MARKET EFFICIENCY WITH RESPECT TO CORPORATE CREDIT CONDITIONS AND INTERNAL CAPITAL ALLOCATION

By

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DECLARATION

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed.

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ABSTRACT

This thesis consists of three key papers, which are presented in chapters 2, 3 and 4. The three chapters examine three different issues in financial risk management and corporate investment. Chapter 2 evaluates the effect of International Monetary Fund (IMF) programs on corporate default risk. Chapter 3 investigates the relationship between Internal Capital Market Efficiency and diversified firm default risk. Chapter 4 studies the role of Internal Capital Market Efficiency in predicting the subsequent stock returns of diversified firms. Chapter 3 is the bridge that links the three key chapters in this thesis together. It shares the same scope with chapter 2 in the financial risk management area and with chapter 4 in the corporate investment area.

Using firm-level expected default frequency (EDF) metrics from Moody's KMV and an event study style approach, chapter 2 investigates how corporate default risk responds to IMF intervention and whether the magnitude and direction of the effect are different for the financial versus non-financial sector and for various program sizes and types during the period from 1996 to 2012. Our findings suggest that corporate default risk increases consistently before and after IMF announcements, and is mainly driven by the financial sector in the countries receiving Standby Arrangement (SBA). We also find that countries receiving the smallest IMF program sizes experience greater increases in corporate default risk than the ones receiving the largest loan sizes. These results are robust to the control for the issue of endogeneity.

Sharing the same scope with chapter 2 in the financial risk management area, chapter 3 seeks to establish the link between corporate investment and corporate default risk by studying the effect of Internal Capital Market Efficiency (ICM) on diversified firm default risk, and how this effect varies in firms with different levels of external financial constraints during the period 1997-2014. Following Billett and Mauer (2003), we define ICM as the movements of funds from the segments with low return on assets to the segments with high return on assets. Using panel data of 11,202 firm-year observations in the US, we find a negative association between diversified firm default risk and their use of internal funds. However, this relationship is only

economically significant in highly leveraged firms. Our findings are robust to the three measures of credit risk: Merton-style default probabilities, the Altman Z-score and S&P credit rating. In addition, though the theory suggests that ICM has a stronger effect on the default risk of financially constrained firms, we find weak evidence supporting this argument. Our result shows that ICM only has a larger impact on financially constrained firm default risk in the case of the Altman Z-score.

Taking the ICM computed in chapter 3 as a proxy for diversified firms' expected profitability, chapter 4 investigates the role of this measure in predicting stock returns of diversified firms during the period 1997-2015. Our expected profitability proxy is distinguished from other proxies suggested in the literature since our measure takes into account the firm's current level of external financial constraints. We find that ICM can help predict stock returns, and this predictive ability is incremental to the other stock return predictors identified in the literature such as book to market ratio, firm size, default risk, accruals and Piotroski's (2000) F-score. Furthermore, when examining the relationship between ICM and future stock returns separately for financially constrained and non-financially constrained firms, we find that ICM is only important in predicting stock returns in the former group.

Chapter 1 : Introduction

This thesis consists of three key chapters – chapters 2, 3 and 4 – which examine three different issues in financial risk management and corporate investment. Chapter 3 is the bridge that links the three key chapters in this thesis together. It shares the same scope with chapter 2 in the financial risk management area and with chapter 4 in the corporate investment area. In particular, chapter 2 and chapter 3 investigate the sensitivity of corporate default risk to IMF events and Internal Capital Market Efficiency (ICM) respectively, and chapter 4 studies the role of ICM in determining the subsequent stock returns of diversified firms.

This thesis concentrates on the three areas, and in each area we aim to investigate a specific/set of research question(s):

- IMF programs and Corporate Default Risk
  - ✓ Do IMF programs influence Corporate Default Risk?
- ICM and Corporate Default Risk
  - ✓ Does ICM affect Corporate Default Risk, and is this effect conditional on the firm's level of external financial constraints?
- ICM and Subsequent Stock Returns
  - ✓ Can ICM predict diversified firm stock returns, and does the ability to predict returns of ICM depend on the firm's level of external financial constraints?

This introduction discusses the motivation, methodology and the main findings for each of the aforementioned topics and provides an overview of the thesis.

1.1. IMF programs and Corporate Default Risk

The IMF's role in the world economy is often regarded as that of a 'financial crisis fire-fighter' since its loans and services are utilised the most during periods of crisis. With the aim of helping the recipients overcome balance of payment crises, does IMF financial assistance help reduce corporate default risk? In the face of substantial debate about the effectiveness of IMF interventions, this question has not been addressed in previous studies. Our paper contributes to the literature by providing a new perspective on economic conditions surrounding the announcement of IMF assistance packages; a perspective obtained through studying the dynamics of corporate credit risk exposures in twenty countries receiving assistance over the period from 1996 to 2012.

In the last 70 years, the Fund has received intense criticism from the public, media, economists and researchers. However, evaluating the effect of IMF programs is not an easy task. Most previous studies used macroeconomic variables such as GDP, balance of payments, inflation, and current accounts to measure the effectiveness of IMF programs (for recent surveys see Haque (1998); Joseph (2004); Bird (2007); Steinwand and Stone (2008)). Some other researchers evaluate the impact of IMF intervention on stock performance and financial indicators in a firm's balance sheets (Lau and McInish (2003), Evrensel and Kutan (2007), Can and Ariff (2009)). Our study bridges these two strands of the literature by providing an understanding of the effect of IMF programs on a single measure of corporate default risk; an understanding which incorporates financial health information of both the broad economy and the corporate sector.

We argue that the corporate default risk used in this study is of particular interest for the purpose of evaluating the economic effect of IMF programs for various reasons. Firstly, Altman and Rijken (2011) show that corporate default risk is informative for sovereign health. Therefore, evaluating the effect of IMF programs on corporate default risk does not only help us understand how corporations are affected but also how the IMF event influences the economy. Secondly, EDF is a particularly appealing measure of credit risk exposure insofar as it is forward-looking and reflective of a broad information set. Lastly, the span and coverage of Moody's KMV data affords an outstanding opportunity to gauge the impact of IMF intervention over a period covering several financial crises across Europe, Asia and South America by reference to a large sample of firms, across diverse industries, and a representative sample of IMF program types.

We use an event study style approach to evaluate the impact of IMF intervention on corporate default risk. We compare the IMF participants' corporate default risk with the average default risk of characteristic-matched non-participants based on propensity scores. Propensity scores are the probability that a country receives IMF financial assistance according to the following country characteristics: GDP growth, the ratio of external public and private short-term debt to GDP, the ratio of current account to GDP, the ratio of total reserves to GDP and whether a country was in IMF programs in the previous three years. By controlling for these factors, we can avoid the situation that our results are driven by the differences in country characteristics rather than by the IMF events.

Our results show that corporate default risk consistently increases in the twelve months both prior to and subsequent to the IMF intervention, and this phenomenon is driven mainly by financial firms and programs with attached conditions. When evaluating the effect of liquidity injection, we find that the countries receiving the smallest IMF programs experience a higher degree of risk increase since they are the ones that need the IMF loan most as measured by the propensity scores.

1.2 Internal Capital Market Efficiency and Corporate Default Risk?

While chapter 2 aims at evaluating the effect of external factors such as IMF intervention on corporate default risk, chapter 3 focuses on investigating the effect of internal factors. Using Billett and Mauer's (2003) Internal Capital Market Efficiency (ICM) measure, we complement the literature on corporate diversification by examining the role of ICM in determining diversified firm default risk. Whether ICM has a greater impact on default risk of financially constrained firms is also investigated in this chapter.

Unlike single segment firms, a diversified firm can move its internal funds among its business segments, establishing an internal capital market. This internal capital market is argued to be efficient if the funds are channelled to the productive segments (Meyer, Milgrom et al. (1992), Ambrus-Lakatos and Hege (2002), Billett and Mauer (2003)). However, previous studies find that diversified firms, on average, use their internal capital inefficiently due to agency issues (Berger and Ofek (1995), Rajan, Servaes et al. (2000), Billett and Mauer (2003)). Meyer, Milgrom et al. (1992) and Scharfstein and Stein (2000) show in their theoretical model that a weak division's managers tend to engage in rent seeking or power grabbing behaviours to drain more corporate resources to protect their jobs. These behaviours are shown by Berger and Ofek (1995), Rajan, Servaes et al. (2000) and Billett and Mauer (2003) to have negative effects on the firms' asset values and profitability. Thus, how a diversified firm uses its internal funds is expected to influence its default risk.

Nonetheless, when diversified firms are external financially constrained, headquarters tend to allocate internal funds more efficiently (Hovakimian (2011), Kuppuswamy and Villalonga (2015)). With limited access to external capital, these firms will not be able to obtain external funds to finance their productive segments if their internal funds are directed to the unproductive ones. Meanwhile, non-financially constrained firms with inefficient internal capital markets still can invest in their profitable projects by using external funds. Therefore, the way internal capital is used is expected to have a greater impact on the default risk of financially constrained firms than that of the non-financially constrained firms.

Three different measures of corporate default risk are employed in this study: Merton-style default probability computed as in Bharath and Shumway (2008), the Altman Z-score and S&P credit rating. Since each default risk measure has unique statistical characteristics, we use different models in each case to estimate the relationship between ICM and default risk. In particular, in the case of default probability which have 0 and 1 as the lower and upper bound values, we add (subtract) these values by 0.0001 respectively. Since the new values generated are no longer bounded by 0 and 1, we can transform our dependent variable to the inverse normal cumulative distribution so that we can conduct the analysis using Ordinary Least Square (OLS) regression. For the Altman Z-score, we first group the firms into three ordered categories basing on certain Z-score thresholds. We then employ an ordered logistic regression to estimate the relationship between ICM and default risk for both the case of Altman Z-score categories and S&P credit ratings. For external financial constraints, we employ three different measures that have been widely used in the literature: the Kaplan Zingales index (Lamont, Polk et al. (2001)), the Whited and Wu index (Whited and Wu (2006)) and the Size and Assets index (Hadlock and Pierce (2010)).

Our empirical results show that ICM is an important determinant of corporate default risk in highly leveraged diversified firms. The more efficiently these firms use their internal funds, the lower their default risk. This result is robust to all three corporate default risk measures. However, we find weak evidence supporting the argument that ICM should have a stronger impact on default risk when firms are external financially constrained. ICM is only found to have a greater impact on default risk of financially constrained firms in the case of the Altman Z-score.

1.3 Internal Capital Market Efficiency and Diversified Firms' subsequent returns

Taking Internal Capital Market Efficiency (ICM) introduced in chapter 2 as a proxy for the expected profitability of diversified firms, we investigate whether this measure is an important indicator for their future stock returns, especially in firms subject to external financial constraints.

Previous studies have demonstrated the role of financial strength, which is constructed from a firm's financial statement information, in helping to predict stock returns (Ou and Penman (1989), Holthausen and Larcker (1992), Lev and Thiagarajan (1993), Abarbanell and Bushee (1997), Piotroski (2000)). This predictive ability comes from the market's slow response to the information underlying the financial strength, which leads to the delay in revising the stock price expectation. This phenomenon, it is argued, is a result of the information uncertainty issue, which potentially comes from two sources: the volatility of a firm’s underlying fundamentals and poor information (Hirshleifer (2001), Zhang (2006)). Due to their complex business structures, diversified firms are well fitted in the context of information uncertainty. Supporting this argument, Habib, Johnsen et al. (1997), Gilson, Healy et al. (1998) and Thomas (2002) show that misvaluation is more likely to happen in diversified firms. With multiple business segments, it is expected that the market’s responses to diversified firms’ ICM information will be delayed. This study draws a link between the efficiency of internal and external capital markets through the investigation of whether ICM can predict diversified firm stock returns.

Previous studies have shown that the way a firm uses its internal funds is most important in the context of external financial constraints (Ambrus-Lakatos and Hege (2002), Billett and Mauer (2003), Kuppuswamy and Villalonga (2015)). If a financially constrained firm uses its internal capital inefficiently, it is less likely to have access to the external capital market to finance its profitable investments. However, in the absence of such constraints, a firm can still use external funds to finance its positive NPV projects if all of its internal funds are channelled to its unproductive ones. Thus, the effect of ICM on subsequent return is arguably stronger in the financially constrained firms.

In this study, ICM is measured as in Billett and Mauer (2003). For external financial constraints, we use two different financial constraint indexes: Whited and Wu index (Whited and Wu (2006)) and Size and Assets index (Hadlock and Pierce (2010)), which have been widely used in the literature. We conduct both a univariate analysis and a multivariate regression analysis to investigate the effect of ICM on future stock returns and whether this effect is stronger in the financially constrained firms.

Our results show that ICM can predict diversified firms’ stock returns. This predictive ability remains important after controlling for other factors that have been shown to influence future returns such as firm sizes, book to market ratio, default risk, accrual and Piotroski's (2000) F-score. When examining the relationship between ICM and future stock returns in the context of external financial constraints, we find that the effect of ICM on future stock returns is stronger in financially constrained firms than in non-financially constrained firms.

1.4 Structure of the Thesis

This PhD thesis consists of three research papers, which can be assigned to the research areas discussed above in the following order:

Chapter 2 presents the working paper titled *The Effect of IMF Programs on Corporate Default Risk*. This paper was presented at the 8th Portuguese Finance Network International Conference 17^{th} -19^{th} 2014, Vilamoura, Portugal.

Chapter 3 presents the working paper titled *Internal Capital Market Efficiency and Diversified Firms' Default Risk.* This paper was presented at the following conferences:

- ✓ *AFAANZ Doctoral Symposium 2015 2^{nd} – 4^{th} July, Hobart, Australia*
- ✓ *2016 AFAANZ Conference 3^{rd} -5^{th} July, Gold Coast, Queensland, Australia*

Chapter 4 presents the working paper titled *Does Internal Capital Market Efficiency Predict Future Stock Returns?*

Finally, chapter 5 summarizes the thesis with the conclusion from each article as well as the potential direction for future research.

Chapter 2 : The Effect of IMF Programs on Corporate Default Risk

Thanh Truc Nguyen (Contribution 70%), Egon Kalotay (Contribution 20%) and

Geoffrey Loudon (Contribution 10%)

Abstract

This study evaluates the economic impact of IMF assistance programs through documenting the effect of such programs on corporate default risk in 20 countries over the 1995-2012 period. Using firm-level expected default frequency (EDF) metrics from Moody's KMV and an event study style approach we show that IMF assistance is associated with an abnormal increase in corporate default risk in the twelve months prior to and subsequent to announcements of IMF intervention. Our findings are robust to control for endogeneity and thus call into question, from a new perspective, the immediate and longer term economic impact of IMF assistance programs.

2.1 Introduction

The role of the International Monetary Fund (IMF) is often likened to that of a financial fire fighter: a provider of loans and structural reform assistance during times of financial crisis. However, evaluating the economic impact of IMF assistance programs is no easy task, and the question of their effectiveness is an issue in ongoing debate amongst policy-makers, academic researchers and the media. We contribute to this debate by providing a new perspective on economic conditions surrounding the announcement of IMF assistance packages obtained through studying the dynamics of corporate credit risk exposures in twenty countries receiving assistance over the period spanning 1995 to 2012. Using firm-level expected default frequency (EDF) metrics from Moody's KMV and an event study style approach, our results suggest that IMF announcements of assistance are preceded and succeeded by a robust and pervasive increase in corporate credit risk in recipient countries relative to characteristic-matched counterparts in countries which do not receive IMF assistance over the same period. While our findings are robust to the program type, the magnitude of intervention and benchmark specifications, the phenomenon is driven, to a large extent, by companies in the financial sector and companies in the countries receiving the smallest program sizes.

Most extant studies of IMF program effects are conducted with reference to macroeconomic aggregates such as GDP, balance of payments and inflationary outcomes – Haque (1998), Joseph (2004), Bird (2007), and Steinwand and Stone (2008) provide surveys of the literature. More recently, studies have evaluated the effectiveness of IMF programs with reference to accounting and market-based indicators of firms' financial performance – see for example Lau and McInish (2003), Evrensel and Kutan (2007) and Can and Ariff (2009). As will be discussed, the results of these studies yield mixed signals about the effectiveness of IMF programs; hence there is not only a need for further empirical evidence, but also a need for evidence that maps the broad range of disparate information to clear (unambiguous) economic outcomes. Accordingly, we argue that the Merton (1974) model-based measure of corporate default risk, embodied in Expected Default Frequency (EDF) provided by Moody's KMV, of particular interest in the current context for several reasons.

Firstly, at a general level, the credit risk exposure of the corporate sector not only reflects, but is also a key determinant of the financial health of the broader economy. Altman and Rijken (2011) use this line of reasoning to argue, and demonstrate, that this characterization of financial health is reflected in the risk premiums associated with sovereign debt. As such, aggregated measures of corporate credit risk exposures suggest themselves as a natural, but as yet unexplored, measure of the economic impact of IMF financial assistance packages.[1] Secondly, EDFs are particularly appealing measures of credit risk exposure insofar as they are forward-looking and reflective of a broad information set. Being derived from market data, these

[1] However, while Altman and Rijken (2011) use corporate credit scoring model to measure credit risk exposures, we use a market measure of credit risk – KMV's expected default frequency.

measures embody market expectations of future outcomes, as well as the uncertainty reflected in the volatility of past price outcomes. Furthermore, the breadth of the information used to construct firm-level risk exposures includes accounting data, market prices and returns, and also historical default experience. As such, EDF distils a combination of historical and market-based information to a single, unambiguous measure of firm-level financial health.

Finally, the span and coverage of Moody's KMV data affords an outstanding opportunity to gauge the impact of IMF intervention over a period covering several financial crises across Europe, Asia and South America by reference to a large sample of firms, across diverse industries, as well as a representative sample of IMF program types.

2.2 How do IMF programs influence corporate default risk?

A member country approaches the Fund when it is in or near a state of balance of payment crisis (Barro and Lee (2005), Dreher and Walter (2010), Jorra (2012), Presbitero and Zazzaro (2012)). With the aim of helping member countries overcome this situation, loans provided by the IMF are expected to help reduce the corporate default risk which is an important measure of a country's economic and financial health (Altman and Rijken (2011), Borensztein, Cowan et al. (2013)). However, while some studies find that IMF programs help to improve current economic conditions as measured by lower sovereign bond spreads, higher fiscal surpluses and higher profitability in the banking sector (Atoyan and Conway (2006), Eichengreen, Kletzer et al. (2006), Evrensel and Kutan (2008)), other studies find that IMF programs lead to lower GDP growth, higher sovereign default probabilities and lower asset values (Przeworski and Vreeland (2000), Brealey and Kaplanis (2004), Barro and Lee (2005), Jorra (2012)). Empirical evidence of the net macroeconomic effects of IMF assistance programs is equivocal at best.

Since a country's economic and financial health are closely connected with its private sector's performance, literature about the effect of an IMF loan on sovereign risk can provide an overview of how corporate default risk is impacted by IMF interventions. One of the common sovereign risk measures used in the literature is bond spreads. Despite using different methodologies and focusing on different time frames, most studies using bond spreads to measure sovereign risk have results that are in favour of IMF programs. For instance, Evrensel and Kutan (2008) find that news about IMF program approval and negotiation decreased sovereign bond spreads in Indonesia and Korea. Eichengreen, Kletzer et al. (2006) also find that a country's bond spreads are lower if the bonds are issued while receiving IMF assistance. However, when using sovereign default probabilities to measure sovereign risk, Jorra's (2012) result indicates negative effects of IMF interventions. He shows that, on average, participating in IMF programs leads to an increase in sovereign default probabilities by approximately 1.5 to 2 percentage points. Due to the strong connections between sovereign risk and corporate default risk (Altman and Rijken (2011), Borensztein, Cowan et al. (2013)), these contradictory findings present conflicting signals about the effect of IMF programs on corporations. By using a direct measure of corporate default risk (EDF), which reflects both economic and private sector conditions, we not only provide an understanding of how IMF intervention influences corporate default risk but also help to establish whether the risk impacts measured at corporate level are consistent with those measuring at sovereign level found in the literature.

At a general level, IMF programs are intended to avert macroeconomic crises through a temporary injection of liquidity, and such cash assistance may or may not include a package of attached conditions intended to impose fiscal discipline and structural reforms to deliver the benefits of efficiently functioning markets. Such reforms may include programs of privatisation and trade liberalisation. While the injection of liquidity, appropriately distributed, is likely to provide at least a temporary benefit to recipients and their creditors, such benefits may well be attenuated or outweighed by the effects of fiscal austerity measures and the increased exposure to competition and market forces. Forward-looking private sector credit metrics, such as KMV's EDF measures, capture the market's assessment of these impacts, to the extent that credit risk metrics reflect the economic output and productivity of the private sector, as argued and demonstrated in the context of sovereign risk assessment by Altman and Rijken (2011).

The three program types considered in this study are the Standby Arrangement (SBA), Extended Fund Facility (EFF) and the Flexible Credit Line (FCL). Details of IMF programs are outlined in Table 2.1. Among the three program types, FCL is only given out to the countries that have strong fundamentals, policies and track records of policy implementation. Therefore, this type of IMF arrangement does not rely on traditional program conditionality. On the contrary, both SBA and EFF have many attached conditions. However, while a SBA targets country with short-term balance of payment issue, an EFF is given out to the one with long-term or medium term balance of payment problem. Therefore, countries receiving SBA assistance need to implement economic and financial reform policies intensively in a short time period to be eligible for additional, agreed funds within the program's duration (1-2 years) and to quickly tackle their current balance of payment issue. Meanwhile, EFF recipients have 3-to-4 years to conduct economic and financial reform policies.

Table 2.1 Summaries on the characteristics of different IMF program types

	Standby Arrangement (SBA)	**Extended Fund Facility (EFF)**	**Flexible Credit Line (FCL)**
Recipients	Being in an economic crisis and needing urgent funding to meet external financing needs	Facing serious long term or medium term balance of payments problems due to structural weaknesses or experiencing slow economic growth and a weak balance of payment position	Having strong economic fundamentals and policy track record, but in high risk of having a crisis
Conditions	- Quantitative conditions such as the targets for international reserves and government deficits or borrowing - Requirements to implement structural reform such as privatisation, fiscal austerity, free trade etc. to meet the IMF's structural measures - Conditions vary with the recipients' economic conditions but must focus on these areas: macroeconomic stabilization, monetary, fiscal and exchange rate policies and financial system issues	- Having attached conditions focusing on structural reform such as privatisation, fiscal austerity, free trade etc. to tackle institutional and economic issues and maintain macroeconomic stability - Conditions vary with the recipients' economic conditions but must focus on these areas: macroeconomic stabilization, monetary fiscal and exchange rate policies and financial system issues	No attached conditions
Duration	- 1-2 years	- 3-4 years	- 1-2 years
Repayment period	- 3.25-5 years	- 4.25-10 years	- 3.25 to 5 years

Source: International Monetary Fund factsheets on Standby Arrangement, Extended Fund Facility, Flexible Credit Line (2016) and IMF Guidelines on Conditionality (2002)

Though IMF program conditions vary with the recipients' situations, the requirement to implement financial policies to tackle financial system issues and enhance financial system stability is one of the conditions attached to all SBA and EFF (IMF Guidelines on Conditionality (2002)). Due to this specific characteristic, literature about the effect of IMF programs on corporations focuses mainly on the financial sector's performance. For instance, Can and Ariff (2009) show that with IMF financial assistance, the banking sector in East Asian countries became more efficient and sound, implying potential lower default risk. The impact of IMF programs on the other corporate performance measures, such as bank stock returns and volatility, is also considered. However, while abnormal stock price appreciation on the IMF program approval dates are found in Lau and McInish (2003) and Evrensel and Kutan (2007), Evrensel and Kutan's (2007) results indicate an increase in stock return volatilities. The Merton-style EDF metric used in our study accounts for both volatility and value effects and thus yields a particular economic evaluation of the trade-off between the effects.

Loans provided by the IMF are not only used to help the recipients repay short-term debts and resolve current account deficits, but they are also channelled to the private sectors in the form of liquidity support for financial institutions, private sector investment spending or to implement economic reform policies (Benelli (2003), Barro and Lee (2005), Can and Ariff (2009)). All else being equal, the benefits conferred by a liquidity injection are related to program sizes. Though previous studies that take size into account when examining the effect of IMF loans focus only on examining the impact of IMF programs on macroeconomic variables, their results have implications for the effect of IMF program sizes on corporate default risk. For example, a theoretical model developed by Zettelmeyer (2000) shows that IMF loans that meet only part of a country's liquidity needs have counterproductive effects and trigger debt runs. However, Jorra (2012) finds that countries receiving large loan sizes have higher sovereign default probabilities. Similarly, Benelli's (2003) results show that the success of IMF programs, defined as whether the program's targets for net private capital flow are met, is negatively related to program size. Some other studies find no association between IMF program size and economic growth rates or the likelihood of currency crisis (Barro and Lee (2005), Dreher and Walter (2010)). Inconsistent results regarding the size effects of IMF programs on macroeconomic conditions raise a question of how the corporate sector's default risk is impacted by different program sizes.

2.3 Methodology and data

2.3.1 Methodology

An event study methodology is adopted in this research to examine the impact of IMF programs on corporate default risk. This method provides a clear view of the direction and magnitude of how corporate default risk responds to IMF events.

2.3.1.1 Event definition

The main event month in this paper is the month of the official IMF announcement. All information relating to the conditions, size and duration of the program will be publicly available in this month. Though only a certain proportion of the agreed loans are given to the recipients at the time of the announcement and the rest will be dispensed in instalments depending on whether the prescribed conditions are met, loan size information is released on the announcement date. Because an IMF loan agreement is the result of a negotiation between IMF officers and the government, potential early market anticipation of an IMF program should be taken into account (Brealey and Kaplanis (2004), Evrensel and Kutan (2007), Evrensel and Kutan (2008)). Therefore, the twelve months before the event month will be considered. In addition, as new economic policies prescribed in the IMF arrangements need time to take effect, the twelve months after the IMF's official announcement will also be examined (Jorra (2012)).

2.3.1.2 Measuring normal and abnormal default risk

To isolate the effect of IMF events on corporate default risk, we need to compute the abnormal percentage changes in corporate default risk. Our objective is to identify the percentage changes (cumulative) in default risk attributable to the IMF announcement events. In this paper, corporate default risk is measured by KMV's Expected Default Frequency (EDF) collected from KMV's Expected Default Frequency database. The KMV's EDF is an estimate of the probability that a firm defaults in the next year and is computed based on an extension of the Merton (1974) model. In the first step, a firm's asset value and asset volatility is estimated from the market value and volatility of its equity and the book value of its liabilities. This is done by expressing the observed equity value and equity volatility as implied option-related functions of a firm's asset value, asset volatility, capital structure, and the risk free rate. The distance to default is then computed, which measures the number of standard deviations away from default a firm's current asset value is. Next, using the proprietary database on historical default, KMV determines the distribution of changes in distance to default and the EDF is computed based on that distribution.

Details of how to compute normal and abnormal percentage changes in EDF are outlined below.

Firstly, monthly percentage changes in EDF are calculated for each company i in country j at time t

$$\Delta EDF_{jit} = \frac{EDF_{jit} - EDF_{ji(t-1)}}{EDF_{ji(t-1)}} \tag{1}$$

Percentage changes in EDF for each country j at time t are the average of the percentage changes in EDF across all companies in that country at time t

$$\Delta EDF_{jt} = \frac{1}{n}\sum_{i=1}^{n} \Delta EDF_{jit} \tag{2}$$

For each country j that received IMF arrangements during the research period,[2] abnormal percentage changes in EDF at time t are computed as the differences between its percentage changes in EDF and normal percentage changes in EDF at time t:

[2] Our EDF data covers the period Jan 1995-Dec 2012. However, as the effects of IMF intervention on corporate default risk are evaluated for twelve months before and after the event, we only examine the IMF events occurring between Jan 1996 and Dec 2011.

$$\Delta \mathrm{AEDF_{jt}} = \Delta \mathrm{EDF_{jt}} - \Delta \mathrm{NEDF_{jt}} \quad (3)$$

In which:

- ΔEDF_{jt}: observed percentage changes in EDF for country j at time t
- $\Delta NEDF_{jt}$: normal percentage changes in EDF for country j at time t
- $\Delta AEDF_{jt}$: abnormal percentage changes in EDF for country j at time t.

To ensure that $\Delta AEDF_{jt}$ reflects only the impact of IMF intervention on corporate default risk, $\Delta NEDF_{jt}$ must be the approximately true values for country j's average percentage changes in EDF at time t as if it had not received the IMF arrangements. As the countries that do not enter into IMF programs may be systematically different from the ones that do, the $\Delta AEDF_{jt}$ may reflect the differences in macroeconomic conditions between the participant and non-participants apart from the effect of IMF events, resulting in an endogeneity issue. To tackle this issue, we use the propensity score matching method to compute the $\Delta NEDF_{jt}$. Based on this approach, we match each IMF participant's ΔEDF to the mean ΔEDF of N non-IMF participants that most closely match the IMF participant at time t based on a propensity score. This approach helps to ensure that $\Delta AEDF_{jt}$ are driven only by the IMF intervention. In the first step of this approach, we use the common factors that affect the decision of entering into an IMF program identified in the literature to calculate the probability (propensity score) that a country receives the IMF loans at time t. These factors are the ratio of total reserves to GDP, GDP growth, the ratio of short-term external public and private debt to GDP, the ratio of current account to GDP and a dummy variable indicating whether a country was in an IMF program in the previous three years (Atoyan and Conway (2006), Dreher and Walter (2010), Presbitero and Zazzaro (2012)). Next, for each IMF participant at time t, we find another five non-IMF participants that have the nearest propensity scores to that country. Average ΔEDF across these five countries at time t is a country j's $\Delta NEDF_t$, which can be considered as the participant's ΔEDF as if it had not received the IMF financial assistance. We also repeat our analysis when

$\Delta NEDF_{jt}$ is computed in the robustness test as the average of the percentage changes in EDF across non-IMF participants.

