Labour Market Friction Effect on Corporate Performance: Evidence in the Global Market

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Abstract

This thesis represents the first academic endeavour to investigate the impact of labour market friction on corporate performance in a global context. In traditional neoclassical economic theory and relevant research, human capital was considered merely an input to generate economic value. Unemployed workers were assumed to fill vacant job positions perfectly, similar to interchangeable machine parts. However, as understanding has evolved, economists now recognise the complexities of filling a job vacancy, which needs to take into account the skills, geographic locations, labour preferences, and various objective factors of the labour force. Consequently, a mismatch often occurs between unemployed workers and vacant jobs, resulting in simultaneous unemployment and job vacancies. This phenomenon is termed labour market friction.

This thesis comprises three subprojects, each contributing a distinct essay. The first essay examines the effect of labour market friction on expected stock returns in the Chinese stock market. Utilising the portfolio sorting approach and the Fama-MacBeth regression model, the findings indicate that firms with higher labour friction risk are likely to experience higher stock returns in the subsequent month. This suggests that labour friction risk serves as a significant risk factor in asset pricing. Additionally, the study reveals that the positive effect of labour friction on expected stock returns is more pronounced in firms with either high productivity or poor employee welfare. Furthermore, firms in regions with high levels of development are more likely affected by the labour friction risk.

The second essay expands the scope from the Chinese stock market to global stock markets, including North America, Asia-Pacific, and Europe. The results reveal regional variations in the impact of labour market friction on expected stock returns. Specifically, labour friction risk has a negative association with expected stock returns in North American markets, whereas it is positively correlated in Asia-Pacific markets. The significant labour market friction effects are pronounced in different industries due to the varieties of labour market structures, where the North American markets contain a large partial of high technology companies, while

the Asia-Pacific markets are dominated by numerous industrial companies. There is no significant relationship between labour friction risk and expected stock returns in European markets. The study also finds that the effect of labour friction is particularly pronounced in markets that are non-immigrant or non-English-speaking, providing higher external labour supply and mobility in such markets, which reduces firms' recruitment pressures.

The third essay centres on Corporate Social Responsibility (CSR) behaviours under the influence of labour market friction in a global setting. The results suggest that firms facing higher labour friction risks are more inclined to engage in CSR activities, even when controlling for year, industry, and region effects in the regression model. This CSR engagement is notably more prominent in markets with a higher demand for labour, characterised by a higher number of new businesses and job vacancies. These findings remain consistent across markets that encourage business creation and expansion through strong investor protection and low labour taxation policies. Markets with higher levels of advanced education have a more significant labour market friction effect on CSR decision-making as they have numerous labour-intensive firms which require a large labour force. Additionally, when labour unions have the strong bargaining power to protect the welfare of employees, firms are less inclined to conduct CSR activities due to the less function in controlling the labour market friction risk.

In summary, this thesis contributes to the existing literature by providing empirical evidence of the effects of labour market friction on corporate performance and behaviours across different global markets. It demonstrates that the impact of labour market friction varies due to differing labour market policies and structures and is significantly influenced by the dynamics of labour supply and demand. The insights derived from examining labour market friction across diverse markets have critical implications for both corporate managers and policymakers seeking to mitigate the associated risks.

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Chapter 1. Overview and Introduction

1.1. Introduction

Economists are consistently interested in labour market studies because labour plays a crucial role in both macro and microeconomic contexts. Macroeconomic research explores the relationship between the labour market and overall economic performance, particularly focusing on factors that influence unemployment rates. According to neoclassical theory, unemployment and corresponding wage levels are determined by the supply and demand for labour. This theory operates under the assumption that all labourers and job positions have no difference, meaning any person could fill any job in theory. However, this simplification often fails to capture the complexities of the real world.

On the other hand, microeconomic studies emphasise the individual impacts on firm production and goods markets. Various attributes such as skills, personality, and other individual characteristics can significantly influence one's job performance. Labourers have their suitability for specific job roles varies among individuals. Additionally, they have the freedom to select jobs based on compensation, working conditions, and personal preferences. Recognising these complexities, macroeconomic studies are increasingly accounting for labour differentiation and establishing models under the constraints of a frictional labour market. Research on labour market friction has been extensive in macroeconomic literature, examining its impact on wage levels, unemployment rates, economic growth, and market policies among other aspects. Labour market friction sets barriers to the matching process between labourers and job positions, thereby affecting wage levels and unemployment rates. These frictions naturally delay the production process, leading to a decline in aggregate output.

From a microeconomic perspective, labour market friction impacts are more individualised, affecting specific persons and corporations. Only a handful of studies have examined the relationship between labour market friction and corporate performance like growth, productivity, and liquidity (see Felbermayr et al., 2011; Lentz & Mortensen, 2012; Kaas & Kircher, 2015; Favilukis et al., 2020). All business operations and innovation must be implemented by humans, but labour market friction increases the likelihood of job vacancies, reducing the speed of corporate growth. The lack of skilled labour can pause or even stop business operations and expansions, diminishing a company's competitive advantages. Kuehn et al. (2017) treat labour market friction as a systematic risk factor, incorporating it into traditional asset pricing models. Although this study starts a new field in understanding the impact of labour market friction on financial markets, it is limited to the US context. This raises several relevant questions that are worth further investigation: Is the effect of labour market friction on financial markets consistent beyond the US? Do other variables influence the impact of labour market friction? Are there strategies to either amplify or mitigate these effects? Answering these questions requires more comprehensive and in-depth research.

1.2. Pricing Labour Market Friction Risk in the Chinese Stock Market

This thesis initially explores the effect of labour market friction on financial markets outside the United States. Instead of selecting a highly capitalised market similar to the US, we turn our focus to the Chinese market. China offers a distinct labour market structure characterised by a large population and numerous labour-intensive businesses. According to Kuehn et al. (2017), labour market friction negatively impacts expected returns due to abnormal investment behaviours. In contrast, theories suggest that firms are likely to incur higher recruitment costs and operational leverage in a frictional labour market, thereby raising corporate operational risks (see Danthine & Donaldson, 2002; Chen et al., 2011; Vernimmen et al., 2014; Favilukis & Lin, 2016). This heightened risk prompts investors to seek higher returns as compensation, leading to an expectation of increased stock returns in subsequent periods.

Motivated by this apparent contradiction, Chapter 2 of this thesis analyses the effect of labour market friction on expected excess stock returns in the Chinese stock market. The chapter provides robust empirical evidence demonstrating a positive relationship between labour market friction risks and expected excess stock returns in China, a finding that contradicts the US situation. Employing a portfolio sorting approach, firms are categorised into quintile groups based on their labour market friction risk. Firms with higher levels of labour market friction risk outperform those with lower levels by up to 5.4% per annum. Moreover, in the Fama-MacBeth regression model, labour market friction risk is positively correlated with expected excess stock returns at a 5% significance level.

Chapter 2 also investigates the effect of labour market friction on firms with varying levels of productivity and welfare benefits. The positive impact of labour market friction is consistent for firms that exhibit high productivity but offer poor welfare benefits. Since high-productivity firms demand highly skilled employees capable of generating more value, the recruitment process becomes more challenging. Firms with inadequate welfare benefits face additional hiring barriers, as prospective employees often weigh factors like the working environment and company sustainability. Such companies run a higher risk of job vacancies and operational challenges.

Furthermore, Chapter 2 investigates the geographic variance of labour market friction effects, revealing that the impact is more pronounced for firms located in capital cities, cities with high levels of marketisation, and cities with a well-educated populace. These developed cities have a higher demand for skilled labour to maintain competitiveness. The chapter also finds that the impact of labour market friction becomes more substantial when labour demand exceeds supply. Given the limited availability of skilled labour against numerous job vacancies, companies find themselves in competition to strive for employees. Consequently, increased labour demand amplifies the risks associated with labour market friction, as well as its impact on expected stock returns.

1.3. The Labour Market Friction Risk in the Global Stock Markets

Chapter 3 extends the study of labour market friction risk to expected stock returns in global stock markets. Covering 36 markets worldwide, empirical evidence reveals inconsistent effects of labour market friction across different regions. In North American stock markets, firms with low labour friction risk outperform those with high labour friction risk by 4.56%

annually. This negative association aligns with the findings of Kuehn et al. (2017). Conversely, in Asia-Pacific stock markets, firms with high labour friction risk outperform those with low risk by 2.64% annually, indicating a positive effect of labour market friction on expected stock returns. Interestingly, no significant effect of labour market friction on expected stock returns is observed in European stock markets.

To discern the underlying causes of these variances, Chapter 3 analyses deeper into the effects of labour market friction across sectors. Statistical analysis reveals that high-technology companies take a large part in North American markets, whereas industrial firms are dominated in Asia-Pacific markets. Utilising the Fama-Macbeth regression model, the labour market friction effect is more pronounced among high-tech firms in North America and industrial companies in the Asia-Pacific. Additionally, the effect is more significant in North American firms with high labour productivity, but more pronounced in Asia-Pacific firms with low labour productivity. These findings suggest that differing labour market structures contribute to the observed variations.

This prompts a new question: Why are European firms seemingly impervious to labour market friction effects? Chapter 3, therefore, explores the impact of labour market friction in immigration-centric and non-immigration markets, as well as English-speaking and non-English-speaking markets. The analysis shows that the labour market friction effect is significant only in non-immigration and non-English-speaking markets. Immigration markets, with an abundant external labour supply due to a high influx of migrant workers, appear to mitigate the labour market friction effect. Similarly, English-speaking markets have easier access to a broader labour pool, thus reducing labour market friction. This suggests that the 'Free Movement of Workers' policy in European Union countries, which allows for unrestricted movement between member states, helps European firms to have adequate external labour supply, thereby mitigating the effects of labour market friction. This finding holds even in culturally permissive markets that offer people more job mobility and turnover freedom. Lastly, Chapter 3 observes that markets with high inflation also exhibit no significant labour market friction effects when compared to low-inflation markets. High inflation seems to incentivise workers to seek or change jobs with better compensation, thereby increasing labour mobility and turnover in the labour market.

1.4. The Influence of Labour Market Friction on Firm's Corporate Social Responsibility (CSR) Engagement

Chapter 4 shifts focus to examine how labour market friction influences corporate social responsibility (CSR) engagement. Utilising a fixed-effects regression model and controlling for time, industry, and region effects, the results indicate that firms facing higher labour market friction risks are more inclined to engage in CSR activities. Specifically, for each standard deviation increase in labour market friction risk, a firm's CSR score can improve by up to 1.23 points. Since CSR activities can enhance a firm's social image and working conditions, they serve to attract more qualified candidates (Sirgy, 1982; Keller, 1993) As a result, a higher attractiveness helps corporates secure the "right" employees from the larger scale of recruitment candidates, and a good corporate image helps prospective employees make their job decisions to work in the "right" place (Turban & Greening, 1996; Riordan et al., 1997; Ewing et al., 2002).

Chapter 4 also investigates how varying levels of labour demand affect CSR engagement across markets. It reveals that firms in markets with a higher number of new businesses and job vacancies are more likely to conduct CSR activities. Increased business activity and job openings increase labour demand, thereby intensifying competition to strive for employees. Similarly, markets with strong investor protections and lower labour taxation also see a greater likelihood of CSR engagement among firms, as these policies allow firms to raise capital and save operational expenses more easily, supporting business growth and workforce expansion (La Porta et al., 2000; Hyytine & Takalo, 2003; Atanassove & Kim, 2009; Daveri & Tabellini, 2000), which as well as increase labour demand and firms' competition in the labour market. The finding is robust to the markets that have a low level of advanced education because these low-eduction markets contain numerous labour-intensive companies while the high-eduction markets have more capital-intensive companies.

From the workers' viewpoint, Chapter 4 finds that the impact of labour market friction on CSR engagement would be mitigated in markets with strong power of labour unions. In environments where unions are less effective in protecting workers' rights and benefits, employees are more inclined to seek positions in firms that are actively engaged in CSR. These firms are often perceived as more employee-friendly, focusing on a positive corporate image and an improved working environment. Conversely, when labour unions can provide sufficient protections, labourers would not desire to seek a job with good welfare benefits, and conducting CSR activities will be less effective than expected.

At the firm level, this CSR engagement is particularly notable for companies that offer lower wages and have less efficient hiring processes. Compared with firms offering high compensation to attract candidates, these low-wage firms are more inclined to improve welfare benefits and working conditions. For firms with inefficient hiring practices, the urgency to reach full productivity makes CSR engagement a compelling strategy to attract a greater number of qualified applicants.

1.5. Contributions

In summary, this thesis enriches existing literature by offering empirical evidence on how labour market friction impacts both corporate performance and behaviour across global markets. Chapter 2 specifically focuses on the Chinese stock market, initially filling a gap in the literature by examining the role of labour market friction within asset pricing models in emerging markets. Contrary to findings in the US stock market, this chapter reveals a positive relationship between labour market friction risk and expected excess stock returns in China. This finding proves the idea that the impact of labour market friction is not universally consistent. Additionally, this chapter suggests that a firm's labour productivity and welfare policies can influence the effects of labour market friction on expected stock returns. Other significant determinants include the overall level of economic development and aggregate labour demand.

Chapter 3 takes a broader approach, investigating the universality of labour market friction effects in global stock markets. This chapter proves that the positive effects of labour market friction are not limited to China. It also reveals that these effects can vary due to differing labour market structures. For instance, North American markets, with a higher proportion of high-tech firms, require a more skilled and productive workforce compared to the Asia-Pacific markets, which have a preponderance of industrial companies requiring lower-skilled labour. Lastly, this chapter identifies ways to mitigate the impact of labour market friction on stock markets, primarily through increasing labour supply or allowing greater labour mobility and turnover.

Chapter 4 focuses on the influence of labour market friction on corporate social responsibility (CSR) engagement across global markets. Its primary contribution is in establishing a connection between labour market friction and CSR activities. This linkage demonstrates that heightened labour market friction can incentivise firms to adopt CSR initiatives. The findings of this chapter also fill the existing literature on the role of CSR in enhancing corporate image and competitiveness within labour markets. Finally, the chapter shows that high labour demand can intensify competition for employees, thus encouraging firms to engage in CSR activities to make themselves more appealing to potential hires.

1.6. Structure of Dissertation

This thesis comprises three essays, and the structure of this dissertation is briefly described as follows. Chapter 2 examines the labour market friction effect in the Chinese stock market. This analysis focuses on the relationship between labour market friction risk and the expected stock returns of firms. In the meantime, this chapter figures out the firm characteristics that are more likely to be affected by the labour market friction. Chapter 3 expands the examination of the labour market friction effect on expected stock returns to global markets. The analysis focuses on the possible reasons causing the different labour market friction effects across markets. It further investigates the methods to control the labour market friction risk and mitigate the effects. Chapter 4 turns to examine the labour market friction effect on corporate social responsibility (CSR) engagement in global markets. The analysis investigates whether the labour market friction risk can drive firms to conduct CSR activities. Chapter 5 concludes and discusses the intended direction of future research.

Chapter 2. Labour Market Friction Effect on the Chinese Stock Market

Abstract

This chapter examines the labour market friction loading (LFB) on expected stock returns for Chinese firms from 2001 to 2019. We document a robust positive effect on the cross-section stock returns, which is persistent over ten months, suggesting that labour market friction loading (LFB) is a significant risk factor for asset pricing. Our main finding is robust when we control for various firm characteristics. Further investigation reveals that the effect of labour market friction is more pronounced for high labour productivity firms, firms located in high marketisation regions, and firms offering poor employee welfare. Our main finding is only pronounced when labour demand exceeds supply. Finally, we find that the labour market friction factor significantly prices the stock portfolio returns and could improve the explanatory power of the traditional asset pricing models.

2.1 Introduction

Under neoclassical and Keynesian economics, the labour market is assumed to be frictionless, based on the equilibrium condition of labour supply and demand. Ironmonger (2000) documents that labour is an essential ingredient in the production process that helps transform raw materials into finished products. There are several macroeconomic investigations under frictionless assumptions. However, labour has distinct characteristics as opposed to commodities, which can be freely traded. As documented (Littek, 2001; Rueschemeyer, 1986), there is a pervasive assumption in economics that a relationship of equal power between employers and employees exists. Even though this assumption may diminish freedom in and out of the workplace and undermine legal protections, employers have the power to hire/fire employees based on their qualifications, skills and capacities, and employees have the freedom to accept/reject job offers depending on working conditions such as compensation, location, position, timetable, welfare, and corporate policies (Karpuz et al., 2023). This inevitably results in difficulties matching job vacancies and qualified labourers, defined as labour market friction (Lindbeck, 1999).

Kuehn et al. (2017) document that labour search frictions are an essential determinant of the cross-section of equity returns, using a labour capital asset pricing model for a sample of US firms. Motivated by Kuehn et al. (2017), we examine the labour market friction loading (LFB) on stocks' expected returns for a sample of 2,371 Chinese-listed firms from 2001 to 2019. For three reasons, China stock markets provide an ideal setting to examine the relationship between a firm's labour market friction risk and the stock's expected return. First, during the last twenty years, labour market friction has been an upward trend, with low volatility in the China labour market. Since 2010, the China labour market appears to have a surplus in labour demand due to the high national economic growth rate, which means the number of job vacancies is greater than the number of job seekers. This situation is opposite to the features of the US labour market. Therefore, we could expect the relationship between Chinese firms' labour market friction risk and expected stock returns to be different from the US stock markets. Besides, due to the

"Global Manufacturing" with intensive labour products and the fact that China has only one legal labour union (ACFTU, All-China Federation of Trade Unions), Chinese labour market provides a different context to examine the effects of labour friction on stock returns.

We adopt an alternative approach to measure the labour market frictions based on the search and matching model and apply a Fama-French five-factor model to calculate the labour market friction loadings on expected stocks' returns for the world's largest emerging market with some unique labour market settings, which a high labour market friction loading (LFB) indicates to have a high labour market friction risk. We find that the labour market friction loading (LFB) is negatively correlated to the market risk, the firm value, the maximum stock return, the idiosyncratic risk and the debt-to-equity ratio, and it has positive correlation to the book-to-market ratio, the operating profitability and the asset growth rate. Moreover, we find that high labour market friction loading (LFB) stocks tend to be small firms, value firms and firms with low debt-to-equity ratios. The Fama-MacBeth regression results confirm that the labour market friction loading (LFB) is persistent over a 10-month period, which is consistent with the unique setting of the Chinese labour market, in which unemployed workers who have not paid sufficient taxes in the previous job only receive unemployment benefits for up to 12 months.

Using the portfolio sorting approach, we find that the high labour market friction loading (LFB) portfolio outperforms the low labour market friction loading (LFB) by 0.16% (0.17%) per month for the equal-weighted (value-weighted) sorting, but the results are insignificant. We also estimate the risk-adjusted returns of each portfolio by using either the Fama-French 3-factor model (1993), the Pástor-Stambaugh model (2003), the Fama-French 5-factor model (2015), or Liu et al.'s (2019) China three-factor model (CH-3). The results show that the return differences between the high and low labour market friction loading (LFB) portfolios range from 0.29% per month to 0.45% per month for both equal-weighted and value-weighted sorting, respectively. This implies that the high labour market friction loading (LFB) portfolio outperforms the low labour market friction loading (LFB) portfolio by as much as 5.4% annually on average during the testing period. Further analysis using multivariate Fama-MacBeth regression confirms our findings after controlling various combinations of firm characteristics. Our results contradict Kuehn et al.'s (2017) findings in the US stock markets, presenting a significant negative labour market friction effect. We argue that the difference in the results between China and the US is due to the unique characteristics of the China labour markets. During the testing period, Chinese firms post more job vacancies than there are available job seekers, resulting in hiring difficulties. Therefore, labour market friction might be a risk to Chinese firms.

We further investigate the effect of labour market friction on expected stock returns based on various firm heterogeneity, including the labour productivity effect, the regional marketisation effect, and the employee welfare effect. Our results indicate that our main finding is more pronounced for high labour productivity firms, firms located in high marketisation regions, and firms offering poor employee welfare. A further robustness test is undertaken to examine the sensitivity of our results to the periods when the labour market is tighter. We show that the positive relationship between a firm's labour market friction loading (LFB) and its expected return is more pronounced when labour demand exceeds labour supply. Finally, we construct a labour market friction factor (LFF) to examine its explanatory power in stock portfolio returns. The results show that 80% of coefficients of LFF are statistically significantly different from zero. Moreover, the beta coefficients of LFF increase monotonically from the low to high labour market friction loading (LFB) portfolios, supporting the positive labour market friction effect. More importantly, our results indicate that the new model, the traditional asset pricing model with an LFF factor, exhibits a supreme explanatory power on the expected stock portfolio returns, evident through an improved value of adjusted R square.

We contribute to the existing literature in several important ways. First, to the best of our knowledge, our paper is the first study to estimate dynamic labour market friction loading (LFB) for Chinese stocks and examine its role in asset pricing. The traditional view regards the frictional labour market as a fixed condition. Moreover, the spread between labour supply and demand is the cause of unemployment. Therefore, it does not matter whether or not an individual company addresses labour market friction because job vacancies and job seekers should be instantly matched. Kuehn et al. (2017) find that labour market friction exists at the aggregate and firm levels. Therefore, we fill a significant gap in the literature on labour market friction risk as an essential factor in an asset pricing framework for the world's largest emerging market. Second, we use an alternative method to calculate the labour market friction beta, which proves to be better methodologically and economically. More importantly, we find that labour market friction loading (LFB) is significantly positively related to the expected stock return in China, which contradicts Kuehn et al.'s (2017) findings in the US markets. Our results emphasise the significance of in-country verification of certain phenomena initially documented in the US stock markets. Finally, we also find that a firm's labour productivity, regional marketisation level, and a firm's employee welfare policy are important determinants of the labour market friction effect in China stock markets.

The rest of this chapter is structured as follows. Section 2 reviews the relevant literature. Section 3 presents our data and summary statistics. Section 4 reports the empirical results, and Section 5 concludes.

2.2. Literature Review

2.2.1. Labour Market Friction

Literature on the topic of labour market friction can be traced back to Hutt (1939), who argues that firms and workers can cause labour idleness. Phelps (1968) documents that Keynes' (1937) General Theory of Employment mistakenly assumes frictionless unemployment for aggregate labour demand. Therefore, Phelps (1968) proposes an excess-demand theory to explain the wage dynamic for a frictional labour market. Following the search and matching theory documented in Herrnstein (1961), Pissarides (2000) introduces the unemployment equilibrium theory based on the standard labour equilibrium model. In addition, Pissarides (2011) highlights certain economic essentials while simultaneously considering the effect of labour market frictions, suggesting the importance of labour compensation under the frictional labour market. Yashiv (2007) also emphasises the difficulties of using the neoclassical model under the frictionless labour market assumption in macroeconomic analysis, and documents that unemployment and vacant jobs are important factors in the labour equilibrium model. Thus, under the frictional market assumption, it is possible for academic researchers to examine economic equilibrium or wage settings free from certain restrictions. Hornstein et al. (2011) conclude that labour market friction causes wide dispersion in wages for a data sample of 3.9 million individuals reported in the 1990 Census of the US and recommend a frictional wage dispersion strategy to help improve a firm's performance. Arseneau and Chugh (2012) document a need to examine personal income tax to minimise possible tax distortion under the frictional labour market from 1947 to 2009 in the US, and they conclude a welfare-related model improves a firm's labour search efficiency.

There is a strand of literature that investigates the effects of labour market factors on corporates' operations and governance, assuming the frictional labour market as a fixed condition (Arseneau and Chugh, 2012; Belo et al., 2014; Hornstein et al., 2011; Phelps, 1968; Pissarides, 2011). For a sample of US firms, Kuehn et al. (2017) directly investigate the relationship between labour market frictions and the cross-section of stock return under an asset pricing framework. They document that labour search frictions are an important determinant of the cross-section of equity returns. Firms with low LFB are more exposed to adverse matching efficiency shocks and require higher expected stock returns. Prior studies document that firms' equity premium increases due to higher labour expenses (Chen et al., 2011; Danthine and Donaldson, 2002; Favilukis and Lin, 2016; Vernimmen et al., 2014). Therefore, labour market friction represents an essential premium when firms are forced to increase their expenses on vacancy advertising, candidate screening, training, and paying wages. The labour market friction is then believed to be positively related to asset pricing.

2.2.2. Asset Pricing

Under a frictionless labour market assumption, the firm value is unaffected by the labour force. However, in a frictional labour market, labour is found to be an essential factor in an asset pricing framework. For example, Danthine and Donaldson (2002) document that the operating leverage increases the equity risk premium for a sample of US firms from 1947 to 1998. Chen et al. (2011) investigated the labour union effect on the cost of equity in the US using the Current Population Survey (CPS) data from 1984 to 2006. They conclude that unionisation increases the cost of equity, implying that investors consider the union as a risk factor and require compensation. Belo et al. (2014) find that higher hiring rates likely result in lower equity returns for US firms. Merz and Yashiv (2007) establish a model to present that firms with more labour investment produce greater outputs and increase profit. Kuehn et al. (2017) apply an asset pricing model to examine the relationship between labour market friction and equity returns. By using the vacancy to unemployment ratio as a proxy for labour market friction, their results show that labour market friction is an important factor in determining asset pricing, and they also find that the labour market friction loading (LFB) is negatively related to equity returns in the US market from 1951 to 2014.

2.2.3. Chinese Labour Market

The Chinese population reached 1.41 billion in 2021. Out of 783.9 million economically active individuals, 750.6 million were employed in 2020 according to the National Bureau of Statistics of China. In 2021, the employment rate decreased to approximately 63.5% from 65.1% in the previous year, implying around 12 million people lost their jobs. The labour participation rate is approximately 66.8% of the total population aged 15 and older. As a "Global Manufacturer", Chinese industrial output is 3.9 trillion US dollars, representing approximately 28.3% of global output. In 2019, there were about 3,000 firms publicly listed firms on the Chinese stock markets, with over 2,000 industrial firms relying heavily on their labour force for their operational outputs. Therefore, it is essential to examine the effect of the labour market on the Chinese stock market.

Unlike most developed countries, China provides limited insurance to unemployed workers. According to the policies announced by the State Council of the People's Republic of China in 2004, unemployed workers can receive unemployment benefits for up to 24 months. Those who have not paid sufficient taxes in their previous employment only receive unemployment benefits for up to 12 months. However, the US provides substantial unemployment insurance (UI), impacting the labour market friction significantly. Zhang (2017) highlights that increasing extended unemployment insurance is a significant factor leading to the US's cyclical unemployment. The US workers can remain unemployed until the compensation exceeds the benefits from the unemployment insurance. However, the unemployment insurance policy in China sets a time limit for unemployed workers and pushes them to seek employment, which may help to increase labour market efficiency.

Under the unique setting of the union system, China has only one legal labour union, The All-China Federation of Trade Unions (ACFTU). This unique labour union regulates all individual unions and is under the control of the Chinese government. All ACTFU policies are required to ally with corresponding government policies, comprehensively adjusting labour benefits when necessary (Bai, 2011). Both Chen et al. (2011) and Favilukis and Lin (2016) suggest that labour unions bring a fixed industry wage, namely creating wage stickiness, likely increasing firms' labour expenses and operating leverage in the US market. Due to the uniqueness of the Chinese labour union setting, we expect that the sticky wage effect is weaker in the Chinese labour market.

2.3. Data and Summary Statistics

2.3.1. Sample Data

We include all A-shares listed on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE) in our sample from January 2001 to December 2019[1]. Data on equity and all other firm-level attributes are from the CSMAR database, including daily and monthly dividend-adjusted stock returns[2], the book-to-market ratio, the market capitalisation, the monthly closing price, and the number of shares outstanding. We also collect the total assets, total long-term debt and shareholders' equity, sales, labour costs, operating income, and the number of employees annually. After omitting observations with missing values, our sample contains 301,502 monthly firm-level observations over 2,371 stocks, with 1,383 firms per month on average. We use the 1-year fixed-term deposit rate as the risk-free rate. Data related to the labour market are collected from the Chinese Ministry of Human Resource and Social Security, including the number of job vacancies, the number of unemployed workers, and the labour force participation rate, for the same period. Our data are winsorised at 1% on both tails. Table A2.1 in the Appendix provides a detailed description of these variables.

2.3.2. Labour Market Friction Loading

Our labour market data include the number of job vacancies and the number of job seekers, where the number of job seekers is the product of the number of unemployed workers and the

1 Our sample starts in January 2001 as the job vacancy data starts in the first quarter of 2001. Due to the Covid-19 pandemic, Chinese market was locked down for a long period while a large number of businesses were stopped or shut down. Labour market was significantly impacted as unemployment rate surged suddenly. To eliminate this extreme event impact, our sample period ends in December 2019.

2 We delete the daily return on a firm's IPO date and the monthly return on a firm's IPO month to eliminate the effect of outliers.

labour force participation rate[3]. According to Pissarides (2000), the job-matching ratio is determined by the ratio of the number of job vacancies to the number of unemployed workers, using the following equation:

$$mL = m(uL, vL) \tag{2.1}$$

where mL is the total number of matching jobs, uL is the total number of unemployed workers, and vL is the total number of vacant jobs. For each matching job, Equation (2.1) is then standardised by the total number of workers in the labour force as follows:

$$m = m(u, v) \tag{2.2}$$

Thus, the probability of matching vacant jobs with unemployed workers is then estimated using the following equation:

$$p(\theta) = m(\frac{1}{\theta}, 1) = m(\frac{u}{v}, 1) \tag{2.3}$$

where θ is the ratio of vacant jobs to unemployed workers, and $p(\theta)$is the probability of matching vacant jobs. According to Equation (2.3), θ is negatively related to the probability of matching vacant jobs. The labour market friction is also negatively associated with the probability of matching vacant jobs. The vacancy-to-unemployment ratio could be the proxy of labour market friction. However, to eliminate those who are not actively seeking employment, we use the vacancy-to-seek ratio (VTS) to proxy the labour market friction:

[3] The frequency of the data from the Chinese Ministry of Human Resources and Social Security is quarterly. We interpolate the data into monthly data accordingly.

$$VTS = \frac{Job\ Vacancy}{Unemployed\ Labour \times Participation\ Rate} = \frac{Job\ Vacancy}{Job\ Seeker} \tag{2.4}$$

Figures 2.1 and 2.2 plot the quarterly time series of the number of job vacancies, job seekers, and the VTS for the US and Chinese labour markets, respectively. In Figure 2.1, the number of job vacancies is less than the number of job seekers for the majority of the period before 2015, indicating a persistent surplus in labour supply in the US. The labour market frictions fluctuate over time, mainly driven by the pro-cyclicality of job vacancies and the counter-cyclicality of job seekers. On the other hand, we observe a different picture of the Chinese labour market in Figure 2.2. The labour market frictions have maintained an upward trend, with low volatility over time. Job vacancies and job seekers are moving in the same direction, with job vacancies greater than job seekers since 2010, indicating surplus demand in the Chinese labour market. The result is not surprising, given the unique settings of the Chinese labour market and the more than 40 years with a high national economic growth rate. This results in significant labour mobility, which promotes improved labour market efficiency and eliminates the sticky wage effects in the labour market.

Insert Figure 2.1 here

Insert Figure 2.2 here

We define the labour market friction in month t as the change of logs of the vacancy-to-seek ratio VTS:

$$\Delta VTS_t = log(VTS_t) - log(VTS_{t-1}) \tag{2.5}$$

Table 2.1 reports summary statistics for the monthly labour market friction (VTS), changes in the vacancy index (VAC), changes in job seekers (SEEK), changes in the unemployment rate (UNEMP), and changes in the labour participation rate (PART). The mean value of the change of VTS is 1.08% per quarter during the sample period, implying that job vacancies are constantly higher than the number of job seekers in China during the testing period. The percentage change in job vacancies is 1.09% per quarter, and the percentage change in job seekers is only 0.28%. The percentage change of the quarterly unemployment rate is about 0.55%, or 2.2% annually, similar to those reported by the China Statistics Bureau. The change in the labour participation rate in our sample is -0.02%.

Table 2.1 also reports the correlation coefficients among these variables. Not surprisingly, the change of VAC is highly positively correlated to the change of SEEK, which is 0.9534. The change of VTS negatively correlates to all variables except the change of VAC. The change of UNEMP negatively correlates to all variables, meeting our expectations.

Insert Table 2.1 here

We estimate the sensitivity of a stock's return to the changes in labour market friction, controlling the Fama-French five-factor model. Specifically, at the end of each month, the loadings for each stock are estimated from the following five-factor model, including the market premium (MP), size factor (SMB), value factor (HML), operating factor (RMW), and investment factor (CMA)[4], and the estimation regression model is:

$$Ret_{i,t} = \alpha_{i,t} + \beta_{i,t}^{LF}\Delta VTS_t + \beta_{i,t}^{mkt}MP_t + \beta_{i,t}^{smb}SMB_t + \beta_{i,t}^{hml}HML_t + \beta_{i,t}^{rmw}RMW_t + \beta_{i,t}^{cma}CMA_t \tag{2.6}$$

where $\beta_{i,t}^{LF}$ is the labour market friction loading (LFB) for stock i in month t, and $\beta_{i,t}^{mkt}$ is then the market beta (MB) for stock i in month t. As the Chinese labour market only offers limited insurance for unemployed workers that less than 12 months, we expect that the labour friction presents a short-term effect in the Chinese labour market. Unemployed workers are pressed to find a job before the restricted benefits terminates. Besides, there would be a time interval between the job seeking and offer acceptance, and it is expected to be one or two months in general. Therefore, we estimate the labour friction loading (LFB) with an 11-month rolling window, and there must be more than 6 months of valid returns to match the requirements of

4 We construct the Fama-French five factors using our sample stocks, following Fama and French's (2015) method. We report the descriptive statistics of the five factors in Table A2 in the Appendix.

running the regression. The limitation of this estimation model is that a full year rolling window (e.g., 12-month, 24-month) would be more typical in experiments, however, the full year windows might not match the real practices in this empirical studies.

Table 2.2 reports the summary statistics for the cross-sectional time-series sample and the correlation matrix among all variables from January 2001 to December 2019. Panel A reports the mean, standard deviation, skewness, and values in quintile. This includes the monthly return, the labour market friction loading (LFB), the vacancy-to-seek ratio (VTS), and nine control variables. The average stock return is 1.18% per month, with a loss of 6.79% in the lower 25% quartile and a gain of 8% in the upper 75% quartile. The mean and median values of labour market friction loading (LFB) are -0.0190 and 0, respectively, with a slightly negative skewness of -0.0461. The minimum and maximum labour market friction loading (LFB) values are -12.3172 and 11.9706, respectively. The mean vacancy-to-seek ratio is 1.0614, and the median is 1.07, indicating a slight surplus in job vacancies. The sample market beta (MB) is 0.9954 on average, within the range of 0.3643 and 1.7776, indicating our sample firms are following the overall market. The market value range (in logarithm) is between 496.75 million RMB and 135.30 billion RMB, with mean and median values of 5.05 billion RMB (about 757.91 million USD) and 4.57 billion RMB (about 685.10 million USD), respectively. The mean and median values of the book-to-market ratio (BTM) are 0.4925 and 0.4101, respectively. However, the maximum book-to-market ratio is 1.7036, while the upper 75% quintile value is 0.6438, indicating that the majority of our sample firms are overvalued. Panel A also reports the maximum average daily return from the previous month (MAX) as 5.75% following Bali et al. (2011), a monthly idiosyncratic risk (IVOL) of 0.0193 estimated by the Fama-French 3-factor model, a debt-to-equity ratio of 1.6454, operating profitability of 4.74%, and asset growth rate of 15.79%, for our sample firms. The average closing price of our sample stocks is 8.95 RMB per share.

Panel B presents the correlation matrix for each pair of variables. The LFB is negatively related to the MB, MV, MAX, IVOL, and DE, it is positively related to the BTM ratio, OP and AG.

