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R&D investment, innovative efficiency and financial constraints: empirical analysis using structural equation model and mixed-effects zero-inflated-Poisson model

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ABSTRACT

BORRI, K.T. **R&D investment, innovative efficiency and financial constraints: empirical analysis using structural equation model and mixed-effects zero-inflated-Poisson model**. 2022. 82p. Thesis (Doctor) - UNIVERSITY OF SÃO PAULO, São Carlos, 2022.

Innovation has been considered as a key element for long term economic growth. Given that R&D investment have unique characteristics, the implementation of proper instruments to foment innovation requires a clear study of the necessary strategies to operate efficiently. Therefore, many empirical studies have been exploring the relation between investment in R&D and financial constraints, and have shown that R&D investment is more sensitive to financial constraints than other types of investments. However, contrary to the wisdom idea that financial constraints may understate innovation, a few empirical studies have suggested a bright side of financial constraints to innovation. There is evidence that higher level of financial constraint may be associated with a higher level of innovative efficiency. The aim of this study is to provide robust empirical analysis of how financial constraints are related to R&D investment and innovative efficiency. Besides, we explore the role of financial development in R&D investment and the relation between R&D tax subsidies and innovative efficiency. Using two databases, we perform two different approaches. First, we employ the Structural Equation Model via Maximum Likelihood (ML-SEM) methodology to estimate the relation between R&D investment and the financial variables in both emerging and developed countries. The findings suggest that firms extensively use internal resources to finance their R&D activities. Also, credit supply is an important channel to release resources to R&D projects, especially for more constrained firms. Second, we employ a mixed-effects zero-inflated Poisson model to study the impact of financial factors and firm's characteristics on innovative efficiency, and extend our analysis to observe the relation between innovative efficiency and R&D tax incentive. Our results highlights that smaller firms have a higher probability of been more innovative efficient. We find strong evidence that the agency problems faced by larger firms jeopardize the selection of innovation projects, leading to a decrease in innovative efficiency. Moreover, tax credits to R&D have a negative impact on innovative efficiency, which raises the doubt of whether this is a public efficient instrument to foment innovation.

Keywords: R&D investment. Financial constraints. Financial development. Innovative efficiency. Structural equation model. Poisson model.

RESUMO

BORRI, K.T. **Investimento em P&D, eficiência inovativa e restrição financeira: análise empírica usando modelo de equação estrutural e modelo de Poisson inflacionado de zeros com efeitos mistos**. 2022. 82p. Thesis (Doctor) - UNIVERSITY OF SÃO PAULO, São Carlos, 2022.

A inovação tem sido considerada como um elemento-chave para o crescimento econômico de longo prazo. Dado que o investimento em P&D tem características únicas, a implementação de instrumentos adequados para fomentar a inovação requer um estudo claro das estratégias necessárias para operar com eficiência. Portanto, muitos estudos empíricos vêm explorando a relação entre investimento em P&D e restrições financeiras, e têm demonstrado que o investimento em P&D é mais sensível a restrições financeiras do que outros tipos de investimentos. No entanto, ao contrário da ideia de que as restrições financeiras podem subestimar a inovação, alguns estudos empíricos têm sugerido um lado positivo das restrições financeiras à inovação. Há evidências de que um nível mais alto de restrição financeira pode estar associado a um nível mais alto de eficiência inovativa. O objetivo deste estudo é, então, fornecer uma análise empírica robusta de como as restrições financeiras estão relacionadas ao investimento em P&D e à eficiência inovativa. Além disso, explorar o papel do desenvolvimento financeiro no investimento em P&D e a relação entre subsídios fiscais em P&D e eficiência inovativa. Usando dois bancos de dados, duas abordagens diferentes foram realizadas. Primeiramente, empregou-se a metodologia do Modelo de Equação Estrutural via Máxima Verossimilhança (ML-SEM) para estimar a relação entre o investimento em P&D e as variáveis financeiras, tanto em países emergentes quanto em países desenvolvidos. Os resultados sugerem que as empresas usam amplamente os recursos internos para financiar suas atividades de P&D. Além disso, a oferta de crédito é um importante canal de liberação de recursos para projetos de P&D, principalmente para empresas mais restritas. Em segundo lugar, empregou-se um modelo de Poisson inflacionado de zeros com efeitos mistos para estudar o impacto de fatores financeiros e características da empresa na eficiência inovativa. Estendeu-se a análise para observar, também, a relação entre eficiência inovativa e incentivo fiscal de P&D. Os resultados destacam que empresas menores têm maior probabilidade de serem mais eficientes em termos de inovação. Foram encontradas fortes evidências de que os problemas de agência enfrentados por empresas maiores prejudicam a seleção de projetos de inovação, levando a uma diminuição da eficiência inovativa. Além disso, os créditos tributários para P&D impactam negativamente na eficiência inovativa, o que levanta a dúvida se este é um instrumento público eficiente para fomentar a inovação.

Palavras-chave: Investimento em P&D. Restrição financeira. Desenvolvimento financeiro. Eficiência inovativa. Modelo de equação estrutural. Modelo de Poisson.

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1 INTRODUCTION

The innovation dynamics have been considered essential for the sustainable long-term economic growth and a key element of firms' competitive advantage. However, although several benefits of innovation such as value creation, new production processes and new business may foster economic development, there are some key issues that concern the financing of technological innovation. High adjustment costs, uncertainty and risk associated with innovative activities make the investment in research and development (R&D) more complex than a standard problem of capital allocation.

Innovation projects are risky, unpredictable, require substantial human effort, and they are not easily comparable to other projects. Besides, R&D investment is highly exposed to agency problems due to uncertainty of its output and information asymmetry (HOLMSTROM, 1989; HALL, 2002; HSU; TIAN; XU, 2014). Given the characteristics of such investment, many empirical studies have been conducted exploring the relationship between investment in R&D and financial constraints [1]. Although some of the results appear to be controversial, there are a few evidences that R&D investment are more sensitive to financial constraints than other types of investments.

As a consequence of this, financial constraints may directly affect the firm's level of R&D expenses, which could end up understating investment in innovation projects to a sub-optimal level. On the other hand, the literature also points to a different role of financial constraints as enabler of innovation.

A few studies have suggested the existence of a potential benefit of financial constraints on innovation. Additional to the widespread idea that access to financial resources is a key determinant of innovation, empirical evidences have shown that more financial resources do not necessarily result in more and better innovation outputs. Actually, there is evidence that higher level of financial constraint may be associated with a higher level of innovative efficiency (See, e.g., Katila and Shane (2005), Hoegl, Gibbert and Mazursky (2008), Almeida, Hsu and Li (2013), Merz (2021), Zhang, Chen and Zhang (2022).

The arguments are based on the fact that large and established firms are highly subject to agency problems, which may thwart the investment decision, particularly for innovation projects, since they are high uncertain and intangible. For that reason, firms with excess of free cash flow may invest in less productive R&D projects that are out of their areas of expertise (ALMEIDA; HSU; LI, 2013). In contrast, financially constrained firms will probably invest only in their most promising projects as consequence of their high cost of capital and scarce availability of

[1] See, e.g., Hall (2002), Bond, Harhofff and Reenen (2003), Brown, Fazzari and Petersen (2009), Brown, Martinsson and Petersen (2012), Hsu, Tian and Xu (2014), Ayyagari, Demirgüç-Kunt and Maksimovic (2011), Czarnitzki and Hottenrott (2011)

resources to R&D.

While all these debate involving financial constraints, R&D investment and innovative efficiency appear to be well rooted in theory, robust empirical evidences are relatively scarce due to availability of R&D and patent related data. Thus, in this study we aim to fill this gap providing empirical analysis of how financial constraints and financial development are related to R&D investment, and how financial constraints and R&D tax incentives are related to innovative efficiency.

This study is divided in two main parts. In the first part, we explore the relation between financial constraints, liquidity management, financial development and R&D investment. We do so by measuring R&D-cash flow sensitivity and also by analysing the effect of change in cash holdings to test for the presence of financial constraints[2] and liquidity management. Besides, we explore the role of equity and credit market development on R&D and their effects on internal cash requirements. In the second part, we investigate the dynamics of the relation between financial constraints, R&D tax credits and innovative efficiency. By defining innovative efficiency as the ratio of patents valued per R&D expenses, we analyse how innovative efficiency varies with firm size and age, and with different levels of R&D tax incentive.

Given that, the first contribution of this study is the better understanding of the impacts of microeconomics factors and financial development on R&D investments under financial constraints. Extending the study of Brown, Martinsson and Petersen (2012), who explore the role of change in cash holdings to test the existence of financing constraints on R&D, we study firms from a large number of countries, including emerging and developed countries.

We apply the Structural Equation Model via Maximum Likelihood (ML-SEM) to estimate the model parameters instead the GMM-system, which is the commonly employed in this literature. Therefore, another important contribution of this study is the applied methodology using ML-SEM approach for dynamic longitudinal data, as far as we know, no previous studies applied this methodology on R&D investments.

In this approach the latent time-invariant variable is allowed to be correlated with some financial liquidity variables and control for endogeneity. Recent studies with Monte Carlo simulation have shown that the ML-SEM method is more efficient and less biased than the GMM approach under several conditions (ALLISON; WILLIAMS; MORAL-BENITO, 2017; BUN; SARAFIDIS, 2013; BAZZI; CLEMENS, 2013; BOLLEN; BRAND, 2010; MORAL-BENITO, 2013). Therefore, we use the ML-SEM to overcome the following problems of GMM methodology : (*i*) the assumptions about the unrealistic stationarity, which assumes that the initial values of the data generating process (DGP) are stationary; (*ii*) the concern about the

2 Since the effect of cash flow can be ambiguous on investment decisions, by representing either financial constraint or investment opportunities, we also include the change in cash holdings to test the presence of financial constraints. Brown, Martinsson and Petersen (2012) consider to be the first to explore the effect of cash reserves in the presence of financial constraints on R&D investment.

choice of instruments that could be invalid or weak, and (*iii*) the use of several different possible combinations of instruments, which can diverge from the optimal set.

To employ the ML-SEM, we use a data sample that includes financial data from Compustat Global database and financial development indicators from the Global Financial Development Database of Cihäk *et al.* (2012). The samples includes R&D expenses of 11,807 firms from 61 countries over the period of 2010 - 2017. Thus, it is important to highlight that the construction of the database is also a great differential of this study.

Lastly, we conduct the empirical analysis regarding the effect of financial constraints on innovative efficiency. As already pointed out, there are just a few empirical evidences that support the view that financially constrained firms may outperform firms with high availability of resources by increasing their innovative productivity, i.e., generating more patents per dollar of R&D invested. Therefore, to further investigate this behavior, we employ another approach by estimating a mixed-effects zero-inflated-Poisson model (mixed-effect ZIP model) to take into account the counting nature of the patent variable and the high number of zeros in our sample. For this second part, the database was constructed by collecting financial indicators and patent data of publicly tradded firms from ORBIS. The sample consists of more than 3400 observations from 16 countries covering the period of 2011 - 2017.

Overall, our findings provide some important insights. First, firms rely intensively on internal resources to finance R&D even when there is an increase in the external credit availability. Second, instead of releasing cash holdings to smooth R&D costs, firms act more rebuilding stock of cash as precautionary measures. Third, firms in developed economies do not rely on equity market to finance their R&D projects. Fourth, credit market plays different roles for firms in emerging and developed countries. While in emerging economies, which are mostly “bank based", credit market is an important source to finance R&D. For firms in developed countries, which are mostly “market based", credit market discourage the investment on R&D activities. Fifth, we find that that lower resources can benefit innovative efficiency, lowering the impact of agency problems on the selection of innovation projects, mainly in smaller firms. Finally, an increase in R&D tax credits decreases the probability of generating a patent per R&D spent.

The results provide new insights on the general relation between innovation and financial factors. We show that policy makers could promote innovation by expanding the credit system, and therefore releasing firms’ resources to invest in innovative activities. Besides, it is fundamental to foment innovation in small firms, since they are more efficient on the production of valuable innovation. Also, we give evidences that tax incentive to R&D may not be an efficient instrument to foment the creation of innovation.

This study is organized in 5 chapters. Chapter 2 gives a review of the literature about R&D investment, financial constraints, financial development, innovative efficiency, R&D tax credits and other topics that we explore throughout the research. Chapter 3 shows the empirical model and describes the data and methodology for both parts of our analysis. Chapter 4 presents the discussion of our estimation results. Lastly, in Chapter 5 we present our main conclusions.

2 LITERATURE REVIEW

2.1 Innovation and R&D as investment

Although innovation is regarded as a key source of competitive advantage and economic growth, financing and fostering innovation can be very difficult. In the literature, R&D expenditure and number of patents are the most widely used measure for innovation, mainly because R&D spending is an important measure of innovation input and the number of patents captures the quantity of innovation output (HSU; TIAN; XU, 2014).

Some peculiarities of R&D make it differs from an ordinary capital investment. Innovation projects are risky, unpredictable, require substantial human effort, and they are not easily comparable to other projects. Besides, innovation investment is highly expose to agency problems due to uncertainty of its output and information asymmetry (HOLMSTROM, 1989).

The asymmetric-information problem involving innovation and R&D investment usually refers to the fact that the inventor has better information regarding the commercial success and the potential returns to innovation than external investors (HALL, 2002; COAD; SEGARRA; TERUEL, 2016). Hall (2002) emphasizes that the financing of R&D is similar to the idea of the “lemons" market proposed by Akerlof (1970) [1]. The lemons’ premium for R&D investment is greater than short-term or low-risk investments because distinguishing good investments from bad investment when dealing with long-term R&D projects can be very difficult. As consequence, the information asymmetry enhance the gap between the cost of external and internal finance for R&D.

Besides the information asymmetry, the reluctance of risk averse managers to invest in innovation projects due to uncertainty of its success leads to a principal-agent problem. Managers usually avoid R&D investment to prevent the increase of riskiness of the firm, therefore they may reject innovation projects which shareholders would like to undertake to reduce uncertainty and moral hazard problems (HALL, 2002).

Another important feature of R&D investment relates to the fact that unlike other investments, the most important innovation output is the knowledge of new services, products or process. Thus, large part of private R&D spending is designated to wages and salaries of highly qualified R&D employees. This characteristic has an important implication for R&D since part of the investment disappears when such worker leave the firm. As consequence, firms tend to smooth their innovation investment over time to avoid great losses due to its high adjustment costs (BROWN; MARTINSSON; PETERSEN, 2012).

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[1] Akerlof (1970) use the example of the automobiles market to explain the asymmetrical information problem. The difficulty of distinguishing good quality cars from bad cars ("lemons") represent the market uncertainty inherent in the business world.

All these unique features of R&D make the investment in innovation particularly interesting because support the view that innovative activities are expensive and may be difficult to finance with external sources. Consequently, firms rely more on internal funds to finance their R&D projects. However, a few empirical evidences have suggested that firms that are more likely to be financial constrained produce more patents per R&D invested. Based on that, this chapter investigate the main works that link innovation, financial constraints, financial development and innovative efficiency.

Section 2.2 presents a introduction about the definition of financial constraints and Section 2.3 discuss some of the principal researches that explore the effect of financial frictions on R&D investment. Section 2.4 examines some of the key features of financial development and its relation to the financing of innovation, Section 2.5 explore the main concepts of innovative efficiency and previous findings involving the relationship between financial constraints and innovative efficiency, and lastly, Section 2.6 briefly presents the main characteristics of R&D Tax Subsidies.

2.2 Financial constraints

According to the economic theory, a firm can be considered financially constrained if it faces a wedge between the cost of internal and external finance (FAZZARI; HUBBARD; PETERSEN, 1988; KAPLAN; ZINGALES, 1997). Bond, Harhofff and Reenen (2003) argue that the cost premium associated with the external source of financing reflects the asymmetric information problems and conflicts of interest between managers and shareholders. The literature has suggested many possible approaches for measuring financial constraints, including investment-cash flow sensitivities (FAZZARI; HUBBARD; PETERSEN, 1988), the Kaplan and Zingales (KZ) index (LAMONT; POLK; SAA-REQUEJO, 2001), the Whited and Wu (WW) index (WHITED; WU, 2006), and the Size-Age (SA) index (HADLOCK; PIERCE, 2010).

The empirical investigation of the role of financial constraints on firm's investment initiated with the study of Fazzari, Hubbard and Petersen (1988) about the impact of financial market imperfections and differences in the access of firms to capital. The authors explore the hypothesis that "imperfect" capital markets[2] have difficulty to evaluate the quality of investment opportunities, thereby the cost of external finance may differ substantially from the cost of internal finance - generated by cash flows and retained earnings. Thus, the investments of firms that use almost all of their internal funds to invest should be very sensitive to cash flow shocks. Based on this idea, they classify a sample of 422 firms during the period 1970 - 1984 by dividend policies, and analyze the cash flow coefficient when estimating a classical investment model using Tobin's Q to control investment opportunities. The results obtained indicate a greater sensitivity of investment to cash flow shocks and liquidity in firms that use almost all their

[2] Fazzari, Hubbard and Petersen (1988) refers to "imperfections" in capital markets mainly as the asymmetric information problems.

low-cost internal funds to invest. The authors emphasize that these empirical differences are consistent with the theory that financial constraints are a direct consequence of capital market imperfections.

Although the standard approach for testing for financial constraints has been the investment-cash flow sensitivity, potential weaknesses of such measure have been criticized in the literature. The main argument is that the controls for investment opportunities are imperfect, consequently cash flow may be capturing information about the profitability of investments. Also, most part of the studies do not address the endogeneity of cash flow and the decision of using external finance.

In this vein, Kaplan and Zingales (1997) investigate the relationship between investment-cash flow sensitivities and financial constraints by studying a sample of 44 firms considered high constrained by Fazzari, Hubbard and Petersen (1988). They find that there is no evidence that investment-cash flow sensitivities increase proportionally with the degree of financial constrains, evidencing that sensitivity of investment to cash flow is not a good measure of financial constraints. In only 15 percent of the firms they find a connection between the firm's access to internal or external finance and the increase in investment. The rest of the firms, previously considered as financially constrained, they did not observe this behavior.

