Radboud Universiteit

Formal and informal ways of financing SME innovation in emerging markets

A quantitative study on formal and informal credit as well as connected institutions

Master Thesis Strategic Management

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June 16, 2019

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Abstract

Extant literature establishes that firm innovation in developed markets is driven by access to external finance provided by well-performing formal institutions, but does not detail whether these mechanisms hold true for SMEs in emerging economies, that are characterized by "institutional voids" and informal contexts. In this study, a formal and informal way of financing SME-innovation were researched, as well as the interaction with the quality of their respective institution. Results were primarily derived from the World Bank Enterprise Survey (WBES) using multilevel logistic regression. Firstly, formal credit delivered by a bank was assessed, and the associated quality of the national money market. Second to be examined was informal credit delivered by a Rotating Savings and Credit Association (ROSCA) – a communal fund that periodically distributes a lumpsum of contributions among its members - and the associated quality of ROSCA-management as proxied by national trust in people known personally. This study provides strong evidence that both bank and ROSCA-credit increase firm innovativeness, although entrepreneurs that use both types of credit simultaneously benefit most, as they are successfully embedded in both a formal and informal context. Furthermore, some evidence is found for a positive relationship between ROSCA-management and its innovative outcomes, confirming trust is an important concept in ROSCAs. Some evidence is too found for a negative effect of money market quality on the innovative performance of formal credit users, suggesting scarcer credits may be more valuable, and well-performing firms are better equipped to obtain it. This study is the first to deliver a large-scale empirical validation of the ROSCA.

Contents

Chapter 1: Introduction

1.1. Access to external finance and innovation

In developed markets, (access to) external finance enhances the innovative performance of firms (Levine, Loayza, & Beck, 2000). Efficient financial markets supported by well-functioning formal institutions facilitate effective external financing (Atanassov, Nanda, & Seru, 2007). Emerging markets on the other hand, are characterized by the absence of many well-functioning institutions present in developed markets (Khanna & Palepu, 1997). Research by Ayyagari, Demirgüç-Kunt, and Maksimovic (2011) reveals the relationship between external finance and innovation also exists in emerging markets. This suggests underdeveloped formal financial institutions hamper innovation; firms in emerging markets face limited access to external finance and any external financing that is available in these markets often comes at a premium (Aghion, Howitt, & Mayer-Foulkes, 2005). Fombang and Adjasi (2018) nuance this finding however, and suggest that next to bank overdraft and asset credit derived through formal financial institutions, trade credit between businesses can also play an important role in financing innovation. Functioning informal institutions that, for example, uphold a trade practice to finance counterparties, may therefore be able compensate for the (poor) quality of formal financial institutions in emerging markets.

The Rotating Savings and Credit Association (ROSCA) is one such interesting informal financial institution. The ROSCA is in essence a communal, informal fund to which members of the association contribute a periodic fee, with the lumpsum of collected fees then distributed to a particular member (Henry, 2003). ROSCAs are used around the world (van den Brink & Chavas, 1997). Some authors argue that firms seeking to escape poor formal money markets may join a ROSCA to find informal ways to finance innovation (Zoogah, Peng, & Woldu, 2015). This study explores the effects of formal and informal ways of financing innovation, given the institutional circumstances in which external financing is arranged.

1.2. Innovation & institutional voids

In the context of emerging markets, the Organisation for Economic Co-operation and Development (OECD) defines innovation as “new-to-firm (…) implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices, workplace organization, or external relations (Ayyagari et al., 2011, p. 1549; OECD/Eurostat, 2005, para. 146). A meta-analysis by Rubera and Kirca (2012) of 153 studies with almost 37,000 firms, shows firm innovation results in superior financial positions, market shares, and firm value. Innovation is viewed as one of the most important drivers of macroeconomic growth as well, in both developed and emerging markets (Ayyagari et al., 2011; Chudnovsky, López, & Pupato, 2006; Crespi & Zuniga, 2010). As strong positive associations have been uncovered between the size of the SME-sector and economic growth in emerging markets, growth and innovation of these small and medium enterprises is beneficial for both the firm and macroeconomy (Beck, Demirgüç-Kunt, & Levine, 2005). Especially in emerging economies however, (SME) firm innovation is often hampered by "institutional voids," meaning these markets operate inefficiently and ineffectively due to absent or failing trade-facilitating institutions (Khanna & Palepu, 1997, 2010). Said markets suffer from issues such as information asymmetry, low trust, and increased transactions costs that reduce "the likelihood of efficient outcomes" (Doh, Rodrigues, Saka-Helmhout, & Makhija, 2017, p. 294). It is emphasized nonetheless that these emerging markets are heterogenous, and some are closer to developed markets than others (Bekaert & Harvey, 2002; Khanna & Palepu, 2010). Moreover, the institutional voids present in these countries do not necessarily exist in or hinder all submarkets; some submarkets may even outperform those in what are considered developed economies.[1]

Institutions are "multifaceted, durable social structures" (Scott, 2013, p. 75) popularized as "the rules of the game" (North, 1990, p. 471). Broadly speaking, institutions can be categorized as formal and informal (Scott, 2013). Formal institutions are codified and enforced by an established authority (North, 1990), while informal institutions are rather latent and profound, stemming from (societal) values and beliefs (North, 1990; Scott, 1995). Classical institutional theory incorporates sociology and regards institutions as exogenous constants by which firms are normatively and mimetically pressured (DiMaggio & Powell, 1983). Other branches of institutional research include economic and organizational elements, which focus on transaction costs (North, 1990), shaping institutions by bargaining

[1] For example, according to the World Bank (2019a, p. 134) the Netherlands has an inefficient credit market, caused by a legal system that does not facilitate lending. The Netherlands is, in this specific regard, outranked by countries such as Zambia, Rwanda, and Colombia. This also shows that even in developed markets institutional voids can exist (Gao, Zuzul, Jones, & Khanna, 2017).

(Oliver, 1991), or institutional voids as “opportunity spaces” to be filled by opportunistic agents (Mair & Marti, 2009, p. 433; McKague, Zietsma, & Oliver, 2015). Krammer (2017), among others, suggests multiple institutions can have compensatory effects. In his study, a weak formal anti-bribery framework was offset by a high degree of societal trust that decreased the prevalence and effectiveness of bribing. This is an example of a poor formal institution being compensated by an informal institution. ROSCAs may work similarly as informal institutions that compensate for poor quality formal money markets.

1.3. Literature gaps

Existing research on the relationship between (access to) external finance and innovation has several gaps. Although it has been suggested that the relationship between external finance and firm innovation also exists in emerging markets (Ayyagari et al., 2011), little is known about the moderating effect of the (formal and informal) institutional context, incorporating both the firm and institutional (macro) level. Moreover, most research on the links between finance and innovation takes (macroeconomic) developed markets and large (listed) firms as a focal point (e.g. Cainelli, Evangelista, & Savona, 2006). It remains unclear if the outcomes of such studies are applicable to developing markets and their small and medium enterprises (SMEs). Furthermore, little research and empirical validation exists regarding ROSCAs (van den Brink & Chavas, 1997; van Rooyen, Stewart, & de Wet, 2012). While their basic and theoretical mechanisms are well documented (Henry, 2003), their actual performance is largely unknown. Although some conceptual overlaps exist between ROSCAs and modern microfinance programs - as these have taken over some traditional ROSCA-characteristics such as group-based lending - it is not likely research on microfinance is entirely applicable to ROSCAs (van Rooyen et al., 2012).

1.4. Thesis aim

This study aims to deepen both finance literature and institutional theory. Several studies have demonstrated that informal institutional quality can moderate the relationship between firm innovation and formal institutional quality (Crost & Kambhampati, 2010; Harriss-White, 2010; Krammer, 2017; Miller, Lee, Chang, & Le Breton-Miller, 2009; Puffer, McCarthy, & Boisot, 2010). This study seeks to confirm such a relationship, by exploring its nuances in the specific context of firm access to external finance. As such, this study extends previous work such as Krammer (2017) who, for example, researched this topic within the specific context of bribery. Secondly, while Ayyagari et al. (2011) make clear that a positive relationship exists between access to external finance and firm innovation in emerging markets, they do not explicitly consider the differential effects of formal (e.g. formal money market) and informal (e.g. ROSCAs) institutions on innovation. Responding to this gap, Fombang and Adjasi (2018) suggest that informal institutional financing can compensate for the ineffectiveness of formal institutional financing. This study seeks to build on and extend both studies, in the specific contexts of SME innovation.

1.5. Research question

The research question of this study is as follows: *What is the effect of the firm-specific access to external finance on SME firm innovation in developing markets, as moderated by the quality of formal and informal financial institutions?*

1.6. Relevance

This research aims to be both managerially and societally relevant. First of all, it aims to introduce a deeper understanding of the antecedents of innovation, which both policymakers and entrepreneurs can use to position, respectively, their countries and firms to derive sustainable competitive advantage. More specifically, this study uncovers financial antecedents of innovation, analyzing both the SME and the institutional context. Economists have long focused on formal institutions and argued that the way for developing countries to prosper is to open their markets for free trade; this research aims to provide a more complete perspective by also taking the informal institutional context into account.

1.7. Thesis structure

This thesis has a total of six chapters. Chapter 2 will outline the theoretical framework, focusing among others on innovation, the resource-based view, institutional theory, and ROSCAs. Hypotheses and a conceptual model are also presented in this chapter. Chapter 3 details the (quantitative) methodology to be used. Chapter 4 then, presents the results of the analyses. Chapter 5 discusses and interprets the results, while Chapter 6 provides a conclusion with theoretical, managerial, and societal implications, as well as limitations of this study and directions for further research.

Chapter 2: Theoretical framework

This chapter outlines the theoretical framework of this research. Firstly, a general literature review discusses the concepts of innovation, the resource-based view, and institutional theory – these are key to this study. Secondly, specific literature is reviewed on the topic of financial resources derived from formal money markets and through ROSCAs, and finally hypotheses and a conceptual model are formulated.

2.1. General literature review

2.1.1. Innovation

Next to the definition provided in Chapter 1, firm innovation can also be defined as "the introduction of new products, processes, quality certification, activities, technology and knowledge transfer" (Bloch, 2007; Fombang & Adjasi, 2018, p. 2). Other definitions refer to the process[2] of innovation, the results of this process, or the novelty of the innovation at hand (Mahemba & Bruijn, 2003). Innovation can be imitative (i.e. copied from other parties), acquisitive (i.e. acquired through licensing, take-overs or partnering) or incubative (i.e. the result of internal research and development, Mahemba & De Bruijn, 2003). In the context of emerging markets, it is especially important to gauge the novelty of an innovation. Innovations that are "new-to-world" or "new-to-market" are rarely introduced as these are believed to require "a high level of technological capabilities [and] strong R&D" here typically absent (Mahemba & Bruijn, 2003, p. 163). Most innovation is therefore "new-to-firm" (Adeboye, 1997; Ayyagari et al., 2011; Carayannis & Provance, 2008; Levitt, 2006).