Insert Table 2.2 here

2.3.3. Persistence of Labour Market Friction Risk

We use a Fama-MacBeth regression to examine the persistence of labour market friction loading (LFB). Specifically, we use the following regression of the future labour market friction loading (LFB) in month t + h on the current labour market friction loading (LFB):

$$\beta_{i,t+h}^{LF} = \lambda_1 + \lambda_2 \beta_{i,t}^{LF} + \lambda_n X_{i,t} + \varepsilon_{i,t} \tag{2.7}$$

where h equals 1 to 12, $\beta_{i,t}^{LF}$ is the current labour market friction loading (LFB) of stock i in month t, and $\beta_{i,t+h}^{LF}$ is the future labour market friction loading (LFB) of stock i in month t+h, and $X_{i,t}$ denote the control variables, including MB, MV, BTM, MAX, IVOL, DE, OP, AG, and CP. Table 3 presents the estimated coefficients on the labour market friction loading (LFB) up to 12 months. Our results show strong statistically positive coefficients on labour market friction loading (LFB) for up to 10 months, indicating that labour market frictions are persistent for up to 10 months. It gradually reverses after the 10-month period, which is consistent with the unique setting of the Chinese labour market.

Insert Table 2.3 here

2.3.4. Firm Characteristics

The portfolio sorting approach documented by Cattaneo et al. (2020) is used to examine the relationship between labour market friction as a risk factor and the stock return. At the end of each month t, we rank our sample firms into quintiles by labour market friction loading (LFB), estimated by the Equation (2.6). We then form five portfolios of stocks from the lowest labour market friction loading (LFB) to the highest labour market friction loading (LFB) with monthly rebalancing. Table 2.4 presents the summary statistics of portfolio characteristics sorted by the labour market friction loading (LFB), and the last column is the difference between the highest quintile and lowest quintile portfolios. The average labour market friction loading (LFB) for the highest (lowest) quintile portfolio is 3.1821 (-3.2461) and the difference is 6.4282, which is statistically significant at the 1% level.

In terms of the other firm characteristics, there are no significant differences between the market beta (MB) across our quintile portfolios, suggesting the market risk may not be affected by the labour market friction risk. The average market value (in logarithm) for our quintile portfolios decreases, indicating small firms experience relatively greater labour market friction risk. The BTM ratios are lower for both the highest and the lowest portfolios, exhibiting a reversed "U" shape. The difference in the BTM ratio between the highest- and the lowest portfolio is 0.0066, which is statistically significant at the 5% level. The difference in the debt-to-equity (DE) ratio between the highest and lowest portfolios is negative and significant, indicating that firms with a high level of debt are likely to experience greater labour market friction risk. The differences in the maximum daily returns (MAX), idiosyncratic risk (IVOL), and asset growth rate (AG) are positive. The differences are negative on operating profitability (OP), and closing price (CP), but none of these results are statistically significant. Overall, our results suggest that a firm's labour market friction risk is not relevant to most of the firm's characteristics.

Insert Table 2.4 here

Furthermore, following the Kuehn et al. (2017)'s analysis, we use the portfolio sorting approach to examine the firms' recruitment characteristics, including the hiring rate, employee growth rate, and wage level. The sample firms are sorted into decile portfolios based on their labour friction loadings (LFB), and the sorted portfolios are reformed every month. Table 2.5 reports the value-weighted average of the hiring rate, employee growth rate, and wage level for the decile portfolios. The last row of Table 2.5 shows the difference between the high and low loading (LFB) portfolios. The average hiring rate of low loading (LFB) portfolios is 4.26% while that of high loading (LFB) portfolios is -8.16%, and the difference is -12.42%. Similarly, the average employee growth rate of low (high) LFB portfolios is 18.02% (-1.06%) and the differences between high and low LFB portfolios is -19.07%, which is consistent with the result of hiring rate. The results indicate that Chinese firms with low loadings (LFB) have strong capability to hire employees on average, but those with high loadings (LFB) are more likely to layoff current employees. In addition, the average logarithm wage of low LFB portfolios is 10.9538 (about 57,180 CNY per year) while that of high LFB portfolios is 10.7162 (about 45,080 CNY per year). The difference between the high and low LFB portfolios is -0.2377 (about -12,090 CNY per year), and the result illustrates that the low LFB firms are capable to offer relatively higher wages to employees compared to high LFB firms.

In contrast, the recruitment characteristics of US firms represent opposite scenarios (Kuehn et al., 2017). The average hiring rate and employee growth rate of low LFB portfolios are negative, while that of high LFB portfolios are positive. The average wage difference between the high and low LFB portfolios is positive[5]. Firms with high loadings (LFB) are more likely to hire employees but pay less wages, and this scenario in the US market is defined as "Counter-cyclical" by Kuehn et al. (2017). Therefore, as these labour characteristics of Chinese firms is opposite to firms in the US, we argue that the recruitment pattern in China is "Cyclical".

Insert Table 2.5 here

[5] The original results are represented in Table XII of the Kuehn et al. (2017).

2.4. Result Analysis

2.4.1. Univariate Portfolio Sorting

In this section, we calculate both raw return and the risk-adjusted return for our labour market friction beta sorted portfolios estimated by asset pricing models, including the Fama-French 3-factor model (Fama & French, 1993), the Pástor and Stambaugh's (2003) 5-factor model, the Fama-French 5-factor model (Fama & French, 2015), and the Liu et al.'s (2019) China 3-factor model. Table 2.6 reports both the raw and risk-adjusted returns for the equal-weighted quintile portfolios in Panel A and value-weighted quintile portfolios in Panel B. The return differences between the highest and lowest LFB portfolios are reported in the bottom line of Table 2.6.

Table 2.6 shows that the difference in raw return between the highest and lowest labour market friction loading (LFB) portfolios is 0.0016 while portfolios are equal-weighted formed, and the difference is 0.0017 while portfolios are value-weighted formed. In other words, the highest LFB portfolios outperform the lowest LFB portfolios at 1.92% per year while equal-weighted formed and 2.04% per year while value-weighted formed. However, none of these values is statistically significant at any level. The risk-adjusted return between the highest quintile and the lowest quintile portfolios is positive and statistically significant at the 5% level for all risk-adjusted models in both panels. Panel A of Table 2.6 shows that the risk-adjusted returns between the highest quintile and the lowest quintile EW portfolios range between 0.0029 per month and 0.0045 per month, implying the highest labour market friction loading (LFB) portfolios outperform the lowest labour market friction loading (LFB) portfolios by as much as 5.40% per year for equal-weighted portfolios according to the Pástor and Stambaugh's (2003) 5-factor model. On the other hand, the risk-adjusted returns between the highest quintile and the lowest quintile value-weighted portfolios range between 0.0030 per month (3.60% per year) and 0.0045 per month (5.40% per year), as reported in Panel B.

The results in Table 2.6 suggest that the labour market friction loading (LFB) is considered an essential risk factor for asset pricing. This finding is opposite to the empirical evidence in the

US market, which suggests a negative difference between the highest and the lowest labour friction loading (LFB) portfolios. The US investor are able to short the high loading portfolios and long the low loading portfolios to arbitrage benefits from the short-sell. However, due to the absence of the short-sell mechanism in the Chinese stock market, the effect of labour friction on corporates is treated as a risky factor rather than an investment opportunity for Chinese investors because they cannot employe the short-sell approach. Therefore, the positive equity premium from the labour friction in the Chinese stock market is not the result of an investment anomaly, but represents fair price of the stock.

Insert Table 2.6 here

2.4.2. Bivariate Portfolio Sorting

In this section, we employ the bivariate portfolio sorting approach to examine whether labour market friction premiums exist in the China stock markets. Specifically, our sample stocks are first categorised into terciles based on various firm characteristics, including MB, MV, BTM, MAX, IVOL, DE, OP, AG, and CP. Next, stocks are sorted into five portfolios based on their labour market friction loading (LFB) within each firm characteristic sorted group. We then estimate the risk-adjusted returns for the 15 double-sorted portfolios using the Fama-French 5-factor model. Table 6 reports the average risk-adjusted return from the lowest loading portfolios to the highest loading portfolios based on the firm characteristic terciles for both equally-weighted and value-weighted portfolios. We also report the difference between the highest and lowest-loading portfolios[6].

[6] To save space, we only report the average risk-adjusted return from the lowest LFB to the highest LFB portfolios based on the firm characteristic terciles. However, the whole table results are available upon request.

The results in Table 2.7 show that 12 out of 18 of the average alpha spreads between the high-loading portfolio and low-loading portfolios are all highly significant, being statistically significant at the 1% level. The remaining 6 out of 18 of the average alpha spreads are also statistically significant at the 5% level. Our evidence suggests a labour friction risk premium in China when we hold portfolios for 1-month.

Insert Table 2.7 here

2.4.3. Multivariate Analysis

This section uses the Fama-MacBeth regression approach (Fama and MacBeth, 1973) to check the robustness of the significance of the labour market friction on the expected stock returns. Table 2.8 reports the results, in which the dependent variable is a stock's excess return in month t+1. The independent variable is the labour market friction loading (LFB) under various combinations of control variables presented in Column (1) to Column (11).

First, the result in Column (1) shows that the coefficient of labour market friction loading (LFB) is positive and statistically significant at the 5% level without controlling any variables. Second, the results from Column (2) to Column (10) show that the coefficients of labour market friction loading (LFB) are also positive and statistically significant at the 5% level. Moreover, we also observe significant negative coefficients of MV, MAX, IVOL, and CP, consistent with the literature (Ang et al., 2006; Bali et al., 2012; Nartea et al., 2017; Nartea and Wu, 2013). The results in Columns (4), (8), and (9) show strong positive BTM, OP, and AG effects in the China stock markets, in which all coefficients are statistically significant at the 1% level. Our results are consistent with the literature. For example, Cheema and Nartea (2014) report a significant positive BTM effect in the China stock markets from 1995 to 2013. Hou et al. (2015) and Jiang et al. (2018) find that Chinese firms with high profitability outperform substantially low-profitability firms, even controlling for firms' other characteristics and risks. Wang et al. (2015) report an asset-growth premium in the China stock markets between 1996 and 2010, supported by Chue and Xu (2022). We do not observe significant coefficients of market beta (MB) and debt-to-equity ratio (DE). Finally, the last column's result shows that the labour market friction loading (LFB) coefficient remains positive and statistically significant at the 5% level in multivariate regression.

Overall, our results indicate that firms with higher labour market friction loading (LFB) are more likely to have higher expected excess returns in the following month. The results in Table 2.8 are consistent with the findings in Table 2.7, suggesting that increasing labour market friction leads to a positive risk premium. Our results contradict Kuehn et al.'s (2017) findings in the US stock markets, in which they find a negative labour market friction premium. Our results suggest that labour market friction is likely a risk to Chinese firms, as Chinese firms post more job vacancies than job seekers. Firms cannot achieve their expected productivity and outputs when a job position remains vacant. The difference between the expected and actual outputs can be seen as firms' losses. The higher labour market friction leads to a higher risk of loss, thereby resulting in higher expected stock returns.

Insert Table 2.8 here

2.4.4. Firm Heterogeneity Analysis

In this section, we further examine the labour market friction risk premium on the various firm heterogeneity. Firstly, we examine the effect of labour productivity on labour market friction betas. The effects of vacant job positions vary across firms/industries; for example, positions producing high-value products and/or more outputs cause more losses during the vacant period. Firms with higher productivity positions may experience higher risks due to the rising labour market friction. However, recognising the productivity of individual vacant jobs is challenging. Following Jiang and Chen (2021), we use the labour-to-sales ratio (LTS) and labour costs-to-sales ratio (LCTS) as proxies to measure labour productivity, which are both defined in Table A2.1. Given constant sales, the average output per worker is more significant when firms have fewer workers, thereby a lower labour-to-sales ratio indicates a higher labour productivity. Similarly, a lower labour costs-to-sales ratio indicates a higher labour productivity.

Therefore, we expect a significant labour market friction premium to exist in firms with high labour productivity (low LTS or LCTS), but not in firms with low labour productivity (high LTS or LCTS).

We divide our sample firms into terciles based on the LTS (LCTS) and defined as low LTS (LCTS), median LTS (LCTS), and high LTS (LCTS) portfolios. Table 2.9 reports the Fama-Macbeth regression results for each sorted group. Results for the LTS sorted groups are reported in Panel A, while the LCTS sorted groups are reported in Panel B. The coefficients on LFB are positive and statistically significant at the 1% level for both low LTC and LCTS firms in Panels A and B but insignificant for medium and high LTC and LCTS firms. Therefore, the labour market friction premium is more pronounced for high labour-productivity firms.

Insert Table 2.9 here

Secondly, we examine the labour market friction premium for firms domiciled in regions with varying degrees of development. It is believed that firms in higher-development regions have high productivity (Wen, 2007; Heshmati & Su, 2014; Ren et al., 2023). Therefore, we expect a significant labour market friction premium to exist in firms located in highly developed regions but not in firms in less developed regions. Three proxies are used to measure the regional marketisation level: 1. whether a firm's headquarters is located in a provincial/non-provincial capital city; 2. whether a firm's headquarters is located in a city with a high/low level of marketisation measured by Fan et al. (2011)[7]; and 3. whether a firm's headquarters is located in a city with a relatively higher/lower education level[8]. The results in Table 2.10 show strong positive LFB coefficients for firms located in more developed regions. For example, the

[7] We measure a city as being a high development region if the city's marketisation score is higher than the median value in Fan et al.'s (2011) marketisation index.

[8] We use the number of "Project 985" and "Project 211" universities to measure a city's overall level of education. The Chinese government sponsors these universities in research and teaching. Admission into these universities is highly competitive; therefore, cities with more key universities may be considered highly developed regions.

coefficients on LFB are only positive and statistically significant for firms located in the provincial capital, in a city with a high level of marketisation, and in a city with a high level of education. In contrast, the coefficients of LBE are insignificant for firms located in other cities. Therefore, the labour market friction premium is more pronounced for firms located in highly developed cities.

Insert Table 2.10 here

Thirdly, we examine the effect of labour market friction risk on the risk-adjusted return for firms with varying levels of employee welfare. Firms offering better welfare and a good working environment are attractive to unemployed workers. Vacant positions in these firms can receive many applications and are easier to fill. Thus, the rising labour market friction only causes minor effects on these firms. In contrast, those firms that fail to offer stable and secure working conditions may encounter serious hiring difficulties. The rising labour market friction makes the hiring process more challenging, resulting in a high labour market friction risk. We use the SOE status (state-owned enterprise) and employee protection policy to classify firms' hiring difficulties. SOEs are usually considered to provide better employee welfare compared to non-SOEs (Su and Xue, 2023). We classify our sample firms into labour-protected and non-labour-protected firms, depending on: 1. whether a firm implements labour protection and/or workplace safety policies; 2. whether a firm is classified as a SOE firm or a non-SOE firm. We expect the labour market friction premium to be more pronounced for firms with poor welfare, but not for those with good welfare. Table 2.11 presents the regression results. Table 2.11 shows that the coefficients on non-labour-protected firms and non-SOE firms are positive and statistically significant at the 1% level, suggesting a more pronounced labour market friction risk.

Insert Table 2.11 here

2.4.5. Robustness Test

We undertake further robustness tests to examine the sensitivity of our results during the periods when the labour market is tighter. Specifically, we split our sample period into two subperiods based on the number of job vacancies and job seekers. We define the sub-period as low hiring difficulty if the number of job vacancies is less than the number of job seekers, as the demand is less than the labour supply. We define the sub-period as high hiring difficulty if the number of job vacancies is more than the number of job seekers, as the labour demand is greater than the labour supply. In the meantime, we generate a dummy variable, which equals to 0 when the number of job vacancies less than the number of job seekers. The dummy variable equals to 1 when the number of job vacancies over the number of job seekers. Table 2.12 presents the results from our Fama-MacBeth regressions: Models (1) and (2) are regressions for each sub-period without the dummy variable, and we use a dummy variable in Model (3) for the overall sample period. Moreover, we add an interaction term of labour market friction loading (LFB) and the dummy variable in Model (4). The coefficient on labour market friction loading (LFB) is positive and statistically significant at the 1% level in Model (2) for the high hiring difficulty sub-period, indicating that labour market friction risk is more pronounced when labour demand is greater than labour supply. This result is also supported by the positive coefficients on labour market friction loadings (LFB) in Models (3) and (4).

Insert Table 2.12 here

We also undertake another robustness test to examine the effect of labour market friction risk on risk-adjusted returns for various holding period returns. Table 2.13 presents results from our Fama-MacBeth regressions for one- to six-month holding periods. Coefficients on labour market friction loading (LFB) are positive and statistically significant at the 5% level for up to three months, indicating that the labour market friction risk is persistent in the short term.

Insert Table 2.13 here

2.4.6. Labour Market Friction Factor

Previous sections present a significant labour market friction premium in the China stock markets during the testing period. We conduct further tests by constructing a labour market friction factor and examining its explanatory power in stock portfolio returns. We follow Fama and French's (2015) method by using a 2x3 sorting approach to construct the labour market friction factor (LFF). Stocks are firstly sorted into two Size groups (Small and Big) and independently sorted into three groups (Low, Medium, and High) using the 30th and 70th percentiles of labour market friction loadings (LFB). This will provide us with six Size-LFB portfolios, i.e. SL, SM, SH, BL, BM, and BH. Then, we estimate the VW returns for each portfolio. The labour market friction factor LFF is the average return of two high labour market friction loading (LFB) portfolios minus the average return of two low labour market friction loading (LFB) portfolios. Finally, we examine the explanatory power of the LFF factor in stock portfolio returns by adding it to the Fama-French 3-factor Model, Pástor-Stambaugh Liquidity Model, or the Fama-French 5-factor Model. We also estimate the VW returns for each LBF-sorted portfolio as the dependent variable.

We expect the coefficient of LFF to be significantly different from zero if the labour market friction loading (LFB) is priced in the asset returns. Also, the coefficient of LFF should monotonically increase from low to high labour market friction loading (LFB) to confirm the positive relationship between the labour market friction loading (LFB) and stock returns. We employ the Breusch-Godfrey serial correlation LM (GB-LM) approach and the autoregressive conditional heteroscedasticity (ARCH) approach to examine the serial correlation and heteroscedasticity. The results are reported in Table 2.14, and there is no heteroscedasticity in the error terms according to the BG-LM test, while the ARCH rejects the null of no autoregressive conditional heteroscedasticity for all models.

Panel A reports the regression results for the Fama-French 3-factor model and the Fama-French 3 factors pulsing the LFF factor. First, the results show that the coefficient of LFF increases monotonically from low (-0.6653) to high (0.6355) labour market friction loading (LFB) portfolios, which is consistent with a positive labour market friction effect. More importantly, four out of five coefficients of LFF are statistically significant at the 1% level. Second, the average adjusted R square of the Fama-French 3-factor model in Panel A is 0.9159, and the average adjusted R square of the new model is 0.9893. The difference indicates that the explanatory ability of the new model for the lowest and the highest labour market friction loading (LFB) portfolios is better than the original Fama-French 3-factor model. In particular, the adjusted R square of the Fama-French 3-factor model for the lowest (highest) labour market friction loading (LFB) portfolio is 0.8091 (0.8458), while the adjusted R square of the new model is 0.9835 (0.9879). We also observe similar patterns in Panel B using the Pástor-Stambaugh Liquidity Model and in Panel C using the Fama-French 5-factor model[9].

Insert Table 2.14 here

2.5. Conclusion

Motivated by Kuehn et al. (2017), we examine the effect of labour market friction risk on the expected stock returns for a sample of 2,371 Chinese-listed firms from 2001 to 2019. Based on the search and matching model, labour market friction is measured by the ratio of available vacancies to unemployed workers. Taking into consideration non-active unemployed workers, we incorporate the labour participation rate to calculate the number of job seekers. Therefore, we use the vacancy-to-seek ratio to measure labour market friction and apply the Fama-French 5-factor model to calculate the labour market friction loading (LFB) for each sample stock.

We employ quintile-sorted portfolios to examine whether the labour market friction loading (LFB) is priced in the China stock markets. We find that the risk-adjusted returns between the highest and the lowest labour market friction loading (LFB) quintile portfolios are positive and statistically significant at the 5% level for all risk-adjusted models, with the labour market friction premium as much as 5.4% per annum under the Pástor-Stambaugh Liquidity Model. Next, we examine the labour market friction loadings (LFB) on risk-adjusted returns

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[9] We also use the EW returns for each LBF-sorted portfolio as the dependent variable and replicate our analysis. The results are quantitatively as same as the results reported above. To save space, we do not report these results. However, the results are available upon request.

using the bivariate portfolio sorting approach using various firm characteristics. Finally, significant positive labour market friction premiums still exist in our sample stocks. The multivariate Fama-Macbeth regression results further confirm our findings. Overall, our results suggest that firms with high labour market friction loading (LFB) could produce a risk premium in the following month, which is contradictory to Kuehn et al.'s (2017) findings in the US stock markets. This might be due to the unique characteristics of the Chinese labour market, in which there are more job vacancies than job seekers. Therefore, labour market friction is likely a risk to Chinese firms.

Furthermore, we explore our main findings according to various firm heterogeneities. We find that the positive labour market friction effect only significantly exists in firms with high labour productivity, highly developed regions, and poor employee welfare. We also find that our main result is more pronounced when labour demand is more than labour supply, i.e., for a hiring difficulty period. Evidence suggests that the positive labour market friction effect can last up to three months, indicating that the labour market friction risk is persistent in the short term. Finally, we create a labour market friction factor (LFF) and find that the coefficient of LFF increases monotonically from the low labour market friction loading (LFB) portfolio to the high labour market friction loading (LFB) portfolio. When we add the LFF factor to the Fama-French 3-factor model, Pástor-Stambaugh Liquidity Model, or Fama-French 5-factor Model, the new models express stronger explanatory ability than the original models.

Our study fills a vital literature gap on labour market friction risk as an essential factor in asset pricing models for the world's largest emerging market with unique labour market settings. On the one hand, our findings imply a trading strategy for investors in which investors could realise a 5% annual arbitrage risk-adjusted return by longing the highest labour market friction loading (LFB) stocks and shorting the lowest labour market friction loading (LFB) stocks. On the other hand, our results confirm that labour market friction is one of the critical factors in determining firm value. Importantly, our paper has important policy implications related to ownership structure, regional marketisation, the importance of quality education, and employee/social welfare. These are significant factors that contribute to economic growth.

Chapter 3. Labour Market Friction Effect on the Global Stock Market

Abstract

In this chapter, we examine the labour market friction effect on global stock returns for a sample of 36 markets from the North American, Asia-Pacific, and European regions for the period from 2000 to 2019. We document a significant negative relationship between a firm's labour market friction loading and expected stock returns in the North American region and a significant positive effect in the Asia-Pacific region. We do not find any significant labour market friction effect in the European region. In addition, our results suggest that the labour market friction effect is more pronounced for firms in high (low) labour-productive industries in the North American (the Asia-Pacific) region. We also find that the labour market friction effects are stronger for firms located in non-immigration and non-English speaking countries. Firms in immigration and English-speaking countries mitigate the effect due to a higher level of labour mobility. The labour market friction effect only exists in countries with restrictive social cultures but is insignificant in those with open cultures. In addition, the labour market friction effect is also strong when the inflation rate is low, but it is not significant when the inflation rate is high. These findings prove that a higher labour supply can mitigate the labour market friction effect on stock returns.

3.1. Introduction

Labour market friction, defined as the difficulty in matching vacant jobs, is widely discussed and related to business cycles and monetary policy (see Ambler et al., 2012; Cheremukhin & Restrepo-Echavarria, 2014; Patureau, 2012). Other studies use labour market friction as an underlying assumption while establishing models to investigate its relationship with corporate governance practices (see Belo et al., 2014; Hornstein et al., 2011; Pissarides, 2011; Sim & Oh, 2017). Kuehn et al. (2017) are the first to consider labour market friction as a risk factor and investigate the effect on the cross-sectional stock return in an asset pricing framework for the US stock market and document a negative relationship between labour market friction and stock returns in the period from 1951 to 2014. However, Mortensen and Pissarides (2001) emphasise the labour market differences between the US and European countries and suggest that firms are expected to react differently based on their local labour market policies. Motivated by Kuehn et al. (2017) and Mortensen and Pissarides (2001), we expand the current literature to a global setting and examine the labour market friction effect on expected stock returns in 36 countries from the North American, Asia-Pacific, and European regions, given significant labour market differences across these regions.

Under Keynesian and neoclassical models, the labour market is assumed to be frictionless based on an equilibrium condition of labour supply and demand (Keynes, 1937). Ironmonger (2000) documents that the labour force is an important ingredient in the production process, facilitating the production process. Matching jobs is considered difficult, even though a pervasive assumption in economics promotes a relationship of equal power between employers and employees, as documented in Rueschemeyer (1986) and Littek (2001). Given that this assumption may diminish the freedom in and out of the workplace and undermine legal protections, employers have the power to hire/fire staff based on certain criteria, which inevitably results in difficulties in matching jobs, thus defined as labour market friction (Lindbeck, 1999).

Kuehn et al. (2017) use the Help Wanted Index (HWI) to proxy the job vacancy, which simultaneously takes account of job advertisements posted on newspapers and websites. However, the HWI is only available in the US market and cannot be applied in an international study. In this chapter, we use the actual job vacancies published by the respective government statistic departments for the global investigation. We also take into consideration the labour market participation rate and consider only those who actively seek jobs in our sample. Due to data availability, our sample includes 36 markets in the North American, European, and Asia-Pacific regions. We find a significant negative labour market friction effect in the North American markets and a significant positive effect in the Asia-Pacific markets. Using a portfolio sorting approach, our results indicate that the North American firms with higher labour market friction loading present lower expected excess stock returns of about 4.56% per year. However, firms in Asia-Pacific markets with higher labour market friction loadings present higher expected excess stock returns of 2.64% per year on average. No significant results are observed in the European region. Our results from the Fama-MacBeth regression support our portfolio sorting results, indicating that our results are robust. A negative labour market friction effect for firms in North America and a positive labour market friction effect for firms in Asia-Pacific can be explained by the fact that firms in Asia-Pacific have a higher labour-intensive nature due to the large number of industrial companies, while firms in North America have a lower labour-intensive nature due to more technology and financial companies.

We further examine the labour market friction effect on firms with different productivity levels. Our results suggest that higher labour productivity firms are more likely affected by labour market friction in the North American region. However, lower labour productivity firms are more likely affected by labour market friction in the Asia-Pacific region. In addition, the labour market friction effect is more significant in high-technology firms in the North American region but more significant in industrial firms in the Asia-Pacific region. These results align with the previous finding, as high-technology firms are naturally capital-intensive and need employees who are highly productive, while industrial firms are naturally labour-intensive and have low requirement for labour productivity. The great number of high-technology firms leads to a high demand for high-productivity labour in North American markets, and the great number of industrial firms causes a high demand for lower-productivity labour in Asia-Pacific markets. Even though the labour market friction effect is significant in different sectors in North America and Asia-Pacific the results can be summarised, as the effect is more pronounced in high labour-demand sectors.

In addition, we investigate the effect of external labour support on labour market friction because the adequate labour supply is expected to reduce hiring difficulties. Specifically, we categorise our sample firms into immigration and non-immigration and English-speaking and non-English-speaking countries to examine the labour market friction effects. Firms domiciled in non-immigration and non-English-speaking countries are believed to have a lower level of external labour supply, and our results confirm that firms in these countries experience a higher labour market friction effect. We do not find any significant effect for all European firms due to the higher level of labour mobility and lesser language barrier. We also prove the strength of the finding by examining the labour market friction effect in markets with restrictive and permissive cultures using Value Survey Module (VSM) cultural indicators, and in low and high inflation markets using the CPI and economic inflation rates. Our results show that the labour market friction effect is only significant in restrictive cultures and low-inflation markets. We do not find any significant effect in permissive cultures and high-inflation markets.

We contribute to the existing labour market friction literature in several important aspects. Firstly, very little literature investigates the relationship between labour market friction and stock returns (see Belo et al., 2014; Kuehn et al., 2017). All the literature concentrates on the US market, but none have yet expanded their investigation to other markets. Our experiment provides empirical evidence to fill the literature gap in an international setting. It indicates that the negative labour market friction effect on stock returns in the US cannot be applied in the global market. Secondly, this chapter provides evidence that labour market friction is a significant corporate risk in sectors demanding more new labour. In North America, more vacancy demands stem from capital-intensive and high-technology firms, but in the Asia-Pacific, more vacancy demands stem from labour-intensive and industrial firms. These firms are more likely affected by labour market friction. Finally, this chapter provides a country-level mitigative approach that increases the external labour supply to reduce the effect of labour market friction.

The rest of this chapter is structured as follows. Section 2 presents the related literature and develops our hypotheses. Section 3 describes our sample data. Section 4 reports our empirical results, and Section 5 concludes.

3.2. Literature Review

3.2.1. Labour Market Friction

Economists and sociologists used New Keynesian and neoclassical models to examine the effect of the labour market on the economy, as the labour market is an important element within any economy. The labour equilibrium is determined by the demand and supply of labour. The labour market is assumed to be competitive when employers and employees are well-informed (Tomaskovic-Devey, 2013). Ironmonger (2000) documents that labour is considered a source of production in the absence of human rights concerns, thereby any unemployed worker is assumed to fill a vacant job and start the production process immediately. However, matching jobs in the real world is complicated and challenging due to the mismatch between job vacancies and unemployed labour (Hutt, 1939; Lindbeck, 1999). Employers hire staff based on candidates' qualifications, skills, and personalities. Job seekers accept offers based on working locations, remuneration, and corporate benefits and policies. Social networks also play an essential role in individual job-matching (Brass, 1985; McDonald & Elder, 2006). Therefore, the costs and difficulties in matching job vacancies and unemployed labour are usually defined as labour market friction.

Labour market friction has been widely used to understand the standard labour equilibrium model, which highlights certain economic essentials while simultaneously considering the effect of labour market friction under the neoclassical model in macroeconomics. Phelps (1968) documents that Keynes' General Theory of Employment mistakenly assumes frictionless unemployment for aggregate labour demand. This is also supported by Yashiv (2007), in that it is difficult to use a neoclassical model under frictionless assumptions in macroeconomic analysis. Results derived from a perfectly competitive model would likely cause misleading conclusions due to the substantial labour market friction (Dube et al., 2011). Ambler et al. (2012) developed a model to reflect the labour market friction impacts on the monetary policy in the US market. Patureau (2012) adds a labour market friction factor to the New Keynesian model, which helps explain business cycles in the G7 countries. Cheremukhin and Restrepo-Echavarria (2014) also document that the labour market friction shock describes approximately half of business cycle variations in the US. Sim and Oh (2017) then develop an endogenous growth model that considers labour market friction in order to analyse the labour market contributions to economic growth in Japan.

A strand of literature investigates the effects of labour market friction on corporate affairs under several labour market policy settings. Chen et al. (2011) conclude that there is a higher cost of equity for firms when the labour market is highly unionised. For example, the level of unionisation is positively related to firms' operating leverage from 1984 to 2006 in the US. Firms are likely to lose bargaining power in hiring and be forced to pay higher wages/salaries due to the sticky wages (Favilukis & Lin, 2016). In a highly unionised labour market, firms are under enormous pressure to find suitable job seekers to fill the vacant positions, which makes the labour market friction effects on a firm's operations more pronounced. Zhang (2017) reveals that unemployment insurance is essential in the US. However, unemployment insurance helps to support the living expenses of unemployed labourers. Thus, without the pressure of paying living expenses, they are more likely to remain unemployed until they are able to secure a preferred job, increasing the difficulty and costs of filling a vacant job. For non-US markets, the labour market friction effects on firms differ due to different labour market settings. Atanassov and Kim (2009) find that labour protection policies vary substantially across countries. Firms suffer higher labour expenses in high labour protection countries due to a higher labour management cost. Donovan et al. (2018) suggest that job-matching efficiency and risk significantly differ between developed and emerging countries. Skilled labourers in emerging markets have a 2 to 3 times higher probability of quitting their jobs than those in developed countries, even though emerging countries pay relatively higher wages to their skilled labourers.

The impact of labour market friction on firms can be channelled through business options. labour market friction is considered an essential premium when firms are forced to increase the expense of vacancy advertising, candidate screening, training, and remuneration. There are also indirect costs, such as adjustment costs, which need to be considered (Gries & Jungblut, 2007). The difficulty of filling vacant jobs varies when the labour market friction fluctuates; thus, a firm's labour expenses and operating leverage increase when the labour market friction rises. Danthine and Donaldson (2002) support this finding and conclude increasing operating leverage increases a firm's equity premium from 1947 to 1998 in the US market. García-Feijóo and Jorgensen (2010) also document a positive relationship between the degree of operating leverage and stock returns for a sample of US firms. Following the literature, labour market friction is a risk factor in the asset pricing model. Hence, firms with higher labour market friction sensitivities have high operational risk, and investors expect higher future returns as compensation. Therefore, we propose our first hypothesis:

H1(a)*: A significant positive relationship between a firm's labour market friction risk and the expected stock returns.*

On the other hand, firms can hedge the labour market friction risk. Belo et al. (2014) find that firms with high hiring rates present lower equity premiums because they can hedge the adjustment costs due to labour market friction fluctuations. Kuehn et al. (2017) reveal a negative relationship between labour market friction risk and expected stock returns in the US stock market. The labour market friction effect is considered an anomaly in investment activities. Investors may experience arbitrage profits through portfolio strategies, such as taking a long position in a low labour market friction risk portfolio and a short position in a high labour market friction risk portfolio. Therefore, we propose our alternative hypothesis:

H1(b)*: A significant negative relationship between a firm's labour market friction risk and the expected stock returns.*

3.2.2. Labour Demand

The labour market friction effects on corporates vary across firms and industries due to the nature of their operations. The skills required to fill vacancies also vary substantially between firms (Deming & Kahn, 2018). Capital-intensive businesses rely on large capital investments to purchase equipment before producing goods and services. With these tools and machinery, a few people can cover a complicated process, and each person can generate highly valuable outcomes. In contrast, labour-intensive businesses depend on high quantities of labour for production, spending more capital on training many labourers. Therefore, capital-intensive firms are more likely to seek highly skilled and highly productive labour, and labour-intensive firms need reliable labour but have no specific requirement for productivity. In general, capital-intensive firms are more productive than labour-intensive firms. The level of labour productivity differs across sectors in developed countries, and the differences are more pronounced in less-developed countries (Durate & Restuccia, 2010; McMillan & Rodrik, 2011).

As capital-intensive sectors are expected to generate more economic benefits, both developed and emerging countries encourage these businesses in their markets (Cameron, 1996). Nagi and Pissarides (2007) document that one important factor causing economic structure changes is the growth rate of sectoral productivity. North American and European countries have developed capital-intensive sectors over a long period of time. Asian and Latin American countries are experiencing structural change to transform firms from labour-intensive to capital-intensive sectors (ElFayoumi, 2019). In North America, an outstanding share of capital-intensive firms provide many job opportunities and present high labour demand. The more significant share of labour-intensive firms in Asia-Pacific markets still dominates labour demand.

In a frictional labour market, a firm must compete with other firms in hiring new staff if there is a limited number of labourers but for a higher number of vacant positions. Firms with high labour market friction sensitivity have less bargaining power in the hiring process. As a consequence, they are more likely to make compromises, such as offering higher compensation to fill positions swiftly. Otherwise, these firms could face extended hiring periods and high operational risks. If these high-sensitive firms also exhibit high labour demand, they take on more hiring stress, making the labour market friction effect more critical. As such, we expected that the labour market friction risk would be more pronounced in firms with high labour demand. Based on this, we propose our second hypothesis:

***H2**: The labour market friction effect on the expected stock returns is more significant in firms with high labour demand.*

3.2.3. Labour Supply

Globalisation causes substantial labour market inequality worldwide (Wood, 1998). Labour flows from poor to rich countries, emerging to developed markets, and low-growth to high-growth societies. Developed economies continuously attract skilled labour, while less developed economies are the main labour contributors due to high population growth rates (Salt, 1992). Ortega and Peri (2009) conclude that countries enjoy growth in their aggregate GDP from migrants in the short run, partially due to the capital inflows from the migrants, as documented in Gollin and Lange (2013). According to the International Migrant Stock Report 2019, global migrants rose from 5.33 billion in 1990 to 7.71 billion in 2019. Theoretically, migrants directly supplement the domestic labour market (Topel, 1986).