A posterior investigation of Alti (2003) about the usage of investment-cash flow sensitivity to address financial constraints provides evidence that Tobin's Q fails to control for the investment opportunity. Consequently, wrong economic interpretations could emerge from the empirical cash flow sensitivity analysis. The author argues that part of the Tobin's Q for young and small firms captures the option value of long-term growth potential, which limitates the variable as a weak measure of short-term investment expectations. Thus, higher investment-cash flow sensitivities may be obtained simply because cash flow is reflecting informations about short-term investment opportunities, rather than the level of financial constraints.

Using a different strategy, Moyen (2004) uses two models based on the work of Fazzari, Hubbard and Petersen (1988) and Kaplan and Zingales (1997) to investigate whether the results from both studies are obtained by the usage of the cash flow as a proxy for testing financial restrictions. In the first model, called the unconstrained model, the firms have access to external financial markets. In the second model, called the constrained model, firms do not have access to external funds. By simulating series from the two models to represent the theoretical samples, the author finds that using low dividends to capture financial constraints conduct to the results of Fazzari, Hubbard and Petersen (1988). Nevertheless, using the constrained model the results are consistent with those of Kaplan and Zingales (1997). Moyen (2004) explains that since cash flow is highly correlated with investment opportunities, in a favorable scenario constrained and unconstrained firms invest more. However, unconstrained firms can also issue debt to finance additional investments, which magnifies the cash flow sensitivity of unconstrained firms leading to the Kaplan and Zingales (1997)'s result . On the other hand, the author identifies that the low-dividend firms are mostly presented in the unconstrained model, which is the group that display a higher cash flow sensitivity, reproducing the Fazzari, Hubbard and Petersen (1988)'s findings. Therefore, Moyen (2004) concludes that both constrained and unconstrained models may prove useful in identifying firms with financial constraints. Yet, it remains unclear whether the sensitivities in the data are generated more by learning or by financing constraints.

Taking a different approach to identify financial restrictions, Almeida, Campello and Weisbach (2004) evaluate a study that links financial constraints to firm's demand for liquidity. The idea proposed by the authors is that constrained firms choose their optimal level of cash reserves to equilibrate the profitability of current and future investments. In contrast, financially unconstrained firms do not have a systematic propensity to hold cash, therefore they should not exhibit a cash holding sensitivity to cash flow. Based on this hypothesis, the authors examine the difference in the cash flow sensitivity of cash using five subsamples classified by: payout dividend policy, asset size, bond rating, commercial paper rating, and the “KZ index" proposed by Lamont, Polk and Saa-Requejo (2001). They find that for the first four classifications, the cash flow sensitivity is not statistically significant for firms considered unconstrained, but positive and statistically significant for the constrained firms. In spite of that, they obtain opposite results for the cash flow sensitivity of cash when using the KZ index.

The KZ index was created by Lamont, Polk and Saa-Requejo (2001) to test whether part of the factor structure in stock return reflects the degree of financial constraint. Using the results from Kaplan and Zingales (1997) to classify firms into portfolios based on their level of financial constraints, the authors take the regression coefficients to construct an index composed by a linear combination of five accounting ratios: cash flow to total capital, the book-to-market ratio, debt to total capital, dividends to total capital, and cash holdings to capital. By construction, the KZ index is greater for more constrained firms that have high debt, low cash, and low dividend. They find evidence that financial constraints affect firm value, and that constrained firms earn lower returns than unconstrained which contrasts the existing asset-pricing models. Although the contradictory results, the authors argue that the KZ index is attractive because it is based on an in-depth analysis of firms.

Following Lamont, Polk and Saa-Requejo (2001), Whited and Wu (2006) construct an index (called WW index) of financial constraints based on a structural investment model builded to account for financial frictions. Whited and Wu (2006) argue that *“The model predicts that external finance constraints affect the intertemporal substitution of investment today for investment tomorrow via the shadow value of scarce external funds"* (p.531). Therefore, the WW index is obtained from the fitted values of the shadow value using the Generalized Method of Moments (GMM) to estimate the model. Taking into account the index, they find that the firms classified as “constrained" exhibit characteristics related to exposure to external finance constraints. Also, contrasting with Lamont, Polk and Saa-Requejo (2001), they show that more constrained firms do earn higher returns.

An additional financial constraint index was proposed by Hadlock and Pierce (2010). Exploiting the work of Kaplan and Zingales (1997), the authors analyzed detailed information from statements made by financial managers to categorize the firms by the degree of financial constraints using different quantitative factors. Based on that, the authors evaluate new measures of financial constraints and find that only two of the five components of the KZ index - size and age - appear to effectively predict constraints. The link between age, size, and financial constraint appears to be robust. Therefore, they represent this relation in a new index called size-age or SA index. The index imply that financial constraints fall as young and small firms start to become mature and bigger. Among the advantages of SA index are its intuitive appeal and its independence from theoretical assumptions.

2.3 Innovation and financial constraints

Investment in innovation differs in many aspects from conventional capital investment. Bond, Harhofff and Reenen (2003) emphasize that intangible assets, such as R&D, tend to be more susceptible to financing constraints due to the fact that their are riskier and harder to collateralize. As a result, the external financial source for innovation development might be very expensive and consequently some innovations are not developed purely because of the cost of external capital is too high (CZARNITZKI; HOTTENROTT, 2011). Based on this idea, the literature has tried to investigate the existence of some financial constraints for more R&D-intensive firms due to the difficulty to get financial resources.

Hall (2002) surveys the various theoretical and empirical evidences of the difference between the cost of external and internal finance of R&D activities. He argues that it is fairly clear that small and start-up firms in innovative intensive sectors face a higher cost of capital than large and established firms. The presence of either asymmetric information problem or principal-agent conflict indicates that debt finance or equity finance will be more expensive for R&D than for an ordinary investment.

Similarly, Gorodnichenko and Schnitzer (2013) show that the firm's decision to finance innovation is highly sensitive to financial constraints which can impede firms from less developed economies to developed and adopt new technologies. They differentiate from previous work by employing a finer definition of innovation and direct measures of financial constraints. The authors emphasize that the reduction of the cost and facilitating the access to external finance is an important incentive to more innovation and exporting activities, which can foster the development of new goods and technologies.

Bond, Harhofff and Reenen (2003) investigate whether the impact of cash flow differ between firms in Britain and Germany. They find that within Britain there is a greater sensitivity of fixed investment to cash flow for non-R&D performing companies than for R&D performing companies. For German firms they do not observe these differences. These results suggest that UK firms face a higher gap between the costs of external and internal finance than German firms. Similarly, Mulkay, Hall and Mairesse (2000) explore the differences of R&D investment behavior in France and United States. They find that cash flow has a larger impact on R&D investment in the U.S. than in France. They argue that the differences in behavior are due to divergences in the structure of financial markets rather than due to investment type.

Czarnitzki and Hottenrott (2011) study the German manufacturing sector during the period of 1992 to 2002 to show that the availability of internal funds is indeed decisive for R&D investment. They find that small and young firms are more affected by external constraints than large firms. Furthermore, the level of R&D spending increases as condition for access to external financing improve. This finding is consistent with the work of Gorodnichenko and Schnitzer (2013) and Hall (2002) who demonstrate that R&D expenses of young firms are much more sensitive to cash flow and external equity than mature firms.

Although the literature has widely studied the impact of cash flow shocks to R&D to address financial constraints, we have already pointed out that a potential weakness of this methodology is that cash flow can capture information about new investment opportunities and profitability. Taking into account this idea, Brown, Martinsson and Petersen (2012) include the change in cash holdings to test whether firms use cash reserves to smooth R&D from transitory shocks to finance. The premise is that for R&D-intensive firms facing financial constraints, external finance can be extremely costly during periods of negative shocks to internal finance and they have to use buffer stocks of internal liquidity to smooth R&D. They examine a panel of firms across 16 European countries from 1995 to 2007 and find that controlling for investment smoothing can be crucial for testing financial frictions on investments with high adjustment cost as R&D. For all groups of firms, they find a strong relationship between financial factors and R&D when including cash holdings in the regression.

Another work of Brown, Fazzari and Petersen (2009) investigate whether the supply shifts of internal and external sources of financing can explain the 1990s boom and subsequent decline in U.S. R&D investment. They show that a change in the reserves of internal and external equity finance in the 1990s reduced the financial constraints for young firms, suggesting that stock market can be a key source for financing innovation. An important finding of this study is that it highlights a crucial link between stock market and R&D investment. It suggests that stock market development can foster innovation since well-developed stock markets can support a larger number of firms that are dependent on external finance and facilitate the access to external credit, which can be essential for the maintenance of R&D projects.

2.4 Innovation and financial market development

Since Schumpeter (1911), the relationship between the development of the financial sector and economic growth has long been a large topic of study in the literature. The fundamental idea is that the services provided by the financial intermediaries by reallocating capital overcoming moral hazard, adverse selection and transaction costs are a key channel to technological innovation and economic growth. Given that, Levine (2005) defines financial development as the process when financial instruments, markets, and intermediaries alleviate the effects of information asymmetry, execution, and transactions costs by providing improvements in the five substantial financial functions. These are: (i) the acquisition of ex ante information about available investments and allocation of capital, (ii) the supervision of investments and implementation of corporate governance, (iii) the facilitation of exchange of goods and services, (iv) the mobilization and pooling of savings, and (v) the promotion of trading, diversification and management of risk.

Besides the substantial body of theoretical work involving finance and growth, proper empirical studies assessing the impact of financial markets on economic growth perform an important role in promoting policies to foster growth by stimulating the development of the financial sector. Levine (2005) highlights that basically three main conclusion emerge from the existing empirical literature. First, countries with better functioning banks and financial market grow faster. Second, there is no simultaneity bias driving the conclusions. Third, better functioning financial sector ameliorate the external financing constraints that retard industrial expansion, suggesting that this could be a channel through which financial development affects growth.

The first robust empirical work was conducted byKing and Levine (1993), who investigate whether higher levels of financial market development are positively associated with higher rates of economic growth, capital accumulation, and productivity growth. They find a robust relationship between the annual rate of per capita GDP growth and the level of financial development over the 1960-1989 period using four indicators of financial development. First, they measure the financial depth which is defined as the overall size of the financial intermediary system, calculated as the ratio of liquid liabilities to GDP. Also, they measure the level of intermediation conducted by financial institutions which equals the ratio of bank credit divided by bank credit plus central bank domestic assets. And lastly, they use two measures of financial development to capture the domestic assets distributed by the financial system, which are obtained by the credit issued to nonfinancial private firms to total credit and credit issued to nonfinancial private firms to GDP.

Levine (2005) emphasizes that although the indicators used by King and Levine (1993) capture the flow of society's savings and capital allocation, these measures do not entirely represent the five financial functions. They only focus on banks and do not directly measure the level which financial systems reduce information and transaction costs. Empirical proxies for financial development usually do not measure entirely the concepts from theoretical models, therefore authors usually focus on specific functions provided by the financial sector.

A posterior analysis of Rajan and Zingales (1998) investigate the hypothesis that markets with higher dependence on external finance experience relatively higher growth rates in countries with more developed financial sector. Contrasting with prior analysis that focused on cross-country analysis, they study the causality between finance and growth at the industry-level using data of 36 industries across 42 countries. They find that better functioning financial market help to reduce the wedge between the cost of external and internal finance. Therefore, the financial development positively affects industrial growth by the expansion of firms and formation of new ventures. As a proxy to financial development, the authors use the total stock market capitalization to GDP and accounting standards. Although the stock market capitalization does not capture how efficiently the market exchange, the accounting standards, which is an indicator of the quality of the firm's annual financial reports, measure how ease the firms can raise external funds (LEVINE, 2005).

Following Rajan and Zingales (1998), Beck *et al.* (2008) extend the analysis by investigating whether industries from well-developed financial sector that are naturally composed of small firms grow faster by easing constraints. They examine the growth rates of 36 different manufacturing sectors across 44 countries with different levels of financial development. Using a difference-in-differences approach, they show that well-developed financial system disproportionately foster the growth of industries that are mainly formed by small firms for technological innovation reasons. Also, the results show that in countries with better developed financial systems small-firms industries represent a greater part of total manufacturing sector than in economies with lower financial development. These findings are consistent with the idea that small firms face greater difficulty to raise funds than large firms, thus financial development become essential for the growth of small-firms industries.

Love (2003) shows that an improvement in the financial market reduces firm's financing constraints even when controlling for future growth opportunities. The author provides evidence that the financial factors have a greater impact on the intertemporal allocation of capital investment in economies with less developed financial systems. Also, in concordance with Beck *et al.* (2008), Love (2003) provides evidences that small firms are more disadvantaged in lower financial developed countries than are large firms. On other words, an amelioration in the efficiency of financial market facilitates the access to external finance and this improvement accelerate growth.

Although the recent empirical work investigate different mechanisms through which development of financial instruments and markets affect economic growth, there are some channels through which firm growth is affected by access to finance that remain unclear. For example, historians have identified technological advances (broadly defined) and innovation as one essential channel for economic growth (SCHUMPETER, 1911; HOLMSTROM, 1989). However, the literature is still deficient in studying how the development of financial markets promotes growth by stimulating innovation. Hsu, Tian and Xu (2014) highlight that rigorous empirical researches that link financial development and technological innovation are scarce.

Based on this idea, Ayyagari, Demirgüç-Kunt and Maksimovic (2011) examine the firm level data for over 19000 firms in 47 developing countries to study how innovation in developing economies is affected by firm's access to external finance. Broadly defining innovation as a firm's adoption of new technology and introduction of new products, they provide evidence that firm's access to external financing is crucial for the extent of innovation that the firm undertakes. Also, the results suggest that, in developing economies, the access to finance and, in particular, foreign financing, is directly associated with higher rates of innovative activities.

Using a different strategy, Hsu, Tian and Xu (2014) study how financial development promotes growth by contrasting the impact of equity market and credit market on technological innovation. The basic argument is that equity market and credit market could have different roles in determining the cost of external finance. Using a sample of 32 countries, they find that equity markets have a positive effect on innovation in firms that are more dependent on external finance. Equity markets encourage investors to finance projects with higher risk - but also with higher returns - like innovative projects. In contrast, credit markets are less able to overcome information asymmetry and agency problems. Therefore, the development of credit markets is more likely to impede innovation in industries that are more dependent on external finance. Banks usually avoid risky activities and failure, leading firms to under-invest in R&D projects with high uncertainty.

2.5 Financial Constraints and Innovative efficiency

As noted, an increasing number of studies have striven to understand the effect of financing constraints and financial development on R&D and innovation. Although some of the results show a few controversial conclusions, there are strong evidences that the high cost of capital to finance R&D decreases the possibility of external financing for projects with positive expected net present value, specially for more constrained firms.

As consequence, by reducing R&D investment, financial constraints could be expected to decrease firm's innovative activity. However, a few studies have questioned the real impact of financial constraints on innovative efficiency, by suggesting a possible positive effect of financial constraints on the selection of more assertive innovative projects, and consequently, on the increase of the production of patents per level of R&D invested.

We define innovative efficiency as the firm's capacity of generating patents and/or citations per dollar of R&D spent (HOLLANDERS; ESSER, 2007; ALMEIDA; HSU; LI, 2013; HIRSHLEIFER; HSU; LI, 2013). R&D spending is an important measure of financial resources to innovation and it is commonly used as a proxy for innovation input. On the other hand, patents and citations are a common measure of innovation output because new products, services or processes are usually introduced to the market as approved patents (GRILICHES, 1990).

For an invention to become a patent, it must be new, industrially valuable and involve an original feature. These requirements and the fact that the applications need to be accepted by the patent office through a certification process indicated that possessing a patent is the result of R&D investment, hence signaling the firm's general R&D success. Therefore, according to Hottenrott, Hall and Czarnitzki (2016), patents give information about the firms' ability to create valuable research as patents measure the outcome of R&D and thus 'advertise' the firms' innovative performance.

By investigating the role of patenting activity on financial constraints, Hottenrott, Hall and Czarnitzki (2016) show that patenting activity facilitates the access of small firms to external finance when compared to non-patenting firms. Therefore, these firms rely less on internal funds to promote their R&D investments.

Following this idea, Katila and Shane (2005) examine a model of environmental conditions to explore whether lack of resources promotes or constraints innovation. They find that new firms were notably more innovative than established firms in highly competitive and small markets. Another study of Hoegl, Gibbert and Mazursky (2008) propose that financial constraints act as a stimulus, rather than an inhibitor of innovation teams' performance by leveraging creativity, engagement, cohesion and team potency.

A later work of Almeida, Hsu and Li (2013) investigate whether firms that are more likely to be constrained are associated with higher rates of innovative efficiency. By proposing an econometric model, they find that more constrained firms have more granted patents and citation per dollar of R&D. This relationship is stronger among firms with large cash holdings and low investment opportunities.

Merz (2021) study a contest model to investigate whether more financially constrained firms have higher ability of transforming investment in R&D into new technologies. Interestingly, he finds that for several scenarios, small firms have a higher or at least the same innovative efficiency level of large firms.

A recent study of Zhang, Chen and Zhang (2022) provide evidence supporting the view that financial constraints is positively related to innovative efficiency. By using the break of rigid payment in the Chinese bond market as a proxy to financial constraints, they show that as higher the abundance of researches and R&D investment lower is the innovation output, specially in cases when agency problem is severer.

2.6 Innovative Efficiency and R&D Tax Incentive

Extending the analysis of how the availability of internal funds affects the investment in innovation and its role on innovative efficiency, there are a few studies that also explore the effect of R&D tax credits on innovation.

The principal instrument of government support to R&D are direct grands and tax credits. The main difference regarding these two types of subsidies is that tax incentive programs may minimize the discretionary decisions of project selection in government grants. The question of whether R&D tax incentives is an effective government intervention to correct the insufficient supply of R&D has been already investigated by the literature.

Hall and Reenen (2000) argue that R&D tax incentives may reduce the marginal cost of R&D investment. This reduction of cost to finance R&D may shift firms' allocation of capital for innovation projects. However, this could motivate firms from investing in R&D more than the necessary, so firms may invest in innovation projects that have lower marginal rate of return. Therefore, this argument raises the doubt of whether firms that use tax R&D credits have a superior innovative performance.

Czarnitzki, Hanel and Rosa (2011) surveys the effect of R&D tax incentive on innovation activities of Canadian firms. By employing a non-parametric apporach, the authors find that tax credit for R&D actually increases innovation output of firms. However, their analysis did not take into account the amount of investment in R&D, which limited the investigation of whether the tax credits have an positive or negative effect on the firm's innovative efficiency.

