that directly affect the task at hand are less likely to experience social categorization (Schubert & Tavassoli 2020; Tang et al., 2021). As such, I draw on information-processing perspectives on diversity. I believe these benefits will likely accrue from TMT confidence diversity for several reasons.

First, TMT confidence diversity can provide general information processing benefits for decision-making like those gained from other types of diversity. Indeed, TMT diversity research suggests that diversity creates information processing advantages as diverse teams lead members to consider different information sources, analyze issues from different perspectives, avoid making decisions prematurely, and be more willing to challenge each other and incorporate feedback (Eesley et al. 2014; Hambrick et al., 1996; Chen et al. 2016). Collectively, these information processing benefits can help TMTs make better decisions, and, as a result, I expect better innovation decisions as they rely on information processing throughout the top management team.

Second, beyond these general decision-making benefits, TMT confidence diversity is likely to lead to specific information process benefits that are unique to how confidence diversity shapes innovation processes. Along these lines, confidence diversity is expected to be associated with a more optimal level of investment in R&D and idea-generation activities. Within a TMT with high-confidence diversity, highly confident (or overconfident) executives are likely to be eager to invest in innovation-related projects (Li & Zhang 2022). These executives are likely prone to lead the industry and are confident they can succeed by investing in R&D (Heavey et al., 2022; Simon & Houghton 2003). However, low-confident executives are likely to be more cautious about investing in innovation pursuits. These executives are likely to be overly concerned about the risks associated with R&D investments and underestimate the likelihood of success. Together, I expect this will result in an appropriate level of innovation investments that balances risk and caution. In contrast, a TMT with low confidence diversity may easily overinvest in pursuing innovation (if the team consists of highly overconfident executives) or underinvest in pursuing innovation (if the team consists of low-confident executives; Simon & Houghton 2003).[22]

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[22] Although I expect this to be less common, a TMT with low confidence diversity could also be made up of a team of all moderately confident executives. I believe that these teams will also be less effective than a TMT with high confidence diversity because they miss out on the eagerness benefits of having some highly

Third, as early results of these research efforts come in, TMT members are faced with decisions about which projects are worthy of further investment. Again, I believe that a TMT with high confidence diversity will make the best decisions about which projects deserve continued investment. In this vein, the highly confident members of the diverse TMT are likely to push for a wide range of projects to invest in because they are exceedingly confident in their ability to be successful (Galasso & Simcoe 2011) and overestimate the payoffs when the products make it to market (Tang et al., 2015). On the other hand, the low-confident members of a highly diverse team are likely to be sceptical about many of the projects. These executives will challenge the ideas, seek more information, and push for more project discussions (see Tang et al., 2015). Thus, teams with high confidence diversity are unlikely to reach conclusions too quickly but, instead, conduct proper due diligence around the potential projects to invest in. Ultimately, this should lead the TMT with high confidence diversity to choose the best projects. In contrast, low-confidence diversity teams may be at risk of investing in projects too quickly if the team is made up of highly confident executives, and thus use up the allocated budget on the first projects (rather than the best) or otherwise make wasteful investment decisions (Duran et al., 2016; Simon & Houghton 2003). Alternatively, suppose a TMT has low confidence diversity because the team comprises executives with low confidence. In that case, the team is likely to miss out on profitable investments as these executives will underestimate their potential for success.

Finally, I expect similar issues to occur as the TMT makes decisions about bringing the products to market, and again expect TMTs with high confidence diversity to make better decisions when launching new products. When a product has been developed, the TMT must decide when and how to introduce the new product (Srivastava & Lee 2005). I hypothesise that

confident members and miss out on the careful examination of ideas promoted by the low confident members.

a team with high TMT confidence diversity will likely make the best decisions about when to launch the new product. In contrast, a (low confidence diversity) TMT consisting of all highly confident executives may rush to launch new products and introduce products that require greater resource investment because they overestimate the benefits and underestimate the associated risks (Simon & Shrader 2012). Similarly, a (low confidence diversity) TMT comprised of all low confidence executives may be overly concerned about the potential risks associated with introducing a new product, thus underestimating the value of speed to market and moving too slowly. In contrast, a TMT with high confidence diversity is likely to consider both the benefits of an early launch (promoted by highly confident executives) and the costs of an early launch (as expressed by low confident executives) and thus make better launch choices.

***Hypothesis 1**: TMT confidence diversity is positively related to innovation efficiency.*

2.4.2. The moderating effect of the decision-making context

As I have hypothesised, TMT confidence diversity creates information processing benefits when TMTs make decisions around innovation processes, thus resulting in increased innovation efficiency. To further test my Hypothesis 1, I next turn to an examination of the contingent effects of the decision-making context. If the primary mechanism by which TMT confidence diversity shapes innovation efficiency is through improved decision-making, the decision-making context should moderate the relationship. As such, I examine two specific contexts that are likely to affect the frequency and intensity of decision-making at the TMT level—the level of industry competitive intensity and the firm's level of financial maturity. I argue that when the context dictates that the TMT is required to frequently meet to discuss intense business decisions (such as in a particularly intense competitive environment), TMT confidence diversity is likely to be more important in shaping innovation efficiency. In contrast, when the context dictates that the TMT is required to meet less frequently and has less intensity surrounding its business decisions (such as in financially mature firms), TMT confidence diversity is likely to be less important in shaping innovation efficiency.

When a firm operates in a particularly intense competitive environment, the TMT is likely required to meet more frequently and make more intense decisions. Competitive intensity reflects the overall level of competition faced by the firm (Jaworski & Kohli 1993). When firms experience high competitive intensity, they are likely to face more aggressive actions from competitors, engage in more advertising and price wars, introduce more products and services, and generally make more frequent decisions (Wang et al. 2014). As such, I expect that the level of competitive intensity will strengthen the relationship between TMT confidence diversity and innovation efficiency for three primary reasons.

First, when competitive intensity is high, firms are likely to feel threatened by rivals and, consequently, be forced to make frequent decisions and changes (Giachetti & Dagnino 2013). Further, as rivals similarly feel threatened, they are likely to make more frequent moves again, accelerating the degree to which TMTs must respond (Su et al. 2020; Wang et al., 2014). Thus, when competitive intensity is high, “the frequency whereby informational inputs are needed and shared among TMT members to facilitate decision-making is much higher in order for the firm to benefit from short-lived opportunities” (Wang et al., 2014: 692). In contrast, when competitive intensity is low, TMTs have less incentive to work together when making decisions (Wang et al., 2014). In these contexts, TMTs will meet less frequently and make feIr decisions, thus reducing the value of the decision-making benefits linked to confidence diversity.

Second, when competitive intensity is high, TMTs will likely experience more significant stress when making decisions. Along these lines, Hambrick et al. (2005) argue that intense rivalry can make more demanding decision-making. Indeed, competitive intensity creates time pressures as TMTs are required to “make decisions quickly and take actions swiftly (Su et al., 2020: 1265). As a result, there is a greater risk that decisions will be driven by heuristics and emotions rather than carefully reasoned logic (Hambrick et al., 2005; Qian et al. 2013). In contrast, low competitive intensity means less pressure to make quick decisions (Su et al., 2020). This should allow TMTs to be more careful in making decisions and follow more logical decision-making processes (Hambrick et al., 2005). Thus, I expect that the decision-making benefits associated with TMT confidence diversity will be more important when competitive intensity is high because decision-making becomes more challenging.

Third, and more specifically to innovation-related decisions, when competitive intensity is high, the decisions TMT makes surrounding innovation become more challenging due to increased resource and attentional constraints. Indeed, when competitive intensity is high, resources are scarce, and organizations need to do more within these constraints (Boone et al. 2004). As I argued earlier, when TMT confidence diversity is high, TMTs are likely to make better decisions both in the initial allocation of resources to research and development and in terms of choosing which early-stage projects are worth further investment. This benefit is likely to be particularly valuable in competitively intense environments due to these resource constraints. Further, when competitive intensity is high, TMTs are likely to face significant demands on their attention (Gatignon & Xuereb 1997; Su et al., 2020). This will likely cause substantial problems for innovation decisions when TMT confidence diversity is low. Indeed, if attentional demands are high, a team of all highly confident executives (low in TMT confidence diversity) is even more likely to follow their natural tendencies to invest quickly in a wide range of projects without considering the associated risks (Hambrck et al., 2005; Li & Zhang, 2022; Simcoe & Houghton, 2003). In contrast, when attentional constraints are high, the natural tendency of a team made up of all low-confident executives (again low in confidence diversity) will be to heuristically dismiss all risky endeavors because they will underestimate the potential value of these investments.

In sum, when competitive intensity is high, it is likely to lead TMTs to make more rapid and frequent decisions and find the decision-making process more stressful (Giachetti & Dagnino 2013; Hambrick et al., 2005; Wang et al., 2014). This is likely to be particularly impactful for TMTs when making innovation decisions as they are likely to face significant resource constraints (Boone et al., 2004) and have their attention drawn to other issues (Gatignon & Xuereb 1997). As a result, the decision-making benefits for innovation processes associated with TMT confidence diversity are likely to be particularly important when competitive intensity is high. I therefore hypothesize:

> ***Hypothesis 2****: The relationship between TMT confidence diversity and innovation efficiency is moderated by industry competitive intensity, such that the relationship is stronger when industry competitiveness is high.*

Next, I argue that the decision-making benefits associated with TMT confidence diversity are likely less important for financially mature firms. More financially mature firms are generally older firms that are more financially stable and have greater access to financial resources, either through their own financial savings or through easier ability to raise funds through investors or financial institutions. When firms are high in financial maturity, the TMT experiences fewer decision-making constraints, and therefore, the benefits associated with TMT confidence diversity are likely to be less important. In contrast, when firms have low financial maturity (i.e., more financially immature firms), the decision-making process is expected to be more challenging, making TMT confidence diversity more impactful. As such, I theorize that the level of firm financial maturity will Iaken the relationship between TMT confidence diversity and innovation efficiency for three primary reasons.

First, when firms are high in financial maturity, TMTs are likely to make fewer decisions, reducing the importance of the decision-making benefits associated with confidence diversity. Indeed, older and financially mature firms are likely to be more bureaucratized and routinized than more immature firms (Wagner et al. 1984; Zheng et al. 2010). These firms, therefore, are likely to have more path-dependent decision-making processes that rely less on the TMT and are more inertial (Sirén et al. 2017). In contrast, when firm financial maturity is low, the TMT is likely to make more decisions. Indeed, more financially immature firms are likely to have fewer routines and rely more on frequent and specific decisions (see Siren et al., 2017; Zheng et al., 2010). In these contexts, the TMT will meet more frequently and make more decisions, thus increasing the value of the decision-making benefits linked to confidence diversity.