Peng (2002) offers a more formative description of innovation, and suggests it can be viewed as an outcome of the interaction between market pressure (Mahemba & Bruijn, 2003; Porter, 1980), institutions, and resources and capabilities (Barney, 1991; Teece, Pisano, & Shuen, 1997). Delving into these antecedents further, the resource-based view and institutional theory are discussed next.[3]

[2] Innovation is not to be viewed as "an instantaneous act [but as] a *process* that occurs over time and consists of a series of different actions" (Rogers, 1995, p. 163, italic in original).
[3] For the sake of brevity, market pressure (i.e. competition and demand) is not further discussed.

2.1.2. Resource-based view (RBV)

Barney (1991, 2001) presents the resource-based view framework that enables analyses of which resources and capabilities yield competitive advantage under what conditions. Here, resources are "stocks of tangible or intangible assets, such as fixed assets, information, brand, technology, human capital. Firms use these as inputs into production processes for conversion into products or services" (Grant, 1991). Capabilities on the other hand, are a special type ("subset") of resources, that intermediate, transform, and configure (the productivity of) other resources (Amit & Schoemaker, 1993, p. 35; Makadok, 2001, p. 389; Teece et al., 1997; Zoogah et al., 2015).[4] Resources and capabilities that yield sustainable competitive advantage are those which are valuable, rare, inimitable and organizationally embedded (VRIO) (Barney, 2001). Resources typically do not yield sustainable competitive advantage, as they are easily traded, transferred or imitated. Capabilities however, are generally more "VRIO" than resources as they are harder to acquire and imitate (Amit & Schoemaker, 1993; Lu, Zhou, Bruton, & Li, 2010; Makadok, 2001).

A causal chain can be construed as existing from resources, to the transformation of resources through capabilities, to the end-result of produced goods and services (Sirmon, Hitt, & Ireland, 2007). This makes clear that the availability of resources is prerequisite to using and developing capabilities. Firms in emerging markets typically face greater resource constraints than firms in developed markets, which could lead to more production problems (Lu et al., 2010). Such shortages also cause capabilities that foster innovation to remain underdeveloped by lack of "repetition and reinforcement" and trial and error (Mahemba & Bruijn, 2003; Tidd, Bessant, & Pavittkeith, 1997, p. 32). In conclusion, although the significance of capabilities is recognized, the availability of resources is an important prerequisite for firms to engage in innovation. For this study, it is important to note that possessed resources may be even more "Rare" and "Valuable" in emerging markets than they are in developed markets, in which resource allocation is generally more effective and efficient (Beck & Demirgüç-Kunt, 2006; Fombang & Adjasi, 2018). Hence, the effect of resources on innovation is a central topic in this research. Next, institutional theory is discussed.

[4] Some authors view "resources" and "capabilities" as synonyms or as non-overlapping concepts; the partial overlap described appears to be the dominant view (Lu et al., 2010). For the sake of clarity, in the remainder of this research, "resources" and "capabilities" are used as distinct concepts.

2.1.3. Institutional theory

Davis and North (1971, p. 6) were among the first to emphasize the importance of the "institutional framework [which is] the set of fundamental political, social and legal ground rules" on firm behavior and performance. Institutional theory emphasizes that firms are "never fully rational profit maximizing entities" as they reside in an institutional context with coercive, normative, and mimetic pressures (Scott, 2013; van Kranenburg & Voinea, 2017, p. 31). Current institutional theory combines sociological elements concerned with legitimacy (e.g. DiMaggio & Powell, 1983) and economic elements that focus on transaction costs (e.g. North, 1990) possibly heightened as a result of market failure caused by institutional voids (Khanna & Palepu, 1997). As the first chapter made clear, institutions can be broadly categorized as formal - codified and enforced by an established authority - or informal - more latent and profound stemming from certain values and beliefs (Scott, 2013). Scott (1995, p. 33) further subdivides informal institutions as normative (socially obliged, morally governed, associated with shame and honor) and cultural-cognitive (taken-for-granted through mutual tacit understanding and beliefs, associated with certainty and confusion).[5] Scott (1995, p. 132) also notes that if formal institutions fail, informal institutions can reduce said uncertainty and provide organizations with constancy. However, it is important to note that constancy does not necessarily imply effectiveness or efficiency, as it could mean the normalization of a poor status-quo (Scott, 2013; van Kranenburg & Voinea, 2017).

Various authors link innovation with institutions (e.g. Davis & North, 1971; Edquist & Johnson, 1997; Silve & Plekhanov, 2018). For example, Zoogah et al. (2015, p. 20) state that innovation is positively influenced by "institutional beneficence," referring to "the degree in which [institutional] environments facilitate organizational effectiveness." Such environments are "not only devoid of shocks, uncertainties, and chaos, but they also enable organizations to counter transaction costs and institutional voids." Donges, Meier, and Silva (2019) confirm this view, in their careful (quantitative and qualitative) analyses of an exogenous and sudden institutional upheaval, that was shortly followed by positively altered innovation outcomes. Donges et al. analyze the French occupation of (contemporary) German regions in the Napoleonic era: these German regions had been characterized by institutions preserving the

[5] Scott (1995, 2013, p. 59) describes the "regulative systems, normative systems, [and] cultural cognitive systems" as "the three pillars [that are] making up or supporting institutions."

power and wealth of the local elite, but as the French occupied these territories, they also swiftly exported their own institutions. First of all, the French abolished the hegemonic cartel-like guilds and introduced commercial freedom. Secondly, independent judges were installed, to replace the system in which public administration and judiciary were not separated. Thirdly, the French installed their civil code, outlawed serfdom, created equality before the law for all citizens, and introduced egalitarian property rights. These transformations created an institutional environment conducive to innovation, as measured by the number of high-value patents held by firms in the occupied regions, which was twice the number per capita held by firms in unoccupied regions.[6] Donges et al. (2019, p. 2) conclude that such "inclusive institutions (…) that provide broad access to economic opportunities instead of favoring the few at the expense of the many" are vital for innovation.

Although Donges et al. mainly focused on formal institutions, they are also attentive to informal institutions. The aforementioned French institutions provided competitive advantage to local firms at least until the first World War almost a century later, even though the French occupation lasted shorter than two decades. This resilience suggests the institutions had not only been rooted at a formal level – which means the legislators that returned to power could have easily overturned them if so desired – but also at an informal (normative) level, as the institutions provided new norms for doing business, and were believed to be appropriate.[7] This phenomenon is in line with Scott's (2013, p. 62) argument that "institutions supported by one pillar may, as time passes and circumstances change, be sustained by different pillars."

Furthermore, Donges et al. (2019, p. 4) find that these progressive French institutions had a weaker (although still significantly positive) effect in "counties that were part of former ecclesiastical states, where society was more conservative and social norms were dominated by the Catholic Church." This suggests that even though the French institutions received both regulative support and normative support in business contexts, their effect was diminished in

[6] Controlling for alternative explanations such as patent numbers prior to occupation, local GDP per capita, wealth concentration, knowledge and technology transfer, migration, education, and literacy rates.
[7] In regions that had only been under French rule for a short period, indeed "German sovereigns recalled some of the Napoleonic institutions" (Donges et al., 2019, p. 7).

those regions in which Catholicism dominated (normative and cultural-cognitive) institutions. This history makes clear that institutions can also exist at odds with each other even if both are (at least partly) informally rooted.

2.2. Specific literature review

This section of the literature review will describe the ways in which institutions and (financial) resources interact and detail how institutions can facilitate or complicate resource acquisition.

2.2.1. Interaction institutions and (financial) resources

Resources are embedded in a broader institutional environment (Oliver, 1997). Institutions can facilitate or complicate the acquisition of resources (Scott, 2013); this interaction, part of the larger above-mentioned interaction by Peng (2002), affects innovation (Zoogah et al., 2015). In developed markets, a firm's ability to innovate has been linked to its possession of several types of resources as well as the presence of institutions that facilitate its acquisition of such resources. Examples of these resources include human capital (Badinger & Tondl, 2003; Dakhli & De Clercq, 2004), technology (García-Morales, Ruiz-Moreno, & Llorens-Montes, 2007; Love & Roper, 1999), and financial resources (Camisón-Zornoza, Lapiedra-Alcamí, Segarra-Ciprés, & Boronat-Navarro, 2004; Damanpour, 1991; Gassmann & Zedtwitz, 2003).

While some research confirms that this link between innovation and resource acquisition holds true in emerging markets, evidence is relatively scarce. Moreover, quantitative analyses around this topic often fail to combine the resource (at the firm-level) and the institution (at the macrolevel). For example, Ayyagari et al. (2011) analyze only firm-level financial resources; Barro (2001) focuses on macrolevel human capital (education); and Fu, Pietrobelli, and Soete (2011) focus on macrolevel institutions that support R&D.

Zoogah et al. (2015, p. 17) emphasize the need for cross-level analyses and state that firms in emerging markets often turn to resources provided by informal institutions, to "supplement[,] compensate or substitute for the absence, insufficiency, or disutility of (…) formal resources." They name several examples (p. 13-15). Instead of formal markets regulating trade, firms can rely on acquisition by informal barter. In the absence of a functioning job market, (public) positions are not distributed by competence but by nepotism and tribalism, and the lack of formal education and technology is substituted by indigenous knowledge and ingenuity.

In this research, financial resources and the associated formal and informal institutions are central. On the one hand, formally regulated financial money markets are discussed, from which firms can get credit from a formally regulated institution. On the other hand, the informal institution and informal credit of the ROSCA is elaborated. The "Rotating Savings and Credit Association" is, as Chapter 1 made clear, in its most basic form an informal communal fund to which members of the association contribute a periodic fee, after which the lumpsum of collected fees is distributed to a member (Henry, 2003; van den Brink & Chavas, 1997; van Rooyen et al., 2012).

2.2.2. Use of formal credit

In developed markets, the positive relationship between innovative firm performance and the use of external finance is well established (Levine et al., 2000). If firms lack internal financial resources, they seek external resources to fund short-term and long-term expenses. Innovation is generally considered a long-term business expense that requires external capital (Krammer, 2017). Ayyagari et al. (2011) suggest that the above-mentioned relationship between innovation and financial resources also exists in emerging markets, making clear that external financing and bank financing are both predictors of various innovation outcomes (see also Demirgüç-Kunt & Maksimovic, 1998). More specifically, Ayyagari et al. (2011) report that bank financing is a highly significant predictor of whether a firm will introduce new product lines, upgrade existing product lines, implement new technology, open a new plant, commence a joint venture with foreign partners, and sign new licensing agreements (p. 1565). Fombang and Adjasi (2018) confirm Ayyagari et al. (2011), reporting that firms in Cameroon, Kenya, Morocco, South Africa and Nigeria financed by formally-regulated institutions are more likely to innovate.

However, it is important to note that differences in efficacy emerged between these countries in relation to credit type (e.g. overdraft versus asset finance).[8] Taking these studies into consideration, the use of formal credit and firm innovativeness is hypothesized to be positively related.