Abnormal percentage changes in EDF are then aggregated across N events at time t to generate average abnormal percentage changes in EDF, $\overline{AEDF_t}$, expressed by:

$$\overline{AEDF_t} = \frac{1}{N}\sum_{k=1}^{N} AEDF_{kt} \qquad (4)$$

We define $CAEDF_k\,(t_1,t_2)$ as cumulative abnormal percentage changes in EDF for event k from t_1 to t_2 of the event window. It is computed as follows:

$$CAEDF_k(t_1,t_2) = \sum_{t=t_1}^{t_2} AEDF_{kt} \qquad (5)$$

Average cumulative abnormal percentage changes in EDF across N events are then calculated:

$$\overline{CAEDF}(t_1,t_2) = \frac{1}{N}\sum_{k=1}^{N} CEDF_k|t_1,t_2| \qquad (6)$$

A t-test of the null hypothesis that the mean is equal to zero is conducted for selected event months. To conduct these tests, variances are calculated as follows:

$$var(\overline{AEDF_t}) = \frac{1}{N^2}\sum_{k=1}^{N} var(AEDF_{kt}) \qquad (7)$$

$$var(\overline{CAEDF}\,(t_1,t_2)) = \frac{1}{N^2}\sum_{k=1}^{N} var(CAEDF_k(t_1,t_2)) \qquad (8)$$

2.3.2 Sample characteristics

a. Data description

Sample countries are chosen based on data availability. Among the 70 countries included in the KMV's EDF database, 20 countries received IMF financial assistance between 1996 and 2011. Information about IMF program announcement dates, sizes and types was hand-collected from the IMF Monitoring of Fund Arrangements Database (MONA).

The three types of IMF financial assistance examined in this study are: Standby Arrangement (SBA), Extended Fund Facility (EFF) and Flexible Credit Line (FCL). Following Dreher and

Walter (2010) and Benelli (2003), the sizes of these three IMF programs are measured as the ratio of IMF loans to the recipients' GDP in the year of the IMF announcement. Program sizes will then be divided into quartiles to help us study the size effect.

Table 2.2 shows that among the three regions, South American countries are the most frequent users of IMF programs. They participated in 26 programs during our research period, which is more than double the number of programs entered by European countries. However, the total amount of money agreed under the IMF arrangements in Europe is nearly 68% of the agreed loans in South America. IMF program types also vary in each region. While European and Asian countries received 6 and 9 Standby Arrangements respectively, South American countries received 15 Standby Arrangements between 1996 and 2011.

Information about different IMF program sizes is also provided in Table 2.2. It is clear that the majority of countries receiving the largest amount of IMF financial assistance are in Europe. Meanwhile, most IMF loans given to South American countries are in the bottom 25 percentile. This reconfirms the bigger sizes of IMF programs in Europe compared to the other regions.

For the purpose of computing the propensity scores, other macroeconomic variables such as GDP, short-term external public and private debt, current account balance (CA) and total reserves (TR) were collected from the World Economic Development Indicator Database (World Bank Database). GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. Short-term external public and private debt is the debt that has an original maturity of one year or less. CA is the sum of net exports of goods and services, net primary income, and net secondary income. Total reserves comprise holdings of monetary gold, special drawing rights, reserves of IMF members held by the IMF, and holdings of foreign exchange under the control of monetary authorities.

b. Propensity score matching

Table 2.2 List of countries by geographic regions

This table lists countries in the top 25, middle 50 and bottom 25 percentiles of IMF program size, number of IMF programs in each country, total number of IMF programs and total amount of money agreed under IMF arrangements in the three regions: Asia, South America and Europe. Size is computed as the ratio of the IMF's agreed loan at time t to the recipient's GDP at time t. IMF loans are quoted in SDR which is a basket of Euro, Japanese yen, Pound Sterling, and U.S. dollar.

Percentiles \ Region	Asia	South America	Europe
Top 25% IMF program size ≥ 0.004	Indonesia (1) Pakistan (1)	Argentina (2) Brazil (1) Mexico (1)	Greece (1) Hungary (1) Iceland (1) Ireland (1) Portugal (1) Turkey (2)
Middle 50% 0.004 ≥IMF program size ≥ 0.001	Indonesia (2) Korea (1) Pakistan (1) Philippines (1) Sri Lanka (3) Thailand (1)	Brazil (2) Colombia (5) Mexico (2) Panama (1) Venezuela (1)	Hungary (1) Poland (2) Turkey (1)
Bottom 25% IMF program size ≤ 0.001	Pakistan (2)	Argentina (2) Colombia (1) Mexico (1) Panama (1) Peru (6)	
Total number of IMF programs	13	26	11
Standby Arrangement	9	15	6
Extended Fund Facility	4	5	2
Flexible Credit Line	0	6	3
Total amount of money agreed under IMF programs (in SDR)	48,919,030	212,771,117	143,744,020

Following Atoyan and Conway's (2006) study,[3] the propensity scores are the fitted values from the following probit regression:

$$P_{jt} = \beta_0 + \beta_1 GDPG_{j(t-1)} + \beta_2 \frac{Debt_{j(t-1)}}{GDP_{j(t-1)}} + \beta_3 \frac{CA_{j(t-1)}}{GDP_{j(t-1)}} + \beta_4 \frac{TR_{j(t-1)}}{GDP_{j(t-1)}}$$

$$+ \beta_5 Dummy_{jt} + \varepsilon_{jt} \qquad (9)$$

In which:

- P_{jt}: dummy variable, equals 1 if country j receives IMF loans at time t and equals 0 otherwise
- $GDP_{j(t-1)}$: country j's GDP at time t-1
- $TR_{j(t-1)}$: country j's total reserves at time t-1
- $GDPG_{j(t-1)}$: proportional changes of country j's GDP at time t-1 comparing to time t - 2.
- $Debt_{j(t-1)}$: total external short-term public and private debt of country j at time t-1
- $CA_{j(t-1)}$: current account of country j at time t-1
- $Dummy_{jt}$: prior assistance indicator which equals 1 at time t if country j received IMF's financial assistance in the previous three years

The dependent variable in the equation (9) is a dummy variable, equalling 1 if country j receives an IMF loan in year t and 0 otherwise. All the other controlled variables are lagged 1 year except the $Dummy_{it}$. Fitted values from the equation (9) is the probability that a country receives IMF financial assistance in year t.

Regression results for the equation (9) are presented in Table 2.3. Table 2.3 shows that all the coefficients have the expected signs and are statistically significant. These results indicate that the variables specified in our model are statistically significant predictors for the probability

[3] Atoyan and Conway (2006) include the following variables in their probit regression: one year and two year lag of GDP growth, one year and two year lag of changes in the ratio of fiscal balance to GDP and one year and two year lag of changes in the ratio of current account balance to GDP; one year lag of GDP, one year lag of the ratio of fiscal balance to GDP and one year lag of the ratio of current account balance to GDP; and the number of years in the last 10 years that the country spent in IMF programs

that a country participates in IMF programs. In particular, Table 2.3 shows that a country with higher GDP growth rate, higher total reserves to GDP ratio and higher current account to GDP ratio has a lower probability of being in an IMF program. Meanwhile, when a country has higher short-term debt to GDP ratio and was in the IMF program in the previous 3 years, it tends to have a higher probability of receiving IMF loans.

Predicted values estimated from the equation (9) are the propensity scores. They measure the probability that country j receives IMF financial assistance in year t. An IMF participant's ∆NEDF at time t is the average ∆EDF of the five non-IMF participants that have the nearest propensity scores at time t.[4]

Panel A of Table 2.4 reports descriptive statistics for the propensity scores. As can be seen in this table, IMF participants have average propensity scores of 0.20 while the figure for non-IMF participants is only 0.05. The median propensity score for a non-IMF participant is also lower than for IMF participants. When examining the differences in propensity score between IMF participants and their five matched countries, Panel B of Table 2.4 shows that the mean difference between two groups of countries is 0.02 and the maximum value is 0.11.

[4] The choice of matching with the 5 nearest propensity score non-IMF participants is arbitrary. We also conduct our analysis when varying the choice of matching with 1 to 7 nearest propensity score non-IMF participants. Our results remain statistically similar.

Table 2.3: Results for propensity score matching

This table presents the regression results for the following equation: $P_{jt} = \beta_0 + \beta_1 GDPG_{j(t-1)} + \beta_2 \frac{Debt_{j(t-1)}}{GDP_{j(t-1)}} + \beta_3 \frac{CA_{j(t-1)}}{GDP_{j(t-1)}} + \beta_4 \frac{TR_{j(t-1)}}{GDP_{j(t-1)}} + \beta_5 Dummy_{jt} + \varepsilon_{jt}$ *with* P_{jt} *is dummy variable, equals 1 if country j receives IMF loans at time t and equals 0 otherwise;* $GDP_{j(t-1)}$*: country j's GDP at time t-1;* $TR_{j(t-1)}$*: country j's total reserves at time t-1;* $GDPG_{j(t-1)}$*: proportional changes of country j's GDP at time t-1 comparing to time t -2;* $Debt_{j(t-1)}$*: total short-term external private and public debt of country j at time t-1;* $CA_{j(t-1)}$*: current account of country j at time t-1;* $Dummy_{jt}$*: prior assistance indicator which equals 1 at time t if country j received IMF financial assistance in the previous three years. ***, ** and * denote significance levels of 1%, 5% and 10%*

Variable	Coefficients	p-values
GDPG	-0.04*	0.08
Debt/GDP	0.03**	0.02
CA/GDP	-0.06***	0.00
TR/GDP	-2.94**	0.01
Dummy	1.20***	0.00
Constant	-1.76***	0.00
Pseudo R square	0.26	
Obs	850	

Table 2.4: Descriptive statistics for the propensity scores

Panel A of Table 2.4 presents descriptive statistics for the propensity scores. Propensity scores are the fitted values from the following regression $P_{jt} = \beta_0 + \beta_1 GDPG_{j(t-1)} + \beta_2 \frac{Debt_{j(t-1)}}{GDP_{j(t-1)}} + \beta_3 \frac{CA_{j(t-1)}}{GDP_{j(t-1)}} + \beta_4 \frac{TR_{j(t-1)}}{GDP_{j(t-1)}} + \beta_5 Dummy_{jt} + \varepsilon_{jt}$ *with* P_{jt} *is dummy variable, equals 1 if country j receives IMF loans at time t and equals 0 otherwise;* $GDP_{j(t-1)}$*: country j's GDP at time t-1;* $TR_{j(t-1)}$*: country j's total reserves at time t-1;* $GDPG_{j(t-1)}$*: proportional changes of country j's GDP at time t-1 comparing to time t -2;* $Debt_{j(t-1)}$*: total short-term external private and public debt of country j at time t-1;* $CA_{j(t-1)}$*: current account of country j at time t-1;* $Dummy_{jt}$*: prior assistance indicator which equals 1 at time t if country j received IMF financial assistance in the previous three years*

Panel B presents descriptive statistics for the differences in the propensity scores between IMF participants' and their five matched countries.

Panel A: Propensity scores						
	Mean	**Median**	**Std**	**Min**	**Max**	**N**
Non-participants	0.05	0.02	0.09	0.00	0.70	800
Participants	0.20	0.20	0.13	0.01	0.46	50
Panel B: differences in the propensity scores between IMF participants and their five matched countries						
	Mean	**Median**	**Std**	**Min**	**Max**	**N**
Differences in the propensity scores	0.02	0.01	0.02	0.00	0.11	50

2.4 Empirical results

2.4.1 Overall results for 20 sample countries

Table 2.5 reports mean abnormal and mean cumulative abnormal percentage changes in EDF for selected event months. It shows that abnormal percentage changes in EDF are consistently positive and statistically significant at the 1% level in selected event months except the month before the announcement. Evidence of the event effect is strengthened when accumulating over the event period. Column 2 of Table 2.5 shows that cumulative abnormal percentage changes in EDF are all positive and statistically significant, indicating that IMF intervention results in higher corporate default risk. A clearer view of how corporate default risk responds to IMF events over time is presented in Figure 2.1.

Figure 2.1 shows that the corporate sector persistently becomes riskier before IMF announcements, indicating negative early market response to the upcoming IMF events. After the approval of IMF loans, corporate default risk continues to rise. The increases in default risk are especially large from month 3 to month 5 after the event, but become more stable after that. Our results here not only show the negative corporate default risk effects of IMF intervention, but also suggest there is a negative effect of IMF events on sovereign risk due to the close connection between a country's sovereign risk and its corporate sector's financial health (Altman & Rijken (2011), Borensztein, Cowan et al. (2013)). These findings are consistent with Jorra (2012) in which he finds that participating in IMF programs leads to higher sovereign default probabilities.

Table 2.3: Mean abnormal and mean cumulative abnormal percentage changes in EDF for selected event months

This table reports mean abnormal and mean cumulative abnormal percentage changes in EDF for selected event months across all IMF events in 20 sample countries.

Abnormal percentage changes in EDF can be computed as follows:

$AEDF_{jt} = EDF_{jt} – NEDF_{jt}$

In which:

- $AEDF_{jt}$*: country j's abnormal percentage changes in EDF at time t*
- EDF_{jt}*: country j's actual percentage changes in EDF at time t*
- $NEDF_{jt}$*: country j's normal percentage changes in EDF at time t computed as the average of percentage changes in EDF across the five countries that do not participate in IMF programs and have the closest propensity scores.*

Calculated abnormal percentage changes in EDF are accumulated and then averaged at each point in the event time across 20 countries to form cumulative abnormal percentage changes in EDF. A t-test is conducted to test for the null hypothesis that the mean equals zero for selected event months.

Month	**Abnormal %ΔEDF**	**Cumulative abnormal %ΔEDF**
-12	34.081*	34.081***
-11	5.013*	39.094***
-9	6.237***	49.367***
-7	5.836**	82.828***
-5	6.453**	116.548***
-4	10.953***	127.501***
-2	10.512***	147.053***
-1	17.689	164.743***
0	11.595***	176.337***
1	6.601**	182.939***
2	11.265**	194.204***
4	28.834*	249.255***
5	11.321***	260.5756***
7	5.417***	274.468***
9	3.981*	287.938***
11	8.293***	292.346***

***, ** and * denote significance levels of 1%, 5% and 10%

Figure 2.1: Mean cumulative abnormal percentage changes in EDF over the 25-month event period across all IMF events in 20 sample countries

This figure shows mean cumulative abnormal percentage changes in EDF for 25 event months across all IMF events in 20 sample countries.

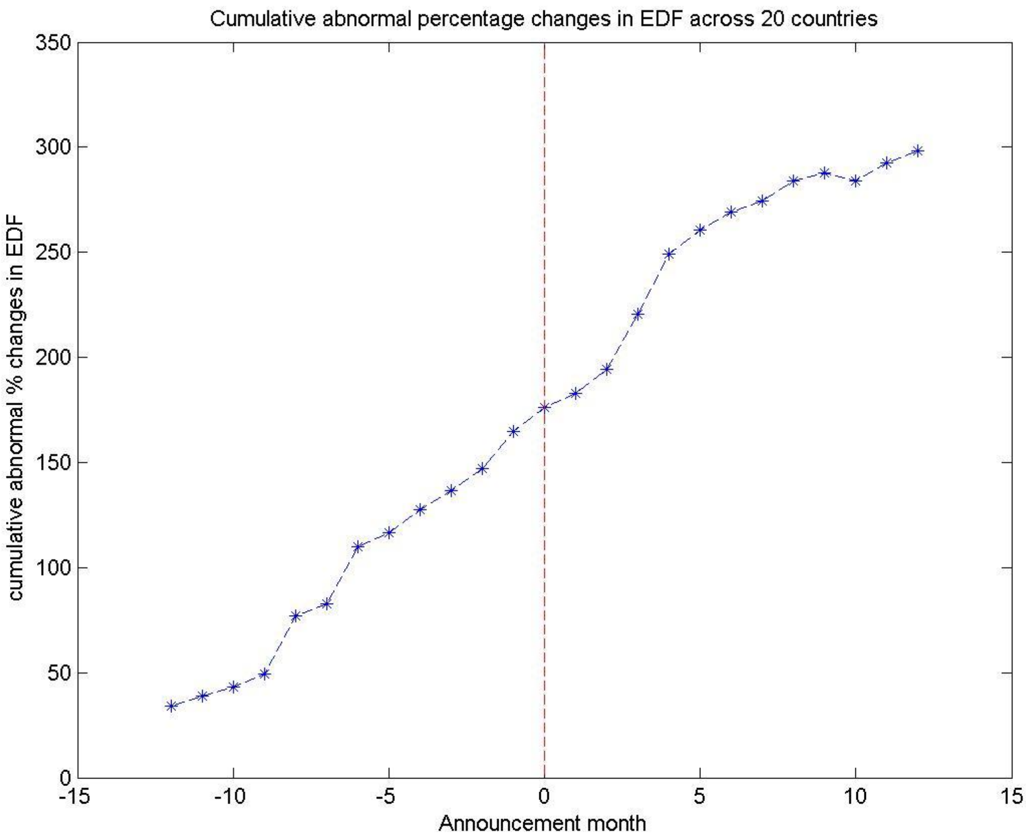
Abnormal percentage changes in EDF are computed as follows:

$AEDF_{jt} = EDF_{jt} – NEDF_{jt}$

In which:

- $AEDF_{jt}$*: country j's abnormal percentage changes in EDF at time t*
- EDF_{jt}*: country j's actual percentage changes in EDF at time t*
- $NEDF_{jt}$*: country j's normal percentage changes in EDF at time t computed as the average of percentage changes in EDF across the five countries that do not participate in IMF programs and have closest propensity scores.*

Calculated abnormal percentage changes in EDF are accumulated and then averaged at each point in the event time across 20 countries to form cumulative abnormal percentage changes in EDF. A t-test is conducted to test for the null hypothesis that the mean equals zero for selected event months.



2.4.2 The effect of IMF programs on financial and non-financial industries

IMF assistance programs and their associated reform conditions tend to focus on and impact the financial industry most directly, hence we compare the effect of IMF interventions on financial and non-financial industries separately.

Separating financial and non-financial companies, Figure 2.2 shows that IMF events have a stronger effect on corporate default risk in the financial sector. In the first six months of the 25-month event period (from month -12 to month -7), the financial industry has lower cumulative abnormal percentage changes in EDF compared to the other industries. However, the financial industry experiences significant increases in default risk from month -7 to month -6 and cumulates more risk than the other industries until the end of the event period.

Table 2.6 reports the mean and mean differences in cumulative abnormal percentage changes in EDF between the financial industry and non-financial industries for selected time intervals. Significant t-statistics for mean differences in all selected time intervals confirm that the difference in risk effect of IMF events on financial and non-financial companies is highly statistically significant. In addition, in all selected time intervals, mean cumulative abnormal percentage changes in EDF observed in the financial industry exceed those of non-financial firms. These results indicate that the risk effects of IMF interventions found in Figure 2.1 are driven primarily by the financial industry. As enhancing financial system stability is one of the conditions attached to the SBA and EFF programs, the strong negative effect of IMF events found in the financial industry raises a question regarding the effectiveness of these conditions or at least the market's perceptions of these effects are captured by EDF metrics. In the next section, we examine this issue by investigating the effect of different IMF program types (programs with conditions and programs without conditions) on financial industry default risk.

Figure 2.2: Mean cumulative abnormal percentage changes in EDF for financial and non-financial industries during the 25-month event period

This figure graphs the mean cumulative abnormal percentage changes in EDF for 25 event months across all IMF events in 20 sample countries.

Abnormal percentage changes in EDF are computed separately for financial and non-financial industries as follows:

$AEDF_{jt} = EDF_{jt} - NEDF_{jt}$

In which:

- $AEDF_{it}$*: abnormal percentage changes in EDF for the financial industry (nonfinancial industries) in country j at time t*
- EDF_{it}*: actual percentage changes in EDF for the financial industry (nonfinancial industries) in country j at time t*
- $NEDF_{it}$*: normal percentage changes in EDF for the financial industry (nonfinancial industries) in country j at time t computed as the average of percentage changes in EDF across all financial companies (nonfinancial companies) in the five countries that do not participate in IMF programs and have the closest propensity scores.*

Calculated abnormal percentage changes in EDF are accumulated and then averaged at each point in the event time across 20 countries to form cumulative abnormal percentage changes in EDF. A t-test is conducted to test for the null hypothesis that the mean equals zero for selected event months.

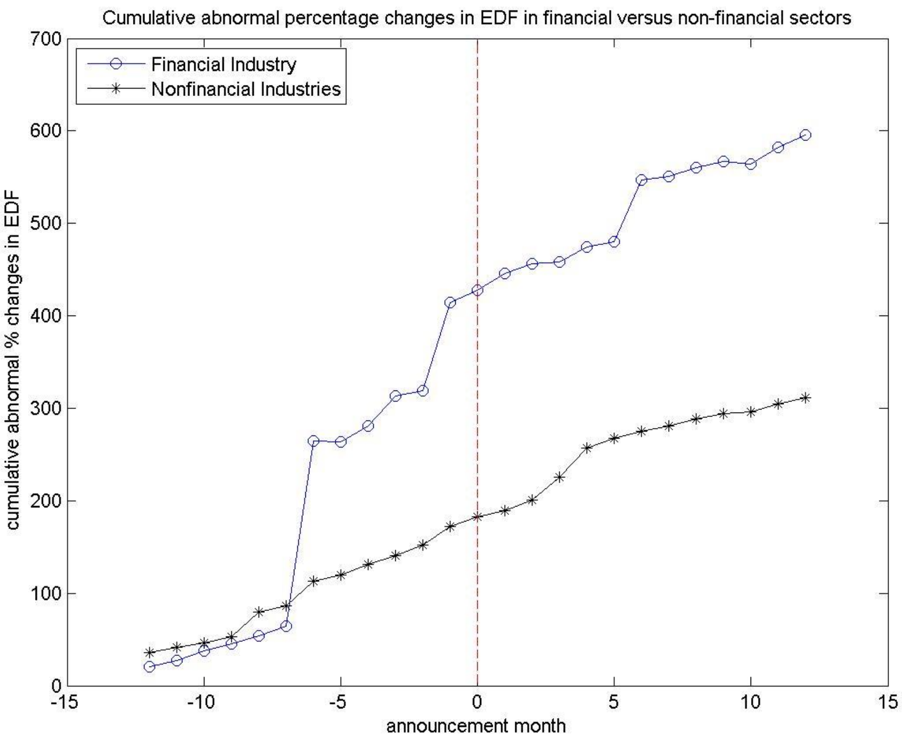


Table 2.4: Average of mean cumulative abnormal percentage changes in EDF in financial and non-financial industries in selected time intervals

This table reports the average of mean cumulative abnormal percentage changes in EDF in financial and non-financial industries and mean differences across all IMF events in 20 sample countries in the selected time intervals.

A t-test is conducted to test for the null hypothesis that the mean equals zero for selected time intervals.

Time intervals	Financial Industry	Non-financial Industries	Difference
(-3, 0)	368.44	161.71	206.74***
(0,+3)	446.75	199.73	247.01***
(-6,-1)	326.30	144.39	181.91***
(+1,+6)	469.76	228.49	241.26***
(-12,-1)	175.43	97.62	77.80*
(+1,+12)	523.34	266.12	257.22***

***, ** and * denote significance levels of 1%, 5% and 10%

2.4.3 The effect of different IMF program types on corporate default risk

To evaluate the distinction between the effect of IMF intervention with and without mandated reforms, we split the sample by program type.

Among the three IMF programs, the SBA and the EFF have attached conditions while the FCL does not. However, in the conditional program group, each program targets different recipients and has different durations and attached conditions. In particular, the EFF has a much longer duration and repayment period, and many more structural conditions, than the SBA. Hence, separately investigating the impact of each program type on corporate default risk can help us take into account each program's unique characteristics. In addition, to investigate whether the attached conditions are the main determinant of the negative impact of an IMF program on the financial sector's default risk, we also examine separately the risk effect of different IMF program types on the financial and non-financial industries.

Figure 2.3 shows that corporate default risk increases over time during the pre-event and post-event periods in all three program categories. However, among the three program types, countries receiving FCL experience the smallest rise in corporate default risk. Their cumulative abnormal percentage changes in EDF are consistently lowest over the 25-month event period, and are relatively constant since month 4, post-event. This program type is only given out to the countries that have a high risk of crisis but strong fundamental economies and a good track record of policy implementation. Therefore, a country that has access to FCL arrangements does not necessarily signal to the market that it is in a crisis. Furthermore, FCL represents a pure (albeit temporary) liquidity injection: there are no reform conditions or financial austerity conditions attached.

When comparing the effect of SBA and EFF on corporate default risk, it can be seen in Figure 2.3 that the SBA results in larger increases in corporate default risk compared to the EFF. These results are consistent with the severity of the conditions. The most intensive short-term reforms conditions attached to the SBA imply the largest risk increases.

Table 2.7 reports the differences in mean cumulative abnormal percentage changes in EDF between conditional and unconditional programs. Table 2.7 shows that conditional programs (SBA and EFF) have larger cumulative abnormal percentage changes in EDF than the unconditional program (FCL) in all the selected time intervals. Mean differences between the two groups of programs are always positive and statistically significant. These results confirm that programs with attached conditions result in larger increases in corporate default risk than the ones without attached conditions.

Table 2.5: Average of mean cumulative abnormal percentage changes in EDF in selected time intervals for different IMF program categories

This table reports the average of mean cumulative abnormal percentage changes in EDF for the three IMF program categories: Extended Fund Facility (EFF), Flexible Credit Line (FCL) and Standby Arrangement (SBA) and mean differences in selected time intervals.
A t-test is conducted to test for the null hypothesis that the mean equals zero for selected time intervals.

Time intervals	EFF	FCL	SBA	EFF-FCL	SBA-FCL
(-3, 0)	102.98	78.27	204.50	24.71**	126.23***
(0,+3)	124.14	99.15	257.00	24.99***	157.84***
(-6,-1)	86.79	63.97	176.34	22.81**	112.37***
(+1,+6)	137.16	110.05	313.41	27.11***	203.36***
(-12,-1)	65.07	48.04	121.76	17.03*	73.72***
(+1,+12)	167.09	125.24	349.80	41.85***	224.56***

***, ** and * denote significance levels of 1%, 5% and 10

Figure 2.3: Cumulative abnormal percentage changes in EDF during the 25-month event period for different IMF program categories

This figure graphs mean cumulative abnormal percentage changes in EDF for 25 event months across all IMF events in 20 sample countries.

Abnormal percentage changes in EDF are computed for different IMF program types as bellow:

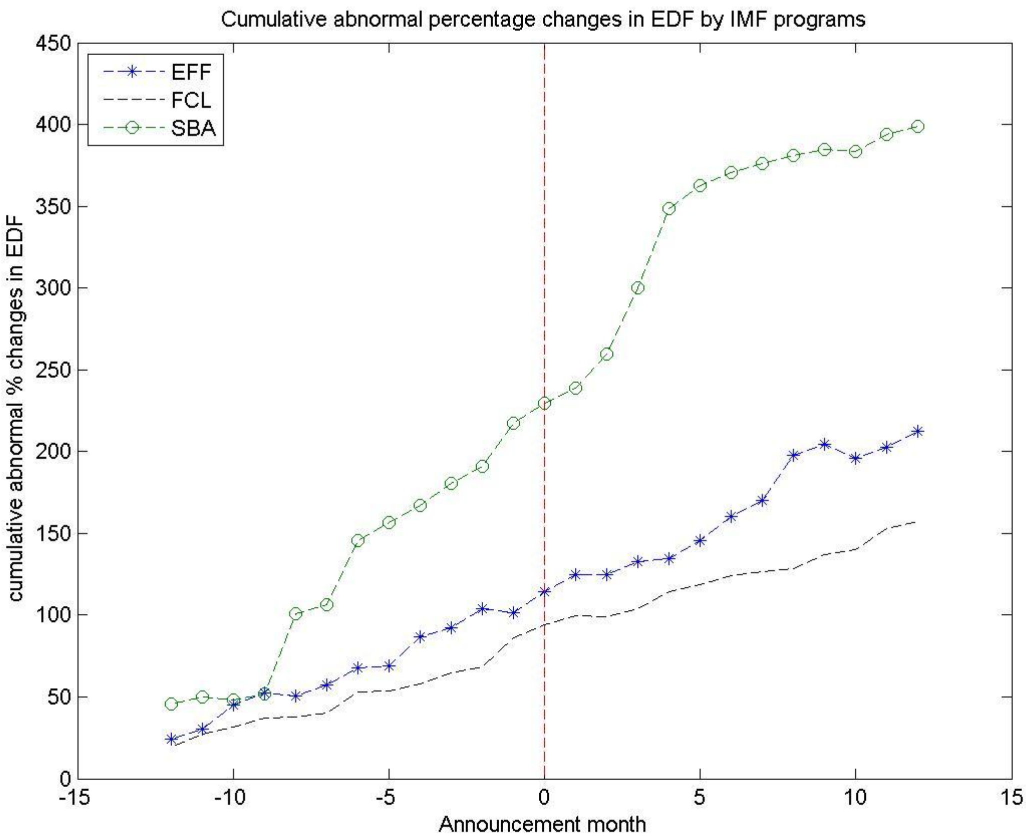
$AEDF_{jt} = EDF_{jt} - NEDF_{jt}$

In which:

- $AEDF_{jt}$*: country j's abnormal percentage changes in EDF at time t*
- EDF_{jt}*: country j's actual percentage changes in EDF at time t*
- $NEDF_{jt}$*: country j's normal percentage changes in EDF at time t computed as the average of percentage changes in EDF across the five countries that do not participate in IMF programs and have the closest propensity scores.*

Calculated abnormal percentage changes in EDF are accumulated and then averaged at each point in the event time across 20 countries to form cumulative abnormal percentage changes in EDF for each IMF program types. T-test is conducted to test for the null hypothesis that the mean equals zero for selected event months.