Second, when financial maturity is high, TMTs are likely to experience less stress when making decisions. Consistent with this, more financially mature firms are likely to have fewer resource constraints and greater freedom in their decisions (Cheng et al. 2013). As a result, these decisions are likely to be less stressful, allowing for more rational decision-making processes (Hambrick et al., 2005). In contrast, when financial maturity is low, TMTs are likely to experience significant decision-making constraints (Cheng et al., 2013). In these situations, each decision is more impactful and, thus, more stressful to the TMT. As stress in decision-making increases, executives are likely to be drawn to heuristic decision-making that emphasizes easy, quick decisions rather than carefully thought-out decisions (Hambrick et al., 2005). Thus, when firm financial maturity is high, TMT confidence diversity is likely to be less important because executives have the time and ability to make quality decisions about innovation. In contrast, when firm financial maturity is low, the stress and constraints that shape decision-making make TMT confidence diversity more important, as quality decision-making will become more valuable.

Third, and more specifically to innovation-related decisions, when firm financial maturity is high, the TMT has more flexibility in making innovation decisions. Indeed, greater financial maturity will give executives a long-term orientation and the financial resources needed to take more risks and explore new opportunities (Kim et al. 2008; Song et al. 2022).

This greater flexibility means that any given innovation decision is less important for the overall innovation efficiency of the organization. In contrast, firms with low financial maturity are more restricted in their ability to invest in innovation projects. Thus, if low TMT confidence diversity causes the team to make investment projects too quickly (if the TMT consists of all high-confidence executives) or miss out on key investment projects (if the TMT consists of all low-confidence executives), the impact on firm innovation efficiency is likely to be substantial.

In sum, when financial maturity is high, TMTs are likely to make fewer decisions due to the increased routinization and bureaucracy throughout the organization (Wagner et al., 1984; Zheng et al., 2010). Furthermore, executives in more financially mature firms are likely to find decision-making less stressful because of fewer resource constraints (Cheng et al., 2013). As a result, the decision-making benefits for innovation processes associated with TMT confidence diversity are likely to be less important for firms with greater financial maturity. I thus hypothesize:

> ***Hypothesis 3****: The relationship between TMT confidence diversity and innovation efficiency is moderated by firm financial maturity, such that the relationship is Iaker for more financially mature firms.*

3. DATA, VARIABLES & METHOD

3.1. Sample

The sample used in this study included all firms listed in the ExecuComp database between 1992 and 2017. As my measure of TMT confidence diversity is based on how TMT members manage their vested stock options, I filter my sample based on the availability of each TMT's compensation information. For most firm-years, ExecuComp provides data for the top five highest-paid executives, which scholars have used to identify the top management team (Christensen et al. 2015; Bushman et al. 2016; Steinbach, Holcomb, Holmes Jr, et al. 2017). I follow the extant literature (Henderson & Fredrickson 2001; Carpenter & Sanders 2002;

Steinbach, Holcomb, Holmes Jr, et al. 2017) and exclude firms in any given year with stock option compensation data for less than five executives in the ExecuComp database. However, I utilise only the top five highest-paid executives' information if there is data on more than five executives to ensure similarity in the number of TMT members across firms in my sample. Finally, to ensure that I accurately capture TMT confidence diversity, I only include firms where at least three executives had unexercised exercisable options that were in the money[23].

I gather additional data from several sources. First, I collect innovation data from the database developed and published by Kogan et al. (2017). Second, I source firm- and industry-level controls from Compustat. Finally, I collect executives' demographic characteristics from ExecuComp and BoardEx. My final sample has data on 1,262 unique firms from 40 two-digit SIC industries. All independent and control variables are lagged by one year and used to predict the dependent variable in the following year. After implementing this lag structure and accounting for missing data, my sample contains 12,716 firm-year observations in the primary analysis.

3.2. Dependent Variables

A firm's innovative efficiency is measured based on the input-output efficiency matrix of a firm's innovation investments. To gauge the innovation input, I follow the method described by Hall (1990), depreciating all reported R&D spending at a rate of 20% over five years (see also, Hirshleifer et al. 2013). I use the number of *forward patent citations* to measure a firm's innovation outputs because it reflects the success of a firm's innovative activities regarding the scientific value of those patents the firm generated (Hirshleifer et al. 2012). Forward patent citation is the total number of future citations received by each patent[24]. I

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[23] For firm-year observations with all TMT members with unexercised exercisable options that Ire out-of-the-money, our metric of confidence diversity would assign zero diversity to the TMTs. HoIver, this is unlikely capturing the confidence dynamics of these TMTs correctly so that I have dropped these firm-year observations to minimise the measurement error of our measure of TMT confidence diversity.

[24] My patent sample exclusively comprises patents that have been successfully applied for and granted.

aggregate the number of forward patent citations to firms based on patents' application year to form a panel data structure. This annualized method is superior in capturing the actual time of innovation (Griliches et al. 1986; He & Tian 2013). I follow Hirshleifer et al. (2013) and use the input-output ratio to measure firms' innovative efficiency. This measure of innovation efficiency is a strong predictor of future financial returns, even after controlling for other firm financial and risk characteristics (Hirschleifer et al., 2013). Since innovation investment may take some time to be realized (Hall et al. 2005), I use a 2-year gap between innovation inputs and outputs to consider this time gap between an innovation investment and its subsequent outcomes. Therefore, I measured the main dependent variable, ***innovative efficiency***, using *citation count* at year *t*, scaled by *R&D capital* at year *t-2*. Finally, I apply the natural log transformation to account for skewness (i.e., ln(1+ *forward patent citations*)).

3.3. Independent Variables

TMT confidence diversity is measured in two steps. First, I calculate each TMT member's confidence levels at each time period (t). Then, I calculate the standard deviation among those members' confidence levels within each TMT[25].

In the first step, I follow prior research on CEO overconfidence that uses stock option exercising behaviour to capture an executive's confidence regarding the firm's future performance (Malmendier & Tate 2005; Campbell et al. 2011; Humphery-Jenner et al. 2016). The intuition behind examining executives' stock option exercising behaviour is that since an executive's wealth is undiversified, a rational executive will exercise deep-in-the-money options soon after the options vest. In contrast, highly confident executives are likely to "overestimate the future returns" and "believe that the stock prices of their companies will continue to rise under their leadership more than they objectively should expect" (Malmendier

[25] The top management team is defined as the CEO along with the four highest-paid executives. Consequently, the size of the team remains consistent across the empirical context of this study.

& Tate 2005: 2671). As a result, the more confident an executive is, the more likely they will postpone option exercises to capture these expected future gains. Therefore, the degree to which executives retain vested in-the-money options signals their degree of confidence in the firm's future financial success.

While the options measure of executive confidence is most common in management and finance research (Malmendier 2018; Pavićević & Keil 2021), I recognize that scholars have used other measures such as CEO tweets or CEO language during speeches (e.g., Liu et al. 2009; Lee et al. 2017). Critical to my study, however, these measures are not available for all members of the TMT, making it impossible to calculate confidence diversity at the TMT-level. Further, this measure is particularly relevant for my context as it captures the degree to which executives perceive the future value of the firm (Pavićević & Keil 2021), which is directly related to the firm's innovation efficiency (Hirschleifer et al., 2013). Importantly, this measure is highly validated, including a detailed recent study that validates the options holding measure with a unique dataset that includes direct personality assessments of managers (Kaplan et al. 2022). Prior research shows consistent results across these measures, providing additional convergent validity for options-based confidence level measures.

Precisely, I measure each executive's confidence level by calculating the moneyness of the retained vested options for each executive (Chen et al. 2015; Gamache & McNamara 2019; Pavićević & Keil 2021; Lee et al. 2023):

$$Confidence\ level\ (moneyness) = \frac{Average\ value\ per\ vested\ option}{Average\ strike\ price} \qquad \textbf{(1)}$$

The higher the moneyness, the higher the executive's confidence level is.

Second, once confidence levels have been calculated for each TMT executive, I can estimate the primary variable of interest, ***TMT confidence diversity***, which is equal to the standard deviation of the top five executives' confidence levels in a given year (for other similar measures for TMT diversity, see Boone et al. 2005; Boone & Hendriks 2009; Bushman et al., 2016; Hambrick et al. 2015).

3.4. Moderator Variables

I measure ***industry competitive intensity*** using belonged firms' sales in each industry and then calculate the Herfindahl-Hirschman Index (HHI)(Hou & Robinson 2006; Luo et al. 2015). This moderator represents the rate of product market competition within an industry. Since HHI is a market concentration index, I thus take its negative value and use it to measure industry competition.

Firms' ***financial maturity*** is measured by the size-age (SA) index, introduced by Hadlock and Pierce (2010). Conceptually, the SA index reflects the extent to which a firm is financially mature (i.e., the accessibility to financial resources) based on the logic that larger and older firms typically have greater access to financial resources than smaller, younger firms. Relative to smaller firms, larger firms often have more assets that can be used as collateral for loans (Almeida & Campello 2007). In addition, larger firms tend to have more established relationships with financial institutions, and their size may make them more attractive to investors, as they are perceived as less risky (Diamond 1989; Boot & Thakor 1994). Similarly, the age of a firm can also affect its financial maturity. Older firms have had more time to establish credit histories, develop relationships with lenders, and demonstrate their viability and profitability, making them more attractive to financial institutions and investors, compared to younger firms (Diamond 1989; Boot & Thakor 1994; Sakai et al. 2010). Indeed, Hadlock and Pierce (2010) show that firm size and age can predict a firm's access to financial resources, with young and small firms generally having less access to financial resources than mature and big firms, and Hennessy and Whited (2007) show external financing costs decreasing sharply as a firm grows. As such, the SA index is calculated as (-0.737 * *firm size*) + (0.043 * *firm size*^{2}) – (0.04* *firm age*), where *firm size* is the natural logarithm of the firm's total asset and *firm age* is the difference in years between the current year and the first year that the firm's stock data appears on the CRSP database (Hadlock & Pierce 2010; Cheng et al. 2013). I reverse coded the SA index so for my final measure higher values indicate greater financial maturity.

3.5. Control Variables

I consider a large number of potential control variables that could impact a firm's innovative efficiency. Additionally, as described below, I use firm fixed-effects estimation, which controls for unobservable firm effects. I also include year dummy variables to control for other temporal reasons for variation in firms' innovative efficiency. I include controls at the firm-, team-, and CEO- levels.

To ensure my controls align with research examining innovation efficiency, I followe Hirshleifer et al. (2012) and Shen and Zhang (2018) in selecting firm-specific controls. I control for *firm size* measured as the natural log of total assets. Firm size could represent a firm's knowledge set and ability to innovate, which may affect the firm's innovative efficiency. I control for *firm performance*, measured as return on assets, to account for conditions that may encourage or inhibit TMTs from innovation investment. Additionally, because innovation investment may involve higher levels of risk I control for a firm's riskiness by the *leverage ratio*, measured as total debts divided by total assets.