However, Gries and Jungblut (2007) believe that labour inflows increase local labour supply and result in a rise in unemployment. They suggest that skilled and unskilled labour inflows lead to different consequences for labour markets. Unskilled labour inflows only affect unskilled labour markets, but have no significant effects on skilled labour markets. Skilled labour inflows have negative impacts on both unskilled and skilled labour markets. Most countries are becoming more selective and prefer skilled foreign labour (Salt, 1992). For instance, Canada reformed its immigration policies, favouring more skilled migrants than less skilled ones (Antecol et al., 2003), and New Zealand has adopted similar immigration policies over time (Kahn, 2004). Compared to unskilled jobs, skilled vacant positions are more challenging to fill, and firms spend more effort hiring and training labour to achieve the position requirements.

Therefore, immigration brings an external labour supply to skilled labour markets, and firms can apply less effort to match skilled jobs, mitigating the hiring difficulty and labour friction effect on firms. In other words, firms still struggle with the labour friction effect if the market has an inadequate labour supply. Therefore, we propose our third hypothesis:

H3*: The labour friction effect on the expected stock returns is more significant in markets with low labour supply.*

3.3. Methodology

3.3.1. Sample Data

This chapter examines the labour market friction effect on the expected excess stock returns in a global setting. Due to labour market data availability, our sample contains 36 stock markets from the North American, Asia-Pacific, and European regions. Our labour market data include the number of job vacancies, the number of unemployed labourers, and the labour force participation rate for the period from 2000 to 2019[1]. The job vacancy data for countries in the

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[1] Due to labour market data availability, the sample periods are different across markets. For instance, US data starts in December 2000, and data for Canada starts in 2015. All sample data ends in 2019 due to the COVID-19 pandemic.

North American and Asia-Pacific regions are collected from the statistical departments in each country, such as the Bureau of Labour Statistics in the US, and the Ministry of Health, Labour, and Welfare in Japan. Many European countries publish labour market information through their respective government departments. However, some keep their labour market information confidential, such as Denmark. Therefore, the job vacancy data for these countries are collected from the EUROSTAT, a statistics database maintained by the European Commission. A list of countries and sources of job vacancy data is presented in Appendix Table A3.1[2].

The firm-level data are collected from various sources: COMPUSTAT and CRSP databases for the US, CSMAR database for China, and DataStream for the remaining markets. Due to the limitations of the DataStream database, we fix the sample data issues from DataStream using several approaches. The first issue is that the firm-level data on stocks are recorded continuously even if the companies were delisted from the markets, so we delete the post-delisted data from our sample based on the delisted date. Secondly, according to Ince and Porter (2006), there would be important issues of coverage and classification when using the DataStream data. Therefore, we distinguish the Class A ordinary common shares among various of classifications and eliminate the equity shares, like Class B share, preferred shares, restricted shares, closed-end funds, and exchange-traded funds. Moreover, we identify companies shares that are misclassified in multiple trading exchanges throughout the sample period and eliminate the error data from the sample. Besides, we delete the data of stocks trading with foreign currencies and focus on stocks trading with domestic currencies. To avoid survivorship bias, we also include the observations of delisted stocks during the periods when they were listed. In addition, following the suggestion of Ince and Porter (2006) and Hou and Van Dijk (2019), we adjust the equity return outliers in the DataStream data by using the winsorise approach with

[2] Job vacancies and job seekers exclude military positions.

the range from 1% to 99%, replacing the extreme values with less extreme equity returns for each stock market.

3.3.2. Labour Market Friction Risk

According to Pissarides (2000), the aggregate job matching is determined by the number of unemployed workers and the number of job vacancies, illustrated by the following equation:

$$mL = m(uL, vL) \tag{3.1}$$

where mL refers to the aggregate number of matching jobs, uL refers to the number of unemployed labourers, and vL refers to the number of unemployed labourers and vacant jobs in the labour markets. By scaling the function with the number of the aggregate labour force, an individual successful job matching is then determined by the following function:

$$m = m(u, v) \tag{3.2}$$

Therefore, the possibility of a successful job matching is derived as follows:

$$p(\theta) = m(\frac{1}{\theta}, 1) = m(\frac{u}{v}, 1) \tag{3.3}$$

where $p(\theta)$ is the probability of successful job matching. In this equation, θ is the ratio of vacant jobs and unemployed labourers, which is negatively related to the probability of successful job matching and used as the labour market friction proxy. We modify θ by eliminating individuals who are not active job seekers, and the adjusted θ is then defined as the following vacancy-to-seek ratio (VTS):

$$VTS = \frac{Job\ Vacancy}{Unemployed\ Labour \times Participation\ Rate} = \frac{Job\ Vacancy}{Job\ Seeker} \tag{3.4}$$

Therefore, we define the change of the VTS as the labour market friction shock:

$$\Delta VTS_t = log(VTS_t) - log(VTS_{t-1}) \tag{3.5}$$

Table 3.1 reports summary statistics of the labour market variables, including the mean and standard deviation of the number of vacant jobs, job seekers, vacancy-to-seek ratios, unemployed labourers, and labour participation rates. In Table 3.1, Denmark has the lowest number of vacant jobs at 4,000, the US has the highest number at 4.58 million, with China second at 4.39 million. The US and China also have the highest number of job seekers, at 5.74 million and 4.21 million, respectively. The vacancy-to-seek ratio (VTS) ranges from 0.035 in Denmark to 1.073 in Malta. China has a VTS of 1.029, indicating more job vacancies than job seekers. The number of unemployed labourers ranges from 100,000 in Luxembourg to more than 9.18 million in China, with the US at 8.95 million, being the second highest behind China. Other countries with over 1 million unemployed labourers include Canada, Japan, France, Germany, Poland, Spain, and the UK. The labour market participation rate ranges from 50.44% in China to 72.91% in Thailand, indicating there are insignificant differences in labour participation across these countries.

Insert Table 3.1 here

Following Kuehn et al. (2017), we examine the firm sensitivity of stock returns to labour market friction shocks, defined as labour market friction loading. The loadings of each stock are estimated using the following model:

$$Ret_{i,t} = \alpha_{i,t} + \beta_{i,t}^{LF} \Delta VTS_t + \beta_{i,t}^{mkt} (Rm - Rf)_t + \varepsilon_{i,t} \tag{3.6}$$

where Rm is the domestic stock market return, and Rf is the risk-free rate measured by the 10-year government bond yield in each country. The $\beta_{i,t}^{LF}$ is the labour market friction loading (LFB) of stock i in month t, and the monthly loadings are derived from 12-month rolling regressions for our sample markets. Similarly, $\beta_{i,t}^{mkt}$ is the market beta (MB) of stock i in month t.

3.4. Result Analysis

3.4.1. Panel Regression and Summary Statistics

We first conduct a panel regression for our sample markets, and Table 3.2 presents the statistics of labour market friction loadings (LFB) and the market beta (MB). Table 3.2 also involves the statistical summary of control variables, including the logarithm of market value (MV), the momentum (MOM), the maximum daily return (MAX), the idiosyncratic volatility (IVOL), the illiquidity (ILLIQ), and the short-term reversal (STR). The statistical summary of North American countries is reported in Panel A, Asia-Pacific countries in Panel B, and European countries in Panel C. The momentum (MOM) is the average stock return from month t-2 to t-12 with one month lag. The maximum daily return (MAX) is the highest daily return over the last calendar month. The idiosyncratic volatility (IVOL) is estimated using a Fama-French 3-factor model. The illiquidity (ILLIQ) is calculated using the approach developed by Amihud (2002). The short-term reversal (STR) is the t-1 monthly stock return. In Panel A, the North American sample countries have 819,864 monthly observations with 5,025 stocks per month on average, the Asia-Pacific sample countries have 1,918,127 monthly observations with 8,418 stocks per month on average, and the European sample countries have 612,331 monthly observations with 3,497 stocks per month on average. The observations with missing values are eliminated from the sample, and all variables are winsorised at 1% on both tails.

The average labour market friction loadings (LFB) equal -0.0005, 0.0090, and 0.0163 in the North American, Asia-Pacific, and European regions, respectively. The average market beta (MB) is 0.9834 in the North American sample, 0.7654 in the Asia-Pacific sample, and 0.5927 in the European sample. The mean illiquidity (ILLIQ) is -0.1497 for the North American countries, -6.7540 for the Asia-Pacific countries, and -6.7824 for the European countries, indicating that the European stock markets are less liquid than stock markets in the other two regions. The market value (MV) does not have significant differences between countries in the three regions, ranging from 18.8721 to 18.9209. There are also no significant differences in MOM, MAX, IVOL, and STR across the three regions.

Insert Table 3.2 here

3.4.2. Univariate Analysis

We use the portfolio sorting approach documented in Cattaneo et al. (2020) to examine the labour market friction effects on the expected stock returns in our sample firms from three regions: the North American, Asia-Pacific, and European regions. At the end of each month, our sample stocks in each region are independently sorted into portfolios based on their labour market friction loading (LFB) in the current month. The quintile portfolios are rebalanced every month. We then calculate both raw returns and the risk-adjusted returns for each portfolio using the Fama-French 3-factor Model (FF3), Pástor-Stambaugh Liquidity Model (PS), and the Fama-French 5-factor Model (FF5). More importantly, we also report the return differences between the highest-loading and lowest-loading portfolios. Table 3.3 reports both the equal-weighted and value-weighted portfolios' returns. Panels A, B, and C report the results for the North American, Asia-Pacific, and European markets, respectively.

The results in Panel A show that the quintile portfolio returns are positive for both the equal-weighted and value-weighted portfolios, except for the risk-adjusted returns for the highest quintile portfolios, according to the Fama-French 3-factor Model (FF3) and Pástor-Stambaugh Liquidity Model (PS). More importantly, the return differences between the highest and lowest quintile portfolios are all negative regardless of the raw returns or risk-adjusted alphas. For example, the equal-weighted (value-weighted) risk-adjusted alpha between the highest and lowest quintile portfolios for the Fama-French 3-factor Model (FF3), Pástor-Stambaugh Liquidity Model (PS), and Fama-French 5-factor Model (FF5) are -0.0031 (-0.0031), -0.0030 (-0.0031), and -0.0039 (-0.0038), respectively. Furthermore, these results are statistically significant at the 10% level, except for the results of the Fama-French 5-Factor Model, which are statistically significant at the 5% level. Our results in Panel A are aligned with Kuehn et al. (2017) and support our hypothesis H1(b).

Panel B reports the results from the Asia-Pacific region. Unlike the results reported in Panel A, we observe significant positive raw returns and risk-adjusted alphas for both the equal-weighted and value-weighted portfolios. For example, the equal-weighted and value-weighted raw returns difference between the highest and lowest quintile portfolios is 0.0021 and 0.0020, respectively, and significant at the 5% level. More importantly, the equal-weighted (value-weighted) risk-adjusted alpha between the highest and lowest quintile portfolios for the Fama-French 3-factor Model (FF3), Pastor-Stambaugh Liquidity Model (PS), and Fama-French 5-factor Model (FF5) are 0.0026 (0.0024), 0.0023 (0.0021), and 0.0023 (0.0022), respectively. Furthermore, these results are statistically significant at the 10% level except the results of the Fama-French 3-factor Model, which are statistically significant at the 5% level. These findings are consistent with our hypothesis H1(a). Panel C reports the results from the European markets, but we do not find any significant developments. It appears that a firm's labour market friction risk is irrelevant to its stock returns in the European markets.

Insert Table 3.3 here

3.4.3. Multivariate Analysis

In this section, we employ the Fama-Macbeth (1973) approach to examine the labour market friction effect on excess stock returns while controlling multiple firm characteristics. Table 3.4 reports the Fama-MacBeth regression results, in which Panel A presents the results for the North American region, Panel B for the Asia-Pacific region, and Panel C for the European region. The dependent variable is a stock's excess return in month t+1. The main independent variable is a firm's labour market friction loading (LFB) while controlling different firm characteristics, including MV, MOM, MAX, IVOL, ILLIQ, and STR.

In Panel A, all coefficients on labour market friction loading (LFB) are negative and statistically significant at the 5% level for Models (1), (2), and (3), at the 10% level for Models (4), (5) and (6), and at the 1% level for Models (7) and (8). This indicates that firms with higher labour market friction risk are more likely to have lower expected excess returns in the following month. For other control variables, the coefficients on MV are negative and statistically significant at the 5% level for Model (6) and at the 1% level for Models (7) and (8), which is consistent with Bali et al. (2011). Coefficients on IVOL are negative and statistically significant at the 1% level for Models (6), (7), and (8). These results align with Ang et al. (2006; 2009). The coefficients on ILLIQ are also negative and statistically significant at the 1% level for Models (7) and (8).

In Panel B, all coefficients on the labour market friction loading for the Asia-Pacific stock markets are positive and statistically significant at the 5% level for all models except for Model (7), which is statistically significant at the 1% level. In terms of control variables, the coefficients on MV are negative and statistically significant at the 5% level for Models (3), (4), and (5), and at the 1% level for Models (6), (7), and (8). The coefficients on MAX are negative and statistically significant at the 1% level for Models (5), (6), (7), and (8). The coefficients on IVOL are negative and statistically significant at the 1% level for Models (7) and (8). In contrast, the coefficients on ILLIQ are positive and statistically significant at the 10% level for Models (6), (7), and (8). The relationships of MV, MAX, IVOL, and ILLIQ on expected excess stock returns align with Nartea et al. (2013) and Nartea et al. (2017). However, we do not find any significant labour market friction effect on stock returns in the European region, as all coefficients are statistically insignificant, as shown in Panel C.

Overall, the results in Table 3.4 are in line with the results from our univariate analysis in Table 3.3. The results reported in Tables 3.3 and 3.4 are mixed across each region. We find a significant negative relationship between a firm's labour market friction risk and the expected stock returns in the North American region. However, the relationship is significant and positive in the Asia-Pacific countries. We do not observe any significant relationship between a firm's labour market friction risk and the expected stock returns in the European region. The following sections explore some reasons behind this phenomenon.

Insert Table 3.4 here

3.4.4. Firms Heterogeneity Analysis

To further examine the inconsistent results across each region, we start our analysis from the firm's heterogeneities. Firstly, the effect of labour productivity on labour market friction is investigated. Schneider (2011) and Giandrea and Sprague (2017) use the labour share, calculated by the aggregate labour compensation divided by total outputs, as the indicator of aggregate labour productivity in the labour market. Following this approach, we use the firm-level total revenue to labour costs ratio (RTLC) to measure a firm's labour productivity. Firms with higher RTLC have higher productivity and are more capital-intensive. Our sample categorises labour-intensive and capital-intensive firms based on the median value of RTLC.

Table 3.5 reports the Fama-MacBeth regression results for the low RTLC and high RTLC portfolios. The coefficient of labour market friction loading (LFB) is only negative and statistically significant at the 1% level for high RTLC firms in the North American markets. The coefficient of the labour market friction loading (LFB) is only positive and statistically significant at the 10% level for the lower RTLC firms in the Asia-Pacific markets. There is no significant coefficient of labour market friction loading (LFB) in both low RTLC and high RTLC firms in the European markets. The finding supports our second hypothesis H2 that high labour demand firms are more likely affected by labour market friction.

The North American markets contain many capital-intensive firms, and this number keeps increasing due to the government's encouragement of economic growth (Cameron, 1996). Therefore, capital-intensive firms present a higher labour demand in the North American markets. However, in the Asia-Pacific markets, labour-intensive firms still occupy the most prominent position. Labour-intensive firms present a higher labour demand in Asia-Pacific markets. Even though labour market friction effects are significant in different sorts of firms in North America and the Asia-Pacific region, both findings suggest that the labour market friction effect is more pronounced in firms with high labour demand.

Insert Table 3.5 here

Secondly, we examine the labour market friction effects based on firm industry categories. Intuitivelly, the effect of labour market friction is believed to be more sensitive for labour-intensive firms than non-labour-intensive firms. Industrial businesses such as manufacturing and customer services generally have lower labour productivity. The operation of such firms naturally relies on a large labour force. Technology firms generally have relatively higher labour productivity, presenting a lower labour-intensive nature. These firms invest heavily in new products and R&D projects and thus have a capital-intensive nature. Therefore, we categorise our sample firms into three sub-samples based on their business sectors, including the high-technology, industrial, and financial sectors.

Table 3.6 presents the percentage of our sample firms in each sector in the local market and specific region. In Panel A, for firms in the North American region, 65.29% of firms are in the industrial sector, 16.83% in the high-tech sector, and 17.88% in the financial sector. These divisions are 80.49%, 12.59%, and 6.93% in Panel B, respectively, for firms in the Asia-Pacific region. In Panel C, for firms in the European region, 72.06% of firms are in the industrial sector, 12.94% in the high-tech sector, and 15.00% in the financial sector. Therefore, the highest percentage of firms in the North American region are in the industrial sector, but the highest percentage are in the high-tech and financial sectors. On the other hand, the highest percentage of firms in the Asia-Pacific region are in the industrial sector, but the lowest are in the high-tech and financial sectors. This may help to explain the significant differences in the effect of labour market friction between these regions.

Insert Table 3.6 here

We use the Fama-MacBeth regression to examine the labour market friction effects on firms in different sectors, and the results are reported in Table 3.7. The labour market friction effect for firms in the high-tech sector is negative and statistically significant at the 1% level for the North American markets. The labour market friction effect for firms in the industrial sector is positive and statistically significant at the 5% level for the Asia-Pacific markets. The remaining coefficients on labour market friction are statistically insignificant. A negative effect of labour market friction on stock returns in the high-tech sector is because high-tech firms are more capital-intensive, while a positive effect of labour market friction in the industrial sector in the Asia-Pacific region is due to the high labour-intensive nature of firms in the region. These capital-intensive firms in the North American markets present a higher labour demand, but the labour-intensive firms in the Asia-Pacific markets present a higher labour demand. The findings also support our hypothesis H2 that the labour market friction effect is more significant in firms with high labour demand.

Insert Table 3.7 here

3.4.5. Labour Market Friction and External Labour Supply

It is believed that labour supply plays a specific role in the effect of labour market friction. In this section, we investigate the labour market friction effect on stock returns in countries with different degrees of external labour supply. Firstly, migrants are an important source of external labour supply. We categorise countries as migrant and non-migrant countries based on the median value of the ratio of the number of migrants to the total population in a country. This ratio is collected from the statistics of the World Migrant Report 2019. Language is considered a significant barrier preventing labour mobility across countries. It is easier for English speakers to find a job and settle quickly in another English-speaking country. Non-English speakers must learn a new language and take time to integrate into an English environment. Therefore, English-speaking countries typically have more migrants than other countries. Appendix Table A3.3 presents a list of the immigration and non-immigration countries, as well as the English-speaking and non-English-speaking countries for our sample firms. We find that all English-speaking countries have relatively higher migrant ratios (see Appendix Table A3.3).

We then undertake further analysis to examine the labour market friction effect on stock returns for immigration and non-immigration countries, and for English-speaking and non-English-speaking countries, using the Fama-MacBeth regression. The results are reported in Table 3.8. The coefficients on the labour market friction for firms from non-immigration countries are positive and statistically significant at the 5% level before controlling firm characteristics, and at the 10% level when controlling firm characteristics. The coefficients on the labour market friction for firms from non-English speaking countries are also positive and statistically significant at the 5% levels for both models. The labour market friction effects are stronger for firms in non-immigration and non-English speaking countries due to the limited external labour supply and language barrier. These findings prove our hypothesis H3 that the labour market friction effect is more significant in markets with insufficient labour supply. The results also suggest that the external labour supply can mitigate the effect of labour market friction. In addition, our findings in this section also help to explain the insignificant labour market friction effects in the European region due to the higher level of labour mobility and lower language barrier in the European Union.

Insert Table 3.8 here

3.4.6. Labour Market Friction and Social Culture

To prove the strength of the phenomenon that a higher labour supply can mitigate the labour market friction effect we examine the global labour market friction effect with the Value Survey Module (VSM) indicators (Hofstede et al., 2010). VSM involves six different indicators illustrating the culture of a society, including the Power distance index (PDI), individualism index (IDV), Masculinity Index (MAS), Uncertainty Avoidance Index (UAI), Long Term Orientation Index (LTO), and Indulgence versus Restraint Index (IVR). PDI reflects whether the people in the society have equal power; IDV reflects whether the people in the society treat themselves as the central focus; MAS reflects whether the males and females in the society have distinguished working purposes; UAI reflects whether the people in the society feel threatened by uncertainty and unknown situations; LTO reflects whether the people in the society are more likely to look forward to the future or follow traditional rules; and IVR reflects whether the people in the society are free to enjoy their life and leisure time rather than focusing on their work. Higher scores for these indicators illustrate that the society's culture has more restrictions and less freedom. Lower scores for these indicators illustrate that society is more open-minded, and people have more rights and choices.

In this chapter, the markets with higher scores are categorised as restrictive markets, and those with lower scores are categorised as permissive markets. People in a restrictive market carry many rules and pressures due to the culture. For example, in Japan, most people prefer to find a permanent job and stay in the same workplace from graduation to retirement. Japanese culture does not encourage people to change their jobs, and employees suffer critical mental stress in a new workplace (Cole, 1971; Inoue et al., 2013). Under cultural pressure, labour forces lose the ability to find a better position, or they simply remain unemployed, which makes the labour market friction worse. However, people in a permissive market do not need to worry about society's cultural pressure. They have enough freedom and power to choose their lives and jobs. If they find a workplace that can better satisfy their requirements, they are free to move, which can increase the labour supply. Therefore, the labour market friction effect in restrictive markets is expected to be significant, and the effect in permissive markets could be mitigated.

Using the Fama-MacBeth regression approach, we examine the relationship between labour market friction loading and expected excess returns in permissive and restrictive markets. Notably, as the IDV and MAS are related to personality and gender, which cannot cover the overall labour market, we only employ the PDI, UAI, LTO, and IVR to distinguish the restrictiveness or permissiveness of the market. Table 3.9 reports the regression results. Overall, we find the coefficients of labour market friction loading are positive and statistically significant at the 10% level for firms located in countries with high values of PDI, UAI, LTO, and IVR, separately. The coefficients of labour market friction loading are insignificant for firms in low UAI, low LTO, and low IVR countries. This finding is consistent with the hypothesis that the labour market friction effect is still strong in restrictive markets due to the limited labour supply, and the effect can be mitigated in permissive markets due to the higher labour mobility.

Insert Table 3.9 here

3.4.7. Labour Market Friction and Economic Condition

In addition, we examine the global labour market friction effect in the subperiods with different levels of inflation. When inflation is high in the market, the prices of products increase rapidly, and the quality of life reduces due to the higher cost of living. According to the Prospect theory (Kahneman & Tversky, 1979), people are more risk-seeking when they are suffering loss. Higher inflation and worsening life quality push labourers to take risks in order to secure a high-paying job, which increases the labour supply in the market. Firms have more opportunities to find suitable labourers to fit their vacant positions.

This chapter uses the change in the consumer price index (CPI) and inflation rate to measure inflation. Based on the change in the CPI and inflation rate, the global sample is separated into low and high inflation subperiods. We examine the relationship between labour market friction loading (LFB) and expected stock returns during the two subperiods using the Fama-MacBeth regression approach. The results are reported in Table 3.10. The coefficient of the labour market friction loading is positively significant at the 5% level in the period with the low change in the CPI, but the coefficient is not significant in the period with the high change in the CPI. The coefficient of the labour market friction loading is positively significant at a 10% level in the period with a low inflation rate, and the coefficient is not significant in the period with a high inflation rate. The results prove that the labour market friction effect is strong during the period with low inflation. The finding is consistent with the hypothesis that higher inflation can reduce the labour market friction effect because more labourers participate in job seeking. It also supports the finding that labour supply can mitigate the labour market friction effect on stock returns.

Insert Table 3.10 here

3.5. Conclusion

There is a strand of literature that focuses on labour market friction in business cycles and monetary policy, as well as on examining the relationship between labour market friction and corporate governance, corporate recruiting activities and operating activities. Kuehn et al. (2017) are the first to consider the labour market friction effect as a risk factor and link it to the stock return in a capital asset pricing framework, in which they document a negative labour market friction effect on expected stock returns in the US stock market. According to prior literature, the labour market friction shock causes difficulties for firms to match job seekers to vacant jobs. Firms spend more on hiring, training, remuneration, and administrative duties. The higher labour costs increase a firm's operating leverage, thus increasing the equity cost. Therefore, labour market friction should be positively associated with expected stock returns. In this chapter, we expand the research on labour market friction and investigate the effect on stock returns in a global market setting.

We first examine the labour market friction effect on stock returns using the portfolio sorting approach and Fama-MacBeth regression. Portfolio abnormal returns are estimated by the Fama-French 3-factor model, the Pástor-Stambaugh Liquidity model, and the Fama-French 5-factor model. The abnormal return differences between the high and low labour market friction loading portfolios are negative and statistically significant in the North American region, consistent with Kuehn et al. (2017) in their US-based study. The low labour market friction loading portfolios yield a 4.56% annual risk-adjusted premium over the high-loading portfolios. This provides a potential arbitrage opportunity to take a long position in low-loading portfolios and a short position in high-loading portfolios. However, the high minus low portfolio abnormal returns are positive and statistically significant in the Asia-Pacific region. The high-loading portfolios have a 2.64% annual premium over the low-loading portfolios. No significant results are found for the European region. Our further investigation using the Fama-MacBeth regression analysis supports the results from our portfolio approach.

Secondly, we analyse the labour market friction effects on expected stock returns for firms with different degrees of labour productivity. We find a significant effect of labour market friction in high labour-productive firms in the North American region. This phenomenon is observed in low labour-productive firms in the Asia-Pacific region. We further examine the labour market friction effect under different sectors and categorise our sample firms into industrial, high-tech, and financial sectors. The results suggest a significant negative labour market friction effect for firms in the high-tech sector in the North American region and a significant positive labour market friction effect for firms in the industrial sector in the Asia-Pacific region. These findings are consistent with labour productivity analysis.

Furthermore, we investigate the labour market friction effect for firms in countries with different and varied levels of external labour supplies. The levels of external labour supplies are measured by distinguishing whether a country is an immigration or a non-immigration country. We find that the labour market friction effect is positive and statistically significant for firms in non-immigration countries, but insignificant for firms in immigration countries. We also use English/non-English speaking as an alternative method to proxy the external labour supply levels for countries. English-speaking countries have a larger external labour supply because English-speaking people face a lower language barrier when moving to another English-speaking country. People who speak other languages have more barriers to working mobility. Our results suggest that the labour market friction effect is positive and statistically significant for firms in non-English-speaking countries. To prove the strength of our findings, we examine the labour market friction effect for firms in markets with different cultural values. The cultural differences are measured by the Value Survey Model (VSM) cultural indicators (Hofstede et al., 2010), which distinguish between restrictive and permissive cultures. We find that the labour market friction effect is only positively significant for firms located in restrictive markets, but the effect is not significant for firms in permissive markets.

Finally, we examine the labour market friction effect in markets with different inflation levels. The results show that the labour market friction effect is only significant when markets have a low inflation rate, but the effect is not significant when the inflation rate is high. These two tests can prove the benefits of labour supply because permissive markets allow people to find better jobs without any pressure, and higher inflation rates push labourers to find a position with better remuneration, which increases the internal labour supply in those markets.

Chapter 4. Labour Market Friction Effect on CSR Engagement

Abstract

This chapter investigates the relationship between firms' engagement in Corporate Social Responsibility (CSR) and their risk of labour market friction in a global setting. We find that firms with a high risk of labour market friction are more likely to engage in CSR activities. Furthermore, the positive effect of labour friction on CSR engagement is more pronounced in markets characterised by a high level of business creation and job vacancies, which can be attributed to high labour demand. This positive relationship holds consistent in markets with strong investor protections and low labour taxation rates, factors that promote business creation and expansion in conjunction with higher labour demand. Our findings remain robust in markets with a low advanced education ratio, as more labour-intensive companies require a large workforce for production. Additionally, we find that the positive effect of labour friction on CSR engagement is more pronounced in markets where labour unions have limited power. Finally, firms with low wages and low labour investment efficiency are more likely to engage in CSR activities to mitigate labour friction risk.

4.1. Introduction

In the neoclassical growth theory (Solow, 1956; Swan, 1956), technological advancement, capital accumulation, and labour force growth are viewed as essential factors that indicate a country's potential for economic growth. The applicability of this economic theory is not only at the broader economic level but also at the individual enterprise level. A firm's growth similarly hinges on improvements in technology, capital, and labour. Technological advancement is not an automatic process; it necessitates individuals who can provide insights and diligent efforts. Likewise, capital growth requires the integrated contributions of all employees, who essentially serve as the backbone of any company, determining its success or failure.

Labour markets are inherently frictional; unemployed workers do not always perfectly match vacant job positions. Job choices are often based on individual preferences, such as compensation, transportation, and working conditions. Given that employees have the right to decline job offers or leave their current positions if their needs are unsatisfied, the recruitment process becomes challenging for employers to find the “right” people. Ewing et al. (2002) suggest that employees can be viewed as internal customers and job positions as internal products. Striving to hire the most qualified candidates necessitates additional efforts to meet prospective employees' requirements, which can be costly. Alternatively, companies may compromise, hiring less ideal candidates and subsequently investing more in training to achieve full productivity. Failure to fill vacant positions results in operational delays and short-term losses. Therefore, the uncertainty inherent in job matching becomes a form of operational risk for companies, and the consequences are exacerbated when labour market frictions are high.

To mitigate the negative consequences of labour market friction risk, one effective strategy for firms is to engage in socially responsible activities. Over the years, Corporate Social Responsibility (CSR) has evolved to signify business practices that go beyond pure economic interests and positively impact stakeholders (Davis, 1960; McWilliams and Siegel, 2001; Campbell, 2007; Turker, 2009). Recently, CSR initiatives have extended to contributions to the natural environment, economy, and social community, including activities such as waste reduction, emissions control, fair customer treatment, employee rights protection, and community support. Doing these actions not only contributes to society but also enhances the firm's public image. According to brand equity theory (Keller, 1993), employees are more likely to be attracted to companies with strong symbolic characteristics and positive social images. The self-image congruency theory (Sirgy, 1982) suggests that job seekers assess whether a company's values align with their own self-image. Companies that prioritise CSR activities focused on employee rights and well-being create a more appealing work environment (Judge & Bretz, 1992). Such an environment fosters the perception that the company is a "good place to work" (Ewing et al., 2002). Therefore, CSR has evolved into a competitive advantage in labour markets. Firms with strong CSR engagement are more likely to attract a larger pool of candidates, thereby increasing the likelihood of successful job matching.

In this chapter, we investigate whether labour market friction risk encourages firms to engage in Corporate Social Responsibility (CSR) activities in the global market. Labour market friction is quantified using the ratio of job vacancies to job seekers, as suggested by Pissarides (2000). Following the methodology of Kuehn et al. (2017), labour market friction risk is estimated by regressing current stock returns against changes in labour market friction while controlling for market premiums. The loading on the change in labour friction serves as the measure of labour market friction risk, indicating a firm's sensitivity to shocks in labour market friction. Due to data availability constraints, our sample involves 27 markets across North America, the Asia-Pacific, and Europe. Using the fixed effects regression model, we examine the relationship between labour friction loading (LFB) and firms' CSR scores, controlling for year effects, industry effects, and regional effects. Our findings indicate that firms' labour market friction risk is positively correlated with their CSR engagement with statistical significance at the 1% level. This result offers strong empirical evidence for the impact of labour market friction on CSR engagement in global markets.

We further explore the impact of labour market friction on CSR engagement across markets that vary in new business density and job vacancy rates. New business density is the number of new businesses per thousand people, while job vacancy rates are the number of job vacancies scaled by the total labour force, serving as indicators of labour demand across markets. Our findings reveal that the positive impact of labour market friction on CSR engagement is more pronounced in markets with high new business density and high job vacancy rates. This suggests that firms are more inclined to engage in CSR activities in markets with high labour demand. When the labour force remains constant, increased business creation and job vacancies heighten competition in the labour market. Companies thus face intensified pressure to recruit effectively and secure talented employees. To succeed in this competitive environment, firms are motivated to enhance their social image and improve the working environment in order to attract potential employees.

Furthermore, we investigate the effect of labour friction on CSR engagement in markets with different levels of investor protection and labour taxation. Our results indicate that the positive effect of labour market friction on CSR engagement is more pronounced in markets with strong investor protection and low labour taxation rates. This is consistent with our prior findings, supporting the notion that firms are more inclined to engage in CSR activities in markets with high labour demand. To test the robustness of our results, we examine the effect of labour market friction on CSR engagement across markets with different advanced education ratios. Markets with lower levels of advanced education contain more labour-intensive companies (see Figure 1). These companies require a substantial workforce and increase the labour demand. Our findings reveal that only in markets with a low advanced education ratio is there a significant positive effect of labour market friction on CSR engagement.

Additionally, we examine the effect of labour market friction on CSR engagement in markets with varying degrees of labour union power. The result suggests that the positive effect of labour market friction is more pronounced in markets with weaker labour union power. Finally, at the firm level, we consider firms with diverse wage levels and labour investment efficiencies. The results indicate a more significant effect of labour market friction in firms that offer lower wages and have lower labour investment efficiency.

This chapter makes several contributions to the existing literature. First, it fills a gap by providing empirical evidence that labour market friction risk can drive CSR activities in a global context. Numerous studies have explored various internal and external factors influencing CSR activities, such as government regulations, investor preferences, and market competition, and most of them are qualitative. The few existing quantitative studies have a narrower focus; for instance, Platonova et al. (2018) concentrate solely on CSR performance in the banking sector, and He et al. (2022) look only at the relationship between social responsibility and managerial behaviour in China. To the best of my knowledge, no other quantitative study has investigated the drivers of CSR on a global scale. Second, this chapter suggests that corporations can compete in labour markets through their CSR performance. While most literature examines labour market competition from the perspective of employees, advising job seekers to improve personal skills and experience, only a handful of studies address corporate competition in labour markets (e.g., Bhaskar et al., 2002; Mosca & Pastore, 2009). These few studies focus solely on wage competition and ignore the role of corporate social image and the working environment. Third, prior research mainly considered labour market friction risk as a factor related only to a firm’s financial performance (Kuehn et al., 2017). This chapter is the first to connect labour market friction risk with corporate governance behaviour. Specifically, higher labour market friction risk increases firms' operational concerns, thereby motivating them to undertake CSR activities as a strategy to mitigate employee shortages.

The rest of this chapter is structured as follows. Section 2 presents the literature review of labour friction risk and CSR, and we also develop the hypotheses based on the literature. Section 3 describes our sample data and data sources. Section 4 reports our empirical results and interpretations, and Section 5 is the conclusion.

4.2. Literature Review

4.2.1. Labour Market Friction Risk

Contrary to neoclassical economic theory, which seeks to maximise personal utility and often treats humans primarily as economic inputs, the labour market in reality is far more complex (Ironmonger, 2000). The simplistic notion that an unemployed person can immediately fill a vacant position is not true; vacancies and unemployment often coexist because of imperfect job matching (Lindbeck, 1999). The hiring process extends beyond mere candidate screening to meet company requirements. Employers must also meet both the basic and intrinsic needs of employees, such as remuneration, welfare, personal achievements, and prestige. Consequently, the recruitment process can be challenging and time-consuming, and the difficulty is commonly referred to as labour market friction.

Several political factors influence labour market frictions. Atanassovv and Kim (2009) note substantial cross-country differences in labour protection policies. For instance, in the US, comprehensive unemployment insurance lessens the pressure on unemployed individuals to seek jobs, as it often covers a significant portion of living expenses (Zhang, 2017; Rothstein, 2011). In contrast, Chinese unemployment benefits are less generous, lasting only 12 months[1]. The strength and capacity of labour unions can also shift recruitment difficulty because the high bargaining power of labour unions raises the costs of hiring employees (Thelen, 2001; Favilukis & Lin, 2016). As labour market conditions and policies vary between countries and over time, employers face different challenges in filling vacancies.