EFF is Extended Fund Facility; SBA is Standby Arrangement; and FCL is Flexible Credit Line. EFF and SBA are conditional programs, and FCL is a non-conditional program.



As the conditions attached to the SBA and EFF require the recipients to implement fiscal austerity measures and structural reforms that are focused on the financial industry, the impact of the conditions attaching to the SBA and EFF are likely to be most evident in financial firms. Thus, we further examine the effect of different IMF program types on corporate default risk separately for the financial industry and non-financial industries. Figure 2.4 and Figure 2.5 provide the graphs of cumulative abnormal percentage changes in EDF for financial and non-financial firms respectively. As can be seen in Figure 2.4, the financial industries in the countries that receive SBA experience the largest increase in corporate default risk, with the largest changes being observed from month -7 to -6 and from month -2 to -1. At the end of the event period, financial industries in these countries had cumulative abnormal percentage changes in EDF of nearly 1000%, which is more than double the figure for the non-financial industries presented in Figure 2.5. For the EFF and FCL participants, though IMF intervention also results in larger risk effect in the financial industry, differences in the cumulative abnormal percentage changes in EDF between the financial and non-financial industries in these countries are much smaller compared to the SBA recipients. These results indicate that the negative risk effects in the financial industry are driven mainly by the SBA program – a program with attached conditions aiming at tackling short-term balance of payments crises.

Figure 2.4: The effect of different IMF programs on financial industry's default risk

This figure graphs mean cumulative abnormal percentage changes in EDF for the financial industry under the effect of different program types.

Abnormal percentage changes in EDF are calculated separately for the financial industry as follows:

$AEDF_{jt} = EDF_{jt} – NEDF_{jt}$

In which:

- $AEDF_{jt}$: *abnormal percentage changes in EDF for the financial industry in country j at time t*
- EDF_{jt}: *actual percentage changes in EDF for the financial industry in country j at time t*
- $NEDF_{jt}$: *normal percentage changes in EDF for the financial industry in country j at time t computed as the average of percentage changes in EDF across all financial companies in the five countries that do not participate in IMF programs and have the closest propensity scores.*

Calculated abnormal percentage changes in EDF are accumulated and then averaged at each point in the event time across 20 countries to form cumulative abnormal percentage changes in EDF. A t-test is conducted to test for the null hypothesis that the mean equals zero for selected event months.

EFF is Extended Fund Facility; SBA is Standby Arrangement; and FCL is Flexible Credit Line. EFF and SBA are conditional programs, and FCL is a non-conditional program.

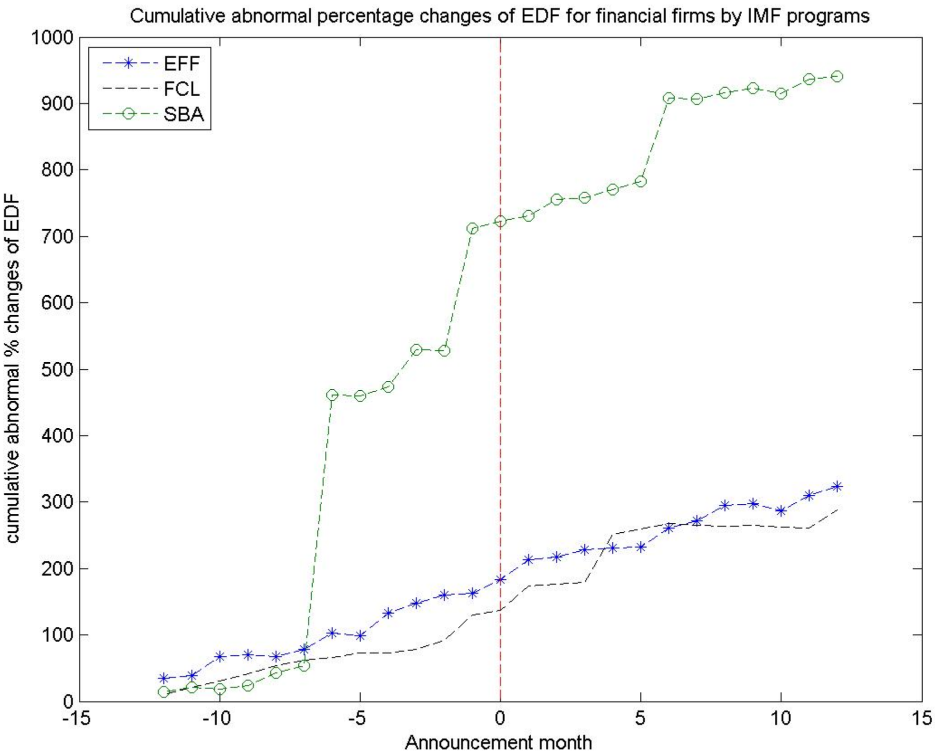


Figure 2.5: The effect of different IMF programs on non-financial industries' default risk

This figure graphs mean abnormal and mean cumulative abnormal percentage changes in EDF for non-financial industries under the effect of different program types.

Abnormal percentage changes in EDF are calculated as follow:

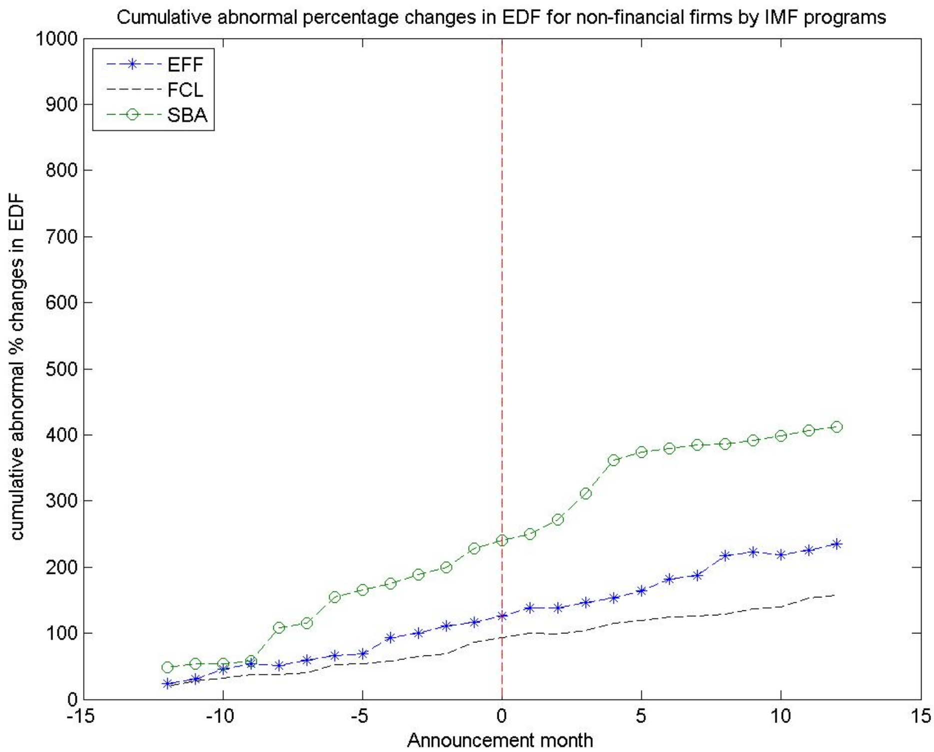
$AEDF_{jt} = EDF_{jt} – NEDF_{jt}$

In which:

- $AEDF_{jt}$*: abnormal percentage changes in EDF for non-financial industries in country j at time t*
- EDF_{it}*: actual percentage changes in EDF for non-financial industries in country j at time t*
- $NEDF_{jt}$*: normal percentage changes in EDF for non-financial industries in country j at time t computed as the average of percentage changes in EDF across all non-financial companies in the five countries that do not participate in IMF programs and have the closest propensity scores.*

Calculated abnormal percentage changes in EDF are accumulated and then averaged at each point in the event time across 20 countries to form cumulative abnormal percentage changes in EDF. T-test is conducted to test for the null hypothesis that the mean equals zero for selected event months.

EFF is Extended Fund Facility; SBA is Standby Arrangement; and FCL is Flexible Credit Line. EFF and SBA are conditional programs, and FCL is a non-conditional program.



2.4.4 The effect of different IMF program sizes on corporate default risk

As discussed previously, loans provided by the IMF will not only be used to meet short-term debt obligations but also channelled to the private sector to help enhance their performance through the provision of liquidity support. All else being equal, the benefit of liquidity support may reasonably be expected to be linked to program size.

Consistently with previous cases, Figure 2.6 shows that, regardless of the smallest or largest IMF program sizes, the corporate sector becomes riskier over the 25-month event period. However, the smallest program size recipients experience a greater degree of risk increasing effect, especially from month 2 to month 3, post-event. These findings are confirmed in Table 2.8, in which mean cumulative abnormal percentage changes in EDF in the bottom 25 percentiles in all selected time intervals are always larger than the top 25 percentiles, and statistically significant in most selected time intervals except in the three months post-event.

To understand why small program sizes lead to larger increases in percentage changes in EDF, we further examine whether the countries that receive small program sizes are the ones that need the IMF loan the most. We use the propensity scores to measure a country's need for an IMF loan. Because propensity scores are computed from various macroeconomic measures, higher propensity scores are associated with worse economic conditions and thus indicate the more urgent need of the IMF loans.

Figure 2.6: The effect of different IMF programs sizes on corporate default risk

This figure reports the mean cumulative abnormal percentage changes in EDF for the top and bottom 25 percentiles of IMF program size across all IMF events in 20 sample countries. Size is computed as the ratio of IMF's agreed loan at time t to the recipient's GDP at time t

Abnormal percentage changes in EDF are calculated as follows:

$AEDF_{jt} = EDF_{jt} – NEDF_{jt}$

In which:

- $AEDF_{jt}$: *country j's abnormal percentage changes in EDF at time t*
- EDF_{it}: *country j's actual percentage changes in EDF at time t*
- $NEDF_{jt}$: *company i's normal percentage changes in EDF at time t computed as the average of percentage changes in EDF across the five countries that do not participate in IMF programs and have the closest propensity scores.*

Calculated abnormal percentage changes in EDF are accumulated and then averaged at each point in the event time across 20 countries to form cumulative abnormal percentage changes in EDF. A t-test is conducted to test for the null hypothesis that the mean equals zero for selected event months.

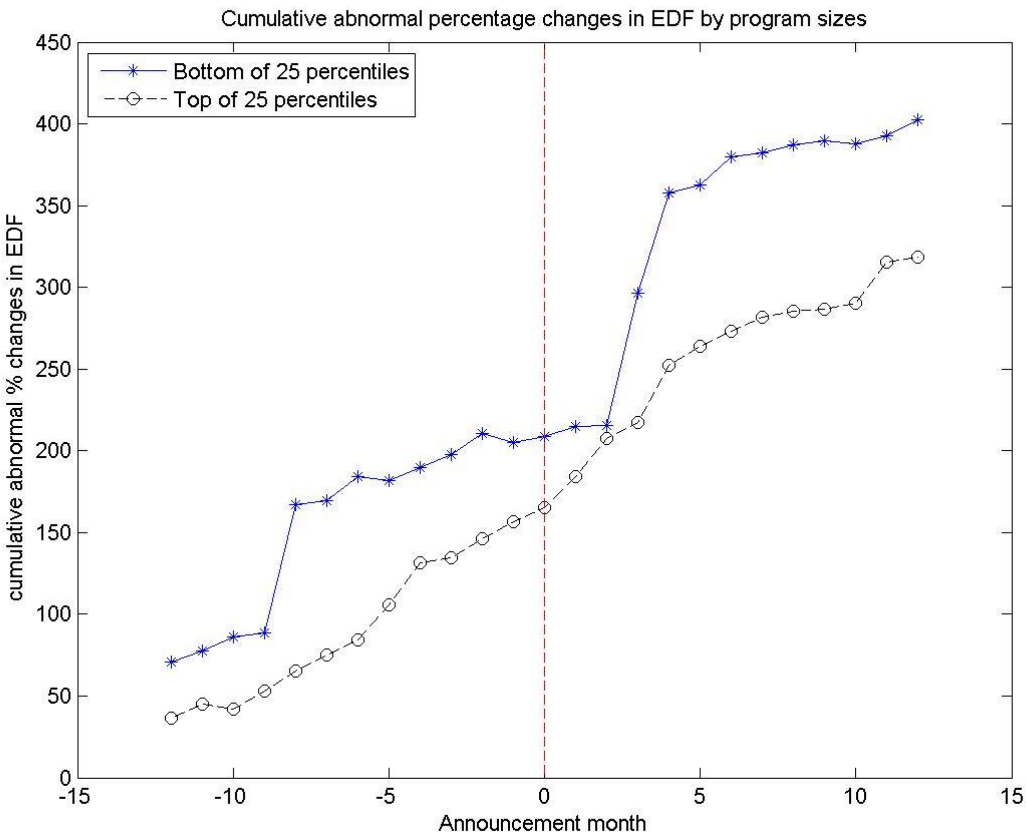


Table 2.6: **Average of mean cumulative abnormal percentage changes in EDF in selected time intervals by IMF program sizes**

This table reports the average of mean cumulative abnormal percentage changes in EDF for the bottom and top 25 percentiles of IMF program size and mean differences in selected time intervals. Size is computed as the ratio of the IMF's agreed loan at time t to the recipient's GDP at time t.
A t-test is conducted to test for the null hypothesis that the mean equals zero for selected time intervals.

Time intervals	Bottom 25 percentiles	Top 25 percentiles	Difference
(-3, 0)	205.51	150.76	54.75***
(0,+3)	233.99	193.64	40.35
(-6,-1)	194.85	126.55	68.29***
(+1,+6)	304.47	233.08	71.39*
(-12,-1)	152.47	89.70	62.78***
(+1,+12)	347.42	264.78	82.64***

***, ** and * denote significance levels of 1%, 5% and 10%

Table 2.7: Summary statistics for the propensity scores for two groups of countries: countries receive small IMF loans and countries receive large IMF loans

This table reports descriptive statistics for the propensity scores for two groups of countries: countries that receive small IMF loans and countries that receive large IMF loans. 25% and 75% cut-off points are used to classify small and large IMF loan size. Size is computed as the ratio of the IMF's agreed loan at time t to the recipient's GDP at time t. Propensity scores are the fitted values from the following regression $P_{jt} = \beta_0 + \beta_1 GDPG_{j(t-1)} + \beta_2 \frac{Debt_{j(t-1)}}{GDP_{j(t-1)}} + \beta_3 \frac{CA_{j(t-1)}}{GDP_{j(t-1)}} + \beta_4 \frac{TR_{j(t-1)}}{GDP_{j(t-1)}} + \beta_5 Dummy_{jt} + \varepsilon_{jt}$ *with* P_{jt} *is dummy variable, equals 1 if country j receives IMF loans at time t and equals 0 otherwise;* $GDP_{j(t-1)}$*: country j's GDP at time t-1;* $TR_{j(t-1)}$*: country j's total reserves at time t-1;* $GDPG_{j(t-1)}$*: proportional changes of country j's GDP at time t-1 comparing to time t -2;* $Debt_{j(t-1)}$*: total external short-term public and private debt of country j at time t-1;* $CA_{j(t-1)}$*: current account of country j at time t-1;* $Dummy_{jt}$*: prior assistance indicator which equals 1 at time t if country j received the IMF's financial assistance in the previous three years. A t -test is conducted to test for the mean difference. Wilcoxon sign rank test is conducted to test for the median differences.*

	Mean	Med	Std	Min	Max
Bottom 25 percentile	0.28	0.27	0.11	0.12	0.44
Top 25 percentile	0.18	0.16	0.14	0.03	0.37
Difference	0.10***	0.11*			

***, ** and * denote significance levels of 1%, 5% and 10%

Table 2.9 reports descriptive statistics for the propensity scores for two groups of countries: countries receiving small IMF programs and countries receiving large IMF programs. Table 2.9 shows that the mean propensity score for small IMF program recipients is 0.28 while the figure for the other group is only 0.18. The mean and median differences in the propensity scores between two groups are 0.1 and 0.11 respectively and statistically significant. The minimum and maximum propensity scores are also higher in the countries that receive small IMF programs. These results show that countries most in need of the IMF programs receive the smallest IMF loans. As countries with high propensity scores are associated with low GDP growth, low current account, low total reserves and high debt, stronger negative effects on corporate default risk found in these countries may reflect a negative market response to the small loan size news and the counterproductive effect of partially fulfilling liquidity needs, as shown in Zettelmeyer's (2000) theoretical model.

2.5 Robustness test

To test the robustness of our results, we employ a different method to compute normal percentage changes in EDF. In this method, normal percentage changes in EDF are the average percentage changes in EDF at time t across all companies which are non-IMF participants.[5] This analysis helps us to re-check whether our results are sensitive to the benchmark specification.

Table 2.10 presents the results for abnormal and cumulative abnormal percentage changes in EDF in the selected event months. It is clear that though abnormal and cumulative abnormal percentage changes in EDF are larger compared to the results reported in Table 2.3, they are all positive over the 25-month event period, implying a rise in default risk during an IMF event. Figure 2.7 helps us reconfirm that, regardless of the method used to calculate normal percentage

[5] $\Delta \text{NEDF}_{jt} = \frac{1}{n}\sum_{i=1}^{n} \Delta EDF_{it}$, with ΔNEDF_{jt} is normal percentage changes in EDF of country j at time t; ΔEDF_{it} is observed percentage changes in EDF of company i in non-IMF participants at time t.

changes in EDF, abnormal percentage changes in EDF increase consistently both before and after the IMF announcements.

All the other reported results are also robust to the benchmark for normal EDF, but the magnitudes are larger, as may be expected. In addition, our results are robust to the exclusion of firm level outliers.[6] We classify an observation as an outlier if it is above (below) the 99th (1st) percentile of the EDF distribution.

[6] These results are available upon request

Table 2.8: Mean abnormal and mean cumulative abnormal percentage changes in EDF for selected event months when normal percentage changes in EDF are computed as the average of percentage changes in EDF across all countries that do not receive IMF programs

Abnormal percentage changes in EDF are computed as follows:

$AEDF_{jt} = EDF_{jt} - NEDF_{jt}$

In which:

- $AEDF_{jt}$: *country j's abnormal percentage changes in EDF at time t*
- EDF_{jt}: *country j's actual percentage changes in EDF at time t*
- $NEDF_{jt}$: *country j's normal percentage changes in EDF at time t computed as the average of percentage changes in EDF across all countries that do not participate in IMF programs*

Calculated abnormal percentage changes in EDF are accumulated and then averaged at each point in the event time across 20 countries to form cumulative abnormal percentage changes in EDF. A t-test is conducted to test for the null hypothesis that the mean equals zero for selected event months.

Month	Abnormal %ΔEDF	Cumulative abnormal %ΔEDF
-12	34.208*	34.208*
-10	3.877	44.212***
-8	28.318	77.784***
-6	27.892**	111.552***
-3	10.687**	141.110***
-2	9.839**	150.949***
-1	18.994*	169.943***
0	9.778***	179.721***
1	6.455**	186.176***
2	11.587**	197.764***
3	25.522	223.286***
6	8.230**	272.064***
8	7.777*	283.772***
10	0.285	289.266***
12	5.294***	303.153***

***, ** and * denote significance levels of 1%, 5% and 10%

Figure 2.7: The effect of IMF programs on corporate default risk when normal percentage changes in EDF are computed as the average of percentage changes in EDF across all countries that do not participate in IMF programs

This figure reports mean cumulative abnormal percentage changes of EDF across all IMF events in 20 sample countries over the 25-month event period.

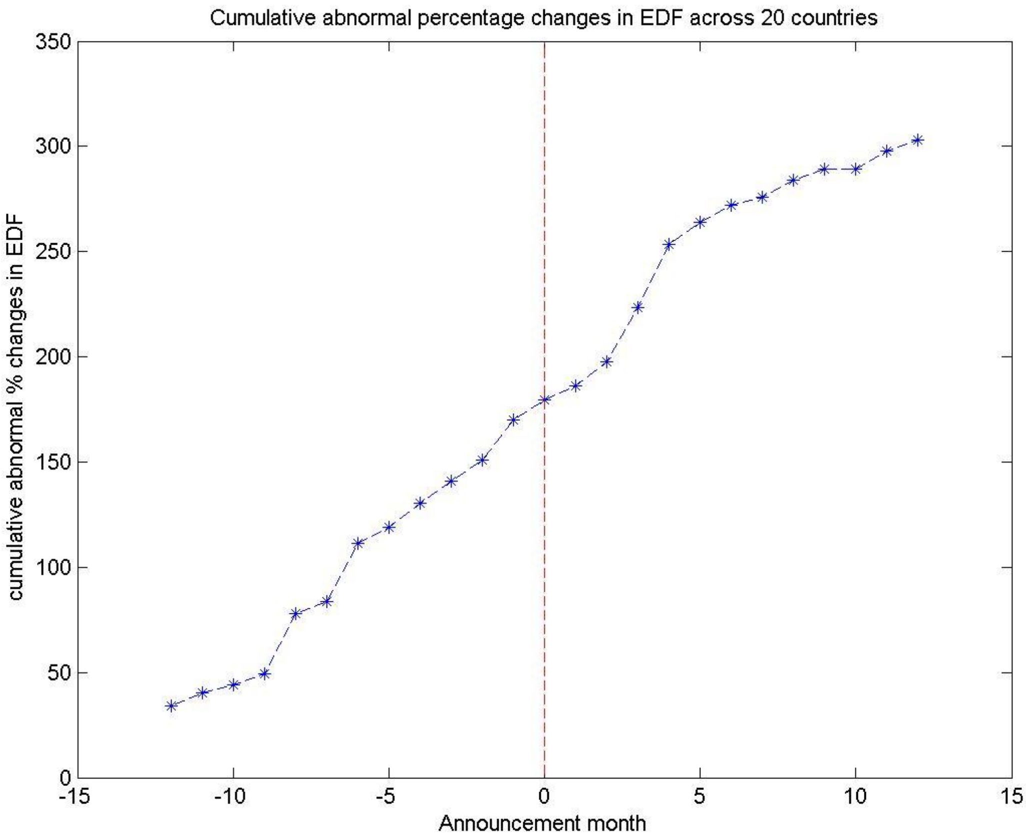
Abnormal percentage changes in EDF are calculated as follows:

$AEDF_{jt} = EDF_{jt} - NEDF_{jt}$

In which:

- $AEDF_{jt}$: *country j's abnormal percentage changes in EDF at time t*
- EDF_{it}: *country j's actual percentage changes in EDF at time t*
- $NEDF_{jt}$: *country j''s normal percentage changes in EDF at time t computed as the average of percentage changes in EDF across all countries that do not participate in IMF programs*

Calculated abnormal percentage changes in EDF are accumulated and then averaged at each point in the event time across 20 countries to form cumulative abnormal percentage changes in EDF. A t-test is conducted to test for the null hypothesis that the mean equals zero for selected event months.



2.6 Conclusion

This paper contributes to the literature by examining the impact of IMF programs on corporate default risk. IMF program characteristics such as size and attached conditions are also taken into account. The focus on default risk not only helps us to understand how corporations react to an IMF event but also provides an overview on whether the IMF fulfils its goal of helping a member country recover from crisis through examining the effect of intervention on the economic health of the private sector.

Overall, our results strongly suggest that all forms of IMF intervention are associated with a deterioration in the financial health of the private sector over the twelve months prior to and subsequent to the announcement of intervention. Specifically, corporate default risk, as measured by KMV's Merton-style EDF metric, escalates in anticipation of an announcement of intervention and subsequent to the announcement relative to private sector default risk in a matched sample where no such intervention takes place. To the extent that private sector credit risk dynamics yield a bottom-up measure of country-level economic risks, these findings call into question the net benefits of assistance programs. While prior studies have reported contradictory effects on asset values and the volatility of asset values, our EDF-based results afford an insight into the net economic impact of intervention.

While the overall abnormal impact of IMF intervention appears negative, the strongest effects are associated with the financial sector and programs that tie liquidity assistance to fiscal austerity and economic reform conditions. These findings are complementary to the extent that financial firms are often the focal point of the structural reforms associated with assistance programs. Furthermore, our results also suggest a negative association between the relative size of the assistance program (or the liquidity injection) and the magnitude of the positive abnormal risk impact, a finding that is consistent with the theoretical predictions of Zettelmeyer (2000) with respect to the negative impact of only partially fulfilling liquidity requirements. Accordingly, we also find an inverse relationship between financial needs (as measured by propensity scores) and program size. The smallest (biggest) assistance programs are provided to countries with the highest (lowest) propensity scores

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Chapter 3 : Internal Capital Market Efficiency and Diversified Firms' Default Risk

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Abstract

This paper examines the effect of Internal Capital Market Efficiency (ICM) on diversified firm default risk, and how this effect varies in firms with different levels of external financial constraints. Following Billett and Mauer (2003), ICM in this study is defined as the movements of funds from business segments with low return on assets to business segments with high return on assets. Using a panel of 11,202 firm-year observations in the US, we find that ICM plays an important role in determining corporate default risk in highly-leveraged firms. This result is robust to the measurement of default risk with reference to Merton-style default probability, Altman's Z-score and S&P credit ratings. However, though the theory suggests that ICM has a stronger effect on corporate default risk in financially-constrained firms, we find only weak evidence supporting this argument.

3.1 Introduction

Combining different business segments under the control of a single parent entity enables a diversified firm to shift its capital between different segments, establishing an internal capital market (Stein (1997)). A diversified firm's internal capital market is considered efficient if its internal funds are transferred from poorly-performing segments to strongly-performing segments, with performance being measured by return on assets (Billett and Mauer (2003)) or Tobin Q ratio (Rajan, Servaes et al. (2000)) or sales growth (Singhal and Zhu (2013)). However, whether the efficiency of this internal capital market influences diversified firm default risk is a question that has not been examined in the literature.

The availability of an internal capital market brings an advantage to a diversified firm over a single segment firm, especially when external funding is limited. Under such circumstances, a diversified firm can transfer surplus funds generated in one segment to other segments in need of capital. An internal capital market, thus, helps to alleviate diversified firms' external financial constraints. However, the benefits brought by an internal capital market depend on how the funds are used by a diversified firm. Previous studies find that diversified firms, on average, use their internal capital inefficiently due to the rent seeking or power grabbing behaviours of underperforming divisional managers (Meyer, Milgrom et al. (1992), Berger and Ofek (1995), Rajan, Servaes et al. (2000), Scharfstein and Stein (2000), Billett and Mauer (2003)). This direction of fund movement is shown to have a negative effect on a firm's asset values and profitability (Berger and Ofek (1995), Rajan, Servaes et al. (2000), Billett and Mauer (2003)). Thus, how a firm uses its internal fund is expected to influence its default risk.

However, when diversified firms have limited access to external capital, their headquarters tend to allocate internal funds more efficiently (Hovakimian (2011), Kuppuswamy and Villalonga (2015)). In this situation, productive segments of diversified firms without access to external funds are adversely affected when internal funds are directed to unproductive segments. As a result, well-performing segments can be dragged down by poorly-performing segments as demonstrated in Ambrus-Lakatos and Hege's (2002) theoretical model. Meanwhile, in the absence of external financial constraints, firms with inefficient internal capital markets can still invest in their profitable projects by using external funds. Therefore, the impact of ICM on corporate default risk is expected to be greater in financially-constrained firms. Using Billett and Mauer's (2003) ICM measure, our paper complements the literature on corporate diversification by examining the role of ICM in determining diversified firm default risk. We also investigate whether ICM has a greater impact on the default risk of highly-financially constrained firms.

Our empirical results show that ICM is an important determinant of corporate default risk in highly-leveraged diversified firms. The more efficiently these firms use their internal funds, the lower their default risk. This result is robust to the three corporate default risk measures: default probability computed by using Merton's distance to default model, Altman's Z-score and S&P credit ratings. However, although the theory suggests that ICM has a stronger impact on default risk when firms are financially constrained, we only find weak evidence supporting this argument.

3.2 Hypothesis development

The concept of default risk reduction benefits resulting from diversification originates from modern portfolio theory, but is also applied to corporate diversification. One of the first studies examining this issue was conducted by Lewellen (1971) in which he demonstrated that combining different business segments with imperfect cash-flow correlation into a single entity can help to alleviate a firm's default risk. Testing Lewellen's (1971) theory, Singhal and Zhu (2013) empirically examined the effect of diversification on the probabilities that a firm files for Chapter 11 bankruptcy between 1991 and 2007. Using number of business segments defined by the 4-digit SIC code as a diversification measure, Singhal and Zhu (2013) found that the higher the number of business segments a firm has, the lower the probability that it goes bankrupt, all else being equal, which supports Lewellen's (1971) theory. They also find that diversified firms use their internal funds inefficiently and spend more time in bankruptcy processes than single segment firms. However, a direct link between the internal capital market efficiency and diversified firm default risk is not established in their study.

Other researchers examine whether diversification helps to increase the firm's borrowing capacity, which is a result of default risk reduction effect. Berger and Ofek (1995) and Comment and Jarrell (1995) find no economic significant relationship between leverage and diversification. They argue that either diversification does not help increase debt capacity or diversified firms' managers do not want to take advantage of their greater debt capacity.

Therefore, their tests do not provide a clear-cut answer on whether diversification helps reduce corporate default risk.

When examining changes in corporate default risk measured by KMV's Expected Default Frequency from 1 month before to 6 months after company mergers, Furfine and Rosen's (2011) results show that diversification via mergers tends to increase default risk, and that this effect is driven not only by the acquisition of risky targets but also by managerial behaviour. Such findings with respect to the risk effects of diversification suggest that there are wider consequences of diversification that reduce or even outweigh the default risk reduction benefit arising from a pure diversification perspective.