Further, I control for some TMT characteristics to ensure my results are not driven by other TMT characteristics that may affect firm innovation outcomes. These include *TMT average confidence* measured as the mean of TMT members' confidence level, *TMT gender diversity* calculated using Blau's (1977) index (i.e., 1 - $\sum P_i^2$ where P is the proportion of male or female TMT executives; and i represents a specific gender category), *TMT national diversity* captured by a dummy indicator, which equals one for firms with at least one non-US executives on the TMT in a given year and zero otherwise, and *TMT average tenure* is measured as the mean of the number of years that each TMT member has been with the focal company.

Lastly, given that the CEO is the most important executive in the TMT (Shen & Zhang

2018), I control for several CEO characteristics. In particular, Sheikh (2012) finds that *CEO delta* (i.e., the dollar change in a CEO's compensation portfolio if the stock price increases by 1%) is positively related to investment in innovation projects. Also, Coles et al. (2006) show that *CEO vega* (i.e., the dollar change in a CEO's compensation portfolio if the stock return volatility increases by 1%) incentivizes CEOs to invest in risky projects. Following Coles et al. (2006), I estimate CEO delta and vega and add them to my control set. I also control for *CEO overconfidence* to ensure my results are not being driven purely by CEO behavior.

3.6. Methodology

I use a panel regression methodology because the sample data has multiple observations nested within firms, making ordinary least squares inappropriate due to the non-independence of error terms. I analyse my data using firm fixed-effect models and specify the clustering option to account for autocorrelation within firms (Certo et al. 2017). Specifically, I estimate the following model:

$$\begin{aligned} Ln(Innovation\ efficiency_{i,t+1}) \\ &= \beta_0 + \beta_1 TMT\ confidence\ diversity_{i,t} + \delta \boldsymbol{X}_{i,t} + Year\ FE_t + Firm\ FE_i \\ &+ \varepsilon_{i,t} \qquad (\mathbf{2}) \end{aligned}$$

where *i* and *t* indicate firm and year, respectively. The dependent variable in equation (2), *Innovation efficiency*, refers to the innovation efficiency measure (i.e., *Ln(Citation efficiency)*) in year t+1. The coefficient β_1 is the main coefficient of interest for this study as it measures the effect of TMT's confidence diversity on innovation efficiency. Hypothesis 1 predicts β_1 will be positive. That is, the higher the TMT confidence diversity, the higher innovation efficiency the firm will achieve. All continuous variables are standardized before regression analysis and before creating interaction variables. I also conduct a Hausman's (1978) test, which confirms that a fixed-effect model was the appropriate choice to test my hypotheses ($\chi^2 = 357.14$, $p < 0.00$). All control and independent variables are lagged one year to mitigate the reverse causality concerns in my preliminary analyses.

4. EMPIRICAL RESULTS

4.1. Descriptive Statistics

I report the descriptive statistics and pairwise correlation for the study variables in Table Ch4-1. Consistent with my predictions, TMT confidence diversity is positively correlated with *Innovative efficiency* (r = 0.156). It is also interesting to note that *TMT confidence diversity* and *Firm size* is negatively correlated (r = -0.153), suggesting that the TMT of large firms tend to have lesser confidence dispersion regarding their firm's prospects.

Table Ch4-1. Summary Statistics

This table presents the descriptive statistics of the variables used in the study. Correlation coefficients in bold are significant at the 1% level. Sample size is 12,716.

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Innovative efficiency (ln)	0.571	0.895	**1.000**															
2. TMT confidence diversity	0.364	0.709	**0.156**	**1.000**														
3. Firm size	7.256	1.704	**-0.061**	**-0.153**	**1.000**													
4. Firm performance	0.026	0.184	**0.043**	**0.079**	**0.237**	**1.000**												
5. Leverage ratio	0.200	0.189	**-0.063**	**-0.113**	**0.267**	**-0.166**	**1.000**											
6. Financial maturity	4.016	0.888	**-0.076**	**-0.217**	**0.674**	**0.193**	**0.210**	**1.000**										
7. Industry competitive intensity	-0.058	0.044	**-0.026**	0.022	**-0.087**	**-0.039**	**-0.062**	**-0.089**	**1.000**									
8. CEO Overconfidence	0.688	0.463	**0.039**	**0.181**	**0.028**	**0.136**	**-0.055**	**-0.079**	-0.019	**1.000**								
9. CEO delta	5.399	1.458	**0.072**	**0.183**	**0.482**	**0.290**	-0.012	**0.204**	**0.050**	**0.330**	**1.000**							
10. CEO vega	4.060	1.818	**-0.031**	**-0.128**	**0.516**	**0.173**	**0.081**	**0.312**	**0.035**	**0.105**	**0.554**	**1.000**						
11. TMT gender diversity	0.126	0.227	**-0.098**	0.006	0.000	0.016	**-0.027**	-0.008	**0.026**	0.017	**0.030**	**0.044**	**1.000**					
12. TMT nationality diversity	0.129	0.335	-0.011	-0.013	**0.133**	0.013	0.022	**0.050**	-0.011	0.007	**0.101**	**0.108**	0.001	**1.000**				
13. TMT average tenure	6.129	4.477	-0.019	**-0.087**	**0.227**	**0.117**	0.016	**0.272**	-0.020	**0.086**	**0.198**	**0.099**	**-0.073**	**0.025**	**1.000**			
14. TMT average confidence	0.840	1.475	**0.174**	**0.556**	**-0.108**	**0.132**	**-0.106**	**-0.171**	0.011	**0.228**	**0.252**	**-0.154**	-0.007	0.003	-0.019	**1.000**		
15. TMT confidence diversity × Industry competitive intensity	-0.029	0.045	**-0.145**	**-0.410**	**0.106**	**-0.044**	**0.060**	**0.182**	**0.401**	**-0.173**	**-0.066**	**0.148**	**0.027**	0.001	**0.040**	**-0.425**	**1.000**	
16. TMT confidence diversity × Financial maturity	1.927	2.191	**0.132**	**0.489**	**-0.052**	**0.058**	**-0.087**	**-0.122**	**0.031**	**0.226**	**0.192**	**-0.087**	-0.008	0.002	-0.021	**0.519**	**-0.734**	**1.000**

4.2. Baseline Results

In Table Ch4-2, I present the fixed-effects regression results predicting innovative efficiency. Column (1) includes the control variables only, several of which are significant. Interestingly, firm size and firm performance are both significant predictors of innovative efficiency but in opposite directions. Additionally, CEO pay-for-performance incentive (*CEO delta*) is a positive and significant predictor of firms' innovative efficiency. Interestingly, the coefficient for CEO overconfidence is not significant, but TMT average confidence is significant and positive. These results shed light on the importance of the top management team in examining the psychological attributes, echoing one of the core assertions of upper echelons theory that has been often ignored in the recent focus on CEO-level attributes (Hambrick & Mason 1984; Hambrick 2007).

In Column (2), I add TMT confidence diversity. Columns (3) and (4) add the interactions between TMT confidence diversity and industry competitive intensity and financial maturity, respectively. The last regression in Column (5) is the full model used for testing my hypotheses, which includes both interactions. Hypothesis 1 predicted that TMT confidence diversity would be positively related to innovative efficiency. Supporting this hypothesis, the coefficient for TMT confidence diversity is positive and significant ($\beta = 0.033$; $p < .01$), suggesting that the more confidence diversity in the entire top management team, the more success in innovation given a fixed amount of innovation spending. In practical terms, a change in TMT confidence diversity from one standard deviation below the mean to one standard deviation above the mean is associated with a 6.6% increase in the efficiency of generating future patent citations.

Table Ch4-2. Baseline regression

This table presents the firm fixed effects panel regression results for testing main hypothesis and the moderating effects of decision-making context on the relationship between TMT confidence diversity and innovation efficiency. Column (1) shows the results without including the main independent variable (i.e., TMT confidence diversity) and the two moderators. Column (2) add TMT confidence diversity to the regression. Columns (3) and (4) include the two moderators to the regression, separately. Columns (5) show the results with the complete regression specification. Standard error clustered at firm level are in parentheses. Year dummy variables included but not reported. ***, **, and * indicate the p-value less than 0.001, 0.01, and 0.05, respectively.

VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Constant	0.195*	0.192*	0.192*	0.186*	0.187*
	(0.079)	(0.078)	(0.078)	(0.077)	(0.078)
Control Variables					
Firm size	-0.293***	-0.280***	-0.279***	-0.276***	-0.275***
	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)
Firm performance	40.152**	36.787**	36.837**	35.429**	35.525**
	(12.766)	(12.685)	(12.683)	(12.749)	(12.746)
Leverage ratio	0.059	0.020	0.013	0.001	-0.004
	(0.750)	(0.745)	(0.743)	(0.732)	(0.731)
Industry competition intensity	-0.003	0.004	0.001	0.005	0.003
	(0.056)	(0.055)	(0.057)	(0.055)	(0.057)
Financial maturity	-0.088	-0.085	-0.085	-0.086	-0.087
	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
CEO Overconfidence	0.020	0.019	0.018	0.022	0.021
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
CEO delta	0.063**	0.055**	0.055**	0.056**	0.056**
	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)
CEO vega	-0.023	-0.017	-0.017	-0.019	-0.019
	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)
TMT gender diversity	0.016	0.017	0.016	0.017	0.017
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
TMT nationality diversity	0.051	0.053	0.053	0.052	0.052
	(0.029)	(0.030)	(0.029)	(0.030)	(0.030)
TMT average tenure	-0.017	-0.015	-0.015	-0.015	-0.014
	(0.016)	(0.015)	(0.015)	(0.016)	(0.016)
TMT average confidence	0.051***	0.039***	0.040***	0.039***	0.039***
	(0.010)	(0.011)	(0.010)	(0.011)	(0.011)
TMT confidence diversity		0.035***	0.026**	0.041***	0.033**
		(0.010)	(0.010)	(0.011)	(0.011)
TMT confidence diversity × Industry competitive intensity			0.023**		0.021*
			(0.009)		(0.010)
TMT confidence diversity ×Financial maturity				-0.027**	-0.026**
				(0.010)	(0.010)

4.2. The Moderating Effects

Hypothesis 2 predicted that industry competitiveness would moderate the relationship between TMT confidence diversity and innovation efficiency. As such, I created an interaction term, *TMT confidence diversity* × *Industry competitive intensity*. The coefficient for this interaction is positive and significant ($\beta = 0.021; p < 0.05$) providing support for Hypothesis 2. I visually show the moderating effect of industry competitive intensity on the relationship between TMT confidence diversity and innovative efficiency in Figure Ch4-1 and calculated the marginal effects (see Busenbark, Graffin, et al. 2022) in Column (1) of Table Ch4-3. These analyses show the marginal effects of TMT confidence diversity increase monotonically when the industry competitiveness gets higher. For firms are in industries with highly competitive intensity (the 75% percentile), the marginal effects of TMT confidence diversity equal 0.024 ($p < 0.05$), so that one standard deviation increase in TMT confidence diversity is associated with a 2.4% increase in innovative efficiency. In contrast, for firms operating in a lower (the 25% percentile) competitive intensity industries, the marginal effect of TMT confidence diversity is not distinguishable from zero ($dy/dx = 0.009, p > 0.1$). Interestingly, for firms with extremely low competitive intensity (the 1% percentile), the relationship between TMT confidence diversity and innovation efficiency turns negative ($dy/dx = -0.085, p = 0.089$). Although this negative effect is only shown in extreme circumstances it does suggest that TMT confidence diversity may be detrimental in some unique contexts, and future scholarship can further explore this possibility.