Besides tax credits being a costly way of public support to R&D, there are theoretical arguments to support the view that they do not appear to be the most efficient instrument to be used as a correction of the 'market imperfections' that causes the under investment in R&D.

3 DATA AND METHODS

The objective of this chapter is to present a brief description of the databases used in this study, and to explore the methodologies that we employ in the estimation of the econometric models. We divide this chapter in two main sections to present our data and estimation methodologies. Both strategies proposed in this work represent new approaches in the study of the determinants of R&D investment and innovative efficiency.

Section 3.1 explains the data, empirical model and the methodology estimation using the structural equation model. Section 3.2 explains the data, empirical model and the methodology estimation using the mixed-effects zero-inflated-Poisson model.

3.1 The structutal equation model

3.1.1 Data

We get yearly financial data of 11.897 listed firms in 61 countries over the period 2010 - 2017 from Compustat Global Database. The country-level associated with the measure of financial development were obtained from the Global Financial Development Database (provided by The World Bank Group) of Cihäk *et al.* (2012), Beck, Levine and Demirgüç-Kunt (2000), updated in May, 2017. The description of the variables are in Appendix B.

Given that R&D expenditure has changed over time and due to different accounting standards across countries, attention must be taken in sample selection to ensure consistency in the interpretation of the R&D data. Our sample therefore focus only on firms that report at least one year positive R&D expenditure, and excludes any firm that does not have any R&D spending during the sample period. Additionally, we select only firms with a primary SIC code (SIC 2000 - 3999) because innovation is more crucial and valuable to manufacturing industries than other industries (BROWN; MARTINSSON; PETERSEN, 2012).

Since one of the focus of this study is to understand the effects of financial development in innovation investment, we employ two measures of the financial system, as suggested by Hsu, Tian and Xu (2014). To study how equity market and credit market development differently affect the firm's R&D investment decision, we use two proxies. The proxy for equity market - called stock market - is calculated as the ratio of a county's stock market capitalization over its GDP. Stock market capitalization is defined as the product of the sum of share price times the number of shares of each listed stock. The proxy for credit market is calculated as the ratio of a country's domestic credit provided by the banking sector over its GDP. Domestic credit provided by the banking sector is defined as all credit to several sectors - excluding central government - provided by monetary authorities, deposit money banks, and other banking institutions (HSU; TIAN; XU, 2014).

3.1.2 Empirical model

Following Brown, Martinsson and Petersen (2012) and Hsu, Tian and Xu (2014), we propose an extension of the traditional investment model, by adding credit and stock market development. These two variables measures country's overall financial development system. The general model to be estimated is:

$$
\begin{aligned}
R\&D_{ijt} = \beta_1 R\&D_{ijt-1} + \beta_2 Cash\_flow_{ijt} + \beta_3 Sales_{ijt} + \\
+ \beta_4 \Delta CashHoldings_{ijt} + \beta_5 Debt_{ijt} + \beta_6 Log(Total\_assets)_{ijt} \\
+ \beta_7 Credit\_market_{jt} + \beta_8 Stock\_market_{jt} + \alpha_i + \epsilon_{ijt}
\end{aligned} \tag{3.1}
$$

where i is the firm, j is the country and t is the year. $R\&D$ denotes R&D expenses scaled by the beginning-of-period of firm's total assets; $Cash\_flow$ represents the cash flow divided by the beginning-of-period of firm's total assets; $Sales$ is defined as the sales growth rate; $\Delta CashHoldings$ is the change in cash holdings, calculated as the change in cash reserves scaled by the beginning-of-period of firm's total assets; $Debt$ indicates the company's long term debt divided by the beginning-of-period of firm's total assets; $Credit\_market$ is the the ratio of a country's domestic credit provided by the banking sector over its GDP; and $Stock\_Market$ is measured by the ratio of a county's stock market capitalization over its GDP. The model also includes a firm fixed effect (α_i) and the error term (ϵ_{ijt}). To consider the effects of financial development and liquidity management on R&D investment, we employ versions of the model (1) by introducing interactions among the variables credit market and stock market with cash flow and change in cash holdings.

In order to compare the determinants of R&D investment between emerging and developed economies, we classify the data in emerging and developed countries according to the International Monetary Fund (2017). Further, to study the effects of financial constrains on R&D expenses, we group the sample considering firm size and age which are a common criteria used in the literature to classify groups of constrained and unconstrained firms (FAZZARI; HUBBARD; PETERSEN, 1988; BROWN; MARTINSSON; PETERSEN, 2012; GORODNICHENKO; SCHNITZER, 2013).

Regarding the construction of the groups of financially constrained (small and young) and unconstrained (large and mature) firms, we first aggregate the sample by emerging and developed countries. Then, we divide the firms into quintiles and sort them in ascending order considering the value of total assets. The firms located in the first two quintiles were classified as being small and the firms located in the last two quintiles were classified as being large. To the age classification, we use the year of first Compustat reports. Firms are classified as young if the first year is after 2000.

The literature has questioned if the cash flow sensitivity to investment is a effective indication of overall financial constraints (KAPLAN; ZINGALES, 1997), so we also use the relationship between R&D and change in cash holdings to control and test the effect of financial constraints on R&D. This strategy is suggested by Brown, Martinsson and Petersen (2012), who argue that the variation of cash holdings should have a negative relation to R&D, as reduction in cash holdings free liquidity for R&D investment specially in firms facing financial constraints. Also, controlling for the R&D smoothing with cash holdings should increase the effect of other financial variables. Therefore, the connection between R&D and cash holding should be present most likely for firms that face financial frictions.

3.1.3 Estimation methodology

We estimate the model presented in Equation 3.1 by applying the Structural Equation Model via Maximum Likelihood (ML-SEM) methodology. The ML-SEM approach allow us to address the endogeneity of the lagged variable and the potential endogeneity of financial variables. Although the literature has intensively treated this problem by using the System Generalized Method of Moments (GMM-system), developed by Arellano and Bond (1991) and Blundell and Bond (1998), recent studies with Monte Carlo simulation have shown that the ML-SEM method is more efficient and less biased than the GMM approach under several conditions (Allison, Williams and Moral-Benito (2017); Bun and Sarafidis (2013); Bazzi and Clemens (2013); Bollen and Brand (2010)).

Even yielding to consistent estimators and relying on minimal assumptions, the GMM-system estimators are not fully efficient, given that all moment restrictions are not employed by the estimator. Another problem of the GMM-system refers to the uncertainty about the choice of instruments. There are many possible combination of instruments - which can be used in level, as differences or both - that can be employed. The extension of the numbers of instruments can diverge from the optimal set, which makes the method inconsistent (ROODMAN, 2006). As point out by Bazzi and Clemens (2013), the concern about the number of instruments has intensified in recent years with the GMM method for dynamic panel.

Besides, the assumption about the stationarity of the initial values of the data generating process (DGP) has shown to be unrealistic and controversial in many empirical works (ROODMAN, 2006; ALLISON; WILLIAMS; MORAL-BENITO, 2017). This assumption relies on the hypothesis that the variables of the database come from dynamic systems that began in the past and have already reached the equilibrium in a state distribution. This is hard to assume in panels with young firms or country panels.

To overcome the problems in the GMM approach, studies has suggested the use of Structural Equation Model via Maximum Likelihood (ALLISON; WILLIAMS; MORAL-BENITO, 2017; BUN; SARAFIDIS, 2013; BAZZI; CLEMENS, 2013; BOLLEN; BRAND, 2010). In this approach the model of the dynamic panel data can be represented as a special case of the Structural Equation Modeling.

We consider the following model:

$$y_{it} = y_{it-1}\lambda + x'_{it}\beta + \alpha_i + \epsilon_{it} + \xi_t \qquad i = 1,...,N,\ t = 1,...,T \tag{3.2}$$

$$E(\epsilon_{it}|y_i^{t-1}, x_i^t, \alpha_i) = 0 \qquad \forall i, t \tag{3.3}$$

where y_{it} is a response variable and x_{it} is a vector of time-varying covariates for individual i at time t. β is the vector of intercepts for the exogenous/predetermined covariates. α_i is the unobservable time-invariant fixed effect and ϵ_{it} is the time-varying error term. x_i^t and y_i^{t-1} denotes the vectors of the observations accumulated up to t and $t-1$, respectively. This condition implies that the error term of time t is uncorrelated with variable x for all lagged t's.

Besides the condition in Equation 3.3, ML-SEM requires more two fundamental assumptions. First, all the endogenous and exogenous variables are assumed to have a multivariate normal distribution. [1] Second, the correlation between α_i and the time-invariant variables are constrained to zero. Third, ML-SEM assumes that there is no serial correlation in the error term.

To further analyse the model in Equation 3.3, we define the following vector of observed data ($\mathbf{R}_i$) and disturbances ($\mathbf{U}_i$) as

$$\mathbf{R}_i = (y_{i1}, ..., y_{iT}, x_{i1}, ..., x_{iT})' \tag{3.4}$$

$$\mathbf{U}_i = (\alpha_i, \epsilon_{i1}, ..., \epsilon_{iT}, \xi_1, ...\xi_T) \tag{3.5}$$

Given the condition imposed by Equation 3.3, the covariance matrix of the disturbances becomes:

$$Var(\mathbf{U}_i) = \Sigma = \begin{pmatrix} \sigma^2_\alpha & & & & & & & \\ 0 & \sigma^2_{\epsilon_1} & & & & & & \\ \vdots & \vdots & \ddots & & & & & \\ 0 & 0 & \dots & \sigma^2_{\epsilon_T} & & & & \\ \phi_0 & 0 & \dots & 0 & \sigma^2_{\epsilon_0} & & & \\ \phi_1 & 0 & \dots & 0 & \omega_{01} & \sigma^2_{\xi_1} & & \\ \phi_2 & \psi_{21} & \dots & 0 & \omega_{02} & \omega_{12} & \sigma^2_{\xi_2} & \\ \vdots & \vdots & & \vdots & \vdots & \vdots & \ddots & \\ \phi_T & \phi_{T1} & \phi_{T2} & \dots & \omega_{0T} & \omega_{1T} & \dots & \sigma^2_{\xi_T} \end{pmatrix} \tag{3.6}$$

where ϕ parameters captures the correlation between the fixed effects and the regressors, and

$$cov(\epsilon_{ih}, \xi_{it}) = \begin{cases} \psi_{th} & \text{if } h < t \\ 0 & \text{otherwis} \end{cases} \tag{3.7}$$

[1] Moral-Benito (2013) shows that ML-SEM produces consistent estimators even when violating the normality assumption.

Next, we define the matrices of coefficients as follows:

$$\mathbf{B} = \begin{pmatrix} 1 & 0 & 0 & \dots & 0 & -\lambda & -\beta & 0 & \dots & 0 \\ -\lambda & 1 & 0 & \dots & 0 & 0 & 0 & -\beta & \dots & 0 \\ 0 & -\lambda & 1 & \dots & 0 & 0 & \vdots & & \ddots & \\ \vdots & & & \ddots & & \vdots & & & & \\ 0 & \dots & & -\lambda & 1 & 0 & 0 & \dots & 0 & -\beta \\ 0 & & \dots & & 0 & & & & & \\ \vdots & & \ddots & & \vdots & & & I_{T+1} & & \\ 0 & & \dots & & 0 & & & & & \end{pmatrix} \tag{3.8}$$

$$\mathbf{D} = \begin{pmatrix} d & I_{2T+1} \end{pmatrix} \tag{3.9}$$

where. $d = (1, ..., 1, 0, ..., 0)'$ is a column vector with T ones and $T + 1$ zeros.

Now, we rewrite Equation 3.2 in matrix form:

$$\mathbf{BR}_i = \mathbf{DU}_i \tag{3.10}$$

By assuming normality of $\mathbf{U}_i$, its joint distribution is:

$$\mathbf{R}_i \sim N(0, \mathbf{B}^{-1}\mathbf{D}\Sigma\mathbf{D}'\mathbf{B}'^{-1}) \tag{3.11}$$

Therefore, the resulting log-likelihood is:

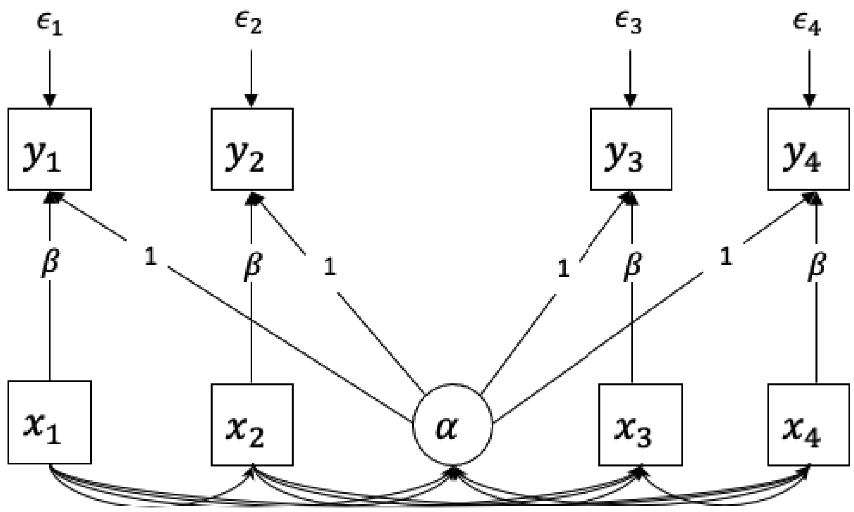
$$L \propto -\frac{N}{2}\log\det(\mathbf{B}^{-1}\mathbf{D}\Sigma\mathbf{D}'\mathbf{B}'^{-1}) - \frac{1}{2}\sum_{i=1}^{N}\mathbf{R}_i'(\mathbf{B}^{-1}\mathbf{D}\Sigma\mathbf{D}'\mathbf{B}'^{-1})^{-1}\mathbf{R}_i \tag{3.12}$$

As pointed out by Allison, Williams and Moral-Benito (2017), the maximizer of L is asymptotically equivalent to Arellano and Bond (1991) GMM estimator regardless of non-normality assumption.

Figure 1 shows a path diagram for the simplified version of the model in Equation 3.1 for the case where $T = 4$. As we see, all explanatory variables can be allowed to be correlated in all time points, and they can also be correlated to the latent variable that represents the fixed effects. Besides,the coefficient β is fixed for all time points.

Allison, Williams and Moral-Benito (2017) and Moral-Benito (2013) also highlight that among the advantages of ML-SEM approach over GMM is that there is no "incidental parameter", and initial conditions are considered as completely exogenous; no difficulties arise when the lagged dependent variable is at or near 1; missing data can be easily handled by full-information maximum likelihood (FIML); and ML-SEM also allow to estimate parameters of time-invariant predictors.

Figure 1 – Path Diagram



Simplified path diagram for a dynamic SEM model with fixed effects for t = 4.

Following Allison, Williams and Moral-Benito (2017), we implement the ML-SEM using the *Lavaan* package for R.[2] We assume all firm-level variables as predetermined and allow them to freely correlate with each other. The estimates parameters are constrained to be the same at all time points, and the latent variable α_i is allowed to correlate with all the predetermined variables. The code used to do the estimation is in Appendix B.

3.2 The mixed-effects zero-inflated-Poisson model

3.2.1 Data

We construct our database by collecting financial indicators and patent-related data of publicly traded firms around the world from ORBIS[3]. We get a databse of 3482 observations from 16 countries over the period 2010 - 2018. We select only manufacturing firms (SIC code 2000 - 3999) that report at least one year positive R&D expenditure and had at least one patent granted during the sample period.

Our main proxy for innovative efficiency is patents scaled by R&D expenses. Where patents are the firm total number of patents granted and R&D is measured as the firm' R&D expenses.

Similar to our analysis of financial constraints and R&D investment, We use two measures of financial constraints: firm age (number of years since the first IPO) and firm size (logarithm

2 Although the package is a beta version, we perform robustness tests comparing the results of *Lavaan* and *SAS*, which is a more estable software for structural equation model estimations.

3 Orbis is Bureau van Dijk's flagship company database that contains information on 300 million companies across the world and focuses on private company information.

of total assets). Hadlock and Pierce (2010) emphasize that firm size and age are closely linked to the level of financial constraints, and these variables have the advantage of being much less endogenous than other firm characteristics.

Besides the financial constraints variables, we also include long term debt and cash flow to capture the effect of firm's capital structure and availability of internal resources on R&D and patenting activities, Tobins'Q to control the effect of growth opportunities and to capture agency problems (GUGLER; MUELLER; YURTOGLU, 2004), and cash holdings also as a indirect measure of agency issues (ALMEIDA; HSU; LI, 2013).

3.2.2 Estimation Methodology

As already presented in the previous sections, we define innovative efficiency as the number of patents granted per dollar of R&D invested. Since the counting nature of the patent variable, a traditional linear regression model may results in biased parameter estimates and misleading inferences. Moreover, there is a preponderance of zeros in the data, which needs to be considered in the model. Because we are interested in studying the innovative efficiency at a firm and country level over the years, we also need to handle the inherent heterogeneity between countries.

To address all these peculiarities of our data, we implement a mixed-effects zero-inflated-Poisson model. The usual approach to deal with counting data with excess of zeros is the zero-inflated-Poisson (ZIP) regression model. The ZIP model is a mixture of Poisson distribution and a degenerate component of point mass at zero, leading to an increase in the probability mass at zero. When the data are clustered within units, multilevel approaches are required as well.