HYPOTHESIS 1A: Firms that use formal credit are more likely to innovate

2.2.3. Quality of formal money market

Demirgüç-Kunt and Maksimovic (1998) show that firms are predicted to grow and innovate at higher rates if they reside in a country with more developed financial markets, regardless of their own use of external credit. Comparatively, Yawe and Prahbu (2015, p. 216) argue that "the level of development of a country's financial system determines the nature of innovations." Arguably, as more firms are appropriately financed, competitive innovation efforts become more intense, and even firms that lack external finance must innovate to survive market pressure. From an institutional view, firms active in an institutional environment conducive to innovation, will also face mimetic and normative pressures be innovative (Scott, 1995). In an underdeveloped financial market however, "the inability to access financial services prevents investment in income-generating activities" (Yawe & Prabhu, 2015, p. 216). As a result, competitive, mimetic, and normative pressures to be innovative are weaker or absent in countries with lower quality money markets.

HYPOTHESIS 1B: The quality of the formal money market has a positive effect on firm likelihood to innovate, controlling for firm use of formal credit

[8] Also, trade credit successfully predicted innovation in Nigeria, South Africa and Cameroon, indicating credit is not necessarily provided by a banking institution, but can also be the result of trade practices, possibly as a reaction to underdeveloped money markets.

2.2.4. Use of formal credit & quality of formal money market

Multiple authors state the circumstances under which credit is acquired impact on innovation (Ayyagari et al., 2011; Cornaggia, Cornaggia, & Hund, 2012; Fang, Tian, & Tice, 2014; Fombang & Adjasi, 2018; Nanda & Nicholas, 2014). Four simplified scenarios can be distinguished out of the 2x2 contingencies of *credit versus no credit; lower quality market versus higher quality market*.

Firms that acquired a credit in a higher quality money market, are likely to have paid the least transaction costs and an optimal price (i.e. interest) as supply and demand are efficiently matched: the market is supported by well-functioning institutions (Atanassov et al., 2007). Moreover, because higher quality markets beget well-financed firms who can thus innovate effectively, firms active in these markets experience mimetic, normative, and competitive pressures to innovate. It is therefore expected these firms are the most likely to innovate.

Meanwhile, firms that acquired a credit in a lower quality money market, are likely to have paid high transaction costs, because of lacking information or power imbalances between firms and credit providers. What is more, Freel (2007, p. 24) argues that banks in underdeveloped markets engage in "credit rationing." This means that banks do not provide firms with the total amount of funds they requested, but only a part of these funds, even if these firms are willing and able to pay (higher) interest. Another reason banks only provide firms with partial credit is because they lack information to establish the risk and the appropriate price of credit (i.e. interest). Hence, even though the firms, strictly speaking, acquired external finance through formal institutions, it is likely to be less than the sum needed to fund their (innovative) strategy (Lee, Sameen, & Cowling, 2015).[9] It is therefore expected that firms that have acquired a credit in a lower quality money market, are less likely to innovate.

[9] It is noted that banks, even in developed markets, often turn down firms for credit that innovate at a level that is "new to the world," as no reasonable metric of risk is available to establish the creditworthiness for products that do not yet exist– such firms are thus usually financed by outside investors with higher appetites to risk, such as venture capitalists (Kortum & Lerner, 1998) or trough public listing (Atanassov et al., 2007). However, this research focuses on emerging markets, in which "new to the world" innovations are not likely.

Firms without credit and active in a higher quality money market, are expected to be even less likely to innovate, although they do experience mimetic, normative, and competitive pressures to be innovative, as other firms are well financed and will exploit more innovative activities. The least likely to innovate are firms that have no credit and are active in a lower quality money market, as they do not even experience the above-mentioned pressures.

Finally, firms in lower quality markets that use credit may benefit relatively more compared to a no-credit scenario than do firms in higher quality markets, as financial resources in such environments are rarer and can make the firm gain an innovative competitive advantage over other firms.

HYPOTHESIS 1C: The quality of the formal money market moderates the relationship between formal credit and firm innovation, such that:

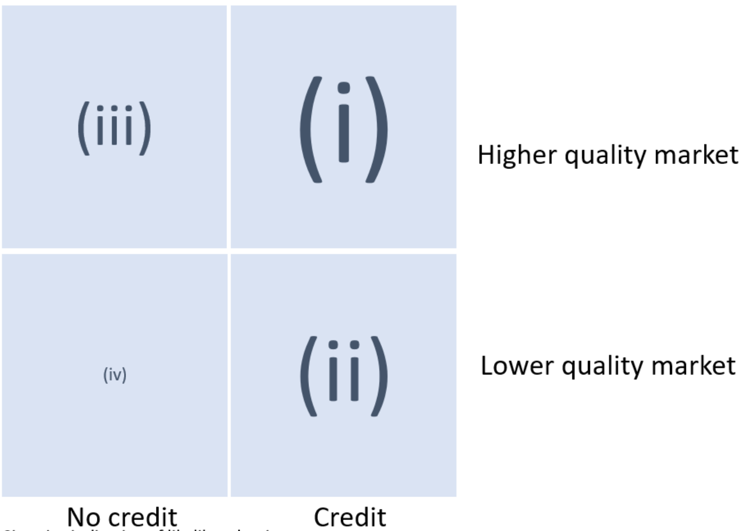
(i) Firms that use credit in a higher quality money market, are the most likely to innovate

(ii) Firms that use credit in a lower quality money market, are less likely to innovate

(iii) If no credit is acquired, firms in higher quality money markets are even less likely to innovate

(iv) If no credit is acquired, firms in lower quality markets are the least likely to innovate

(v) Firms in lower quality markets that use credit, innovate relatively more compared to a no-credit scenario, than do firms in higher quality markets



Sign size indicative of likelihood to innovate

(Adapted from Atanassov et al., 2007; Freel, 2007; Lee et al., 2015)

Figure 1. Visualization of Hypothesis 1C

2.2.5. ROSCA prevalence

With the hypotheses regarding formal credit formulated, the ROSCA is now elaborated. The "Rotating Savings and Credit Association" (ROSCA) is a group-based system with some form of communal fund (Henry, 2003). It unites "relatives, neighbours, friends or colleagues," exists in both "urban and rural" sectors and typically lacks formal registration (Bruchhaus, 2016, pp. 38–39). ROSCAs are prevalent in Asia, Latin America, and parts of Europe, but particularly in Africa (Gugerty, 2007). The ROSCA is often referred to as a "poor man's bank," (Bouman, 1983, p. 5) but this characterization does not do justice to the economic reality. ROSCAs are not restricted to the poor, but are used by all layers of society (Henry, 2003). To illustrate, Henry (2003, p. 2) identified ROSCAs with a monthly contribution of the equivalent of 2,000 euro with a monthly lump sum equating 250,000 euro - although such large sums appear to be exceptional.

In 1997, Chavas and Van den Brink noted that "the performance of informal institutions specialized in financial intermediation remains poorly understood" (p. 2). Since then, ROSCAs have rarely been the subject of empiric research (van Rooyen et al., 2012).[10] However, specifically in the context of businesses, field experiments conducted by Kast, Meier, and Pomeranz (2012) with 3,000 Chilean microentrepreneurs offer some insights: the study reports that collective saving schemes increased the number of deposits in the community almost fourfold and the average savings balance almost twofold.

Modern microfinance programs are often based on group-lending schemes with strict rules and occasionally high levels of "ritual preservation", frequently managed or kickstarted by NGOs (Henry, 2003, p. 10; Morduch, 2000, p. 2). As such, research on microfinance could be relevant for ROSCAs too. However, the effect of modern[11] microfinance schemes on business outcomes is mixed (Banerjee, Breza, Duflo, & Kinnan, 2017; van Rooyen et al., 2012). For example, Banerjee et al. (2017) conducted a randomized controlled trial in certain Indian regions, with the availability of microcredit as intervention, and measured results two years

[10] E.g. in small-scale research, informal group-based savings and credit schemes were shown to have very large health effects (Dupas & Robinson, 2013).

[11] Up until 2000, "subsidized credit programs failed nearly universally, and disaster stories are well-catalogued," among others because loans were government-guaranteed (Morduch, 2000, p. 620). For this reason, banks had an incentive to avoid the transaction cost associated with collection.

post-intervention. They report that while experienced entrepreneurs benefitted significantly from microcredit, inexperienced entrepreneurs did not. Furthering this argument, Banerjee et al. attribute this difference to “heterogeneity in entrepreneurial ability” (p. 1). On an additional note, after the introduction of microfinance, the social ties in treated neighborhoods were significantly weakened, and hence many informal financial ties severed.[12]

Van Rooyen et al. (2012, pp. 2258–2259) start their system-level review of microfinance in sub-Saharan Africa by voicing strong concerns about the quality of contemporary microfinance research, as “the positive rhetoric [has] a negative impact on the quality of evidence.” In their view, "rhetoric, unfounded assumptions, anecdotal accounts and advocacy research” are used too often to validate microfinance. For their study, they selected 15 reliable and relevant studies for meta-analysis, predominantly in rural settings. These assessed studies showed mixed results regarding impact on business income - some studies revealed decreasing incomes, and two studies showed farmers diversifying their crops, which classifies as “new-to-firm” innovation.

As little empirical evidence on ROSCAs exists, more attention will be paid to conceptual exploration of the functioning of a ROSCA in order to derive hypotheses.

2.2.6. The ROSCA as an economic institution

The economic institution of the ROSCA can be described as a “collective mechanism for individual self control in the presence of time inconsistent preferences” (Yawe & Prabhu, 2015, p. 218). Van den Brink and Chavas (1997) outline how ROSCAs are organized in their most basic form (although many complex variations are possible and prevalent). Members of a ROSCA make a monetary contribution to the ROSCA’s fund at a certain interval and the total contribution of that period is distributed to one member as a lump sum.

[12] The authors argue that the external financial stimuli reduced mutual interdependence, suggesting these social ties were only instrumental to financial reciprocity. Even after the stimuli were removed, the number of ties did not restore to its original amount.

This contribution/distribution-pattern is repeated until every member has had a turn in receiving the lump sum. The ROSCA hence provides a microeconomic solution to the "problem of the indivisible good" (van den Brink & Chavas, 1997, p. 11) A simplified example can clarify this. Assume a ROSCA has three members, each of them wanting to save money to build a house. The saving time per individual without cooperation, is one year. If the three pool and distribute their savings however, the first individual to receive the money will be able to build the house in 1/3 of a year and the second one in 2/3 of a year. Hence, the ROSCA provides 2/3 of the members a "strictly reduced waiting time," whilst the third member is not disadvantaged as his waiting time remains one year. The solution of the ROSCA is therefore Pareto-efficient and solves the "lumpiness problem" sequentially (van den Brink & Chavas, 1997, p. 754).[13] In conclusion, as members of a ROSCA on average have faster access to finance than those that are not involved in a ROSCA, firms that use a ROSCA-credit are expected to be more likely to innovate.