However, filling a vacant position does not signal the end of recruitment challenges. Employers may still need training for new hires who fall short of position requirements to improve their productivity (Silva & Toledo, 2009). Alternatively, employers might hire

[1] According to the policy announcement by the State Council of the People's Republic of China in 2004.

overqualified employees or those seeking temporary work, who would not stay in the same job position for a long time, leading to repeated recruitment processes (Allen & Velden, 2001). A variety of factors contribute to these mismatches, ranging from individual issues to organisational structures and position characteristics (Wolbers, 2003). Research also shows that the likelihood of successful job matching differs significantly between developed and emerging economies (Donovan et al., 2018).

As labour markets grow increasingly frictional, the challenge of successfully filling job vacancies escalates, driving up costs and business uncertainty, and consequently, increasing operational risk for firms. While higher labour costs have been shown to affect operating leverage and equity premiums (Danthine & Donaldson, 2002), they also influence stock returns (García-Feijóo & Jorgensen, 2010). However, operational risk comes from various sources, arising from system and process failures, employee errors, and external events. Using operating leverage as the sole metric for labour market friction risk is insufficiently precise. Kuehn et al. (2017) were the first to propose a more targeted measure, focusing on a firm's sensitivity to labour market friction and setting the labour market friction risk apart from broader operational risks. Their study indicated that labour market friction risk can reduce expected stock returns in the US market due to investment anomalies.

4.2.2. CSR

The concept of Corporate Social Responsibility (CSR) traces its origins to the Victorian Era, during which industrialists offered non-monetary welfare benefits like education and housing to their employees (Turner, 2009). Though limited academic attention was given to the concept before the 1950s, Bowen (1953) is often credited with the foundations for modern CSR by exploring the symbiotic relationship between businesses and societies. Over the years, CSR has evolved into an essential corporate governance behaviour globally. It has expanded to encompass responsibilities toward the natural environment, economics, and business ethics. At the micro-level, CSR requires companies to manage waste and emissions, utilise recycled materials, treat customers equitably, offer employee protection and insurance, and support local communities through donations, among other actions.

Various scholars have refined the definition of CSR over time. Davis (1960) posited that CSR involves business decisions and actions extending beyond a firm's immediate economic and technical interests. This definition was later expanded by McWilliams and Siegel (2001), who argued that CSR activities should surpass mere compliance with legal requirements. Building on Freeman's Stakeholder Theory (1984), CSR is now understood as an organisation's commitment to sustaining relationships with its stakeholders. Campbell (2007) narrowed this definition to a set of minimum behavioural standards, arguing that corporations should refrain from harming stakeholders in any way. These evolving definitions share two common threads: CSR activities should beyond business self-interests and positively impact stakeholders (Turker, 2009). Moreover, stakeholders now expect companies to consider the "triple bottom line," which includes economic, social, and environmental performance (Aguinis & Glavas, 2012; El Akremi et al., 2015; Chandan & Das, 2017).

The motivations driving CSR have been rigorously examined, primarily falling into two categories: “maximising firm value" and "enhancing market competitiveness" (Baron, 2001). An abundance of empirical studies, notably in the US, have established a positive correlation between a company's CSR initiatives and its financial performance (Spicer, 1978; Anderson & Frankle, 1980; Cocharn & Wood, 1984). However, McWilliams and Siegel (2000) argue that the correlation between CSR and financial performance in the US is inconsistent due to other overriding business strategies, such as R&D. Research in other countries, such as Australia and those in the ASEAN region, also indicates a strong link between CSR activities and financial performance (Torugsa et al., 2012; Waworuntu et al., 2014; Chen and Wang, 2011). Velte's (2022) meta-analysis, incorporating 54 quantitative studies on CSR, also supports this positive correlation.

Improved financial performance is often attributed to increased market competitiveness. Because "competitiveness" is a broad concept, various studies have analysed how CSR boosts competitive advantages. Becchetti et al. (2020) argue that while CSR might increase operational costs due to high ethical and public standards, it differentiates products in the market. Firms engaged in CSR activities attract customers and investors with socially responsible preferences, willing to pay a premium for ethical practices (Riedl & Smeets, 2017). Besides, CSR acts bring stronger competitiveness against market risks. Studies show that companies engaging in CSR are better positioned to reduce the consequences of systematic risks and market downturns, as evidenced during the 2008 financial crisis (Albuquerque et al., 2019; Lin et al., 2017). This resilience ability from the trust built between firms and their stakeholders secures more long-term investments (Starks et al., 2017; Nguyen et al., 2020).

Acknowledging the CSR benefits economic and sustainability advantages, government policies increasingly advocate CSR practices (Turner, 2009). Analyses of European policies indicate that a country's social-political context significantly influences CSR performance and sustainability (Albareda et al., 2007). In China, firms that contribute to social welfare often foster stronger relationships with the government, enhancing their value (Chandan & Das, 2017). Global trends demonstrate that CSR is shifting from a voluntary obligation to a mandated code of conduct (Albareda et al., 2007; Liang & Renneboog, 2017). Moreover, institutional investors are also significant contributors to the global promotion of CSR. These investors tend to invest in firms with strong CSR preferences, thus encouraging even low-performing firms to adopt better social practices (Chen et al., 2020; Chava, 2014; Nofsinger et al., 2016; Dyck et al., 2019).

4.2.3. Link CSR and Labour Market Friction Risk

Labor market friction risk represents the operational uncertainty that arises from difficulties in recruitment, and the negative consequences that ensue when a company fails to fill its vacant positions appropriately. To mitigate the impact of labour market friction, firms can optimise their recruitment processes to increase the likelihood of successful job matching.

While employers may not have control over meeting the "ideal" candidate, they can widen the scope and scale of their recruitment efforts.

Levy (1959) argues that consumer behaviours are notably influenced by recognisable symbols in the market, and this principle can also be applied to job seekers. Drawing from Self-Concept Theory (Sirgy, 1982), individuals are more likely towards entities that align with their self-image and values. Similarly, Organizational Identity Theory (Cable & Judge, 1996) suggests that employees are naturally attracted to companies whose values, attitudes, and cultures are consistent with their own. Consequently, crafting a strong organisational brand can serve as a magnet for potential employees (Andreassen & Lanseng, 2010).

Corporate Social Responsibility (CSR) serves dual purposes, which not only represents ethical preference but also enhances a company's public image. Research by Zhu et al. (2014) and Saeidi et al. (2015) supports the notion that CSR indirectly improves a company's social image and business performance. From a marketing view, a positive corporate image provides firms with differentiated products and helps in maintaining market share (Clark & Montgomery, 1998). From a labour perspective, employees are equally concerned with CSR investments relating to the work environment, like job safety, healthcare, interpersonal relations, and overall dignity (Arnetz, 1999; Raziq & Maulabakhsh, 2015). Creating a nice work environment shapes employee perceptions, "This is a great place to work" (Ewing et al., 2002). It also significantly enhances job satisfaction, employee efficiency, and productivity (Raziq & Maulabakhsh, 2015; Taheri et al., 2020).

Furthermore, Turban and Greening (1996) argue that strong CSR performance effectively captures the attention of both existing and prospective employees. An appealing social image and work environment are expected to draw more job seekers into the recruitment process, thereby increasing the likelihood of successful job matching. Moreover, a strong corporate image serves to deepen the ties between companies and their stakeholders (Chun, 2005). Studies by Kim et al. (2010) and Riordan et al. (1997) indicate that CSR activities can maintain the relationship between employers and employees, thereby boosting employee loyalty and reducing turnover. This is proved by the Institute of Directors (1999), Cazes and Tonin (2010), and Lee et al. (2013), which suggest that companies with high CSR capabilities tend to retain employees for longer periods and benefit from increased productivity and performance.

In sum, in a period of high labour market friction, where companies compete with the downside of unsuccessful recruitment, CSR initiatives can be a strategic tool for reducing job mismatches and managing risks from labour market friction, and we propose our first hypothesis:

***H1(a)**: Firms with higher labour market friction risk are more likely to engage in CSR activities.*

However, the adoption of CSR initiatives is not without its drawbacks. Bénabou and Tirole (2010) and Masulis and Reza (2015) argue that CSR can cause managerial agency problems within organisations. Specifically, executives may over-invest in CSR activities to obtain their personal reputations by sacrificing the corporate benefit. Moreover, La Porta et al. (2000) and Masulis et al. (2009) argue that corporate leaders are more inclined to pursue investments for personal interests when companies have ample cash or liquid assets at their disposal.

Additionally, transmitting CSR initiatives to stakeholders can incur substantial costs (Dubbink et al., 2008). Beyond the operational aspects of CSR, firms may also need to acquire specialised certifications and invest in promotional activities to advertise their social commitments. Failing to do so can significantly diminish the impact of CSR efforts (Luo & Bhattacharya, 2009; Becchetti et al., 2020).

This is further complicated by the costs associated with recruitment. Operations such as advertising, candidate screening, interviews, and training demand considerable financial resources, potentially conflicting with CSR expenditures. When a firm is struggling with recruitment challenges but failing to match candidates to job vacancies, both time and money are consumed in the recruitment process. This poses a dilemma for firms operating under budget constraints, forcing them to balance the trade-offs between CSR activities and recruitment efforts. Consequently, companies facing expensive recruitment expenses are likely to decline the investment in CSR performance due to the limited resources. Therefore, we propose an alternative hypothesis:

H1(b)*: Firms with higher labour market friction risk are less likely to engage in CSR activities.*

4.2.4. Competition in Labour Market

While the majority of existing literature on business competition focuses on gaining competitive advantages in product markets, it often forgets the labour market. Porter (1980) argues that improving product quality can offer smaller businesses a niche approach against larger competitors, as superior quality often commands premium pricing. Phillips et al. (1983) argue that higher product quality does not necessarily increase costs, suggesting that firms can simultaneously cut costs and maintain quality to gain a competitive advantage. In the 1990s, businesses shifted their strategies from efficient production to mass market which relies on large-scale investments to maximise their market impact and returns (Ghemawat, 2002). Subsequent numbers of market strategies have emerged, such as integrated business models and multi-divisional corporations, but these strategies focus on product-centred approaches to capture market share.

In contrast, relatively few studies explore competition in the labour market. Bansal and DesJardine (2014) argue that a focus solely on short-term competitive strategies has not considered the need for corporate sustainability and long-term advantages. Lazonick and O'Sullivan (2000) stress that firms should aim to balance the interests of all stakeholders to sustain growth and withstand market competition. They suggest that a focus on employee performance is crucial, given that both innovation and production are highly dependent on the contributions of employees. Raziq and Maulabakhsh (2015) and Saidi et al. (2019) note that a positive work environment can promote employee productivity by mitigating distractions and concerns. Talented employees not only contribute to product or service innovation but also to operational efficiency within firms (Cummings & Oldham, 1997). As a result, competition for skilled labour has intensified to levels comparable to product market competition (Berthon et al., 2005).

In a frictional labour market where employees have the freedom to choose employers based on their needs and preferences, firms face substantial competitive pressure. This is especially true for companies requiring a large labour force, where recruitment challenges can be daunting. In labour-intensive sectors, the competition is particularly high. To enhance the likelihood of successful job matching, firms are motivated to differentiate themselves and conduct CSR activities to foster a favourable public image. Therefore, we have our second hypothesis:

***H2**: The labour market friction effect on CSR engagement is more significant in markets with high labour demand.*

4.3. Methodology

4.3.1. Sample Data

This chapter examines the labour friction effect on the CSR performance of publicly listed firms worldwide, including 5,384 firms in 28 stock markets from the North American, Asia-Pacific, and European regions. Due to the data availability, our sample only covers the period from 2002 to 2021. In the experiment, we use the firm-level CSR Strategy Score (Code: TRESGCGVSS), which is collected from the DataStream database, to measure the CSR performance of each listed firm. The CSR Strategy Score reflects the comprehensive company practices on the community in day-to-day operations. The score range is between 0 and 100, and the higher score refers to better CSR engagement. Table 4.1 shows the CSR performance summary statistics for each market in our sample. Panel A reports the CSR performance in the North American region including the US and Canada, Panel B reports the CSR performance in the Asia-Pacific region including 8 markets, and Panel C reports the CSR performance in the European region including 18 markets. Although the US market has 31772 CSR disclosures during the years, most of them have not engaged in CSR activities. The average CSR score in the US is only 18.80, which is the lowest market in our sample. Hungry has the highest average

CSR score in our sample; however, there are only 108 CSR disclosures in this market. Notably, most markets have firms with a high CSR over 99 scores, but the highest score is only 87.50 in Hungry, 87.50 in Romania, and 61.90 in Luxembourg, which means these countries do not have a well-developed CSR system and regulations.

Insert Table 4.1 here

We also collect the labour market data, including the number of vacant jobs, the number of unemployed labourers, and the labour force participation rates across markets. The labour market data of North American and Asia-Pacific markets come from the statistical department in each country. The labour market data for most European countries are published by their government departments; however, the labour market data of a few European countries are only available in the EUROSTAT database which belongs to the European Commission.

The market characteristics, including the new business density, the investor protection strength index, and labour taxation rates, are collected from the World Bank, Doing Business Database. The new business density is defined as the number of new businesses created for every one thousand people in the domestic market. The strength of investor protection is an index in the range from 0 to 30, where the higher index refers to stronger protections for the benefit of investors. The labour taxation rate is the percentage of labour tax paid by companies to the total profits. In addition, the labour force with advanced education across countries is collected from the World Bank, Education Statistics Database. It is a rate of the number of labour forces who have completed advanced education to the number of total labour forces. The labour union density is collected from the OECD Statistics and defined as the ratio of the wage level of union members to the wage level of the overall economy, which is used as a measurement indicating the power of labour unions across countries.

Furthermore, we collect the US firm characteristics from the CRSP and Compustat databases, including the risk-adjusted stock returns, market value, total assets, total debt, total shareholder's equity, net income, operating cash flows, and property, plant, and equipment. The Chinese firm data are collected from the CSMAR database. Data from the rest of the global markets are collected from the DataStream. Due to the DataStream limitation, we need multiple steps to clean these data. Firstly, the DataStream still records the same data after the firms are delisted from the market. Hence, we eliminate those mistakenly recorded data. Secondly, DataStream does not categorise Class A shares, Class B shares, preferred stocks, restricted stocks, and exchange-traded funds. We eliminate all the other types of shares and only keep the ordinary Class A shares. Lastly, firms on the same stock exchange may trade with multiple currencies, and then we eliminate those stocks traded with foreign currencies.

4.3.2. Variables

One main part of this chapter is to measure the labour friction risk for each firm. We employ the approach of Kuehn et al. (2017), which uses the corporate sensitivity of labour market friction as the measurement to indicate a firm's operational risk that comes from the labour market friction shock. In the first step, based on the theory of Pissarides (2000), labour market friction is measured by the ratio between job vacancy and unemployment. We also eliminate those who are not actively seeking jobs by multiplying the number of unemployed people by the participation rate, and then the labour market friction is measured by the vacancy-to-seek ratio (VTS):

$$VTS = \frac{Job\ Vacancy}{Unemployed\ Labour \times Participation\ Rate} = \frac{Job\ Vacancy}{Job\ Seeker} \tag{4.1}$$

The labour market friction shock is then calculated by the difference between the current and one-period lagged logarithms VTS:

$$\Delta VTS_t = log(VTS_t) - log(VTS_{t-1}) \tag{4.2}$$

According to the study of Kuehn et al. (2017), a firm's labour friction risk is estimated by regressing the current stock returns and the change of labour market friction while controlling the market premium, and the model is:

$$Ret_{i,t} = \alpha_{i,t} + \beta_{i,t}^{LF} \Delta VTS_t + \beta_{i,t}^{mkt} (Rm - Rf)_t + \varepsilon_{i,t} \tag{4.3}$$

where $Ret_{i,t}$ refers to the current stock returns in the period t, $(Rm - Rf)_t$ refers to the market premium which is the difference between the value-weighted market returns and risk-free rates in the period t. The risk-free rate uses the 10-year government bond yields in each country. Lastly, $\beta_{i,t}^{LF}$ (LFB) is the loading that reflects the labour market friction risk of each firm.

In terms of the control variables, the firm size (SIZE) is measured by the logged total assets. Tobin's Q ratio (TOBIN) is defined as the ratio of market value to total assets. The value of property, plant, and equipment (PPE) is scaled by the total assets. Similarly, the cash flows of operating activities (OCF) are scaled by the total assets as well. The leverage (LEV) is the ratio of total debt to total assets. The return on equity (ROE) is calculated using the firm net income divided by shareholder's equity. As the firms are traded with different currencies, all these values and cash flows are converted into the US dollar based on the exchange rates. Lastly, the standard deviation of stock returns (RETSTD) is calculated by the monthly dividend-adjusted stock returns during each fiscal year. The monthly dividend-adjusted stock returns of firms in the US and Chinese markets are directly collected from the CRSP, Compustat, and CSMAR databases, but the data of firms listed in markets other than the US and China are collected from the DataStream. Notably, the DataStream only provides the return index (RI), not the stock return. We calculate the dividend-adjusted stock returns based on the return index (RI), and the formula is:

$$Ret_{i,t} = \frac{RI_{i,t}}{RI_{i,t-1}} - 1 \tag{4.4}$$

where $RI_{i,t}$ refers to the return index of stock i in the month t, and $Ret_{i,t}$ is the dividend-adjusted stock return because the return index (RI) has adjusted the issue of dividend reinvestment. All these firm characteristics are adjusted by the winsorise method with the range from 1% to 99% in order to avoid bias from data outliers.

Table 4.2 is the statistical summary reporting the number of observations, mean value, standard deviation, and values of quintiles for the CSR scores, labour market friction loadings (LFB), and relevant control variables. The control variables include the number of board members (BOARD), the percentage of independent board (IBOARD), the age of firms (FAGE), the logarithm total asset (SIZE), the Tobin's Q ratio (TOBIN), the property, plant, and equipment (PPE), the operating cash flow (OCF), the firm leverage (LEV), the return on equity (ROE), and the standard deviation of stock returns (RETSTD). In our sample, there are 32,552 observations in total after eliminating the observations with any missing value. The average score of CSR is 35.7894 in the global market, and both the minimum value and the 25% percentile equal 0, which means there are at least one-fourth of firms that did not engage any CSR activity over the years. The mean value of the labour market friction loading (LFB) is 0.0045, and the range is from -2.5384 to 2.4867 in the global market. The average corporate board size (BOARD) is 10 people, the minimum corporate board has only one person, and the largest corporate board has 53 people. On average, the independent board rate (IBOARD) is 58.01%, and some firms do not have any independent board members. Interestingly, there are a few companies where all the board members are independent. The average firm age (FAGE) is 26 years, and the longest-existing corporation has operated for 71 years. The average logarithm firm size (SIZE) is 24.0069, which is about 26.67 billion US dollars, the smallest one worth 19.59 million US dollars, and the largest one worth even 7.43 trillion US dollars. The average value of Tobin's Q ratio (TOBIN) is 1.2332, roughly equal to 1, meaning most firms are generally fairly valued. However, some special cases in a few companies have been considerably undervalued with Tobin's Q down to 0.0002 or considerably overvalued with Tobin's Q up to 19.1954. The property, plant, and equipment (PPE) take 28.05% of total assets on average. Some companies spend very few costs on PPE which only takes less than 0.01% of total assets, and some companies spend a large partial of total assets, over 99.46%, to purchase PPE. The average of the operating cash flow-to-total assets (OCF), the debt-to-total assets

(LEV), the return on equity (ROE), and the standard deviation of stock returns (RETSTD) are equal to 8.04%, 34.53%, 9.30%, and 8.95%, respectively.

Insert Table 4.2 here

Table 4.3 is the Pearson correlation matrix, reporting the relationship between the CSR scores, labour friction loadings, and all the relevant control variables. It shows that the CSR scores are positively related to labour market friction loadings (LFB) at a 1% significance level. Besides, the CSR scores are also positively related to the number of board members (BOARD), the firm age (FAGE), the firm size (SIZE), the property, plant, and equipment (PPE), the operating cash flow (OCF), and return on equity (ROE) at a 1% significance level. In contrast, the CSR scores are negatively related to the percentage of independent board members (IBOARD), Tobin's Q ratio (TOBIN), the firm leverage (LEV), and the standard deviation of stock returns (RETSTD) at a 1% significance level.

Insert Table 4.3 here

4.4. Result Analysis

4.4.1. Univariate Analysis

This chapter examines the relationship between labour market friction risk and CSR engagement of firms in the global market using the fixed effect regression model. We consider the time effect, industry effect, and region effect in the examination. The time effect is based on the year of observations, and the sector effect is based on the firm industries that are categorised into six general industries according to the Global Industry Classification Standard (GICS). Table 4.4 reports the results of fixed effect regressions, indicating the relationship between labour market friction loadings (LFB) and the CSR scores. Model (1) shows that the estimated coefficient of the labour market friction loading (LFB) to the CSR score is 4.4368 at a 1% significance level while controlling the year effect and firm sector effect. Model (2) shows that the estimated coefficient of the labour market friction loading (LFB) to the CSR score is 3.4061 with a 1% significance level while considering the ten relevant control variables, including the

BOARD, IBOARD, FAGE, SIZE, TOBIN, PPE, OCF, LEV, ROE, and RETSTD, but this model does not control the year effect and firm sector effect. Model (3) shows that the estimated coefficient of the labour market friction loadings (LFB) to the CSR score is 3.4645 with a 1% significant level while simultaneously controlling the relevant control variables, the year effect, and the firm sector effect. In Model (4), we also control the region effect in the regression model, including the North American, Aisa-Pacific, and European regions, and the estimated coefficient of the labour market friction loadings (LFB) to the CSR score is 2.5368 with a 1% significance level.

The results indicate that the labour friction risk presents a significant positive effect on CSR engagement in global firms. With one standard deviation increase in labour market friction loadings (LFB), the CSR score of firms increases by 0.70 to 1.23. This empirical finding provides evidence to support our hypothesis H1(a). Firms with high labour friction risk are more worried about their labour friction risks, and then they are more likely to improve their corporate image to potential employees by investing in CSR activities. This finding is consistent with the literature of Zhu et al. (2014) and Saeidi et al. (2015), who argue that CSR activities can improve the corporate image indirectly. It is also consistent with the literature of Kim et al. (2010), who argue that CSR activities can tie the relationship between firms and employees. Therefore, prospective employees are more likely to seek a job in these high CSR firms (Turban and Greening, 1996), and current employees are less likely to leave their positions (Riordan et al., 1997). As a result, firms with good CSR performance can mitigate the negative consequences of labour friction and get benefits from sustainable business operations and high productivity[2].

Insert Table 4.4 here

[2] We also use the ESG scores as an alternative indicator of social responsibility and firm reputation. The estimated coefficients of labour friction loading (LFB) are positively significant on the ESG scores at a 1% significant level. The results are reported in Appendix Table A4.1.

4.4.2. Labour Market Friction Effect and Labour Demand

This section examines the labour market friction effect on CSR engagement in markets with different levels of labour demand. Firstly, we use the new business density and job vacancy to measure the labour requirement across the markets. The new business density refers to the number of business creations for every one thousand people, where a high density indicates more new businesses created during the year. When more businesses are running in the market, there will be more job positions which require more labourers for produce. Similarly, the level of job vacancy is the ratio of the job vacancy volume to the total number of labour forces, which also measures the labour demand in the markets. Given a constant number of labour forces, firms in markets with a higher level of labour demands are facing more intensive competition to strive for more talented or experienced employees. Otherwise, they can only find ones who are not perfectly matching the job, which might generate more costs on screening, training, and adjustment until achieving full productivity.

Table 4.5 reports the fixed effect regression results of labour market friction loading (LFB) to CSR scores in markets with different labour demands. The first two columns report the estimated coefficients of labour market friction loading (LFB) to CSR scores in low and high new business density markets. Markets are categorised as low- and high-density markets based on the median value of the new business density. The estimated coefficient of labour market friction loading (LFB) to CSR scores is positively significant at 2.2385, with a 5% significance level, for firms in high-density markets. The estimated coefficient of labour market friction loading (LFB) to CSR scores is negative but not significant for firms in low-density markets. The last two columns report the estimated coefficients of labour market friction loading (LFB) to CSR scores in low and high ratios of job vacancy markets, and the sample is defined as low- and high-vacancy markets based on the median value of job vacancy ratios. The estimated coefficient of labour market friction loading (LFB) to CSR scores is positively significant at 3.0477, with a 1% significance level, for firms in high-vacancy markets. However, the estimated coefficient of labour market friction loading (LFB) to CSR scores is insignificant for firms in low-vacancy markets. The results are consistent with our second hypothesis H2, suggesting that the labour market friction effect on CSR engagement is only significant when the markets have high labour demands. When there are a large number of vacant jobs in the labour market, firms are pushed to show their differentiation and attractiveness for more attention, and they are more likely to engage in CSR activities. In contrast, firms in markets with low labour demand have less recruitment pressure to strive for good employees, and they do not have strong motivations to improve competitive advantages in labour markets by fostering their corporate image.

Insert Table 4.5 here

Next, this section examines the labour market friction effect on CSR performance across markets with different strengths of investor protection. Investor protection help businesses to raise fund more easily, solving the problem of lacking the necessary funds and promoting business start-ups and expansions (La Porta et al., 2000; Hyytinen & Takalo, 2008; Atanassove & Kim, 2009). Our sample is separated into weak- and strong-protection markets based on the median value of the investor protection strength index. Alternatively, we also examine the labour market friction effect on CSR performance across markets with different levels of labour taxation. Labour taxation is defined as the tax contribution on labour that is paid by employers. A low labour taxation rate helps businesses save operational expenses, but higher labour taxation reduces labour demand as firms are suffering from excessive labour costs (Daveri & Tabellini, 2000). We separate our sample into low- and high-taxation markets based on the median value of their labour taxation rates. The first two columns of Table 4.6 report the estimated coefficients of labour market friction loading (LFB) to CSR scores in the weak- and strong-protection markets. The estimated coefficient of labour market friction loading (LFB) is positively associated with CSR scores in strong-protection markets at 4.716 with a 1% significance level, but the estimated coefficient is not significant in weak-protection markets. The last two columns of Table 4.6 report the estimated coefficients of labour market friction loading (LFB) to CSR scores in the low- and high-taxation markets. The result shows that the estimated coefficient of labour market friction loading (LFB) is only positively associated with

CSR scores in low-taxation markets at 2.3996 with a 1% significance level, but it is not significant in high-taxation markets. The results suggest that firms with more capital are more likely to engage in CSR activities because the strong investor protection allows them to raise funds easily and the low labour taxation helps them to save labour costs. In the meantime, the results are also consistent with our previous findings that the positive labour market friction effect is more significant in markets with high labour demand. Both the strong investor protection and the low labour taxation encourage business creation and expansion, which also brings more job opportunities and higher labour demand to the markets.

Insert Table 4.6 here

4.4.3. Robustness Test

In order to prove the strength of our findings, we examine the labour market friction effect on CSR engagement in markets with low and high ratios of advanced education. Firstly, we sort the markets into five groups based on the ratio of advanced education and define the groups as low- to high-education markets, and then we compare the average labour intensity of firms from the low- to high-education markets. Following the approach of Teicholz et al. (2001), the labour intensity is measured by the ratio of revenue to labour costs (RTLC), where a low ratio indicates the firm is more labour-intensive as the low productivity per labour investment, and a high ratio indicates the firm is more capital-intensive as the high productivity per labour investment. Figure 4.1 reports the average labour intensity of firms in the low- to high-education markets. The result shows that the average ratios of revenue to labour costs (RTLC) are monotonically increasing from the low- to high-education markets, indicating that low advanced education markets have more labour-intensive companies while high advanced education markets have more capital-intensive companies.

Insert Figure 4.1 here

Secondly, we examine the relationship between labour market friction loading (LFB) and CSR scores in low- and high-education markets using the fixed effect regression model. The low- and high-education markets are categorised based on the median value of the advanced education ratio. Table 4.7 reports the estimated coefficients of labour market friction loading (LFB) to CSR scores in the low- and high-education markets. The regression results show that the labour market friction loading (LFB) is positively associated with CSR scores in low-education markets at 2.0513 with a 1% significance level, but there is no significant relationship between the labour market friction loading (LFB) and CSR scores in high-education markets. The finding is consistent with our previous results which suggest the positive labour market friction effect is more pronounced when the markets have high labour demands. Compared with high-education markets, low-education markets have higher labour demand because the more labour-intensive companies require a large number of labourers for produce.

Insert Table 4.7 here

Furthermore, we examine the labour market friction effect on CSR engagement in markets with weak and strong labour unions. Employees might receive considerably different compensation from employers even if they are doing the same job in the same city (Bhaskar et al., 2002). Labour unions protect their members and fight for labour rights, wages, and working conditions. Based on the median value of Union Density, we generate the dummy variable reflecting the weak or strong union power of the markets, where the dummy variable equals 0 if the markets have weak union power and equals 1 if the markets have strong union power. In Table 4.8, the fixed effect regression results show that the estimated coefficient of labour market friction loading (LFB) to CSR scores is still positively significant at 1.2010 with a 10% significance level while considering the union power dummy variable. The estimated coefficient of labour market friction loading (LFB) to CSR scores is significantly positive when adding the interaction term, which multiplies the labour market friction loading (LFB) and the union power dummy variable. Notably, the interaction term is negatively significant to the CSR scores at -3.9306 with a 1% significance level. The finding suggests that a strong labour union power exhibits an inhibition effect on the labour market friction impact. In markets with a weak labour union, the working conditions and payments of employees could be considerably different in the same job. As employees feel unsafe and unfair, they are more likely to seek a job that offers fair remunerates and better working conditions. However, in a strong labour union market, employees have been well protected and they do not desire to seek jobs with good working environment and welfare. Therefore, a good corporate image cannot produce sufficient attractiveness to employees, and firms lose the strong motivation to engage in CSR activities.

Insert Table 4.8 here

Finally, we examine the labour market friction effect on CSR performance with different firm-level characteristics. We consider the situation of firms' human resources, including the wage level and labour investment efficiency. The employee data is directly collected from the CRSP, Compustat, CSMAR, and DataStream databases. The wage level is defined as the average wage per capita in a firm, which is dividing the total labour expenses by the total number of employees, and the wage level is scaled by the total assets. According to Pinnuck and Lillis (2007), the labour investment efficiency is estimated based on the model:

$$\begin{aligned}\Delta EPM_{i,t} = \alpha_0 &+ \beta_1 Sales\ Growth_{i,t} + \beta_2 Sales\ Growth_{i,t-1} + \beta_3 \Delta Profit_{i,t} + \beta_4 \Delta Profit_{i,t-1} \\ &+ \beta_5 Proft_{i,t} + \beta_6 Return_{i,t} + \beta_7 Size_{i,t-1} + \beta_8 Quick\ Ratio_{i,t-1} \\ &+ \beta_9 \Delta Quick\ Ratio_{i,t} + \beta_{10} Quick\ Ratio_{i,t-1} + \beta_{11} Leverage_{i,t-1} \\ &+ \beta_{12} \sum Sector\ Dummy_t + \beta_{13} \sum Loss\ Portfolio\ Dummy_t \\ &+ \beta_{14} \sum Gain\ Portfolio\ Dummy + \varepsilon_{i,t}\end{aligned} \tag{4.5}$$

where ΔEPM refers to the percentage change in employee numbers, the *Sales Growth* is the percentage change in total revenue. The *Profit* refers to the current net income that is scaled by total assets in the previous period, and the $\Delta Profit$ is the difference between the current net income and the net income in the previous period, which is also scaled by the total assets in the previous period. The *Return* refers to the annual stock returns, and the *Size* refers to the market value. The *Quick Ratio* is defined as the ratio of the current assets to the current liabilities, and the $\Delta Quick\ Ratio$ is the percentage change in the *Quick Ratio*. The *Leverage* is defined as the total debt divided by the total assets. The *Sector Dummy* is a series of dummy variables that indicate a firm's business sector. We categorise the business sectors based on the 4-digit Global Industry Classification Standard (GICS), and there are 27 sectors in our sample. To generate the

Loss Portfolio Dummy and *Gain Portfolio Dummy*, we first separate the firms into two groups based on their *Profit* every year. The negative *Profit* firms are categorised as loss portfolios, and the positive *Profit* firms are categorised as gain portfolios. Secondly, in each group, we sort the firms into five portfolios based on the value of *Profit*, and then we have ten portfolios in total, including five loss portfolios and five gain portfolios. Therefore, we generate the *Loss/Gain Portfolio Dummy* for the firms based on their portfolios and the dummy variables are named from *Loss-1* to *Loss-5* and from *Gain-1* to *Gain-5*. The last step is using the regression model to estimate the residual terms ($\varepsilon_{i,t}$) of each firm, and the absolute value of the residual term reflects the labour investment efficiency of stock i in the year t, where the lower value means the firms have higher efficiency and the higher value means the firms have lower efficiency.

Table 4.9 reports the regression results of labour market friction loading (LFB) to the CSR scores for firms with different wage levels and labour investment efficiencies. Based on the median value of the indicators, we separate the sample firms into two portfolios, respectively. The estimated coefficient of labour market friction loading (LFB) is positively significant for low-wage firms at a 1% significance level, but it is insignificant for high-wage firms. High-wage firms are naturally attractive to employees because people always seek a higher income. The higher compensation is their competitive advantage in the labour market. Compared with paying higher wages, low-wage firms choose to attract employees by conducting CSR activities. They are more likely to improve the working environment or implement labour protection governance as a part of welfare, standing out for themselves in the labour market.

The estimated coefficient of labour market friction loading (LFB) to the CSR score is positively significant for firms with low labour investment efficiency at a 1% significance level, and the estimated coefficient is not significant for firms with high labour investment efficiency. Firms making inefficient labour investments are suffering from two dilemmas. The first one is that firms have recruited many employees but still cannot achieve full productivity, and the other one is that firms have spent much money on hiring but cannot hire enough employees to achieve full productivity. These two scenarios represent the mismatch of vacant jobs. Firms that hire many low-productive employees are looking for high-quality employees, and firms that cannot fill their vacant positions need more candidates. Therefore, both of them are motivated to improve their attractiveness in the labour market by conducting CSR activities.

Insert Table 4.9 here

4.5. Conclusion

This chapter investigates the Corporate Social Responsibilities (CSR) behaviours promoted by the pressure of labour market frictions. Companies need to recruit adequate employees to fill their vacant positions and then achieve a sustainable business operation. However, as the labour market is naturally frictional, vacant jobs cannot automatically find a person to start producing, and humans are not machines that can be placed anywhere. Therefore, letting prospective employees accept their job offers is a challenging task for every employer, and the possibility of a successful job matching is uncertain. Based on the theory of Pissarides (2000), labour market friction is measured by the ratio of job vacancy to unemployment. Given a constant number of unemployed forces, a higher labour market friction indicates more vacant positions that do not have the right person. When labour market friction increases, the possibility of matching the job is even lower, and companies will suffer considerable uncertainty and negative consequences following the lack of employees.

To avoid the negative consequences, companies are motivated to increase the possibility of successful job matching actively. One potent approach for companies to increase the possibility of job matching is conducting Corporate Social Responsibility (CSR) activities. CSR activities can contribute to the corporate image by fostering the social image and improving the working environment. According to the theory of Sirgy (1982) and Keller (1995), employees are more likely attracted by companies with symbolic characteristics and good images, especially those who have the same values as themselves. Employees can also be attracted by a good working environment, which can protect their rights, security, and value attainment (Judge & Bretz, 1992). Therefore, firms engaged in CSR activities can attract more prospective employees to participate in their recruitment, increasing the possibility of successful job matching.

In this chapter, we investigate whether the labour market friction risk promotes firms to conduct CSR activities in the global market. Due to the data availability, our empirical analysis covers 27 markets across North America, Asia-Pacific, and Europe. Using the fixed effect regression model, we find a significant positive relationship between labour market friction loading (LFB) and CSR performance while controlling the year effect, firm industry effect, and region effect. With one standard deviation increase of labour market friction risk, the CSR score increases by 1.23. The result provides strong empirical evidence of the labour market friction effect on CSR performance in the global market.