3.2.2.1 Mixed-Effects zero-inflated-Poisson Model

Following Donald and D. (2006), consider the dependent variable y_{ij} and $\mathbf{x_{ij}} = (1, x_{ij}, ..., x_{ij})'$ and $\boldsymbol{\omega_{ij}} = (1, \omega_{ij,q}, ..., \omega_{ij,p})'$ the $(p+1) \times 1$ and $(s+1)$ covariate vectors for the Poisson and logistic (ZIP) parts, respectively. There are $i = 1, ..., N$ subjects and $j = 1, ..., n_i$ repeated observations for each subject i. Then, the total number of observations is $n = \sum_{i=1}^{N} n_i$. Denote $\boldsymbol{\beta} = (\beta_0, \beta_1, ..., \beta_p)'$ and $\boldsymbol{\gamma} = (\gamma_0, \gamma_1, ..., \gamma_s)'$ as the Poisson and logistic regression parameter vectors associated with covariates $\mathbf{x_{ij}}$ and $\boldsymbol{\omega_{ij}}$. Also, assume that the normality of random effects $\upsilon_i \sim N(0, \sigma^2)$ and $\nu_i \sim N(0, \sigma_2^2)$. Thus, the model is defined as follows:

$$\Pr(y_{ij}) = \mathrm{p}(y_{ij}) = (1 - \pi_{ij}) f(y_{ij}) + \mathbf{I}(y_{ij}) \pi_{ij} \tag{3.13}$$

where

$$f(y_{ij}) = \frac{\exp(-\lambda_{ij}) \lambda_{ij}^{y_{ij}}}{y_{ij}!} \tag{3.14}$$

with

$$logit(\pi_{ij}) = \boldsymbol{\omega_{ij}}'\gamma + \nu_i \\ = \boldsymbol{\omega_{ij}}'\gamma + \sigma_2\theta_{2,i} \tag{3.15}$$

and

$$log(\lambda_{ij}) = \mathbf{x'_{ij}}'\gamma + \nu_i \\ = \mathbf{x'_{ij}}'\gamma + \sigma_1\theta_{1,i} \tag{3.16}$$

where $\mathbf{I}(y_{ij})$ is an indicator functions that takes value of 1 if the observed response is 0 and a value of 0 if the observed response is positive.

In this mixed-effect ZIP model, $\boldsymbol{\beta}$ captures the change in the conditional log of the mean response variable with the covariates $\mathbf{x_{ij}}$ for subject i described by υ_i. Similarly, $\boldsymbol{\gamma}$ measures the change in the conditional logit of the probability of response with the covariates $\boldsymbol{\omega_{ij}}$ for subject i described by ν_i. The components σ_1 and σ_2 represent the variation parameters for the Poisson and logistic components, respectively.

By rewriting the model as functions of $\mathbf{x_{ij}}$ and $\boldsymbol{\omega_{ij}}$, we get

$$\pi_{ij} = \frac{\exp(\boldsymbol{\omega_{ij}}'\boldsymbol{\gamma} + \sigma_2\theta_{2,i})}{1 + \exp(\boldsymbol{\omega_{ij}}'\boldsymbol{\gamma} + \sigma_2\theta_{2,i})} \tag{3.17}$$

and

$$\lambda_{ij} = \exp(\mathbf{x'_{ij}}'\gamma + \sigma_1\theta_{1,i}) \tag{3.18}$$

The log-likelihood can be expressed as

$$\log l(\mathbf{y_i}|\theta) = \sum_{j=1}^{n_i} \log[(1 - \pi_{ij})f(y_{ij} + \mathbf{I}(y_{ij})\pi_{ij}] \tag{3.19}$$

3.2.3 Empirical Model

The model presented by Equations 3.17 and 3.18 is ideal for considering the dependent variable as the patent counting. However, we are interested in how many patents a firms generates per million dollar of R&D spent. So, we need to consider the variable scaled by R&D expenses. To do that, we use an offset term that will take into account this rate.

The transformation that we need to make to use the offset term is to consider it as a known parameter in the model, as follows:

$$\log(\lambda_{ij}) = \mathbf{x'_{ij}}'\gamma + \sigma_1\theta_{1,i} + \log(\Gamma_{ij}) \tag{3.20}$$

Then,

$$\frac{\lambda_{ij}}{\Gamma_{ij}} = \exp(\mathbf{x'_{ij}}'\gamma + \sigma_1\theta_{1,i}) \tag{3.21}$$

So, the basic model that we estimate is

$$\begin{aligned}\frac{\lambda_{it}}{\Gamma_{it}} = \frac{Patents_{it}}{R\&D_{it}} &= \text{exp}(\beta_0 + \beta_1 CF_{it-1} + \beta_2 DE_{it-1} + \beta_3 Q_{it-1} + \beta_4 CH_{it-1} \\ &\quad + \beta_5 Size_{it-1} + \beta_6 Age_{it-1} + \nu_i)\end{aligned} \tag{3.22}$$

where $Patents_{it}$ is the number of patents granted by firm i during year t. $R\&D$ is the firms R&D expenses (per million of dollars); CF is the firm's cash flow scaled by firm's total assets; DE represents the firm's long term debt scaled by firm's total assets; Q is the firm's Tobins' Q; CH is the firms cash holdings; $Size$ is the firm's size, measured by the natural logarithm of total assets; Age is the number of years since the first IPO; and ν is the Country random effect.

Also, we estimate a second model including R&D tax credits in the model:

$$\begin{aligned}\frac{\lambda_{it}}{\Gamma_{it}} = \frac{Patents_{it}}{R\&D_{it}} &= \text{exp}(\beta_0 + \beta_1 CF_{it-1} + \beta_2 DE_{it-1} + \beta_3 Q_{it-1} + \beta_4 CH_{it-1} \\ &\quad + \beta_5 Size_{it-1} + \beta_6 Age_{it-1} + \beta_7 R\&D\ Tax_{it-1} + \nu_i)\end{aligned} \tag{3.23}$$

where $R\&D\ Tax$ is the firm's country R&D tax incentive.

We estimate Model in Equation 3.22 and 3.23 using the Generalized Linear Mixed Models using Template Model Builder (glmmTMB) Package for R. 'glmmTMB' fit generalized linear mixed models with various extensions, including zero-inflation. The models are fitted using maximum likelihood estimation via 'TMB' (Template Model Builder). Random effects are assumed to be Gaussian on the scale of the linear predictor and are integrated out using the Laplace approximation. Gradients are calculated using automatic differentiation.

4 EMPIRICAL ANALYSIS AND RESULTS

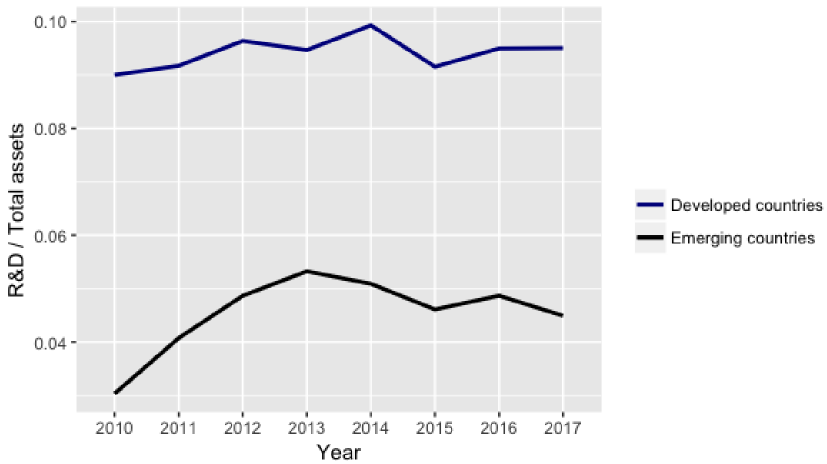
This chapter aims to present an explanatory analysis of the datasets and the main estimation results from the investigation of the factors that affect the financing of R&D projects and innovative performance. The chapter is divided in two sections.

The first section (4.1) explores the data and estimations results related to our investigation of the relation between financial constraints, financial development and R&D investment. The second section (4.2) presents the database and the estimations results of our analysis of the effect of financial constraints and R&D tax credits on innovative efficiency.

4.1 Estimation results using ML-SEM approach

Regarding the analysis and interpretation of the raw data, this section introduces an explanatory analysis of the sample. Table 1 shows the mean and the standard deviation of the firms' financial indicators as well as the macroeconomic variables. The firms are grouped by developed and emerging countries and classified by age and firm size.

Figure 2 – Firm's average R&D expenses per year



The substantial difference of the investment on R&D between emerging and developed countries is clear. Figure 2 highlights this difference and suggest how innovation can be a critical point especially for emerging economies. The mean of R&D expenses for firms located in developed countries is more than twice higher than the mean for firms in emerging countries, even for firms considered as less constrained. This difference may indicate that firms in emerging economies may be struggling to channel resources to R&D activities.

Table 1 – Summary Statistics

	Emerging									
	All		Young		Mature		Small		Large	
	Mean	Stand. Dev	Mean	Stand. Dev.	Mean	Stand. Dev.	Mean	Stand. Dev.	Mean	Stand. Dev.
$R\&D$	0.043	0.088	0.038	0.076	0.046	0.094	0.028	0.064	0.060	0.108
$Cash\_flow$	0.340	0.543	0.281	0.473	0.379	0.582	0.223	0.422	0.477	0.641
$Sales\ growth$	3.697	7.717	2.660	6.592	4.469	8.397	2.019	6.089	5.680	9.091
$\Delta CashHoldings$	0.029	0.115	0.028	0.109	0.029	0.117	0.024	0.099	0.036	0.129
$Debt$	0.315	0.599	0.236	0.519	0.377	0.64	0.193	0.472	0.463	0.705
$Credit\_market$	1.025	0.436	1.194	0.363	0.888	0.440	1.043	0.419	0.960	0.455
$Stock\_market$	0.636	0.322	0.594	0.271	0.676	0.326	0.638	0.356	0.640	0.307
$Log(Total\_assets)$	7.754	1.761	7.356	1.618	8.062	1.788	6.546	1.369	8.864	1.650
$Firms$	4641		1940		1790		1783		1756	

	Developed									
	All		Young		Mature		Small		Large	
	Mean	Stand. Dev	Mean	Stand. Dev.	Mean	Stand. Dev.	Mean	Stand. Dev.	Mean	Stand. Dev.
$R\&D$	0.095	0.137	0.082	0.123	0.132	0.159	0.098	0.139	0.093	0.136
$Cash\_flow$	0.382	0.614	0.293	0.517	0.599	0.754	0.333	0.577	0.425	0.640
$Sales\ growth$	5.006	9.278	3.976	8.350	7.615	10.808	4.648	9.232	5.188	9.199
$\Delta CashHoldings$	0.030	0.124	0.028	0.120	0.037	0.139	0.029	0.126	0.029	0.120
$Debt$	0.369	0.655	0.276	0.552	0.606	0.812	0.325	0.615	0.401	0.677
$Credit\_market$	1.394	0.342	1.368	0.314	1.287	0.403	1.206	0.399	1.506	0.200
$Stock\_market$	1.475	2.416	1.426	2.301	1.718	2.850	1.673	2.788	1.074	1.472
$Log(Total\_assets)$	8.454	2.758	7.356	1.618	8.062	1.788	6.546	1.369	8.864	1.650
$Firms$	4492		1728		1850		1263		3879	

Table 1 reports the mean and the standard deviation of variables for firms in emerging and developed countries, and also by firm size and age subsamples. The sample is constructed from Compustat Global Database covering the period 2010-–2017. The sample consists only of listed firms from 61 countries.

Young and small companies are expected to be more innovative to be able to compete with well established firms (HOLMSTROM, 1989). However, when focusing at the groups, small and young firms from emerging countries invest less on R&D than large and mature firms. Almeida, Hsu and Li (2013) show that more constrained firms face a high cost of capital and scarce availability of resources to finance innovation projects, so they invest only on their most promising R&D projects, which results in lower R&D spending but higher average innovation efficiency (See Section 4.2).

By comparing the mean of stock market capitalization and the mean of credit to private sector, Table 1 shows that firms in developed economies have a higher access to external finance. The mean of credit market for developed countries is 1.394 while for emerging countries 1.025, and the mean of stock market is 1.475 and 0.636 for developed and emerging economies, respectively. This difference is consistent with the view that firms in emerging countries rely more on the credit market to finance their investments than equity market because emerging economies are mostly “bank based" while developed economies are mostly “market based". Therefore, comparing emerging and developed countries is also a way to test the impact of different financial systems on R&D.

As expected, young firms are smaller than mature firms. Small and young firms have average cash flow and debt levels lower than large and mature firms, suggesting that these firms may have limited capital to finance their own investments. The change of cash holdings proposed by Brown, Martinsson and Petersen (2012) to test whether firms may draw on cash reserves to alleviate macroeconomic shocks is very similar for firms in emerging and developed countries. The market opportunities measured by the sales growth show that on average large and mature firms are experiencing good market opportunities and growing faster than young and small firms.

In order to analyze the effects of financial indicators and financial development on R&D investment decisions, we start by regressing several versions of the model expressed by Equation 3.1 using the ML-SEM approach. First, we estimate using only the firm-level variables and test the effect of adding $\Delta CashHoldings$ and cash flow (columns (1) - (3)). Then, we add the financial development variables (column (4)) and interaction terms between cash flow and credit market (column (5)); cash flow and stock market (column (6)); $\Delta CashHoldings$ and credit market (column (7)) and $\Delta CashHoldings$ and stock market (column (8)). The results are shown in Table 2. Also, we perform some robustness check that are presented in Appedix A.

Columns (1)-(3) of Table 2 shows that omitting either cash flow or $\Delta CashHoldings$ declines the model fit indicators, especially when omits $\Delta CashHoldings$. As expected, excluding cash flow enhances the parameter of sales growth, debt and $\Delta CashHoldings$ because they capture the information about investment resources and opportunities. As point out by Brown, Martinsson and Petersen (2012), controlling for liquidity management can be crucial for studying R&D investment.

By looking at $\Delta CashHoldings$, we get information about the firm’s efforts to smooth

R&D investment from transitory financial shocks. Although Brown, Martinsson and Petersen (2012) find a negative and significant relationship between $\Delta CashHoldings$ and R&D investment for four European countries with well-developed stock and credit markets, they find no strong evidence that firms use liquidity stocks available to soften R&D investment for the rest of Europe (remaining 12 countries). In our regressions, we find a positive and significant parameter for firms in both emerging and developed economies.

Releasing liquidity for R&D investment imply in a negative change of cash reserves, because decreases in cash holdings are used to smooth capital cost adjustment for more innovative firms. However, during periods of lower investment opportunities, weak demand or high uncertainty, firms can act by rebuilding or recomposing depressed cash holdings from previous periods. Therefore, firms may increase cash reserves as a precautionary measure.

Table 2 also shows that the effects of cash flow on R&D investment decisions are positive and statistically significant. Consistent with Gorodnichenko and Schnitzer (2013) and Hall (2002), this result highlights that firms rely intensively on cash flow to finance their innovative activities. We can see this clearly by looking at the interaction term between credit provided by the banking sector and cash flow. It indicates that increases in the credit market development enhance the dependence of internal resources for financing R&D.

The existence of either asymmetric information, principal-agent conflict, or lack of collateral is greater for R&D investment. Therefore, there is a reduction on the likelihood of external finance because new debt will be relatively more expensive for financing R&D than for financing fixed investment (HALL, 2002; BROWN; MARTINSSON; PETERSEN, 2012; BROWN; FAZZARI; PETERSEN, 2009). Thus, firms may prefer to exhaust internal available resources to finance their R&D activities. However, when cash flow is fully exploited and debt is not a feasible option, firms may turn to new equity finance (BROWN; FAZZARI; PETERSEN, 2009).

When analyzing the separate effects of credit market and stock market development on R&D expenses, it is possible to study the impact of overall financial market development (HSU; TIAN; XU, 2014). Table 2 shows that credit market and stock market play different roles for financing R&D in emerging and developed economies. Considering that emerging economies are mostly “bank based" and developed economies “market based", when comparing these two groups of countries, we are also comparing two different financial system.

Table 2 – Regression results for firms in emerging and developed countries

	Emerging								Developed							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$R\&D_{t-1}$	0.06***	0.06***	0.08***	0.06***	0.06***	0.06***	0.07***	0.06***	0.05***	0.04***	0.07***	0.04***	0.04***	0.04***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Cash\_flow$	0.45***	0.46***		0.46***	0.20***	0.46***	0.53***	0.46***	0.62***	0.62***		0.49***	0.49***	0.49***	0.49***	0.48***
	(0.01)	(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\Delta CashHoldings$	0.02**		0.06***	0.02**	0.01*	-0.03***	0.02*	0.03***	0.02***		0.06***	0.02**	0.02**	0.02***	0.02**	0.02**
	(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)		(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
$Sales$	0.19***	0.19***	0.48***	0.19***	0.17***	0.19***	0.18***	0.18***	0.19***	0.18***	0.43***	0.19***	0.18***	0.18***	0.19***	0.19***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Log(Total\_assets)$	-0.00	-0.01	0.02**	0.01*	0.00	0.01	0.01	0.01	-0.06***	-0.06***	-0.03***	-0.05***	-0.05***	-0.05***	-0.05***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Debt$	0.05***	0.06***	0.12***	0.06***	0.06***	0.06***	0.06***	0.06***	0.11***	0.11***	0.26***	0.11***	0.11***	0.11***	0.11***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Credit\_market$				0.10***	0.03***	0.10***	0.10***	0.11***				-0.03***	-0.04***	-0.03***	-0.03***	-0.03***
				(0.01)	(0.01)	(0.01)	(0.01)	(0.01)				(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Stock\_market$				-0.03***	-0.03***	-0.03***	-0.01**	-0.03***				-0.00	0.00	-0.00	0.01	-0.00
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)				(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Credit\_market * Cash\_flow$					0.31***								0.07***			
					(0.01)								(0.01)			
$Credit\_market * \Delta CashHoldings$						0.05***								-0.00		
						(0.01)								(0.00)		
$Stock\_market * Cash\_flow$							-0.07***								-0.02*	
							(0.01)								(0.01)	
$Stock\_market * \Delta CashHoldings$								-0.01								-0.00
								(0.01)								(0.01)
CFI	0.99	0.93	0.96	0.97	0.94	0.94	0.95	0.95	0.99	0.93	0.96	0.95	0.92	0.92	0.93	0.93
TLI	0.93	0.72	0.85	0.94	0.87	0.87	0.89	0.89	0.93	0.75	0.85	0.89	0.83	0.83	0.86	0.85
RMSEA	0.04	0.10	0.06	0.06	0.09	0.09	0.08	0.08	0.05	0.10	0.07	0.09	0.11	0.11	0.09	0.09
Number of firms	4641	4641	4641	4435	4435	4435	4435	4435	5571	5571	5571	4492	4492	4492	4492	4492

Table 2 reports the estimations results by ML-SEM method for cross-lagged panel models with fixed effects for emerging and developed countries. Standard errors robust are reported in parenthesis. ***, **, and * denote statistical significance at the 1%,5%, and 10% levels, respectively. Our sample includes industries with two-digit SIC codes between 20 and 39. The sample period is 2010—2017. Regarding the validity of the models, we present the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI) and Root Mean Square Error of Approximation (RMSEA). For the CFI and TLI, a larger value than 0.9, and for the RMSEA, a value between 0.05 and 0.09 indicate a good fit, respectively.