HYPOTHESIS 2A: Firms that use ROSCA-credit are more likely to innovate

2.2.7. The ROSCA as a social institution

The ROSCA can be viewed as a "social phenomenon" as well, in which "social gathering" is important (Henry, 2003, p. 2). Periodic meetings are central to a ROSCA; at these meetings members pay their contributions and the ROSCA distributes the lump sum. While some ROSCAs have clear and simple rules (Bruchhaus, 2016), others are "very complex and sophisticated" (Henry, 2003, p. 1). Typically, however, and especially in Africa, ROSCA-meetings are highly traditional and ritualized (Henry, 2003). Inside and outside meetings, ROSCAs are led by a democratically appointed "president," a position associated with great prestige (van den Brink & Chavas, 1997, p. 748). The president, who is not necessarily a member of the ROSCA, often already holds a position of authority within the local community and is not even necessarily financially literate. The president is often given the authority to fine ROSCA-members that miss meetings, are late, or do not adhere to its rituals.

[13] As said, this is the most basic ROSCA-form. Many more (complex) variants exist, for example providing insurance against calamities (Bruchhaus, 2016), paying interest over a lump-sum as long as it is not paid back, bidding to acquire the lump sum, or even using all pooled resources as an "investment fund" that distributes the benefits (Henry, 2003; van den Brink & Chavas, 1997).

At the core of the concept of a ROSCA is “reciprocal solidarity” (Bruchhaus, 2016, p. 2), a norm enforced by social pressure that works to reduce the risk of member defaults (van den Brink & Chavas, 1997).[14] ROSCAs strengthen their members’ senses of community as well as their socio-cultural identities (Bruchhaus, 2016, p. 2). In this way, ROSCAs serve to build trust, kindness, and mutual aid among their members (Henry, 2003). Members who fail to provide sufficient mutual aid may be fined by some ROSCA; fines may for example be incurred if a member fails to visit other members who are sick or have experienced the loss of a family member (Henry, 2003, p. 5).

Some ROSCAs however, appear not to be ruled by trust but by suspicion. In these ROSCAs, “peer pressure” is so extreme that it normalizes a “threat of social ostracism”, situating members who default as “morally and socially bankrupt” (van den Brink & Chavas, 1997, p. 753). Henry (2003, p. 4) notes that a ROSCA-member stated that he would rather “sell his house to cover his repayments than face the shame of the tontine.”[15] Social sanctions can even be so fierce that defaulting results in (self-chosen) exile (Henry, 2003).[16]

What is more, in schemes like these social capital is often abused by dominant community members to disproportionally lay hold on economic gain from group efforts, which particularly women fall victim to (Mayoux, 2001). As a consequence, hierarchies are enforced and (financial) inequality can be exacerbated. In these scenarios, next to creating negative social externalities, ROSCAs are likely to be economically ineffective too.

[14] Legal action is considered expensive and unreliable to enforce a ROSCA-payment, but most importantly deemed incompatible with the obligation that is considered social (Henry, 2003). It is noted that some ROSCAs do allow the president to fine late payments.
[15] Tontine is the dominant term for a ROSCA in Francophone Africa; other African terms include dashi, isusu, susu, ekub, upatu, njangeh, chilemba, upatu; outside of Africa the ROSCA is for example named arisan (Indonesia), pia huey (Thailand), ko (Japan), ho (Vietnam), Kye (Korea), and hui (China) (van den Brink & Chavas, 1997, p. 767).
[16] These sanctions can also be relatively mild. Referring to heavy (social) sanctions, one ROSCA-member claimed: “(…) here in the village, we don’t do that, we say: ‘‘sorry for our money’’ and forget about it. Another *njangeh* can take the man, and if he changes his fashion, all the better” (van den Brink & Chavas, 1997, p. 752, quotation marks and italic in original).

2.2.8. Further ROSCA-management

In addition to above-described social pressure and presidential authority, several more mechanisms to manage risk and transaction costs exist. First, most ROSCAs vet new members based on their social standing and perceived trustworthiness within their community. In other words, a ROSCA uses social information as a proxy to gauge the expected economic behavior of an individual. This process provides a measure of ex-ante risk reduction unavailable to formal money lenders who lack such communal information (van den Brink & Chavas, 1997).

Secondly, after the selection procedure, risk is managed by determining the order in which each member will receive a lump sum. Members that receive the lump sum early, have only made small contributions, and therefore the theoretical impact of default for the rest of the ROSCA is greatest. Although the president generally decides, this is why new members are typically placed late in the rotation order of the lump sum. In other words, their contributions have been so significant compared to the lump sum, that even in the event of default, the economic risk for the other members is minimized (van den Brink & Chavas, 1997).

As members demonstrate their ability to pay their periodic contribution, they move up in the rotating order of receipt of lump sum. The social pressure described above is likely to prevent a "permanent default." Nevertheless, behavior within ROSCA cycles still provides valuable (economic) information about members such as when a member makes a late payment, struggles to make payments, or fails to conform to the ROSCA's traditions. The behavior of a ROSCA member is evaluated by the group and the president and leads to an adjustment of a member's order in the rotation in an attempt to adjust the economic risk of the group vis-à-vis the individual. Some ROSCAs require their presidents to participate in the ROSCA and to take last place in the rotating order of receipt to incentivize his management of the ROSCA and prevent agency problems (Henry, 2003).[17]

[17] Then, the social prestige the president derives from his position, is in part a compensation for his personal financial exposure, instead of a "free benefit." Presidential candidates are motivated to take the financial risk into account, and incompetent candidates arguably self-select out.

Such mechanisms - the list is not exhaustive - determine how effective and efficient a ROSCA is, influencing transaction costs. For example, if a ROSCA fails to properly vet its aspiring members, it may refuse individuals who would have significantly contributed to the ROSCA and admit others who struggle to make payments. Members who struggle to make their payments prove especially problematic for a ROSCA that seeks to grow by increasing period contributions, a strategy that is often decided by unanimity or a strong majority. For ROSCAs that employ complex interest schemes for saving and borrowing, the correct allocation of capital is especially important.

HYPOTHESIS 2B: The quality of ROSCA-management positively moderates the relationship between ROSCA-credit and firm likelihood to innovate.

2.2.9. ROSCA-credit formal money market quality

It has been demonstrated the ROSCA is theoretically microeconomically sound. Furthermore, a clear advantage of ROSCAs that may be valued highly, is that all contributions (i.e. savings) are "locally transformed into credit" so money is retained within the community (van den Brink & Chavas, 1997, p. 761). Some authors make the case that the informal ROSCA is a solution to poor-functioning formal money markets (van den Brink & Chavas, 1997).[18] As discussed earlier, such money markets are characterized by high transaction costs, which among others is caused by information asymmetry, absence of information, and power imbalances. While Zoogah et al. (2015) indeed contend that firms lacking access to the financial resources of regulated markets may join ROSCAs, no evidence exists that makes clear under what conditions entrepreneurs use ROSCA-credit over formal credit. It is expected however, that as the formal money market quality is lower, the relationship between ROSCA-credit and innovativeness is stronger, as well-performing firms that - in a better functioning market - would have gotten a formal credit, but are currently unable to obtain one, now instead seek financial resources through a ROSCA.

HYPOTHESIS (cross-interaction) 3: The quality of formal money markets negatively moderates the relationship between ROSCA-credit and firm likelihood to innovate.

[18] Besley, Coate and Loury (1994) demonstrate mathematically that a ROSCA is less efficient than an idealized, theoretical money market, but Van den Brink and Chavas (1997) dismiss this evidence as perfect money markets do not exist.

Even as alternative institutions for saving and credit become available, ROSCAs continue to hold great appeal (van den Brink & Chavas, 1997; Yawe & Prabhu, 2015). For example, although the use of mobile money transfers has boomed in Zimbabwe, complementary savings and credit options are rarely used – people remain reliant on traditional savings and borrowing schemes (Thulani, Chitakunye, & Chummun, 2014). In the abovementioned randomized controlled trial, Banerjee et al. (2017) find that access to both formal and informal credit is highly complementary. It is therefore argued that firms that find ways to mix financial resources from various sources, formal and informal, are most successful. This yields the following hypothesis:

HYPOTHESIS (cross-interaction) 4: Firms that use both formal credit and ROSCA-credit, are more likely to innovate than firms that use only one or neither forms of credit.

2.3. All hypotheses

The research question of this study is: *What is the effect of the firm-specific access to external finance on SME firm innovation in developing markets, as moderated by the quality of formal and informal financial institutions?* The following hypotheses have been formulated:

HYPOTHESIS 1A: Firms that use formal credit are more likely to innovate

HYPOTHESIS 1B: The quality of the formal money market has a positive effect on firm likelihood to innovate, controlling for firm use of formal credit

HYPOTHESIS 1C: The quality of the formal money market moderates the relationship between formal credit and firm innovation, such that:

(i) Firms that use credit in a higher quality money market, are the most likely to innovate
(ii) Firms that use credit in a lower quality money market, are less likely to innovate
(iii) If no credit is acquired, firms in higher quality money markets are even less likely to innovate
(iv) If no credit is acquired, firms in lower quality markets are the least likely to innovate
(v) Firms in lower quality markets that use credit, innovate relatively more compared to a no-credit scenario, than do firms in higher quality markets

HYPOTHESIS 2A: Firms that use ROSCA-credit are more likely to innovate

HYPOTHESIS 2B: The quality of ROSCA-management positively moderates the relationship between ROSCA-credit and firm likelihood to innovate.

HYPOTHESIS (cross-interaction) 3: The quality of formal money markets negatively moderates the relationship between ROSCA-credit and firm likelihood to innovate.

HYPOTHESIS (cross-interaction) 4: Firms that use both formal credit and ROSCA-credit, are more likely to innovate than firms that use only one or neither forms of credit.