Table Ch4-3. The marginal effects of TMT confidence diversity

This table shows the marginal effects TMT confidence diversity on Innovation efficiency in regard to different decision-making context. Column (1) show the marginal effect of TMT confidence diversity on corporate innovation efficiency under different industry competitive intensity levels. Column (2) show the effect regarding firms with different levels of financial maturity. ***, **, and * indicate the p-value less than 0.001, 0.01, and 0.05, respectively.

Value of Moderator Variable	**The Marginal Effect of TMT confidence diversity on Innovation efficiency**			
	Column (1): Industry competitive intensity		**Column (2): Financial maturity**	
	dy/dx	***p*-value**	***dy/dx***	***p*-value**
1st Percentile	-0.085	0.089	0.103**	0.001
5th Percentile	-0.030	0.221	0.083**	0.001
25th Percentile	0.009	0.378	0.055***	0.000
Median	0.018	0.046	0.041***	0.000
75th Percentile	0.024*	0.013	0.028**	0.002
95th Percentile	0.026**	0.008	-0.003	0.807
99th Percentile	0.027**	0.008	-0.035	0.159

Figure Ch4-1. TMT confidence diversity by industry competitive intensity

This figure presents the moderating effect of industry competitiveness on the effect between TMT confidence diversity and innovation efficiency. The blue solid line represents the relationship between TMT confidence diversity and innovation in industries with low competitiveness, whereas the red dash line shows the relationship in industries with high competitiveness.

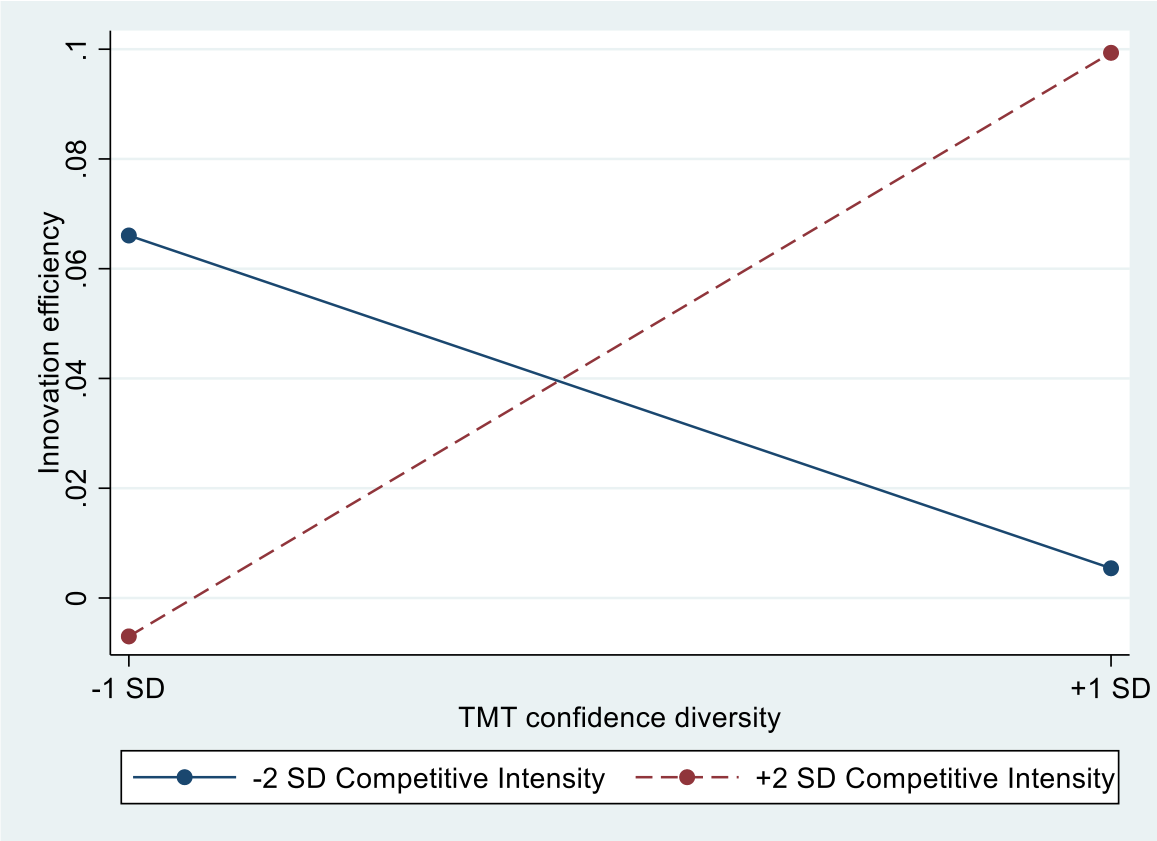
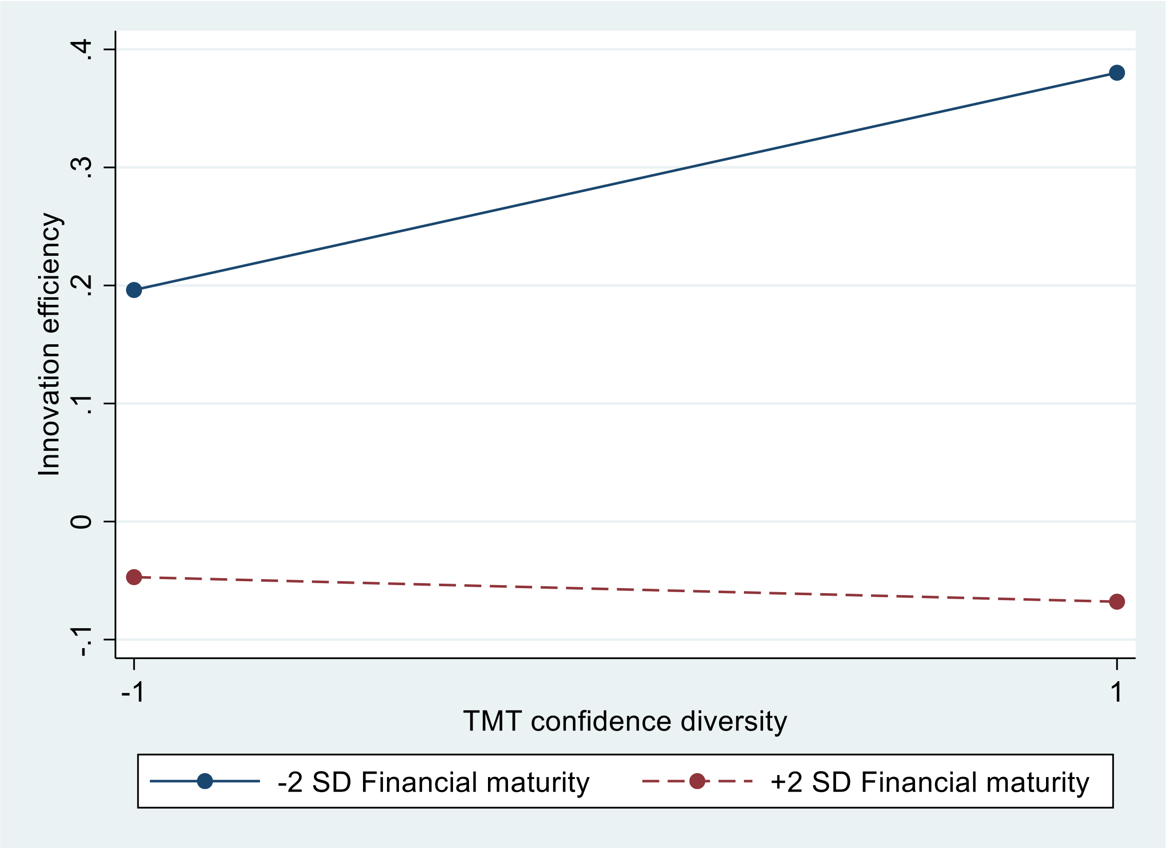


Figure Ch4-2. TMT confidence diversity by financial maturity

This figure shows the moderating effect of firm's financial maturity on the effect between TMT confidence diversity and innovation efficiency. The blue solid line represents the relationship between TMT confidence diversity and innovation in firms with low financial maturity, whereas the red dash line shows the relationship in firms with high financial maturity.



Hypothesis 3 predicted a moderating effect of firm financial maturity on the relationship of TMT confidence diversity and innovative efficiency. To test this hypothesis, I created an interaction term as the product of TMT confidence diversity and financial maturity. The coefficient for the interaction is negative and significant, supporting my Hypothesis 3 ($\beta = -0.026; p < .01$). This relationship is represented visually in Figure Ch4-2. I also conducted a marginal effect analysis at different levels of financial maturity (Busenbark et al., 2022). As shown in Column (2) of Table Ch4-3, the marginal effects of TMT confidence diversity decrease monotonically when financial maturity increases. For firms with low levels (the 25% percentile) of financial maturity, one standard deviation increase in TMT confidence diversity is associated with a 5.5% increase in innovative efficiency (dy/dx = 0.055, p <0.001). In contracts, at high levels (the 75% percentile) of financial maturity, the marginal effects of TMT confidence diversity equal 0.028 (p < 0.01), so that one standard deviation increase in TMT confidence diversity is associated with a 2.8% increase in innovative efficiency. Furthermore, for firms with very high levels of financial maturity (the 95th percentile and above), the relationship betIen TMT confidence diversity and innovation efficiency is not significant. These findings strongly support Hypothesis 3.

4.3. Potential Endogeneity Issues

4.3.1. ITCV method

As with most corporate finance research, results of confidence diversity on innovation efficiency are subject to endogeneity concerns. For instance, there may be an omitted factor that can affect both innovation efficiency and TMT confidence diversity simultaneously. An alternative explanation could be that firms with high innovation efficiency may have a diverse corporate culture, which also positively impacts innovation activities (Østergaard et al. 2011). As a result, it is possible that there may be an omitted factor that can simultaneously affect both innovative efficiency and TMT confidence diversity which could bias my findings (Semadeni et al. 2014).