Regardless the fact that external financing may be more expensive than internal finance, there is a positive and significant relationship between R&D and credit market for firms located in emerging countries. This result indicates that credit market is an important source to channel funds to R&D for firms in emerging countries. On the other hand, for firms in developed countries, credit market discourage the investment in R&D. Hsu, Tian and Xu (2014) argue that credit market does not encourage innovation in industries that rely more on external finance because banks usually avoid risky investments, and credit market can be less able to control for information and agency problems in more R&D intensive firms.

The overall results from Table 2 point to an important impact of the availability of internal and external finance. The firm's decision to invest into innovative projects may be very sensitive to cash flow and credit availability. Therefore, to explore the effects of financial constraints, we classify the firms in emerging countries by age and size. Although the literature has questioned if these classification is an effective indication of overall financial constraints (KAPLAN; ZINGALES, 1997), we evaluate the role of liquidity management in R&D, as proposed by Brown, Martinsson and Petersen (2012), to control and test the effect of financial constraints on R&D.

Table 3 and Table 4 presents the parameter estimates considering the young and mature classification for firms in emerging and developed economies, respectively. The pattern of the results is similar to that of Table 2. However, there are some differences. In Table 3 we can see that young firms in emerging countries have a slightly higher R&D-cash flow sensitivity. Also, there is a greater effect when higher level of credit market enhance the dependence of internal resources for both cash flow and $\Delta CashHoldings$ for investment R&D, particularly for young firms. Young firms may have limited access to external finance specially in less developed financial markets, therefore an increase in the development of credit market could release internal funds to finance R&D, since external resources may be more expensive to this kind of investment. We can see that also by looking the debt parameter. There is a reduction in the impact of debt to R&D, supporting the idea that young firms may also experience a high cost of capital to finance their R&D projects. As point out by (BROWN; MARTINSSON; PETERSEN, 2012), this result may be a consequence of the lack of collateral value and asymmetric information problems.

For mature firms in emerging economies, there is a reduction in the dependence of internal resources to finance R&D. Even though there is still a relationship between credit availability and cash flow, this effect is lower than for young firms, and the impact of debt is greater. Coad, Segarra and Teruel (2016) argue that old firms may avoid investment in radical innovation projects and focus on R&D projects that are more incremental and developmental. They exploit their routines and capabilities, lowering the uncertainty surrounding R&D investments and the gap between internal and external finance.

When classifying the firms by age in emerging economies, we do not find a significant parameter between $\Delta CashHoldings$ and R&D investment. For this classification, the change in

Table 3 – Regression results for firms in emerging countries grouped by age

	Emerging									
	Young					Mature				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
$R\&D_{t-1}$	0.05***	0.05***	0.05***	0.05***	0.05***	0.07***	0.07***	0.07***	0.07***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Cash\_flow$	0.53***	0.20***	0.53***	0.63***	0.53***	0.39***	0.21***	0.40***	0.45***	0.40***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$\Delta CashHoldings$	0.01	0.00	-0.06***	0.01	0.00	0.02	0.02	-0.02	0.02	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Sales$	0.16***	0.15***	0.16***	0.15***	0.16***	0.21***	0.19***	0.21***	0.20***	0.20***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
$Log(Total\_assets)$	0.01	0.00	0.01	0.00	0.01	0.00	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Debt$	0.04*	0.04**	0.04*	0.04*	0.04*	0.08***	0.09***	0.09***	0.09***	0.09***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$Credit\_market$	0.08***	0.01	0.08***	0.08***	0.09***	0.10***	0.04***	0.11***	0.10***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Stock\_market$	-0.03***	-0.02**	-0.03***	-0.00	-0.03***	-0.03***	-0.04***	-0.03***	-0.02*	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Credit\_market * Cash\_flow$		0.37***					0.24***			
		(0.02)					(0.02)			
$Credit\_market * \Delta CashHoldings$			0.07***					0.04***		
			(0.01)					(0.01)		
$Stock\_market * Cash\_flow$				-0.11***					-0.05**	
				(0.02)					(0.02)	
$Stock\_market * \Delta CashHoldings$					0.01					-0.02
					(0.01)					(0.01)
CFI	0.97	0.94	0.94	0.95	0.95	0.97	0.94	0.94	0.95	0.95
TLI	0.94	0.86	0.86	0.88	0.88	0.94	0.87	0.88	0.88	0.88
RMSEA	0.06	0.09	0.09	0.08	0.08	0.06	0.09	0.09	0.08	0.08
Number of firms	1940	1940	1940	1940	1940	1790	1790	1790	1790	1790

Table 3 reports the estimations results by ML-SEM method for cross-lagged panel models with fixed effects for firms in emerging economies classified by age. Standard errors robust are reported in parenthesis. ***, **, and * denote statistical significance at the 1%,5%, and 10% levels, respectively. Our sample includes industries with two-digit SIC codes between 20 and 39. The sample period is 2010—2017. Regarding the validity of the models, we present the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI) and Root Mean Square Error of Approximation (RMSEA). For the CFI and TLI, a larger value than 0.9, and for the RMSEA, a value between 0.05 and 0.09 indicate a good fit, respectively.

cash reserves seems to not be capturing financial constraints, as proposed by Brown, Martinsson and Petersen (2012). On the other hand, in Table 4 $\Delta CashHoldings$ is positive and significative for young firms in developed economies, suggesting that these firms may be building stock of cash reserves.

Contrasting with emerging economies, for young firms the R&D-cash flow sensitivity is lower and the debt parameter is greater, which makes it difficult to identify the presence of a financial gap for young firms in developed economies. The results in Table 4 also suggest that mature firms in developed economies use extensively internal resources to finance their R&D activities. Credit and equity market development are not significative, and an increase in the credit and stock market development does not have a great impact in the use of internal resources, suggesting that these firms may have the capacity to fund all their innovation projects internally.

Table 5 show the estimation results for firms in emerging economies classified by size.

Table 4 – Regression results for firms in developed countries grouped by age

	Developed									
	Young					Mature				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
$R\&D_{t-1}$	0.04***	0.05***	0.04***	0.04***	0.04***	0.03***	0.03***	0.02**	0.02**	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Cash\_flow$	0.42***	0.30***	0.43***	0.42***	0.42***	0.56***	0.53***	0.56***	0.57***	0.55***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
$\Delta CashHoldings$	0.03*	0.03*	0.03**	0.03*	0.03*	0.01	0.01	0.03***	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Sales$	0.17***	0.18***	0.17***	0.17***	0.17***	0.19***	0.17***	0.18***	0.18***	0.18***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
$Log(Total\_assets)$	-0.07***	-0.07***	-0.07***	-0.07***	-0.07***	-0.03**	-0.03***	-0.03***	-0.04***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Debt$	0.12***	0.13***	0.13***	0.13***	0.13***	0.11***	0.09***	0.10***	0.10***	0.10***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
$Credit\_market$	-0.07***	-0.08***	-0.06***	-0.07***	-0.06***	0.00	-0.00	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Stock\_market$	0.01	0.01	0.01	0.01	0.01	-0.01	-0.01	-0.01	-0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Credit\_market * Cash\_flow$		0.11***					0.04***			
		(0.01)					(0.01)			
$Credit\_market * \Delta CashHoldings$			0.00					-0.02***		
			(0.01)					(0.01)		
$Stock\_market * Cash\_flow$				0.01					-0.02*	
				(0.01)					(0.01)	
$Stock\_market * \Delta CashHoldings$					0.01					-0.01
					(0.01)					(0.01)
CFI	0.94	0.92	0.92	0.93	0.93	0.95	0.92	0.92	0.93	0.93
TLI	0.88	0.82	0.83	0.85	0.85	0.90	0.83	0.83	0.85	0.85
RMSEA	0.09	0.11	0.11	0.09	0.09	0.09	0.12	0.11	0.10	0.10
Number of firms	1728	1728	1728	1728	1728	1850	1850	1850	1850	1850

Table 4 reports the estimations results by ML-SEM method for cross-lagged panel models with fixed effects for firms in developed economies classified by age. Standard errors robust are reported in parenthesis. ***, **, and * denote statistical significance at the 1%,5%, and 10% levels, respectively. Our sample includes industries with two-digit SIC codes between 20 and 39. The sample period is 2010—2017. Regarding the validity of the models, we present the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI) and Root Mean Square Error of Approximation (RMSEA). For the CFI and TLI, a larger value than 0.9, and for the RMSEA, a value between 0.05 and 0.09 indicate a good fit, respectively.

Cash flow remains positive and statistically significant for both small and large firms. The impact of credit market development is slightly greater for large firms. The non-significance of debt to R&D for small firms indicates that there is a reduction on the likelihood of external finance because new debt will be relatively more expensive for R&D than for ordinary investment especially for more constrained firms (HALL, 2002; BROWN; MARTINSSON; PETERSEN, 2012; BROWN; FAZZARI; PETERSEN, 2009).

There is also evidence that for small firms, the higher the development of stock market the higher the variation of cash holdings. Since emerging economies experiences a weak stock market capitalization, where the presence of asymmetric information problems and principal-agent conflict is greater, firms may increase the use of cash reserves to smooth R&D investment due to its riskiness and uncertainty, instead of equity finance. However, for large firms we observe that an increase in equity market development decreases the dependence of cash flow and $\Delta CashHoldings$. These firms can offer sufficient collateral for equity financing given their total assets value. Therefore an increase in stock market development, decreases the dependence

Table 5 – Regression results for firms in emerging countries grouped by size

	Emerging									
	Small					Large				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
$R\&D_{t-1}$	0.03**	0.04**	0.04**	0.04***	0.04**	0.09***	0.08***	0.08***	0.08***	0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Cash\_flow$	0.52***	0.24***	0.53***	0.58***	0.53***	0.40***	0.15***	0.40***	0.48***	0.40***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
$\Delta CashHoldings$	-0.01	-0.01	-0.06***	-0.00	-0.04***	0.03**	0.02**	-0.05***	0.03**	0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Sales$	0.10***	0.08***	0.10***	0.08***	0.10***	0.23***	0.21***	0.22***	0.22***	0.22***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
$Log(Total\_assets)$	0.01	0.00	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Debt$	0.02	0.02	0.01	0.02	0.02	0.07***	0.08***	0.08***	0.08***	0.08***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
$Credit\_market$	0.08***	0.01	0.08***	0.08***	0.08***	0.13***	0.05***	0.13***	0.13***	0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Stock\_market$	-0.03***	-0.03***	-0.03***	-0.02*	-0.03***	-0.04***	-0.04***	-0.04***	-0.01	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Credit\_market * Cash\_flow$		0.34***					0.30***			
		(0.02)					(0.02)			
$Credit\_market * \Delta CashHoldings$			0.08***					0.08***		
			(0.01)					(0.01)		
$Stock\_market * Cash\_flow$				-0.03					-0.08***	
				(0.02)					(0.02)	
$Stock\_market * \Delta CashHoldings$					0.06***					-0.05***
					(0.01)					(0.01)
CFI	0.96	0.93	0.93	0.94	0.94	0.98	0.94	0.95	0.95	0.95
TLI	0.91	0.84	0.84	0.86	0.86	0.95	0.88	0.89	0.89	0.89
RMSEA	0.07	0.10	0.09	0.09	0.09	0.06	0.08	0.08	0.08	0.08
Number of firms	1783	1783	1783	1783	1783	1756	1756	1756	1756	1756

Table 5 reports the estimations results by ML-SEM method for cross-lagged panel models with fixed effects for firms in emerging economies classified by size. Standard errors robust are reported in parenthesis. ***, **, and * denote statistical significance at the 1%,5%, and 10% levels, respectively. Our sample includes industries with two-digit SIC codes between 20 and 39. The sample period is 2010—2017. Regarding the validity of the models, we present the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI) and Root Mean Square Error of Approximation (RMSEA). For the CFI and TLI, a larger value than 0.9, and for the RMSEA, a value between 0.05 and 0.09 indicate a good fit, respectively.

of cash flow and cash reserves to finance R&D (CZARNITZKI; HOTTENROTT, 2011).

The results for firms in developed countries classified by size are shown in Table 6. The findings are similar to Table 4. We also observe that small and large firms use extensively internal funds to finance R&D. Even though, for small firms we see that an increase in credit market development reduces the sensitivity of cash flow to R&D. Since the access to equity finance may be more difficult to small firms for financing innovation activities, small firms may use credit market to raise capital to R&D when internal resources may not be enough.

Table 6 – Regression results for firms in developed countries grouped by size

	Developed									
	Small					Large				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
$R\&D_{t-1}$	0.03**	0.04**	0.03**	0.03**	0.03**	0.05***	0.04***	0.04***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Cash\_flow$	0.43***	0.49***	0.44***	0.43***	0.43***	0.51***	0.42***	0.51***	0.52***	0.50***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\Delta CashHoldings$	0.03*	0.03*	0.01	0.03*	0.03*	0.01	0.01*	0.02***	0.01*	0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
$Sales$	0.18***	0.18***	0.17***	0.17***	0.17***	0.19***	0.19***	0.18***	0.19***	0.19***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Log(Total\_assets)$	0.00	0.00	0.00	0.00	0.00	-0.01*	-0.02**	-0.02**	-0.02**	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Debt$	0.11(0.02)***	0.11***	0.11***	0.11***	0.11***	0.11***	0.11***	0.11***	0.11***	0.11***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Credit\_market$	-0.04***	-0.02*	-0.04***	-0.04***	-0.04***	-0.02**	-0.02**	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Stock\_market$	-0.01	-0.02	-0.01	-0.01	-0.01	-0.00	0.00	-0.00	0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Credit\_market * Cash\_flow$		-0.08***					0.08***			
		(0.01)					(0.01)			
$Credit\_market * \Delta CashHoldings$			0.02					-0.01		
			(0.01)					(0.00)		
$Stock\_market * Cash\_flow$				-0.01					-0.02**	
				(0.01)					(0.01)**	
$Stock\_market * \Delta CashHoldings$					-0.00					-0.00
					(0.01)					(0.01)
CFI	0.95	0.93	0.93	0.94	0.94	0.95	0.92	0.92	0.93	0.93
TLI	0.90	0.84	0.84	0.87	0.87	0.89	0.83	0.83	0.85	0.85
RMSEA	0.08	0.10	0.10	0.09	0.08	0.09	0.11	0.11	0.10	0.10
Number of firms	1263	1263	1263	1263	1263	3879	3879	3879	3879	3879

Table 6 reports the estimations results by ML-SEM method for cross-lagged panel models with fixed effects for firms in developed economies classified by size. Standard errors robust are reported in parenthesis. ***, **, and * denote statistical significance at the 1%,5%, and 10% levels, respectively. Our sample includes industries with two-digit SIC codes between 20 and 39. The sample period is 2010—2017. Regarding the validity of the models, we present the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI) and Root Mean Square Error of Approximation (RMSEA). For the CFI and TLI, a larger value than 0.9, and for the RMSEA, a value between 0.05 and 0.09 indicate a good fit, respectively.

4.2 Estimation of the results using mixed-effects ZIP model

The results from previous section show that financial constraints appear to play a significant role in the firm's extent of R&D investment, since they rely on internal funds to promote innovation. Now, we turn our analysis to investigate the impacts of financial constraints on the production of patents per R&D spent, which is defined in the literature as innovative efficiency [1].

Table 7 reports the summary statistics of our main variables of interest. We provide the mean and standard deviation for all sample, and then we present separate statistics for firms grouped by their age and size. To classify firms into small-large and young-mature groups, we sort the sample into quintiles according to their size (measured by the logarithm of total assets) and age, respectively. Firms in the first two quintiles were classified as small/young and firms in the last two quintiles were classified as large/mature.

[1] See, e.g., Hollanders and Esser (2007), Almeida, Hsu and Li (2013), Hirshleifer, Hsu and Li (2013)

Table 7 – Descriptive Statistics

	All sample		Young		Mature		Small		Large	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
$Number\ of\ Patents$	2.907	6.538	2.406	6.051	3.690	7.264	1.484	4.540	4.145	7.709
$Log(R\&D\ expenses)$	16.237	2.015	16.030	2.106	16.550	1.886	14.666	1.474	17.744	1.536
$Innovative\ Efficiency$	0.452	3.598	0.618	5.153	0.369	1.880	0.898	5.472	0.101	0.476
$Cash\ Flow$	0.079	0.089	0.070	0.098	0.088	0.078	0.048	0.110	0.097	0.057
$Debt$	0.122	0.120	0.118	0.123	0.131	0.120	0.074	0.107	0.180	0.113
$Tobin'sQ$	1.199	0.954	1.274	0.997	1.174	0.914	1.380	1.063	0.993	0.756
$Cash\ Holdings$	0.172	0.140	0.180	0.149	0.165	0.133	0.216	0.160	0.128	0.103
$Log(Total\ Assets)$	19.959	2.136	19.635	2.154	20.489	2.000	17.792	0.879	22.173	0.986
Age	15.010	6.889	9.085	3.102	22.197	5.483	13.959	5.926	16.034	7.622
$Obs.$	3482		1470		1211		1393		1392	

Table 7 reports the mean and the standard deviation of variables for groups classified by size and age. The sample is constructed from ORBIS Database covering the period 2011–2017.

From Table 7, we observe that the average number of patents granted to young and small firms is lower than mature and large firms. However, when looking at the level of innovative efficiency, we see that small firms have a mean of 0.898 compared to 0.101 of large firms. Which means that small firms have a level of innovative efficiency more than seven times the average level of large firms. Similarly, younger firms have almost twice the level of innovative efficiency than older firms.

The values of the financial variables are quite similar between groups, except by the lower average level of cash flow and debt of small firms, which is expected, since small firms are expected to have lower internal funds and lower access to external finance.

To have a clear understanding of how our data is clustered among the countries, Figure 3 shows the average number of patents of the firms grouped by country. Firms located in Australia, Austria and Belgium have greater averages of patents valued. On the other hand, firms from Canada, Greece, Ireland and Singapore have the lowest averages of number of patents.