2.4. Conceptual model

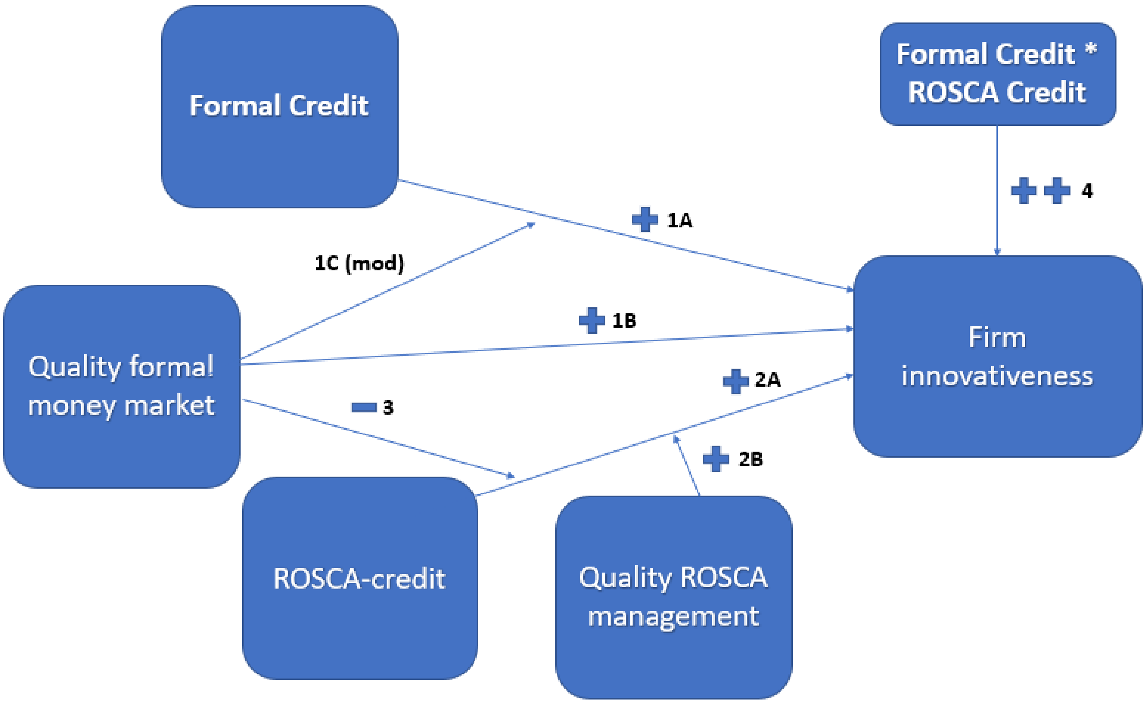


Figure 2. Conceptual model describing derived hypotheses

Chapter 3: Methodology

3.1. Sample characteristics

25,681 SME firms from 19 emerging markets were selected as the research setting (Appendix 2). Firm-level data from the World Bank Enterprise Survey (WBES) for the period 2010-2017 was used (World Bank, n.d.-c). This was supplemented with country-level data from the Global Innovation Index (GII) (Cornell University, Institut Européen d'Administration [INSEAD], & World Intellectual Property Organization [WIPO], 2018) and the World Values Survey (Inglehart et al., 2014). SMEs were defined, following WBES measures, as firms having less than 100 employees (World Bank, n.d.-c).

3.2. Method of analysis

Multilevel logistic regression is the analytical procedure of choice in this study.[19] Logistic regression is a fitting method when the dependent variable is binary (Field, 2013; Hair, Black, Babin, & Anderson, 2010).[20] Contrary to regular regression in which a value Y is predicted for predictor(s) X_n, logistic regression predicts "the probability of Y occurring given known values" of X_n (Field, 2013, p. 762). Multilevel-analysis recognizes the nested or hierarchical structure within data, and is appropriate if the higher level within the data is deemed to be an important "contextual variable" (Field, 2013, p. 815; Steele, 2008). The country of residence of firms can be viewed as such an important contextual variable that affects innovation, as countries differ along the economic and institutional context they provide (Hitt, 2016). Hence, multilevel analysis is required.

Most statistical models assume uncorrelated error terms across all subjects (Field, 2013; Xing Liu, 2015; Steele, 2008). This assumption is not tenable if an underlying hierarchical structure is present, as it is in this research. Because firms operating in the same country are more likely to display similar behavior due to "common experiences," compared to firms operating in other countries, their error terms are correlated (Stephan, Uhlaner, & Stride, 2015, p. 316).[21] Multilevel modelling takes this interdependence into account. Additionally, multilevel

[19] Multilevel models are also known as hierarchical models, nested data models, mixed models, and random-effects models (Field, 2013).
[20] See dependent variable further.
[21] The exact degree of interrelatedness is called "intraclass correlation (ICC)" (Field, 2013, p. 817). The ICC will be calculated in the analyses.

modelling does not assume that regression slopes across groups are equal (here: firms in a country) (Field, 2013; Sommet & Morselli, 2017). This allows for a country-by-country estimation of the effect of variables on innovation. By measuring country variables at the appropriate level, multilevel modeling prevents Type 1 errors (false-positives) (Stephan et al., 2015). Inserting country-level controls at the firm level would result in a severe understatement of associated standard errors (Field, 2013; Sommet & Morselli, 2017; Steele, 2008).

3.3. Reliability and validity

The data used in this research are the results from the World Bank Enterprise Survey (WBES). The methodology applied in this survey is deemed state-of-the-art (Ayyagari et al., 2011; Fombang & Adjasi, 2018; Krammer, 2017). The World Bank takes explicit measures to ensure reliability and validity, and to that end adheres to its "Global Methodology" across countries since 2005 (World Bank, n.d.-c). This include intensive pretesting, careful translation, the use of face-to-face interviews, the use of professional private interviewers unaffiliated with governments, elaborate interview manuals, strict confidentiality arrangements, and the use of business owners and top managers as interview subjects supplemented with statements from company accountants (World Bank, n.d.-c, 2019b). Self-report bias however, cannot be completely prevented (Field, 2013).

The possibility of external validity (generalization) is a common reason to choose quantitative analysis (Field, 2013; Vennix, 2011). A generally accepted rule of thumb is that a sample (n) of 400 suffices to generalize to any population (N) of 20,000 (Hill, 1998). Meeting this quantity is a necessary-but-not-sufficient condition for generalizability, however: sample representativeness is also commonly stressed (Field, 2013; Hair et al., 2010; Hill, 1998; Kukull & Ganguli, 2012). The sample will need to be representative of the population, in order to be externally valid (Field, 2013). Samples that form just a fraction of the total population can deliver generalizable results, provided they represent the population very well (Cook, Heath, & Thompson, 2000). In sum, a sample must meet quantitative and qualitative thresholds in other to be deemed generalizable. This sample meets the quantitative threshold for generalization to the population of SMEs in emerging markets as n=25,681. Regarding sample quality, the World Bank (2009, pp. 2–3) used a "uniform sampling methodology" in each country to “generate a sample representative of the whole non-agricultural private economy” by stratified sampling based on firm sector, size, and geographical location. Although non-response bias cannot be ruled out (Field, 2013; World Bank, 2009), the sample quality of the WBES is deemed sufficient. In conclusion, this sample is deemed representative of the population of SMEs in emerging markets, and hence external validity is possible.

3.4. Dependent variable

The dependent variable chosen to measure innovation is new product introduction.[22] The WBES-question is worded as follows: “During the last three years, has this establishment introduced new or improved products or services?”, to which the responses are binary (World Bank, 2018, p. 18). This measure is used in several other studies, and deemed to be a good gauge of the innovativeness of a firm (e.g. Ayyagari et al., 2011; Barasa, Knoben, Vermeulen, Kimuyu, & Kinyanjui, 2017; Chadee & Roxas, 2013; Fombang & Adjasi, 2018; Krammer, 2017; Mohnen & Hall, 2013).[23]

3.5. Independent variables

3.5.1. Firm use of formal credit (Level 1)

The WBES survey has several measures that can be used to measure formal credit use. A dummy variable will be used, that asked whether an enterprise has a line of credit or loan from a bank (e.g. Ayyagari et al., 2011; Fombang & Adjasi, 2018). Another option was to use percentage-based data (e.g. percentage of working capital and fixed assets financed), but literature does not suggest that as higher proportions of the firm are externally financed, innovation will proportionally increase – thus, the percentage-based data is deemed inadequate.

[22] Please refer to Appendix 1, which contains a legend for variable names, meaning, and measurement. Interpretable nominators will be used in the main body of text (e.g. “firm size”), whilst the appendices will use original dataset variables (e.g. “h8”).
[23] Patents are possibly the most frequently used indicator of innovativeness (Lanjouw & Schankerman, 2004), but deemed unsuitable for this study: as mentioned, new-to-market/world innovations are scarce in emerging markets (Ayyagari et al., 2011).

3.5.2. Firm use of ROSCA-credit (Level 1)

For the use of ROSCA-credit, the proportion of working capital and fixed assets financed are available. These too will be dummified into one variable. The WBES measures the amount "[b]orrowed from non-bank financial institutions, which include microfinance institutions, credit cooperatives, credit unions, or finance companies" (World Bank, 2018, pp. 25–26). Credit cooperatives and credit unions refer to ROSCAs. It is emphasized that this indicator is not a perfect measure of ROSCA-credit use, as the variable is contaminated by borrowings from microfinance institutions and finance companies. It is however expected, that the measurement error is manageable. First of all, this measure explicitly does not include financial resources from "equity shares, moneylenders, friends, relatives and bonds etc.," which are included as a separate residual category (World Bank, 2018, p. 26). Secondly, ROSCAs are likely to be more prevalent than microfinance schemes in the sample, as the WBES only surveyed formally registered, non-agricultural firms (World Bank, 2009) while microfinance efforts are mostly focused on informal, agricultural settings (Henry, 2003). Thirdly, because modern microfinance schemes implement group-based lending and mime some elements characteristic of traditional ROSCAs, they may logically be interpreted as likely to be governed by degrees of trust, preventing the relationship between independent variables from being distorted (Henry, 2003).

3.5.3. Quality of formal money market (Level 2, Appendix 3)

To gauge the quality of the formal money market, several measures from the Global Innovation Index (GII) are used that correspond to the year the survey was administered (e.g. Cornell University et al., 2018). The GII aggregates and collects information on factors that increase the innovativeness of economies, and its quality of research is independently audited by the Joint Research Centre of the European Commission. This research uses the measure "ease of getting credit,"[24] which the GII uses to indicate market sophistication (Cornell University et al., 2018, p. 356). It is a composite of firstly the strength of "legal rights of borrowers and lenders" measuring "whether certain features that facilitate lending exist within the applicable collateral and bankruptcy laws," and secondly depth of credit

[24] It is noted that the label "ease" of getting credit is not fully representative of market sophistication, as in a poorly functioning money market (e.g. lacking consumer protection), credit may be distributed too easily, leading to over indebtedness and market distortions. Rather, "ease of getting credit" should be understood as the effective and efficient allocation of credit.

information, defined as the "coverage, scope, and accessibility of credit information available through credit reporting service providers such as credit bureaus or credit registries" (p. 356). This variable is sample mean centered to facilitate interpretation and avoid multicollinearity in the interaction effect models (Field, 2013; Hair et al., 2010).

3.5.4. Quality of ROSCA-management (Level 2, Appendix 3)

The WBES database does not provide direct measures of country or firm-level ROSCA quality. Therefore, an appropriate proxy is required. Trust and reciprocity are important concepts within ROSCAs (van den Brink & Chavas, 1997). Krammer (2017, p. 8) describes trust as a "belief in the honesty, integrity, and reliability of others and thus [as] an expression of adherence to a moral community, which lays the basis for cooperation between different actors in a society."

Higher levels of trust mean ROSCAs are managed with less mutual suspicion. Higher trust may increase the number of members a ROSCA allows as well as the sums of money it distributes and, moreover, may enable the ROSCA to more efficiently and effectively allocate resources because binding mutual expectations allow social control mechanisms to be less strict and time consuming (Scott, 1995). The World Value Survey (2012) measures societal trust, an indicator used in institutional research (e.g. Krammer, 2017). However, instead of using societal trust (which also measures how a society evaluates its strangers and foreigners), this research incorporates the World Value Survey's measure of how much trust is put in "people you know personally" (World Value Survey, 2012, p. 8.). As ROSCA members are typically selected from within specific geographic and social limits, the measure of how much trust is put in personal connections serves as a better measure for this study than general societal trust. This variable is sample mean standardized to facilitate interpretation and avoid multicollinearity in the interaction effect models (Field, 2013; Hair et al., 2010).