Agency-based theory suggests that diversification can result in an inefficient internal capital market, and that its effects may negatively influence a firm's default risk. An inefficient internal capital market occurs when strongly-performing segments of a diversified firm cross subsidize poorly-performing or even failing segments (Meyer, Milgrom et al. (1992), Rajan, Servaes et al. (2000), Scharfstein and Stein (2000)). Meyer, Milgrom and Roberts (1992) argue that this direction of fund movement is prompted by managers in the failing segments, who try to gain access to corporate resources that can be used to prevent or delay downsizing to protect their jobs. Scharfstein and Stein's (2000) model demonstrates that the rent-seeking or power-grabbing behaviour of division managers is more likely to happen in a weak division and undermine the workings of the internal capital market. Though neither Scharfstein and Stein (2000) nor Meyer, Milgrom and Roberts (1992) show how inefficient internal capital markets affect a firms' default risk, the shift of funds from productive segments to unproductive segments will result in higher cash-flow volatility and lower firm values, which in turn causes a rise in bankruptcy probability.

Empirical evidence also supports the theory that diversified firms have inefficient internal capital markets (Berger and Ofek (1995), Rajan, Servaes et al. (2000), Billett and Mauer (2003)). For example, using a sample of 13,947 firm-segment-year observations, Rajan, Servaes et al. (2000) find that multi-segment firms use their internal funds inefficiently by allocating more funds to the segments with poor investment opportunities. They also find that inefficient internal capital markets destroy firm values, explaining why diversified firms trade at lower values than single segment counterparts. Billett and Mauer (2003) finesse these findings to show that diversified firms, on average, have inefficient internal capital markets, but the effect of this market on diversified firm values is only important if the segments that receive internal funds are externally financially constrained. Similarly, Berger and Ofek (1995) find that the poorly-performing segments of a diversified firm drain value from the other segments, signalling a negative effect of cross-subsidization in diversified firms. Their results also indicate that diversified firms earn lower profits and have lower values than comparable portfolios of single segment firms.

A negative association between the efficiency of internal capital markets and diversified firm default risk is also suggested indirectly in the corporate diversification literature. For instance, Furfine and Rosen (2011) examine the effect of diversification via mergers on corporate default risk, measured by KMV's Expected Default Frequency (EDF). Furfine and Rosen's (2011) results indicate an increase in EDF after mergers, and this effect is driven by aggressive managerial behaviours that affect corporate default risk enough to outweigh the benefits brought by diversification. Though their study does not directly examine the impact of internal capital market on default risk, the agency cost measures used in their research, i.e. information asymmetry and CEO motivation to undertake risky acquisitions, are associated with the inefficient use of internal funds. Related work by Kuppuswamy and Villalonga (2015) shows that diversified firms' leverage was 2% lower than that of single segment firms before the Global Financial Crisis 2008, but 4% higher during the crisis period. Since diversified firms' internal capital markets are expected to be more efficient during recessions (Hovakimian (2011), Kuppuswamy and Villalonga (2015)), this finding implies that the efficiency of internal capital markets may play a role in changes in diversified firms' leverage relative to single segment firms under different economic conditions.

Though ICM arguably influences corporate default risk, the effect is expected to be larger in financially constrained firms. With limited access to external funds, financially-constrained firms have to rely on their internal capital markets to finance their investments. Therefore, all else being equal, they are more likely to forfeit positive NPV projects if their internal funds are used inefficiently. By contrast, the non-financially-constrained firms are still able to invest in their profitable projects if ever their internal funds are allocated inefficiently. As a result, the way internal funds are used is expected to have a larger impact on default risk in financially constrained firms than in non-financially-constrained firms. These arguments are consistent with Ambrus-Lakatos and Hege's (2002) theoretical model in which they demonstrate that the inefficient use of internal funds in the context of external financial constraints will magnify financial distress. They show that a severe shortfall of external funds may place productive segments in a vulnerable situation as they cannot obtain external funds to finance their investments where internal funds are misallocated.

In summary, both empirical evidence and theoretical arguments support the hypothesis that ICM influences corporate default risk, and that this effect is relatively stronger in firms that are financially constrained. Based on these findings and arguments, we argue that there is a linkage between ICM and corporate default risk, and that this relationship is conditional on external financial constraints. Our paper attempts to investigate these linkages by testing the following hypotheses:

Null hypothesis 1: there is no relationship between Internal Capital Market Efficiency and corporate default risk

Alternative hypothesis 1: Internal Capital Market Efficiency is negatively related to corporate default risk

Null hypothesis 2: the negative effect of Internal Capital Market Efficiency on corporate default risk is not different between financially constrained and non-financially constrained firms

Alternative hypothesis 2: the negative effect of Internal Capital Market Efficiency on corporate default risk is larger in financially constrained firms than in non-financially constrained firms

3.3 Methodology

To examine the effect of ICM on corporate default risk, we need to construct measures of corporate default risk, Internal Capital Market Efficiency and external financial constraints.

3.3.1 Corporate default risk

We use three different measures of corporate default risk: Merton-style corporate default probabilities computed according to Bharath and Shumway (2008), Altman's Z-score and S&P credit rating for long term issuers. The Merton-style measure is market based and default occurs when a firm's market value of assets is lower than a liability threshold. Meanwhile, Altman's Z-score is a hybrid based measure. It is a scoring model based on ratios and contains information about a firm's ability to repay its debt. The resultant Z-scores are then divided into groups based on threshold cut points. The third credit risk measure we employ is S&P's credit rating. It not only takes into account a firm's financial information but also incorporates information about industry characteristics, country risk and other entity specific factors. Since each measure employed in this study evaluates corporate default risk from very different perspectives, investigating the effect of ICM on these three measures helps us test the robustness of our results.

Due to the unique statistical characteristics of each default risk measure, somewhat different modelling frameworks are employed in each case. In particular, when the dependent variable is a default probability, the choice of linear regression model is inappropriate since this method does not guarantee that the predicted default probabilities are bounded by 0 and 1; and hence we transform the data prior to regression modelling. We first increase (decrease) the lower (upper) bounded default probabilities by 0.0001, and then compute the inverse cumulative normal distribution for this default risk measure. Next, we apply standard OLS estimation techniques to the transformed values. For the other two measures of default risk, Altman's Z-score categories and S&P credit rating categories, the ordered logit regression model is employed. Details of variable construction are provided below.

Corporate default probabilities

A firm's default probabilities are measured by using Bharath and Shumway's (2008) method. It mimics the functional form of the Merton (1974) model, but is much simpler to calculate. Bharath and Shumway (2008) find that their default risk measure performs as well as the Merton (1974) model since the Merton model's default forecasting ability comes from its functional form rather than the iterative procedure to solve the model.

Bharath and Shumway's (2008) method requires the estimation of market value and volatility of a firm's assets, the expected return on assets and the market value of firm debt.

A firm's debt (D) is assumed to be equal to the face value of its debt (F), which is the sum of its debt in current liabilities plus one half of its long-term debt.

$$D = F \tag{1}$$

As the risk of a firm's debt (σ_D) is correlated with its equity risk (σ_E), the volatility of each firm's debt is approximated in the equation below:

$$\sigma_D = 0.05 + 0.25 * \sigma_E \tag{2}$$

σ_E is the annualized standard deviation of returns and is computed from the prior-year stock return for each month.

Total volatility of the firm can then be computed:

$$\sigma_V = \frac{E}{E+D}\sigma_E + \frac{D}{E+D}\sigma_D \tag{3}$$

The market value of a firm's equity (E) in equation (3) is the product of year-end share price and number of shares outstanding.

Expected return on firm assets is set to equal the firm's cumulated monthly returns over the previous year:

$$\mu = r_{it-1} \tag{4}$$

Then, distance to default (DD) can be computed as follow:

$$DD = \frac{ln\left[\frac{E+F}{F}\right]+\left(\mu-0.5\ \sigma_v^2\right)T}{\sigma\sqrt{T}} \tag{5}$$

From the DD, we can infer the one-year default probability:

$$\Pi = N(-\ DD) \tag{6}$$

Altman's Z-score

Altman's Z-score is computed separately for manufacturing and non-manufacturing firms as follows:

For manufacturing firms, Altman's Z-score is calculated as in Altman (1968):

$$Z\text{-}score = 1.2\ (WC/\ TA) + 1.4\ (RE/\ TA) + 3.3\ (EBIT/TA) + 0.6\ (MV_E/\ BV_L) + 0.99\ (Sales/\ TA) \tag{7}$$

For non-manufacturing firms, the ratio sales to total assets is taken out of the equation (7) to minimize the potential industry effect (Altman (2000)).

$$Z\text{-}score = 6.56\ (WC/\ TA) + 3.26\ (RE/\ TA) + 6.72\ (EBIT/TA) + 1.05\ (MV_E/\ BV_L) \tag{8}$$

WC is the firm's working capital; TA is the firm's total assets; RE is the firm's retained earnings; EBIT is the firm's earnings before interest and taxes; MV_E is market value of equity and BV_L is book value of liabilities.

The Z-scores are used to group firms into three different categories based on the cut-off values suggested by Altman (1968) and Altman (2000). For manufacturing firms, category 1 is a 'safe zone' with Z-score larger than 2.99; category 2 is a 'grey zone' with Z-score between 1.81 and 2.99; category 3 is a 'distress zone' with Z-score less than 1.81. For non-manufacturing firms, category 1 is a 'safe zone' with Z-score larger than 2.90; category 2 is a 'grey zone' with Z-score between 1.23 and 2.90; category 3 is a 'distress zone' with Z-score less than 1.23. With this classification method, the riskiest firms will be placed in category 3 and the safest firms will be placed in category 1.

S&P credit rating

We collect the S&P credit rating for long-term issuers from the Compustat database during the period 1997-2014. For each firm, credit outcomes at year-end are matched to financial data over the same year. There are 22 rating categories ranging from AAA to SD in the S&P rating scale. Assuming that the differences between successive ratings are equal, we then assign a score for each credit-rating category, with the lowest score (1) for the highest credit-rating category (AAA). Hence, the higher the score, the higher the firm's default risk according to S&P credit rating. We assign the scores in this order to ensure that our discussion is consistent across the three corporate default risk measures. Details of how the rating scores are assigned for S&P credit ratings can be found in Table 3.1.

3.3.2 Internal Capital Market Efficiency

In this paper, we adopt Billett and Mauer's (2003) method to compute internal capital market efficiency (ICM). They define ICM as the way that funds move among business segments with different return on assets (ROA). A firm has an efficient internal capital market when internal funds flow to segments with higher ROA. By contrast, a firm has an inefficient internal capital market when internal funds flow to lower ROA segments. Other studies, such as Berger and Ofek (1995) and Rajan et al. (2000), define the ICM as the movement of funds from the segments having low investment opportunities (low Tobin Q ratio) to segments having high investment opportunities (high Tobin Q ratio). However, Erickson and Whited (2000) and Whited and Wu (2006) show that Tobin's Q measure has a great deal of measurement error in its role as a proxy for investment opportunities. Furthermore, since it is impossible to compute Tobin Q ratio given the reported segment data, Berger and Ofek (1995) or Rajan et al. (2000) use the industry Tobin Q ratio computed from a sample of standalone firms as a proxy for each segment's investment opportunities. This assumption, it is claimed, causes bias if investment opportunities of firms that decide to diversify are systematically different from those that decide to remain as single-segment firms (Campa and Kedia (2002), Hyland and Diltz (2002), Billett and Mauer (2003), Villalonga (2004)).

Table 3.1 Rating Categories

This table presents the assigned scores for S&P credit rating for long-term issuers, collected from the Compustat database. For each firm, we take the reported rating available in the last fiscal month of the financial year, and assume that it is the firm's rating in that year. 1 is assigned for AAA rating which is the highest rating quality, and this score increases by a value of 1 for each rating in the next rating category.

S&P credit rating	**Rating score**
AAA	1
AA+	2
AA	3
AA-	4
A+	5
A	6
A-	7
BBB+	8
BBB	9
BBB-	10
BB+	11
BB	12
BB-	13
B+	14
B	15
B-	16
CCC+	17
CCC	18
CCC-	19
CC	20
D	21
SD	22

In Billett and Mauer (2003), a segment is categorized as a provider of internal capital in year t if its after-tax cash-flow is larger than its capital expense. The surplus capital in this segment can be used to subsidize the other segments in need, an action which is defined as 'Transfer'. By contrast, a segment will be classified as a receiver of internal funds if its after-tax cash-flow is less than its capital expense. The extra capital it gets to finance its expenses is called 'Subsidy'.

We calculate the subsidy that segment i of a sample diversified firm receives as

$$Subsidy_i = max(CAPEX_i - ATCF_i\ , 0) \qquad (9)$$

where CAPEX is the segment's reported capital expenditures and $ATCF_i$ is the segment's after-tax cash-flow. Segment i's after-tax cash-flow ($ATCF_i$) is computed as

$$ATCF_i = EBIT_i - I_i - T_i + D_i \qquad (10)$$

I_i is the segment i's interest expense which is calculated by multiplying the assets share of segment i in a diversified firm with the firm's interest expense, T_i is the segment i's tax expenses computed as the assets share of segment i multiplied by the firm's taxes paid, and D_i is segment i's reported depreciation. A segment's assets share is computed as the ratio of segment i's assets reported in the Compustat segment database to the firm's total assets. In Billett and Mauer (2003), segment i's interest expense is calculated as the product of segment i's reported sales and the median ratio of interest expense to sales of single-segment firms in segment i's industry; and segment i's tax expense is a product of segment i's earnings before taxes and the median tax rate of single-segment firms in segment i's industry. We do not employ this method to compute our segment i's interest expense and tax expense for two reasons. Firstly, since same-industry single-segment firms may fundamentally differ from diversified firm segments, the use of single-segment firm data may cause bias in our results as argued by Berger and Ofek (1999), Campa and Kedia (2002), and Hyland and Diltz (2002). In particular, diversified firms are found to have more cash on hand, lower sales growth, lower total asset values, lower ROA, and more leverage, and that their spending on research and development is less than their matched single-segment firms (Berger and Ofek (1999), Hyland and Diltz (2002)). Therefore, the use of tax expense and interest expense of single-segment firms to apply to the same industry segment may overstate the taxes paid and understate the interest expense. Secondly, when Billett and Mauer (2003) cannot find at least five single-segment firms that operate in segment i's industry defined as a 4-digit SIC code, they vary their industry definition to a 3-digit SIC code and a 2-digit SIC code. However, this approach adds inconsistencies to the computation of segment i's tax expense and interest expense. Our method can overcome these shortcomings and is in line with Billett and Mauer's (2003) method of computing segment dividends, which will be discussed later in this section.

If $subsidy_i = 0$, then $ATCF_i >= CAPEX_i$ and segment i is a potential contributor of resources to the firm's internal capital market. We can only say segment i is a potential contributor of resources as it is not necessarily the case that all of the segment's surplus will be transferred to the other segments. Therefore, we first compute segment i's potential transfer of resources as

$$Ptransfer_i = max(ATCF_i – w_iDIV – CAPEX_{i,} ,0) \tag{11}$$

where DIV is the cash dividend paid by the sample firm and w_i is the asset share of transfer segment i, which is computed as the ratio of segment i's assets to the total assets of all the transfer segments.

Similar to Billett and Mauer (2003), we allow the total subsidy to be larger than the total transfer since the firms can borrow from their external capital markets, but the total transfer will not to exceed the total subsidy. Therefore, segment i's transfer can be calculated as follows:

$$Transfer_i = min\ [Ptransfer_i\ , \frac{PTransfer_i}{\sum_{i=1}^{n} PTransfer_i} (\sum_{i=1}^{n} Subsidy_i)\ ] \tag{12}$$

Billett and Mauer (2003) suggest two measures of relative efficiency for segment subsidies and transfers. The first is based on the segment's sibling-adjusted return on assets (ROA), and the second is based on a fitted Tobin Q ratio for each segment. We adopt the adjusted ROA to measure ICM since we would like to use only the information pertaining to each segment to construct the ICM. If $ROA_i > \overline{ROA}$ ($ROA_i < \overline{ROA}$), a subsidy is classified as efficient (inefficient), where ROA_i is the ratio of earnings before interest, taxes and depreciation to total assets for segment i, and $\overline{ROA}$, is the corresponding asset-weighted average ROA of a diversified firm's remaining segments. Thus, a subsidy is efficient (inefficient) if the segment receiving the subsidy has a larger (smaller) ROA than the asset-weighted average of the firm's other segments, and a transfer is efficient (inefficient) if the segment making the transfer has a smaller (larger) ROA than the asset-weighted average of the firm's other segments. We acknowledge that the use of ROA measure to determine the firm's ICM efficiency may not be the best choice, as this measure does not take into account the risk difference among the firm's segments. However, with the current, limited available reported segment data, the use of segment ROA is arguably the best measure of each segment's operating efficiency, and this can help us understand how a diversified firm uses its internal funds.

Total ICM is computed as below:

$$ICM = \sum_{i=1}^{n} \frac{(ROA_i - \overline{ROA})(Subsidy_i) + (\overline{ROA} - ROA_i)(Transfer_i)}{TA} \qquad (13)$$

The higher the ICM measure, the more efficiently a firm allocates its internal funds. When ICM equals to 0, diversified firm internal capital markets do not operate at all. Meanwhile, the positive or negative ICM values mean that firms use their internal funds efficiently or inefficiently respectively. All the data used to compute ICM can be collected at the segment level from the Compustat segment database. The taxes paid, interest expense and dividend payment are collected from the Compustat fundamental database.

3.3.3 External financial constraints

In this paper, we employ the Kaplan-Zingales index (KZ index) proposed by Lamont, Polk et al. (2001), the Whited and Wu index (WW index) proposed by Whited and Wu (2006) and the Size and Assets index (SA index) proposed by Hadlock and Pierce (2010) to measure a firm's external financial constraint. These financial constraint indexes are distinguished from the financial distress measure although they are undoubtedly correlated (Lamont, Polk et al. (2001), Whited and Wu (2006), Hadlock and Pierce (2010)). All three indexes have been widely used in the literature (Campello (2002), Livdan, Sapriza et al. (2009), Duchin (2010), Hadlock and Pierce (2010), Hann, Ogneva et al. (2013)), but Hadlock and Pierce (2010) argue that the SA index is more reliable than the other two measures. The SA index has substantial intuitive appeal, includes only factors that are exogenously determined and has been shown to be a strong predictor of firms' financial constraints. They show that the KZ index is an unreliable financial constraints measure and their results provide mixed support for the WW index. We include the three indexes in our analysis not only to test the robustness of our results, but also to further validate Hadlock and Pierce's (2010) argument. If the three indexes convey very different information about a firm's financial constraint level as shown in their study, the impact of ICM on corporate default risk conditional on financial constraint will vary across the three measures.

a. Kaplan-Zingales index (KZ index)

The first measure of financial constraint used in this paper is Kaplan-Zingales index (KZ index) constructed by Lamont, Polk et al. (2001), who follow the same procedure as in Kaplan & Zingales (1997). Lamont, Polk et al. (2001) divide their sample of manufacturing firms into five discrete categories of financial constraints based on both qualitative and quantitative information collected from the companies' financial reports and CEOs' public statements from 1971 to 1996 including changes in cash dividend payments, stock purchasing announcements and indication of liquidity conditions.

A firm is put into the non-financially constrained group (group 1) if it starts paying dividends or increases its dividend payments, repurchases stocks or states clearly in its financial statement that it has more liquidity than it needed to finance its investments in the foreseeable future, had large cash reserves, low debt, as well as large amounts of internal funds and collateralizable resources. The second group contains firms that are not likely to be financially constrained. These firms have sizable cash reserves, unused lines of credit and healthy interest coverage. The third group consists of possibly financially-constrained firms. These firms are hard to classify either as financially-constrained or non-financially-constrained firms or have contradictory signs of financial constraints. They do not report any clear signs of financial constraints, but they do not look liquid either. The fourth group includes firms that are likely to be financially constrained. They are the ones that postpone an equity or convertible debt offering, or say that they need equity capital but are waiting for better market conditions. Firms in the last group are financially-constrained firms. These companies do not comply with debt covenants, need debt payment negotiation, declare the liquidity issue and/or their usual source of credit has been cut.

After placing sample firms into these five groups, Lamont, Polk et al. (2001) run an ordered logit regression to relate the firms' classifications to the five accounting variables including cash-flow to total capital, debt to total capital, dividends to total capital, cash holding to total capital and market to book ratio (Tobin Q ratio). Lamont, Polk et al. (2001) use the results from this regression to construct an index called the Kaplan-Zingales index (KZ index). Higher KZ index values indicate financial constraint is more severe.

Based on Lamont, Polk et al.'s (2001) regression results, the index is computed as followed:

$$\begin{aligned} \textit{KZ index} = & -1.002(\textit{Cashflow/K}) + 3.139\ (\textit{Total Debts/Capitals}) \\ & -39.368\ (\textit{Total Dividends/ K}) - 1.315\ (\textit{Cash/ K}) + 0.283\ \textit{Tobin Q ratio} \end{aligned} \tag{14}$$

All the variables in equation (14) aim to capture the firm's liquidity conditions, except the Tobin Q ratio that measures the firm's investment opportunities. Cash-flow is the firm's end-of-year operating income plus depreciation. Debt is defined as the firm's end-of-year short-term debt plus long-term debt. Dividends are the annual total dividends payments. Cash is end-of-year cash plus marketable securities, and K is the beginning of year property, plant and equipment. Capital is the end-of-year debt plus book value of preferred stock and book value of common equity. All the coefficient signs in equation (14), except the one for Tobin Q ratio are consistent with the rationale that financially-constrained firms have low cash, low cash-flows, low dividend paid and more debts. One explanation for the unexpected Tobin Q ratio's coefficient sign is the high correlation between this variable and the cash-flows variable. Kaplan and Zingales (1997) shows that the Tobin Q ratio's coefficient tends to be negative when the cash-flow variable is removed from the regression. This result suggests that, conditional on having a low cash-flow, a firm is classified as more likely to be financially constrained if it has more investment opportunities. The results of Lamont et al. (2001) affirms Kaplan and Zingales's (1997) arguments.

b. *Whited and Wu index (WW index)*

The second index used in this study is the Whited and Wu index (WW index) proposed by Whited and Wu (2006). Whited and Wu (2006) employed a structural model to construct the financial constraint index for a sample of non-financial firms from January 1975 to April 2001. WW index is the value calculated from this equation:

$$\begin{aligned} \textit{WW index} = & -0.091\ \textit{Cash-flow/Assets} - 0.062\ \textit{Dividend Dummy} \\ & + 0.021\ \textit{Long-term debts/Assets} - 0.044\ \textit{size} \\ & + 0.102\ \textit{Industry sales growth} - 0.035\ \textit{Firm sales growth} \end{aligned} \tag{15}$$

Cash-flow/assets is defined as the ratio of the firm's operating income plus depreciation to the beginning of year book assets. Dividend dummy equals 1 if the firm pays dividends, and 0 otherwise. Industry sales growth is defined as the annual percentage changes in the 3-digit industry sales. Firm sales growth is the firm's annual percentage change in sales. Size is the logarithm of the firm's assets. Long-term debt/assets is the ratio of the firm's long-term debt to total assets.

Similar to the KZ index, the WW index comprises cash-flow, long-term debt and dividends to capture the firm's liquidity condition. Whited and Wu (2006) include industry sales growth and firm sales growth in their index equation as a replacement of the Tobin Q ratio variable used in the KZ index. These two new variables aim to capture the idea that only firms having good investment opportunities are likely to want to invest enough to be constrained. In addition, the size variable is included to take into account the argument that large firms are less financially constrained. All the coefficients for these variables are significant and have signs consistent with Whited and Wu's (2006) expectation.

c. Size and Age index (SA index)

The third measure of financial constraint used in this paper is the SA index constructed by Hadlock and Pierce (2010). Hadlock and Pierce (2010) follow Kaplan and Zingales's (1997) procedures to classify 365 sample firms into five different financial constraint levels over the period 1995 to 2004. In particular, they use both qualitative and quantitative information collected from the companies' financial reports and 10K filings to assess the firm's ability to raise funds or finance its current or future operations. After placing the firms into five different financial constraint groups, Hadlock and Pierce (2010) estimate an ordered logit regression of financial constraint levels on various firm characteristics, which had been identified in the literature to be related to financial constraints. Their results indicate that firm size and age play dominant roles in determining a firm's financial constraint levels. Based on these findings, they propose a new financial constraint index called the SA index, which is computed as followed:

$$SA\ index = (-0.737 * Size) + (0.043 * Size^2) - (0.040 * Age) \tag{16}$$

Size is calculated as the logarithm of the firm's total assets, and age is the number of years that a firm has been on Compustat with non-missing stock prices. Following Hadlock and Pierce (2010), we also replace the size with log ($4.5 billion) and age with 37 years if the actual values exceed these thresholds in order to reflect the essentially flat relationship between financial constraints and size (age) for very large (mature) companies.

3.4 Data

We obtain our sample from the Compustat historical segment database and Compustat annual fundamentals database for the period 1997–2014. We use the Compustat historical segment database to identify multi-segment firms, and segment level information including sales, assets, capital expenditure, earnings before interest and taxes, and depreciation. A firm is categorized as a multi-segment firm if it has more than one business segment reported at a 4-digit SIC code.[7] This level of granularity means that a multi-segment firm can have all segments operating in one industry, with reference to a 3-digit SIC code. Our initial sample in the Compustat historical segment database has 104,479 firm-year observations, with 37,772 multi-segment firm-year observations and 66,707 single-segment firm-year observations. Following Berger and Ofek (1995), we require that (1) the sum of segment sales (assets) be within 1% (25%) of consolidated firm totals to ensure the integrity of segment data, (2) all firm-years have at least 20 million dollars in sales, and (3) all firms with at least one segment in the financial industry (SIC codes between 6000 and 6999) be excluded from the sample. These requirements reduce our data to 26,387 multi-segment firm-year observations. In addition, we require the sample firms have all necessary data on both the Compustat fundamental database and Compustat segment database to compute all the variables used in the analysis. We lose the majority of our observations when using segment-level data to calculate internal capital market efficiency, leaving a final sample of 11,202 multi-segment firm-year observations. Since there are some extreme values among observations of each variable constructed from the raw COMPUSTAT data, to ensure that our results are not heavily influenced by the outliers, we set all the values higher than the 99^{th} percentile of each variable to that value. All the observations lower than the 1^{st} percentile of each variable are winsorized in the same manner.

Table 3.2 provides descriptive statistics for multi-segment firms over the research period from 1997 to 2014. Consistent with previous findings that multi-segment firms use internal funds inefficiently, the mean ICM in our sample is negative at -0.01. In addition, while the median ICM is 0, the minimum and maximum ICM in our sample is -0.17 and 0.01 respectively, implying that the majority of multi-segment firms in our sample have negative or close to zero ICM. In addition, similar to Bharath and Shumway (2008), our sample firms have default

[7] Diversification is defined as unrelated business segments based on 4-digit SICs code. We also repeat the analysis when diversification is defined as unrelated business segments based on 2-digit SICs code and Fama and French's 49 industry classes

probabilities ranging from 0 to 100%. The mean default probability and its standard deviation in our sample are 6.52% and 20.1% respectively, which is marginally lower than for the sample firms in Bharath and Shumway (2008) since our sample includes only big firms. We also show correlation matrix in table 3.3, which helps us identify potential multicollinearity issue in the regression analysis. As can be seen in table 3.4, only the correlation between Size and WW is of the concern. All of the other correlation coefficients do not raise the multicollinearity issue.

Table 3.2 Descriptive statistics for multi-segment firms during 1997-2014

KZ index, WW index and SA index are calculated as in the equation (14), (15) and (16). Size is the logarithm of the firm's year-end assets. DP is the firm's default probabilities calculated as in Bharath and Shumway's (2008). ICM is computed as in Billett and Mauer (2003), which is outlined in section 3.3.2. Volatility is the annualized standard deviation of the firm's monthly stock returns. Leverage is calculated as the ratio of the firm's year-end total debt to market value. Number of segments is defined using 4-digit SIC codes reported in the Compustat segment database. Z-score is calculated separately for manufacturing and non-manufacturing firms as in equation (7) and equation (8). All the variables are in annual values. Except number of segments and default probabilities, all the values higher than the 99th percentile of each variable are set to that value. All the observations lower than the 1st percentile of each variable are winsorized in the same manner.

Variable	Obs	Mean	Med	Std	Min	Max
KZ index	11,202	0.59	0.62	0.95	-2.34	2.63
WW index	11,202	-0.31	-0.31	0.11	-0.53	-0.1
SA index	11,202	-3.56	-3.5	0.69	-4.64	-2.15
Size	11,202	6.3	6.26	1.91	2.88	10.49
DP (in percentage)	11,202	6.52	0	20.1	0	100
ICM	11,202	-0.01	0	0.03	-0.17	0.01
Volatility	11,202	0.49	0.4	0.3	0.13	1.51
Leverage	11,202	0.86	0.27	1.88	0	10.92
Number of segments	11,202	2.89	2	1.24	2	10
Z-score	11,202	2.03	2.35	2.54	-8.13	6.48

Table 3.3 Correlation Matrix

This table reports correlation matrix for all of the variables used in the analysis. KZ index, WW index and SA index are financial constraint indexes which are calculated as in the equation (14), (15) and (16). Size is the logarithm of the firm's year-end assets. DP is the firm's naïve default probabilities calculated as in Bharath and Shumway's (2008). ICM is computed as in Billett and Mauer (2003), which is outlined in section 3.3.2. Volatility is the annualized standard deviation of the firm's monthly stock returns. Leverage is calculated as the ratio of the firm's year-end total debt to market value. Number of segments is defined using 4-digit SIC codes reported in the Compustat segment database. Z-score is calculated separately for manufacturing and non-manufacturing firms as in the equation (7) and equation (8). All the variables are in annual values. Except number of business segments and default probabilities, all the values higher than the 99th percentile of each variable are set to that value. All the observations lower than the 1st percentile of each variable are winsorized in the same manner.