When taking into account the firm's average innovative efficiency (Figure 4), firms from Australia and United Kingdom have higher averages. This divergence indicates that it is crucial to look not just for the output of innovation, but the capacity of the firms generating patents according to the resources available.

When considering R&D tax incentives of the countries (Figure 5) and comparing the average of innovative efficiency with tax incentive, we observe that some countries like Belgium, Canada, France and Ireland have high values of R&D tax credits, but low level of innovative efficiency.

Overall, the summary statistics show that although young and small firms appear to have lower resources, they have a higher rate of patent generated per R&D invested. This first result

Figure 3 – Average firm's number of patents per country

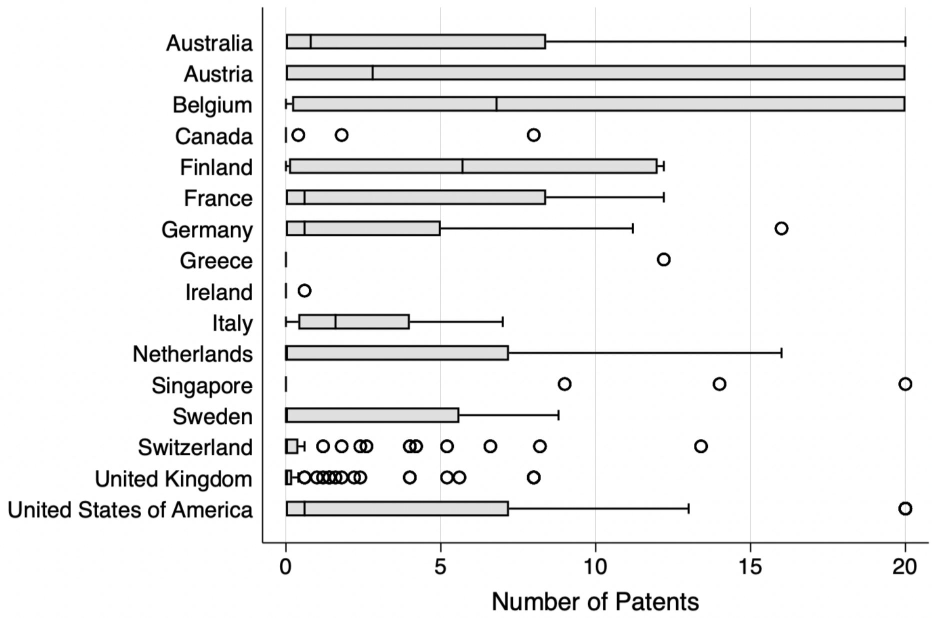
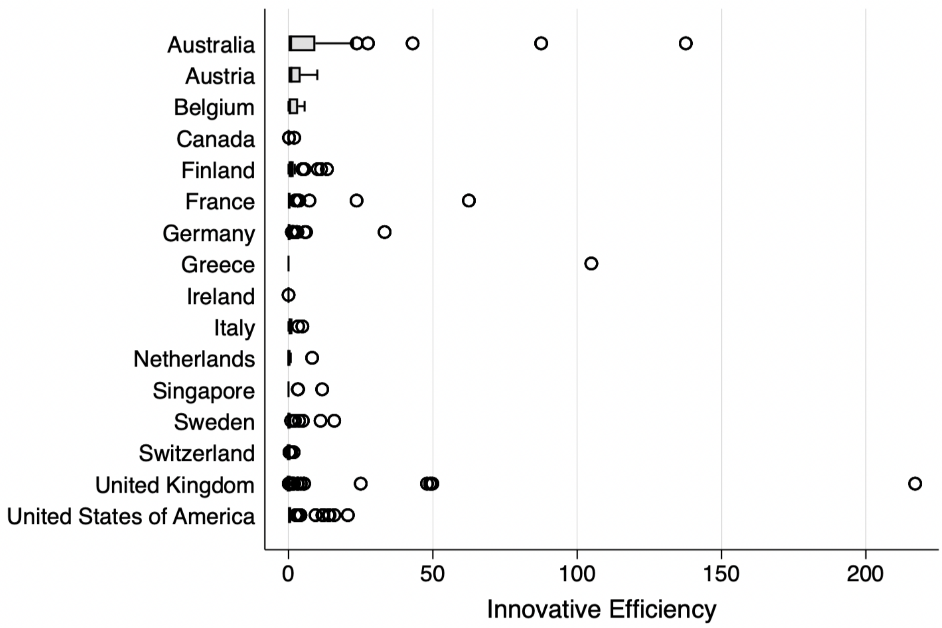
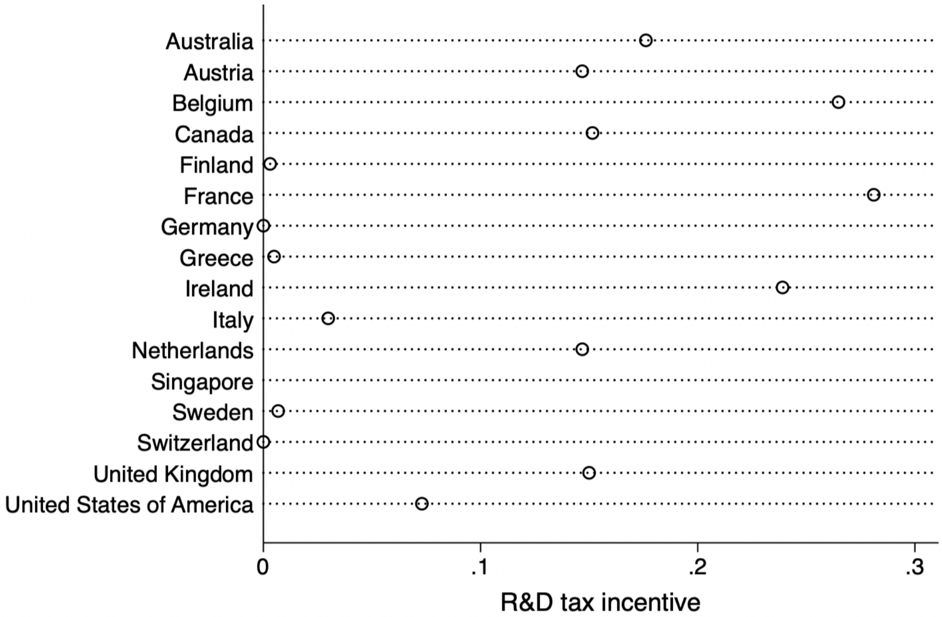


Figure 4 – Average firm's innovative efficiency per country



already suggests that financial constraints may act as an incentive for production of innovation. Besides, we observe that at a country level, there isn't a direct correlation between R&D tax credits and firm's innovative efficiency.

Figure 5 – Average R&D tax incentives



To further investigate, we employ the mixed-effects zero-inflated-Poisson regression model presented in Chapter 3 to estimate Equation 25. By using this approach, we address the counting nature of the patent variable, the excess of zeros, and the country heterogeneity in our data.

Table 8 presents the results for the estimations. We show the marginal and conditional r-squared. The marginal r-squared takes into account only the variance of the fixed effects, while the conditional r-squared considers both the fixed and random effects. We fit six models, adding interaction terms between cash flow with size/age, variation of cash holdings with size/age, and Tobins'Q with size/age.

For all models, cash flow have a negative and significant effect on the probability of a firm generating a patent per dollar of R&D. On other words, a higher availability of internal funds, measured by cash flow, decreases the probability of a firm having a higher level of innovative efficiency. We also find that Tobins'Q and cash holdings is negatively related to innovative efficiency.

According to (GUGLER; MUELLER; YURTOGLU, 2004), Tobins'Q can be used as a proxy to control not only investment opportunities, but it can also be a indicator of firms' potentially agency problems. Therefore, increasing Tobins'Q increases the probability of a firm suffering from agency problems. The argument supporting this idea is that the higher the firm's stock price is, the greater the freedom managers have to overinvest. Since Tobins'Q and

Table 8 – Estimation results via mixed-effects ZIP model

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
CF	−0.989***	−7.858***	−2.698***	−0.493**	−0.935***	−0.825***	−0.932***
	(0.149)	(1.467)	(0.352)	(0.160)	(0.151)	(0.158)	(0.150)
DE	0.152	0.071	0.126	0.025	0.153	0.114	0.136
	(0.115)	(0.116)	(0.115)	(0.117)	(0.115)	(0.116)	(0.115)
Q	−0.236***	−0.252***	−0.236***	−0.261***	−0.242***	0.154	−0.127***
	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)	(0.127)	(0.030)
CH	−0.413***	−0.499***	−0.457***	7.629***	0.993***	−0.461***	−0.400***
	(0.112)	(0.113)	(0.112)	(0.910)	(0.220)	(0.113)	(0.111)
$Size$	−0.497***	−0.520***	−0.494***	−0.426***	−0.487***	−0.472***	−0.497***
	(0.008)	(0.009)	(0.008)	(0.011)	(0.008)	(0.012)	(0.008)
Age	0.015***	0.015***	0.006*	0.017***	0.030***	0.014***	0.024***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
$CF * Size$		0.351***					
		(0.075)					
$CF * Age$			0.104***				
			(0.019)				
$CH * Size$				−0.397***			
				(0.045)			
$CH * Age$					−0.079***		
					(0.011)		
$Q * Size$						−0.019**	
						(0.006)	
$Q * Age$							−0.007***
							(0.002)
Obs.	2774	2774	2774	2774	2774	2774	2774
R2 Marg.	0.318	0.315	0.319	0.314	0.310	0.313	0.317
R2 Cond.	0.900	0.897	0.901	0.907	0.900	0.902	0.901
AIC	11 938.3	11 918.1	11 911.5	11 861.5	11 885.6	11 930.7	11 922.6
BIC	12 009.4	11 995.1	11 988.6	11 938.6	11 962.7	12 007.8	11 999.7

Table 8 reports the estimations results by Mixed-Effects ZIP model. Standard errors are reported in parenthesis. ***, **, and * denote statistical significance at the 1%,5%, and 10% levels, respectively. Our sample includes industries with two-digit SIC codes between 20 and 39. The sample period is 2010—2017. Regarding the validity of the models, we present the R-squared marginal (R2 Mar.) and conditional (R2 Cond.).

innovative efficiency have a negative and significant relationship, it suggests that firms with higher probability of suffering with agency problems have a lower probability of increasing their innovative efficiency.

The same applies to cash holdings. Almeida, Hsu and Li (2013) argue that firms with large cash holdings are more subject to agency problems. They show that unconstrained firms with excess of cash holdings have a stronger negative effect on innovative efficiency. In other words, firms with high cash holdings are more likely to spent R&D on negative net present value innovation projects, which may impact their innovative efficiency.

Turning now our analysis to size and age, we observe that size has a negative and significant impact on the probability of an increase in innovative efficiency, whereas age has a positive impact. These results are similar to the o work of Almeida, Hsu and Li (2013), who empirically find controversial coefficients for age, whereas a negative and significant coefficient for size when modelling their innovative efficiency model.

The primary explanation to understand why smaller firms have a higher innovative efficiency is the decreasing returns to scale in R&D activity. As pointed out by Almeida, Hsu and Li (2013), firms with excess of free cash flow are more susceptible to make sub-optimal R&D investment decisions, especially in innovation projects where the level of uncertainty is high. On the other hand, smaller firms need to cut costs because they have to compensate the resources that they can not get on financial markets, consequently they tend to invest only in their most potential innovation projects.

Merz (2021) argues that innovative efficiency is a “lever” which firms can overcome their low stimulus to innovate, by producing more valuable patents with lower financial resources. The author modelled different contest scenarios varying innovative efficiency, patent valuation and financial resources. In several scenarios, small firms have a higher or at least the same innovative efficiency than large firms.

Although young firms are also more susceptible to financial constraints, specially for R&D investment, as we show in previous sections, we do not capture the same effect of small firms. Age has a positive coefficient, which indicates that age increases the probability of an increase in innovative efficiency. This result can be support by the argument proposed by Okat and Paaso (2022) that young firms may be high subject to agency problems in the first years after the IPO.

The interaction variables show that an increase in cash flow diminishes the negative impact of size in the probability of having an increase in innovative efficiency. Also, increasing cash flow increases the positive relation of age on innovative efficiency. The interaction between variation of cash holdings with size and age does not shown significance.

The interaction between Tobins’Q with size and age is negative and significant for both variables. This particular result supports the view that agency problems increases the negative impact of size on innovative efficiency. The same happens with age. If Tobins’Q is greater, then the positive effect of age on innovative efficiency decreases due to a higher probability of a firm suffering from agency problems. This result is consistent with the work of (ZHANG; CHEN; ZHANG, 2022), who found that the negative effect of abundance of researches and R&D investment innovative efficiency is more pronounced when agency problems is more severe.

We extend our analysis to observe the effect of R&D tax incentives on innovative efficiency. Table 9 presents the results of the estimation taking into account the effect of R&D subsidies on innovative efficiency. As we can see in Model 1, the coefficient for R&D tax incentives is negative and significant. Firms in countries with higher R&D subsidies have a lower probability of an increase in innovative efficiency.

As stated by Czarnitzki, Hanel and Rosa (2011), R&D tax incentives may reduce the marginal cost of R&D investment. This reduction of cost to finance R&D may shift firms’ allocation of capital for innovation projects. Our finding shows that this increase of resources to R&D may impact firm's innovative performance since firms may invest in R&D more than the necessary, which may result in investing in projects that have lower marginal rate of return.

The interaction between R&D tax incentive and size shows that a higher R&D subsidy, increase the negative impact of size on innovative efficiency. For age, an increase in tax incentive increases the positive effect of age on innovative efficiency.

Again we find evidence that agency problem is liked to innovative efficiency. The results suggest that firms may invest in low quality R&D projects only to take advantage of the tax credits.

Table 9 – Estimation results via mixed-effects ZIP model - R&D tax incentive

	Model 1	Model 2	Model 3
CF	-1.091***	-1.063***	-1.182***
	(0.150)	(0.149)	(0.151)
DE	0.167	0.107	0.129
	(0.116)	(0.116)	(0.116)
Q	-0.243***	-0.240***	-0.250***
	(0.016)	(0.015)	(0.016)
CH	-0.268*	-0.327**	-0.158
	(0.113)	(0.112)	(0.114)
$Size$	-0.495***	-0.441***	-0.489***
	(0.008)	(0.011)	(0.008)
Age	0.015***	0.014***	0.003
	(0.002)	(0.002)	(0.003)
$R\&D\ Tax$	-3.230**	5.510***	-4.550***
	(1.040)	(1.606)	(1.063)
$R\&D\ Tax * Size$		-0.416***	
		(0.059)	
$R\&D\ Tax * Age$			0.086***
			(0.014)
Num.Obs.	2710	2710	2710
R2 Marg.	0.346	0.334	0.347
R2 Cond.	0.894	0.895	0.893
AIC	11 731.5	11 683.4	11 697.1
BIC	11 808.3	11 766.1	11 779.8

Table 9 reports the estimations results by Mixed-Effects ZIP model. Standard errors are reported in parenthesis. ***, **, and * denote statistical significance at the 1%,5%, and 10% levels, respectively. Our sample includes industries with two-digit SIC codes between 20 and 39. The sample period is 2010—2017. Regarding the validity of the models, we present the R-squared marginal (R2 Mar.) and conditional (R2 Cond.).

Overall, our results gives some important evidences on how the excess of funds may decrease firms' innovative efficiency. The scarcity of resources of small firms forces firms to improve their efficiency in order to remain on the markets. Such behavior is consistent with previous works (MUSSO; SCHIAVO, 2008) who show that financial frictions are associated with higher productivity, and suggest that financial pressure help diminishing agency problems and therefore increases firms performance. This is especially true for innovation projects due to the fact that they are uncertain and intangible, in large firms managers can more easily seek private interests and, consequently, disguise their suboptimal investment decisions.

5 CONCLUSION

In the first part of this study, we investigate how the availability of internal and external resources impact the investment in R&D for firms in emerging and developed countries. We analyze the R&D expenses of 11897 firms in 61 economies over 2010 to 2017. Although the literature has been extensively used the GMM-system to treat the endogeneity problem, we employ the Structural Equation Model via Maximum Likelihood (ML-SEM) for dynamic panel data. The ML-SEM approach allow us to address the endogeneity problem of the lagged dependent variable with a considerable flexibility and allow the unobserved effects to have correlations with the time-varying predictors in a more efficient way than the GMM approach under several conditions.

By imposing an explicit relationship among the unobserved effects, financial variables and R&D expenses via structural model, we show that the R&D-cash flow sensitivity remains significant even when adding liquidity management. Also, by controlling for credit market and equity market development, we observe that the investment on R&D by firms in emerging economies is more financed through credit markets and financial intermediaries than by stock market. Thus, credit supply is an essential channel to finance R&D for firms in emerging countries, evidencing that these economies are mostly “bank based" financial systems.

We find a positive and direct relationship between the development of credit market and the dependence on internal resources for financing new R&D projects. An increase on credit market development enhances the use of cash to invest on new R&D projects, particularly for young and small firms. This effect indicates that the use of external finance on R&D is expensive, therefore firms use internal resources to finance R&D even when there is an increase in credit availability.

The incorporation of change in cash reserves to capture liquidity management shows that instead of using cash reserves to smooth R&D adjustment costs, firms act by rebuilding stock of cash to alleviate the risk and uncertainty of R&D investment. We could not identify, however, that controlling for liquidity management test the presence of financing constraints.

In the second part, we employ the mixed-effects zero-inflated-Poisson model to a panel of 3482 observations from 16 countries over the period 2010-2018. By measuring innovative efficiency as the number of patents per dollar of R&D invested, we find that increasing internal funds decreases the probability of an increase in innovative efficiency. Also, we find negative and significant coefficients for Tobins’Q and cash holdings. According to the literature, both variable can be used as proxies to agency problems. Therefore, agency problems have a negative impact on firm’s innovative efficiency.

Turning the analysis to size, we show that smaller firms have a higher probability of having a higher innovative efficiency. This result is in line with the arguments that the agency problems faced by large firms jeopardize their efficiency on selecting innovation projects. The excess of free cash flow enables managers to spend money in projects that are out of their area of expertise. This argument is supported by our interaction variables, that show that the negative effect of size on innovative efficiency is even higher when increasing cash holdings or Tobins'Q, which can be used as an indirect measure of agency problems.