3.6. Control variables

Level 1

Firm size & age

Different relationships between firm size and innovativeness have been suggested. While some authors suggest that smaller firms have the upper hand because the absence of bureaucracy within their organizations enables swift decision-making and the ability to more quickly adapt to change (Mahemba & Bruijn, 2003), others argue that larger firms have a competitive advantage when it comes to innovating because they typically have larger resource bases to put to use (Ayyagari et al., 2011; Y. Luo & Peng, 1999). Similarly, the age of a firm may impact its ability to innovative – older firms may have a better resource base than younger firms (Ayyagari et al., 2011; Barasa et al., 2017; Lu et al., 2010; Zhou, Wu, & Luo, 2007). This study therefore uses both firm age and size as controls.

Sector

To account for sector differences in innovativeness (e.g., due to competition or the kinds of products and services and investment opportunities central a particular industry), this study controls for the different sectors distinguished by the WBES, as outlined in Appendix 4 (e.g. Ayyagari et al., 2011; Krammer, 2017).[25] To prevent issues surrounding incomplete information and complete separation, the sector variable was collapsed (Field, 2013).

R&D

Firms that engage in specific R&D activities, are associated with more innovation (McGrath & Romeri, 2003). The WBES has a binary question phrased "During last fiscal year, did this establishment spend on formal research and development activities, either in-house or contracted with other companies?" (World Bank, 2018, p. 19). This measure is relatively narrow, focusing on formal and substantial activities (e.g. laboratory research), excluding activities such as "market research surveys or internet surfing" (World Bank, 2019b, p. 19). This variable is included as a dummy (Krammer, 2017).[26]

[25] Strictly speaking, firms are nested within sectors that are nested within countries. Hence, the data has three levels instead of the two on which this research design is based. The two levels are maintained, however, to prevent model over-specification, complete separation, and incomplete information leading to failure of model convergence, and because the institutional differences of interest researched are measured at the country level.

[26] It is noted that a metric variable (e.g. the percentage of total costs attributed to R&D) had possibly been a better control variable, as the intensity of R&D is likely to influence innovation. However, such a measure is absent in the data.

Foreign ownership

Foreign direct investment, mergers, and acquisitions in developing markets are associated with higher innovation, as these outside forces may provide the target with novel resources and capabilities (Xiaohui Liu & Zou, 2008). Specifically in the context of formal money sources, foreign ownership may also lead to "institutional borrowing" from credit institutions outside the host country (Doh et al., 2017). Hence, the percentage of foreign ownership is included as a metric variable to prevent distortion of the influence of the independent variable (Pinkham & Peng, 2017).

Financial performance

Better performing firms are more likely to innovate, as they have more resources to do so, have developed superior capabilities, and are hence looking to sustain their competitive advantage (Kostopoulos, Papalexandris, Papachroni, & Ioannou, 2011). Using Krammer's (2017) approach, firm performance is proxied by sales minus labor costs. This measure is preferred over gross revenue, to approximate profitability rather than total sales. It is noted that this proxy understates financial performance of labor-intensive firms compared to capital intensive firms, but no better measures are available in the WBES. Although some variance in labor intensity is thought to be covered by the industry-control, this measure also corrects for further between-country variance in labor intensity which can be expected given the large differences in country wealth (Appendix 3).

Managerial experience

Managerial experience is associated with increased innovation, as experienced managers are "likely to explore more, and more varied, innovation projects" (Barasa et al., 2017, p. 282; Bloom & Van Reenen, 2010). This study measures managerial experience by the years the top manager is active in the sector.

International exposure and competition

Golovko and Valentini (2011, p. 362) argue that "innovation and export positively reinforce each other in a dynamic virtuous circle" due to learning effects of international exposure (Barkema & Drogendijk, 2007) and competition (Ayyagari et al., 2011). Specifically in the context of financial resources, exporting firms may have better access to money markets outside of their domestic market (Ayyagari et al., 2011; Lu et al., 2010). Hence, the percentage of sales that are obtained through export is included as a control variable.

Level 2: Gross domestic product (Appendix 3)

Country wealth, defined as gross domestic product (GDP) based on purchasing power parity (PPP), is viewed as an important nation-level predictor of innovativeness (Cornell University et al., 2018). Therefore, GDP PPP per capita based on 2011 USD is included as a control variable for the corresponding years of firm activity (World Bank, n.d.-b).[27]

3.7. Sample size and cell size assumptions

Sample size calculations for multilevel logistic models are complex and unreliable (Field, 2013). However, if cross-level interactions are researched (such as in this research between firm- and country-level variables), the advised absolute minimum of researched contexts is 20 (Field, 2013; Kreft & de Leeuw, 1998). It is noted that the n=19 in thus study falls short of the absolute minimum and may therefore impact the estimation of cross-level interaction effects. What is more, it is noted that Indian firms make up 27.17% of observations (Appendix 2). This means this group of firms is influential and could bias the results – this influence will need to be assessed in a robustness check.

Next to overall sample sizes, cell sizes (or group sizes) are of special interest in logistic regression. The term cell is here used to refer to a combination of binary and categorical variables, like in a cross tabulation. If cell sizes are inadequate, "incomplete information" and "complete separation" can occur, which can lead to biased outcomes of "goodness-of-fit tests" or model convergence failure (Field, 2013, p. 770). Firstly, incomplete information occurs if a cell is empty, in other words, if a certain combination of variables is not present in the data (i.e. the combination has a frequency of 0). Secondly, complete separation is present if Y is perfectly predicted by a state of X_n (e.g. 100% of companies in a certain sector are innovative). Because expected probabilities are therefore 100% or 0%, the logistic model cannot converge. To prevent these issues, empty cells (n=0) must be avoided, and as a heuristic rule, no more than 20% of non-empty cells should have frequencies of 5 or less

[27] Possibly, GDP PPP per capita is highly correlated to quality of money markets. This will have to be assessed carefully.

(Field, 2013). Typical remedies for inadequate cell sizes include merging comparable groups or deleting categorical variables. Because the problem of missing data is closely related to that of inadequate cell sizes, the next section discusses a missing data analysis.

3.8. Missing data analysis and imputation

A missing data analysis was conducted from which cell size issues (n=0-5) arose, caused by the sector variable with 23 distinct sectors (Appendix 5). Data imputation techniques can be used to remedy missing values by replacing them with non-missing values (Hair et al., 2010). With regard to the data set of this study, data imputation can first be used to attempt to increase cell frequencies. As more complete cases become available, logistic regression estimates – especially those regarding estimated country-specific effects – become more stable.

As Little's MCAR-test is significant (χ^2 (888) = 2091.60, p<0.001), Hair et al. (2010) state the data cannot be assumed to be MCAR[28]. The data are therefore assumed to be MAR[29]. The MAR nature of data means that not all imputation techniques are acceptable (Hair et al., 2010). More specifically, this situation rules out simple techniques, such as substituting missing values by the mean of non-missing values. Multiple imputation is generally considered the best imputation method, especially in the event of MAR data (Bartlett & Carpenter, 2013; Hair et al., 2010; StataCorp, 2017c). It estimates and creates multiple versions of a completed dataset, after which the desired statistical analysis is conducted on all imputed versions, and finally pools and averages these repeated results. Both the pooling of results and the estimation technique yield nuanced outcomes. Meanwhile, a simple technique "underestimates the variance of the estimates and so overstates precision and results in confidence intervals and significance tests that are too optimistic" (StataCorp, 2017c, p. 3). Multilevel logistic regression in Stata, however, does not fully support multiple imputation in the sense that pooled results can be generated. Therefore, this study only uses one complete database. While this means that the full benefits of multiple imputation are not enjoyed, the decision is made to continue the imputation for three reasons. First, it is the only

[28] Missing Completely at Random: missingness of a variable is not correlated to the value of another observed value.
[29] Missing at Random: missingness of a variable is explained by values of other variables.

solution to increase the cell frequencies required for logistic regression other than dropping the sector variable altogether. Second, logistic regression benefits from greater sample sizes. Third, some authors prescribe imputation if data are MAR, as the non-random missingness by itself biases results and should therefore be remedied (e.g. Bartlett & Carpenter, 2013).

To estimate missing values, a chained multiple imputation is used, which "fills in missing values in multiple variables iteratively by using chained equations, a sequence of univariate imputation methods with fully conditional specification (FCS) of prediction equations" (StataCorp, 2017c, p. 140). FCS means that "imputations are generated sequentially by specifying an imputation model for each variable given the other variables" (Y. Liu & De, 2015, p. 289). In other words, the non-missing values of specified variables are used to estimate missing values, which are in turn used to estimate other missing values. Notably, imputation did not solve the cell frequency issues caused by the sector variable, which is therefore excluded from further analyses. For a complete specification of the imputation, please see Appendix 6.

3.9. Linearity

Regular OLS regression requires independent variables to have a linear relationship with the dependent variable (Field, 2013). Logistic regression on the other hand, requires a linear relationship with the logit of the dependent variable (Field, 2013).[30] Hence, logistic linearity is not established by regular zpred-zresid plots.[31] Instead, Stata is used to perform a so-called "locally weighted regression" to establish the bivariate relationship (StataCorp, 2017a, p. 1384). This graph can be inspected and compared to a fitted linear regression, to assess linearity. Because the probabilities are plotted on the y-axis, instead of the logit itself, and because a typical logistic curve is s-shaped, some deviations from the linear line can be expected, especially at the beginning and end of the curve (Field, 2013). It is also noted that the relationship between the dependent variable and the independent binary (and categorical) variables does not need to be inspected, as these latter variables are inserted in a logistic regression model with data points that can only be 0 or 1. With only two values

[30] Compared to other regressions, logistic regression is also unconcerned by violation of (multivariate) normality (Hair et al., 2010).
[31] It is noted that no uniform procedure to assess linearity appears to exist for logistic regression (Field, 2013).

available per independent variable, the only possible relationship is by definition linear (i.e. a perfectly straight line). Thus, only the continuous variables were checked for their linear relationship with the logit of the dependent variable (Appendix 7). No continuous variable showed a problematic non-linear relationship with new product introduction and therefore no transformations were conducted.

3.10. Descriptive statistics and pairwise correlations

The results of the imputation, which are also the descriptive statistics of the sample that will be analyzed, are displayed on the next page with pairwise correlations (Table 1). Firm-level and country-level variables are analyzed separately, to avoid estimation errors (Stephan et al., 2015). The correlation tables show high correlations between new product introductions and the other firm-level variables, except for financial performance.[32] 33% of firms have introduced a new/improved product, while 25% and 6% respectively use formal and ROSCA-credit. Furthermore, the country-level variables show no significant correlations, so collinearity is no issue at that level (Field, 2013).