Therefore, I took two approaches to considering the potential for endogeneity to be biasing my findings. In both cases, I focus on the potential for endogeneity to be biasing the main effect relationship between TMT confidence diversity and innovation efficiency because recent research suggests that interaction terms are unlikely to suffer bias due to endogeneity (Bun & Harrison 2019; Pavićević & Keil 2021; Gamache et al. 2023).

First, I conducted the Impact Threshold for a Confounding Variable (ITCV) test (Frank et al. 2013; Busenbark, Yoon, et al. 2022). The ITCV calculates "an empirical measure to test the potential influence of omitted variable bias" (Gamache et al., 2023: 19). In unreported results, I find the ITCV value is 0.107 (α = 0.10) which reflects how strongly an omitted variable would need to be correlated with the independent variable and dependent variable for my findings to be biased. To evaluate the strength of this value, I follow guidance on using the ITVC and compare the ITCV with the multiplied path of the partial correlations of the independent variable and dependent variable with each of my control variables and compared the square root of that value with the ITCV (Busenbark et al., 2022). Only one control variable demonstrated a partial correlation with the independent variable and dependent variable greater than the ITCV, which is unsurprisingly, the TMT average confidence diversity. Among the other control variables, none had a multiplied path of partial correlations even greater than 75% of the ITCV value providing strong evidence that an omitted variable is unlikely to be biasing my findings.

4.3.2. The 2SLS approach

I also employ the two-stage least square (2SLS) approach to mitigate potential endogeneity concerns. Specifically, I run the 2SLS models as the following:

First-stage regression:

$$TMT\ confidence\ diversity_{i,t} = \beta_0 + \beta_1 Peer\ mean_{i,t} + \beta_2 Geographic\ mean_{i,t} +$$

$$\delta \boldsymbol{X}_{i,t} + Year\ FE_t + Firm\ FE_i + \varepsilon_{i,t} \quad \textbf{(3)}$$

Second-stage regression:

$$Ln\left(Innovation\ efficiency_{i,t+1}\right) = \beta_0 + \beta_1 \widehat{TMT\ confidence\ diversity}_{i,t} + \delta \boldsymbol{X}_{i,t} + Year\ FE_t + Firm\ FE_i + \varepsilon_{i,t} \quad \textbf{(4)}$$

AND

$$Ln\left(Innovation\ efficiency_{i,t+1}\right) = \beta_0 + \beta_1 \widehat{TMT\ confidence\ diversity}_{i,t} + \beta_2 \widehat{TMT\ confidence\ diversity}_{i,t} \times Industry\ competition_{i,t} + \beta_3 \widehat{TMT\ confidence\ diversity}_{i,t} \times Financial\ constraints_{i,t} + \delta \boldsymbol{X}_{i,t} + Year\ FE_t + Firm\ FE_i + \varepsilon_{i,t} \quad \textbf{(5)}$$

The success of the 2SLS method hinges on finding a valid instrument variable (IV). I expect that there are spillover effects of other firms' TMT confidence diversity to focal firms. I first examine whether peers' TMT confidence diversity has a spillover effect on focal firms. Firms may adopt similar corporate policies within a peer group, leading to similar TMT confidence diversity. Thus, peer mean TMT confidence diversity may satisfy the relevant criteria of a valid IV. In addition, firms' corporate innovation decision is less likely to be affected by peer mean TMT confidence diversity. To mitigate further the exclusion restriction concern, I exclude the focal firm and firms with the same SIC 2-digit code as the focal firm when calculating peer mean TMT confidence diversity. The peer firms of each focal firm are defined based on Hoberg and Phillips (2016) product similarity database. Firms that produce similar products are defined as peers for each other. Thus, my first IV (i.e., $Peer\ mean_{i,t}$ in equation (3)) is the mean of peers' TMT confidence diversity.

Firms' TMT confidence diversity may affect by other geographical near firms' TMT confidence diversity. Top managers in a nearby location are more likely to communicate with each other by attending corporate events or joining the same golf club. Hence, corporate policies may tend to be similar for geographic near firms. I thus expect that the geographic mean of TMT confidence diversity is positively related to the endogenous variable, i.e., TMT confidence diversity. I also expect that the mean of geographic near firms' TMT confidence diversity may not correlate to each firm's innovation decisions, especially when I only consider firms in different industries to each focal firm. To construct my second IV (i.e., $Geographic\ mean_{i,t}$ in equation (3)), I first find firms within a 250-km radius of each focal firm. Then, I calculate the average of these firms' TMT confidence diversity, excluding near firms with the same SIC 2-digits code as the focal firm.

Table Ch4-4. IV analysis

This table presents IV analysis results. Column (1) shows the first stage regression results, and Columns (2) to (5) contain results from the second stage regressions. Standard error clustered at firm level are in parentheses. Year dummy variables are included but not reported. ***, **, * and + indicate the p-value less than 0.001, 0.01, 0.05, and 0.1, respectively.

	First stage	Second stage			
	TMT confidence diversity	Citation Efficiency			
VARIABLES	(1)	(2)	(3)	(4)	(5)
Peers mean (excluding firms with the same sic 2-digits code)	0.016^{+} (0.009)				
Geographic mean (including firms within 250kms and excluding firms with the same sic 2-digits code)	0.069*** (0.017)				
TMT confidence diversity (fitted)		0.537* (0.215)	0.501* (0.216)	0.545* (0.214)	0.509* (0.215)
TMT confidence diversity (fitted) *Industry competition intensity			0.041* (0.016)		0.041* (0.016)
TMT confidence diversity (fitted) *Financial maturity				-0.026* (0.013)	-0.026* (0.013)
Controls	Yes	Yes	Yes	Yes	Yes
Weak instrument test:					
F-statistic	34.44				
Stock-Yogo weak IV critical value (10% maximal IV size)	19.93				
Underidentification test:					
Kleibergen-Paap rk LM statistic	19.446				
P-value	0.000				
Overidentification test:					
Hansen J statistic	0.003				
P-value	0.958				

Table Ch4-4 presents the 2SLS regression results. Before re-testing my hypotheses using the 2SLS method, I perform validation tests for my instruments. In the first stage regression, I confirm that the two instruments satisfy the relevant criteria of being valid instruments. In column (1), I find the coefficients of *Peer mean* and *Geographic mean* are positive and significant ($\beta_1 = 0.016$, p-value <0.1; $\beta_2 = 0.069$, p-value <0.01). These results support my argument that both the mean of peer's TMT confidence diversity and geographic near firms' TMT confidence diversity can positively affect focal firms' TMT confidence diversity. I also perform several tests to ensure that my IVs are robust and report the results at the bottom of column (1) of Table Ch4-4. First, 2SLS regression can induce biased estimation (Angrist & Pischke 2008), which worsens when IV is weak (Stock & Yogo 2002). I thus record the F-statistic from the first-stage regression and compare that with Stock and Yogo (2002) weak IV critical value. I find that the F-statistic from the first-stage regression is higher than the strictest weak IV critical value (i.e., at 10% maximal IV size), suggesting that my IVs are strong. I also find that my first-stage regression can pass the under-identification test (Kleibergen-Paap rk LM statistic = 19.446, p-value < 0.01) and over-identification test (Hansen J statistic = 0.003, p-value = 0.365), suggesting my IV regression results are robust. Column (2) present the second-stage regression results by estimating the regression model (4), while columns (3) and (4) show the results from the regression model (4), adding the interaction between the fitted TMT confidence diversity and the two moderators. Columns (5) present the results with the full set of independent variables similar to the column (5) in Table Ch4-2. These results are consistent with my results from the baseline regression and moderating analysis (in Table Ch4-2), mitigating potential endogeneity concerns.

4.4. Robustness and Supplemental Analyses

I perform several tests to ensure that my results are robust and report these results in Table Ch4-5. I first check whether my results are sensitive to the measure of innovation efficiency. Prior research has argued that the scientific value of a patent need not coincide with the private and economic value of the patent (Kogan et al. 2017). As such, I conducted robustness checks by using patents' private value and the number of applied patents as the outcome variable when measuring firms' innovative efficiency.

Columns (1) and (2) show the results when I estimate my baseline regression model (2) with alternative measures of innovation efficiency. In there, instead of using patent citation count as the measure of firms' innovative outcomes, I use the total nominal economic value of applied patents and total applied patent count to measure innovative outcomes. The nominal and economic value of each patent are from Kogan et al. (2017) where they estimate the private economic value of each patent based on patent issuance events. I scale the total nominal economic value of applied patents and the total applied patent count by *R&D capital* to measure innovation efficiency. I find the coefficients of TMT confidence diversity are both positive and significant (column 1: $\beta = 0.042$, p-value < 0.01; column 2: $\beta = 0.008$, p-value < 0.01). These results suggest that TMT confidence diversity can yield a higher dollar-to-dollar return (i.e., efficiency) of innovation decisions and a higher outcome per expense ratio, which is consistent with my main hypothesis.

Table Ch4-5. Robustness tests and Supplementary analysis

This table presents additional tests to complement the main analysis. Columns (1) and (2) show the results with additional measures of innovation efficiency, showing the robustness of the main analysis. Column (3) extend the analysis to corporate innovation strategy. Standard error clustered at firm level are in parentheses. Year dummy variables are included but not reported. ***, **, and * represent the p-value less than 0.001, 0.01, and 0.05.

VARIABLES	**(1)**	**(2)**	**(3)**
	Innovative efficiency measured by patent value	**Innovative efficiency measured by # applied patent**	**Explorative innovation**
Constant	0.435	0.264***	0.786***
	(0.298)	(0.055)	(0.078)
Control Variables			
Firm size	-0.170***	-0.020**	-0.011
	(0.030)	(0.006)	(0.008)
Firm performance	0.065	0.046***	0.031
	(0.034)	(0.013)	(0.024)
Leverage ratio	-0.037	-0.008	0.034
	(0.060)	(0.013)	(0.026)
Industry competition intensity	-0.135	0.177	-0.026
	(0.651)	(0.207)	(0.170)
Financial maturity	0.280***	-0.012	-0.003
	(0.083)	(0.012)	(0.016)
CEO Overconfidence	0.139***	0.008	0.001
	(0.026)	(0.006)	(0.010)
CEO delta	0.054***	0.010***	-0.002
	(0.013)	(0.003)	(0.004)
CEO vega	-0.005	-0.002	-0.000
	(0.008)	(0.003)	(0.002)
TMT gender diversity	0.042	0.024*	-0.016
	(0.040)	(0.010)	(0.016)
TMT nationality diversity	0.056	0.011	-0.011
	(0.033)	(0.006)	(0.011)
TMT average tenure	0.000	-0.002*	-0.002*
	(0.003)	(0.001)	(0.001)
TMT average confidence	0.044***	0.004*	-0.001
	(0.008)	(0.002)	(0.002)
TMT confidence diversity	0.042**	0.008*	0.011*
	(0.013)	(0.003)	(0.005)

My primary analysis shows that TMT confidence diversity can increase firms' innovative efficiency measured by patents' scientific value per previous 5-year cumulative R&D spending. As a supplementary analysis, I extend my analysis to corporate innovation strategy (i.e., exploratory vs. exploitative) when firms with different diversity in confidence among their top executives. Explorative innovation goes beyond existing knowledge base, whereas exploitative innovation extends further the existing knowledge base. Therefore, by its nature, explorative innovation requires more critical thinking that goes out-of-the-box. I expect TMT confidence diversity can facilitate this critical thinking process leading to more explorative innovation applications.