Furthermore, this positive relationship is particularly strong in markets with high labour demand, as indicated by new business density and the ratio of job vacancies to the total labour force. As labour demands are shifted by the intensive business creation and high ratio of job vacancies, our results suggest that firms are more likely to engage in CSR activities in high labour-demand markets. The higher labour demand pushes firms to compete in the labour market for more talented employees, thereby firms are inclined to conduct CSR activities for more attractiveness. Additionally, our study reveals that this relationship is more pronounced in markets with strong investor protections and low labour taxation, suggesting that capital availability encourages business creation and expansion, thereby promoting firms' CSR initiatives. Our findings also remain robust in markets with a lower percentage of highly educated workers, which typically contain more labour-intensive companies.

Furthermore, we find that the effect of labour market friction on CSR is significant in markets where labour union influence is weak. In such environments, employees seek companies that can offer robust labour protections, fair compensation, and a positive working environment. This prompts firms to invest in CSR activities, enhancing their corporate image to attract prospective employees.

Lastly, we investigate the impact of labour market friction on firms' CSR engagement, taking into account wage levels and the efficiency of labour investment. Our findings indicate that the effect of labour market friction on CSR engagement is significantly positive only for firms that pay lower wages and have low labour investment efficiency. For such low-wage firms, offering high compensation is not a feasible competitive advantage, making them more inclined to invest in CSR activities as a recruitment magnet. Similarly, companies with weak labour investment efficiency are keen to attract talents to boost productivity, thereby enhancing their CSR activities to improve corporate image.

Chapter 5. Conclusion Remarks

5.1. Summary of Labour Market Friction Risk in the Chinese Stock Market

An abundance of literature has investigated labour market friction in economic areas, such as the impact on unemployment and wage equilibrium. Only a few studies focus on the effect of labour market friction in the financial area. Motivated by Kuehn et al. (2017) who established a model estimating firms' labour market friction risk, we can expand the labour market friction investigation in different stock markets. The first study of this thesis focuses on the labour market friction effect in the Chinese stock market. Based on previous literature, firms spend more expenses and take a longer time on the recruitment process in frictional labour markets, which increases the labour expenses, the operational leverage, and the equity premium (Danthine & Donaldson, 2002; Chen et al., 2011; Vernimmen et al., 2014; Favilukis & Lin, 2016). As labour market friction raises firms' operational risk, this study then proposes the hypothesis that labour market friction increases the expected stock returns in the Chinese stock market. However, Kuehn et al. (2017) document a negative relationship between the labour market friction risk and expected stock returns in the US market, indicating that the labour market friction risk leads to investment anomaly, and the result is opposite to the hypothesis based on previous literature. Therefore, we set an alternative hypothesis that labour market friction exhibits a negative effect on expected stock returns in the Chinese stock market. The primary purpose of this study is to investigate whether the anomaly and the negative labour market friction effect are consistent in China.

This study employs the approach of Kuehn et al. (2017) to estimate the labour market friction risks by regressing the stock returns and the change of labour market friction while controlling the market risk premium. Following the approach of Pissardes (2000), the labour market friction is measured by the ratio of the number of job vacancies to the number of job seekers. The study examines the labour market friction effect on the Chinese stock market using the sorted portfolio approach and the Fama-Macbeth regression model. As a result, we find a significant positive relationship between the labour market friction risk and expected stock returns in the Chinese stock market, and firms with high labour market friction risk significantly outperform those with low labour market friction risk. The positive relationship supports our original hypothesis and indicates that the investment anomaly is not consistent other than in the US market. The result aligns with the previous literature and suggests that labour market friction is a risk factor in the asset pricing model.

In addition, the positive labour market friction effect is more pronounced in high-productive firms, indicating that firms are more concerned about vacancies in high-productive positions because of the higher potential losses and higher risks. Firms in high-development cities are more concerned about the labour market friction effect because the labourers in these cities are more productive on average. Besides, the firms with weak labour welfare are more likely affected by the labour market friction risk as they are naturally more difficult to hire new employees than those offering good welfare. The labour market friction effect is also more pronounced during the period when labour demand exceeds labour supply. When the number of labourers is limited, firms need to compete in the labour market, and the recruitment process becomes more challenging.

This study first fills the literature on the labour market friction effect in the emerging stock market. It also provides strong empirical evidence indicating that the investment anomalies due to the labour market friction risk are not consistent other than in the US market. Notably, this study proves that labour market friction is a risk factor in the asset pricing model. Lastly, the analysis proves that the labour market friction effect can vary across firms due to different labour productivities and welfare policies. The labour market friction effect can also vary in cities that have different levels of development and labour demand.

5.2. Summary of Labour Market Friction Risk in the Global Stock Markets

Only the US or Chinese stock market phenomena cannot prove the universality of the labour market friction effect. The second study of this thesis focuses on examining the labour market friction effect on stock markets globally. As every labour market has its unique features and special situations, it would be very challenging to adjust our analysis based on every specific scenario. This study comprehensively analyses the labour market friction effect based on regions because the markets in the same region have more similarities in their labour policies and labour structures. Following the first study of this thesis, we propose two hypotheses that explore how labour market friction affects stock returns in global markets, with one hypothesis predicting a positive effect and the other one predicting a negative effect. Using the portfolio sorting approach and the Fama-Macbeth regression model, the labour market friction effect on expected stock returns is negatively significant in the North American markets, aligning with the finding of Kuehn et al. (2017). However, the labour market friction effect is positively significant in the Asia-Pacific markets, supporting our findings in the Chinese stock market. The labour market friction effects are represented in firms with different sectors across markets due to the different market structures. In North American markets, the labour market friction effect is primarily on high technology and capital-intensive firms, but the labour market friction effect is more pronounced on industrial and labour-intensive firms in Asia-Pacific.

In terms of the European markets, this study finds no significant labour market friction effect on their stock markets. The insignificant labour market friction effect can be explained by the "Free Movement of Workers" policy of the European Union, which allows their citizens to move to any other European country without restriction. Free labour mobility can increase the labour supply for the destination market and mitigate the labour market friction risk. This finding is proved by the insignificant labour market friction effect in the immigration markets and English-speaking markets, which receive a large number of foreign labourers. It is also robust to markets with high cultural permissive and high inflation, which have more labour mobilities and turnovers.

The study contributes to the literature by examining the universality of the labour market friction effect in global markets, and the results prove that the labour market friction effect on stock markets is not consistent across markets due to the different labour structures. Besides, the study suggests that the labour market friction risk is more severe for firms due to the high labour demand, but the labour market friction effect can be mitigated by increasing the labour supply.

5.3. Summary of Labour Market Friction Effect on Corporate Social Responsibility (CSR) Engagement

In the previous two studies of this thesis, labour market friction has been proven as a risk for firms. This study therefore steps ahead to investigate whether the labour market friction risk can affect corporate investment behaviours, and we focus on corporate social responsibility (CSR) engagement. As labour market friction increases the difficulty of matching the right people in the right job position, firms have to spend more expenses on the recruitment process. It also promotes corporate managers to control the labour market friction risk by increasing the possibility of successfully matching jobs. This study proposes the hypothesis that firms are more likely to engage in CSR activities due to the higher labour market friction risk. Besides, as labour demand exhibited a considerable impact on raising labour market friction risk in the previous two studies of this thesis, we also propose that firms with high labour demand are more likely to engage in CSR activities due to the more severe labour market friction risk.

Using the fixed effect regression model, the CSR performance will rise by up to 1.23 scores for each standard deviation increase in labour market friction risk while considering the year effect, industry effect, and region effect. The positive labour market friction effect driving CSR engagement is consistent in the markets with more business creations and expansions. The finding indicates that firms are more concerned with labour market friction risk in markets with high labour demand because they need to participate in more intensive labour market competition for more talented or skilled employees. From the employees' perspective, if the labour markets cannot protect their rights and welfare, employees are more likely to choose firms that have a corporate image and provide a good working environment, which also boosts the attractiveness of firms engaging in CSR activities. As a result, firms are more likely to conduct CSR activities to strive for more employees and mitigate the labour market friction risk.

This study first fills the literature on the motivations of firms conducting CSR activities, and it is the first one that links labour market friction and CSR engagement. In the meantime, it supports the previous literature arguing firms can show their social preference and improve the working environment by conducting CSR activities. This study also emphasises the importance of competition in the labour market, and it suggests to firm managers that conducting CSR activities is a good approach to attracting employees and controlling the risk from labour market friction.

5.4. Research Limitation

Even though this thesis has found strong empirical evidence regarding the labour market friction effect in global stock markets, there are still limitations in the research. First, the entire research is designed based on the firm's labour market friction risk. However, the discussion of labour market friction was only in economic studies but a few previous studies support its effect in stock markets. The only estimation model of labour market friction risk was established by Kuehn et al. (2017), and there are insufficient studies to examine its effectiveness and accuracy. The model still has the potential to adjust and improve. As the differences of labour market and specific relevant policies across countries, the effect of labour friction is expected to represent with different time intervals. The estimation of labour friction loading can also take the political factors into account. The rolling window periods of the estimation model could vary across the markets as well. In this thesis, we only employ the unified standards to estimate the labour friction risk in the global stock market to examine the general applicability of labour friction effect. For individual market, the standard estimate model could not the most suitable one and require a large number of political investigations for specific scenarios.

Second, this thesis makes the assumption that firms face labour market friction risk solely from their domestic labour markets. However, multinational corporations may also encounter recruitment challenges in foreign markets. For example, firms with overseas manufacturing facilities must hire workers from the local labour market, and this introduces an additional dimension to labour market friction risk. Moreover, the findings of this thesis offer a generalised view of labour market friction across global markets. Labour markets differ considerably due to variations in policies, labour structures, and cultures. For instance, while German firms prioritise employee qualifications, US firms tend to value experience and skill sets over formal qualifications (Rynes et al., 1997). Multi-ethnic countries have additional complexities like racial equality requirements in hiring (Waheed et al., 2015). These variances could lead to different kinds of relationships between firms and employees and diverse impacts of labour market friction.

Regarding empirical analysis, data limitations restrict the scope of the study. The thesis relies on aggregated job vacancy and unemployment data, without the granularity of information at the industry or firm level. For instance, the labour demands of construction firms differ from those in the healthcare or culinary sectors. Besides, the levels of labour demand and labour supply are not always aligned in different industries. For example, information technology has been a popular industry in recent years, and there have been a lot of people who study programming and data science. As a result, there will be adequate labour supply in the IT industry, but other industries might still be in labour shortage. Labour demands might be different across industries and across firms as well. Therefore, the estimation of labour market friction risk could be more accurate if the labour market data could be more detailed at the industry level or the firm level.

Another constraint is sample bias due to unbalanced data periods across markets and inconsistent statistical rules among countries. For example, the labour market data of Canada only covers the period from 2015 to 2019, while the US data starts from 2000 onwards. In the whole sample, the impact of Canadian data is minor. Similarly, as the numbers of listed stocks are not balanced in different exchanges, some European countries only have stocks of less than 100, but the US stocks take a large proportion of the sample. Second, based on the different statistical rules, a few countries only record the quarterly data for their labour markets, such as Canada and China. We calculate the quarterly change of labour market friction and apply the changes for the three months in a quarter. This compromised process is acceptable but still reduces the accuracy when estimating the labour market friction risk. Lastly, in examining CSR engagement, this thesis only has comprehensive CSR performance for firms in the global markets but does not have detailed CSR expenditure records. It is also challenging to distinguish CSR investments from all investment behaviours. For instance, a company established a new production line with new equipment generating less wastewater. This investment not only improves productivity but also contributes to the natural environment. Besides, not all the stock markets require listed companies to disclose CSR behaviours. In the financial reports, if the company do not disclose detailed information, people can only find general investment expenditures but cannot recognise how much of them contribute to CSR.

5.5. Future Task

As discussed above, the analytical framework of this thesis mainly relies on the labour market friction risk of each firm, and the estimation model of the labour market friction risk is according to the approach of Kuehn et al. (2017). The estimation model only focuses on the comprehensive labour market vacancy and unemployment. Due to the data limitation, the model cannot consider the detailed job vacancies for specific firms and estimate the labour market friction risk with more accuracy. The estimation could be improved by simultaneously considering more factors, such as the industry dummy, labour expenses, or business cycle. Besides, the labour market friction effects could be persistent for different periods due to the different labour market situations across markets. For instance, the labour market friction effect is significant in the long term in the US market, but the effect is only significant within one year in the Chinese market. The future research can engage on the underlying economic mechanisms to explain the long-term or short-term labour friction risk, and investigate the channels of the labour friction to corporate risks across markets. It worth further research to improve the understanding of relationship between the labour market changes and financial market performance.

Next, this thesis primarily investigates the labour market friction risk for publicly listed firms because these firms disclose sufficient information. These listed firms initially have strong abilities or high potential, which can naturally attract much attention from the public. Especially those large firms which have established stable recruitment resources have less pressure on hiring employees, and labour market friction would only make minor impacts. The labour market friction risk could be more pronounced in private firms. The investigation of the labour market friction effect could be more valuable for private firms that have not advertised themselves or are in a very beginning status. These firms desire more talented and experienced employees to help them survive and compete in the market. However, private firms are not required to disclose their information to the public, and it is challenging to collect adequate and reliable data from these private firms. If the private firm data is available and trustable, the investigation would have a high potential and make significant contributions.

In the analysis conducted by Chapelle et al. (2008), operational risk is defined as encompassing all potential risks of loss stemming from internal and external processes, people, and systems. Given the extensive scope of the operational risk, our research narrows its focus to the labour market risk. This targeted approach allows for a more detailed examination of how labour market fluctuations can influence operational stability and financial performance, without the confounding variables presented by other operational risk factors. Nevertheless, operational risk is a multifaceted concept, influenced by a plethora of factors beyond just labour market conditions. These factors include, but are not limited to, operational efficiency, technological advancements, cash flow dynamics, funding mechanisms, strategic decisions, and reputation management. Each of these elements has the potential to either mitigate or exacerbate operational risk, indicating the complex interplay between various operational risk components. Given this complexity, there is a substantial opportunity for further research in this domain. A comparative analysis that distinguishes between the impacts of different operational risk factors on financial markets would not only contribute to academic knowledge but also offer practical insights for risk management practices.

This thesis explores the connection between labour market frictions and corporations' engagement in Corporate Social Responsibility (CSR) activities. While the initial findings suggest a significant link, establishing a definitive causal relationship between these two variables requires more in-depth analysis. To unravel the complexities of this relationship, one research direction involves examining global events with significant impacts on labour markets across the world. Such events, including economic recessions, pandemics, or geopolitical tensions, can create uniform conditions that affect labour markets universally, thereby providing a unique opportunity to isolate and study the direct effects of labour market frictions on corporate decisions regarding CSR investments.

Moreover, there would be more direct and efficient risk management methods, such as advertisement expenses or social media reports, to control the labour market friction risk by increasing the possibility of successful job-matching. Further investigations could also focus on examining the efficiencies of different risk management methods on labour market friction risk. On the other hand, this thesis focuses on the labour market friction on corporate behaviours in different labour market situations. Future investigations could turn to emphasising the labour market friction effect in firms with different characteristics. For example, firms with high innovation investments demand more talented employees (Simonen & McCann, 2008), and the next investigation could expect that high-innovation firms are more concerned about the labour market friction risk, driving firms to control the risk.

One more step, further research could also investigate which factors exhibit a causal relationship to the labour market friction risk. Innovation could be a good example, and there would be more factors causing firms to face more recruitment challenges and take high labour friction risks, such as specific regulations or requirements from investors. New regulations force firms to operate additional projects, and the investors' higher expectations push firms to grow and expand. Both of them are expected to increase the demand for the labour force and raise the labour market friction risk. In contrast, there would also be some factors causing the reduction of the labour market friction risk. Government encouragement and new technology evolution urge employees to participate in specific industries, which could be potential factors reducing the labour market friction risk for related firms. The factors described above need more experiments and empirical evidence to prove their causal effects.

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Tables

Table 2.1. Summary Statistics on Labour Market Variables

This table reports the summary statistics for the relevant labour market variables including the changes in labour friction (VTS), percentage changes in vacancy number (VAC), percentage changes in job seeker numbers (SEEK), percentage changes in unemployed numbers (UNEMP), and changes in the participation rate (PART), for the period from 2000 to 2019.

			Correlations				
Symbol	Mean	Std	ΔVTS	ΔVAC	$\Delta SEEK$	$\Delta UNEMP$	$\Delta PART$
ΔVTS	0.0108	0.0505	1.0000				
ΔVAC	0.0109	0.1616	0.1966	1.0000			
$\Delta SEEK$	0.0028	0.1624	-0.1053	0.9534	1.0000		
$\Delta UNEMP$	0.0055	0.0191	-0.1487	-0.1517	-0.0963	1.0000	
$\Delta PART$	-0.0002	0.0779	-0.0697	0.9546	0.9883	-0.1842	1.0000

Table 2.2. Summary Statistics

This table presents summary statistics for the sample of the Chinese stock market from January 2001 to December 2019. Panel A reports the mean value, standard deviation, skewness, minimum value, lower quartile (25%), median, upper quartile (75%), maximum value, and the number of observations for each variable. The variables include the monthly dividend adjusted stock returns, labour friction loading, vacancy-to-seek ratio, market beta, logged market value, book-to-market ratio, maximum daily returns in the previous month, idiosyncratic risk, debt-to-equity ratio, operating profitability, asset growth rate and monthly logged stock closing price. All variables in the sample are Winsorised at the 1% level on both tails. Panel B reports the Pearson correlations for each pair of variables in our sample, where the significance is defined as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Summary Statistics

Variable	Symbol	Mean	Std	Skew	Min	25%	Median	75%	MAX	Obs.
Monthly Stock Return	Ret	0.0118	0.1338	0.5422	-0.3178	-0.0679	0.0008	0.0800	0.4584	301,502
Labour Friction Loading	LFB	-0.0190	3.0352	-0.0461	-12.3172	-0.9963	0.0000	0.9453	11.9706	301,502
Vacancy-to-Seek Ratio	VTS	1.0614	0.1224	-0.1774	0.7300	0.9700	1.0700	1.1300	1.2800	301,502
Market Beta	MB	0.9954	0.2535	0.1794	0.3643	0.8357	0.9957	1.1492	1.7776	301,502
Market Value (log)	MV	22.3432	1.1048	0.5153	20.0236	21.5751	22.2422	22.9939	25.6381	301,502
Book-to-Market Ratio	BTM	0.4925	0.3380	1.3595	0.0370	0.2507	0.4101	0.6438	1.7036	301,502
Maximum Daily Return	MAX	0.0575	0.0382	1.8164	0.0110	0.0316	0.0477	0.0721	0.2164	301,502
Idiosyncratic Risk	IVOL	0.0193	0.0100	0.9981	0.0047	0.0118	0.0173	0.0249	0.0528	301,502
Debt-to-Equity Ratio	DE	1.6454	2.1889	4.0183	0.0676	0.5456	1.0319	1.8577	15.0716	301,502
Operating Profitability	OP	0.0474	0.0852	0.5164	-0.2953	0.0128	0.0381	0.0769	0.4178	301,502
Asset Growth Rate	AG	0.1579	0.3946	4.4776	-0.4368	-0.0052	0.0784	0.2021	2.8890	301,502
Closing Price (log)	CP	2.1920	0.6516	0.3300	0.8065	1.7370	2.1518	2.6093	4.1026	301,502

Panel B Correlation Matrix

	Ret_{t+1}	LFB	MB	MV	BTM	MAX	IVOL	DE	OP	AG	CP
Ret_{t+1}	1.0000										
LFB	-0.0030	1.0000									
MB	-0.0030^{*}	-0.0085^{***}	1.0000								
MV	-0.0634^{***}	-0.0051^{***}	-0.2950^{***}	1.0000							
BTM	0.0675^{***}	0.0074^{***}	-0.2060^{***}	0.0881^{***}	1.0000						

MAX	-0.0147***	-0.0047**	0.1110***	0.0050***	-0.1809***	1.0000					
IVOL	-0.0028	-0.0039**	0.1391***	-0.0380***	-0.2648***	0.7372***	1.0000				
DE	-0.0048***	-0.0063***	-0.0169***	0.0508***	0.0161***	-0.0105***	0.0024	1.0000			
OP	0.0548***	0.0065***	-0.1878***	0.2844***	-0.0196***	-0.0101***	-0.0041**	-0.2578***	1.0000		
AG	0.0356***	0.0067***	-0.0047***	0.1329***	0.0607***	0.0478***	0.0671***	0.0077***	0.4653***	1.0000	
CP	-0.0666***	-0.0009	-0.1085***	0.4486***	-0.4402***	0.1507***	0.1844***	-0.1254***	0.3829***	0.2161***	1.0000

Table 2.3. Persistency of Labour Friction Loading

This table examines the persistence of the labour friction loading (LFB) using the Fama-MacBeth regression model. The table reports the correlation coefficients of the current labour friction loading (LFB_t) to the future labour friction loadings (LFB_{t+h}). Newey-West t-statistics are reported in the parentheses, where the significance is defined as * p < 0.1, ** p < 0.05, *** p < 0.01.

	1-month LFB	2-month LFB	3-motnh LFB	4-month LFB	5-month LFB	6-month LFB	7-month LFB	8-month LFB	9-month LFB	10-month LFB	11-month LFB	12-month LFB
LFB	0.7362***	0.5714***	0.4444***	0.3500***	0.2666***	0.1986***	0.1404***	0.1040***	0.0748***	0.0303***	-0.0120*	-0.0139*
	(36.45)	(21.95)	(15.73)	(12.14)	(9.77)	(7.78)	(6.29)	(5.45)	(5.03)	(3.17)	(-1.83)	(-1.67)
MB	-0.0482	-0.0484	-0.0480	-0.0068	0.0131	0.0160	0.0038	-0.0012	0.0105	0.0472	0.0711	0.0358
	(-0.53)	(-0.43)	(-0.39)	(-0.05)	(0.09)	(0.11)	(0.03)	(-0.01)	(0.09)	(0.59)	(1.11)	(0.59)
MV	-0.0116	-0.0120	-0.0184	-0.0274	-0.0314	-0.0373	-0.0414	-0.0433	-0.0399	-0.0370*	-0.0285	-0.0303
	(-1.01)	(-0.77)	(-1.01)	(-1.35)	(-1.31)	(-1.45)	(-1.51)	(-1.60)	(-1.60)	(-1.67)	(-1.46)	(-1.53)
BTM	-0.0084	-0.0286	-0.0460	-0.0533	-0.0594	-0.0523	-0.0367	0.0009	0.0264	0.0451	0.0625	0.0807*
	(-0.19)	(-0.39)	(-0.53)	(-0.61)	(-0.69)	(-0.64)	(-0.54)	(0.02)	(0.55)	(0.97)	(1.39)	(1.81)
MAX	-0.4938	-0.0347	-0.2282	0.2486	0.5366	0.6811	0.4626	-0.1353	0.0802	-2.1206	-0.8837**	-0.2279
	(-0.89)	(-0.05)	(-0.34)	(0.33)	(0.63)	(0.67)	(0.52)	(-0.15)	(0.08)	(-1.60)	(-2.14)	(-0.54)
IVOL	3.4956**	2.4683	3.2240	1.0339	-0.9427	-1.8777	-3.0360	-2.1691	-3.0583	0.4717	-1.3225	-0.8521
	(2.13)	(1.09)	(1.32)	(0.45)	(-0.34)	(-0.54)	(-0.84)	(-0.61)	(-1.00)	(0.17)	(-0.65)	(-0.42)
DE	-0.0039	-0.0060	-0.0074	-0.0074	-0.0071	-0.0098	-0.0102	-0.0097	-0.0084	-0.0046	-0.0027	-0.0022
	(-1.05)	(-1.21)	(-1.25)	(-1.15)	(-1.10)	(-1.48)	(-1.58)	(-1.51)	(-1.36)	(-0.82)	(-0.47)	(-0.39)
OP	-0.0909	-0.1016	-0.1184	0.0202	0.1853	0.2425	0.2710	0.2914	0.3234	0.3742	0.3926	0.3558
	(-0.71)	(-0.51)	(-0.53)	(0.08)	(0.69)	(0.95)	(1.00)	(1.12)	(1.21)	(1.42)	(1.54)	(1.38)
AG	0.0181	0.0353	0.0414	0.0363	0.0325	0.0140	-0.0122	-0.0366	-0.0714**	-0.0865***	-0.0988***	-0.1072***
	(1.04)	(1.46)	(1.46)	(1.21)	(1.07)	(0.46)	(-0.41)	(-1.27)	(-2.15)	(-2.64)	(-3.08)	(-3.45)
CP	0.0288	0.0515	0.0701	0.0741	0.0606	0.0381	0.0317	0.0346	0.0341	0.0260	0.0274	0.0254
	(0.88)	(1.08)	(1.27)	(1.21)	(0.98)	(0.63)	(0.57)	(0.69)	(0.72)	(0.64)	(0.68)	(0.65)
Cons.	0.1872	0.1354	0.2012	0.3418	0.4616	0.6533	0.8158	0.8678	0.7885	0.7695	0.5357	0.5568
	(0.55)	(0.29)	(0.36)	(0.57)	(0.67)	(0.88)	(1.07)	(1.19)	(1.20)	(1.37)	(1.27)	(1.29)
Obs.	296922	292644	289074	285998	283263	280811	278563	276394	274261	272163	270086	268016

Adj.R2	0.5924	0.3931	0.2763	0.2047	0.1594	0.1277	0.1027	0.0845	0.0720	0.0567	0.0230	0.0213

Table 2.4. Characteristics on Sorted Portfolios

This table reports the average characteristics for stock portfolios sorted based on labour friction loadings (LFB) in the Chinese market. The firm characteristics include the labour friction loading, market beta, logged market value, book-to-market ratio, maximum daily returns in the previous month, idiosyncratic risk, debt-to-equity ratio, operating profitability, asset growth rate, and logged stock closing price. According to the value of LFB, sample stocks are split into five portfolios defined as from low to high labour friction loading portfolios. The sorted portfolios are reformed each month. The last row of the table presents the differences of the average characteristics between the high and low labour friction loading portfolios. T-statistics are reported in parentheses, where the significance is defined as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Low LFB	2	3	4	High LFB	$High - Low$
LFB	-3.2461***	-1.1458***	-0.0084	1.1212***	3.1821***	6.4282***
	(-17.76)	(-14.48)	(-0.74)	(13.42)	(17.65)	(17.73)
MB	1.0102***	0.9920***	0.9850***	0.9882***	1.0083***	-0.0019
	(496.30)	(658.07)	(636.72)	(607.39)	(500.68)	(-0.55)
MV	22.2071***	22.1849***	22.1905***	22.1844***	22.1799***	-0.0272***
	(515.38)	(493.56)	(486.67)	(492.93)	(506.67)	(-2.98)
BTM	0.4350***	0.5059***	0.5293***	0.5092***	0.4416***	0.0066**
	(49.97)	(50.41)	(50.01)	(49.38)	(47.65)	(2.16)
MAX	0.0600***	0.0545***	0.0532***	0.0545***	0.0603***	0.0003
	(41.14)	(39.02)	(38.07)	(39.66)	(43.00)	(0.28)
IVOL	0.0206***	0.0181***	0.0176***	0.0182***	0.0207***	0.0001
	(56.96)	(53.52)	(52.46)	(54.29)	(61.12)	(0.37)
DE	1.6878***	1.6287***	1.6407***	1.6232***	1.6287***	-0.0591***
	(128.66)	(119.77)	(116.48)	(129.57)	(126.75)	(-3.55)
OP	0.0483***	0.0453***	0.0436***	0.0450***	0.0480***	-0.0003
	(39.47)	(48.71)	(42.96)	(47.06)	(43.78)	(-0.39)
AG	0.1719***	0.1466***	0.1410***	0.1448***	0.1751***	0.0032
	(36.32)	(39.96)	(37.67)	(37.45)	(34.57)	(1.02)
CP	2.2245***	2.1188***	2.0886***	2.1253***	2.2214***	-0.0032
	(89.62)	(88.31)	(88.19)	(89.89)	(90.59)	(-0.42)

Table 2.5. Chinese Cyclical Firm Characteristics

This table reports firms' average recruitment characteristics of sorted portfolios. Sample stocks are firstly separated into decile portfolios based on the labour friction loading (LFB), which are defined from Low LFB to High LFB portfolios, and the portfolios are reformed each month. For each portfolio, this table reports their average characteristics, including the hiring rate (HR), employee growth rate (EGR), and the logarithm wage level (WAGE). The last row of the table shows the differences of the average characteristics between the High LFB and Low LFB portfolios.

	HR	EGR	WAGE
Low LFB	0.0426	0.1802	10.9538
2	0.0215	0.1163	11.0597
3	-0.0260	0.0482	11.0355
4	0.0345	0.1010	11.0924
5	0.0286	0.1130	11.0991
6	0.0313	0.0955	11.0835
7	0.0016	0.0925	11.1142
8	0.0435	0.1552	10.9415
9	0.0135	0.1007	11.0701
High LFB	-0.0816	-0.0106	10.7162
High − Low	-0.1242	-0.1907	-0.2377

Table 2.6. Univariate Portfolio Sorting

This table reports the raw excess returns and risk-adjusted return for the sorted portfolios based on the labour friction loading (LFB) in the Chinese market. According to the value of LFB, sample stocks are split into five portfolios defined as from low to high labour friction loading portfolios. The sorted portfolios are reformed each month. This table reports the average excess returns for the sorted portfolio in the column of raw excess return. This table also reports the risk-adjusted alphas for the sorted portfolios estimated by the Fama-French 3-factor model, Pastor-Stambaugh model, Fama-French 5-factor model, and CH-3 factor model. The last row shows the differences of excess returns and estimated alphas between the high and low labour friction loading portfolios. Panel A reports the results that portfolios are formed equal-weighted, and Panel B reports the results that portfolios are formed value-weighted. T-statistics are reported in parentheses, where the significance is defined as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A. Equal-weighted Portfolios					Panel B. Value-weighted Portfolios				
	Raw Excess Return	FF3-Factor Alpha	PS Model Alpha	FF5-Factor Alpha	CH3-Factor Alpha	Raw Excess Return	FF3-Factor Alpha	PS Model Alpha	FF5-Factor Alpha	CH3-Factor Alpha
Low LFB	0.0087	0.0072	0.0060	0.0079	0.0074	0.0085	0.0071	0.0058	0.0078	0.0073
	(1.37)	(0.92)	(0.65)	(0.99)	(1.06)	(1.35)	(0.91)	(0.64)	(0.98)	(1.04)
2	0.0121*	0.0104	0.0094	0.0113	0.0111	0.0119*	0.0103	0.0093	0.0112	0.0109
	(1.94)	(1.37)	(1.05)	(1.46)	(1.61)	(1.92)	(1.36)	(1.03)	(1.45)	(1.59)
3	0.0123*	0.0112	0.0104	0.0121	0.0117*	0.0122*	0.0111	0.0103	0.0120	0.0116*
	(1.97)	(1.45)	(1.14)	(1.54)	(1.70)	(1.95)	(1.45)	(1.14)	(1.54)	(1.69)
4	0.0123**	0.0116	0.0109	0.0125	0.0119*	0.0122*	0.0115	0.0107	0.0124	0.0117*
	(1.98)	(1.51)	(1.21)	(1.60)	(1.72)	(1.96)	(1.51)	(1.20)	(1.60)	(1.71)
High LFB	0.0103	0.0107	0.0104	0.0118	0.0104	0.0102	0.0106	0.0104	0.0118	0.0103
	(1.62)	(1.36)	(1.13)	(1.48)	(1.47)	(1.61)	(1.36)	(1.12)	(1.48)	(1.46)
$High - Low$	0.0016	0.0035**	0.0045**	0.0039**	0.0029**	0.0017	0.0035**	0.0045**	0.0039**	0.0030**
	(1.29)	(2.31)	(2.51)	(2.54)	(2.17)	(1.33)	(2.32)	(2.52)	(2.56)	(2.20)

Table 2.7. Portfolio Double-Sorting Analysis

This table reports the average Jensen's alphas estimated by the Fama-French 5-factor model for the bivariate sorted portfolios based on the labour friction loading (LFB) and control variables in the Chinese market. Sample stocks are firstly separated into terciles based on a control variable, and then sorted again into five portfolios based on the labour friction loading (LFB) in each tercile. We report the average risk-adjusted return for the three portfolios with the same rank, and the last column reports the return difference between the high and low labour friction loading portfolios. Panel A reports the results of sorted portfolios based on the market beta and labour friction loading, Panel B reports the results of sorted portfolios based on the logged market value and labour friction loading, Panel C reports the results of sorted portfolios based on the book-to-market ratio and labour friction loading, Panel D reports the results of sorted portfolios based on the maximum daily returns in the previous month and labour friction loading, Panel E reports the results of sorted portfolios based on the idiosyncratic risk and labour friction loading, Panel F reports the results of sorted portfolios based on the debt-to-equity rate and labour friction loading, Panel G reports the results of sorted portfolios based on the operating profitability and labour friction loading, Panel H reports the results of sorted portfolios based on the asset growth rate and labour friction loading, and Panel I reports the results of sorted portfolios based on the logged closing price and labour friction loading. T-statistics are reported in parentheses, where the significance is defined as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Equal-weighted Portfolios (FF5-Factor Alpha)						Value-weighted Portfolios (FF5-Factor Alpha)					
	Low LFB	2	3	4	High LFB	$High - Low$	Low LFB	2	3	4	High LFB	$High - Low$
Panel A. Double sort on MB and LFB												
Average	0.0071	0.0106	0.0111	0.0116	0.0109	0.0038**	0.0070	0.0105	0.0110	0.0115	0.0109	0.0039**
	(0.91)	(1.38)	(1.44)	(1.51)	(1.39)	(2.53)	(0.90)	(1.38)	(1.44)	(1.50)	(1.39)	(2.55)
Panel B. Double sort on MV and LFB												
Average	0.0079	0.0114	0.0122	0.0121	0.0120	0.0041***	0.0078	0.0114	0.0122	0.0121	0.0120	0.0041***
	(0.99)	(1.47)	(1.57)	(1.55)	(1.50)	(2.86)	(0.98)	(1.47)	(1.57)	(1.55)	(1.50)	(2.86)
Panel C. Double sort on BTM and LFB												
Average	0.0075	0.0102	0.0108	0.0109	0.0118	0.0043***	0.0074	0.0101	0.0107	0.0108	0.0118	0.0044***
	(0.96)	(1.34)	(1.41)	(1.43)	(1.51)	(2.97)	(0.95)	(1.33)	(1.40)	(1.42)	(1.51)	(3.00)
Panel D. Double sort on MAX and LFB												
Average	0.0047	0.0083	0.0088	0.0091	0.0095	0.0048***	0.0046	0.0082	0.0088	0.0090	0.0095	0.0048***
	(0.60)	(1.06)	(1.13)	(1.16)	(1.19)	(3.39)	(0.59)	(1.06)	(1.12)	(1.16)	(1.19)	(3.42)
Panel E. Double sort on IVOL and LFB												
Average	0.0062	0.0082	0.0085	0.0094	0.0100	0.0037***	0.0061	0.0082	0.0084	0.0094	0.0099	0.0038***
	(0.81)	(1.07)	(1.09)	(1.23)	(1.27)	(2.68)	(0.80)	(1.07)	(1.09)	(1.23)	(1.27)	(2.70)

Panel F. Double sort on DE and LFB												
Average	0.0081	0.0114	0.0120	0.0124	0.0119	0.0038**	0.0080	0.0113	0.0120	0.0123	0.0118	0.0039**
	(1.03)	(1.48)	(1.57)	(1.61)	(1.51)	(2.49)	(1.02)	(1.48)	(1.57)	(1.61)	(1.51)	(2.52)
Panel G. Double sort on OP and LFB												
Average	0.0080	0.0113	0.0122	0.0127	0.0115	0.0035**	0.0079	0.0112	0.0121	0.0126	0.0114	0.0035**
	(1.03)	(1.47)	(1.59)	(1.65)	(1.46)	(2.35)	(1.01)	(1.45)	(1.58)	(1.64)	(1.44)	(2.37)
Panel H. Double sort on AG and LFB												
Average	0.0077	0.0114	0.0125	0.0123	0.0119	0.0041***	0.0076	0.0113	0.0124	0.0122	0.0118	0.0042***
	(0.99)	(1.48)	(1.63)	(1.60)	(1.51)	(2.77)	(0.97)	(1.47)	(1.62)	(1.59)	(1.50)	(2.80)
Panel I. Double sort on CP and LFB												
Average	0.0070	0.0109	0.0110	0.0115	0.0108	0.0038***	0.0069	0.0108	0.0110	0.0114	0.0108	0.0039***
	(0.89)	(1.44)	(1.44)	(1.51)	(1.37)	(2.71)	(0.88)	(1.43)	(1.44)	(1.51)	(1.37)	(2.75)

Table 2.8. Labour Friction Loading Effect on Expected Excess Returns

This table reports the correlation coefficients of labour friction loadings (LFB) to the expected excess returns $(Ret - Rf)_{t+1}$ using the Fama-MacBeth regression model. Model (1) reports the result of univariate regression, Models (2) to (10) report the results of bivariate regression with one control variable, and Model (11) reports the results of multivariate regression that simultaneously consider all control variables. The control variables include the market beta, logged market value, book-to-market ratio, maximum daily return in the previous month, idiosyncratic risk, debt-to-equity ratio, operating profitability, asset growth rate, and logged closing price. Newey-West t-statistics are reported in parentheses, where the significance is defined as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Expected Excess Returns $(Ret - Rf)_{t+1}$										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
LFB	0.0007**	0.0007**	0.0008**	0.0008**	0.0007**	0.0008**	0.0007**	0.0008**	0.0007**	0.0007**	0.0008**
	(2.03)	(1.99)	(2.30)	(2.15)	(2.14)	(2.20)	(1.99)	(2.22)	(2.04)	(2.00)	(2.59)
MB		-0.0008									0.0037
		(-0.23)									(1.46)
MV			-0.0027*								-0.0056***
			(-1.66)								(-4.43)
BTM				0.0188***							0.0096***
				(5.59)							(4.33)
MAX					-0.1528***						-0.0145
					(-7.90)						(-0.85)
IVOL						-0.8142***					-0.6778***
						(-10.58)					(-9.19)
DE							-0.0004				-0.0001
							(-1.61)				(-0.78)
OP								0.0779***			0.1040***
								(6.42)			(14.46)
AG									0.0116***		0.0034***
									(7.51)		(4.06)
CP										-0.0051*	-0.0049**
										(-1.93)	(-2.23)
Cons.	0.0097	0.0105*	0.0711*	0.0020	0.0181***	0.0261***	0.0104	0.0101	0.0082	0.0211**	0.1512***

	(1.43)	(1.94)	(1.79)	(0.28)	(2.69)	(3.70)	(1.54)	(1.50)	(1.20)	(2.01)	(4.73)
Obs.	299083	299083	299083	299083	299083	299083	299083	299083	299083	299083	299083
Adj.R2	0.0039	0.0218	0.0418	0.0216	0.0157	0.0194	0.0096	0.0295	0.0108	0.0393	0.1106

Table 2.9. Labour Friction Loading: Effect of Labour Productivity

This table reports the correlation coefficients of labour friction loadings (LFB) to the expected excess returns $(Ret - Rf)_{t+1}$ using the Fama-MacBeth regression model in firms with different labour productivities. Observations are split into three groups based on the labour productivity proxies, the ratio of labour to sales (LTS) and the ratio of labour costs to sales ($LCTS$) with breakpoints of 33.33% and 66.67%. Firms with low LTS and $LCTS$ are defined as high labour productivity firms. Newey-West t-statistics are reported in parentheses, where the significance is defined as * p < 0.1, ** p < 0.05, *** p < 0.01.