3.11. Research ethics

The respondents agreed to a declaration of confidentiality before conducting the survey, that guaranteed their data will be used solely for the purpose of research (World Bank, n.d.-c). Although the researcher was not party to this specific agreement, he is still bound by this on the basis of academic principles, and because agreeing to the Data Access Protocol for Outside Researchers including Confidentiality Provisions (World Bank, n.d.-a), was a condition to gain access to the relevant datasets. These standards have been upheld: the data provided by the respondents was and will solely be used for the research it has been permitted to be used for. Next to this, the researcher is committed to common academic principles, such as the frank reference to intellectual property (American Psychological Association, 2017), and he has signed the research integrity form (Appendix 12).

[32] As is detailed in Appendix 6, the variable financial performance (PERFORMANCE) was not imputed because of these low and insignificant correlations with other variables.

Descriptive statistics and pairwise correlations (firm-level)

	Mean	SD	New product	Foreign ownership	Managerial experience	Firm size	R&D	Formal credit use	ROSCA-credit use	Both credits	Export	Firm age	Financial performance
New product	0.33	0.47	1										
Foreign ownership	2.80	14.19	0.0304***	1									
Managerial experience	16.09	10.56	0.0335***	-0.012	1								
Firm size	26.19	22.43	0.0773***	0.028***	0.0488***	1							
R&D	0.18	0.39	0.3691***	0.0069	-0.0141*	0.1577***	1						
Formal credit use	0.25	0.44	0.0977***	-0.0101	0.0877***	0.1399***	0.1176***	1					
ROSCA-credit use	0.06	0.24	0.0449***	0.0468***	-0.0392***	-0.0193**	0.0311***	0.0834***	1				
Both credits	0.02	0.15	0.0441***	0.0087	0.0063	0.0162**	0.0497***	0.2662***	0.6202***	1			
Export	7.34	21.40	0.038***	0.1269***	0.0087	0.0936***	0.0696***	0.0274***	0.1693***	0.0473***	1		
Firm age	16.84	13.07	0.0404***	-0.0119	0.4139***	0.1075***	0.0131*	0.0463***	-0.0082	0.0139*	0.0166**	1	
Financial performance	7.17E+09	4.17E+11	-0.0052	0.0027	0.0014	0.019**	-0.0026	0.0101	-0.0037	-0.002	0.0053	0.0116	1

*** p<0.001, ** p<0.01, * p<0.05

n=25,681 for pairwise correlations without Financial performance; n=20,335 for pairwise correlations with Financial performance

Descriptive statistics and pairwise correlations (country-level)

	Mean	SD	Money market quality	Trust	GDP PPP
Money market quality	68.35	15.43	1		
Trust (ROSCA-quality)	3.00	0.24	-0.0292	1	
GDP PPP	12220.23	7575.03	-0.0813	0.1549	1

*** p<0.001, ** p<0.01, * p<0.05

n=19

Table 1. Descriptive statistics and pairwise correlations (firm-level and country-level)

Chapter 4: Results

This chapter presents the results of the multilevel logistic regressions conducted. Multiple models are fitted in order to test hypotheses. Models (and their associated hypotheses) are accepted and rejected based on three commonly used criteria (Hair et al., 2010; Sommet & Morselli, 2017). First of all, the statistical significance of parameter estimates in a model can be individually assessed. Secondly, two models can be compared using a likelihood-ratio test (lrtest), which compares whether one model is significantly more likely to be correct (Field, 2013). In this test, a general model is compared to a nested model. A model is said to be nested in a general model, if it is a subset of that general model. In other words, the general model includes all the variables of the nested model, and at least one additional variable (Hair et al., 2010). Thirdly, the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) of multiple models can be compared. Although both of these goodness-of-fit measures correct for model complexity (Field, 2013), BIC does so more harshly (Kass & Raftery, 1995).[33] No academic consensus exists as to which criterion is better - some authors assert the BIC is too strict (Vrieze, 2012), while others assert the AIC is too lenient (A. Luo et al., 2010). It is hence convention to report both measures, and let other factors be decisive if these are contradictory (Field, 2013).[34] The BIC, AIC, and likelihood-ratio test all require that compared models are derived from the same sample, as they are measures of relative fit (Hair et al., 2010). This means their values have no interpretable meaning outside of the context of the model comparison they are used in.[35]

The results are presented in the table on the next page (Table 2), displaying odds ratios for interpretation. Corresponding log odds are listed in the model overview.[36] After these results, all models are discussed in detail. Then, a final model is selected and subjected to several robustness checks. After that, an adjusted sample is tested. Finally, the results from both the full sample and the adjusted sample are interpreted.

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[33] To reduce model complexity and prevent rejection by BIC, insignificant (control) variables in a certain model specification are dropped from subsequent model specifications.

[34] Both measures come in a less-is-better form. Exact criteria and interpretation are described in Appendix 8.

[35] Opposed to these are absolute measures of fit, which are comparable across contexts. These are not available in multilevel logistic regression in Stata. Also, no adjusted R^2 (i.e. the percentage of explained variance) exist for logistic regression. While pseudo R^2s have been developed, these are not uniformly used or interpreted, and unavailable in multilevel logistic regression in Stata.

[36] This overview and the complete Stata output per model, are found after the general appendices.

Full sample odds ratios		VARIABLES	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Controls		Foreign ownership		1.004***	1.004***	1.004***	1.004***	1.004***	1.004***	1.004***	1.004***	1.004***
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
		Managerial experience		1.010***	1.010***	1.010***	1.010***	1.010***	1.010***	1.010***	1.010***	1.010***
				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
		Firm size		1.003***	1.002***	1.003***	1.002***	1.002***	1.002***	1.002**	1.002**	1.002**
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
		R&D		5.916***	5.798***	5.878***	5.798***	5.797***	5.801***	5.793***	5.794***	5.785***
				(0.228)	(0.224)	(0.226)	(0.224)	(0.224)	(0.224)	(0.223)	(0.223)	(0.223)
Firm level	H1A	Formal credit use			1.290***		1.290***	1.289***	1.289***	1.296***	1.296***	1.293***
					(0.047)		(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)
	H2A	ROSCA-credit use			1.154*		1.154*	1.153*	1.218**	1.153*	1.153*	1.213**
					(0.074)		(0.074)	(0.074)	(0.092)	(0.074)	(0.074)	(0.085)
	H4	Use of both forms of credit				1.574***						
						(0.154)						
Country level		Trust						0.636*	0.633*	0.639*	0.637*	0.637*
		Standardized						(0.115)	(0.115)	(0.115)	(0.115)	(0.116)
	H1B	Money market quality					1.004			1.004		
		Centered					(0.013)			(0.011)		
Interactions	H2B	ROSCA-credit*Trust							1.111			
									(0.088)			
	H1C	Formal credit*Market quality								0.995*	0.995*	0.996
										(0.002)	(0.002)	(0.002)
	H3	ROSCA-credit*Market quality										0.993
												(0.004)
		Constant	0.364***	0.208***	0.194***	0.205***	0.196***	0.168***	0.167***	0.169***	0.167***	0.167***
		[fixed effect]	(0.088)	(0.047)	(0.044)	(0.046)	(0.044)	(0.034)	(0.034)	(0.035)	(0.034)	(0.034)
		Constant	1.095***	0.930**	0.918**	0.937**	0.913**	0.686**	0.690**	0.681**	0.687**	0.693**
		[random effect variance]	(0.360)	(0.307)	(0.303)	(0.310)	(0.302)	(0.228)	(0.229)	(0.227)	(0.228)	(0.230)
		AIC	29616.76	27107.68	27053.97	27088.50	27055.90	27050.56	27050.81	27050.36	27048.51	27047.52
		BIC	29633.07	27156.61	27119.20	27145.58	27129.28	27123.94	27132.35	27140.05	27130.05	27137.21
		df	2	6	8	7	9	9	10	11	10	11
		Compared with	-	Model 0	Model 1	Model 1	Model 2	Model 2	Model 5	Model 5	Model 5	Model 8
		Delta AIC	-	-2509.08	-53.71	-19.18	1.93	-3.41	0.25	-0.20	-2.05	-0.99
		Delta BIC	-	-2476.46	-37.41	-11.03	10.08	4.74	8.41	16.11	6.11	7.16
		Delta df	-	4	2	1	1	1	1	2	1	1
		LR chi2	-	2517.08***	57.71***	21.18***	0.07	5.42*	1.74	4.20	4.05*	2.99

Standard errors in parentheses. Colors highlight groups of hypotheses and associated results. Best model in thick frame.

*** p<0.001, ** p<0.01, * p<0.05

Observations	25,681
Number of groups	19

Table 2. Odds ratios of model estimates using full sample

4.1. Null model (Model 0)

A null model is constructed to assess whether multilevel logistic regression fits the data better than a regular logistic regression model. Indeed, the intraclass correlation equals 0.249, indicating 24.9% of the variance in innovativeness[37] is explained by between-country differences. This high proportion warrants multilevel analysis, as the threshold is typically set at 10% (Field, 2013; Hox, Moerbeek, & van de Schoot, 2017). The log odds of being innovative (without taking between-country variation into account) are -1.011, which translates to an odds ratio (OR) of 0.36. Hence, a firm is 2.7 times more likely not to be innovative, than to be innovative.[38] Reviewing the so-called "caterpillar plot" with 95% CI intervals, it is shown that the respective countries substantially deviate from this number. Firms in Malaysia are the least likely to innovate (log odds -1.011-1.765=-2.777, OR=0.06), while firms in Ecuador are the most likely to innovate (log odds -1.011+2.125=1.113, OR=3.04).

4.2. Control model (Model 1)

Next is the construction of a control model that features the discussed control variables. Performance, age, export, and GDP per capita are dropped as control variables, while foreign ownership, managerial experience, size, and R&D are retained. The BIC and AIC of this model are better than the statistics of the null model, providing very strong evidence that the control model is better. Also, the lrtest is highly significant, indicating the control model is more likely to be correct than the null model (Model 0). The control model (Model 1) is thus upheld.

Across all models, foreign ownership, managerial experience, firm size, and R&D are significant control variables. Foreign ownership, managerial experience, and firm size show a .4%-1% increase in likelihood to innovate per unit increase. R&D expenditure shows a remarkable increase in likelihood to innovate; firms that have spent on R&D, are about 6 times more likely to innovate than firms that have not. As only formal R&D activities qualify – e.g. market research is excluded - this difference is not unexpected.

[37] It is noted that the dependent variable is a binary answer to the question: "During the last three years, has this establishment introduced new or improved products or services?", used to gauge firm innovation. Therefore, the results are discussed using terms such as "firm innovativeness," "firm innovation," and "likelihood to innovate."

[38] Logistic regression predicts the likelihood of an event occurring: log odds, odds ratios, and probabilities contain essentially the same information, but odds ratios are preferred for purposes of interpretation (Xing Liu, 2015). Appendix 9 lists how these values are transformed in one another, and how odds ratios are interpreted.

A Stata “best fit” (bfit) procedure was also used, to assess if interaction effects between firm-level variables that are not accounted for would improve model fit (StataCorp, 2017a). This is not the case, as the bfit preferred models with few degrees of freedom (i.e. no interaction effects).