To test this conjecture, I run a regression similar to the regression in equation (3) model but use *explorative innovation* as the dependent variable. I measure *explorative innovation* as the ratio of the total number of explorative patents over the total number of applied patents by a firm in a given year. Following the existing literature (Benner & Tushman 2002; Gao et al. 2018), I characterize each applied patent into explorative or exploitative innovation by firms' existing expertise (i.e., a portfolio that contains a firm's patent and its citation over the past 5 years). I define a patent being "explorative" if 80% or more of its citations are not from a firm's existing expertise other dimensions of corporate innovation (Gao et al. 2018).

Column (3) in Table Ch4-5 shows the result. I find the coefficient for TMT confidence diversity is positive and significant ($b = 0.011$, $p < 0.05$), suggesting that TMTs with high confidence diversity tend to engage in more exploratory innovation behavior. from the regression with *explorative innovation* as the dependent variable. This result suggests high confidence diversity TMTs are prone to invent explorative patents, which is likely to receive more citations by its nature. Collectively, these robustness test and supplementary results indicate that high confidence diversity TMTs improve their firms' innovative efficiency by lowering the cost per applied patent and by taking an explorative innovation strategy.

5. CONCLUSION

In this study, I introduce the construct of TMT confidence diversity. I hypothesise that TMT confidence diversity will positively impact TMT decision-making, particularly within the context of innovation. As such, I predict and find a positive relationship between TMT confidence diversity and firm innovation efficiency. Further, I argue that this relationship is moderated by decision-making contexts that shape the frequency and intensity of decision-making. Along these lines, I find that the relationship between TMT confidence diversity and innovation efficiency is stronger when competitive intensity is high but Iaker within financially mature firms. I believe my study contributes to upper echelons research on TMT diversity, executive confidence, and research on innovation.

CHAPTER 5: CONCLUSION

1.SUMMARY OF FINDINGS

In a constantly changing and complex market environment, corporations face numerous factors that significantly influence their market valuation, strategic choices, and operational efficiency. These variables stem from diverse origins, including market-level dynamics, organization-specific strategies, and individual managerial conduct. This thesis aimed to provide insight into the importance of labour market conditions, CEO incentive structures, and top management team diversity in influencing firm behaviour and subsequent outcomes.

Initially, this thesis explored the impact of labour market competition on firm valuation. Labor markets, as the cornerstone of any economy, have a profound impact on firm performance. While traditional labour economics has concentrated on wage dynamics and employment rates, this thesis expanded the horizons by introducing a novel metric for labour market competitiveness. Utilizing a unique dataset from Burning Glass Technologies, the study uncovered a negative correlation between job-specific competitiveness and aggregate market excess returns, particularly pronounced for portfolios of smaller firms.

Subsequently, the focus shifted to the executive labour market, examining the determinants of organization-specific strategies. Drawing upon upper echelons theory and agency theory, the study investigated the role of CEO Industry Tournament Incentives (CEO ITIs) in shaping a firm's strategic distinctiveness. Empirical evidence supported the differentiation proposition, indicating that lower relative CEO pay is associated with unique, value-maximizing strategies, especially in firms with effective governance structures and significant product-market competition.

The last study in this thesis investigated the realm of behavioral finance by examining the role of psychological diversity within Top Management Teams (TMTs) and its impact on firm innovation efficiency. The empirical analysis of this study demonstrated that firms with higher levels of TMT confidence diversity exhibit significantly greater innovation efficiency. Enhanced efficiency indicated that high confidence diversity within a TMT can offset the costs and benefits of members possessing varied confidence levels, thereby leading to greater information sharing in the TMT.

2.LIMITATIONS & FUTURE RESEARCH

While this thesis provides valuable insights into the complex interactions of competitive dynamics on corporate actions and outcomes, it has limitations that present promising avenues for future research.

Firstly, the study on labour market competitiveness was primarily demand-driven, making an implicit assumption of a static labour supply. This may not entirely capture a complete representation of labour market dynamics, as competitiveness in a labour market can be influenced by both its demand and supply sides. However, given the prevalent challenge many firms face in finding the right candidate for specific roles, it is more likely that job supply is often limited. As such, my measure largely captures the prevailing labour market competitiveness. Nonetheless, a promising avenue for future research lies in refining the labour market competitiveness measure introduced in this thesis. By integrating insights from both the demand and supply facets of a labour market, researchers will capture a more comprehensive dynamic. A key challenge in this endeavour is acquiring supply-side information. This could potentially be addressed using platforms like LinkedIn, as highlighted by Wheeler et al. (2022).

While understanding aggregate labour market competitiveness is crucial, there is merit in exploring labour market competition in a cross-sectional setting, as it can yield valuable insights. Darendeli et al. (2022) demonstrated how a firm's labour hiring behaviour influences its future outcomes and profitability. Following the approach of Hoberg and Phillips (2016) in examining product market competition, future research will be able to adopt a similar methodology to gauge labour market competition in different industries. By doing so, researchers will further enhance our understanding of labour competition in a cross-sectional context thereby complementing my study.

In terms of the study in Chapter 3, the investigation into Industry Tournament Incentives was exclusively focus on CEOs since they are the most important actor in a top management team. This, however, can overlook the potential interplay among other top management team (TMT) members. This limitation could result in a partial understanding of how executive incentives shape corporate strategy. Future research could further examine into the synergistic effects of varying levels of industry tournament incentives within TMTs, thereby offering a more comprehensive view of their impact on firm strategic distinctiveness. This is particularly relevant given that strategic decisions are often the product of collective TMT deliberations (Hambrick & Mason 1984; Murray 1989).

Additionally, industry tournament incentives have received increasing interest in the finance domain, but they remain relatively underexplored by management scholars. A potential avenue in the management field is to shift the focus towards entrepreneurs. Investigating whether industry tournament incentives from a particular industry either incentivize or discourage market entry by entrepreneurs will contributing to the field of entrepreneurship and strategy. Moreover, industry tournament incentives inherently introduce a risk-taking element within an industry. Grasping the implications of these incentives on the compensation framework of entrepreneurs offers a promising direction for future research.

My last study of this thesis also has some limitations. Although examining the psychological diversity within TMTs is innovative, it could be further enriched by accounting for other forms of diversity, such as cultural background. Due to data constraints, this study employed nationality as a proxy for cultural diversity, using a binary variable to indicate the presence of non-U.S. nationals within TMTs. Future research could explore the feasibility of using surnames as a more refined measure of cultural diversity within TMTs. Lastly, each member of the Top Management Team (TMT) may exert varying degrees of influence on corporate innovation decisions. This aspect of differential influence has not been addressed in the study presented in Chapter 4. Future research could yield more robust evidence by examining the specific impact of each TMT member on innovation decisions. This approach would require a more detailed analysis of the backgrounds of each top executive.

In Chapter 4, a novel construct was introduced, paving the way for potential research avenues centred around its utilization. While the study underscored the benefits or 'bright side' of psychological diversity within TMTs, it's plausible that this diversity may also have a 'dark side', particularly in scenarios where a more harmonious team dynamic is essential. A promising research direction could be to examine TMT confidence diversity during crisis periods, such as the global financial crisis or the more recent Covid-19 era. Furthermore, it would be interesting to explore whether the board of the directors cognizant of the diversity within TMTs and actively selects executives to adjust the TMT’s confidence diversity. A potential avenue to address this question is by examining shifts in TMT confidence diversity when a firm faces a hostile merge and acquisition offer.

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APPENDIX

Appendix 2A. Sample firm distribution across various industry sectors

This table compares the industry distribution of matched firms in my dataset to the universe of firms in Compustat. Firms are grouped into 16 two-digit NAICS industries. *job_postings* is the number of high-skilled jobs posts, *firms_BGT* and *firms_BGT(%)* are the number of unique firms in my dataset and their relative percentage, respectively. *firms_COMP* and *firms_COMP(%)* are the number of unique firms from Compustat and its relative percentage. *%Difference* is the difference between *firms_BGT(%)* and *firms_COMP(%).*

Sector	*job_postings*	*firms_BGT*	*firms_BGT(%)*	*firms_COMP*	*firms_COMP(%)*	*%Difference*
Mining & Logging	203,271	131	3.0%	283	3.2%	-0.27%
Construction	150,116	59	1.3%	74	0.8%	0.49%
Durable Goods	4,147,838	925	20.9%	1,479	16.9%	4.05%
Non-Durable Goods	2,299,077	849	19.2%	1,615	18.4%	0.78%
Wholesale Trade	633,340	103	2.3%	144	1.6%	0.69%
Retail Trade	4,076,496	164	3.7%	265	3.0%	0.69%
Trans, Ware, and Util	793,330	136	3.1%	292	3.3%	-0.26%
Information	1,782,929	552	12.5%	1,054	12.0%	0.46%
Finance and Insurance	4,334,532	799	18.1%	2,441	27.8%	-9.78%
Real Estate & Rental	1,259,580	247	5.6%	391	4.5%	1.13%
Prof & Business	2,028,090	229	5.2%	354	4.0%	1.14%
Educational Services	83,234	21	0.5%	46	0.5%	-0.05%
Health Care & Soc Assist	1,687,078	83	1.9%	136	1.6%	0.33%
Arts, Ent, & Rec	128,524	27	0.6%	51	0.6%	0.03%
Acco & Food	2,586,489	83	1.9%	118	1.3%	0.53%
Other Services	43,895	13	0.3%	22	0.3%	0.04%
Total	26,237,819	4,421	100.0%	8,765	100.0%	0.00%

Appendix 2B. Predictor variables

B.1. Stock market predictors

- **S&P 500 returns:** the monthly (end-of-month) returns of the Standard and Poor's 500 Composite Index. Source: Refinitiv Datastream.
- **Implied volatility:** the average daily value of the CBOE VIX index within the month. Source: Refinitiv Datastream.
- **Average correlation:** the average return correlation for the stocks in my matched sample. First, I compute the return correlation between each pair of firms i and j for each month t, $\rho_{i,j,t}$, using daily stock price data. I then calculate the equal-weighted average correlation as $Correl_t = \frac{1}{C(N,2)} \cdot \sum_{i=1}^{N} \sum_{j \neq i} \rho_{i,j,t}$.
- **Realized volatility:** the square root of the sum of squared daily returns of the stocks in my sample. Source: Compustat.
- **Dividend-price ratio:** the difference between the log of dividends paid on the S&P500 index and the log of the index level. Dividends are measured as a sum over the prior 12 months. Source: Amit Goyal online data repository.
- **Dividend-earnings ratio:** the difference between the log of earnings on the S&P 500 index and the log of the index level. Both dividends and earnings are measured as sums over the prior 12 months. Source: Amit Goyal online data repository.