	Default risk	Z-score	Volatility	Size	ICM	NUMSEG	SA	KZ	WW	Leverage	Rating
Default risk	1.00										
Z-score	-0.23	1.00									
Volatility	0.29	-0.25	1.00								
Size	-0.12	0.16	-0.36	1.00							
ICM	-0.07	0.23	-0.11	0.13	1.00						
NUMSEG	-0.05	0.05	-0.13	0.33	-0.04	1.00					
SA	0.17	-0.23	0.41	-0.69	-0.13	-0.23	1.00				
KZ	0.22	-0.22	0.16	-0.01	-0.04	-0.03	0.09	1.00			
WW	0.15	-0.21	0.37	-0.86	-0.13	-0.29	0.64	0.12	1.00		
Leverage	0.59	-0.21	0.24	-0.05	-0.05	-0.03	0.08	0.28	0.08	1.00	
Rating	.	.	0.52	-0.70	-0.09	-0.23	0.44	0.47	0.62	0.40	1.00

Table 3.4 Mean and difference in the mean for financially constrained firms versus non-financially constrained firms basing on the KZ index and the WW index

Financially-constrained firms are defined as firms in the top 20 percentile of the KZ index, WW index and SA index at the end of each financial year. Non-financially-constrained firms are the ones in the bottom 80 percentile of the KZ index, WW index and SA index at the end of each financial year. KZ index, WW index and SA index are calculated as in the equation (14), (15) and (16). Size is the logarithm of the firm's year-end assets. DP is the firm's naïve default probabilities calculated as in Bharath and Shumway's (2008). ICM is computed as in Billett and Mauer (2003), which is outlined in section 3.3.2. Volatility is the annualized standard deviation of the firm's monthly stock returns. Leverage is calculated as the ratio of the firm's year-end total debt to market value. Number of segments is defined using 4-digit SIC codes reported in the Compustat segment database. Z-score is calculated separately for manufacturing and non-manufacturing firms as in the equation (7) and equation (8). All the variables are in annual values. Except number of business segments and default probabilities, all the values higher than the 99th percentile of each variable are set to that value. All the observations lower than the 1st percentile of each variable are winsorized in the same manner.

A t-test is conducted to test for the mean differences between the financially constrained firms and non-financially constrained firms

****,** indicates significantly different from zero at 1% and 5% level*

		Panel A: Financially constrained versus non-financially constrained basing on the KZ index			***Panel B: Financially constrained versus non-financially constrained basing on the WW index***			***Panel C: Financially constrained versus non-financially constrained basing on the SA index***		
Variable		*Non-financially Constrained Firms*	*Financially Constrained Firms*	*Difference*	*Non-financially Constrained Firms*	*Financially Constrained Firms*	*Difference*	*Non-financially Constrained Firms*	*Financially Constrained Firms*	*Difference*
KZ index	Mean	0.283	1.811	1.528***	0.544	0.77	0.226***	0.576	0.643	0.067***
	Std	0.783	0.437		0.952	0.922		0.928	1.033	
WW index	Mean	-0.315	-0.279	0.036***	-0.344	-0.164	0.18***	-0.336	-0.194	0.142***
	Std	0.108	0.095		0.086	0.041		0.096	0.066	

SA index	Mean	-3.61	-3.341	0.269***	-3.732	-2.853	0.879***	-3.786	-2.638	1.148***
	Std	0.703	0.603		0.614	0.516		0.557	0.314	
Size	Mean	6.349	6.115	-0.234***	6.874	4.023	-2.851***	6.839	4.163	-2.676***
	Std	1.939	1.777		1.658	0.852		1.685	1.068	
DP (in percentage)	Mean	3.316	19.302	15.986***	5.355	11.183	5.828***	5.477	10.696	5.219***
	Std	13.615	32.716		18.38	25.3		18.634	24.655	
ICM	Mean	-0.008	-0.012	-0.004***	-0.007	-0.015	-0.008***	-0.007	-0.014	-0.007***
	Std	0.027	0.037		0.026	0.042		0.026	0.04	
Volatility	Mean	0.455	0.608	0.153***	0.444	0.65	0.206***	0.44	0.667	0.227***
	Std	0.279	0.341		0.27	0.346		0.265	0.353	
Leverage	Mean	0.444	2.533	2.089***	0.823	1.021	0.198***	0.844	0.938	0.094**
	Std	0.987	3.197		1.793	2.178		1.822	2.087	
Number of segments	Mean	2.926	2.751	-0.175***	3.001	2.454	-0.547***	2.987	2.511	-0.476***
	Std	1.275	1.073		1.297	0.842		1.293	0.899	
Z-score	Mean	2.454	0.325	-2.129***	2.377	0.63	-1.747***	2.353	0.725	-1.628***
	Std	2.202	3.035		2.006	3.698		2.008	3.738	
N		8954	2248		8954	2248		8954	2248	

Table 3.4 reports the mean, standard deviation and differences in the mean for financially-constrained firms versus non-financially-constrained firms. At the end of each financial year, we use an 80% cut-off point to divide the sample firms into financially-constrained and non-financially-constrained firms.[8] It is clear from Table 3.3 that the former group is riskier than the latter regardless of which financial constraints measures are used, demonstrated by higher mean DP and lower Z-score in the two panels. Mean differences for DP and Z-score between these two groups of firms are 15.986 and -2.129 in panel A, 5.828 and -1.747 in panel B and 5.219 and -1.628 in panel C respectively, and statistically significant at the 1% level. Financially-constrained firms also have higher stock return volatility and leverage, but a lower number of business segments and sizes. In all three indexes, it appears that financially-constrained firms on average use their internal funds less efficiently than non-financial constrained firms. Overall the three financial constraint indexes convey very similar information about the firms' characteristics, though the correlation between the SA index and the KZ index is 9.36%, which is much lower than the correlation between the SA index and the WW index (64.36%).

3.5 Empirical results

3.5.1 The effect of Internal Capital Market Efficiency on Corporate Default Risk

Table 3.5 presents the regression results for testing the effect of Internal Capital Market Efficiency (ICM) on corporate default risk. The regression equation is specified below:

$$\begin{aligned} DP_{it} = \; & \beta_0 + \beta_1 ICM_{it} + \beta_2 Size_{it} + \beta_3 Leverage_{it} + \beta_4 Volatility_{it} \\ & + \beta_5\, Segment\ Dummy_{it} * Industry\ Dummy_{it} + \beta_6\, Segment\ Dummy_{it} \\ & + \beta_7\, Industry\ Dummy_{it} + \epsilon_{it} \qquad (17) \end{aligned}$$

DP_{it} is firm i's default risk at time t, which is measured by Merton-style default probability, Altman's Z-score and S&P credit rating. ICM_{it} is company i's internal capital market efficiency

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[8] The choice of 80% cut-off is arbitrary. We also conduct the sensitivity check by varying our cut-off point between 70% and 90%. Our results remain statistically similar when the cut-off points are between 75% and 90%. When the cut-off points are below 75%, the significance of the ICM variable diminishes.

at time t, computed as in Billett and Mauer (2003). $Size_{it}$ is firm i's size at time t, which is also the logarithm of the firm's year-end assets. $Leverage_{it}$ is firm i's leverage at time t , calculated as the ratio of the firm's year-end total debt to market value. $Volatility_{it}$ is the firm i's annualized monthly stock return volatility at time t. Segment $Dummy_{it}$ is firm i's segment indicator, equalling 1 if firms i have more than 4 segments and 0 otherwise. Industry $Dummy_{it}$ is firm i's industry indicator at time t, equalling 1 if firms have all segments belonging to one industry and 0 otherwise, with industry being defined as 3-digit SIC code.

In line with our expectation, Table 3.5 shows that the coefficients for the ICM variable are negative and statistically significant across the three corporate default risk measures, indicating a negative relationship between ICM and corporate default risk after controlling for other firm characteristics. Since ICM is only available in diversified firms, our result can help explain contradictory findings in the literature regarding the risk effect of diversification (Lewellen (1971), Berger and Ofek (1995), Comment and Jarrell (1995), Furfine and Rosen (2011), Singhal and Zhu (2013)). The risk reduction benefit flowing from diversification shown in Lewellen's (1971) model can be diminished or even offset by the inefficient use of internal funds. Our finding thus support the effects implied by agency theory, which suggest the potential negative impacts of inefficient internal capital markets on a diversified firm's default risk.

The coefficients for all the controlled variables in our regression are also in line with the respective economic rationales when they are statistically significant. Table 3.5 shows that a firm will be more likely to default if it has higher leverage and stock return volatility, but will be less risky if it has larger size. In addition, the coefficient for Segment Dummy variable is found to be negative and statistically significant in the case of S&P credit rating, indicating that a firm with more than four business segments is less risky than firms with fewer business segments.[9] This result is consistent with the rationale that diversification helps reduce corporate default risk. Our results also show that firms will be riskier if all of their business segments belong to the same industry defined by a 3-digit SIC code, demonstrated by positive and statistically significant coefficient for the Industry Dummy variable in the case of S&P credit rating. It is because these firms will have a higher cash-flow correlation compared to the ones operating in various industries.

To evaluate whether the effect of ICM on corporate default risk is economically significant, the results reported in Table 3.5 cannot be interpreted directly. In column 1 of Table 3.5, our dependent variable is transformed default probabilities rather than the original default probabilities. Therefore, to have an understanding of how default probabilities change as a result of changes in the ICM, we need to convert the transformed default probabilities back to the original default probabilities. We present the implied risk sensitivities for firms in different percentiles of leverage in Figure 3.1.

[9] The choice of the cut-off at 4 business segments is arbitrary. We also conduct the sensitivity check when varying the cut-off at 2,3 and 5 business segments. The results remain statistically significant when the cut-off is at 2 segments and 3 segments, but the significance level diminishes at 5 segment cut-off point

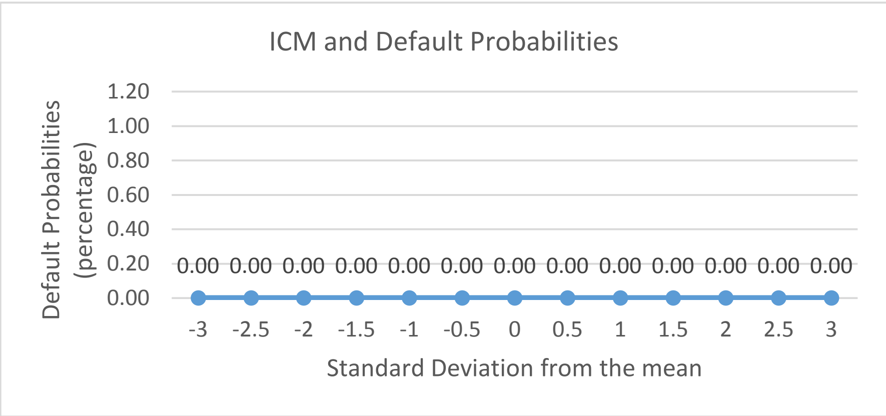
Table 3.5: Regression results for the effect of ICM on diversified firm's corporate default risk

*This table reports the regression results for testing the effect of ICM on diversified firm's corporate default risk. Column 1 of Table 3.5 presents OLS regression results when the lower (upper) bounded values of default probabilities are added (subtracted) by 0.0001 and then transformed to inverse normal cumulative distribution. Default probabilities are calculated as in Bharath and Shumway (2008). Column 2 presents the ordered logit regression results when corporate default risk is measured by Atman Z-score. Altman Z-scores are computed separately for manufacturing and non-manufacturing firms, and then divided into three categories. For manufacturing firms, category 1 is the 'safe zone' with Z-score larger than 2.99; category 2 is the 'grey zone' with Z-score between 1.81 and 2.99; category 3 is the 'distress zone' with Z-score less than 1.81. For non-manufacturing firms, category 1 is the 'safe zone' with Z-score larger than 2.90; category 2 is the 'grey zone' with Z-score between 1.23 and 2.90; category 3 is the 'distress zone' with Z-score less than 1.23. Column 3 presents the ordered logit regression results when default risk is measured by S&P rating, divided into 22 rating categories. ICM calculation can be found in section 3.3.2. Size is the logarithm of the firm's year-end assets. Leverage is calculated as the ratio of the firm's year-end total debt to market value. Volatility is the firm's annualized monthly stock return volatility. Segment Dummy equals 1 if firms have more than 4 segments and 0 otherwise. Industry dummy equals 1 if firms have all segments belonging to one industry and 0 otherwise. Industry is defined as the 3-digit SIC code. The regressions are estimated over the period 1997-2014. White's (1980) heteroskedascity is consistent, clustered at firm level, and p-values are in parentheses below the parameter estimates. An ***, **, * indicates significance at 1%, 5% and 10% level.*

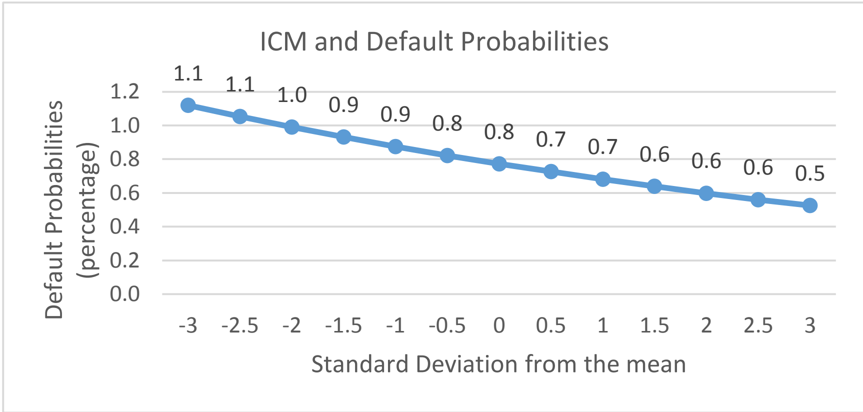
	OLS regression	Ordered Logit regression	Ordered logit regression
	Column 1: transformed default probabilities	***Column 2: zscore categories***	***Column 3: 22 rating categories***
ICM	-1.54**	-3.24***	-3.47*
	(0.02)	(0.00)	(0.07)
Size	-0.023	-0.027	-0.76***
	(0.77)	(0.19)	(0.00)
Leverage	0.28***	0.82***	0.25***
	(0.00)	(0.00)	(0.00)
Volatility	2.56***	1.07***	3.28***
	(0.00)	(0.00)	(0.00)
Segment Dummy* Industry Dummy	-0.40	0.030	-0.23
	(0.49)	(0.92)	(0.42)
Segment Dummy	0.062	0.12	-0.39**
	(0.77)	(0.36)	(0.02)
Industry Dummy	0.015	0.002	0.29**
	(0.93)	(0.98)	(0.03)
N	11,202	11,202	4,006
Adj R-square	0.11		
Pseudo R-square		0.11	0.14

Figure 3.1: ICM and default probabilities

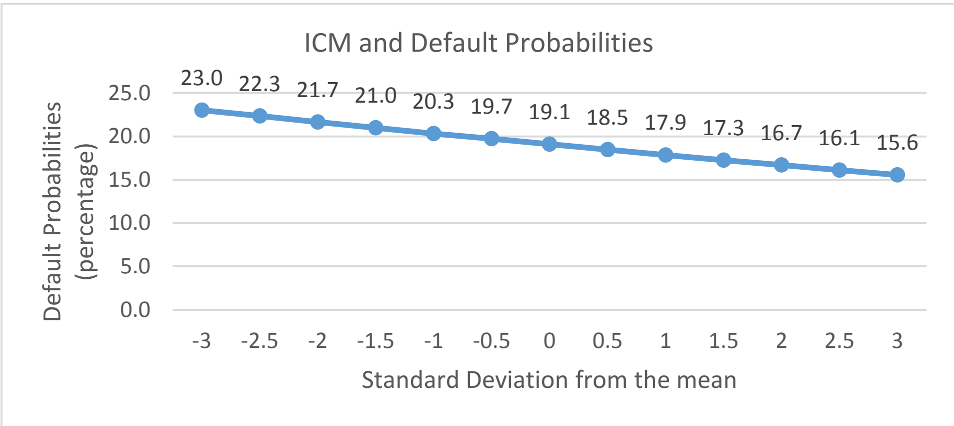
This figure shows predicted default probabilities (in percentages) given different values of ICM for all firms in the sample, firms in the top 10 percentile of leverage and firms in the top 5 percentile of leverage. All the other variables are set at their means.



Panel A: ICM and Default Probabilities for all sample firms



Panel B: ICM and Default Probabilities in the top 10 percentile of leverage



Panel C: ICM and Default Probabilities in the top 5 percentile of leverage

Figure 3.1 shows that changes in the ICM have a more pronounced effect on corporate default risk for firms having higher leverage ratios, and that the effect is asymmetrical between the left side and the right side of the mean. In particular, for firms in the top 5 percentile of leverage, a decrease in ICM from -1.5 to -2.5 standard deviation from the mean leads to a rise in corporate default risk by approximately 1.3%. Meanwhile, a rise in ICM from +1.5 to +2.5 standard deviation from the mean results in a reduction in corporate default risk by only about 1.2%. When expanding our predicted default probabilities to firms in the top 10 percentile of leverage, the same magnitude change in ICM both in the right side and the left side of the mean result in a much smaller change in default risk, but a larger magnitude is still observed in the left side. For instance, default probability increases by only 0.2% when ICM moves from -1.5 to -2.5 standard deviation from the mean, and decreases by only 0.01% when ICM changes by the same amount to the right side of the mean. When we examine the magnitude of the effect across all firms in the sample, panel A of Figure 3.1 shows that corporate default risk remains approximately zero regardless of how much ICM changes. Based on these results, we can conclude that the effect of ICM on corporate default risk appears to be more economically significant when firms have leverage ratios in the highest decile.

Table 3.6 focuses on the relation between variation in ICM and default risk exposures as measured by Z-score zones. The effects of ICM variation are evident with reference to both the entire sample (upper panel), and the highly-levered subsample (lower panel) in Table 3.6. Specifically, when ICM is 1-2 standard deviations below the mean, the probability of the average firm being in the 'safe' to 'grey' zone declines substantially, with a commensurate increase in the probability of distress.[10] The effects are similar, albeit substantially stronger in the highly levered subsample[11].

[10] For the purposes of this discussion, it should be noted that the average firms' Z-score is around the border line of the 'grey' and 'distress' zones.

[11] The average firm in the highly-leveraged sub-sample is in the 'distress' zone; hence the apparent insensitivity of the distress classification to variation in ICM.

Table 3.6: Changes in predicted probabilities for ordered logit regression when default risk is measured by Altman's Z-score categories

This table shows changes in the probabilities (as a percentage) and proportional changes in the probabilities (as a percentage) for a firm to be classified in a specific Z-score zone when ICM changes by a value of one standard deviation and two standard deviations from its mean, holding the other variables at their means. We report the results for the whole sample of firms in panel A and for firms in the top 5 percentile of leverage in panel B

	Changes in probabilities				Proportional changes in probabilities			
Panel A: All sample firms								
Z-score zones	**Mean - 2σ**	**Mean - 1σ**	**Mean +1σ**	**Mean +2σ**	**Mean - 2σ**	**Mean - 1σ**	**Mean +1σ**	**Mean +2σ**
Safe zone	-3.3	-1.6	2.1	4	-12.94	-6.27	8.24	15.69
Grey zone	-0.9	-0.3	0.4	0.5	-2.29	-0.76	1.02	1.27
Distress zone	4.2	4.4	-2.4	-4.5	11.93	12.50	-6.82	-12.78
Panel B: Top 5 percentile of leverage								
Z-score zones	**Mean - 2σ**	**Mean - 1σ**	**Mean +1σ**	**Mean +2σ**	**Mean - 2σ**	**Mean - 1σ**	**Mean +1σ**	**Mean +2σ**
Safe zone	-0.001	-0.000	0.001	0.001	-17.38	-7.45	15.96	29.79
Grey zone	-0.002	-0.001	0.002	0.004	-17.74	-8.06	15.32	29.84
Distress zone	0.000	0.000	0.000	0.000	0.00	0.00	0.00	0.00

In the case of S&P credit ratings, we report changes in the probability of the average firm being assigned a specific rating when ICM changes by a value of one standard deviation and two standard deviation from its mean, holding all the other variables at their means. It can be seen in panel A of Table 3.7 that changes in the probability for the average firm realizing a BBB- rating or higher have opposite signs with the lower rating categories, consistent with the mean rating for all sample firms being around BBB- and BB+. Panel A of Table 3.7 shows that when ICM increases by one standard deviation from its mean, the probability for a firm to receive a higher than average rating increases while the probability for a firm to receive a lower than average rating decreases, confirming the role of ICM in helping to reduce corporate default risk. In both cases, the strongest changes in the probability can be observed around the mean rating. For instance, a one standard deviation increase in the ICM leads to changes in the probability for a firm to be rated BB- (below the average rating) and BBB+ (above the average rating), a value of -0.5% and 0.35% respectively. However, these values change to -0.48% for B+ rating and 0.28% for A- rating respectively, consistently with diminishing probabilities of large magnitude ratings shifts.

When focusing on firms in the top 5 percentile of leverage, panel B of Table 3.7 shows that mean rating for these firms is around B or B-, a higher risk level than the whole sample of firms. Similar to the previous case, when ICM deviates to the right side of the mean by one standard deviation, changes in the probability of a firm receiving a higher than average rating increases, but a lower than average rating decreases. These changes are also found to be largest around the mean rating. For example, a one standard deviation increase in the ICM from its mean results in a reduction in the probability for a firm to be rated CCC and CCC- (lower than average rating), a value of -0.27% and -0.05% respectively. The magnitude of the probability changes around the mean are also found to be larger for the top 5 percentile of leveraged firms compared to the case of all firms reported in panel A. When ICM increases by one standard deviation from its mean, the probability of a firm receiving a higher rating next to the average rating in the case of all firms (BBB-), a value of 0.2% but, in the case of the top 5% of leveraged firms

(B), a value of 0.5%. A clearer trend can be seen when we examine the proportional changes reported in Table 3.8. Compared with all sample firms, the top 5 percentile of leveraged firms experience a larger proportional change in the probability of being in the higher or lower than average rating categories when ICM changes by one or two standard deviation from its mean. Overall, our results show that ICM has a stronger effect on firms with high leverage level.

Table 3.7: Changes in predicted probabilities for ordered logit regression when default risk is measured by S&P credit rating

This table reports the results of the way the probability that a firm being assigned a specific rating will change (as a percentage) when ICM changes by a value of one standard deviation and two standard deviations from its mean, holding the other variables at their means. The results are reported for the whole sample of firms and for firms in the top 5 percentile of leverage. S&P rating are divided into 22 rating categories, with the highest rating quality category being AAA and the lowest rating category being SD. ICM calculation can be found in section 3.

	Panel A: All sample firms				Panel B: top 5 percentile of leverage			
	Mean - 2σ	**Mean - 1σ**	**Mean +1σ**	**Mean +2σ**	**Mean - 2σ**	**Mean - 1σ**	**Mean +1σ**	**Mean +2σ**
AAA	-0.03	-0.01	0.02	0.03	0.00	0.00	0.00	0.00
AA+	-0.02	-0.01	0.01	0.02	0.00	0.00	0.00	0.00
AA	-0.06	-0.03	0.03	0.06	0.00	0.00	0.00	0.00
AA-	-0.09	-0.05	0.05	0.10	0.00	0.00	0.00	0.00
A+	-0.17	-0.09	0.09	0.19	0.00	0.00	0.00	0.00
A	-0.54	-0.28	0.29	0.60	-0.01	0.00	0.01	0.01
A-	-0.53	-0.27	0.28	0.57	-0.01	0.00	0.01	0.02
BBB+	-0.66	-0.33	0.35	0.69	-0.02	-0.01	0.01	0.03
BBB	-1.00	-0.50	0.50	1.00	-0.05	-0.02	0.04	0.08
BBB-	-0.40	-0.20	0.20	0.30	-0.07	-0.03	0.06	0.11
BB+	0.10	0.00	-0.10	-0.20	-0.10	-0.04	0.08	0.15
BB	0.70	0.30	-0.40	-0.80	-0.25	-0.11	0.20	0.37
BB-	1.10	0.60	-0.50	-1.10	-0.55	-0.24	0.43	0.79
B+	1.03	0.50	-0.48	-0.94	-1.30	-0.50	0.90	1.70
B	0.46	0.22	-0.20	-0.40	-0.70	-0.20	0.50	0.70
B-	0.13	0.06	-0.06	-0.11	1.20	0.50	-0.90	-1.70
CCC+	0.03	0.01	-0.01	-0.03	0.89	0.38	-0.63	-1.10
CCC	0.01	0.00	0.00	-0.01	0.40	0.16	-0.27	-0.47
CCC-	0.00	0.00	0.00	0.00	0.08	0.03	-0.05	-0.09
CC	0.00	0.00	0.00	0.00	0.14	0.06	-0.10	-0.17
D	0.01	0.00	0.00	0.00	0.28	0.12	-0.18	-0.31
SD	0.00	0.00	0.00	0.00	0.04	0.02	-0.03	-0.04

Table 3.8: Proportional Changes in predicted probabilities for ordered logit regression when default risk is measured by S&P credit rating

This table reports the results of how the probability that a firm being assigned a specific rating will change proportionally (as a percentage) when ICM changes by a value of one standard deviation and two standard deviations from its mean, holding the other variables at their means. The results are reported for the whole sample firms and for firms in the top 5 percentile of leverage. S&P rating are divided into 22 rating categories, with the highest rating quality category being AAA and the lowest rating category being SD. ICM calculation can be found in section 3.

	Panel A: All sample firms				**Panel B: top 5 percentile of leverage**			
	Mean - 2σ	**Mean - 1σ**	**Mean +1σ**	**Mean +2σ**	**Mean - 2σ**	**Mean - 1σ**	**Mean +1σ**	**Mean +2σ**
AAA	-13.11	-6.80	7.28	15.53	-11.82	-5.15	9.39	17.58
AA+	-13.53	-6.77	7.52	15.79	-11.68	-5.14	9.35	17.29
AA	-13.37	-6.92	7.16	15.04	-11.69	-5.18	9.47	17.60
AA-	-13.01	-6.65	7.37	15.03	-11.59	-5.31	9.73	17.70
A+	-12.88	-6.82	6.82	14.39	-11.42	-5.02	9.59	17.81
A	-12.19	-6.32	6.55	13.54	-11.64	-5.12	9.46	17.65
A-	-11.13	-5.67	5.88	11.97	-11.56	-5.08	9.07	17.71
BBB+	-9.66	-4.83	5.12	10.10	-11.84	-5.26	9.21	17.11
BBB	-6.58	-3.29	3.29	6.58	-11.61	-5.13	9.38	17.41
BBB-	-2.94	-1.47	1.47	2.21	-11.36	-4.87	9.42	17.21
BB+	0.84	0.00	-0.84	-1.68	-11.24	-4.87	9.15	17.03
BB	4.52	1.94	-2.58	-5.16	-10.96	-4.82	8.77	16.23
BB-	8.87	4.84	-4.03	-8.87	-10.17	-4.44	7.95	14.60
B+	12.47	6.05	-5.81	-11.38	-8.07	-3.11	5.59	10.56
B	14.60	6.98	-6.35	-12.70	-2.25	-0.64	1.61	2.25
B-	15.18	7.29	-6.82	-13.18	4.69	1.95	-3.52	-6.64
CCC+	15.31	7.14	-7.14	-13.27	9.46	4.04	-6.70	-11.69
CCC	15.42	7.47	-6.84	-13.20	11.46	4.58	-7.74	-13.47
CCC-	15.45	7.27	-7.27	-13.45	12.13	4.88	-8.03	-14.02
CC	15.42	7.46	-6.97	-13.43	11.76	5.04	-8.40	-14.29
D	15.58	7.65	-6.80	-13.31	13.02	5.58	-8.37	-14.42
SD	15.48	7.53	-6.88	-13.33	13.45	5.52	-8.62	-14.83

3.5.2 The effect of ICM on corporate default risk in financially-constrained firms versus non-financially-constrained firms

Table 3.9 reports the regression results for testing the effect of the interaction between the ICM variable and the financial constraint index dummy (FC dummy) on corporate default risk. The regression equation is outlined below:

$$DP_{it} = \beta_0 + \beta_1 FCDummy_{it}*ICM_{it} + \beta_2 FCDummy_{it} + \beta_3 ICM_{it} + \beta_4 Size_{it}$$

$$+ \beta_5 Leverage_{it} + \beta_6 Volatility_{it} + \beta_7 \, Segment\ Dummy_{it} * Industry\ Dummy_{it}$$

$$+ \beta_8 \, Segment\ Dummy_{it} + \beta_9 \, Industry\ Dummy_{it} + \epsilon_{it} \qquad (18)$$

DP_{it} is firm i's default risk at time t, which is measured by Merton-style default probability, Altman's Z-score or S&P credit rating. $FCDummy_{it}$ equals 1 if firm i is financially constrained at time t and zero otherwise. Financial constraint is measured by the KZ index, WW index and SA index respectively. Financially-constrained firms are defined as firms in the top 20 percentile of the KZ index, WW index and SA index at the end of each financial year. Non-financially-constrained firms are the ones in the bottom 80 percentile of the KZ index, WW index and SA index at the end of each financial year. ICM_{it} is company i's internal capital market efficiency at time t, computed as in Billett and Mauer (2003). $Size_{it}$ is firm i's size at time t, which is the logarithm of the firm's year-end assets. $Leverage_{it}$ is firm i's leverage, calculated as the ratio of the firm's year-end total debt to market value. $Volatility_{it}$ is firm i's annualized monthly stock return volatility at time t. Segment $Dummy_{it}$ is firm i's segment indicator, equalling 1 if firm i has more than 4 segments and 0 otherwise. Industry $dummy_{it}$ is firm i's industry indicator at time t, equalling 1 if firms have all segments belonging to one industry and 0 otherwise, with industry being defined as a 3-digit SIC code.