Extending the analysis to take into account the effect of R&D tax incentive on innovative efficiency, we find that an increase in R&D tax credits decreases the probability of generating a patent per R&D spent. Since R&D tax incentive can reduce the marginal cost of R&D investment, firms may invest in innovation projects that have lower rate of return. In general, we provide evidences about the relevance of liquidity management and the role of credit market to promote investment on R&D for emerging and developed economies, specially on the presence of financial constraints. Besides, in contrast to conventional wisdom that more financial resources are better for innovation, we present evidences that lower resources can benefit innovative efficiency, lowering the impact of agency problems on the selection of innovation projects, mainly in smaller firms.

The findings give new insights to promote innovation by expanding the credit system, and therefore releasing firms' funds to invest in innovative activities. Also, we show the importance of fomenting innovation on small firms, since they play a crucial role on the production of innovation. Finally, we emphasize that tax credits to R&D do not appear to be the most efficient instrument to be used as a correction of the 'market imperfections' that causes the under investment in R&D.

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APPENDIX A – ROBUSTNESS

The results presented in the Section 4.1 are robust to a number of different estimations approaches and model specifications. In this section, we report two of the robustness checks using the sample classified by emerging and developed economies. First, we change the default estimator - Maximum Likelihood - to an alternative estimator called DWLS (Diagonally Weighted Least Squares) and employ the Structural Equation Model via DWLS (DWLS-SEM). As we have seen,the ML-SEM assumes multivariate normality for all endogenous variables (ALLISON; WILLIAMS; MORAL-BENITO, 2017). However, when the assumption of normality is violated, the DWLS gives a more accurate parameter estimates (MîNDRILa, 2010). The estimations via DWLS-SEM are reported on Table 9. Comparing the values of Table 2, we observe a similar pattern of results. Although there are some differences in the parameters of the interactions variables between stock market with cash flow and $\Delta CashHoldings$, the effect that we observe by summing the parameter of cash flow and $\Delta CashHoldings$ is similar to that from Table 2, when we applied maximum likelihood.

In Table 10, we obtain the results from the estimations using the GMM approach. GMM is the most widely used methodology in the literature to deal with the endogeneity problem. Therefore, we estimate this methodology as a robustness check to our results. By employing the GMM estimator using lagged levels dated t-2 as instruments for the regression in differences and lagged differences dated t-2 for the regression in levels, we address the potential endogeneity of all financial variables, including $\Delta CashHoldings$, cash flow, sales growth, logarithm of total assets, and debt. In general, the overall parameter estimates are consistent with ML-SEM estimations. However, there is a reduction on the value of the parameters. As we have already highlighted, the GMM estimator is not fully efficient. The uncertainty about the choice and the number of instruments could bias the results. Furthermore, by using the ML-SEM approach we incorporate theoretical correlations into the model. All these features imply in differences in the parameter's magnitude. However, the directions of the effect of each variable remains the same for the all the three approaches.

Table 10 – Regressions for firms in emerging and developed countries via DWLS-SEM

	Emerging								Developed							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$R\&D_{t-1}$	0.06***	0.05***	0.08***	0.07***	0.06***	0.07***	0.05***	0.07***	0.04***	0.04***	0.09***	0.04***	0.07***	0.06***	0.04***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Cash\_flow$	0.42***	0.32***		0.43***	0.17***	0.31***	0.17***	0.31***	0.53***	0.20***		0.48***	0.10***	0.20***	0.12***	0.17***
	(0.02)	(0.01)		(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)		(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
$\Delta CashHoldings$	0.02*		0.06***	0.02*	0.02**	-0.06***	0.03***	-0.06***	0.02***		0.06***	0.02***	0.02**	-0.02*	0.04***	-0.03***
	(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Sales$	0.23***	0.31***	0.47***	0.22***	0.29***	0.32***	0.32***	0.32***	0.20***	0.42***	0.50***	0.19***	0.43***	0.42***	0.45***	0.44***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Log(Total\_assets)$	0.01	0.00	0.03***	0.01	0.02*	0.00	0.01	0.00	-0.09***	-0.06***	-0.04***	-0.09***	-0.09***	-0.06***	-0.05***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Debt$	0.03**	0.09***	0.15***	0.04**	-0.00	0.08***	0.02	0.08***	0.06***	0.17***	0.21***	0.12***	-0.23***	0.15***	0.14***	0.17***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
$Credit\_market$				0.07***	0.02**	0.07***	0.08***	0.07***				-0.10***	-0.14***	-0.10***	-0.12***	-0.11***
				(0.01)	(0.01)	(0.01)	(0.01)	(0.01)				(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Stock\_market$				-0.04***	-0.04***	-0.04***	-0.09***	-0.05***				0.02	0.01	0.01	-0.03***	-0.00
				(0.01)	(0.01)	(0.01)	(0.01)	(0.01)				(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Credit\_market * Cash\_flow$					0.30***								0.48***			
					(0.01)								(0.01)			
$Credit\_market * \Delta CashHoldings$						0.10***								0.08***		
						(0.01)								(0.01)		
$Stock\_market * Cash\_flow$							0.22***								0.16***	
							(0.02)								(0.01)	
$Stock\_market * \Delta CashHoldings$								0.09***								0.10***
								(0.01)								(0.01)
CFI	1.00	0.95	0.96	0.97	0.95	0.95	0.95	0.95	1.00	0.95	0.97	0.87	0.85	0.85	0.85	0.84
TLI	0.99	0.80	0.86	0.94	0.88	0.89	0.89	0.89	0.99	0.82	0.90	0.73	0.68	0.66	0.66	0.66
RMSEA	0.01	0.09	0.06	0.05	0.07	0.06	0.06	0.06	0.02	0.11	0.07	0.10	0.11	0.11	0.11	0.11
Number of firms	4435	4435	4435	4435	4435	4492	4492	4492	4492	4492						

Results of the estimations using the structural equation model via DWLS for firms in emerging and developed economies. Standard errors robust are reported in parenthesis. The superscripts ***, **, and * denote statistical significance at the 1%,5%, and 10% levels, respectively. Our sample includes industries with two-digit SIC codes between 20 and 39. The sample period is 2010—2017. Regarding the validity of the models, we present the Hansen J-test.

Table 11 – Regressions for firms in emerging and developed countries via GMM

	Emerging								Developed							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$R\&D_{t-1}$	0.28***	0.29***	0.29***	0.24***	0.28***	0.33***	0.33***	0.33***	0.15*	0.05	0.26***	0.26***	0.27***	0.27***	0.27***	0.27***
	(0.09)	(0.09)	(0.10)	(0.09)	(0.05)	(0.06)	(0.06)	(0.06)	(0.09)	(0.11)	(0.09)	(0.09)	(0.07)	(0.07)	(0.07)	(0.07)
$Cash\_flow$	0.07***	0.08***		0.08***	0.03***	0.07***	0.08***	0.07***	0.11***	0.12***		0.10***	0.08***	0.10***	0.10***	0.10***
	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\Delta CashHoldings$	0.02***		0.06***	0.02***	0.01***	-0.04***	0.02***	0.01	0.04***		0.08***	0.03***	0.03***	0.03	0.03***	0.03***
	(0.01)		(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)		(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
$Sales$	0.00***	0.00***	0.01***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.01***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Log(Total\_assets)$	-0.00*	-0.00*	-0.00	-0.00	-0.00	-0.00**	-0.00**	-0.00**	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Debt$	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.04***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Credit\_market$				0.02***	0.01***	0.02***	0.02***	0.02***				-0.00	-0.01**	-0.00	-0.00	-0.00
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Stock\_market$				-0.01***	-0.01***	-0.01***	-0.01***	-0.01***				-0.00	-0.00	-0.00*	-0.00	-0.00*
				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)				(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Credit\_market * Cash\_flow$					0.04***								0.02***			
					(0.00)								(0.00)			
$Credit\_market * \Delta CashHoldings$						0.05***								0.00		
						(0.01)								(0.02)		
$Stock\_market * Cash\_flow$							-0.01								-0.00	
							(0.00)								(0.00)	
$Stock\_market * \Delta CashHoldings$								0.01								-0.00
								(0.01)								(0.00)
$HansenJ - Test$	0.328	0.272	0.067	0.176	0.117	0.255	0.274	0.262	0.221	0.320	0.069	0.130	0.194	0.182	0.181	0.182
N. of observations	32487	32487	32487	31936	31936	31936	31936	31936	38997	38997	38997	32318	32318	32318	32318	32318

Results of the estimations via GMM method for firms in emerging and developed economies. We use lagged levels dated t-2 as instruments for the regression in differences and lagged differences dated t-2 for the regression in levels. We address the potential endogeneity of all financial variables, including Δ*CashHoldings*, cash flow, sales growth, log(total assets) and debt. Standard errors robust are reported in parenthesis. The superscripts ***, **, and * denote statistical significance at the 1%,5%, and 10% levels, respectively. Our sample includes industries with two-digit SIC codes between 20 and 39. The sample period is 2010—2017. Regarding the validity of the models, we present the Hansen J-test.