B.2. Labour market predictors

- **Average job postings:** The average number of jobs posted per month per firm (includes parent company and subsidiaries). Source: Burning Glass.
- **Employment growth rate:** the log growth rate of seasonally adjusted total nonfarm payrolls of all employees over the prior three months. Source: The U.S. Bureau of Labour Statistics.
- **Unemployment rate:** the seasonally adjusted civilian unemployment rate. Source: The U.S. Bureau of Labour Statistics.
- **Economic Policy Uncertainty:** the monthly economic policy uncertainty index from Baker, Bloom, and Davis (2016). Source: https://www.policyuncertainty.com/

B.3. Economic predictors

- **Chicago Fed National Activity Index:** the monthly index designed to gauge overall economic activity and related inflationary pressure. Source: The Chicago Fed.
- **Industrial Production Growth:** the monthly percentage change in the volume of output generated by industrial sectors such as mining, manufacturing, energy, and public utilities. Source: Refinitiv Datastream.
- **NBER business cycle:** month indicators of peaks and troughs that frame economic recessions and expansions. Source: NBER.

- **Term spread:** the difference between the long-term Treasury bond yield and the Treasury Bill yield. Source: Amit Goyal online data repository.
- **Default spread:** the difference between the yield on Moody's Baa-rated corporate bonds and the yield on Moody's AAA-rated corporate bonds. Source: Amit Goyal online data repository.

Appendix 2C. Univariate regression results of real returns on labour market competitiveness

This table reports the univariate regression results of stock market real returns (returns in excess of the inflation rate) on the lagged labour market competitiveness. The dependent variable $Ret_{(t+1:t+h)}$ is the cumulative real returns from month $t+1$ to month $t+h$, where $h =$ Error! Bookmark not defined.. Panels A and B report the results based on equal-weighted and value-weighted returns, respectively. *Portfolio market* is the returns of a portfolio constructed from the firms in my sample. *Portfolio small* is returns based on small stocks in the sample (lower than the size median). *Portfolio large* is returns based on large stocks in the sample (higher than the size median). *Russell 2000* is the returns of a portfolio from the smallest 2000 stocks in the Russell 3000 index. *Russell 1000* is the returns of a portfolio from the largest 1000 stocks in the Russell 3000 index. The sample period is from January 2010 to December 2021. Regression coefficients for the constant are not reported for brevity. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

		Portfolio market			*Portfolio small*			*Portfolio large*			*Russell 2000*			*Russell 1000*		
	Obs	*Competition*	*t-stat*	*Adj. R2*	*Competition*	*t-stat*	*Adj. R2*	*Competition*	*t-stat*	*Adj. R2*	*Competition*	*t-stat*	*Adj. R2*	*Competition*	*t-stat*	*Adj. R2*
Panel A: Equal-weighted returns																
h=1	143	-0.005*	(-1.83)	0.00	-0.007**	(-2.40)	0.01	-0.003	(-1.24)	0.00	-0.005*	(-1.74)	0.00	-0.004	(-1.45)	0.00
h=3	141	-0.022***	(-3.34)	0.05	-0.027***	(-3.94)	0.08	-0.015***	(-2.82)	0.04	-0.022***	(-2.92)	0.04	-0.016***	(-2.91)	0.04
h=6	138	-0.024**	(-2.44)	0.03	-0.032***	(-2.98)	0.06	-0.014*	(-1.83)	0.02	-0.027**	(-2.35)	0.04	-0.018**	(-2.09)	0.03
h=9	135	-0.040***	(-3.29)	0.07	-0.054***	(-3.88)	0.13	-0.026***	(-3.05)	0.05	-0.050***	(-3.32)	0.09	-0.035***	(-3.16)	0.09
h=12	132	-0.036***	(-2.66)	0.04	-0.056***	(-3.62)	0.11	-0.023**	(-2.31)	0.03	-0.053***	(-3.49)	0.08	-0.038***	(-4.04)	0.09
h=15	129	-0.022	(-1.13)	0.01	-0.046**	(-2.43)	0.06	-0.013	(-0.88)	0.00	-0.043**	(-2.27)	0.05	-0.034***	(-3.00)	0.07
h=18	126	0.007	(0.25)	-0.01	-0.021	(-0.86)	0.00	0.008	(0.42)	0.00	-0.015	(-0.60)	0.00	-0.018	(-1.14)	0.01
Panel B: Value-weighted returns																
h=1	143	-0.002	(-0.76)	-0.01	-0.001**	(-2.37)	0.02	-0.002	(-0.75)	-0.01	-0.004	(-1.40)	0.00	-0.001	(-0.63)	-0.01
h=3	141	-0.010**	(-2.18)	0.02	-0.002***	(-3.11)	0.06	-0.010**	(-2.17)	0.02	-0.019***	(-2.62)	0.04	-0.010**	(-2.03)	0.02
h=6	138	-0.006	(-0.91)	0.00	-0.002**	(-2.53)	0.06	-0.005	(-0.84)	0.00	-0.023**	(-2.02)	0.03	-0.008	(-1.05)	0.00
h=9	135	-0.016**	(-2.14)	0.02	-0.003***	(-2.79)	0.05	-0.014**	(-2.09)	0.02	-0.045***	(-3.24)	0.09	-0.020**	(-2.52)	0.04
h=12	132	-0.011	(-1.24)	0.00	-0.002	(-1.51)	0.02	-0.010	(-1.09)	0.00	-0.050***	(-3.77)	0.09	-0.021***	(-2.95)	0.04
h=15	129	0.001	(0.07)	-0.01	-0.001	(-1.06)	0.00	0.001	(0.10)	-0.01	-0.040***	(-2.60)	0.06	-0.014	(-1.44)	0.01
h=18	126	0.020	(1.17)	0.02	-0.001	(-0.82)	0.00	0.018	(1.17)	0.02	-0.017	(-0.82)	0.00	0.000	(0.02)	-0.01

Appendix 2D. Multivariate regression results based on value-weighted next quarter returns

This table reports the multivariate regression results of value-weighted stock market excess returns on labour market competitiveness and other predictors. I use $Ret_{(t+1:t+3)}$ as the dependent variable. Panel A reports the results based on a univariate regression on known predictors (*Predictor*). Panel B reports the coefficients for *Competition* in addition to other known predictors. Panels C and D report the coefficients for *Competition* from the multivariate regressions based on small and large market portfolio returns, respectively. *sign* is the expected relation between predictor and stock returns (based on the literature). The sample period is from January 2010 to December 2021. Details on each of these variables can be found in Appendix B. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent: $Ret_{(t+1:t+3)}$		Panel A: Univariate regression			Panel B: Multivariate regression					Panel C: Portfolio small		Panel D: Portfolio large	
	sign	*Predictor*	*t-stat*	*Adj. R^2*	*Predictor*	*t-stat*	*Competition*	*t-stat*	*Adj. R^2*	*Competition*	*t-stat*	*Competition*	*t-stat*
Stock market predictors													
S&P500 Excess Return	-	-0.299**	(-2.46)	0.026	-0.278**	(-2.33)	-0.009*	(-1.92)	0.039	-0.001***	(-3.71)	-0.009*	(-1.88)
VIX	+	0.005***	(6.60)	0.268	0.005***	(6.77)	-0.010**	(-2.09)	0.288	-0.002***	(-4.27)	-0.009**	(-2.05)
Average Correlation	+	0.200***	(2.86)	0.110	0.195***	(2.91)	-0.009**	(-2.14)	0.122	-0.001***	(-4.42)	-0.008**	(-2.10)
Realized Volatility	+	0.956***	(6.72)	0.169	0.961***	(6.91)	-0.011**	(-2.39)	0.190	-0.002***	(-4.18)	-0.010**	(-2.33)
Dividend-Price Ratio	+	0.066	(0.77)	0.004	0.046	(0.54)	-0.009*	(-1.93)	0.016	-0.001***	(-3.52)	-0.008*	(-1.87)
Dividend-Earnings Ratio	+	0.057	(1.14)	0.022	0.060	(1.18)	-0.011**	(-2.14)	0.042	-0.002***	(-3.77)	-0.010**	(-2.12)
Labour market predictors													
log(average posts)	-	-0.042*	(-1.77)	0.024	-0.035	(-1.39)	-0.008*	(-1.67)	0.031	-0.001***	(-3.01)	-0.007*	(-1.69)
Employment Growth Rate	-	-0.593**	(-2.37)	0.029	-0.575**	(-2.32)	-0.010**	(-2.06)	0.045	-0.002***	(-3.80)	-0.009**	(-2.03)
Unemployment Rate	+	0.661*	(1.80)	0.043	0.573	(1.49)	-0.006	(-1.46)	0.045	-0.001***	(-3.53)	-0.006	(-1.51)
Economic Policy Uncertainty	+	0.042***	(7.09)	0.207	0.044***	(7.62)	-0.014***	(-3.22)	0.245	-0.002***	(-4.30)	-0.012***	(-3.13)
Economic predictors													
Chicago Fed National Activity Index	-	-0.003	(-0.93)	-0.001	-0.003	(-0.85)	-0.010**	(-2.10)	0.016	-0.002***	(-3.79)	-0.009**	(-2.08)
Industrial Production Growth	-	-0.346	(-0.86)	-0.001	-0.336	(-0.86)	-0.010**	(-2.12)	0.016	-0.002***	(-3.80)	-0.009**	(-2.10)
NBER Business Cycle	+	0.153***	(9.88)	0.070	0.149***	(9.66)	-0.009**	(-2.00)	0.084	-0.001***	(-3.79)	-0.009**	(-1.98)
Term Spread	+	-0.601	(-0.80)	0.005	-1.075	(-1.30)	-0.015***	(-2.60)	0.045	-0.001***	(-3.22)	-0.014**	(-2.54)
Default Spread	+	3.568**	(2.07)	0.056	3.263*	(1.90)	-0.008*	(-1.70)	0.062	-0.001***	(-4.33)	-0.007*	(-1.67)

Appendix 2E. Multivariate regression results based on value-weighted next-year returns