	Expected Excess Returns $(Ret - Rf)_{t+1}$					
	Panel A. Sort LTS			Panel B. Sort LCTS		
	Low	Med	High	Low	Med	High
LFB	0.0014***	0.0004	0.0000	0.0010***	0.0006	0.0006
	(3.18)	(1.19)	(0.09)	(3.16)	(1.45)	(1.46)
MB	0.0043	0.0073**	0.0029	0.0019	0.0059**	0.0036
	(1.43)	(2.58)	(1.04)	(0.67)	(2.23)	(1.21)
MV	-0.0051***	-0.0059***	-0.0064***	-0.0055***	-0.0057***	-0.0056***
	(-4.01)	(-4.25)	(-4.52)	(-4.15)	(-4.48)	(-4.23)
BTM	0.0144***	0.0092***	0.0042	0.0129***	0.0093***	0.0088***
	(5.70)	(3.24)	(1.59)	(4.88)	(3.55)	(3.37)
MAX	-0.0313	-0.0053	-0.0182	-0.0013	-0.0308	-0.0047
	(-1.27)	(-0.24)	(-0.79)	(-0.06)	(-1.41)	(-0.22)
IVOL	-0.5390***	-0.7519***	-0.6958***	-0.6987***	-0.6378***	-0.7004***
	(-5.76)	(-7.69)	(-7.61)	(-7.97)	(-7.15)	(-7.78)
DE	0.0002	-0.0002	-0.0005**	-0.0002	-0.0000	-0.0001
	(1.08)	(-0.76)	(-2.16)	(-0.70)	(-0.09)	(-0.41)
OP	0.1255***	0.1112***	0.0875***	0.1205***	0.1193***	0.0883***
	(13.38)	(12.44)	(11.15)	(13.78)	(13.18)	(10.39)
AG	0.0011	0.0033**	0.0052***	0.0023**	0.0039**	0.0045***
	(0.91)	(2.27)	(3.69)	(2.16)	(2.51)	(3.12)
CP	-0.0058**	-0.0028	-0.0067***	-0.0048**	-0.0044*	-0.0057**
	(-2.47)	(-1.30)	(-2.77)	(-2.15)	(-1.95)	(-2.43)
Cons.	0.1391***	0.1537***	0.1778***	0.1485***	0.1527***	0.1548***
	(4.34)	(4.38)	(5.03)	(4.48)	(4.71)	(4.58)
Obs.	119156	96408	82653	99677	99739	99455
Adj.R2	0.1228	0.1112	0.1049	0.1138	0.1165	0.1169

Table 2.10. Labour Friction Loading: Effect of the Level of Development

This table reports the correlation coefficients of labour friction loadings (LFB) to the expected excess returns $(Ret - Rf)_{t+1}$ using the Fama-MacBeth regression model for firms located in cities with different development level. Firstly, cities are split into two groups based on whether the city is a provincial capital city. Secondly, cities are split into two groups based on the market index, which reflect a city's marketisation. Finally, cities are split into two groups based on the number of key universities, which reflect a city's education level. Newey-West t-statistics are reported in parentheses, where the significance is defined as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Expected Excess Returns $(Ret - Rf)_{t+1}$					
	Panel A		Panel B		Panel C	
	Non-Provincial Capital	Provincial Capital	Low Marketisation	High Marketisation	Low Education	High Education
LFB	0.0003	0.0011***	0.0005	0.0009**	0.0004	0.0009***
	(0.80)	(2.86)	(1.13)	(2.29)	(1.14)	(2.72)
MB	0.0023	0.0042	0.0018	0.0053*	0.0036	0.0040
	(0.88)	(1.54)	(0.53)	(1.84)	(1.26)	(1.57)
MV	-0.0057***	-0.0054***	-0.0062***	-0.0069***	-0.0059***	-0.0053***
	(-4.29)	(-4.29)	(-4.01)	(-4.68)	(-4.45)	(-4.13)
BTM	0.0093***	0.0102***	0.0051	0.0119***	0.0094***	0.0093***
	(3.88)	(4.47)	(1.64)	(4.56)	(3.09)	(4.21)
MAX	-0.0146	-0.0154	-0.0224	-0.0089	-0.0093	-0.0141
	(-0.62)	(-0.85)	(-0.86)	(-0.44)	(-0.42)	(-0.76)
IVOL	-0.6599***	-0.6937***	-0.7713***	-0.6978***	-0.6508***	-0.7098***
	(-7.73)	(-8.65)	(-6.67)	(-8.02)	(-6.96)	(-9.44)
DE	0.0000	-0.0003	-0.0003	0.0001	0.0001	-0.0002
	(0.19)	(-1.47)	(-0.86)	(0.51)	(0.41)	(-1.01)
OP	0.1112***	0.0974***	0.1035***	0.1036***	0.1151***	0.0992***
	(13.76)	(12.52)	(10.04)	(12.30)	(12.73)	(13.85)
AG	0.0039***	0.0025**	0.0044***	0.0037***	0.0020	0.0043***
	(3.16)	(2.23)	(2.75)	(3.45)	(1.62)	(4.12)
CP	-0.0055**	-0.0042*	-0.0072**	-0.0056**	-0.0056**	-0.0045**
	(-2.36)	(-1.93)	(-2.40)	(-2.22)	(-2.28)	(-2.10)
Cons.	0.1567***	0.1467***	0.1803***	0.1832***	0.1601***	0.1460***
	(4.68)	(4.57)	(4.66)	(4.95)	(4.81)	(4.45)
Obs.	148461	150622	54166	172197	97268	201723
Adj.R2	0.1173	0.1123	0.1206	0.1203	0.1140	0.1138

Table 2.11. Labour Friction Loading: Effect of Labour Welfare

This table reports the correlation coefficients of labour friction loadings (LFB) to the expected excess returns $(Ret - Rf)_{t+1}$ using the Fama-MacBeth regression model for firms with different labour welfare. Firms are classified as good welfare firms if they announce labour protection or working safety policies, or if they are state-owned-entertainment (SOE) firms. Newey-West t-statistics are reported in parentheses, where the significance is defined as * p < 0.1, ** p < 0.05, *** p < 0.01.

	Expected Excess Returns $(Ret - Rf)_{t+1}$			
	Non-Labour-Protected	Labour-Protected	Non-SOE	SOE
LFB	0.0008***	-0.0002	0.0009***	0.0004
	(2.61)	(-0.24)	(2.99)	(1.25)
MB	0.0044*	-0.0066	0.0021	0.0052*
	(1.91)	(-0.94)	(0.83)	(1.74)
MV	-0.0067***	-0.0054***	-0.0060***	-0.0055***
	(-5.10)	(-2.69)	(-4.31)	(-4.42)
BTM	0.0086***	0.0088	0.0117***	0.0100***
	(3.67)	(1.42)	(4.79)	(4.46)
MAX	-0.0186	0.0903	-0.0203	-0.0058
	(-1.07)	(1.22)	(-0.93)	(-0.30)
IVOL	-0.6953***	-0.6057***	-0.6994***	-0.6916***
	(-9.46)	(-3.35)	(-7.14)	(-8.39)
DE	-0.0004*	0.0009	-0.0002	0.0002
	(-1.93)	(0.97)	(-1.10)	(0.71)
OP	0.1016***	0.0916***	0.0963***	0.1141***
	(14.09)	(4.76)	(12.76)	(12.98)
AG	0.0035***	0.0090*	0.0039***	0.0020*
	(3.92)	(1.70)	(2.88)	(1.80)
CP	-0.0051**	-0.0028	-0.0047*	-0.0043*
	(-2.29)	(-0.94)	(-1.94)	(-1.96)
Cons.	0.1781***	0.1527***	0.1634***	0.1481***
	(5.35)	(3.01)	(4.67)	(4.69)
Obs.	223130	75953	138780	160303
Adj.R2	0.0999	0.1491	0.1056	0.1172

Table 2.12. Labour Friction Loading Effect in Subperiods

This table reports the effects of the labour friction loadings (LFB) on the expected excess returns $(Ret - Rf)_{t+1}$ using the Fama-MacBeth regression model for two subperiods. The sample period is split into two subperiods based on the job vacancy and job seeker volumes. Model (1) shows the results for the subperiod in which job vacancy volume is less than job seeker volume, and Model (2) show the results for the subperiod in which job vacancy volume is greater than job seeker volume. This table also shows the results for the regressions with a dummy variable in Model (3) and a dummy interaction term in Model (4). The dummy variable equals to zero if the job vacancy volume is less than the job seeker volume, and it equals to one if the job vacancy volume is greater than the job seeker volume. Newey-West t-statistics are reported in parentheses, where the significance is defined as * p < 0.1, ** p < 0.05, *** p < 0.01.

	Expected Excess Returns $(Ret - Rf)_{t+1}$			
	(1) $VAC < SEEK$	(2) $VAC > SEEK$	(3)	(4)
LFB	0.0008	0.0007***	0.0008**	0.0006**
	(1.42)	(2.88)	(2.59)	(1.98)
Dummy $\begin{pmatrix} Dummy = 0, & if\ VAC < SEEK \\ Dummy = 1, & if\ VAC > SEEK \end{pmatrix}$			0.0459***	0.0619***
			(2.87)	(4.10)
LFB × Dummy				0.0002*
				(1.87)
MB	0.0077**	0.0002	0.0037	0.0037
	(2.16)	(0.06)	(1.46)	(1.46)
MV	-0.0035*	-0.0073***	-0.0056***	-0.0056***
	(-1.80)	(-4.59)	(-4.43)	(-4.43)
BTM	0.0141***	0.0058*	0.0096***	0.0096***
	(4.19)	(1.97)	(4.33)	(4.33)
MAX	-0.0199	-0.0098	-0.0145	-0.0145
	(-0.69)	(-0.50)	(-0.85)	(-0.85)
IVOL	-0.7446***	-0.6201***	-0.6778***	-0.6778***
	(-6.34)	(-6.64)	(-9.19)	(-9.19)
DE	0.0000	-0.0003	-0.0001	-0.0001
	(0.07)	(-1.28)	(-0.78)	(-0.78)
OP	0.1213***	0.0891***	0.1040***	0.1040***
	(10.01)	(11.19)	(14.46)	(14.46)
AG	0.0051***	0.0020**	0.0034***	0.0034***
	(3.51)	(2.17)	(4.06)	(4.06)
CP	-0.0080*	-0.0021	-0.0049**	-0.0049**
	(-1.94)	(-1.15)	(-2.23)	(-2.23)
Cons.	0.1132**	0.1841***	0.1054***	0.0893***
	(2.22)	(4.59)	(3.70)	(3.20)
Obs.	100320	198763	299083	299083
Adj.R2	0.1284	0.0953	0.1099	0.1092

Table 2.13. Labour Friction Loading Effect on Holding Period Returns

This table reports the correlation coefficients of labour friction loadings (LFB) to the holding period returns using the Fama-MacBeth regression model. The expected holding period return is calculated using the equation:

$$HPR_n = (1 + Ret_{t+1}) \times (1 + Ret_{t+2}) \times \ldots \times (1 + Ret_{t+n}) - 1$$

where HPR_n refers to the expected holding period return from holding stocks for n months. Newey-West t-statistics are reported in parentheses, where the significance is defined as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Expected Holding Period Returns					
	1-month	2-month	3-month	4-month	5-month	6-month
LFB	0.0008**	0.0013**	0.0013**	0.0011	0.0009	0.0002
	(2.58)	(2.29)	(2.06)	(1.59)	(1.29)	(0.29)
MB	0.0037	0.0033	0.0025	0.0006	-0.0010	-0.0036
	(1.46)	(0.74)	(0.45)	(0.09)	(-0.13)	(-0.43)
MV	-0.0056***	-0.0102***	-0.0146***	-0.0183***	-0.0217***	-0.0246***
	(-4.43)	(-4.44)	(-4.74)	(-4.93)	(-5.15)	(-5.33)
BTM	0.0096***	0.0200***	0.0300***	0.0394***	0.0498***	0.0597***
	(4.33)	(5.40)	(6.41)	(7.34)	(8.35)	(9.44)
MAX	-0.0145	-0.0849***	-0.0980***	-0.1273***	-0.1592***	-0.1874***
	(-0.85)	(-3.50)	(-3.38)	(-3.61)	(-4.28)	(-4.68)
IVOL	-0.6778***	-0.6703***	-0.7889***	-0.8457***	-0.8712***	-0.9017***
	(-9.19)	(-6.56)	(-6.83)	(-6.29)	(-5.93)	(-5.56)
DE	0.0009***	0.0019***	0.0029***	0.0039***	0.0051***	0.0063***
	(4.97)	(5.66)	(6.18)	(6.55)	(6.77)	(6.80)
OP	0.1040***	0.2070***	0.3142***	0.4097***	0.4998***	0.5880***
	(14.46)	(16.80)	(18.95)	(19.12)	(18.85)	(17.97)
AG	0.0034***	0.0054***	0.0067***	0.0076***	0.0076***	0.0080***
	(4.06)	(3.66)	(3.45)	(3.30)	(2.91)	(2.77)
CP	-0.0049**	-0.0105***	-0.0159***	-0.0215***	-0.0264***	-0.0311***
	(-2.23)	(-2.61)	(-2.85)	(-3.08)	(-3.31)	(-3.58)
Cons.	0.1466***	0.2675***	0.3833***	0.4844***	0.5754***	0.6586***
	(4.56)	(4.58)	(4.91)	(5.21)	(5.58)	(5.95)
Obs.	299083	291959	287057	282211	277428	272712
Adj.R2	0.1106	0.1270	0.1357	0.1416	0.1460	0.1476

Table 2.14. Labour Friction Factor Premium

This table reports the correlation coefficients of the labour friction factor (LFF) to sorted portfolio excess returns using the OLS regression model. Based on the monthly labour friction loading, sample stocks are sorted into five portfolios defined as low to high labour friction loading portfolios. The portfolios are reformed every month. Panel A shows the regression results when controlling the Fama-French 3 factors, Panel B shows the regression results while controlling the CH 3 factors, Panel C shows the regression results while controlling the Pastor-Stambaugh Liquidity Model factors, and Panel D shows the regression results while controlling the Fama-French 5 factors. The last row of each panel reports the R square of each model. P-values are reported in parentheses, where the significance is defined as * p< 0.1, ** p < 0.05, *** p < 0.01.

	Value-weighted Portfolio Excess Returns $(Ret - Rf)_t$									
	Low LFB		2		3		4		High LFB	
Panel A. Fama-French 3-Factors with Labour Friction Factor										
LFF		-0.6653***		-0.2284***		-0.0030		0.2400***		0.6355***
		(0.00)		(0.00)		(0.76)		(0.00)		(0.00)
MP	0.9482***	0.9803***	0.9920***	0.9997***	0.9846***	0.9847***	0.9996***	0.9915***	1.0196***	0.9815***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SMB	-0.0482	-0.0168	-0.0657**	-0.0409***	-0.0197	-0.0194	0.0072	-0.0188	0.0195	0.0051
	(0.43)	(0.35)	(0.01)	(0.00)	(0.16)	(0.17)	(0.79)	(0.17)	(0.73)	(0.75)
HML	-0.0118	0.0656***	0.1353***	0.1652***	0.1656***	0.1660***	0.1854***	0.1541***	0.1421**	0.0883***
	(0.86)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
Cons.	0.0041	0.0034***	0.0001	0.0002	-0.0008	-0.0008	0.0005	0.0004	0.0037	0.0046***
	(0.27)	(0.00)	(0.94)	(0.72)	(0.28)	(0.29)	(0.72)	(0.59)	(0.28)	(0.00)
Obs.	218	218	211	211	211	211	211	211	216	216
Adj.R2	0.8091	0.9835	0.9685	0.9931	0.9905	0.9905	0.9656	0.9915	0.8458	0.9879
Panel B. CH-3 Factors with Labour Friction Factor										
LFF		-0.6627***		-0.2227***		0.0021		0.2446***		0.6385***
		(0.00)		(0.00)		(0.86)		(0.00)		(0.00)
MP	0.9351***	0.9756***	0.9820***	0.9933***	0.9813***	0.9812***	1.0012***	0.9888***	1.0169***	0.9760***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SMB	-0.0830	-0.0003	-0.0414	0.0022	0.0312	0.0308	0.0769**	0.0290	0.0691	0.0273

	(0.27)	(0.99)	(0.21)	(0.91)	(0.13)	(0.14)	(0.03)	(0.15)	(0.33)	(0.19)
VMG	-0.0833	0.0350	0.0658	0.1132***	0.1300***	0.1296***	0.1751***	0.1231***	0.1092	0.0474
	(0.43)	(0.27)	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.27)	(0.10)
Cons.	0.0036	0.0019*	-0.0030**	-0.0032***	-0.0041***	-0.0041***	-0.0028*	-0.0026***	0.0008	0.0026***
	(0.29)	(0.06)	(0.03)	(0.00)	(0.00)	(0.00)	(0.06)	(0.00)	(0.79)	(0.00)
Obs.	218	218	211	211	211	211	211	211	216	216
Adj.R2	0.8096	0.9827	0.9647	0.9880	0.9856	0.9855	0.9608	0.9876	0.8429	0.9866
Panel C. Pastor-Stambaugh Liquidity Factors with Labour Friction Factor										
LFF		-0.6649***		-0.2280***		-0.0025		0.2411***		0.6352***
		(0.00)		(0.00)		(0.80)		(0.00)		(0.00)
MP	0.9812***	0.9957***	1.0111***	1.0094***	0.9966***	0.9966***	1.0152***	1.0170***	0.9927***	0.9703***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SMB	-0.0479	-0.0167	-0.0669**	-0.0416***	-0.0204	-0.0202	0.0063	-0.0205	0.0192	0.0050
	(0.44)	(0.36)	(0.01)	(0.00)	(0.15)	(0.15)	(0.82)	(0.13)	(0.74)	(0.75)
HML	-0.0473	0.0490**	0.1155***	0.1550***	0.1531***	0.1536***	0.1692***	0.1275***	0.1713**	0.1004***
	(0.57)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)
LIQ	0.0549	0.0256	0.0305	0.0156	0.0193	0.0191	0.0250	0.0408***	-0.0455	-0.0189
	(0.47)	(0.25)	(0.28)	(0.24)	(0.21)	(0.22)	(0.41)	(0.01)	(0.51)	(0.33)
Cons.	0.0058	0.0042***	0.0010	0.0007	-0.0002	-0.0002	0.0013	0.0016*	0.0023	0.0040***
	(0.18)	(0.00)	(0.53)	(0.36)	(0.79)	(0.79)	(0.46)	(0.06)	(0.58)	(0.00)
Obs.	218	218	211	211	211	211	211	211	216	216
Adj.R2	0.8087	0.9835	0.9686	0.9931	0.9905	0.9905	0.9656	0.9917	0.8454	0.9879
Panel D. Fama-French 5-Factors with Labour Friction Factor										
LFF		-0.6612***		-0.2258***		-0.0026		0.2411***		0.6367***
		(0.00)		(0.00)		(0.80)		(0.00)		(0.00)
MP	0.9303***	0.9766***	0.9848***	0.9978***	0.9846***	0.9847***	1.0045***	0.9906***	1.0298***	0.9803***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SMB	-0.1332*	-0.0346*	-0.1120***	-0.0528***	-0.0192	-0.0186	0.0382	-0.0250	0.0631	0.0036

	(0.05)	(0.09)	(0.00)	(0.00)	(0.23)	(0.26)	(0.22)	(0.12)	(0.33)	(0.84)
HML	-0.1263	0.0454*	0.0824***	0.1550***	0.1575***	0.1583***	0.2298***	0.1523***	0.2105***	0.0788***
	(0.12)	(0.06)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
RMW	-0.0167	0.0144	0.0079	0.0181	-0.0405	-0.0404	0.0366	0.0257	0.0542	-0.0337
	(0.90)	(0.71)	(0.87)	(0.43)	(0.13)	(0.13)	(0.49)	(0.33)	(0.66)	(0.33)
CMA	0.3868**	0.0871*	0.1845***	0.0537*	-0.0204	-0.0219	-0.1040	0.0357	-0.1769	-0.0055
	(0.02)	(0.07)	(0.00)	(0.08)	(0.56)	(0.53)	(0.13)	(0.30)	(0.25)	(0.90)
Cons.	0.0031	0.0031***	-0.0005	0.0000	-0.0007	-0.0007	0.0009	0.0003	0.0041	0.0047***
	(0.41)	(0.00)	(0.70)	(0.94)	(0.34)	(0.34)	(0.55)	(0.71)	(0.23)	(0.00)
Obs.	218	218	211	211	211	211	211	211	216	216
Adj.R2	0.8142	0.9836	0.9698	0.9932	0.9905	0.9905	0.9661	0.9915	0.8463	0.9879

Table 3.1. Labour Market Summary Statistics

This table reports the mean values and standard deviations of labour market data, including the number of vacant jobs (VAC), the number of job seekers ($SEEK$), the vacancy-to-seek ratio (VTS), the number of unemployed labourers ($UNEMP$), and participation rate ($PART$) in every stock market in the sample. Besides, the table reports the average number of stocks observed each month. Panel A reports the statistics of markets in North America, Panel B reports the statistics of markets in Asia-Pacific, and Panel C reports the statistics of markets in Europe. There are 2 markets in North America, 8 markets in Asia-Pacific, and 26 markets in Europe, which is 36 markets in total in the sample.

Market	ISO Code	Ave. Stock (monthly)	VAC (million)		SEEK (million)		VTS (%)		UNEMP (million)		PART (%)	
			Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Panel A. North America												
Canada	CA	790	0.4662	0.0747	0.8967	0.1073	0.5509	0.1256	1.3639	0.1904	0.6672	0.0080
The United States	US	4235	4.5820	1.3562	5.7433	1.5939	0.8470	0.4376	8.9508	2.6153	0.6549	0.0164
Panel B. Asia-Pacific												
Australia	AU	1301	0.1415	0.0433	0.4474	0.0771	0.3575	0.1494	0.6900	0.1213	0.6550	0.0051
China (Mainland)	CN	1760	4.3949	1.4264	4.2147	1.2192	1.0291	0.1706	9.1797	0.6908	0.5044	0.0996
China (Hong Kong)	HK	836	0.0557	0.0224	0.0904	0.0368	0.7870	0.5721	0.1439	0.0579	0.6421	0.0198
Japan	JP	2880	0.5498	0.1903	1.6483	0.4209	0.4531	0.1948	2.5389	0.6532	0.6457	0.0164
Malaysia	MY	762	0.2061	0.1643	0.2407	0.0577	0.7515	0.6087	0.3802	0.1061	0.6527	0.0086
New Zealand	NZ	83	0.0257	0.0053	0.0855	0.0181	0.3270	0.0766	0.1275	0.0273	0.6720	0.0145
Singapore	SG	328	0.0386	0.0145	0.0711	0.0248	0.6341	0.3794	0.1054	0.0369	0.6879	0.0169
Thailand	TH	466	0.0435	0.0185	0.3414	0.1916	0.1746	0.1387	0.4623	0.2511	0.7291	0.0236
Panel C. European Union												
Austria	AT	63	0.0357	0.0140	0.1209	0.0230	0.2954	0.1383	0.2025	0.0375	0.6022	0.0097
Belgium	BE	86	0.1111	0.0248	0.1861	0.0282	0.5739	0.2217	0.3537	0.0481	0.5228	0.0219
Bulgaria	BG	59	0.0187	0.0030	0.2184	0.0759	0.1343	0.0563	0.3960	0.1449	0.5438	0.0214
Cyprus	CY	70	0.0073	0.0032	0.0223	0.0172	0.3904	0.3159	0.0358	0.0266	0.6232	0.0161
Czech Republic	CZ	13	0.0954	0.0832	0.1726	0.0604	0.7655	1.1162	0.2859	0.1047	0.5973	0.0126
Denmark	DK	103	0.0040	0.0010	0.1142	0.0326	0.0350	0.0138	0.1770	0.0485	0.6447	0.0190
Estonia	EE	12	0.0086	0.0030	0.0368	0.0139	0.2941	0.1814	0.0587	0.0226	0.6242	0.0166
Finland	FI	6	0.0201	0.0141	0.1611	0.0450	0.1959	0.1350	0.2630	0.0723	0.6085	0.0143

France	FR	634	0.2545	0.0340	1.5408	0.1956	0.1723	0.0389	2.7630	0.3524	0.5566	0.0066
Germany	DE	454	0.3640	0.1925	1.7840	0.5180	0.2831	0.2218	2.9454	0.9006	0.6005	0.0111
Greece	GR	8	0.0166	0.0105	0.3389	0.1698	0.0423	0.0445	0.6635	0.3119	0.5096	0.0139
Hungary	HU	28	0.0462	0.0202	0.1821	0.0548	0.3252	0.2700	0.3401	0.1040	0.5293	0.0247
Ireland	IE	34	0.0130	0.0047	0.1162	0.0537	0.1067	0.0759	0.1811	0.0835	0.6406	0.0246
Latvia	LV	22	0.0153	0.0058	0.0829	0.0332	0.2693	0.1824	0.1345	0.0544	0.6095	0.0183
Lithuania	LT	30	0.0141	0.0062	0.1077	0.0508	0.2213	0.1865	0.1750	0.0803	0.6097	0.0305
Luxembourg	LU	15	0.0042	0.0021	0.0054	0.0032	0.4388	0.1677	0.0099	0.0055	0.5478	0.0329
Malta	MT	15	0.0049	0.0012	0.0058	0.0006	1.0727	0.1658	0.0102	0.0013	0.5670	0.0229
The Netherlands	NL	54	0.1663	0.0542	0.2626	0.0774	0.7477	0.4218	0.4205	0.1200	0.6232	0.0279
Poland	PL	338	0.0549	0.0273	1.1821	0.4451	0.0797	0.0744	2.0182	0.8091	0.5726	0.0185
Portugal	PT	8	0.0076	0.0036	0.2514	0.1130	0.0414	0.0170	0.4161	0.1852	0.6021	0.0110
Romania	RO	109	0.0415	0.0144	0.4376	0.1438	0.1447	0.0788	0.6968	0.1797	0.6101	0.0537
Slovak Republic	SK	11	0.0180	0.0040	0.2106	0.0547	0.1161	0.0609	0.3406	0.0922	0.6084	0.0169
Slovenia	SI	8	0.0128	0.0038	0.0407	0.0081	0.3417	0.1491	0.0687	0.0142	0.5877	0.0106
Spain	ES	91	0.0507	0.0176	1.9424	0.7905	0.0291	0.0242	3.4887	1.2227	0.5500	0.0391
Sweden	SE	146	0.0398	0.0260	0.2242	0.0487	0.1811	0.1219	0.3539	0.0776	0.6407	0.0102
The United Kingdom	GB	1081	0.6298	0.1213	1.2582	0.3338	0.6025	0.2180	1.9606	0.5079	0.6356	0.0069

Table 3.2. Variable Summary Statistics

This table reports the summary statistics of variables, including the labour friction loading (LFB) market beta (MB), the logarithm of market value (MV), momentum (MOM), maximum daily return in the previous month (MAX), idiosyncratic volatility ($IVOL$), illiquidity ($ILLIQ$), and short-term reversal (STR). This table reports the mean value ($Mean$), standard deviation (Std), skewness ($Skew$), the value of quintiles, and the number of observations ($Obs.$) for each variable. Panel A reports the statistics of the North American markets, Panel B reports the statistics of the Asia-Pacific markets, and Panel C reports the statistics of the European markets.