APPENDIX B – LAVAAN MODEL

We employ the ML-SEM using the Lavaan package for R. We present below the code used to regress one of the models. Since the full codification considering the eight models is too long, we show only one general code.

```
## Estimation

model_fit <- lavaan(model, data = base, fit.measures = TRUE, se
    ↪ ="robust", int.ov.free = TRUE, int.lv.free = FALSE, auto.
    ↪ fix.first = TRUE, auto.fix.single = TRUE, auto.var = TRUE,
    ↪  auto.cov.lv.x = TRUE, auto.th = TRUE, auto.delta = TRUE,
    ↪  auto.cov.y = TRUE, std.ov = TRUE)

## Structural model

model <- '

## Main regressions

rd_totalassets_2011 ~ l1 * rd_totalassets_2010 + b1 *
    ↪ cashflow_totalassets_2011 + b2 * change_cashholdings_2011
    ↪  + b3 * sales_growth_2011 + b4 * log_totalassets_2011 +
    ↪ b5 * debt_totalassets_2011
rd_totalassets_2012 ~ l1 * rd_totalassets_2011 + b1 *
    ↪ cashflow_totalassets_2012 + b2 * change_cashholdings_2012
    ↪  + b3 * sales_growth_2012 + b4 * log_totalassets_2012 +
    ↪ b5 * debt_totalassets_2012
rd_totalassets_2013 ~ l1 * rd_totalassets_2012 + b1 *
    ↪ cashflow_totalassets_2013 + b2 * change_cashholdings_2013
    ↪  + b3 * sales_growth_2013 + b4 * log_totalassets_2013 +
    ↪ b5 * debt_totalassets_2013
rd_totalassets_2014 ~ l1 * rd_totalassets_2013 + b1 *
    ↪ cashflow_totalassets_2014 + b2 * change_cashholdings_2014
    ↪  + b3 * sales_growth_2014 + b4 * log_totalassets_2014 +
    ↪ b5 * debt_totalassets_2014
rd_totalassets_2015 ~ l1 * rd_totalassets_2014 + b1 *
```

```
    ↪ cashflow_totalassets_2015 + b2 * change_cashholdings_2015
    ↪  + b3 * sales_growth_2015 + b4 * log_totalassets_2015 +
    ↪ b5 * debt_totalassets_2015
rd_totalassets_2016 ~ l1 * rd_totalassets_2015 + b1 *
    ↪ cashflow_totalassets_2016 + b2 * change_cashholdings_2016
    ↪  + b3 * sales_growth_2016 + b4 * log_totalassets_2016 +
    ↪ b5 * debt_totalassets_2016
rd_totalassets_2017 ~ l1 * rd_totalassets_2016 + b1 *
    ↪ cashflow_totalassets_2017 + b2 * change_cashholdings_2017
    ↪  + b3 * sales_growth_2017 + b4 * log_totalassets_2017 +
    ↪ b5 * debt_totalassets_2017

## Alpha latent variable

alpha =~ 1 * rd_totalassets_2011 + 1 * rd_totalassets_2012 + 1
    ↪ * rd_totalassets_2013 + 1 * rd_totalassets_2014 + 1 *
    ↪ rd_totalassets_2015 + 1 * rd_totalassets_2016 + 1 *
    ↪ rd_totalassets_2017

## Alpha free to covary with observed variables (fixed effects)

alpha ~~ cashflow_totalassets_2011 + cashflow_totalassets_2012
    ↪ + cashflow_totalassets_2013 + cashflow_totalassets_2014 +
    ↪  cashflow_totalassets_2015 + cashflow_totalassets_2016 +
    ↪ cashflow_totalassets_2017 +
change_cashholdings_2011 + change_cashholdings_2012 +
    ↪ change_cashholdings_2013 + change_cashholdings_2014 +
    ↪ change_cashholdings_2015 + change_cashholdings_2016 +
    ↪ change_cashholdings_2017 +
debt_totalassets_2011 + debt_totalassets_2012 +
    ↪ debt_totalassets_2013 + debt_totalassets_2014 +
    ↪ debt_totalassets_2015 + debt_totalassets_2016 +
    ↪ debt_totalassets_2017 +
rd_totalassets_2010

## Correlating DV errors with future values of predetermined
    ↪ predictors

rd_totalassets_2016 ~~ cashflow_totalassets_2017 +
```

```
↪ change_cashholdings_2017 + log_totalassets_2017 +
↪ debt_totalassets_2017 + sales_growth_2017
rd_totalassets_2015 ~~ cashflow_totalassets_2017 +
↪ cashflow_totalassets_2016 + change_cashholdings_2016 +
↪ change_cashholdings_2017 + log_totalassets_2016 +
↪ debt_totalassets_2016 + log_totalassets_2017 +
↪ debt_totalassets_2017 + sales_growth_2016 +
↪ sales_growth_2017
rd_totalassets_2014 ~~ cashflow_totalassets_2017 +
↪ cashflow_totalassets_2016 + cashflow_totalassets_2015 +
↪ change_cashholdings_2015 + change_cashholdings_2016 +
↪ change_cashholdings_2017 + log_totalassets_2015 +
↪ debt_totalassets_2015 + log_totalassets_2016 +
↪ debt_totalassets_2016 + log_totalassets_2017 +
↪ debt_totalassets_2017 + sales_growth_2015 +
↪ sales_growth_2016 + sales_growth_2017
rd_totalassets_2013 ~~ cashflow_totalassets_2017 +
↪ cashflow_totalassets_2016 + cashflow_totalassets_2015 +
↪ cashflow_totalassets_2014 + change_cashholdings_2014 +
↪ change_cashholdings_2015 + change_cashholdings_2016 +
↪ change_cashholdings_2017+ log_totalassets_2014 +
↪ debt_totalassets_2014 + log_totalassets_2015 +
↪ debt_totalassets_2015 + log_totalassets_2016 +
↪ debt_totalassets_2016 + log_totalassets_2017 +
↪ debt_totalassets_2017 + sales_growth_2014 +
↪ sales_growth_2015 + sales_growth_2016 + sales_growth_2017
rd_totalassets_2012 ~~ cashflow_totalassets_2017 +
↪ cashflow_totalassets_2016 + cashflow_totalassets_2015 +
↪ cashflow_totalassets_2014 + cashflow_totalassets_2013 +
↪ change_cashholdings_2013 + change_cashholdings_2014 +
↪ change_cashholdings_2015 + change_cashholdings_2016 +
↪ change_cashholdings_2017 + log_totalassets_2013 +
↪ debt_totalassets_2013 + log_totalassets_2014 +
↪ debt_totalassets_2014 + log_totalassets_2015 +
↪ debt_totalassets_2015 + log_totalassets_2016 +
↪ debt_totalassets_2016 + log_totalassets_2017 +
↪ debt_totalassets_2017 + sales_growth_2013 +
↪ sales_growth_2014 + sales_growth_2015 + sales_growth_2016
↪  + sales_growth_2017
```

```
rd_totalassets_2011 ~~ cashflow_totalassets_2017 +
   ↪ cashflow_totalassets_2016 + cashflow_totalassets_2015 +
   ↪ cashflow_totalassets_2014 + cashflow_totalassets_2013 +
   ↪ cashflow_totalassets_2012 + change_cashholdings_2012 +
   ↪ change_cashholdings_2013 + change_cashholdings_2014 +
   ↪ change_cashholdings_2015 + change_cashholdings_2016 +
   ↪ change_cashholdings_2017 + log_totalassets_2012 +
   ↪ debt_totalassets_2012 + log_totalassets_2013 +
   ↪ debt_totalassets_2013 + log_totalassets_2014 +
   ↪ debt_totalassets_2014 + log_totalassets_2015 +
   ↪ debt_totalassets_2015 + log_totalassets_2016 +
   ↪ debt_totalassets_2016 + log_totalassets_2017 +
   ↪ debt_totalassets_2017 + sales_growth_2012 +
   ↪ sales_growth_2013 + sales_growth_2014 + sales_growth_2015
   ↪  + sales_growth_2016 + sales_growth_2017


## covariances

cashflow_totalassets_2012 ~~ cashflow_totalassets_2011 +
   ↪ log_totalassets_2011 + log_totalassets_2012 +
   ↪ log_totalassets_2013 + log_totalassets_2014 +
   ↪ log_totalassets_2015 + log_totalassets_2016 +
   ↪ log_totalassets_2017 + debt_totalassets_2011 +
   ↪ debt_totalassets_2012 + debt_totalassets_2013 +
   ↪ debt_totalassets_2014 + debt_totalassets_2015 +
   ↪ debt_totalassets_2016 + debt_totalassets_2017 +
   ↪ rd_totalassets_2010 + sales_growth_2011 +
   ↪ sales_growth_2012 + sales_growth_2013 + sales_growth_2014
   ↪  + sales_growth_2015 + sales_growth_2016 +
   ↪ sales_growth_2017 + change_cashholdings_2011 +
   ↪ change_cashholdings_2012 + change_cashholdings_2013 +
   ↪ change_cashholdings_2014 + change_cashholdings_2015 +
   ↪ change_cashholdings_2016 + change_cashholdings_2017
cashflow_totalassets_2013 ~~ cashflow_totalassets_2011 +
   ↪ cashflow_totalassets_2012 + log_totalassets_2011 +
   ↪ log_totalassets_2012 + log_totalassets_2013 +
   ↪ log_totalassets_2014 + log_totalassets_2015 +
   ↪ log_totalassets_2016 + log_totalassets_2017 +
```

```
↪ debt_totalassets_2011 + debt_totalassets_2012 +
↪ debt_totalassets_2013 + debt_totalassets_2014 +
↪ debt_totalassets_2015 + debt_totalassets_2016 +
↪ debt_totalassets_2017 + rd_totalassets_2010 +
↪ sales_growth_2011 + sales_growth_2012 + sales_growth_2013
↪  + sales_growth_2014 + sales_growth_2015 +
↪ sales_growth_2016 + sales_growth_2017 +
↪ change_cashholdings_2011 + change_cashholdings_2012 +
↪ change_cashholdings_2013 + change_cashholdings_2014 +
↪ change_cashholdings_2015 + change_cashholdings_2016 +
↪ change_cashholdings_2017
cashflow_totalassets_2014 ~~ cashflow_totalassets_2011 +
↪ cashflow_totalassets_2012 + cashflow_totalassets_2013 +
↪ log_totalassets_2011 + log_totalassets_2012 +
↪ log_totalassets_2013 + log_totalassets_2014 +
↪ log_totalassets_2015 + log_totalassets_2016 +
↪ log_totalassets_2017 + debt_totalassets_2011 +
↪ debt_totalassets_2012 + debt_totalassets_2013 +
↪ debt_totalassets_2014 + debt_totalassets_2015 +
↪ debt_totalassets_2016 + debt_totalassets_2017 +
↪ rd_totalassets_2010 + sales_growth_2011 +
↪ sales_growth_2012 + sales_growth_2013 + sales_growth_2014
↪  + sales_growth_2015 + sales_growth_2016 +
↪ sales_growth_2017 + change_cashholdings_2011 +
↪ change_cashholdings_2012 + change_cashholdings_2013 +
↪ change_cashholdings_2014 + change_cashholdings_2015 +
↪ change_cashholdings_2016 + change_cashholdings_2017
cashflow_totalassets_2015 ~~ cashflow_totalassets_2011 +
↪ cashflow_totalassets_2012 + cashflow_totalassets_2013 +
↪ cashflow_totalassets_2014 + log_totalassets_2011 +
↪ log_totalassets_2012 + log_totalassets_2013 +
↪ log_totalassets_2014 + log_totalassets_2015 +
↪ log_totalassets_2016 + log_totalassets_2017 +
↪ debt_totalassets_2011 + debt_totalassets_2012 +
↪ debt_totalassets_2013 + debt_totalassets_2014 +
↪ debt_totalassets_2015 + debt_totalassets_2016 +
↪ debt_totalassets_2017 + rd_totalassets_2010 +
↪ sales_growth_2011 + sales_growth_2012 + sales_growth_2013
↪  + sales_growth_2014 + sales_growth_2015 +
```

```
↪ sales_growth_2016 + sales_growth_2017 +
↪ change_cashholdings_2011 + change_cashholdings_2012 +
↪ change_cashholdings_2013 + change_cashholdings_2014 +
↪ change_cashholdings_2015 + change_cashholdings_2016 +
↪ change_cashholdings_2017
cashflow_totalassets_2016 ~~ cashflow_totalassets_2011 +
↪ cashflow_totalassets_2012 + cashflow_totalassets_2013 +
↪ cashflow_totalassets_2014 + cashflow_totalassets_2015 +
↪ log_totalassets_2011 + log_totalassets_2012 +
↪ log_totalassets_2013 + log_totalassets_2014 +
↪ log_totalassets_2015 + log_totalassets_2016 +
↪ log_totalassets_2017 + debt_totalassets_2011 +
↪ debt_totalassets_2012 + debt_totalassets_2013 +
↪ debt_totalassets_2014 + debt_totalassets_2015 +
↪ debt_totalassets_2016 + debt_totalassets_2017 +
↪ rd_totalassets_2010 + sales_growth_2011 +
↪ sales_growth_2012 + sales_growth_2013 + sales_growth_2014
↪  + sales_growth_2015 + sales_growth_2016 +
↪ sales_growth_2017 + change_cashholdings_2011 +
↪ change_cashholdings_2012 + change_cashholdings_2013 +
↪ change_cashholdings_2014 + change_cashholdings_2015 +
↪ change_cashholdings_2016 + change_cashholdings_2017
cashflow_totalassets_2017 ~~ cashflow_totalassets_2011 +
↪ cashflow_totalassets_2012 + cashflow_totalassets_2013 +
↪ cashflow_totalassets_2014 + cashflow_totalassets_2015 +
↪ cashflow_totalassets_2016 + log_totalassets_2011 +
↪ log_totalassets_2012 + log_totalassets_2013 +
↪ log_totalassets_2014 + log_totalassets_2015 +
↪ log_totalassets_2016 + log_totalassets_2017 +
↪ debt_totalassets_2011 + debt_totalassets_2012 +
↪ debt_totalassets_2013 + debt_totalassets_2014 +
↪ debt_totalassets_2015 + debt_totalassets_2016 +
↪ debt_totalassets_2017 + rd_totalassets_2010 +
↪ sales_growth_2011 + sales_growth_2012 + sales_growth_2013
↪  + sales_growth_2014 + sales_growth_2015 +
↪ sales_growth_2016 + sales_growth_2017 +
↪ change_cashholdings_2011 + change_cashholdings_2012 +
↪ change_cashholdings_2013 + change_cashholdings_2014 +
↪ change_cashholdings_2015 + change_cashholdings_2016 +
```

```
↪ change_cashholdings_2017

change_cashholdings_2012 ~~ log_totalassets_2011 +
↪ log_totalassets_2012 + log_totalassets_2013 +
↪ log_totalassets_2014 + log_totalassets_2015 +
↪ log_totalassets_2016 + log_totalassets_2017 +
↪ debt_totalassets_2011 + debt_totalassets_2012 +
↪ debt_totalassets_2013 + debt_totalassets_2014 +
↪ debt_totalassets_2015 + debt_totalassets_2016 +
↪ debt_totalassets_2017 + rd_totalassets_2010 +
↪ sales_growth_2011 + sales_growth_2012 + sales_growth_2013
↪  + sales_growth_2014 + sales_growth_2015 +
↪ sales_growth_2016 + sales_growth_2017 +
↪ change_cashholdings_2011
change_cashholdings_2013 ~~ log_totalassets_2011 +
↪ log_totalassets_2012 + log_totalassets_2013 +
↪ log_totalassets_2014 + log_totalassets_2015 +
↪ log_totalassets_2016 + log_totalassets_2017 +
↪ debt_totalassets_2011 + debt_totalassets_2012 +
↪ debt_totalassets_2013 + debt_totalassets_2014 +
↪ debt_totalassets_2015 + debt_totalassets_2016 +
↪ debt_totalassets_2017 + rd_totalassets_2010 +
↪ sales_growth_2011 + sales_growth_2012 + sales_growth_2013
↪  + sales_growth_2014 + sales_growth_2015 +
↪ sales_growth_2016 + sales_growth_2017 +
↪ change_cashholdings_2011 + change_cashholdings_2012
change_cashholdings_2014 ~~ log_totalassets_2011 +
↪ log_totalassets_2012 + log_totalassets_2013 +
↪ log_totalassets_2014 + log_totalassets_2015 +
↪ log_totalassets_2016 + log_totalassets_2017 +
↪ debt_totalassets_2011 + debt_totalassets_2012 +
↪ debt_totalassets_2013 + debt_totalassets_2014 +
↪ debt_totalassets_2015 + debt_totalassets_2016 +
↪ debt_totalassets_2017 + rd_totalassets_2010 +
↪ sales_growth_2011 + sales_growth_2012 + sales_growth_2013
↪  + sales_growth_2014 + sales_growth_2015 +
↪ sales_growth_2016 + sales_growth_2017 +
↪ change_cashholdings_2011 + change_cashholdings_2012 +
↪ change_cashholdings_2013
```

```
change_cashholdings_2015 ~~ log_totalassets_2011 +
    log_totalassets_2012 + log_totalassets_2013 +
    log_totalassets_2014 + log_totalassets_2015 +
    log_totalassets_2016 + log_totalassets_2017 +
    debt_totalassets_2011 + debt_totalassets_2012 +
    debt_totalassets_2013 + debt_totalassets_2014 +
    debt_totalassets_2015 + debt_totalassets_2016 +
    debt_totalassets_2017 + rd_totalassets_2010 +
    sales_growth_2011 + sales_growth_2012 + sales_growth_2013
     + sales_growth_2014 + sales_growth_2015 +
    sales_growth_2016 + sales_growth_2017 +
    change_cashholdings_2011 + change_cashholdings_2012 +
    change_cashholdings_2013 + change_cashholdings_2014
change_cashholdings_2016 ~~ log_totalassets_2011 +
    log_totalassets_2012 + log_totalassets_2013 +
    log_totalassets_2014 + log_totalassets_2015 +
    log_totalassets_2016 + log_totalassets_2017 +
    debt_totalassets_2011 + debt_totalassets_2012 +
    debt_totalassets_2013 + debt_totalassets_2014 +
    debt_totalassets_2015 + debt_totalassets_2016 +
    debt_totalassets_2017 + rd_totalassets_2010 +
    sales_growth_2011 + sales_growth_2012 + sales_growth_2013
     + sales_growth_2014 + sales_growth_2015 +
    sales_growth_2016 + sales_growth_2017 +
    change_cashholdings_2011 + change_cashholdings_2012 +
    change_cashholdings_2013 + change_cashholdings_2014 +
    change_cashholdings_2015
change_cashholdings_2017 ~~ log_totalassets_2011 +
    log_totalassets_2012 + log_totalassets_2013 +
    log_totalassets_2014 + log_totalassets_2015 +
    log_totalassets_2016 + log_totalassets_2017 +
    debt_totalassets_2011 + debt_totalassets_2012 +
    debt_totalassets_2013 + debt_totalassets_2014 +
    debt_totalassets_2015 + debt_totalassets_2016 +
    debt_totalassets_2017 + rd_totalassets_2010 +
    sales_growth_2011 + sales_growth_2012 + sales_growth_2013
     + sales_growth_2014 + sales_growth_2015 +
    sales_growth_2016 + sales_growth_2017 +
    change_cashholdings_2011 + change_cashholdings_2012 +
```

```
↪ change_cashholdings_2013 + change_cashholdings_2014 +
↪ change_cashholdings_2015 + change_cashholdings_2016

sales_growth_2012 ~~ log_totalassets_2011 +
↪ log_totalassets_2012 + log_totalassets_2013 +
↪ log_totalassets_2014 + log_totalassets_2015 +
↪ log_totalassets_2016 + log_totalassets_2017 +
↪ debt_totalassets_2011 + debt_totalassets_2012 +
↪ debt_totalassets_2013 + debt_totalassets_2014 +
↪ debt_totalassets_2015 + debt_totalassets_2016 +
↪ debt_totalassets_2017 + rd_totalassets_2010 +
↪ sales_growth_2011
sales_growth_2013 ~~ log_totalassets_2011 +
↪ log_totalassets_2012 + log_totalassets_2013 +
↪ log_totalassets_2014 + log_totalassets_2015 +
↪ log_totalassets_2016 + log_totalassets_2017 +
↪ debt_totalassets_2011 + debt_totalassets_2012 +
↪ debt_totalassets_2013 + debt_totalassets_2014 +
↪ debt_totalassets_2015 + debt_totalassets_2016 +
↪ debt_totalassets_2017 + rd_totalassets_2010 +
↪ sales_growth_2011 + sales_growth_2012
sales_growth_2014 ~~ log_totalassets_2011 +
↪ log_totalassets_2012 + log_totalassets_2013 +
↪ log_totalassets_2014 + log_totalassets_2015 +
↪ log_totalassets_2016 + log_totalassets_2017 +
↪ debt_totalassets_2011 + debt_totalassets_2012 +
↪ debt_totalassets_2013 + debt_totalassets_2014 +
↪ debt_totalassets_2015 + debt_totalassets_2016 +
↪ debt_totalassets_2017 + rd_totalassets_2010 +
↪ sales_growth_2011 + sales_growth_2012 + sales_growth_2013
sales_growth_2015 ~~ log_totalassets_2011 +
↪ log_totalassets_2012 + log_totalassets_2013 +
↪ log_totalassets_2014 + log_totalassets_2015 +
↪ log_totalassets_2016 + log_totalassets_2017 +
↪ debt_totalassets_2011 + debt_totalassets_2012 +
↪ debt_totalassets_2013 + debt_totalassets_2014 +
↪ debt_totalassets_2015 + debt_totalassets_2016 +
↪ debt_totalassets_2017 + rd_totalassets_2010 +
↪ sales_growth_2011 + sales_growth_2012 + sales_growth_2013
```

```
↪ + sales_growth_2014
sales_growth_2016 ~~ log_totalassets_2011 +
↪ log_totalassets_2012 + log_totalassets_2013 +
↪ log_totalassets_2014 + log_totalassets_2015 +
↪ log_totalassets_2016 + log_totalassets_2017 +
↪ debt_totalassets_2011 + debt_totalassets_2012 +
↪ debt_totalassets_2013 + debt_totalassets_2014 +
↪ debt_totalassets_2015 + debt_totalassets_2016 +
↪ debt_totalassets_2017 + rd_totalassets_2010 +
↪ sales_growth_2011 + sales_growth_2012 + sales_growth_2013
↪ + sales_growth_2014 + sales_growth_2015
sales_growth_2017 ~~ log_totalassets_2011 +
↪ log_totalassets_2012 + log_totalassets_2013 +
↪ log_totalassets_2014 + log_totalassets_2015 +
↪ log_totalassets_2016 + log_totalassets_2017 +
↪ debt_totalassets_2011 + debt_totalassets_2012 +
↪ debt_totalassets_2013 + debt_totalassets_2014 +
↪ debt_totalassets_2015 + debt_totalassets_2016 +
↪ debt_totalassets_2017 + rd_totalassets_2010 +
↪ sales_growth_2011 + sales_growth_2012 + sales_growth_2013
↪ + sales_growth_2014 + sales_growth_2015 +
↪ sales_growth_2016

log_totalassets_2012 ~~ log_totalassets_2011 +
↪ debt_totalassets_2011 + debt_totalassets_2012 +
↪ debt_totalassets_2013 + debt_totalassets_2014 +
↪ debt_totalassets_2015 + debt_totalassets_2016 +
↪ debt_totalassets_2017 + rd_totalassets_2010
log_totalassets_2013 ~~ log_totalassets_2011 +
↪ log_totalassets_2012 + debt_totalassets_2011 +
↪ debt_totalassets_2012 + debt_totalassets_2013 +
↪ debt_totalassets_2014 + debt_totalassets_2015 +
↪ debt_totalassets_2016 + debt_totalassets_2017 +
↪ rd_totalassets_2010
log_totalassets_2014 ~~ log_totalassets_2011 +
↪ log_totalassets_2012 + log_totalassets_2013 +
↪ debt_totalassets_2011 + debt_totalassets_2012 +
↪ debt_totalassets_2013 + debt_totalassets_2014 +
↪ debt_totalassets_2015 + debt_totalassets_2016 +
```

```
   ↪ debt_totalassets_2017 + rd_totalassets_2010
log_totalassets_2015 ~~ log_totalassets_2011 +
   ↪ log_totalassets_2012 + log_totalassets_2013 +
   ↪ log_totalassets_2014 + debt_totalassets_2011 +
   ↪ debt_totalassets_2012 + debt_totalassets_2013 +
   ↪ debt_totalassets_2014 + debt_totalassets_2015 +
   ↪ debt_totalassets_2016 + debt_totalassets_2017 +
   ↪ rd_totalassets_2010
log_totalassets_2016 ~~ log_totalassets_2011 +
   ↪ log_totalassets_2012 + log_totalassets_2013 +
   ↪ log_totalassets_2014 + log_totalassets_2015 +
   ↪ debt_totalassets_2011 + debt_totalassets_2012 +
   ↪ debt_totalassets_2013 + debt_totalassets_2014 +
   ↪ debt_totalassets_2015 + debt_totalassets_2016 +
   ↪ debt_totalassets_2017 + rd_totalassets_2010
log_totalassets_2017 ~~ log_totalassets_2011 +
   ↪ log_totalassets_2012 + log_totalassets_2013 +
   ↪ log_totalassets_2014 + log_totalassets_2015 +
   ↪ log_totalassets_2016 + debt_totalassets_2011 +
   ↪ debt_totalassets_2012 + debt_totalassets_2013 +
   ↪ debt_totalassets_2014 + debt_totalassets_2015 +
   ↪ debt_totalassets_2016 + debt_totalassets_2017 +
   ↪ rd_totalassets_2010

debt_totalassets_2012 ~~ debt_totalassets_2011 +
   ↪ rd_totalassets_2010
debt_totalassets_2013 ~~ debt_totalassets_2012 +
   ↪ debt_totalassets_2011 + rd_totalassets_2010
debt_totalassets_2014 ~~ debt_totalassets_2011 +
   ↪ debt_totalassets_2012 + debt_totalassets_2013 +
   ↪ rd_totalassets_2010
debt_totalassets_2015 ~~ debt_totalassets_2011 +
   ↪ debt_totalassets_2012 + debt_totalassets_2013 +
   ↪ debt_totalassets_2014 + rd_totalassets_2010
debt_totalassets_2016 ~~ debt_totalassets_2011 +
   ↪ debt_totalassets_2012 + debt_totalassets_2013 +
   ↪ debt_totalassets_2014 + debt_totalassets_2015 +
   ↪ rd_totalassets_2010
debt_totalassets_2017 ~~ debt_totalassets_2011 +
```

```
    ↪ debt_totalassets_2012 + debt_totalassets_2013 +
    ↪ debt_totalassets_2014 + debt_totalassets_2015 +
    ↪ debt_totalassets_2016 + rd_totalassets_2010


## Let DV variance vary across ts

rd_totalassets_2011 ~ 1
rd_totalassets_2012 ~ 1
rd_totalassets_2013 ~ 1
rd_totalassets_2014 ~ 1
rd_totalassets_2015 ~ 1
rd_totalassets_2016 ~ 1
rd_totalassets_2017 ~ 1
'
```