We present the results separately for the KZ index, the WW index and the SA index in panel A, panel B and panel C respectively. As the computation of WW index and SA index includes the size variable, to avoid double counting the effect of size on corporate default risk, we do not control for size when financial constraints are measured by the WW index and SA index. In the case of the KZ index, the size variable is still included as a control variable to capture not only the effect of size on corporate default risk but also the information about a firm's financial constraint level that has not been captured by the KZ index.

It can be seen in Table 3.9 that the coefficients for the interaction between ICM and Financial Constraint Index Dummy (FC dummy) are only statistically significant in the case of Altman's

Z-score categories. Though previous research suggests that ICM plays a more important role in financially-constrained firms (Hovakimian (2011), Kuppuswamy and Villalonga (2015)), our results here find only weak evidence of an interaction between the impact of ICM on default risk and external financial constraints. However, our results still indicate the importance of ICM in determining corporate default risk **when firms are not financially constrained,** as demonstrated by the negative and statistically significant coefficients for ICM variables in most cases. Most of the coefficients for the FC Dummy are positive and statistically significant, meaning that the more financially constrained a firm **with non-operating internal capital market is (ICM =0),** the higher its corporate default risk, which is in line with Lamont, Polk et al.'s (2001), Whited and Wu's (2006), and Hadlock and Pierce's (2010) arguments. In addition, all of the coefficients for size, leverage and volatility have the coefficients with signs being consistent with their economic rationales when they are statistically significant. Similar to table 3.5, the coefficients for Segment Dummy and Industry Dummy are only statistically significant in the case of S&P credit rating. In particular, firms that have more than four business segments are found to be less risky than firms with fewer business segments, as demonstrated by the negative and significant coefficient for Segment Dummy in column 3 of the three panels. Meanwhile, the coefficient for Industry Dummy variable is positive and statistically significant, showing that a firm will have higher corporate default risk if it has all business segments belonging to the same industry defined by the 3-digit SIC codes.

For robustness, we retest hypothesis 2 with respect to alternative definitions of the financial constraint measure. Specifically, at the end of each financial year we classify a firm as being financially constrained at different cut-off points for the KZ index, WW index and the SA index. Our results remain qualitatively similar when the cut-off point is between 75% and 90%. However, we find that the significance of the ICM variable diminishes when the cut-off points are lower than 75%, which is most probably due to the increased correlation between the FC Dummy and its interaction term with ICM.[12]

3.5.3 Robustness tests

To investigate the sensitivity of our results to the definition of multi-segment firms, we re-examine the effect of ICM on corporate default risk when multi-segment firms are defined differently. In particular, a firm is identified as multi-segmented if it has multiple segments according to the 66 industries grouped by 2-digit SIC code, or Fama and French's 49 industries groupings respectively. New regression results for these alternative industry definitions are reported in Table 3.10.

Table 3.10 shows that the coefficients for ICM variables are significantly negative in columns 1 and 2 in both panel A and panel B, confirming the negative effect of ICM on corporate default risk when measured by default probabilities and Altman's Z-score. In the case of S&P credit rating, though the coefficient signs are still consistent with the results reported in Table 3.5, they are insignificant, which may be due to the reduction in the sample size. It also appears that size, leverage and volatility still play important roles in determining corporate default risk in all three default risk measures. Overall this suggests that our results are not driven by the industry definitions as they are largely robust to less granularity in the definition of industry groupings but, as may be expected, the effects are somewhat weakened.

[12] These results are not reported but available upon request

Table 3.9: Regression results for testing the effect of ICM on corporate default risk in financially constrained firms versus non-financially constrained firms

*This table reports the regression results for testing the effect of ICM on corporate default risk in financially-constrained firms versus non-financially-constrained firms. Panel A, panel B and panel C of Table 3.9 present the regression results when financial constraint is measured by the KZ index, WW index and SA index respectively. Financially-constrained firms are defined as firms in the top 20 percentile of the KZ index, WW index and SA index at the end of each financial year. Non-financially-constrained firms are the ones in the bottom 80 percentile of the KZ index, WW index and SA index at the end of each financial year. Column 1 of Table 3.7 presents OLS regression results when the lower (upper) bounded values of default probabilities are added (subtracted) by 0.0001 and then transformed to inverse normal cumulative distribution. Default probability is calculated as in Bharath and Shumway (2008). Column 2 presents the ordered logit regression results when corporate default risk is measured by Atman Z-score categories. Altman Z-scores are computed separately for manufacturing and non-manufacturing firms, and then divided into three categories. For manufacturing firms, category 1 is the 'safe zone' with Z-score larger than 2.99; category 2 is the 'grey zone' with Z-score between 1.81 and 2.99; category 3 is the 'distress zone' with Z-score less than 1.81. For non-manufacturing firms, category 1 is the 'safe zone' with Z-score larger than 2.90; category 2 is the 'grey zone' with Z-score between 1.23 and 2.90; category 3 is the 'distress zone' with Z-score less than 1.23. Column 3 presents the ordered logit regression results when default risk is measured by S&P rating, divided into 22 rating categories. ICM, WW index, KZ index and SA index calculations can be found in section 3. FC dummy equals 1 if the firm has KZ index, WW index and SA index in the top 20 percentile, and 0 otherwise. Size is calculated as the logarithm of the firm's year-end assets. Leverage is calculated as the ratio of the firm's year-end total debt to market value. Volatility is the firm's annualized monthly stock return volatility. Segment Dummy equals 1 if firms have more than 4 segments and 0 otherwise. Industry dummy equal 1 if firms have all segments belonging to one industry and 0 otherwise. Industry is defined as a 3-digit SIC code. The regressions are estimated over the period 1997-2014. White's (1980) heteroskedascity consistent, clustered at firm level, p-values are in parentheses below the parameter estimates. ***, **, * indicates significance at 1%, 5% and 10% level.*

	Panel A: KZ index			Panel B: WW index			Panel C: SA index		
	OLS regression	Ordered logit regression	Ordered logit regression	OLS regression	Ordered Logit regression	Ordered logit regression	OLS regression	Ordered Logit regression	Ordered logit regression
	Column 1: transformed default probabilities	Column 2: Z-score categories	Column 3: 22 rating categories	Column 1: transformed default probabilities	Column 2: Z-score categories	Column 3: 22 rating categories	Column 1: transformed default probabilities	Column 2: Z-score categories	Column 3: 22 rating categories
FC Dummy*ICM	-0.12	-5.02***	2.43	1.51	-6.15***	-0.19	1.29	-3.32***	2.00
	(0.92)	(0.00)	(0.48)	(0.23)	(0.00)	(0.96)	(0.33)	(0.00)	(0.60)
FC Dummy	0.70***	0.84***	1.72***	0.18	0.50***	1.85***	-0.20	0.53***	0.98***
	(0.00)	(0.00)	(0.00)	(0.14)	(0.00)	(0.00)	(0.30)	(0.00)	(0.00)
ICM	-1.24	-2.09***	-4.72*	-2.16**	-0.72	-4.46	-2.11**	-1.85**	-5.91**
	(0.12)	(0.01)	(0.08)	(0.03)	(0.37)	(0.16)	(0.03)	(0.02)	(0.05)
Size	-0.043	-0.041**	-0.72***						
	(0.58)	(0.05)	(0.00)						
Leverage	0.26***	0.63***	0.18***	0.28***	0.86***	0.24***	0.28***	0.87***	0.26***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Volatility	2.55***	0.96***	3.09***	2.57***	0.95***	3.75***	2.57***	0.92***	4.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Segment Dummy* industry Dummy	-0.39	0.0045	-0.36	-0.39	0.087	-0.098	-0.41	0.083	-0.18
	(0.51)	(0.99)	(0.24)	(0.50)	(0.77)	(0.84)	(0.47)	(0.78)	(0.69)
Segment Dummy	0.044	0.20	-0.29*	0.051	0.15	-0.70***	0.048	0.14	-0.74***
	(0.84)	(0.15)	(0.10)	(0.81)	(0.25)	(0.00)	(0.82)	(0.29)	(0.00)
Industry Dummy	-0.0030	-0.022	0.26**	0.0092	0.0040	0.33***	0.017	-0.014	0.34**
	(0.99)	(0.78)	(0.04)	(0.96)	(0.96)	(0.01)	(0.92)	(0.86)	(0.01)
N	11,202	11,202	4006	11,202	11,202	4006	11,202	11,202	4006
Adj R-square	0.12			0.11			0.12		
Pseudo R-square		0.12	0.16		0.11	0.12		0.11	0.10

Table 3.10: Regression results for the effect of ICM on corporate default risk when industry is defined basing on 2 digit SICs code (66 industries) and Fama and French 49 industries

*This table reports the regression results for testing the hypothesis 1 for two different diversification definitions. Panel A of Table 3.10 presents the regression results when diversified firm is identified basing on Fama and French's 49 industries. Panel B reports the regression results when diversified firm is identified basing on 66 industries grouped by 2 digit SIC code. Column 1 presents OLS regression results when the lower (upper) bounded values of default probabilities are added (subtracted) by 0.0001 and then transformed to inverse normal cumulative distribution. Default probabilities is calculated as in Bharath and Shumway (2008). Column 2 presents the ordered logit regression results when corporate default risk is measured by Atman Z-score categories. Altman Z-score are computed separately for manufacturing and non-manufacturing firms, and then divided into three categories. For manufacturing firms, category 1 is the 'safe zone' with Z-score larger than 2.99; category 2 is the 'grey zone' with Z-score between 1.81 and 2.99; category 3 is the 'distress zone' with Z-score less than 1.81. For non-manufacturing firms, category 1 is the 'safe zone' with Z-score larger than 2.90; category 2 is the 'grey zone' with Z-score between 1.23 and 2.90; category 3 is the 'distress zone' with Z-score less than 1.23. Column 3 presents the ordered logit regression results for panel data when default risk is measured by S&P rating, dividing into 22 rating categories. ICM calculation can be found in section 3. Volatility is the firm's annualized monthly stock return volatility. Leverage is calculated as the ratio of the firm's year-end total debt to market value. Size is calculated as the logarithm of the firm's year-end assets. Segment Dummy equals 1 if firms have more than 2 segments and 0 otherwise. The regressions are estimated over the period 1997-2014. White's (1980) heteroskedascity consistent, clustered at firm level, p-value are in parentheses below the parameter estimates. ***, **, * indicates significance at 1%, 5% and 10% level.*

	Panel A: 49 Industries			**Panel B: 66 Industries**		
	OLS regression	Ordered logit regression	Ordered logit regression	OLS regression	Ordered Logit regression	Ordered logit regression
	Column 1: transformed default probabilities	***Column 2: zscore categories***	***Column 3: 22 rating categories***	***Column 1: transformed default probabilities***	***Column 2: zscore categories***	***Column 3: 22 rating categories***
ICM	-0.565**	-0.829**	0.705	-0.958**	-1.377**	1.212
	(0.035)	(0.034)	(0.775)	(0.019)	(0.016)	(0.742)
Size	-0.228*	0.001	0.822***	-0.217*	0.0165	0.907***
	(0.091)	(0.988)	(0.000)	(0.095)	(0.614)	(0.000)
Leverage	0.357***	1.123***	-0.294***	0.353***	1.283***	-0.314***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Volatility	3.231***	0.896***	-3.049***	3.351***	0.911***	-3.224***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Segment Dummy	0.400*	0.194	0.255	0.143	0.0493	0.191
	(0.071)	(0.149)	(0.162)	(0.493)	(0.691)	(0.277)
N	3765	3765	1585	4102	4102	1851
Adj R-square	0.11			0.12		
Pseudo R-square		0.10	0.13		0.11	0.15

3.6 Conclusion

Lewellen (1971) shows that when a firm diversifies its operations across industry segments with imperfectly-correlated cash-flows, the risk of corporate default is expected to diminish due to diversification effects. However, the beneficial effects of such diversification on corporate default risk may be reduced or offset by the misallocation of resources stemming from the agency problems within the firm as underperforming segments seek to divert resources from stronger segments. Prior studies have shown that such inefficiencies of firms' internal capital markets do indeed exist, and that they serve to diminish the value of firm assets.

While prior work, namely Singhal and Zhu (2013), has examined the empirical relationship between the number of firm segments and the risk of financial distress, the current study is the first to examine directly the empirical relation between the efficiency of firms' internal capital markets and distress risk, as well as its interaction with firms' exposure to external financial constraints.

Consistently with theoretical agency effects, we find that, all else being equal, corporate default risk diminishes (increases) when the efficiency (inefficiency) of internal capital markets increases. These effects tend to be most important in more highly-levered companies, and the effects are remarkably robust to three very different measures of default risk: Merton-style default probabilities, Altman's Z-score and agency assigned (S&P) credit ratings. These empirical findings lend support to the theoretical results of Meyer, Milgrom et al. (1992), Rajan, Servaes et al. (2000) and Scharfstein and Stein (2000)

To allow for the effects of external financial constraints, we compute three different firm level metrics: the KZ index, the WW index and the SA index. However, our results provide only weak evidence of an interaction between the impact of ICM and external financial constraints insofar as we identify statistically significant interactions between financing constraints and ICM only with reference to Z-score credit metrics. The latter findings are consistent with both a priori expectation, as well as the inherent difficulty of empirically estimating external financial constraints at firm levels.

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Chapter 4 : Does Internal Capital Market Efficiency Predict Future Stock Returns?

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Abstract

Taking Internal Capital Market Efficiency (ICM) as a proxy for diversified firms' expected profitability, we investigate the role of this measure in predicting diversified firms' stock returns during the period 1997-2015. Our expected profitability proxy is distinguished from the other proxies suggested in the literature since our measure takes into account the firm's current level of external financial constraints. We find that ICM can help predict future stock returns beyond and above the other future stock return predictors identified in the literature such as book to market value, firm size, default risk, accruals and Piotroski's F-score. Furthermore, when examining the role of ICM in predicting future stock returns separately for financially-constrained and non-constrained firms, our results show that ICM is only important in distinguishing high and low future stock returns for financially-constrained firms.

4.1 Introduction

Simple expected profitability proxies such as current profits or total sales to total assets can help predict stock returns due to market inefficiency (Lakonishok, Shleifer et al. (1994), Haugen and Baker (1996), Piotroski (2000), Cohen, Gompers et al. (2002), Fama and French (2006), Novy-Marx (2013)). This paper shows that Internal Capital Market Efficiency (ICM) - a proxy for expected profitability in diversified firms - is an important indicator of future stock returns especially in financially-constrained firms. The role of ICM is incrementally important after controlling for the other factors that influence future stock returns such as book to market value, firm size, default risk, accruals and Piotroski's F-score. Our expected profitability proxy is different from other proxies suggested in the literature since our measure includes information about the firm's current level of external financial constraints.

Diversified firms can transfer available funds among business segments, thereby establishing an internal capital market. An internal capital market is considered to be efficient if a diversified firm transfers funds from underperforming segments to profitable segments. Several performance measures have been suggested including return on assets as in Billett and Mauer (2003), Tobin Q ratio as in Rajan, Servaes et al. (2000) and sales growth as in Singhal and Zhu (2013). Regardless of the specific metric, previous studies show that diversified firms on average use internal funds inefficiently (Rajan, Servaes et al. (2000), Billett and Mauer (2003), Singhal and Zhu (2013)). Our results in chapter 3 reconfirm these findings.

The literature suggests that internal capital market inefficiency may be attributed to the behaviours of the managers in the underperforming segments. Meyer, Milgrom et al. (1992) argue that to minimize the risk of being laid-off, managers in the failing segments attempt to gain access to corporate resources that can be used to prevent or delay downsizing. Similarly, Scharfstein and Stein (2000) show that the rent-seeking or power-grabbing behaviours of managers in weak divisions can undermine the working of internal capital markets. They argue that these behaviours can help increase the managers' bargaining power when negotiating a compensation package with the CEO.

However, when diversified firms are financially constrained, headquarters tend to allocate internal funds efficiently (Hovakimian (2011), Kuppuswamy and Villalonga (2015)). In this situation, firms are less likely to have access to external funds to finance their productive segments if their internal funds have been directed to the unproductive ones. Meanwhile, in the absence of such constraints, firms can still invest in profitable projects by using external funds if the internal funds are used inefficiently. Therefore, ICM is expected to have a larger positive effect on future stock returns of financially-constrained firms than that of non-financially constrained firms. Our results show that this is actually the case.

4.2 Theoretical Background

Using ICM as a proxy for diversified firms' expected profitability, we investigate the relationship between this measure and future stock returns. In this paper, ICM is defined as the transfer of funds from segments with low return on assets to segments with high return on assets (Billett and Mauer (2003)). If the funds are directed from unproductive segments to productive segments, the firm's value will increase as the market becomes efficient with respect to the information. By contrast, when the funds are used to finance unproductive segments, the opposite will be true.

Previous studies show that simple expected profitability proxies such as lagged profitability, ratios of earnings to book equity, operating income to total assets or total sales to total assets can predict stock returns due to the delay in the market's response to newly-public information (Lakonishok, Shleifer et al. (1994), Haugen and Baker (1996), Cohen, Gompers et al. (2002), Fama and French (2006), Novy-Marx (2013)). These studies also find that the slow market response is more pronounced in firms with high levels of information uncertainty.[13] They are usually small firms, high book value to market value firms, firms with low levels of analyst coverage, firms with high fundamental value volatility or firms with poor information quality (Piotroski (2000), Daniel, Hirshleifer et al. (2001), Hirshleifer (2001), Zhang (2006)).

ICM is expected to predict diversified firms' stock returns as these firms possess characteristics consistent with the context of information uncertainty, which leads to the delay in the market's response to ICM information. With several business segments, it is more difficult for the public to evaluate a diversified firm's value. Jiraporn, Kim et al. (2008) argue that the public and analysts need more resources and expertise to accurately analyse such firms' earnings reports. Furthermore, as an analyst usually focuses on one industry, following a diversified firm will take the analysts out of their area of expertise to some extent (Thomas (2002)). As a result, the

[13] Zhang (2006) define information uncertainty as the ambiguous implications of new information for a firm's value, which can be due to the volatility of a firm's underlying fundamentals and poor information.

effectiveness of individual analysts in examining information about diversified firms will be reduced. Supporting this argument, Dunn and Nathan (1998) find that when an analyst follows a larger number of diversified firms, the accuracy of that analyst relative to the others decreases.

The level of information uncertainty in diversified firms is found to increase with the number of business segments. Habib, Johnsen et al.'s (1997) model demonstrates that breaking up a diversified firm into separately-traded firms leads to more informative stock prices. Similarly, Nanda and Narayanan (1999) show that when a firm decides to divest its business segments, a primary motivation is to improve market valuation. After divesting, the analysts' forecast accuracy for these firms is improved (Gilson, Healy et al. (1998), Krishnaswami and Subramaniam (1999)). As the level of information uncertainty tends to increase with the number of business segments, we argue that ICM will have a stronger effect on future stock returns in firms with a larger number of business segments.

We use ICM to proxy for expected profitability for three main reasons. Firstly, ICM contains forward-looking information about a firm's profitability. How a firm uses its internal fund at the present time will influence its value. However, the value effects may be difficult for the market to rapidly discern. Secondly, ICM embeds information about a firm's future cash-flows in light of external financial constraints in ways not captured by previous profitability proxies. Prior research suggests that firms tend to use their internal funds more efficiently when financially constrained, as the managers in these firms have more incentives to select the most deserving projects (Hovakimian (2011), Kuppuswamy and Villalonga (2015)). Thirdly, not only does the ICM metric contain information about the future cash-flows of diversified firms that are not discernable from other metrics, the market response to the ICM metric is likely to be less efficient than it is to simpler proxies of expected future performance.

Literature about corporate diversification strongly supports the existence of internal capital markets in diversified firms (Berger and Ofek (1995), Rajan, Servaes et al. (2000), Scharfstein and Stein (2000), Billett and Mauer (2003)). However, both theoretical and empirical studies suggest that diversified firms on average use their internal funds inefficiently. Diversified firms tend to put more funds to inefficient segments and less funds to efficient segments. This direction of fund movements is argued to occur in weak divisions where the managers tend to attempt to gain access to corporate resources to prevent or delay downsizing to protect their jobs (Meyer, Milgrom et al. (1992), Scharfstein and Stein (2000)). Supporting these arguments, Berger and Ofek (1995) find that the poorly performing segments of a diversified firm drains value from the other segments, signalling the inefficient allocation of internal funds. Similarly, Rajan, Servaes et al. (2000) show that diversified firms on average have inefficient internal capital markets as internal funds are mainly channelled to low Tobin Q ratio segments. When using segment return on assets as a measure of efficiency, Billett and Mauer (2003) also find that diversified firms on average use their internal funds inefficiently.

Though diversified firms on average have inefficient internal capital markets, the literature finds that internal capital markets become more efficient when diversified firms face higher levels of external financial constraints (Stein (1997), Hubbard and Palia (1999), Campello (2002), Kuppuswamy and Villalonga (2015)). As these firms have limited access to external funds, internal capital market becomes their main source of funds to finance their investments. Internal capital market inefficiency in such a situation thus limits the firm's capacity to finance its profitable projects. Meanwhile, in the absence of such constraints, firms that make inefficient use of internal funds can still rely on external sources to finance their profitable investments. Thus, ICM is expected to have a larger impact on future stock returns in financially-constrained firms than in non-financially-constrained firms.

Given the empirical and theoretical evidence of the inefficient pricing of firms with high information uncertainty, we evaluate the usefulness of ICM as a predictor of future returns along the lines of other financial statement variables: firm sizes, book to market ratio, accrual, default risk and F-score. We further evaluate whether this predictive ability is more pronounced in financially-constrained firms than in non-financially-constrained firms because, in the context of financial constraints, firms are less likely to have access to external funds to finance their productive segments if they use their internal funds inefficiently. Specifically, we test the following hypotheses:

Null hypothesis 1: There is no correlation between internal capital market efficiency and a diversified firm's subsequent stock returns. That is, ICM has no incremental ability to forecast future stock returns, controlling for other proxies.

Alternative hypothesis 1: There is positive correlation between internal capital market efficiency and a diversified firm's subsequent stock returns. That is, ICM has an incremental ability to forecast future stock returns, controlling for other proxies.

Null hypothesis 2: The effect of ICM on subsequent stock returns does not interact with the level of external financial constraints.

Alternative hypothesis 2: The effect of ICM on subsequent stock returns interacts positively with the level of external financial constraints.

4.3 Methodology

4.3.1 Internal Capital Market Efficiency

In this paper, internal capital market efficiency (ICM) is computed as in Billett and Mauer (2003). Internal Capital Market Efficiency (ICM) is defined as the way the internal funds move among business segments with different return on assets (ROA). A firm's internal capital market is considered to be efficient when internal funds flow to segments with higher ROA. By contrast, when internal funds flow to lower ROA segments, the internal capital market is inefficient. We use Billett and Mauer's (2003) ICM measure as it evaluates the efficiency of internal capital markets with reference to segment information. Previous studies, such as Berger and Ofek (1995) and Rajan (2000), use Tobin Q's ratio as a measure of segment's investment opportunities. They consider internal capital market to be efficient if internal funds are directed to the segments with high Tobin Q's ratio. However, Tobin's Q measure has a great deal of measurement error in its role as a proxy for investment opportunities (Erickson and Whited (2000), Whited and Wu (2006)). Furthermore, since the reported segment data does not provide enough information to compute Tobin Q, Berger and Ofek (1995) or Rajan et al. (2000) use the industry Tobin Q ratio calculated from a sample of standalone firms as a proxy for each segment's investment opportunities. However, diversified firms are found to be different from their comparable single segment firms with respect to Tobin Q ratio, sales growth and spending on research and development (Hyland and Diltz (2002)). Thus, the assumption that a segment's Tobin Q ratio is the same as a similar single-segment firm's Tobin Q ratio is claimed to cause bias as firms that undertake diversification can have different investment opportunities from those that decide to remain as single-segment firms (Campa and Kedia (2002), Hyland and Diltz (2002), Billett and Mauer (2003), Villalonga (2004)).

Billett and Mauer (2003) classify a segment as a provider of internal capital in year t if its after-tax cash-flow is larger than its capital expense. This segment can use its surplus funds to subsidize the other segments in need, which is defined as 'Transfer'. By contrast, when a segment's after-tax cash-flow is less than its capital expense, it will be categorized as a consumer of internal funds. The extra capital it gets to finance its expenses is called 'Subsidy'.

The subsidy that segment i of a sample diversified firm receives is computed as:

$$Subsidy_i = max(CAPEX_i - ATCF_i\ , 0) \tag{1}$$

where CAPEX is the segment's reported capital expenditures and $ATCF_i$ is the segment's after-tax cash-flow. Segment i's after-tax cash-flow ($ATCF_i$) is computed as

$$ATCF_i = EBIT_i - I_i - T_i + D_i \tag{2}$$

I_i is segment i's interest expense which is the assets share of segment i in a diversified firm multiplied by the firm's interest expense, T_i is segment i's tax expenses computed as the assets share of segment i multiplied with the firm's taxes paid, and D_i is segment's i reported depreciation. A segment's assets share is computed as the ratio of segment i's assets reported in the Compustat segment database to the firm's total assets. In Billett and Mauer (2003), segment i's interest expense is calculated as the product of segment i's reported sales and the median ratio of interest expense to sales of single segment firms in segment i's industry and segment i's tax expense is a product of segment i's earnings before taxes and the median tax rate of single segment firms in segment i's industry. Our segment i's interest expense and tax expense are not computed as in Billett and Mauer (2003) for two reasons. Firstly, using single-segment firm data in our calculation may bias our results since there are fundamentally differences between same-industry single-segment firms and diversified firm segments as argued by Campa and Kedia (2002), Hyland and Diltz (2002). Secondly, when Billett and Mauer (2003) cannot find at least three single-segment firms that operate in segment i's industry defined as a 4-digit SIC code, their industry definition is change to a 3-digit SIC code and a 2-digit SIC code. However, this approach adds inconsistencies to the computation of segment i's tax expense and interest expense. Our method can overcome these short comings and is consistent with Billett and Mauer's (2003) method of computing segment dividends, which will be discussed later in this section.

If $subsidy_i = 0$, then $ATCF_i >= CAPEX_i$ and segment i is a potential contributor of funds to the firm's internal capital market. We can only say segment i is a potential contributor of funds as it is not necessarily the case that all of the segment' surplus will be transferred to the other segments. Therefore, segment i's potential transfer of resources is firstly computed as

$$Ptransfer_i = max(ATCF_i - w_iDIV - CAPEX_{i,} ,0) \qquad (3)$$

where DIV is the cash dividend paid by the sample firm and w_i is the asset share of segment i.

Following Billett and Mauer (2003), total subsidy are allowed to be larger than total transfers since the firms can borrow from external capital markets, but total transfers cannot not exceed total subsidy. Therefore, we compute segment i's transfer as followed:

$$Transfer_i = min\ [Ptransfer_i\, , \frac{PTransfer_i}{\sum_{i=1}^{n} PTransfer_i} (\sum_{i=1}^{n} Subsidy_i)\ ] \qquad (4)$$

Two measures of relative efficiency for segment subsidies and transfers are suggested by Billett and Mauer (2003). The first is based on the segment's sibling-adjusted return on assets (ROA), and the second is based on a fitted Tobin Q ratio for each segment. In this study, we employ the ROA to measure ICM since we would like to use only the segment information to compute the ICM. If $ROA_i > \overline{ROA}$ ($ROA_i < \overline{ROA}$), a subsidy is classified as efficient (inefficient), where ROA_i is the ratio of earnings before interest, taxes and depreciation to total assets for segment i, and $\overline{ROA}$, is the corresponding asset-weighted average ROA of a diversified firm's remaining segments. Thus, a subsidy is efficient (inefficient) if the segment receiving the subsidy has a larger (smaller) ROA than the asset-weighted average of the firm's other segments, and a transfer is efficient (inefficient) if the segment making the transfer has a smaller (larger) ROA than the asset-weighted average of the firm's other segments. We acknowledge that the use of ROA measures to calculate the firm's ICM efficiency may not be the best choice as these measures do not take into consideration the risk difference among the firm's segments. However, given limited available reported segment data, the use of segment ROA is arguably the best available measure of each segment's operating efficiency, and can help us understand how a diversified firm uses its internal funds.

Total ICM is computed as below:

$$ICM = \sum_{i=1}^{n} \frac{(ROA_i - \overline{ROA})(Subsidy_i) + (\overline{ROA} - ROA_i)(Transfer_i)}{TA} \tag{5}$$

When the ICM is larger, a firm is more efficient in allocating its internal funds. All the data used to compute ICM can be collected at the segment level from the Compustat segment database. The taxes paid, interest expense and dividend payment are collected from the Compustat fundamental database.

4.3.2 Subsequent returns

We follow the approach of Piotroski (2000) in computing one-year and two-year buy and hold returns from the fifth month after the firm's fiscal year-end through the earliest subsequent date:

either one (two) years after the start of the period for compounding returns or on the last day of CRSP-traded returns. If a firm delists, we assume that its delisting return is -1.[14] The fifth month is chosen to ensure that all financial information is available to the investors at the time of portfolio formation.

4.3.3 External Financial Constraints

In this paper, we employ two financial constraint indexes, which are the Whited and Wu (WW) index proposed by Whited and Wu (2006) and the Size and Assets (SA) index proposed by Hadlock and Pierce (2010), to measure firms' external financial constraints. As argued by Whited and Wu (2006) and Hadlock and Pierce (2010), their financial constraint indexes are distinguished from financial distress measures although they are undoubtedly correlated.[15] Both of these indexes have been widely used in the literature (Campello (2002), Livdan, Sapriza et al. (2009), Duchin (2010), Hadlock and Pierce (2010), Hann, Ogneva et al. (2013)). However, the SA index is shown by Hadlock and Pierce (2010) to be a more reliable measure as it includes only factors that are exogenously determined and so can predict well the firms' financial constraints. Therefore, the two indexes are included in our analysis not only to test the robustness of our results, but also to further validate Hadlock and Pierce's (2010) argument. If the two indexes convey very different information about a firm's financial constraint level, the ability of ICM to identify mispriced firms conditional on financial constraint will vary across the two measures.

a. ***Whited and Wu index (WW index)***

A structural model is employed by Whited and Wu (2006) to construct the index for a sample of non-financial firms between January 1975 and April 2001. To capture the firm's liquidity condition, the WW index includes cash-flow, long-term debt and dividends. Other factors such as industry sales growth and firm sales growth are also included in their index equation as they

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[14] We test the robustness of reported results to this assumption by using delisting returns set equal to zero

[15] The correlation between Z-score and the SA index (WW index) is -19.38% (-13.27%)

argue that only firms having good investment opportunities are likely to want to invest enough to be constrained. Furthermore, the size variable is included as large firms are argued to be less financially constrained. All the coefficients for these variables are significant and have the signs consistent with Whited and Wu's (2006) expectation.