This table reports the multivariate regression results of value-weighted stock market excess returns on labour market competitiveness and other predictors. I use $Ret_{(t+1:t+12)}$ as the dependent variable. Panel A reports the results based on a univariate regression on known predictors (*Predictor*). Panel B reports the coefficients for *Competition* in addition to other known predictors. Panels C and D report the coefficients for *Competition* from the multivariate regressions based on small and large market portfolio returns, respectively. *sign* is the expected relation between predictor and stock returns (based on the literature). The sample period is from January 2010 to December 2021. Details on each of these variables can be found in Appendix B. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent: $Ret_{(t+1:t+3)}$		Panel A: Univariate regression			Panel B: Multivariate regression					Panel C: Portfolio small		Panel D: Portfolio large	
	sign	*Predictor*	*t-stat*	*Adj. R^2*	*Predictor*	*t-stat*	*Competition*	*t-stat*	*Adj. R^2*	*Competition*	*t-stat*	*Competition*	*t-stat*
Stock market predictors													
S&P500 Excess Return	-	-0.477	(-1.59)	0.018	-0.455	(-1.50)	-0.011	(-1.21)	0.020	-0.004***	(-2.68)	-0.010	(-1.11)
VIX	+	0.011***	(5.05)	0.378	0.011***	(5.06)	-0.013	(-1.35)	0.384	-0.004***	(-2.92)	-0.011	(-1.23)
Average Correlation	+	0.362***	(2.80)	0.112	0.356***	(2.76)	-0.010	(-1.18)	0.113	-0.003***	(-2.94)	-0.009	(-1.05)
Realized Volatility	+	2.098***	(6.29)	0.260	2.106***	(6.34)	-0.014	(-1.55)	0.269	-0.004***	(-2.93)	-0.012	(-1.39)
Dividend-Price Ratio	+	0.386	(1.14)	0.038	0.362	(1.06)	-0.008	(-0.92)	0.035	-0.003**	(-2.43)	-0.007	(-0.78)
Dividend-Earnings Ratio	+	0.174	(1.58)	0.073	0.178	(1.61)	-0.015	(-1.50)	0.081	-0.004***	(-2.73)	-0.013	(-1.37)
Labour market predictors													
log(average posts)	-	-0.111**	(-2.45)	0.055	-0.106**	(-2.26)	-0.007	(-0.69)	0.050	-0.003**	(-2.11)	-0.006	(-0.60)
Employment Growth Rate	-	-1.563**	(-2.16)	0.071	-1.550**	(-2.16)	-0.012	(-1.32)	0.074	-0.004***	(-2.72)	-0.011	(-1.21)
Unemployment Rate	+	1.795**	(2.15)	0.109	1.784**	(2.01)	-0.001	(-0.08)	0.102	-0.002*	(-1.80)	-0.001	(-0.05)
Economic Policy Uncertainty	+	0.114***	(9.24)	0.480	0.117***	(10.57)	-0.022***	(-3.49)	0.511	-0.004***	(-3.15)	-0.019***	(-3.02)
Economic predictors													
Chicago Fed National Activity Index	-	-0.009	(-0.88)	0.009	-0.009	(-0.86)	-0.012	(-1.35)	0.012	-0.004***	(-2.73)	-0.011	(-1.23)
Industrial Production Growth	-	-0.702	(-0.46)	-0.001	-0.710	(-0.47)	-0.013	(-1.40)	0.004	-0.004***	(-2.75)	-0.011	(-1.28)
NBER Business Cycle	+	0.403***	(16.73)	0.161	0.399***	(16.48)	-0.010	(-1.12)	0.162	-0.004***	(-2.69)	-0.009	(-1.03)
Term Spread	+	-2.410	(-1.43)	0.053	-3.261*	(-1.76)	-0.028**	(-2.13)	0.093	-0.003*	(-1.94)	-0.024**	(-2.02)
Default Spread	+	9.436***	(2.84)	0.118	9.210***	(2.73)	-0.007	(-0.77)	0.114	-0.003***	(-3.48)	-0.006	(-0.66)

Appendix 2F. Portfolio sorting (value-weighted returns)

This table reports the average returns for portfolios double-sorted by firm size, followed by (absolute) competition beta. Panel A shows the results for the small stocks (size Q1), and Panel E shows the results for the large stocks (size Q5). The sample period is from January 2015 to December 2022. I report the monthly value-weighted portfolio returns. I also present the Sharpe ratio, average competition beta, and the number of firms in each portfolio. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Panel A: Size Q1						
Return	0.009	0.011**	0.008	0.009	0.021**	0.012**
t-stat	(1.57)	(2.21)	(1.42)	(1.47)	(2.19)	(2.08)
Sharpe Ratio	0.14	0.20	0.13	0.14	0.24	0.23
Competition beta	0.17	0.53	0.96	1.67	4.12	
Average size (‘000)	137,369	141,836	145,348	135,776	132,271	
Firms	86	85	86	85	86	
Panel B: Size Q2						
Return	0.011*	0.010	0.010	0.013*	0.011	0.000
t-stat	(1.74)	(1.60)	(1.45)	(1.91)	(1.32)	(-0.01)
Sharpe Ratio	0.15	0.14	0.12	0.18	0.12	0.00
Competition beta	0.17	0.50	0.91	1.52	3.34	
Average size (‘000)	609,573	611,072	626,050	603,955	583,260	
Firms	86	85	85	85	86	
Panel C: Size Q3						
Return	0.010*	0.008	0.010*	0.011*	0.008	-0.001
t-stat	(1.73)	(1.53)	(1.68)	(1.80)	(1.09)	(-0.33)
Sharpe Ratio	0.14	0.13	0.14	0.15	0.10	-0.04
Competition beta	0.17	0.48	0.84	1.36	2.93	
Average size (‘000)	1,760,266	1,750,317	1,759,275	1,734,632	1,704,006	
Firms	86	85	85	85	86	
Panel D: Size Q4						
Return	0.009*	0.009*	0.007	0.009	0.008	-0.001
t-stat	(1.80)	(1.69)	(1.44)	(1.63)	(1.37)	(-0.56)
Sharpe Ratio	0.14	0.14	0.11	0.13	0.11	-0.05
Competition beta	0.13	0.41	0.72	1.16	2.30	
Average size (‘000)	4,981,108	4,956,824	5,018,690	5,062,311	4,771,297	
Firms	86	85	85	85	86	
Panel E: Size Q5						
Return	0.009**	0.012***	0.009**	0.008*	0.007	-0.002
t-stat	(2.31)	(3.23)	(2.19)	(1.94)	(1.47)	(-0.64)
Sharpe Ratio	0.16	0.25	0.16	0.15	0.10	-0.07
Competition beta	0.11	0.34	0.59	0.92	1.80	
Average size (‘000)	63,063,005	64,728,338	50,346,940	41,917,296	39,242,397	
Firms	86	85	86	85	86	

Appendix 2G. Asset pricing factor tests (value-weighted returns)

This table reports the results from asset pricing factor tests for portfolios sorted on competition beta. The dependent variable is the value-weighted portfolio returns. In Panel A, I use Fama and French (1996) three factors (MKT, SMB, and HML). In Panel B, I use the Fama and French three factors and the Carhart (1997) momentum factor (UMD). In Panel C, I use Fama and French (2015) five factors (MKT, SMB, HML, RMW, and CMA). In Panel D, I use Hou, Xue, and Zhang (2015) q-factors (MKT, SMB, IA, and ROE). The sample period is from January 2015 to December 2022. All coefficients are monthly. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Panel A: FF3						
alpha	0.003*	0.006***	0.003*	0.002	0.013***	0.010**
	(1.80)	(3.75)	(1.81)	(1.01)	(3.18)	(2.31)
MKT	0.007***	0.007***	0.008***	0.009***	0.011***	0.004***
	(13.85)	(16.52)	(15.41)	(21.37)	(8.03)	(2.62)
SMB	0.007***	0.007***	0.008***	0.009***	0.012***	0.005*
	(8.97)	(8.72)	(11.27)	(9.15)	(4.83)	(1.80)
HML	0.004***	0.004***	0.004***	0.002***	0.002***	-0.002**
	(5.40)	(5.71)	(6.70)	(4.11)	(2.92)	(-2.43)
Panel B: FF4						
alpha	0.004**	0.007***	0.004**	0.003	0.012***	0.008**
	(2.29)	(4.18)	(2.21)	(1.25)	(3.44)	(2.10)
MKT	0.007***	0.007***	0.007***	0.009***	0.012***	0.005***
	(15.29)	(13.72)	(16.82)	(20.47)	(7.27)	(3.08)
SMB	0.007***	0.006***	0.008***	0.008***	0.013***	0.006**
	(8.05)	(8.78)	(11.07)	(8.63)	(4.98)	(2.09)
HML	0.003***	0.003***	0.003***	0.002***	0.003**	0.000
	(4.63)	(4.69)	(6.52)	(3.70)	(2.28)	(-0.37)
UMD	-0.002***	-0.001*	-0.002**	-0.001	0.002	0.004
	(-2.55)	(-1.68)	(-2.53)	(-1.53)	(0.97)	(1.52)
Panel C: FF5						
alpha	0.003	0.006***	0.002	0.002	0.013***	0.010**
	(1.36)	(3.55)	(1.41)	(0.97)	(3.36)	(2.43)
MKT	0.007***	0.007***	0.008***	0.009***	0.012***	0.005***
	(12.37)	(15.46)	(13.97)	(21.58)	(7.99)	(3.01)
SMB	0.008***	0.007***	0.008***	0.009***	0.011***	0.003
	(12.01)	(9.02)	(9.96)	(10.27)	(4.51)	(1.14)
HML	0.003***	0.004***	0.003***	0.002***	0.001	-0.002
	(3.85)	(5.38)	(3.98)	(2.86)	(0.92)	(-1.61)
RMW	0.003**	0.002*	0.000	0.001	-0.004*	-0.006***
	(2.28)	(1.78)	(0.31)	(0.78)	(-1.68)	(-2.55)
CMA	-0.001	-0.001	0.001	0.000	0.003	0.004
	(-0.41)	(-1.21)	(1.40)	(-0.06)	(0.99)	(1.15)
Panel D: HXZ						
alpha	0.003	0.006**	0.003	0.003	0.014***	0.011***
	(1.41)	(2.49)	(1.42)	(1.04)	(3.86)	(2.75)
MKT	0.008***	0.007**	0.008***	0.009***	0.011***	0.003**
	(12.17)	(13.54)	(17.94)	(21.09)	(8.22)	(2.36)
SMB	0.007***	0.007***	0.007***	0.008***	0.012***	0.005*
	(5.53)	(5.72)	(6.79)	(7.70)	(5.71)	(1.81)
I/A	0.003***	0.002**	0.004***	0.001*	0.003	0.000
	(3.17)	(2.22)	(4.70)	(1.73)	(1.51)	(0.00)
ROE	-0.002	-0.001	-0.003***	-0.002***	-0.004***	-0.002
	(-1.41)	(-1.38)	(-2.96)	(-3.29)	(-2.60)	(-1.07)