Variable	Mean	Std	Skew	Min	25%	Median	75%	Max	Obs.
Panel A. North America									
LFB	-0.0005	0.7374	0.0985	-2.3222	-0.3534	-0.0098	0.3403	2.3953	819,864
MB	0.9834	1.1160	0.0644	-8.1960	0.3904	0.9483	1.5334	9.4313	819,864
MV	19.8923	2.0851	0.0498	12.2929	18.3620	19.8477	21.3573	24.1911	819,864
MOM	0.0111	0.0362	0.4049	-0.0933	-0.0071	0.0107	0.0278	0.2511	819,864
MAX	0.0675	0.0646	2.8749	0.0000	0.0295	0.0472	0.0797	0.7000	819,864
IVOL	0.0265	0.0224	2.5041	0.0000	0.0123	0.0197	0.0325	0.2515	819,864
ILLIQ	-0.1479	0.9946	-6.5987	-8.3443	0.0007	0.0012	0.0020	0.0097	819,864
STR	0.0090	0.1405	0.6369	-0.4286	-0.0603	0.0046	0.0692	0.8182	819,864
Panel B. Asia-Pacific									
LFB	0.0090	1.6314	0.0580	-6.3090	-0.5313	0.0026	0.5349	6.4144	1,918,127
MB	0.7654	1.4283	0.1632	-9.6150	0.1741	0.7568	1.3173	10.9496	1,918,127
MV	18.8721	1.9223	0.1544	12.6610	17.4836	18.7953	20.1848	24.0243	1,918,127
MOM	0.0103	0.0362	1.1014	-0.1026	-0.0107	0.0063	0.0262	0.2219	1,918,127
MAX	0.0617	0.0627	3.6832	0.0000	0.0263	0.0435	0.0741	0.7142	1,918,127
IVOL	0.0262	0.0234	3.3662	0.0000	0.0125	0.0194	0.0312	0.2569	1,918,127
ILLIQ	-6.7540	0.7457	0.3681	-8.8151	-7.2392	-6.8137	-6.3246	-3.9821	1,918,127
STR	0.0081	0.1346	1.2089	-0.4783	-0.0598	0.0000	0.0599	0.9229	1,918,127
Panel C. Europe									
LFB	0.0163	6.3629	0.0451	-22.4816	-2.5395	-0.0406	2.5294	22.5341	612,331
MB	0.5027	1.3439	0.4002	-8.1139	-0.0432	0.4579	1.0697	21.5435	612,331
MV	18.9209	2.4653	0.0627	10.4112	17.1669	18.8021	20.6598	25.1127	612,331
MOM	0.0112	0.0411	1.9149	-0.1522	-0.0091	0.0098	0.0283	1.0853	612,331
MAX	0.0608	0.0722	4.7088	0.0000	0.0242	0.0406	0.0701	0.9600	612,331
IVOL	0.0271	0.0266	3.7249	0.0000	0.0123	0.0194	0.0316	0.3166	612,331
ILLIQ	-6.7824	0.8595	-0.2523	-12.6692	-7.2961	-6.7896	-6.2583	-3.5632	612,331
STR	0.0062	0.1373	0.9014	-0.5000	-0.0592	0.0000	0.0618	0.9994	612,331

Table 3.3. Univariate Portfolio Sorting

This table reports the test results of the univariate portfolio sorting approach. Sample stocks are sorted into five portfolios based on monthly labour friction loadings (LFB) and the portfolios are defined from the low-loading to the high-loading portfolios. The five portfolios are rebalanced every month. The first column reports the raw excess returns of the five portfolios and the last row in each panel reports the raw excess return difference between the high- and low-loading portfolios. The second to fourth columns report the abnormal returns of each portfolio, which are estimated by the Fama-French 3-Factor model, the Pastor Stambaugh Liquidity model, and the Fama-French 5-Factor model, respectively. The last raw report shows the abnormal return differences between the high- and low-loading portfolios. This table reports the results of the sorted portfolios that are equal-weighted and value-weighted. Panel A reports the results of the North American market, Panel B reports the results of the Asia-Pacific markets, and Panel C reports the results of the European markets. The t-statistics values are reported in the parentheses, where the significance levels are defined as * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

	Equal-weighted Portfolios				Value-weighted Portfolios			
	Raw Excess Return	FF 3-Factor Model	PS Liquidity Model	FF 5-Factor Model	Raw Excess Return	FF 3-Factor Model	PS Liquidity Model	FF 5-Factor Model
Panel A. North America								
Low LFB	0.0060	0.0019	0.0019	0.0056	0.0062	0.0021	0.0022	0.0057
	(1.48)	(0.32)	(0.33)	(0.85)	(1.53)	(0.36)	(0.37)	(0.88)
2	0.0083**	0.0067	0.0068	0.0098*	0.0082**	0.0067	0.0068	0.0097*
	(2.54)	(1.41)	(1.42)	(1.83)	(2.53)	(1.41)	(1.42)	(1.82)
3	0.0082***	0.0064	0.0065	0.0089*	0.0081***	0.0065	0.0066	0.0089*
	(2.65)	(1.43)	(1.45)	(1.76)	(2.65)	(1.45)	(1.47)	(1.78)
4	0.0074**	0.0051	0.0052	0.0077	0.0074**	0.0052	0.0053	0.0078
	(2.23)	(1.05)	(1.07)	(1.41)	(2.25)	(1.07)	(1.09)	(1.44)
High LFB	0.0042	-0.0012	-0.0011	0.0017	0.0044	-0.0010	-0.0009	0.0019
	(1.00)	(-0.20)	(-0.18)	(0.25)	(1.06)	(-0.17)	(-0.15)	(0.29)
$High - Low$	-0.0018*	-0.0031*	-0.0030*	-0.0039**	-0.0017	-0.0031*	-0.0031*	-0.0038**
	(-1.66)	(-1.92)	(-1.89)	(-2.17)	(-1.60)	(-1.94)	(-1.92)	(-2.13)
Panel B. Asia-Pacific								
Low LFB	0.0026	0.0007	0.0015	0.0039	0.0024	0.0004	0.0010	0.0036

	(0.82)	(0.18)	(0.35)	(0.91)	(0.75)	(0.10)	(0.25)	(0.84)
2	0.0036	0.0038	0.0043	0.0067*	0.0034	0.0035	0.0039	0.0063*
	(1.35)	(1.17)	(1.19)	(1.82)	(1.28)	(1.08)	(1.11)	(1.74)
3	0.0022	0.0025	0.0024	0.0055*	0.0020	0.0023	0.0022	0.0053
	(0.91)	(0.88)	(0.74)	(1.71)	(0.85)	(0.80)	(0.69)	(1.63)
4	0.0036	0.0034	0.0036	0.0057	0.0033	0.0031	0.0033	0.0053
	(1.33)	(1.07)	(1.02)	(1.56)	(1.26)	(0.97)	(0.92)	(1.46)
High LFB	0.0047	0.0033	0.0037	0.0062	0.0044	0.0028	0.0031	0.0058
	(1.49)	(0.85)	(0.88)	(1.44)	(1.37)	(0.73)	(0.73)	(1.33)
$High - Low$	0.0021**	0.0026**	0.0023*	0.0023*	0.0020**	0.0024**	0.0021*	0.0022*
	(2.37)	(2.33)	(1.85)	(1.85)	(2.19)	(2.15)	(1.66)	(1.71)
Panel C. Europe								
Low LFB	0.0025	-0.0005	-0.0042	0.0055	0.0025	-0.0005	-0.0044	0.0056
	(1.02)	(-0.14)	(-1.23)	(1.35)	(1.02)	(-0.15)	(-1.26)	(1.36)
2	0.0045**	0.0029	-0.0002	0.0068**	0.0046**	0.0030	-0.0002	0.0070**
	(2.25)	(1.14)	(-0.08)	(2.06)	(2.28)	(1.15)	(-0.07)	(2.08)
3	0.0035**	0.0027	0.0002	0.0064**	0.0037**	0.0029	0.0002	0.0067**
	(2.05)	(1.29)	(0.07)	(2.29)	(2.13)	(1.33)	(0.09)	(2.33)
4	0.0040**	0.0022	-0.0015	0.0075**	0.0041**	0.0024	-0.0013	0.0078**
	(2.00)	(0.86)	(-0.54)	(2.28)	(2.04)	(0.95)	(-0.46)	(2.34)
High LFB	0.0029	-0.0006	-0.0041	0.0068	0.0027	-0.0006	-0.0042	0.0069
	(1.16)	(-0.20)	(-1.17)	(1.62)	(1.07)	(-0.19)	(-1.17)	(1.63)
$High - Low$	0.0004	-0.0002	0.0001	0.0012	0.0002	-0.0002	0.0002	0.0013
	(0.34)	(-0.12)	(0.06)	(0.63)	(0.16)	(-0.10)	(0.12)	(0.64)

Table 3.4. Multivariate Fama-MacBeth Regression

This table reports the correlation coefficients of the labour friction loading (LFB) to the expected excess returns using the Fama-MacBeth regression model. Column (1) reports the univariate regression result of the labour friction loading (LFB) to the expected excess returns. From Column (2) to Column (8), each regression adds one additional control variable. Panel A reports the Fama-MacBeth regression results in the North America market, Panel B reports the results in the Asia-Pacific market, and Panel C reports the results in the European market. Newey-West t-statistics values are reported in the parentheses, where the significance levels are defined as * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

	Expected Excess Returns $(Ret - Rf)_{t+1}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. North America								
LFB	-0.0015**	-0.0016**	-0.0013**	-0.0012*	-0.0012*	-0.0010*	-0.0026***	-0.0035***
	(-2.00)	(-2.14)	(-2.00)	(-1.97)	(-1.95)	(-1.67)	(-3.16)	(-3.29)
MB		-0.0002	-0.0006	-0.0008	0.0002	0.0000	0.0006	0.0005
		(-0.22)	(-0.49)	(-0.68)	(0.21)	(0.03)	(0.56)	(0.51)
MV			0.0005	0.0005	-0.0004	-0.0009**	-0.0014***	-0.0014***
			(1.16)	(1.12)	(-1.10)	(-2.48)	(-4.06)	(-4.13)
MOM				0.0230	0.0127	0.0126	0.0090	0.0066
				(0.97)	(0.55)	(0.56)	(0.40)	(0.29)
MAX					-0.0777***	-0.0035	-0.0037	-0.0023
					(-7.96)	(-0.27)	(-0.29)	(-0.18)
IVOL						-0.2769***	-0.1463**	-0.1513**
						(-4.57)	(-2.23)	(-2.30)
ILLIQ							-2.9780***	-2.9441***
							(-3.80)	(-3.80)
STR								-0.0000
								(-0.01)
Cons.	0.0070*	0.0068*	0.0060	0.0052	0.0051	0.0048	0.4503***	0.4451***
	(1.85)	(1.77)	(1.58)	(1.45)	(1.43)	(1.34)	(3.86)	(3.86)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Obs.	813941	813941	813941	813941	813941	813941	813941	813941
Adj. R^2	0.0019	0.0120	0.0200	0.0251	0.0293	0.0331	0.0354	0.0382
Panel B. Asia-Pacific								
LFB	0.0008**	0.0007**	0.0007**	0.0007**	0.0008**	0.0008**	0.0008**	0.0007**
	(2.19)	(2.12)	(2.16)	(2.18)	(2.29)	(2.33)	(2.53)	(2.10)
MB		0.0001	0.0004	0.0003	0.0010	0.0011*	0.0003	0.0003
		(0.13)	(0.52)	(0.47)	(1.58)	(1.88)	(0.82)	(0.78)
MV			-0.0014**	-0.0014**	-0.0012**	-0.0017***	-0.0015***	-0.0016***
			(-2.38)	(-2.57)	(-2.28)	(-3.45)	(-3.19)	(-3.40)
MOM				-0.0114	-0.0109	-0.0071	-0.0077	-0.0107
				(-0.37)	(-0.36)	(-0.24)	(-0.28)	(-0.40)
MAX					-0.1339***	-0.1282***	-0.1330***	-0.1346***
					(-7.81)	(-7.50)	(-8.44)	(-9.02)
IVOL						-0.1251***	-0.2050***	-0.1945***
						(-3.58)	(-4.37)	(-4.43)
ILLIQ							0.0039*	0.0034*
							(1.85)	(1.73)
STR								0.0017
								(0.32)
Cons.	0.0039	0.0038	0.0293**	0.0286**	0.0248**	0.0369***	0.0627***	0.0595***
	(1.26)	(1.35)	(2.46)	(2.59)	(2.26)	(3.69)	(3.21)	(3.28)
Obs.	1855412	1855412	1855412	1855412	1855412	1855412	1855412	1855412
Adj. R^2	0.0022	0.0091	0.0246	0.0383	0.0431	0.0499	0.0598	0.0664
Panel C. Europe								
LFB	0.0001	0.0001	0.0002	0.0002	0.0002	0.0002	0.0002	0.0003
	(0.53)	(0.39)	(0.61)	(0.76)	(0.78)	(0.88)	(0.85)	(1.12)
MB		-0.0012**	-0.0015**	-0.0014**	-0.0011*	-0.0009*	-0.0010*	-0.0010**
		(-2.00)	(-2.59)	(-2.58)	(-1.92)	(-1.71)	(-1.94)	(-2.12)

MV			0.0003	0.0002	0.0003	-0.0002	-0.0002	-0.0002
			(1.16)	(0.62)	(1.09)	(-0.89)	(-0.74)	(-0.88)
MOM				0.0693***	0.0723***	0.0683***	0.0701***	0.0642***
				(3.19)	(3.33)	(3.20)	(3.47)	(3.26)
MAX					-0.0945***	-0.0956***	-0.0957***	-0.0891***
					(-5.67)	(-5.99)	(-6.07)	(-5.63)
IVOL						-0.1367***	-0.1415***	-0.1326***
						(-5.14)	(-4.06)	(-3.92)
ILLIQ							0.0003	0.0001
							(0.28)	(0.14)
STR								0.0108**
								(2.53)
Cons.	0.0047*	0.0053**	-0.0009	0.0009	-0.0016	0.0118**	0.0129	0.0121
	(1.81)	(2.12)	(-0.14)	(0.15)	(-0.26)	(1.99)	(1.27)	(1.21)
Obs.	598436	598436	598436	598436	598436	598436	598436	598436
Adj. R^2	0.0032	0.0089	0.0161	0.0232	0.0276	0.0314	0.0363	0.0398

Table 3.5. Labour Productivity Fama-MacBeth Regression

This table reports the correlation coefficients of the labour friction loading (LFB) to the expected excess returns using the multivariable Fama-MacBeth regression model for firms with different labour productivities. Stocks are separated into subsamples based on their labour productivity, measured by the ratio of total revenue to labour costs ($RTLC$). A higher ratio stands for higher labour productivity and a lower ratio stands for lower labour productivity. The first two columns report the results for low and high labour-productive firms in the North American market. The two columns in the middle report the results for low and high labour-productive firms in the Asia-Pacific market. The last two column report results for low and high labour-productive firms in the European market. Newey-West t-statistics values are reported in the parentheses, where the significance levels are defined as * p < 0.1, ** p < 0.05, and *** p < 0.01.

	Expected Excess Returns $(Ret - Rf)_{t+1}$					
	North America		Asia-Pacific		Europe	
	Low RTLC	High RTLC	Low RTLC	High RTLC	Low RTLC	High RTLC
LFB	-0.0026	-0.0097***	0.0025*	0.0069	0.0000	0.0002
	(-0.80)	(-3.43)	(1.88)	(1.37)	(0.11)	(0.38)
MB	0.0016	0.0013	-0.0004	-0.0001	-0.0006	-0.0015**
	(1.17)	(0.78)	(-0.54)	(-0.04)	(-1.00)	(-2.43)
MV	-0.0014***	-0.0015***	-0.0014**	-0.0018*	-0.0006*	-0.0003
	(-2.99)	(-2.94)	(-2.08)	(-1.78)	(-1.88)	(-0.86)
MOM	0.0244	0.0742**	-0.0605	-0.0014	0.0872***	0.0401
	(0.67)	(2.12)	(-1.43)	(-0.03)	(3.49)	(1.62)
MAX	-0.0795***	0.0102	-0.1714***	-0.0718*	-0.0513**	-0.0410
	(-2.69)	(0.25)	(-5.68)	(-1.81)	(-2.17)	(-1.65)
IVOL	-0.0902	0.1322	-0.2712***	-0.3964***	-0.2080***	-0.0478
	(-0.71)	(0.82)	(-3.79)	(-3.40)	(-3.63)	(-1.05)
ILLIQ	0.6862	-7.1841***	0.0030	0.0071*	0.0012	0.0004
	(0.44)	(-3.22)	(1.36)	(1.77)	(1.01)	(0.46)
STR	-0.0057	-0.0124	-0.0107	0.0206	0.0094*	0.0140**
	(-0.65)	(-1.35)	(-1.21)	(1.39)	(1.66)	(2.58)
Cons.	-0.0969	1.0800***	0.0560**	0.0951***	0.0270**	0.0146
	(-0.41)	(3.24)	(2.54)	(3.02)	(2.30)	(1.34)
Obs.	92484	58446	561715	576631	233610	253425
Adj. R^2	0.0856	0.0997	0.0945	0.1514	0.0510	0.0539

Table 3.6. Firm Sectors Summary Statistics

This table reports the number of stocks in the industrial, high-technology, and financial sectors in the sample. The table also reports the percentage of stocks in the three sectors. Panel A reports the statistics of the North American market, Panel B reports the statistics of the Asia-Pacific market, and Panel C reports the statistics of the European market.

Market	Industrial		High-Technology		Financial		Total
	Stock Number	Percentage (%)	Stock Number	Percentage (%)	Stock Number	Percentage (%)	
Panel A. North America							
CA	1,047	84.16%	99	7.96%	98	7.88%	1,244
US	5,333	62.53%	1,546	18.13%	1,649	19.35%	8,528
Total	6,380	65.29%	1,645	16.83%	1,747	17.88%	9,772
Panel B. Asia-Pacific							
AU	2,038	86.17%	170	7.19%	157	6.64%	2,365
CN	2,396	81.08%	458	15.50%	101	3.42%	2,955
HK	1,449	76.30%	267	14.06%	183	9.64%	1,899
JP	3,556	80.60%	556	12.60%	300	6.80%	4,412
MY	922	79.21%	175	15.03%	67	5.76%	1,164
NZ	141	77.05%	25	13.66%	17	9.29%	183
SG	497	75.53%	113	17.17%	48	7.29%	658
TH	634	77.60%	55	6.73%	128	15.67%	817
Total	11,633	80.49%	1,819	12.59%	1,001	6.93%	14,453
Panel C. European Union							
AT	74	66.67%	10	9.01%	27	24.32%	111
BE	73	59.84%	16	13.11%	33	27.05%	122
BG	55	63.95%	4	4.65%	27	31.40%	86
CY	105	77.21%	5	3.68%	26	19.12%	136
CZ	17	85.00%	3	15.00%	NA	NA	20
DK	96	49.74%	24	12.44%	73	37.82%	193
EE	18	85.71%	1	4.76%	2	9.52%	21
FI	23	67.65%	5	14.71%	6	17.65%	34

FR	792	72.13%	179	16.30%	127	11.57%	1,098
DE	558	68.30%	125	15.30%	134	16.40%	817
GR	12	80.00%	2	13.33%	1	6.67%	15
HU	33	60.00%	7	12.73%	15	27.27%	55
IE	47	72.31%	4	6.15%	14	21.54%	65
LV	25	83.33%	4	13.33%	1	3.33%	30
LT	40	85.11%	1	2.13%	6	12.77%	47
LU	9	40.91%	13	59.09%	NA	NA	22
MT	12	50.00%	3	12.50%	9	37.50%	24
NL	58	68.24%	13	15.29%	14	16.47%	85
PL	570	75.90%	92	12.25%	89	11.85%	751
PT	7	77.78%	2	22.22%	NA	NA	9
RO	100	78.13%	10	7.81%	18	14.06%	128
SK	4	57.14%	3	42.86%	NA	NA	7
SI	8	57.14%	1	7.14%	5	35.71%	14
ES	143	56.30%	10	3.94%	101	39.76%	254
SE	457	76.81%	88	14.79%	50	8.40%	595
GB	1,892	75.20%	314	12.48%	310	12.32%	2,516
Total	5,228	72.06%	939	12.94%	1,088	15.00%	7,255

Table 3.7. Firm Sectors Fama-MacBeth Regression

This table reports the correlation coefficients of the labour friction loading (LFB) to the expected excess returns using the multivariable Fama-MacBeth regression model for firms in the industrial, high-technology, and financial sectors. Panel A reports the results of the North American market, Panel B reports the results of the Asia-Pacific market, and Panel C reports the results of the European market. Newey-West t-statistics values are reported in the parentheses, where the significance levels are defined as * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

	Expected Excess Returns $(Ret - Rf)_{t+1}$								
	North America			Asia-Pacific			Europe		
Sector	Industrial	High-Tech	Financial	Industrial	High-Tech	Financial	Industrial	High-Tech	Financial
LFB	-0.0014	-0.0046***	-0.0048	0.0009**	0.0001	0.0010	0.0002	-0.0003	0.0002
	(-1.38)	(-3.10)	(-1.47)	(2.27)	(0.16)	(0.94)	(0.86)	(-0.46)	(0.42)
MB	0.0003	0.0010	0.0017	0.0004	0.0001	-0.0002	-0.0009*	-0.0002	-0.0022**
	(0.24)	(0.84)	(1.34)	(0.99)	(0.16)	(-0.25)	(-1.73)	(-0.18)	(-2.58)
MV	-0.0018***	-0.0021***	-0.0018***	-0.0017***	-0.0013**	-0.0009	-0.0002	-0.0003	-0.0003
	(-4.50)	(-4.02)	(-4.05)	(-3.54)	(-2.02)	(-1.62)	(-0.74)	(-0.59)	(-0.71)
MOM	-0.0297	-0.0924***	0.0516	-0.0147	-0.0084	-0.0380	0.0712***	0.0579	0.0772**
	(-1.22)	(-3.58)	(1.39)	(-0.56)	(-0.28)	(-0.84)	(3.52)	(1.54)	(2.09)
MAX	-0.0090	-0.0297	-0.0793***	-0.1355***	-0.1152***	-0.1545***	-0.0565***	-0.0316	-0.1063***
	(-0.60)	(-1.43)	(-3.05)	(-8.89)	(-5.69)	(-4.89)	(-3.33)	(-0.70)	(-2.96)
IVOL	-0.0413	0.0701	0.1805	-0.1998***	-0.2259***	-0.2161***	-0.1478***	-0.1588	-0.1646**
	(-0.57)	(0.72)	(1.50)	(-4.57)	(-3.49)	(-2.66)	(-3.69)	(-1.47)	(-2.10)
ILLIQ	-1.6990	-2.6879*	-1.3446	0.0035*	0.0028	0.0025	0.0005	-0.0006	0.0009
	(-1.45)	(-1.92)	(-0.95)	(1.80)	(1.15)	(1.07)	(0.55)	(-0.28)	(0.80)
STR	-0.0033	-0.0002	-0.0183*	0.0025	0.0007	-0.0124	0.0124**	0.0217**	0.0111
	(-0.73)	(-0.03)	(-1.94)	(0.47)	(0.12)	(-1.47)	(2.56)	(2.25)	(1.26)
Cons.	0.2633	0.4108**	0.2085	0.0621***	0.0539***	0.0401*	0.0139	0.0101	0.0224
	(1.51)	(1.98)	(0.99)	(3.43)	(2.70)	(1.69)	(1.34)	(0.50)	(1.65)
Obs.	378978	106956	110998	1486791	234837	122333	423827	76863	83456
Adj. R^2	0.0399	0.0414	0.0854	0.0675	0.0836	0.1213	0.0413	0.0924	0.1179

Table 3.8. External Labour Supply Fama-MacBeth Regression

This table reports the correlation coefficients of the labour friction loading (LFB) to the expected excess returns using the multivariable Fama-MacBeth regression model for firms in markets with different levels of external labour supply. A labour market in migrant or English-speaking countries is classified as a high external labour supply market. A labour market in non-migrant or non-English-speaking countries is classified as a low external labour supply market. Model (1) reports the results in non-migrant countries, Model (2) reports the results in migrant countries, Model (3) reports the results in non-English-speaking countries, and Model (4) reports the results in English-speaking countries. Newey-West t-statistics values are reported in the parentheses, where the significance levels are defined as * p < 0.1, ** p < 0.05, and *** p < 0.01.

	Expected Excess Returns $(Ret - Rf)_{t+1}$							
	(1)		(2)		(3)		(4)	
	Non-migrant Market		Migrant Market		Non-English Speaking		English Speaking	
LFB	0.0005**	0.0005*	0.0002	0.0003	0.0005**	0.0004**	-0.0001	0.0003
	(2.05)	(1.85)	(0.81)	(1.09)	(2.39)	(2.27)	(-0.26)	(0.97)
MB		0.0004		-0.0005		0.0001		-0.0007
		(0.67)		(-1.07)		(0.26)		(-1.45)
MV		-0.0013***		-0.0006**		-0.0012***		-0.0007*
		(-2.94)		(-2.13)		(-3.07)		(-1.97)
MOM		0.0127		0.0245		0.0295		0.0259
		(0.41)		(1.19)		(1.07)		(1.18)
MAX		-0.1213***		-0.0647***		-0.1122***		-0.0552***
		(-6.90)		(-3.93)		(-6.62)		(-2.86)
IVOL		-0.2443***		-0.1612***		-0.2523***		-0.1296***
		(-5.05)		(-3.78)		(-6.54)		(-2.81)
ILLIQ		0.0042**		0.0000		0.0036**		0.0001
		(2.41)		(0.01)		(2.31)		(0.10)
STR		0.0045		0.0081*		0.0015		0.0143***
		(0.76)		(1.76)		(0.26)		(2.83)
Cons.	0.0048*	0.0618***	0.0053*	0.0185*	0.0040	0.0550***	0.0062**	0.0207
	(1.73)	(3.86)	(1.91)	(1.95)	(1.45)	(3.80)	(2.08)	(1.61)
Obs.	1653525	1653525	1614264	1614264	1937093	1937093	1312955	1312955
Adj.R^2	0.0030	0.0757	0.0026	0.0522	0.0024	0.0649	0.0040	0.0609

Table 3.9. Society Cultural Indicator Fama-MacBeth Regression

This table reports the correlation coefficients of the labour friction loading (LFB) to the expected excess returns using the multivariable Fama-MacBeth regression model for firms in markets with different cultures. The society culture differences are measured by the Value Survey Module (VSM) cultural indicators. The Value Survey Module includes six cultural indicators, and this paper only chooses the four indicators regarding social values, including Power Distance Index (PDI), Uncertainty Avoidance Index (UAI), Long Term Orientation Index (LTO), and Indulgence versus Restraint Index (IVR). Higher indicators illustrate that the society culture has more restrictions and less freedom. Lower indicators illustrate that the society is more open minded, and people have more choices in their lives. This paper defines the high score societies as Restrictive markets, and the low score societies as Permissive markets. This table reports the results of Restrictive and Permissive markets using the four VSM indicators, respectively. Newey-West t-statistics values are reported in the parentheses, where the significance levels are defined as * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

	Expected Excess Returns $(Ret - Rf)_{t+1}$							
	PDI		UAI		LTO		IVR	
	Low	High	Low	High	Low	High	Low	High
LFB	0.0003	0.0005*	-0.0002	0.0005*	-0.0002	0.0004*	0.0002	0.0005*
	(0.95)	(1.89)	(-0.82)	(1.87)	(-0.74)	(1.79)	(0.91)	(1.90)
MB	-0.0007	0.0008	-0.0006	0.0008	-0.0005	0.0009	-0.0007	0.0008
	(-1.13)	(1.48)	(-0.88)	(1.36)	(-0.74)	(1.44)	(-1.16)	(1.49)
MV	-0.0003	-0.0014***	-0.0007**	-0.0011***	-0.0009**	-0.0011***	-0.0003	-0.0014***
	(-0.92)	(-4.15)	(-2.05)	(-3.33)	(-2.51)	(-3.20)	(-1.02)	(-4.15)
MOM	0.0363	-0.0077	0.0229	-0.0163	0.0233	-0.0107	0.0374	-0.0076
	(1.60)	(-0.29)	(0.99)	(-0.60)	(0.97)	(-0.42)	(1.64)	(-0.29)
MAX	-0.0086	-0.1251***	-0.0397**	-0.1360***	-0.0355*	-0.1371***	-0.0098	-0.1248***
	(-0.48)	(-7.96)	(-2.33)	(-8.81)	(-1.93)	(-9.15)	(-0.54)	(-7.94)
IVOL	-0.1701***	-0.1991***	-0.1501***	-0.2243***	-0.1570***	-0.2136***	-0.1653***	-0.1991***
	(-3.62)	(-5.51)	(-3.64)	(-6.38)	(-4.08)	(-6.05)	(-3.51)	(-5.50)
ILLIQ	-0.0004	0.0021*	-0.0008	0.0025**	-0.0008	0.0026**	-0.0004	0.0021*
	(-0.49)	(1.83)	(-0.85)	(2.20)	(-0.79)	(2.38)	(-0.57)	(1.81)
STR	0.0112**	0.0031	0.0061	0.0041	0.0082	0.0025	0.0113**	0.0031
	(2.28)	(0.58)	(1.22)	(0.79)	(1.60)	(0.50)	(2.31)	(0.58)
Cons.	0.0095	0.0480***	0.0146	0.0460***	0.0175	0.0459***	0.0097	0.0479***
	(1.10)	(3.93)	(1.31)	(3.78)	(1.44)	(3.76)	(1.13)	(3.92)
Obs.	1061403	1181426	1168035	1074794	1216833	1025996	1065233	1181963
Adj.R2	0.0567	0.0525	0.0625	0.0556	0.0635	0.0581	0.0568	0.0525

Table 3.10. Global Inflation Fama-MacBeth Regression

This table reports the correlation coefficients of the labour friction loading (LFB) to the expected excess returns using the multivariable Fama-MacBeth regression model for firms in markets during the low and high inflation subperiods. Inflation is measured by the percentage change of the Consumer Price Index (CPI) and Inflation Rate. Based on the median value of the inflation measurements, the sample is separated into low- and high-inflation subperiods. The first two columns report results of the low- and high-inflation periods using the percentage change in the CPI, and the last two columns report the results of low- and high-inflation periods using the Inflation Rate. Newey-West t-statistics values are reported in the parentheses, where the significance levels are defined as * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

	Expected Excess Returns $(Ref - Rf)_{t+1}$			
	Low ΔCPI (%)	High ΔCPI (%)	Low Inflation Rate (%)	High Inflation Rate (%)
LFB	0.0004**	-0.0053	0.0004*	-0.0006
	(2.02)	(-1.25)	(1.88)	(-0.48)
MB	0.0004	0.0019	0.0004	-0.0015
	(0.96)	(0.51)	(0.97)	(-1.16)
MV	-0.0011***	-0.0032**	-0.0010***	-0.0017***
	(-3.54)	(-2.09)	(-3.43)	(-2.63)
MOM	0.0054	-0.2812	0.0007	0.0201
	(0.22)	(-0.85)	(0.03)	(0.53)
MAX	-0.1089***	0.1804	-0.0985***	-0.1368***
	(-7.37)	(0.70)	(-6.63)	(-3.57)
IVOL	-0.1888***	-0.2848***	-0.2273***	-0.1605**
	(-5.71)	(-3.46)	(-7.24)	(-1.98)
ILLIQ	0.0009	-0.0244	0.0013*	-0.0010
	(0.88)	(-0.90)	(1.69)	(-0.50)
STR	0.0044	0.0049	0.0035	-0.0062
	(0.93)	(0.47)	(0.74)	(-0.66)
Cons.	0.0334***	-0.1156	0.0359***	0.0312
	(3.03)	(-0.65)	(3.77)	(1.60)
Obs.	2755856	511933	2766439	501350
Adj.R2	0.0543	0.1001	0.0542	0.1090

Table 4.1. CSR Summary Statistic

This table reports the summary statistics of corporate social responsibility (CSR) scores across markets from North America, Asia-Pacific, and Europe. The table shows the number of observations, the average value, the standard deviation of the CSR scores in each market. It also contains the minimum, the 25th percentile, the median, the 75th percentile, and the maximum CSR scores. Panel A reports the CSR statistic summary of markets in North America, Panel B reports the CSR statistic summary of markets in Asia-Pacific, and Panel C reports the CSR statistic summary of markets in Europe.

Market	Obs.	Mean	Std	Min	25%	Median	75%	Max
Panel A. North American								
US	31,772	18.7969	29.9809	0.00	0.00	0.00	34.10	99.97
CA	9,405	38.2346	33.9171	0.00	0.00	33.82	70.62	99.85
Panel B. Asia-Pacific								
CN	3,307	40.7613	32.2843	0.00	7.11	36.85	68.55	99.95
HK	2,892	36.4718	32.9432	0.00	0.00	30.23	66.30	99.75
JP	7,620	35.8649	33.4355	0.00	0.00	29.08	65.37	99.85
MY	1,000	45.3216	30.3288	0.00	18.60	45.56	68.83	99.57
SG	2,003	33.7822	32.8322	0.00	0.00	32.61	61.63	99.48
TH	659	49.498	30.1788	0.00	24.05	53.26	77.83	99.25
AU	8,915	35.7608	36.4135	0.00	0.00	24.86	71.89	99.76
NZ	841	32.3466	33.9162	0.00	0.00	21.88	61.11	99.02
Panel C. European								
AT	603	38.7116	32.8801	0.00	0.00	36.11	72.12	98.72
BE	1,201	35.4576	35.4986	0.00	0.00	25.58	68.75	98.96
CY	32	27.5912	34.8359	0.00	0.00	7.355	48.44	95.00
CZ	86	41.4443	30.6465	0.00	16.67	37.50	73.75	90.00
DK	1,097	45.0174	32.8495	0.00	12.50	47.37	75.37	98.75
FI	1,367	52.6501	32.6202	0.00	22.21	63.89	78.85	99.34
FR	3,449	48.2811	30.1355	0.00	21.53	50.65	76.47	99.72
DE	7,270	41.2994	32.9833	0.00	7.26	38.59	70.59	99.81
GR	465	25.6424	31.2376	0.00	0.00	10.71	50.00	98.00
HU	108	58.1020	27.7195	0.00	37.50	62.50	77.08	87.50
IE	284	34.1896	31.5391	0.00	0.00	29.25	59.84	97.83
LU	74	25.2780	22.2210	0.00	0.00	26.39	50.00	61.90
NL	917	52.9021	32.7859	0.00	25.00	58.14	82.35	99.32
PT	425	42.4592	32.4410	0.00	9.09	40.00	77.27	95.45
RO	11	42.0455	29.1937	0.00	25.00	37.50	62.50	87.50
ES	1,217	42.7687	31.6445	0.00	11.46	41.89	71.59	99.40
SE	5,183	44.8364	33.0423	0.00	9.74	47.50	75.38	99.80
GB	10,693	50.0896	32.7502	0.00	21.59	55.22	79.89	99.92

Table 4.2. Global Sample Variables Summary Statistic

This table reports the statistical summary of variables in the sample. The first column lists the variables involving in the sample, and the second column shows the abbreviations or symbols of these variables. The table shows the number of observations, the average value, and standard deviation of each variable. It also contains the minimum value, the 25th percentile value, the median value, the 75th percentile value, and the maximum value of the variables. Excepting the corporate social responsibility (CSR), the number of board (BOARD), the independent board rate (IBOARD), and firm age (AGE), all the other variables are Winsorised at the 1% level on both tails.

Variable	Symbol	Obs.	Mean	Std	Min	25%	Median	75%	Max
Corporate Social Responsibility	CSR	32,552	35.7894	33.7689	0.0000	0.0000	29.5000	67.4050	99.8800
Labour Friction Loading	LFB	32,552	0.0045	0.2778	-2.5384	-0.1196	-0.0019	0.1194	2.4867
Number of Board	BOARD	32,552	10.1497	3.6619	1.0000	8.0000	10.0000	12.0000	53.0000
Independent Board Rate	IBOARD	32,552	0.5801	0.2743	0.0000	0.3750	0.6250	0.8182	1.0000
Firm Age	FAGE	32,552	26.4766	13.9492	1.0000	16.0000	24.0000	33.0000	71.0000
Total Assets (log)	SIZE	32,552	24.0669	4.1500	16.7907	21.1957	22.7185	25.9542	36.5439
Tobin's Q	TOBIN	32,552	1.2332	1.5303	0.0002	0.3999	0.7720	1.134753	19.1954
PPE-to-Assets	PPE	32,552	0.2805	0.2519	0.0001	0.0749	0.2061	0.4246	0.9946
Operating Cash Flow-to-Asset	OCF	32,552	0.0804	0.0904	-0.6511	0.0388	0.0780	0.1210	0.5520
Debt-to-Assets	LEV	32,552	0.3453	0.2389	0.0000	0.1548	0.3123	0.5201	0.9572
Return on Equity	ROE	32,552	0.0930	0.3156	-2.9018	0.0470	0.1051	0.1750	4.4825
Stock Return Standard Deviation	RETSTD	32,552	0.0895	0.0520	0.0000	0.0561	0.0775	0.1083	0.4605

Table 4.3. Pearson Correlation Matrix

This table reports the Pearson correlations for each pair of variables in our sample, where the significance is defined as * p < 0.1, ** p < 0.05, and *** p < 0.01.

	CSR	LFB	BOARD	IBOARD	FAGE	SIZE	TOBIN	PPE	OCF	LEV	ROE	RETSTD
CSR	1.0000***											
LFB	0.0380***	1.0000***										
BOARD	0.3068***	0.0227***	1.0000***									
IBOARD	-0.0429***	-0.0734***	-0.2582***	1.0000***								
FAGE	0.2084***	-0.0173***	0.2270***	0.1784***	1.0000***							
SIZE	0.2567***	0.0543***	0.4025***	-0.5473***	0.1213***	1.0000***						
TOBIN	-0.1638***	-0.0116**	-0.2020***	0.1177***	-0.1037***	-0.2554***	1.0000***					
PPE	0.1022***	0.0157***	-0.0222***	-0.0352***	0.0391***	0.0025	-0.1275***	1.0000***				
OCF	0.0414***	-0.0184***	-0.0100*	0.0695***	0.0547***	-0.0512***	0.2596***	0.0996***	1.0000***			
LEV	-0.0546***	-0.0396***	0.0613***	0.3795***	0.2704***	-0.1253***	-0.1349***	0.1410***	-0.0268***	1.0000***		
ROE	0.1053***	0.0049	0.0730***	0.0280***	0.0926***	0.0407***	0.1298***	-0.0348***	0.5106***	0.0092*	1.0000***	
RETSTD	-0.2157***	-0.0299***	-0.2050***	0.0187***	-0.1875***	-0.1964***	0.0466***	-0.0022	-0.2034***	0.0302***	-0.3393***	1.0000***

Table 4.4. Multivariate Fixed-effect Regression

This table reports the correlation coefficients of labour market friction loading (LFB) to CSR scores using the fixed effect regression model. Model (1) shows the result of LFB on CSR scores while considering the year effect and industry effect without any control variable. Model (2) only controls the relevant variables but does not consider any effect. Model (3) controls both year and industry effects and control variables. Model (4) shows the result of LFB on CSR scores by controlling the additional region effect in Model (3). The t-values are showing in the brackets, and the significant levels are defined as * p < 0.1, ** p < 0.05, and *** p < 0.01.

	CSR			
	(1)	(2)	(3)	(4)
LFB	4.4368***	3.4061***	3.4645***	2.5368***
	[6.67]	[5.04]	[5.76]	[4.51]
BOARD		2.0758***	2.1505***	1.7407***
		[39.49]	[40.51]	[33.36]
IBOARD		21.7694***	21.6292***	38.3058***
		[26.32]	[26.06]	[46.56]
FAGE		0.2774***	0.2406***	0.385***
		[20.77]	[17.92]	[29.46]
SIZE		0.8279***	0.9074***	1.0085***
		[17.82]	[19.51]	[17.9]
TOBIN		-1.9696***	-2.1057***	-0.4291***
		[-16.23]	[-17.15]	[-3.66]
PPE		16.4728***	14.8456***	11.489***
		[23.73]	[19.58]	[16.04]
OCF		-1.8752	-2.165	4.3876**
		[-0.83]	[-0.94]	[2.03]
LEV		-24.0141***	-23.9612***	7.5363***
		[-29.65]	[-29.54]	[8.24]
ROE		6.0075***	6.395***	3.2468***
		[9.25]	[9.91]	[5.37]
RETSTD		-56.5251***	-62.3801***	-37.2589***
		[-15.73]	[-16.62]	[-10.56]
Cons.	21.7342***	-4.0932***	-18.9878***	-32.4126***
	[4.85]	[-3.14]	[-4.44]	[-10.62]
Year Effect	Yes	No	Yes	Yes
Industry Effect	Yes	No	Yes	Yes
Region Effect	No	No	No	Yes
Obs.	32552	32552	32552	32552
Adj.R2	0.0321	0.1941	0.2135	0.3146

Table 4.5. Labour Market Friction Effect and Job Creation

This table reports the correlation coefficients of labour market friction loading (LFB) to CSR scores in markets with different levels of new business and job vacancies using the fixed effect model. Markets are separated into two groups based on the median value of new business density and defined as low and high density markets. Markets are also categorised into two groups based on the median value of job vacancy ratios and defined as low and high vacancy markets. The first two columns show the correlation coefficients of LFB to CSR in the low and high new business density markets, and the last two columns show the correlation coefficients of LFB to CSR in the low and high job vacancy markets. The t-values are showing in the brackets, and the significance levels are defined as * p < 0.1, ** p < 0.05, and *** p < 0.01.