The WW index is the value calculated as follows:

$$\begin{aligned} \textit{WW index} = &-0.091\ \textit{Cash-flow/Assets} - 0.062\ \textit{Dividend Dummy} \\ &+ 0.021\ \textit{Long-term debts/ Assets} - 0.044\ \textit{size} \\ &+ 0.102\ \textit{Industry sales growth} - 0.035\ \textit{Firm sales growth} \end{aligned} \tag{6}$$

Cash-flow/ assets is the ratio of the firm's operating income plus depreciation to the beginning of year book assets. The dividend dummy is 1 if the firm pays dividends and 0 otherwise. Industry sales growth is the annual percentage change in the 3-digit industry sales. Firm sales growth is the firm's annual percentage change in sales. Size is the logarithm of the firm's assets. Long-term debts/assets is the ratio of the firm's long-term debt to the beginning of year book assets.

b. Size and Age index (SA index)

Besides the WW index, this study employs the SA index to measure the firm's external financial constraints. SA index is constructed by Hadlock and Pierce (2010), who follow Kaplan and Zingales' (1997) procedures to classify 365 sample firms into five different financial constraint levels for the period 1995 and 2004. The firm's ability to raise funds or finance its current or future operations are determined basing on both qualitative and quantitative information collected from the companies' financial reports and 10K filings.

The non-financially-constrained group (group 1) includes firms that start paying dividends or increases dividend payments, repurchases stocks or states clearly in its financial statement that it has so much liquidity that it would need to fund its investments in a foreseeable future, had large cash, low debt, large quantities of internal funds and collateralizable resources. Firms are put in the second group if they are not likely to be financially constrained. These firms has the following characteristics: sizable cash reserves, unused lines of credit and healthy interest coverage. The third group are those that are hard to be classified either as financially-constrained or non-financially-constrained firms or have contradictory signs of financial constraints. They are called ‘potentially constrained firms”. The fourth group includes firms that are likely to be financially constrained. They are the ones that postpone an equity or convertible debt offering, or say that they need equity capital but are waiting for better market conditions. The last group contains financially-constrained firms. Companies will be classified in this group if they do not comply with debt covenants, need debt payment negotiation, declare the liquidity issues and/or their usual source of credit has been cut.

After the firms are put into five different financial constraint groups, Hadlock and Pierce (2010) estimate an ordered logit regression of financial constraint levels on various firm characteristics which had been identified in the literature to be related to financial constraints. They find that firm size and age play the most important roles in determining a firm’s financial constraint levels. Therefore, they propose a new financial constraint index called the SA index, which is computed as follows:

$$SA\ index = (-0.737 *Size) + (0.043*Size^2) - (0.040 *Age) \qquad (7)$$

Size is the logarithm of the firm’s total assets and age is the number of years that a firm has been on Compustat with non-missing stock prices. Following Hadlock and Pierce (2010), when the size and age exceed $4.5 billion and 37 years respectively, we replace size and age with these values in order to reflect the essentially flat relationship between financial constraints and size (age) for very large (mature) companies.

4.3.4 F-score

The F-score is computed as in Piotroski (2000). It is the sum of nine individual binary variables:

$$F\text{-}score = F\text{-}ROA + F\text{-}\Delta ROA + F\text{-}CFO + F\text{-}Accrual + F\text{-}\Delta MARGIN + F\text{-}\Delta TURN$$
$$+ F\text{-}\Delta LEVER + F\text{-}\Delta LIQUID + EQ\_OFFER \qquad (8)$$

These nine variables convey information about the firm's profitability, leverage, liquidity, source of funds and operating efficiency. F-ROA equals 1 if a firm has positive net income before extraordinary items and 0 otherwise. F- ΔROA equals 1 if a firm's current net income before extraordinary items is larger than the previous year's Figure, and 0 otherwise. F-CFO equals 1 if a firm has positive cash-flow from operations, and 0 otherwise. F-Accrual equals 1 if a firm's cash-flow from operations is larger than its net income before extraordinary items, and 0 otherwise. F-ΔMARGIN equals 1 if a firm's current gross margins ratio is larger than the previous year's gross margins ratio, and zero otherwise. F-ΔTURN equals 1 if a firm's current year asset turnover ratio is larger than the previous year's ratio, and 0 otherwise. F-ΔLIQUID (F-ΔLEVER) equals 1 if a firm's current year current ratio (leverage ratio) is larger than its previous year Figures, and 0 otherwise. *EQ_OFFER* equals 1 if the firm did not issue common equity in the year preceding portfolio formation and 0 otherwise.

4.3.5 Examination of the ICM's ability to predict future stock returns

To investigate the predictive ability of the ICM for future stock returns, we follow the following procedure. Firstly, we sort our portfolios basing on: i. ICM, ii. ICM and external financial constraint indexes, iii. ICM and number of business segments, iv. ICM and F-score. Then, we compare mean one year and two year stock returns of firms belonging to low versus high ICM groups, and firms in these two groups conditional on the other characteristics including external financial constraint levels, number of business segments and F-score. Lastly, we confirm our results by testing the effect of ICM and the effect of the interaction between ICM and i. external financial constraint indexes, ii. number of business segments, iii. F-score on future stock returns controlling for the other factors which potentially influence future stock returns such as firm size, logarithm of book to market value, accrual, F-score, Altman Z-score and number of segments. The regression equations are specified bellows:

$$Return_{i(t+1)} = \beta_1 + \beta_2 Bottom\ ICM_{it} + \beta_2 MiddleICM_{it} + \beta_3\ Size_{it} + \beta_4\ Log(BM)_{it} + \beta_5\ Accrual_{it} + \beta_6\ F\text{-}score_{it} + \beta_7\ Z\text{-}score_{it} + \beta_8\ NUMSEG_{it} + ¥_{it} \quad (9)$$

$$Return_{i(t+1)} = \beta_1 + \beta_2 BottomICM_{it} + \beta_3 MiddleICM_{it} + \beta_4 FCDummy_{it} + \beta_5 BottomICM*FCDummy_{it} + \beta_6 MiddleICM*FCDummy_{it} + \beta_7 \ Size_{it} + \beta_8 \ Log(BM)_{it} + \beta_9 \ Accrual_{it} + \beta_{10} \ F\text{-}score_{it} + \beta_{11} \ Z\text{-}score_{it} + \beta_{12} NUMSEG_{it} + ¥_{it} \quad (10)$$

$$Return_{i(t+1)} = \beta_1 + \beta_2 BottomICM_{it} + \beta_3 MiddleICM_{it} + \beta_4 BottomICM*SEGDummy_{it} + \beta_5 MiddleICM*SEGDummy_{it} + \beta_6 SEGDummy_{it} + \beta_7 \ Size_{it} + \beta_8 \ Log(BM)_{it} + \beta_9 \ Accrual_{it} + \beta_{10} \ F\text{-}score_{it} + \beta_{11} \ Z\text{-}score_{it} + \beta_{12} NUMSEG_{it} + ¥_{it} \quad \textit{(11)}$$

Equation (9) aims at examining the effect of IMF on future stock returns. Equation (10) is employed to investigate the effect of ICM on future stock returns conditional on financial constraint levels, and the equation (11) is used to test the effect of ICM on future stock returns conditional on number of business segments. In all of the three equations, we control for other firms' characteristics which have been found to influence future stock returns.

ICM is computed as in Billett and Mauer (2002), which is outlined in section 2. Bottom ICM is a dummy variable, equalling 1 if a firm has ICM values belonging to the bottom 10% of the ICM distribution at the end of fiscal year and 0 otherwise. Middle ICM is a dummy variable, equalling 1 if a firm has ICM value larger than 10% and smaller than 90% cut-off point at the end of financial year, and 0 otherwise. BM is the logarithm of the firm's book to market value. One-year (two-year) returns are one-year (two-year) buy and hold returns from the fifth month after the firm fiscal year-end through the earliest subsequent date: one year and two year after return compounding began or the last day of CRSP traded returns. Delisting return is assumed to be -1. Size is the logarithm of the firm's market value. F-score is computed as in Piotroski (2000), which is outlined in section 4.3. Z-score is Altman Z-score. LOG(NUMSEG) is the logarithm of the firm's number of business segments identified basing on the 4-digit SICs code reported in the Historical Compustat Segment database. In each financial year, FC Dummy equals 1 if a firm has SA index or WW index in the top 20% of the SA index or WW index distribution, and zero otherwise. SA index and WW index are computed as in Hadlock and Pierce (2010) and Whited and Wu (2006) respectively. SEGDUMMY equals 1 if a firm has more than three business segments, and zero otherwise.

4.4 Sample construction and data description

4.4.1 Sample construction

We obtain our sample from the Compustat historical segment database and CRSP/Compustat Merged database for the period 1997 – 2015.[16] The Compustat historical segment database is used to source firm and segment level information, including sales, assets, capital expenditure, earnings before interest and taxes, and depreciation. A firm is categorized as a multi-segment firm if it has more than one business segment according to its 4-digit SIC code (Lang and Stulz (1993), Berger and Ofek (1995), Billett and Mauer (2003), Hann, Ogneva et al. (2013), Singhal and Zhu (2013)). Our initial sample in the Compustat historical segment database has 104,479 firm-year observations, with 37,772 multi-segment firm-year observations. Following Berger and Ofek (1995), we require that (1) the sum of segment sales (assets) be within 1% (25%) of consolidated firm totals to ensure the integrity of segment data, (2) all firm – years have at least 20 million dollars in sales, (3) all firms with at least one segment in the financial industry (SIC codes between 6000 and 6999) be excluded from the sample. These requirements reduce our data to 26,387 multi-segment firm-year observations. In addition, we require that sample firms have all necessary data on both the CRSP/Compustat Merged database and Compustat segment database to compute all the variables used in the analysis. We lose the majority of our observations when using segment data to calculate the ICM, leaving our final sample of 10,261 multi-segment firm-year observations. The maximum and minimum values for one-year equity returns for our sample firms are -1 and 50.13. To reduce the influence of outliners, we set all the values higher than the 98th percentile of one-year return to that value.

4.4.2 Data description

Table 4.1 provides descriptive statistics for all of the variables used in the analysis. On average our sample firms have a return of 11% per year. The mean for two-year return is 24%, which is

[16] ICM and other fundamental values are collected during the period of 1997-2014. The stock returns are collected during the period 1998-2015.

more than double the return earned in one year. The 1 year (2 year) return is significant lower after adjusting for risk. The ICM measure ranges from -0.27 to 0.02, with the median value of 0. Thus on average, our diversified firms have inefficient internal capital markets, which is consistent with previous findings (Berger and Ofek (1995), Billett and Mauer (2002), Rajan et al. (2001)). Similar to Piotroski (2000), the maximum and minimum F-score values are 9 and 0 respectively. Mean and median for log(BM) in our sample firms are -0.58 and -0.56, indicating that most of our firms have book values lower than market values.

As the main purpose of this paper is to investigate whether ICM can help predict stock returns, to gain some understanding of ICM’s standalone properties, we provide an overview of its distribution. We also need to divide our sample firms into different groups of firms with different levels of external financial constraints and high versus low numbers of business segments. Therefore, we also report the distribution at different percentiles.

Table 4.1 Descriptive statistics

This table reports descriptive statistics for our sample of diversified firms between 1997 and 2015. BM is the logarithm of the firm's book to market value. 1 year (2 year) returns are one year (two year) buy and hold returns from the fifth month after the firm's fiscal year-end through the earliest subsequent date: one year and two years after return compounding began or the last day of CRSP traded returns. Delisting return is assumed to be -1. Size is the logarithm of the firm's market value. SA index, WW index, F-score, Accrual and ICM are computed as outlined in section 4.3. Assets growth is computed as annual proportional changes in assets. NUMSEG is number of business segments reported by Compustat Segment Database. Momentum is 6 month buy and hold return over the six months directly preceding the date of portfolio formation.1 year (2 year) risk adjusted return is the excess return over the expected return computed basing on CAPM model.

stats	mean	median	sd	min	max	10th percentile	25th percentile	75th percentile	90th percentile
SA	-3.62	-3.56	0.69	-4.64	-1.37	-4.62	-4.24	-3.13	-2.50
WW	-0.32	-0.32	0.12	-0.78	2.79	-0.46	-0.39	-0.24	-0.18
Return(1year)	0.11	0.06	0.54	-1.00	1.94	-0.49	-0.22	0.34	0.74
Return(2 years)	0.24	0.12	0.77	-1.00	2.96	-0.59	-0.26	0.56	1.16
ICM	-0.01	0.00	0.04	-0.27	0.02	-0.02	0.00	0.00	0.00
Size	6.22	6.22	2.07	1.71	11.21	3.48	4.72	7.63	8.93
log(BM)	-0.58	-0.56	0.76	-2.84	1.32	-1.52	-1.03	-0.12	0.36
F-score	4.87	5.00	1.56	0.00	9.00	3.00	4.00	6.00	7.00
Z-score	2.36	2.47	2.10	-7.18	7.31	0.44	1.48	3.46	4.57
Accrual	-0.06	-0.05	0.08	-0.38	0.20	-0.15	-0.09	-0.02	0.03
$Profits_{t-1}$	164.58	16.67	557.00	-538.40	4057.00	-22.21	0.61	95.31	384.21
Assets growth	0.12	0.06	0.30	-0.37	1.72	-0.11	-0.02	0.17	0.38
NUMSEG	3.27	2.00	2.62	2.00	10.00	2.00	2.00	6.00	9.00
Momentum	0.11	0.07	0.36	-0.65	1.60	-0.28	-0.10	0.26	0.52
1 year risk adjusted returns	0.03	-0.02	0.55	-2.52	1.82	-0.57	-0.28	-0.02	0.66
2 year risk adjusted returns	0.12	0.03	0.82	-1.46	2.81	-0.78	-0.38	0.46	1.10

Table 4.1 shows there is little variation in the ICM value from the 25th percentile to the 75th percentile. Therefore, to distinguish between firms having efficient internal capital markets with the ones having inefficient internal capital markets, we only compare the returns generated by two groups of firms: firms having ICM values in the top 10% at the end of each fiscal year and firms having ICM values in the bottom 10% at the end of each fiscal year. This method of partitioning ensures that our firms are distinguished in terms of ICM values. Table 4.1 also shows how the two financial constraint indexes used in this study vary at each reported percentile. In each financial year, we classify firms having SA index (WW index) values in the top 20% as the most likely to be financially-constrained firms and firms having SA index (WW index) values in the bottom 20% as the least likely to be financially-constrained firms. We also conduct a sensitivity test by varying our cut-off points from the top (bottom) 20% to 10% to ensure that our results are not sensitive to the arbitrary cut-off points. Regarding the number of business segments, we use the median value to divide our diversified firms into two groups: firms with a large number of business segments versus firms having a small number of business segments. We also conduct a robustness test by taking four business segments as the cut-off point.

Table 4.2 reports descriptive statistics for selected firm characteristics for three groups of firms: firms having ICM values in the top 10%, firms having ICM values in the bottom 10% and firms having ICM values in the middle 80%. All the median differences for the firms' characteristics between the two groups of firms are statistically significant. For the mean differences, only the means for the Z-score are not significantly different. In addition, in both the case of the WW index and SA index, we find no evidence of the contemporaneous increase in internal capital market efficiency when firms are more financially constrained. In addition, consistent with our expectation that high ICM firm earned higher previous year profits, the mean difference between previous year profits between high and low ICM group is positive and statistically significant.

Having a clear understanding of the relationship between different firms' characteristics and returns is necessary in the context of our study since it helps us identify any other potential factors that influence our future stock returns besides our main variable of interest - ICM. Table 4.3 reports correlation matrix for 1 year (2 year) returns, 1 year (2 year) risk adjusted returns and various firms' characteristics. We can see that the correlation between 1 year (2 year) returns and ICM is 0.05 (0.07), signifying positive relationship between future stock returns and ICM. However, when the returns are risk adjusted, the correlations are reduced to only 0.01 for the both 1 year and 2 year returns. The correlation between F-score and future returns is 0.05, which is similar to the case of ICM.

Table 4.2 Descriptive statistics for firms in the bottom, the top 10% and the middle 80% of ICM distribution identified at the end of each financial year

*At the end of each financial year, we select firms in the bottom and top 10% group based on their ICM value. ICM is internal capital market efficiency computed as in Billett and Mauer (2005). SA and WW index are external financial constraint indexes, calculated as in Hadlock and Pierce (2010) and Whited and Wu (2006). NUMSEG is number of business segments reported by Compustat Segment Database. Momentum is 6 month buy and hold return over the six months directly preceding the date of portfolio formation. Two sample t-test and Wilcoxon rank-sum test are used to compare the mean and median differences between two groups of firms. *, ** and *** indicate statistical significance at the 1%, 5% and 10% level, respectively.*

	Firms having ICM values in the bottom 10%			Firms having ICM values in the top 10%			Firms having ICM values in the middle 80%			Top firms – Bottom firms	
	mean	median	std	mean	median	std	mean	median	std	mean	med
NUMSEG	3.47	3	1.6	3.02	2	1.54	4.57	4	2.74	-0.45***	-1***
SA	-3.43	-3.38	0.65	-3.75	-3.7	0.66	-3.62	-3.57	0.69	-0.32***	-0.32***
WW	-0.29	-0.28	0.11	-0.34	-0.34	0.1	-0.32	-0.32	0.12	-0.05***	-0.06***
ICM	-0.08	-0.05	0.08	0.00	0.00	0.01	0.00	0.00	0	0.08***	0.05***
Size	5.71	5.53	2.12	6.42	6.56	2.01	6.25	6.25	2.06	0.71***	1.03***
log(BM)	-0.6	-0.59	0.83	-0.4	-0.41	0.7	-0.61	-0.59	0.75	0.2***	0.18***
F-score	4.46	4	1.64	4.96	5	1.51	4.91	5	1.55	0.5***	1***
Z-score	2.03	2.46	2.65	1.97	2.02	1.71	2.48	2.55	2.07	-0.06	-0.44***
Accrual	-0.09	-0.07	0.11	-0.07	-0.06	0.07	-0.05	-0.05	0.08	0.02**	0.01*
Profitability$_{t-1}$	121.85	2.53	608.38	187.4	25.67	573.53	166.23	18.63	546.7	65.55***	23.14***
Asset growth	0.06	0.02	0.31	0.11	0.06	0.27	0.13	0.06	0.3	0.05**	0.04**
Momentum	0.12	0.07	0.43	0.07	0.05	0.34	0.12	0.08	0.35	-0.05**	-0.02*

Table 4.3 Correlation Matrix

This table reports the correlation matrix for our sample of diversified firms between 1997 and 2015. BM is the logarithm of the firm's book to market value. 1 year (2 year) returns are one year (two year) buy and hold returns from the fifth month after the firm's fiscal year-end through the earliest subsequent date: one year and two years after return compounding began or the last day of CRSP traded returns. Delisting return is assumed to be -1. Size is the logarithm of the firm's market value. SA index, WW index, F-score, Accrual and ICM are computed as outlined in section 4.3. Assets growth is computed as annual proportional changes in assets. NUMSEG is number of business segments reported by Compustat Segment Database. Momentum is 6 month buy and hold return over the six months directly preceding the date of portfolio formation.1 year (2 year) risk adjusted return is the excess return over the expected return computed basing on CAPM model.

	F-score	ICM	1 year return	Size	Log(BM)	Momentum	Accrual	Asset Growth	Profit	SA index	WW index	2 year return	NUMSEG	1 year risk adjusted return	2 year risk adjusted return
F-score	1														
ICM	0.02	1													
1 year return	0.05	0.05	1												
Size	0.23	0.05	-0.04	1											
Log(BM)	-0.13	0.09	0.08	-0.5	1										
Momentum	0.12	-0.04	0.01	0.04	-0.08	1									
Accrual	-0.02	-0.06	-0.05	0.03	-0.01	-0.03	1								
Asset Growth	-0.04	-0.01	-0.08	0.12	-0.21	0.00	0.14	1							
Profit	0.16	0.02	-0.02	0.59	-0.21	-0.01	0.08	0.03	1						
SA index	-0.22	-0.08	-0.01	-0.62	0.12	-0.01	-0.08	0.05	-0.3	1					
WW index	-0.22	-0.1	0.01	-0.86	0.22	-0.01	-0.03	-0.06	-0.55	0.68	1				
2 year return	0.05	0.07	0.68	-0.07	0.13	-0.06	-0.06	0.00	-0.02	-0.02	0.01	1			
NUMSEG	0.00	-0.12	0.03	0.07	0.00	0.00	-0.01	0.01	0.08	0.00	-0.06	0.02	1		
1 year risk adjusted return	0.05	0.01	0.82	-0.05	0.05	-0.02	-0.03	0.05	-0.05	-0.01	0.01	0.03	0.03	1	
2 year risk adjusted return	0.04	0.01	0.489	-0.06	0.07	-0.07	-0.02	0.07	-0.05	-0.02	-0.01	0.02	0.02	0.68	1

4.5 Empirical results

4.5.1 ICM and subsequent returns

Table 4.4 reports descriptive statistics for the distribution of one-year and two-year returns for the lowest and highest groupings of firm ICM using 10% and 90% cut-offs at the end of each financial year. Low ICM firms, on average, earned an annual stock return of 14% over the period 1997–2015, 5% lower than the mean return of high ICM firms. The mean and median differences in one-year returns between the two groups of firms are statistically significant at 10% and 1% level respectively, consistent with our hypothesis that ICM has a positive relationship with future returns. In the case of two-year returns, high ICM firms exhibit mean and median returns exceeding those of low ICM firms by 11% and 12% respectively. These differences are also statistically significantly different from zero at the 5% level. These results suggest a role for ICM in the identification of future performance extremes. Our results here support previous findings of market inefficiency (Rosenberg, Reid et al. (1985), Lakonishok, Shleifer et al. (1994), Piotroski (2000), Choi and Sias (2012)).

Since our ICM measure is constructed from the firm's financial statements, it may well be that the information embodied in the ICM measure is already captured by the F-score. Furthermore, our ICM may be correlated with other factors that have been shown to be associated with future returns such as firm size, book to market value, accrual and default risk. Therefore, we investigate whether ICM can explain future returns after controlling for the factors that have been documented in the literature.

Table 4.5 presents the regression results for the effect of the Bottom ICM and Middle ICM firms on one-year and two-year subsequent returns respectively, controlling for the other firm characteristics. Beside the common factors identified in the literature that influence subsequent returns, we also include LOG(NUMSEG) to control for the number of business segments since our sample includes only diversified firms. As can be seen in Table 4.5, the coefficient for

Middle ICM and Bottom ICM variables are negative and statistically significant for both one-year and two-year returns. Our results show that firms in the bottom 10% of ICM earn a one-year return of 4.3% lower than firms in the top 10% of ICM. In the case of two-year returns, the bottom ICM firms earn 9.9% lower than the top 10% of ICM firms. Also, all else being equal, these effects are incremental when controlling for other factors that influence future returns. In both cases, the coefficients for other variables in the regression are in line with economic intuition and statistically significant either at 5% or 1% level. In particular, the coefficients for Size and Accrual are negative while the coefficients for log (BM), F-score, LOG(NUMSEG) and Z-score are positive. Overall, consistent with hypothesis 1, the results in Table 4.5 highlight the important role of ICM in identifying outperforming firms beyond the other common factors identified in the literature.

Table 4.4 ICM and subsequent returns

*This table presents descriptive statistics for one-year and two-year returns for 2 groups of firms: firms with low ICM and firms with high ICM. 10% and 90% of the end of financial year's ICM distribution are used to classify the sample firms into low ICM and high ICM groups. One- year (two-year) returns are one-year (two-year) buy and hold returns from the fifth month after the firm's fiscal year-end through the earliest subsequent date: one year and two years after return compounding began or the last day of CRSP traded returns. Delisting return is assumed to be -1. ICM is computed as in Billett and Mauer (2002), which is outlined in section 4.3. Two sample t-test and Wilcoxon rank-sum test are used to compare the mean and median differences between two groups of firms. *, ** and *** indicate statistical significance at the 1%, 5% and 10% level, respectively.*

		1 year returns	**2 year returns**
Low ICM	Mean	0.14	0.27
	Med	0.06	0.09
	Std	0.61	0.86
	Obs	1049	906
High ICM	Mean	0.19	0.38
	Med	0.12	0.21
	Std	0.57	0.84
	Obs	1379	1263
High-Low	Mean	0.05*	0.11***
	P-value	0.06	0.00
	Med	0.06***	0.12***
	P-value	0.00	0.00

Table 4.5 One year and two year return prediction

This table reports pooled regression results for the effect of ICM on one-year and two-year subsequent returns, controlling for size, book to market value (BM), accrual, default risk, number of business segments and F-score. The regression equation is specified below:

$Return_{i(t+1)} = \beta_1 + \beta_2 Bottom\ ICM_{it} + \beta_2 MiddleICM_{it} + \beta_3\ Size_{it} + \beta_4\ Log(BM)_{it} + \beta_5\ Accrual_{it} + \beta_6\ F\text{-}score_{it} + \beta_7\ Z\text{-}score_{it} + \beta_8\ NUMSEG_{it} + ¥_{it}$

*ICM is computed as in Billett and Mauer (2002), which is outlined in section 2. Bottom ICM is a dummy variable, equalling 1 if a firm has ICM values belonging to the bottom 10% of the ICM distribution at the end of fiscal year and 0 otherwise. Middle ICM is a dummy variable, equalling 1 if a firm has ICM value larger than 10% and smaller than 90% cut-off point at the end of financial year, and 0 otherwise. BM is the logarithm of the firm's book to market value. One-year (two-year) returns are one-year (two-year) buy and hold returns from the fifth month after the firm fiscal year-end through the earliest subsequent date: one year and two year after return compounding began or the last day of CRSP traded returns. Delisting return is assumed to be -1. Size is the logarithm of the firm's market value. F-score is computed as in Piotroski (2000), which is outlined in section 4.3. Z-score is Altman Z-score. LOG(NUMSEG) is the logarithm of the firm's number of business segments identified basing on the 4-digit SICs code reported in the Historical Compustat Segment database. P-values are in the parenthesis with Newey-West standard errors. *, ** and *** indicate statistical significance at the 1%, 5% and 10% level, respectively.*

Variable	One year returns	Two year returns
Bottom ICM	-0.043*	-0.099**
	(0.07)	(0.01)
Middle ICM	-0.086***	-0.14***
	(0.00)	(0.00)
Size	-0.009***	-0.014**
	(0.00)	(0.02)
Log(BM)	0.054***	0.13***
	(0.00)	(0.00)
Accrual	-0.34***	-0.61***
	(0.00)	(0.00)
F-score	0.021***	0.030***
	(0.00)	(0.00)
Z-score	0.012***	0.019***
	(0.00)	(0.00)
NUMSEG	0.030**	0.023
	(0.01)	(0.31)
Constant	0.083***	0.27***
	(0.01)	(0.00)
N	10,405	9,130
adj. R-sq	0.02	0.03

4.5.2 ICM and subsequent returns in different financial constraints levels

As discussed in section 4.1, ICM is expected to have a stronger effect on future stock returns when firms face external financial constraints. In this situation, firms are less likely to have access to external funds to finance their profitable projects if they allocate their internal funds inefficiently. Meanwhile, in the absence of this constraint, the firm's profitable projects can still be funded by using external finance.

Using the SA index and the WW index as measures of external financial constraints, we examine the relation between ICM and subsequent returns for the firms considered to be the least likely and most likely to be financially constrained. The correlation between SA index and WW index in our study is 0.62, demonstrating that the two indexes convey similar information about external financial constraints. At the end of each financial year, we classify a firm as the least (most) likely to be a financially-constrained firm if its SA index or WW index is in the bottom (top) 10% cut-off point. We then compare the mean of subsequent annual returns between low and high ICM firms.

Table 4.6 reports descriptive statistics for one-year subsequent returns in firms with different ICM and financial constraint levels. When financial constraints are measured using the SA index, mean and median differences in subsequent returns are only statistically significant in the most likely to be constrained category of firms, consistent with the hypothesis that ICM has the strongest value effects in financially-constrained firms. In particular, high ICM financially-constrained firms earn a mean return of 25%. This is 12% higher than low ICM financially-constrained firms. The median difference between the two groups of firms is 15%. Both the mean and median differences are statistically significant. When the WW index is used to measure the degree of financial constraints, the result is similar. The mean and median differences in returns between low and high ICM financially-constrained firms are 15% and 16% respectively, and statistically significant at the 5% level. These results suggest that ICM distinguishes firms earning low and high subsequent returns when the firms are likely to be financially constrained.

Table 4.6 ICM and subsequent returns in different financial constraint levels

*This table presents descriptive statistics for one year subsequent returns for low and high ICM firms belonging to the most likely to be financially-constrained or the least likely to be financially-constrained groups. In each financial year, firms will be classified as most likely to be financially constrained if it has an SA index or WW index in the top 20% in that year, and will be classified as the least likely to be financially constrained if it has an SA index or WW index in the bottom 20% in that year. SA index and WW index are computed as in Hadlock and Pierce (2010) and Whited and Wu (2006) respectively. ICM is computed as in Billett and Mauer (2003). Details of how ICM, SA index and WW index are computed are outlined in section 4.3. 10% and 90% of the end of financial year's ICM distribution are used to classify the sample firms into low ICM and high ICM groups. Two sample t-test and Wilcoxon rank-sum test are used to compare the mean and median differences between two groups of firms. *, ** and *** indicate statistical significance at the 1%, 5% and 10% level, respectively.*

Panel A: SA financial constraint index

		Low ICM	**High ICM**	**High ICM - Low ICM**	**p-values**
Least likely to be constrained	Mean	0.12	0.15	0.03	0.53
	Med	0.07	0.14	0.07	0.24
	Std	0.41	0.37		
	Obs	109	358		
Most likely to be constrained	Mean	0.13	0.25	0.12*	0.06
	Med	-0.06	0.09	0.15**	0.03
	Std	0.71	0.72		
	Obs	267	215		

Panel B: WW financial constraint index

		How ICM	**High ICM**	**High ICM - Low ICM**	**p-values**
Least likely to be constrained	Mean	0.13	0.17	0.04	0.32
	Med	0.1	0	0.04*	0.06
	Std	0.47	0.43		
	Obs	136	367		
Most likely to be constrained	Mean	0.12	0.27	0.15**	0.03
	Med	-0.04	0.12	0.16**	0.01
	Std	0.71	0.73		
	Obs	313	186		

Table 4.7 Return prediction for financially constrained firms versus non-financial constrained firms

This table presents regression results on the interaction between ICM and FC Dummy on one-year subsequent returns.

The regression equation is specified below:

$Return_{i(t+1)} = \beta_1 + \beta_2 BottomICM_{it} + \beta_3 MiddleICM_{it} + \beta_4 FCDummy_{it} + \beta_5 BottomICM{*}FCDummy_{it} + \beta_6 MiddleICM{*}FCDummy_{it} + \beta_7\ Size_{it} + \beta_8\ Log(BM)_{it} + \beta_9\ Accrual_{it} + \beta_{10}\ F\text{-}score_{it} + \beta_{11}\ Z\text{-}score_{it} + \beta_{12} NUMSEG_{it} + ¥_{it}$

*In each financial year, FC Dummy equals 1 if a firm has SA index or WW index in the top 20% of the SA index or WW index distribution, and zero otherwise. SA index and WW index are computed as in Hadlock and Pierce (2010) and Whited and Wu (2006) respectively. ICM is computed as in Billett and Mauer (2003). Details of how ICM, SA index and WW are computed are outlined in section 4.3. 10% and 90% of the end of financial year's ICM distribution are used to classify the sample firms into low ICM and high ICM groups. P-values are in the parenthesis with Newey-West standard errors. *, ** and *** indicate statistical significance at the 1%, 5% and 10% level, respectively.*

	SA index	WW index
Bottom ICM	-0.033	-0.026
	(0.19)	(0.31)
Middle ICM	-0.071***	-0.075***
	(0.00)	(0.00)
FC Dummy	0.043	0.073
	(0.42)	(0.20)
Bottom ICM*FC Dummy	-0.072	-0.095
	(0.29)	(0.19)
Middle ICM*FC Dummy	-0.092*	-0.075
	(0.09)	(0.20)
Size	-0.013***	-0.0081**
	(0.00)	(0.03)
Log(BM)	0.049***	0.054***
	(0.00)	(0.00)
Accrual	-0.35***	-0.35***
	(0.00)	(0.00)
F-score	0.021***	0.021***
	(0.00)	(0.00)
Z-score	0.012***	0.012***
	(0.00)	(0.00)
NUMSEG	0.032***	0.030**
	(0.01)	(0.02)
Cons	0.10***	0.071**
	(0.00)	(0.04)
N	10405	10405
adj. R-sq	0.02	0.02

The current analysis focuses on identifying whether the impact of ICM does indeed vary when firms are confronted by external financial constraints and, clearly, the importance of ICM appears to be greatest when external financial constraints are likely to be binding, in accordance with theory/a priori expectations. We report in Table 4.7 an extension of the analysis wherein we consider the statistical significance of the interaction between high levels of external financial constraints and ICM, controlling for other candidate forecasting variables. While the direction of the estimated relationship is consistent with expectations, the statistical significance is marginal at best. However, it must be noted that this may well be attributable to the high correlation between 'Bottom ICM' and 'Bottom ICM*FC Dummy'.

4.5.3 ICM and subsequent returns in firms having large number of business segments

As previous studies show that splitting up a diversified firm into separate single trading entities will result in more informative stock prices, we further examine whether ICM has a stronger effect on subsequent returns in firms with a larger number of business segments. We expect that, all else being equal, the market will respond more slowly to new public information released by firms with more complex business structures (higher number of business segments). In this study, a diversified firm will be classified as firms having a large number of business segments if it has more than three business segments, as defined with reference to 4-digit SIC codes.[17] Table 4.8 shows that ICM plays a more important role in predicting future returns for firms having more than three business segments. The differences in mean and median annual returns are 11% and 7% and statistically significant for firms having more than three business segments. Meanwhile, firms with fewer than three business segments have mean and median differences in annual returns of only 2% and 8%, but only the median differences are statistically significant. These results suggest the value effects associated with ICM are more pronounced in firms with a higher level of information uncertainty. The findings of Piotroski

[17] We also retest the robustness of our result when a firm is classified as a firm with large number of business segments if it has more than four business segments. The results are reported in section 4.5.5

(2000), Daniel, Hirshleifer et al. (2001), Zhang (2006) are similarly attributable to information uncertainty.

Table 4.8 ICM and subsequent returns in firms with three business segments or less and firms with more than three business segments

*This table presents descriptive statistics for 1 year returns for 2 groups of firms: firms with 3 business segments or less and firms with more than 3 business segments. Number of business segments are identified basing on 4 digit SIC codes reported in Historical Compustat Databases. 10% and 90% of the end of financial year's ICM distribution are used to classify the sample firms into low ICM and high ICM groups. 1 year returns is one year buy and hold returns from the fifth month after the firm fiscal year-end through the earliest subsequent date: one year return after return compounding began or the last day of CRSP traded returns. Delisting return is assumed to be -1. ICM is computed as in Billett and Mauer (2003), which is outlined in section 2. Two sample t-test and Wilcoxon rank-sum test are used to compare the mean and median differences between two groups of firms. *, ** and *** indicate statistical significance at the 1%, 5% and 10% level, respectively.*

		Low ICM	**High ICM**	**high ICM - low ICM**	**p-values**
Firms with three segments or less	mean	0.15	0.17	0.02	0.44
	med	0.03	0.11	0.08**	0.03
	std	0.65	0.57		
	obs	648	1,057		
Firms with more than three segments	mean	0.14	0.25	0.11***	0.01
	med	0.08	0.15	0.07***	0.00
	std	0.54	0.58		
	obs	401	322		

Table 4.9 Return prediction for firms with large number of business segments versus firms with small number of business segments

This table presents regression results on the interaction between ICM and SEGDUMMY on 1 year subsequent returns. The regression equation is specified below:

$$Return_{i(t+1)} = \beta_1 + \beta_2 BottomICM_{it} + \beta_3 MiddleICM_{it} + \beta_4 BottomICM*SEGDummy_{it} + \beta_5 MiddleICM*SEGDummy_{it} + \beta_6 SEGDummy_{it} + \beta_7\, Size_{it} + \beta_8\, Log(BM)_{it} + \beta_9\, Accrual_{it} + \beta_{10}\, F\text{-}score_{it} + \beta_{11}\, Z\text{-}score_{it} + \beta_{12} NUMSEG_{it} + ¥_{it}$$

*In each financial year, SEGDUMMY equals 1 if a firm has more than three business segments, and zero otherwise. Details of how ICM is computed are in section 4.3. 10% and 90% of the end of financial year's ICM distribution are used to classify the sample firms into low ICM and high ICM groups. 1 year returns is one year buy and hold returns from the fifth month after the firm fiscal year-end through the earliest subsequent date: one year return after return compounding began or the last day of CRSP traded returns. Delisting return is assumed to be -1. *, ** and *** indicate statistical significance at the 1%, 5% and 10% level, respectively. P-values are in the parenthesis with Newey-West standard errors. *, ** and *** indicate statistical significance at the 1%, 5% and 10% level, respectively.*

	One year returns
Bottom ICM	-0.019
	(0.55)
Middle ICM	-0.067***
	(0.00)
Bottom ICM*SEGDUMMY	-0.084
	(0.10)
Middle ICM* SEGDUMMY	-0.073*
	(0.06)
SEGDUMMY	0.085**
	(0.02)
Size	-0.008**
	(0.01)
Log(BM)	0.054***
	(0.00)
Accrual	-0.34***
	(0.00)
F-score	0.021***
	(0.00)
Z-score	0.012***
	(0.00)
Cons	0.090***
	(0.00)
N	10,405
adj. R-sq	0.02

Similar to the analysis with respect to financial constraints reported in Table 4.7, we report in Table 4.9 the results of a regression wherein we examine the importance of interaction effects, controlling for other forecasting variables. Again the direction of the relations accords with expectations and the univariate results. However, the correlation between 'Bottom ICM' and 'Bottom ICM*SEGDUMMY' implies that the effects are difficult to discern in a regression context.

4.5.4 ICM and subsequent returns in different F-score levels

Previous studies have demonstrated that F-score can help filter out underperforming and outperforming firms (Piotroski (2000), Fama and French (2006), Choi and Sias (2012)). We repeat this analysis in our sample of diversified firms. In particular, in each financial year, we classify the sample firms into two groups: low F-score firms and high F-score firms. Following Choi and Sias (2012), we define low F-score firms as firms having F-score values of 0, 1 and 2, and high F-score firms as firms having F-score values of 7, 8 and 9. We then investigate whether returns generated by low F-score firms are lower than high F-score firms. In line with previous findings, the results in Table 4.10 show that F-score can help distinguish outperforming firms and underperforming firms. The mean and median differences in one-year returns between low F-score and high F-score firms are 12% and 19% respectively and statistically significant at the 1% level. As we have shown previously that low ICM firms earn significantly lower returns than high ICM firms, we further investigate whether ICM continues to play an important role in predicting returns in low F-score firms and high F-score firms.

Table 4.11 shows that on average high ICM firms always earn higher subsequent returns than low ICM firms regardless of whether the firms belong to the low or high F-score group. However, mean and median differences between high and low ICM firms are only statistically significant in the low F-score firms. Mean and median difference in one-year returns of high and low ICM firms in the low F-score group are 25% and 24% respectively, in comparision to the high F-score group that are only 1% and 6% respectively. These results suggest that using

ICM to segment firms in the low F-score group can generate a mean annual return difference of 13%.

Table 4.10 F-score and subsequent returns

*Table 4.10 presents descriptive statistics for one year subsequent returns for two groups of firms: firms having low F-score and firms having high F-score. A firm will be classified as low F-score firm if its F-score ranging from 0 to 2, and will be classified as high F-score firm if its F-score ranging from 7 to 9. F-score is computed as in Piotroski (2000), which is outlined in section 4.3. 1 year returns is one year buy and hold returns from the fifth month after the firm fiscal year-end through the earliest subsequent date: one year after return compounding began or the last day of CRSP traded returns. Delisting return is assumed to be -1. Two sample t-test and Wilcoxon rank-sum test are used to compare the mean and median differences between two groups of firms. *, ** and *** indicate statistical significance at the 1%, 5% and 10% level, respectively.*

		1 year returns
Low F-score	Mean	0.04
	Med	-0.08
	Std	0.69
	Obs	682
High F-score	Mean	0.16
	Med	0.11
	Std	0.49
	Obs	1566
High F-score-low F-score	Mean	0.12***
	Med	0
	Std	0.19***
	Obs	0

Table 4.11 ICM and subsequent returns in different F-score levels

*This table presents descriptive statistics for 1 year subsequent returns for low and high ICM firms belonging to the low F-score and high F-score groups. A firm will be classified as low F-score firm if its F-score ranging from 0 to 2, and will be classified as high F-score firm if its F-score ranging from 7 to 9. F-score is computed as in Piotroski (2000), which is outlined in section 2. 1 year returns is one year buy and hold returns from the fifth month after the firm fiscal year-end through the earliest subsequent date: one year and two year after return compounding began or the last day of CRSP traded returns. Delisting return is assumed to be -1. ICM is computed as in Billett and Mauer (2003). Details of how ICM, F-score are computed are outlined in section 4.3. 10% and 90% of the end of financial year's ICM distribution are used to classify the sample firms into low ICM and high ICM groups. Two sample t-test and Wilcoxon rank-sum test are used to compare the mean and median differences between two groups of firms. *, ** and *** indicate statistical significance at the 1%, 5% and 10% level, respectively.*

		Low ICM	**High ICM**	**high ICM - low ICM**	**p-values**
Low F-score	Mean	0.07	0.32	0.25**	0.04
	Med	-0.09	0.15	0.24**	0.04
	Std	0.75	0.85		
	Obs	118	64		
High F-score	Mean	0.14	0.15	0.01	0.79
	Med	0.07	0.13	0.06	0.19
	Std	0.53	0.42		
	Obs	120	214		

4.5.5 Robustness test

Financial constrain indexes and number of business segments

In this section, we retest the effect of ICM on subsequent returns in firms when varying the cut-offs for the level of external financial constraints and the number of the business segments. In particular, firms will be placed into the most likely to be financially-constrained and the least likely to be financially-constrained groups by using 15% and 85% as opposed to 20% and 80% cut-off points of the SA and WW index distribution at the end of each financial year. Moreover, we classify a firm as having a large number of business segments if it has more than four business segments intead of three business segments as previously.

Table 4.12 ICM and subsequent returns in different financial constraint levels when varying definition of firms with high and low level of financial constraints

*This table presents descriptive statistics for 1 year subsequent returns for low and high ICM firms belonging to the most likely to be financially constrained or the least likely to be financially constrained groups. In each financial year, firms will be classified as the most likely to be financially constrained if it has SA index or WW index in the top 15% in that year, and will be classified as the least likely to be financially constrained if it has SA index or WW index in the bottom 15% in that year. SA index and WW index are computed as in Whited and Wu (2006) and Hadlock and Pierce (2010)) respectively. ICM is computed as in Billett and Mauer (2003). Details of how ICM, SA index and WW are computed are outlined in section 4.3. 10% and 90% of the end of financial year's ICM distribution are used to classify the sample firms into low ICM and high ICM groups. Two sample t-test and Wilcoxon rank-sum test are used to compare the mean and median differences between two groups of firms. *, ** and *** indicate statistical significance at the 1%, 5% and 10% level, respectively.*

Panel A: SA financial constraint index

		Low ICM	High ICM	High ICM - Low ICM	p-values
Least likely to be constrained	Mean	0.13	0.17	0.04	0.41
	Med	0.08	0.16	0.08	0.17
	Std	0.45	0.36		
	Obs	74	270		
Most likely to be constrained	Mean	0.07	0.26	0.19**	0.01
	Med	-0.08	0.11	0.19***	0.01
	Std	0.7	0.71		
	Obs	208	148		

Panel B: WW financial constraint index

		Low ICM	High ICM	High ICM - Low ICM	p-values
Least likely to be constrained	Mean	0.1	0.17	0.07	0.17
	Med	0.06	0.15	0.09**	0.02
	Std	0.43	0.41		
	Obs	101	277		
Most likely to be constrained	Mean	0.12	0.28	0.16**	0.03
	Med	-0.04	0.08	0.12**	0.02
	Std	0.72	0.73		
	Obs	246	137		

In Table 4.12, when we vary the definition of the most and the least likely to be financially-constrained firms by taking the 15% and 85% as the cut-off points,[18] our results support the

[18] We also vary the cut-offs points between the top/ bottom 20% and 10% of the SA index or WW index distribution to separate our sample firms to the most likely to be financially constrained and the least likely to be financially constrained groups. Our results remain statistically similar.

hypothesis that ICM only plays a significant role for firms with a high level of external financial constraints. Table 4.12 shows that with both of the index measures, the mean and median differences in one-year returns between the low ICM and high ICM firms are larger and statistically significant in the case of financially-constrained firms. This result reconfirms that ICM can only identify mispriced financially-constrained firms.

Table 4.13 ICM and subsequent returns in firms with four business segments or less and firms with more than four business segments

*This table presents descriptive statistics for 1 year returns for 2 groups of firms: firms with 4 business segments or less and firms with more than 4 business segments. Number of business segments are identified basing on 4 digit SIC codes reported in Historical Compustat Databases. 10% and 90% of the end of financial year's ICM distribution are used to classify the sample firms into low ICM and high ICM groups. 1 year returns is one year buy and hold returns from the fifth month after the firm fiscal year-end through the earliest subsequent date: one year return after return compounding began or the last day of CRSP traded returns. Delisting return is assumed to be -1. ICM is computed as in Billett and Mauer (2003), which is outlined in section 4.3. Two sample t-test and Wilcoxon rank-sum test are used to compare the mean and median differences between two groups of firms. *, ** and *** indicate statistical significance at the 1%, 5% and 10% level, respectively.*

		Low ICM	**High ICM**	**High ICM - Low ICM**	**p-values**
Firms with four segments or less	Mean	0.14	0.18	0.04	0.24
	Med	0.05	0.12	0.07**	0.01
	Std	0.63	0.57		
	Obs	814	1,184		
Firms with more than four segments	Mean	0.14	0.27	0.13**	0.02
	Med	0.07	0.17	0.10**	0.02
	Std	0.51	0.6		
	Obs	235	195		

Table 4.13 reports descriptive statistics for one-year subsequent returns for two groups of firms: firms with more or less than four business segments The differences in mean and median one-year returns between low and high ICM in the group of firms with more than four business segments are statistically significant at 5% and larger than for the firms with fewer than four business segments. Specifically, in firms with more than four segments, mean and median differences in one-year returns are 13% and 10% respectively, while firms with four segments or less have the mean and median returns of only 4% and 7% respectively. Our results here

reiterate that ICM has stronger effects on subsequent returns when firms have a larger number of business segments.

Risk adjusted returns

Our analysis has been focusing on the ability of ICM in predicting raw future stock returns. In this section, we retest our main analysis when 1 year and 2 year returns are adjusted for risk. Risk adjusted returns are computed as followed. Firstly, portfolio is formed at the fifth month after the firm's fiscal year end through the earliest subsequent date: either one (two) year(s) after the start of the period for compounding returns or on the last day or CRSP traded returns. If a firm delists, we assume that its delisting return is -1. For each of these portfolios, we compute next year monthly returns. We then estimate 1 year and 2 year risk adjusted returns as the intercept of the CAPM model. The CAPM model is specified as below:

$$R_t - R_{ft} = \beta_0 + \beta_1 (R_{mt} - R_{ft)} + ¥_t \qquad (12)$$

R_t is the monthly return at time t. β_0 is the risk adjusted return. R_{mt} is monthly return of the S&P500 index at time t. R_{ft} is monthly return of the three month T-bill at time t.

Table 4.14 presents the descriptive statistics for the distribution of one year and two year returns for the lowest and highest groupings of firms ICM using 10% and 90% cut-offs at the end of each financial year. Table 4.14 shows that the mean and median difference in 1 year return between low ICM and high ICM firms are statistically insignificant, but the mean and median difference in 2 year return is still significantly different from 0. These results demonstrate that the ability of ICM in predicting future stock returns is diminishing after taking into account the risk when computing future stock returns.

When the risk adjusted returns are double sorted basing on both the ICM and financial constraint indexes, the result in table 4.15 shows that ICM still remain relatively good predictor of future risk adjusted returns. The difference in mean and median between high and low ICM firms remain to be statistically significant in the most likely to be constrained group when measuring by WW index. In the case of SA index, only the difference in median risk adjusted returns between high and low ICM firms are found in the most likely to be financially constrained firms. Therefore, we can conclude that though ICM's ability to predict future risk adjusted returns is not as strong as in the case of raw returns, it still exists in the group of financially constrained firms.

Table 4.14 ICM and subsequent returns

*This table presents descriptive statistics for one-year and two-year risk adjusted returns for 2 groups of firms: firms with low ICM and firms with high ICM. 10% and 90% of the end of financial year's ICM distribution are used to classify the sample firms into low ICM and high ICM groups. One- year (two-year) returns are one-year (two-year) buy and hold returns from the fifth month after the firm's fiscal year-end through the earliest subsequent date: one year and two years after return compounding began or the last day of CRSP traded returns. Delisting return is assumed to be -1. ICM is computed as in Billett and Mauer (2002), which is outlined in section 4.3. Two sample t-test and Wilcoxon rank-sum test are used to compare the mean and median differences between two groups of firms. *, ** and *** indicate statistical significance at the 1%, 5% and 10% level, respectively.*

		1 year risk adjusted returns	**2 year risk adjusted returns**
Low ICM	Mean	0.06	0.25
	Med	-0.03	0.09
	Std	0.64	0.86
	Obs	1029	890
High ICM	Mean	0.05	0.37
	Med	0	0.21
	Std	0.56	0.83
	Obs	1357	1243
High-Low	Mean	-0.01	0.12
	P-value	0.7021	0.00
	Med	0.04	0.12
	P-value	0.5186	0.00

Table 4.15 ICM and subsequent risk adjusted returns in different financial constraint levels

*This table presents descriptive statistics for one year subsequent risk adjusted returns for low and high ICM firms belonging to the most likely to be financially-constrained or the least likely to be financially-constrained groups. In each financial year, firms will be classified as most likely to be financially constrained if it has an SA index or WW index in the top 20% in that year, and will be classified as the least likely to be financially constrained if it has an SA index or WW index in the bottom 20% in that year. SA index and WW index are computed as in Hadlock and Pierce (2010) and Whited and Wu (2006) respectively. ICM is computed as in Billett and Mauer (2003). Details of how ICM, SA index and WW index are computed are outlined in section 4.3. 10% and 90% of the end of financial year's ICM distribution are used to classify the sample firms into low ICM and high ICM groups. Two sample t-test and Wilcoxon rank-sum test are used to compare the mean and median differences between two groups of firms. *, ** and *** indicate statistical significance at the 1%, 5% and 10% level, respectively*

Panel A: SA financial constraint index

		Low ICM	High ICM	High ICM - Low ICM	p-values
Least likely to be constrained	Mean	0.07	0.01	-0.06	0.25
	Med	0.03	0.01	-0.02	0.47
	Std	0.30	0.32		
	Obs	41.00	197.00		
Most likely to be constrained	Mean	0.06	0.21	0.15	0.17
	Med	-0.11	0.05	0.16*	0.09
	Std	0.81	0.76		
	Obs	152.00	84.00		

Panel B: WW financial constraint index

		Low ICM	High ICM	High ICM - Low ICM	p-values
Least likely to be constrained	Mean	0.04	0.03	-0.01	0.78
	Med	0.03	0.04	0.01	0.77
	Std	0.31	0.42		
	Obs	66.00	191.00		
Most likely to be constrained	Mean	0.05	0.26	0.21**	0.05
	Med	-0.14	0.10	0.24**	0.02
	Std	0.83	0.71		
	Obs	164.00	87.00		

4.6 Conclusion

The value and financial performance of diversified firms depend, amongst other things, on the efficiency with which they allocate scarce capital amongst competing investment alternatives. While the principles of such capital allocation are widely taught and well understood, agency-based imperfections can undermine the process of capital allocation in multi-segment firms in particular. Theoretical models suggest the existence of such imperfections, and prior empirical work demonstrates that multi-segment firms are indeed, on average, inefficient with respect to internal capital allocation.

Given the value relevance of efficient internal capital markets and capital allocation, the current study evaluates the efficiency of equity markets with respect to measures of internal capital market efficiency derived from financial statement information. Given the substantial prior research suggesting that markets do not respond efficiently to simple metrics derived from financial statements such as Piotroski's (2000) F-score, firm sizes, book to market ratio, and accrual), we hypothesize that markets are likely to be inefficient with respect to empirical measures of internal capital market efficiency such as ICM. The efficiency of market responses to financial statement information has been argued to be a function of information uncertainty (Hirshleifer (2001), Zhang (2006)), and multi-segment firms, by their nature, are associated with higher information uncertainty. With these considerations in mind, we study the association between ICM and subsequent returns using both univariate and multivariate metrics. In particular, we show with reference to a 1997-2015 panel of observations, that firms in the high ICM decile outperform firms in the low ICM decile by 5% on an annual basis, on average. Furthermore, the differences in the returns on high and low efficiency firms remain statistically and economically significant after controlling for the other financial statement-based metrics shown to forecast returns: firm size, Piotroski's (2000) F-score, accrual, book to market ratio and default risk in particular.

Given that the efficiency of internal capital markets is likely to be of most economic significance in situations where a firm's access to external capital markets is constrained, we examine whether there is evidence of an interaction between ICM, external capital constraints and the magnitude of value effects. Consistent with our second hypothesis, we find that the association between returns and high and low levels of ICM is highly significant. The valuation effects associated with ICM are in fact concentrated amongst the most financially-constrained firms.

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Chapter 5 : Conclusion

This PhD thesis addresses three topics in financial risk management and corporate investment. Firstly, it evaluates the sensitivity of corporate default risk to IMF events. Secondly, it examines the relationship between ICM and corporate default risk. Lastly, it investigates whether ICM can predict diversified firms' subsequent returns. This chapter summarizes the key findings, implications and limitations for each of these three topics.

5.1 IMF program and Corporate Default Risk

5.1.1 Summary of the findings

Chapter 2 investigates the effect of IMF financial assistance on corporate default risk during the period from 1996 to 2012. Using firm-level expected default frequency (EDF) metrics from Moody's KMV and an event study style approach, we show that IMF programs lead to higher corporate default risk over the twelve months before and after the announcement of IMF programs. We also find that the rise in EDF upon the IMF event is driven mainly by financial companies, especially in the countries receiving SBA. These findings are consistent with the intensive economic reform and fiscal austerity conditions attached to this arrangement. More importantly, using propensity score as a measure of a country's need for its IMF loan, we find that countries that need an IMF loan most are the ones receiving the smallest loan sizes. For this reason, these countries are found to experience larger increases in corporate default risk over the event window than those receiving the largest loans, which is in line with Zettelmeyer's (2002) argument about the counterproductive effect of small loan sizes. Our results are robust to the control of the endogeneity issue and are not influenced by the effect of outliers.

5.1.2 Implications and limitation

Since a country's sovereign risk is a reflection of its corporate sector performance, the negative effect of IMF programs on corporate default risk can also be generalized to the country level.

For this reason, our study has implications for an IMF recipient's government in its implementation of macroeconomic policies while under the IMF programs. Furthermore, our findings not only assist risk managers in forming suitable risk management strategies in the event of IMF intervention, they also help the IMF's governors to design better IMF programs in terms of program sizes and attached conditions so as to minimize the negative risk effects. However, as our research focuses only on the medium term risk effect of IMF intervention, the question of how these programs influence corporate default risk in the long term opens an exciting area for future research.

5.2 Internal Capital Market Efficiency and Diversified Firm Default Risk

5.2.1 Summary of the findings

Chapter 3 provides an answer to the question of how Internal Capital Market Efficiency (ICM) influences the default risk experienced by diversified firm and whether this effect is more pronounced in externally financially-constrained firms. While the literature on corporate diversification suggests that the way internal capital is used will affect corporate default risk, none of this previous research directly established the link between these two factors. Our results indicate that ICM is an important determinant of corporate default risk in highly-leveraged diversified firms and this result is robust to the three different corporate default risk measures: Merton-style default probabilities computed as in Bharath and Shumway (2008), the Altman Z-score and S&P credit rating. However, when taking into consideration the level of external financial constraints, our study provides weak evidence on the hypothesis that the relationship between ICM and corporate default risk is conditional on such constraints. We find that ICM only has a stronger effect on the default risk of financially-constrained firms rather than that of the other group of firms in the case of the Altman Z-score.

5.2.2 Implications and limitation

As ICM is shown to be an important determinant of corporate default risk, this factor should be taken into account when evaluating the risk effect of diversification. The positive risk reduction benefits resulting from diversification demonstrated in Lewellen's (1971) model can be offset or diminished if the internal capital markets in diversified firms function inefficiently. Because the inefficiency of internal capital markets is arguably a result of agency problems, our results imply that tackling the agency issue in diversified firms should be one of the main focuses of the firm's risk management strategy. However, subject to limited segment data, we acknowledge that our ICM measure may contain some noisy information. With the available data, we cannot compute the exact amount of 'Subsidy' and 'Transfer' nor can we adjust the risk for a segment's ROA. Therefore, a different approach to estimating the ICM to overcome these shortcomings is a question for future research.

5.3 Internal Capital Market Efficiency and Diversified Firms' subsequent returns?

5.3.1 Summary of the findings

In chapter 4, we contribute to the literature on market inefficiency by suggesting a new signal for predicting returns – ICM. We demonstrate that ICM can predict diversified firms' stock returns, and this predictive ability is incrementally important after controlling for the other future stock returns predictors suggested in the literature such as F-score, book to market ratio, accruals, firm size and default risk. Due to the complex business structure of diversified firms, the market's response to the ICM information tends to be delayed. As a result, ICM can predict diversified firms' stock returns. Our ICM measure is distinguished from other expected profitability proxies as it contains information about a firm's level of external financial constraints. With limited access to external capital, diversified firm managers tend to allocate internal funds more efficiently.

Our results show that ICM can predict diversified firms' stock returns, and this predictive ability is more important in firms with a large number of business segments as these firms have higher levels of information uncertainty. When examining the effect of ICM on future stock returns separately for financially-constrained firms and non-financially-constrained firms, we find that ICM is only a statistically significant determinant of the stock returns for financially-constrained firms.

5.3.2 Implications and limitation

Our study can help the investors to construct a trading strategy based on ICM information to earn positive future stock returns. This strategy works especially well in the financially-constrained firms, which differentiates our ICM measure from the other return predictors suggested in the literature. As the important role of ICM in predicting stock returns is incremental to the control of Piotroski's (2000) F-score, investors can use ICM to further distinguish firms with high and low prospects of future returns after taking into consideration the F-score criteria.

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