	CSR			
	New Business Density		Job Vacancy Ratio (%)	
	Low	High	Low	High
LFB	-1.2401	2.3851**	-1.6192	3.0477***
	[-0.72]	[2.11]	[-0.78]	[4.62]
BOARD	2.0001***	2.7658***	1.9695***	2.0578***
	[20.19]	[20.06]	[16.56]	[33.26]
IBOARD	31.4675***	30.999***	22.1452***	23.811***
	[17.42]	[16.43]	[10.85]	[25.73]
FAGE	0.5483***	0.7904***	0.6339***	0.2667***
	[9.92]	[18.83]	[10.4]	[18.84]
SIZE	0.2341**	0.5247***	0.5255***	0.9363***
	[2.28]	[2.92]	[3.64]	[18.0]
TOBIN	-2.9138***	-0.8162***	-2.3472***	-1.91***
	[-4.78]	[-3.52]	[-5.37]	[-14.73]
PPE	-9.8108***	15.9636***	7.9936***	15.1771***
	[-4.16]	[12.40]	[3.4]	[18.74]
OCF	31.6019***	7.4722*	22.2957**	-3.7032
	[3.36]	[1.85]	[2.54]	[-1.53]
LEV	16.8580***	3.8066*	7.531**	-27.1313***
	[5.78]	[1.73]	[2.42]	[-30.89]
ROE	9.7794***	1.4322	-1.5647	6.8541***
	[3.78]	[1.30]	[-0.66]	[10.22]
RETSTD	4.7072	-49.4953***	-17.0887	-64.0279***
	[0.37]	[-7.98]	[-1.34]	[-16.05]
Cons.	-21.4888***	-40.7974***	-27.3284***	-28.8447**
	[-3.38]	[-5.32]	[-4.57]	[-2.52]
Year Effect	Yes	Yes	Yes	Yes
Industry Effect	Yes	Yes	Yes	Yes
Obs.	4816	7458	3884	27726
Adj.R2	0.2071	0.2891	0.2178	0.2209

Table 4.6. Labour Market Friction Effect and Investor Protection

This table reports the correlation coefficients of labour market friction loading (LFB) to CSR scores in markets with different levels of investor protection and labour taxations using the fixed effect model. Markets are categorised into weak and strong protection markets based on the median value of investor protection strength index, and markets are categorised into low and high taxation markets based on the median value of the labour taxation rates. The first two columns show the correlation coefficients of LFB to CSR in the weak and strong protection markets, and the last two columns show the correlation coefficients of LFB to CSR in the low and high taxation markets. The t-values are showing in the brackets, and the significance levels are defined as * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

	CSR			
	Strength of Investor Protection		Labour Taxation (%)	
	Weak	Strong	Low	High
LFB	3.2485	4.7176***	2.3996***	1.5429
	[1.47]	[4.06]	[3.12]	[1.44]
BOARD	1.8784***	1.8067***	1.9871***	1.9956***
	[14.3]	[17.27]	[22.33]	[22.65]
IBOARD	28.5236***	24.9206***	26.8871***	18.8661***
	[15.0]	[13.98]	[20.66]	[14.7]
FAGE	0.7677***	0.3032***	0.2682***	0.4145***
	[13.32]	[12.74]	[15.31]	[10.63]
SIZE	3.3597***	0.5471***	1.1998***	3.1058***
	[13.41]	[6.42]	[17.42]	[21.06]
TOBIN	-0.5979*	-3.2461***	-1.8496***	-0.4418**
	[-1.93]	[-9.14]	[-11.77]	[-2.21]
PPE	19.3862***	8.9523***	14.0028***	20.3128***
	[11.17]	[6.12]	[14.11]	[15.23]
OCF	1.8197	-7.1529	0.0391	6.7614
	[0.36]	[-1.26]	[0.01]	[1.64]
LEV	-10.506***	-25.5238***	-22.6616***	-5.9981***
	[-3.89]	[-15.67]	[-20.24]	[-3.18]
ROE	-3.1374*	10.9341***	6.2616***	-2.5721*
	[-1.74]	[9.31]	[7.83]	[-1.91]
RETSTD	-31.3517***	-79.7037***	-63.9515***	-44.9199***
	[-3.63]	[-11.12]	[-13.03]	[-6.54]
Cons.	-96.5123***	-17.4815***	-26.5957***	-90.1284***
	[-9.39]	[-4.46]	[-3.03]	[-8.7]
Year Effect	Yes	Yes	Yes	Yes
Industry Effect	Yes	Yes	Yes	Yes
Obs.	4018	10486	18250	7406
Adj.R2	0.3831	0.1655	0.2273	0.3534

Table 4.7. Labour Market Friction Effect and Advanced Education

This table reports the correlation coefficients of labour market friction loading (LFB) to CSR scores in markets with different levels of advanced education using the fixed effect model. Markets are categorised into low and high advanced education markets based on the median value of advanced education ratios. This table shows the correlation coefficients of LFB to CSR in the low and high education markets. The t-values are showing in the brackets, and the significance levels are defined as * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

	CSR	
	Low Advanced Education	High Advanced Education
LFB	2.0513***	0.0087
	[2.59]	[0.01]
BOARD	2.5521***	2.5784***
	[39.14]	[22.4]
IBOARD	21.4829***	29.7027***
	[20.44]	[18.29]
FAGE	0.3025***	0.7482***
	[20.49]	[20.69]
SIZE	1.7213***	0.5932***
	[27.89]	[3.77]
TOBIN	-1.076***	-1.2957***
	[-7.04]	[-6.72]
PPE	9.9595***	14.9057***
	[9.73]	[13.33]
OCF	-3.5259	7.228**
	[-1.21]	[2.04]
LEV	-15.3437***	1.6824
	[-15.04]	[0.89]
ROE	5.9903***	0.6998
	[7.39]	[0.71]
RETSTD	-55.2527***	-58.6499***
	[-11.2]	[-10.37]
Cons.	-42.1749***	-37.327***
	[-8.49]	[-4.16]
Year Effect	Yes	Yes
Industry Effect	Yes	Yes
Obs.	19850	9031
Adj.R2	0.2741	0.3198

Table 4.8. Labour Market Friction Effect and Labour Union Power

This table reports the correlation coefficients of labour market friction loading (LFB) to CSR scores in fixed effect regression with the interaction term. First, sample is separated into two groups based on the median value of the Union Density and defined as the low union power markets and high union power markets. The interaction term multiplies LFB and the high union power dummy variable, which equals to 1 if the markets have high union power and equals to 0 if the markets have low union power. The first column show the correlation coefficients of LFB to CSR without the interaction term while the second column includes the interaction term. The t-values are showing in the brackets, and the significance levels are defined as * p < 0.1, ** p < 0.05, and *** p < 0.01.

	CSR	
LFB	1.2010*	3.6958***
	[1.78]	[3.31]
$High\ Union\ Power$	19.7101***	19.7193***
	[39.30]	[39.32]
$LFB \times High\ Union\ Power$		-3.9306***
		[-2.80]
BOARD	2.3381***	2.3383***
	[41.25]	[41.26]
IBOARD	31.075***	31.0493***
	[34.61]	[34.59]
FAGE	0.3738***	0.3742***
	[26.54]	[26.57]
SIZE	0.093*	0.0918*
	[1.85]	[1.83]
TOBIN	-1.8467***	-1.86***
	[-13.46]	[-13.55]
PPE	10.6654***	10.6504***
	[13.06]	[13.04]
OCF	3.8986	4.1331*
	[1.58]	[1.68]
LEV	-12.3418***	-12.1953***
	[-12.88]	[-12.71]
ROE	3.6303***	3.66***
	[5.31]	[5.35]
RETSTD	-58.3415***	-57.9222***
	[-14.42]	[-14.31]
Cons.	-16.6199***	-16.7532***
	[-3.96]	[-3.99]
Year Effect	Yes	Yes
Industry Effect	Yes	Yes
Obs.	27134	27134
Adj.R2	0.2634	0.2636

Table 4.9. Labour Market Friction Effect in firm-level Characteristics

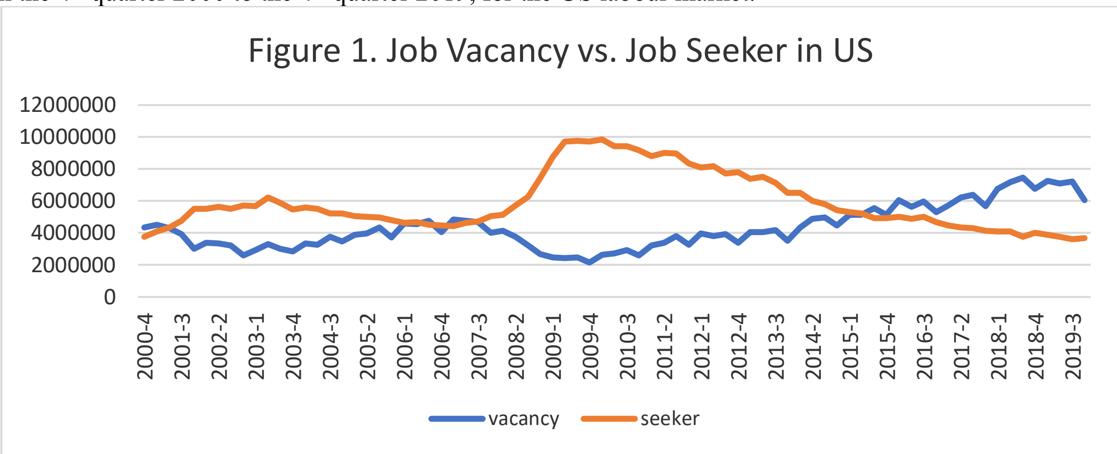
This table reports the correlation coefficients of labour market friction loading (LFB) to CSR scores in firms with different wage levels and labour investment efficiencies using the fixed effect model. Firms are separated into two portfolios based on the median value of their wage levels and defined as the low and high wage firms. Firms are also separated into two portfolios based on the median value of their labour investment efficiencies and defined as the low and high efficiency firms. The first two columns show the correlation coefficients of LFB to CSR for the low and high wage firms, and the last two columns show the correlation coefficients of LFB to CSR for the low and high efficiency firms. The t-values are showing in the brackets, and the significance levels are defined as * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

	CSR			
	Wage Level		Labour Efficiency	
	Low	High	Low	High
LFB	3.8744***	0.1154	3.1991***	1.3550
	[4.25]	[0.11]	[3.03]	[1.57]
BOARD	1.5549***	1.5217***	2.0330***	1.9900***
	[20.66]	[10.35]	[20.11]	[26.45]
IBOARD	30.3436***	18.4003***	16.9108***	24.6107***
	[23.82]	[10.12]	[11.02]	[20.06]
FAGE	0.2214***	0.4862***	0.2627***	0.1961***
	[8.0]	[9.43]	[12.13]	[10.01]
SIZE	-0.1213*	-0.9147***	1.3751***	0.7172***
	[-1.72]	[-7.37]	[15.39]	[11.16]
TOBIN	-3.3240***	-1.5609***	-2.2577***	-2.6406***
	[-10.11]	[-7.35]	[-11.01]	[-13.77]
PPE	9.3766***	21.9409***	13.4836***	13.4979***
	[6.36]	[15.5]	[9.62]	[10.51]
OCF	2.3868	13.9253***	-7.4749**	-1.9395
	[0.40]	[3.13]	[-2.00]	[-0.46]
LEV	-17.8255***	-19.1929***	-21.5224***	-25.3267***
	[-12.05]	[-9.40]	[-14.73]	[-19.7]
ROE	5.9343***	2.0345	6.0017***	10.8168***
	[4.47]	[1.44]	[6.35]	[9.39]
RETSTD	-65.4304***	-41.9086***	-56.7746***	-72.457***
	[-9.24]	[-5.13]	[-9.26]	[-10.81]
Cons.	23.9238***	6.0126	-39.5592***	10.8548
	[4.49]	[0.64]	[-6.95]	[1.26]
Year Effect	Yes	Yes	Yes	Yes
Industry Effect	Yes	Yes	Yes	Yes
Obs.	12996	4462	10370	15383
Adj.R2	0.1339	0.2012	0.2284	0.1883

Figure

Figure 2.1. Job Vacancies, Job Seekers, and Vacancy-to-Seek Ratio in the US

Figure 1 plots the quarterly time series of job vacancies, job seekers, and the vacancy-to-seek ratio for the period from the 4th quarter 2000 to the 4th quarter 2019, for the US labour market.



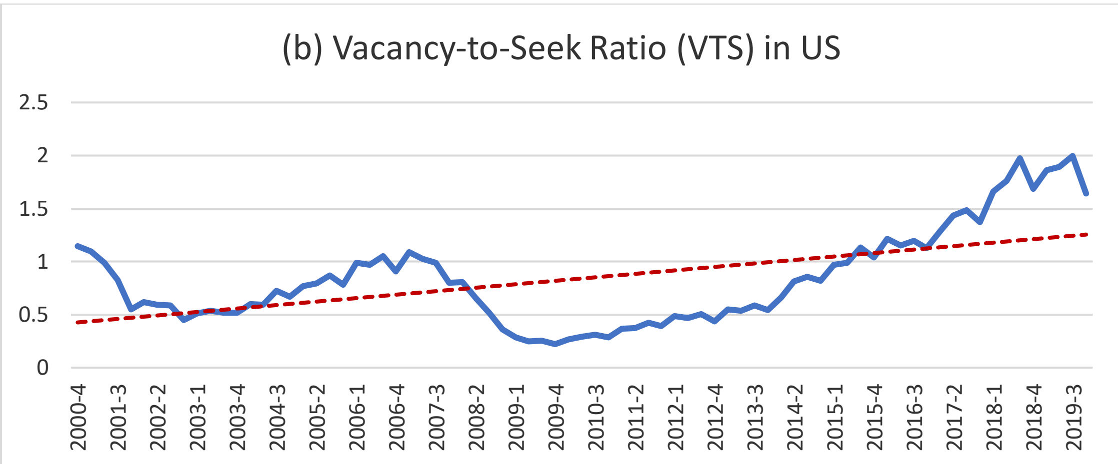
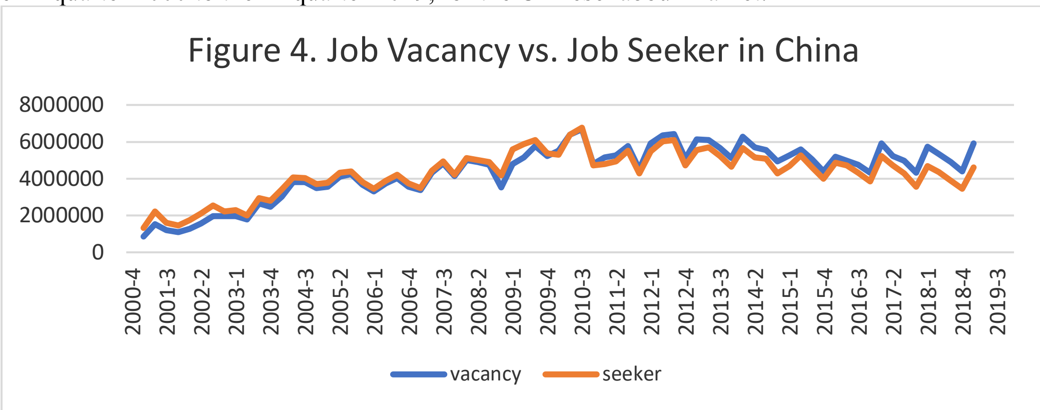


Figure 2.2. Job Vacancies, Job Seekers, and Vacancy-to-Seek Ratio in China

Figure 2 plots the quarterly time series of job vacancies, job seekers, and the vacancy-to-seek ratio for the period from the 4th quarter 2000 to the 4th quarter 2019, for the Chinese labour market.



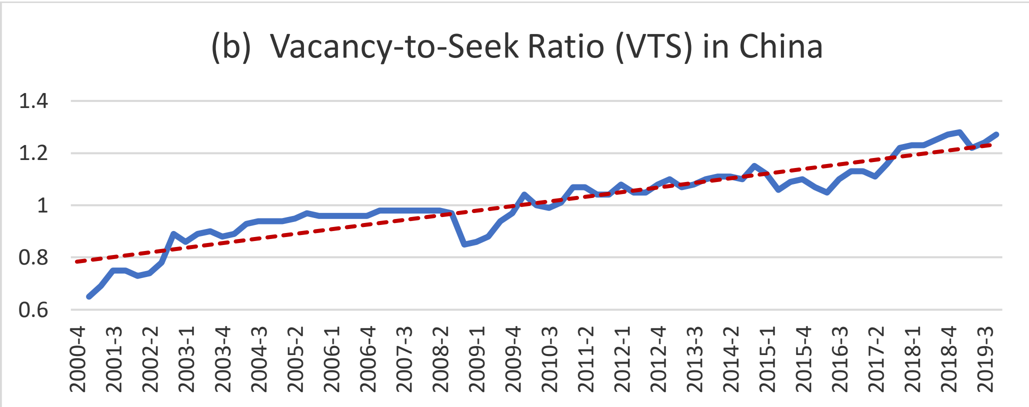
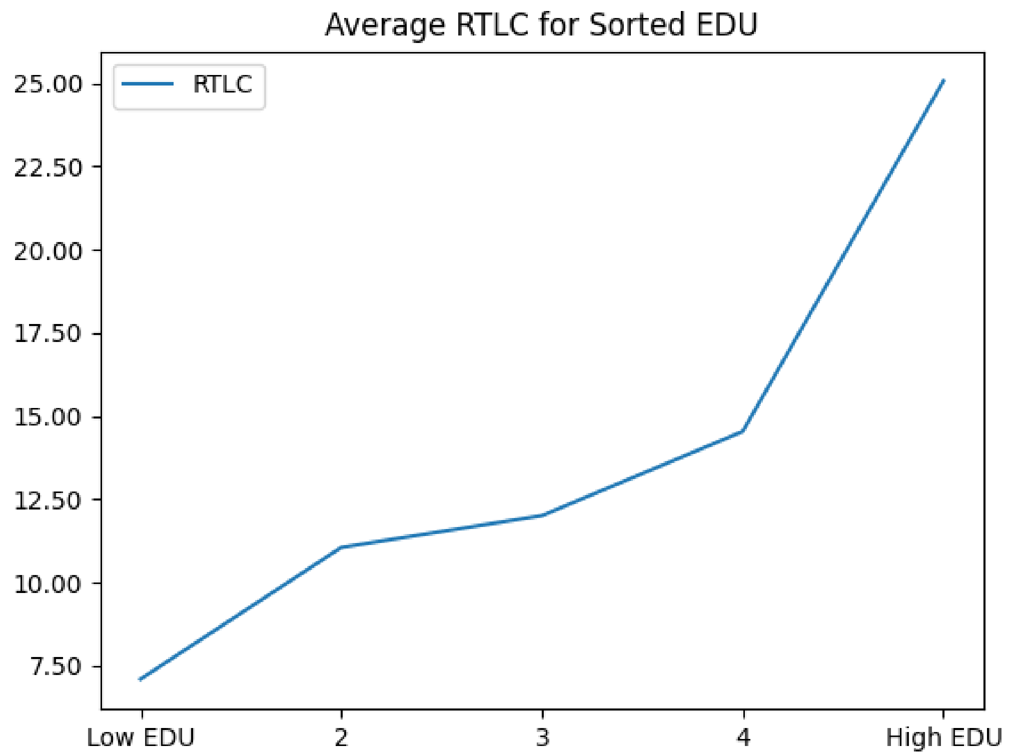


Figure 4.1. Labour Intensity and Advanced Education Level



Appendix

Appendix A2.1. Variable Description

This table provides a description of the variables used.

Symbol	Variable	Description
Ret	Stock Returns	Ret is the monthly dividend-adjusted stock return.
VTS	Vacancy-to-Seek Ratio	VTS is the labour friction proxy, which is calculated by dividing the number of vacancy jobs by the number of job seekers.
LFB	Labour Friction Loading	β^{LF} is the loading of stock returns to the change of labour frictions, which is estimated by the rolling regression with the Fama-French 5-factors: $Ret_{i,t} = \beta_{i,t}^{LF} \Delta VTS_t + \beta_{i,t}^{mkt} MP_t + \beta_{i,t}^{smb} SMB_t + \beta_{i,t}^{hml} HML_t + \beta_{i,t}^{rmw} RMW_t + \beta_{i,t}^{cma} CMA_t$ where Ret is the current stock returns, ΔVTS is the change of labour friction, MP is the market premium which is the difference between the market returns and risk-free rate, SMB is the size factor, HML is the value factor, RMW is the operating factor, and CMA is the investment factor.
MB	Market Beta	β^{mkt} is estimated by the daily stock returns in a calendar month with the CAPM regression model: $Ret_{i,t} = \alpha_{i,t} + \beta_{i,t}^{mkt} \times MP_t + \varepsilon_{i,t}$ where MP is the market premium, which is the difference between the market returns and risk-free rate.
MV	Market Value	MV is the natural logarithm of firm market capitalisation at the end to month t.
BTM	Book-to-Market Ratio	BTM is the ratio between a firm's book value and market value.
MAX	Maximum Daily Return	MAX in the Chinese stock market, the policy restriction limits that maximum daily returns cannot be higher than 10% or lower than -10%. If a daily return hits the boundaries, its real return should be adjusted by summing the current daily return and the return on the next trading day.
$IVOL$	Idiosyncratic Risk	$IVOL$ is estimated by daily stock returns in a calendar month with the Fama-French 3-Factor model: $Ret_{i,t} = \alpha_{i,t} + \beta_{i,t}^{mkt} MP_t + \beta_{i,t}^{smb} SMB_t + \beta_{i,t}^{hml} HML_t + \varepsilon_{i,t}$ where MP is the market premium, SMB is the size factor, and HML is the value factor. The ε refers to observation residuals in the estimation model, and $IVOL$ equals the standard deviation of the residuals during the calendar month.
DE	Debt-to-Equity Ratio	DE is calculated by dividing the total debt by shareholder's equity.
OP	Operating Profitability	OP is the ratio of operating profit to the lagged total assets.
AG	Asset Growth Rate	AG is the percentage change in total firm assets.
CP	Closing Price	CP is the monthly closing stock price.
LTS	Labour-to-Sales Ratio	Following Jiang and Chen (2021), LTS is the proxy reflecting a firm's labour productivity, and the ratio is calculated by dividing the number of staff by total sales.
$LCTS$	Labour Cost-to-Sales Ratio	Following Jiang and Chen (2021), $LCTS$ is the proxy reflecting a firm's labour productivity, and the ratio is calculated by dividing the total labour expenses by total sales.

SOE	State-Owned Enterprise	According to the Equity Nature ID from CSMAR database, firms are classified as state-owned (SOE) and non-state-owned (non-SOE) firms.
LP	Labour Protection	The labour protection firms are categorised based on a firm's staff protection and working environment safety policies. Firms that announced any governance policy regarding staff protection or workplace safety are classified as labour-protection firms. Otherwise, firms without any protection or safety policy are classified as non-labour-protection firms.

Appendix A2.2. Summary Statistics of CH-3 Factors

This table reports the means, standard deviations, and Pearson correlation matrix for the three factors in the CH-3 model. Following the approach of Liu et al. (2019), the monthly size factor (SMB) and value factor (VMG) are estimated based on stock market values (MV) and earning-price ratios (EP). The estimate procedure is similar to the Fama-French 3 factor model (1993). Stocks are separated into small and big size portfolios based on MV, and they are also separated into value, neutral, and growth portfolios based on EP. The size factor (SMB) is the difference in average returns between the small size portfolios and big size portfolios, and the formula is:

$$SMB = \frac{small\ value + small\ neutral + small\ growth}{3} - \frac{big\ value + big\ neutral + big\ growth}{3}$$

The value factor (VMG) is the difference in average returns between the value portfolios and growth portfolios, and the formula is:

$$VMG = \frac{small\ value + big\ value}{2} - \frac{(small\ growth + big\ growth)}{2}$$

The sample period is from January 1991 to December 2019, which has 329 months in total because of missing values.

			Correlations		
	Mean	Std.	MP	SMB	VMG
MP	0.0211	0.1221	1.0000		
SMB	-0.0132	0.0531	-0.1250**	1.0000	
VMG	-0.0111	0.0910	-0.0950*	-0.2339***	1.0000

Appendix A3.1. Vacancy Data Sources

Country	ISO Code	Vacancy Data Sources
Canada	CA	CANSIM - Statistics Canada
The United States	US	Bureau of Labor Statistics, U.S. Department of Labor
Australia	AU	Australia and New Zealand Banking Group
China (Mainland)	CN	Ministry of Human Resources and Social Security, China
China (Hong Kong)	HK	Census and Statistics Department, Hong Kong
Japan	JP	Ministry of Health, Labour and Welfare, Japan
Malaysia	MY	Central Bank of Malaysia
New Zealand	NZ	Ministry of Business, Innovation and Employment, New Zealand
Singapore	SG	Ministry of Manpower, Singapore
Thailand	TH	Bank of Thailand
Austria	AT	AMS - Arbeitsmarktservice Oesterreich
Belgium	BE	Eurostat
Bulgaria	BG	Eurostat
Cyprus	CY	Ministry of Labour, Welfare and Social Insurance, Cyprus
Czech Republic	CZ	Ministry of Labour and Social Affairs, Czech Republic
Denmark	DK	Eurostat
Estonia	EE	Eurostat
Finland	FI	Ministry of Employment and the Economy, Finland
France	FR	DARES - Direction de l'animation de la recherche, des etudes et des statistiques, France
Germany	DE	Deutsche Bundesbank
Greece	GR	Eurostat
Hungary	HU	HCSO - Hungarian Central Statistical Office
Ireland	IE	Eurostat
Latvia	LV	Central Statistical Bureau, Latvia
Lithuania	LT	Statistics Lithuania
Luxembourg	LU	Eurostat
Malta	MT	Eurostat
The Netherlands	NL	CBS - Statistics Netherlands
Poland	PL	Central Statistical Office, Poland
Portugal	PT	Banco de Portugal
Romania	RO	Eurostat
Slovak Republic	SK	Eurostat
Slovenia	SI	IMAD - Institute of Macroeconomic Analysis and Development, Slovenia
Spain	ES	INEM - Instituto de Empleo, Servicio Publico de Empleo Estatal, Spain
Sweden	SE	Swedish Public Employment Service
The United Kingdom	GB	ONS - Office for National Statistics, United Kingdom

Appendix A3.2. Variable Definition

Variable	Symbol	Definition
Stock return	Ret	Stock returns of the US are downloaded from the CRSP, and that of the China markets are downloaded from the CSMAR. For other stock markets, stock returns are calculated by the formula: $$Ret_{i,t} = \frac{RI_{i,t}}{RI_{i,t-1}} - 1$$ where RI is the return index of the stock, which is downloaded from DataStream. RI in DataStream have been adjusted by dividend reinvestments.
Market value	MV	MV across global stock markets are unified by converting all monthly market values into US dollars based on the monthly currency exchange rates over time.
Market beta	MB	β^{mkt} indicates the stock sensitivity to the overall stock market movement, and is estimated by the daily stock returns in a calendar month using the CAPM regression model: $$Ret_{i,t} = \alpha_{i,t} + \beta_{i,t}^{mkt} \times (Rm_t - Rf_t) + \varepsilon_{i,t}$$ where Rm is the market return, and Rf is the risk-free rate measured by the 10-year government bond yield across stock markets.
Momentum	MOM	Momentum is the average stock return from month $t-2$ to $t-12$ with one month lag.
Maximum daily return in the previous month	MAX	MAX is the highest daily return over the last calendar month. Notably, in the Chinese stock market, the policy restriction limits that maximum daily returns cannot be higher than 10% or lower than -10%. If a daily return hits the boundaries, its real return should be adjusted by summing up the current daily return and the return on the next trading day. Stock markets other than China do not need this adjustment.
Idiosyncratic volatility	$IVOL$	$IVOL$ is estimated by daily stock returns in a calendar month using the Fama-French 3-Factor model: $$Ret_{i,t} = \alpha_{i,t} + \beta_{i,t}^{mkt}(Rm_t - Rf_t) + \beta_{i,t}^{smb} SMB_t + \beta_{i,t}^{hml} HML_t + \varepsilon_{i,t}$$ where $(Rm - Rf)$ is the market premium, SMB is the size factor, and HML is the value factor. ε refers to observation residuals in the estimation model, and $IVOL$ equals the standard deviation of the residuals during the calendar month.
Illiquidity	$ILLIQ$	$ILLIQ$ measures a stock's trading liquidity, which is calculated following the approach of Amihud (2002). $ILLIQ$ is calculated as:

		$$ILLIQ_{i,m} = \text{Log}\left(\frac{1}{days_m} \times \sum \frac{\lvert Ret_{i,t} \rvert}{vol_{\text{i,t}}}\right)$$ where vol refers to daily trading values, and $days$ refers to the number of trading days during the month.
Short-term reversal	STR	STR is the monthly stock returns of month $t-1$.

Appendix A3.3. External Labour Supply Country Classification

Country	ISO Code	Migrant Country	Migrant Percentage of the Total Population	English-Speaking Country
Austria	AT	Yes	19.30%	No
Australia	AU	Yes	30.10%	Yes
Belgium	BG	No	17.30%	No
Canada	CA	Yes	21.30%	Yes
China (Mainland)	CN	No	0.10%	No
Cyprus	CY	Yes	15.80%	No
Czech Republic	CZ	No	5.10%	No
Germany	DE	Yes	18.80%	No
Denmark	DK	No	12.40%	No
Estonia	EE	Yes	15.00%	No
Spain	ES	Yes	14.60%	No
Finland	FI	No	7.00%	No
France	FR	No	13.10%	No
The United Kingdom	GB	Yes	13.80%	Yes
Greece	GR	No	12.90%	No
China (Hong Kong)	HK	Yes	39.50%	No
Hungary	HU	No	6.10%	No
Ireland	IE	Yes	17.60%	No
Japan	JP	No	2.20%	No
Lithuania	LT	No	5.30%	No
Luxembourg	LU	Yes	47.60%	No
Latvia	LV	No	12.70%	No
Malta	MT	Yes	26.00%	No
Malaysia	MY	No	10.70%	No
The Netherlands	NL	Yes	13.80%	No
New Zealand	NZ	Yes	28.70%	Yes
Poland	PL	No	2.20%	No
Portugal	PT	No	9.80%	No
Romania	RO	No	3.70%	No
Sweden	SE	Yes	19.80%	No
Singapore	SG	Yes	43.10%	Yes
Slovenia	SI	No	13.40%	No
Slovak Republic	SK	No	3.60%	No
Thailand	TH	No	5.20%	No
The United States	US	Yes	15.30%	Yes

Data Source: United Nations, Population Database, International Migrant Report 2020

Appendix A3.4. VSM Cultural Indicator Definition

Data Source	Values Survey Module (VSM) 2013			
Indicator	**Symbol**	**Definition**	**Low**	**High**
Power Distance Index	PDI	Measures whether less powerful individuals are treated unequally in a society.	Equal	Unequal
Individualism Index	IDV	Measures whether individuals only look after himself/herself (Individualism), or have strong, cohesive relationships with a group in society (Collectivism).	Collectivism	Individualism
Masculinity Index	MAS	Measures whether the social roles of different genders are clearly distinct (Masculinity) or overlap (Femininity). Masculinity Example: Men are expected to be assertive, tough, and focused on material success; Women are expected to be more modest, tender, and concerned with quality of life.	Femininity	Masculinity
Uncertainty Avoidance Index	UAI	Measures whether individuals in a society feel threatened by uncertain, unknown, ambiguous, or unstructured situations.	Less Threatened	More Threatened
Long Term Orientation Index	LTO	Measures whether the culture fosters virtues of a society oriented towards future rewards (Long-term Orientation) or related to past and present achievements (Short-term Orientation). Long-term Orientation Example: Adaptation, Perseverance, Thrift Short-term Orientation Example: Tradition, “Face” Preservation, Society Obligation	Long-term Orientation	Short-term Orientation
Indulgence versus Restraint Index	IVR	Measures whether individuals in a society feel free to engage in leisure activities, merrymaking with friends, spending, consumption, and sex (Indulgence); or need to control such gratifications and are less able to enjoy their lives (Restraint).	Indulgence	Restraint

Appendix A4.1. Labour Market Friction Effect on ESG

This table reports the correlation coefficients of labour market friction loading (LFB) to ESG scores using the fixed effect regression model. Model (1) shows the result of LFB on ESG scores while considering the year effect and industry effect without any control variable. Model (2) only controls the relevant variables but does not consider any effect. Model (3) controls both year and industry effects and control variables. Model (4) shows the result of LFB on ESG scores by controlling the additional region effect in Model (3). The t-values are showing in the brackets, and the significant levels are defined as * p < 0.1, ** p < 0.05, and *** p < 0.01.

	ESG			
	(1)	(2)	(3)	(4)
LFB	1.3576***	1.1623***	1.4007***	0.9773***
	[3.40]	[3.33]	[4.05]	[3.10]
BOARD		1.5712***	1.6770***	1.2244***
		[52.23]	[55.24]	[42.17]
IBOARD		26.6699***	26.8124***	35.6491***
		[56.62]	[56.82]	[78.62]
FAGE		0.2039***	0.1879***	0.2391***
		[27.96]	[25.62]	[34.60]
SIZE		0.2854***	0.3491***	0.8487***
		[10.60]	[12.94]	[26.65]
TOBIN		-0.8408***	-0.9258***	0.0805
		[-12.00]	[-13.08]	[1.23]
PPE		1.4386***	1.4120***	0.0317
		[3.64]	[3.28]	[0.08]
OCF		4.9926***	5.1072***	8.8969***
		[3.88]	[3.89]	[7.42]
LEV		-14.9685***	-14.5629***	3.1204***
		[-33.33]	[-32.40]	[6.30]
ROE		2.3338***	2.4767***	0.3302
		[6.45]	[6.89]	[1.01]
RETSTD		-35.4703***	-41.6368***	-23.6317***
		[-17.41]	[-19.51]	[-12.10]
Cons.	44.665***	21.6662***	22.9138***	-0.8886
	[16.27]	[28.81]	[9.13]	[-0.51]
Year Effect	Yes	No	Yes	Yes
Industry Effect	Yes	No	Yes	Yes
Region Effect	No	No	No	Yes

Obs.	35944	35944	35944	35944
Adj.R2	0.0169	0.2467	0.2647	0.3922

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DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.

Student name:	Hengyu Bai
Name and title of main supervisor:	Liping Zou, Professor in Finance
In which chapter is the manuscript/published work?	Chapter 2
What percentage of the manuscript/published work was contributed by the student?	

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We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.

Student name:	Hengyu Bai
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In which chapter is the manuscript/published work?	Chapter 3
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Student's contribution:
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STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.

Student name:	Hengyu Bai
Name and title of main supervisor:	Liping Zou, Professor in Finance
In which chapter is the manuscript/published work?	Chapter 4
What percentage of the manuscript/published work was contributed by the student?	100%

Describe the contribution that the student has made to the manuscript/published work:
Student's contribution:
Literature and information organisation, insights mining, and the writing process.
Data collection, data cleaning, and in-depth analysis.

Supervisors' contribution:
Guiding the direction of the research, identifying and correcting mistakes within the research, offering critical feedback on the draft, and suggesting revisions to improve clarity and coherence.

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