4.3. Simple models (Model 2 & 3)

Model 2 is created by simultaneously adding ROSCA- and formal credit use to the control model. This model is more likely than the control model (Model 1), as viewed by the lrtest, AIC, and BIC. Firms that use formal or ROSCA-credit are respectively 1.29 and 1.15 times more likely to innovate than firms that do not. Hypothesis 1A and 2A are therefore supported. Likewise, Model 3 tests the combination of both forms of credit, and is too more likely than the control model (Model 1). Therefore, Hypothesis 4 is also supported. Model 2 is used for further model testing, as it shows better fit than the model with the credit combination.

4.4. Contextual models (Model 4 & 5)

The contextual country-level variables are added to Model 2 one by one, to assess individual modelling contributions. First, quality of money market is added, without success (Model 4). No indicators show that the variable improves the simple model. Hence, Hypothesis 1B is not supported.

The level 2 variable trust in people known personally (the proxy for ROSCA-quality of management) is then added (Model 5). The AIC and BIC lead to conflicting conclusions: while the AIC indicates support for this model (Δ-3.41), the BIC indicates it should be rejected (Δ+4.74). Hence, the other indicators are taken into consideration. As the likelihood-ratio test and the trust variable are both significant (resp. p=.0199 and p=0.026), the model is not rejected. Based on this data, for each standard deviation increase from the sample mean in trust, firms become less likely to innovate (OR=.63). Although no hypotheses were formulated regarding this effect, the model is retained as it is significantly better than Model 2.

4.5. Interaction ROSCA-credit use and trust (Model 6)

Next, the interaction effect between ROSCA-credit use and trust is assessed. This model is rejected, as the interaction effect is insignificant (p=.184) along with the likelihood-ratio test (p=.1867, compared to Model 5). The AIC did not improve and the BIC severely worsened. Hypothesis 2C is not supported.

4.6. Interaction formal credit use and money market quality (Model 7 & 8)

Next, the interaction effect between formal credit use and money market quality on innovation is assessed. Two models will be compared to Model 5: one that includes the main effect of money market quality (Model 7), and one that does not (Model 8). It would not be unexpected if the model with the main effect (Model 7) would be rejected, given the last insignificant results.[39]

Indeed, Model 7 is not better than Model 5 as is shown by AIC, BIC, and likelihood-ratio test – the interaction effect however, is significant, but this alone is no ground to accept the model. Model 8 performs better. The AIC indicates some support for Model 8 over Model 5, but the BIC concludes it should be rejected. The interaction effect is just significant judged by conventional significance levels, as is the likelihood-ratio test (resp. p=.044 and p=.044). Model 8 is therefore concluded to be weakly supported. Therefore, it will be more thoroughly checked with robustness tests. It is noted that hypothesis 1C is not supported, as a different effect was expected.[40]

4.7. Interaction ROSCA-credit use and money market quality (Model 9)

Model 9, which includes the interaction effect between money market quality and ROSCA-credit use, is not significantly better than Model 8, and is hence rejected: the AIC has not improved significantly, the BIC worsened, the lrtest is insignificant, as is the added interaction effect. Hence, Model 8 is selected as the best model resulting from these analyses.

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[39] Field (2013) emphasizes that the interpretation of an interaction effect changes if a main effect is omitted; this will carefully be assessed in discussion.

[40] A visual inspection of the scatterplot reported after Model 8 shows no positive relationship between money market quality and the differences in country intercepts either.

4.8. Statistical robustness checks (Models 10A-D)

To test the choices made by the researcher several robustness checks are performed, using the original control variables, examining the influence of the imputation, assessing between-country slope variance, and calculating bootstrapped estimates.

Control variables reinserted (Model 10A)

First of all, the preselected firm level control variables age and export are reentered into Model 8,[41] as well as the categorical sector variable that was excluded for fear of cell size issues. After running Model 10A, the significant effects of formal credit use, trust (the proxy for ROSCA-quality), and the credit/quality-interaction remained significant; the significant effect of ROSCA-credit use is now marginally supported (p=.056). Most indicators suggest this model fits better than the definitive model[42] – the result of the inclusion of the sector variable. It is noted however, that although the model has converged, it is possibly biased due to empty cell problems.

Influence of imputation (Model 10B)

Model 10A is repeated using the non-imputed original sample, to assess whether imputation has caused bias (Model 10B). Formal credit use, ROSCA-credit use, trust, and the credit-quality interaction all remain significant, although this latter interaction approaches the boundary of significance (p=.047). Hence, imputation introduced no noteworthy bias.

Between-country variance in regression slopes (Model 10C) and bootstrapped estimates (Model 10D)

Next, the variable use of formal credit will be checked for between-country heterogeneity of regression slopes, without level 2 variables or interaction effects (Model 10C). This serves to illustrate whether or not the effect of this variable differs between countries, caused by variables not included in the model. This model fits the data better than Model 8 (ΔAIC and BIC both -11.56). This means that this model, 10C, in which the slope of formal credit use can vary freely between countries, more accurately estimates that slope than does Model 8 which uses money market quality. It is noted that it is no surprise that a model that allows the slope

[41] Financial performance was not entered, because its inclusion led to convergence issues.

[42] The Δdf is 22. This explains why the AIC shows a remarkably better fit (Δ-123), but the BIC shows a severely worsened fit (Δ+64). This is a good example of the divergence the AIC and BIC can show in the event of added model complexity. In this specific case, also looking at the significance and size of predictors and the lrtest, the BIC appears too punishing.

to vary freely between countries fits the data better than does a model that constrains the slope by the value of another variable. However, as the random slope model fits the data significantly better than the definitive model, this shows that the definitive model does not fully explain the formal credit use slope. Yet, this is no reason to reject the final model.

Finally, bootstrapping, in which a model (here Model 8) is repeated hundreds of times to provide accurate results, also demonstrates robustness after repeating the final model 100, 200, 500, and 1000 times (Field, 2013; Model 10D). All variables retain their significance in all iterations, although the interaction effect reaches the border of significance in the bootstrap with 1000 iterations (p=.048).

4.9. Alternative explanation of the effect of trust (Appendix 10 & Model 11)

In Model 8, the degree to which people known personally are trusted (country-level; the proxy for quality of management), displays a remarkably strong and unexpected negative relationship with the (firm-level) likelihood to innovate. It is deemed unlikely that this one indicator can have such a strong effect. Therefore, the correlation of trust with cultural values and practices from the GLOBE project is assessed (House, Hanges, Javidan, Dorfman, & Gupta, 2004). Several linkages between innovation and cultural practices and values have been established in research (Dickson, 2004; Rossberger & Krause, 2012). Indeed, trust shows several moderate and significant correlations with GLOBE dimensions, which in turn display moderate to strong correlations with the mean innovation per country (Appendix 10). Trust is positively correlated with the value of power distance (r=.40), and negatively correlated with the value of gender equality (r=-.47) and the practice of performance orientation (r=.45). An exploratory factor analysis confirms a high covariance between these four variables (Appendix 10). It is therefore concluded that (combinations of) these four cultural variables explain the strong effect of the variable trust on innovation. Most notably, if trust decreases, the practice of performance orientation increases, which is in turn strongly positively correlated with innovation (r=.65). This strong and positive link between performance orientation and innovation has been confirmed in other research (Rossberger & Krause, 2012). If the variable practice of performance orientation is added to Model 8, trust becomes insignificant while performance orientation is highly significant (Model 11). Therefore, Model 8 is rejected insofar as the main effect of trust is concerned.

4.10. Sample variation (Models 12-20)

Ideally, models are also validated using a newly drawn sample from the same population (Field, 2013; Hair et al., 2010). This is not possible in this research, however. Several authors also recommend to assess if a model is biased due to influential observations (Field, 2013; Hair et al., 2010; Krammer, 2017; Vennix, 2011). Hence, as mentioned before, the influence of Indian firms is assessed, which make up 27.17% of the sample (Appendix 2). Model 12, with two interaction effects (for H1C and H2B) is run, and the Anscombe residuals are calculated, which can be used to detect influential observations and outliers (StataCorp, 2017b).[43] Indeed, Indian firms are shown to be the most influential in this sample by absolute numbers. The decision is therefore made to create a sample without the Indian firms. This way, both the influence of Indian firms is omitted, and a different sample is used to assess all hypotheses. The results are presented on the next page (Table 3).[44]

In summary, these results differ from those of the full sample in two ways. First of all, no (negative) interaction effect between formal credit use and money market quality is now found (Model 14). Secondly, the interaction effect between trust (ROSCA-quality) and ROSCA-credit use, is now (positively) significant (Model 14). If the practice of performance orientation is added to the model, trust loses its direct effect – like in the full sample – but the significant interaction effect remains (Model 15). Model 16, which only includes significant variables from previous iterations, then is the best model. It is robust to the inclusion of the original control variables (Model 17)[45] and bootstrap estimates (Model 18)[46]. In conclusion, the findings from this adjusted sample reinforce some findings from the full sample, while casting doubt on others. In what follows, the relevant results are repeated and compared.

[43] Other measures of influence, such as Cook's Distance, hat value, leverage or dfBeta are not available in the Stata melogit procedure (StataCorp, 2017b).

[44] Again, odd ratios are in the main body and corresponding log odds in the model overview; trust and money market quality are not rescaled, and remain centered at full sample means to facilitate comparison with the full sample.

[45] Except for financial performance, which caused the model not to converge.

[46] Some findings border significance.

Resampled odds ratios		VARIABLES	Model 13	Model 14	Model 15	Model 16	Model 19	Model 20
Controls		Foreign ownership	1.004*** (0.001)	1.004*** (0.001)	1.004*** (0.001)	1.004*** (0.001)	1.004*** (0.001)	1.004*** (0.001)
Controls		Managerial experience	1.009*** (0.002)	1.009*** (0.002)	1.009*** (0.002)	1.009*** (0.002)	1.009*** (0.002)	1.009*** (0.002)
Controls		Firm size	1.002* (0.001)	1.002* (0.001)	1.002* (0.001)	1.002* (0.001)	1.003** (0.001)	1.002* (0.001)
Controls		R&D	5.909*** (0.308)	5.900*** (0.308)	5.899*** (0.308)	5.901*** (0.308)	6.057*** (0.315)	5.899*** (0.308)
Firm level	H1A	Formal credit use	1.465*** (0.067)	1.480*** (0.071)	1.480*** (0.071)	1.462*** (0.066)		1.460*** (0.066)
Firm level	H2A	ROSCA-credit use	1.164* (0.083)	1.312** (0.120)	1.310** (0.120)	1.310** (0.120)		1.211* (0.090)
Firm level	H4	Use of both forms of credit					1.555*** (0.168)	
Country level		Trust Standardized		0.622* (0.116)	0.768 (0.140)			
Country level	H1B	Money market quality Centered		0.999 (0.012)	0.994 (0.011)			1.002 (0.014)
Country level	±	Performance orientation Cultural practice			4.340* (2.607)	6.163*** (3.395)		
Interactions	H2B	ROSCA-credit*Trust		1.196* (0.104)	1.195* (0.104)	1.191* (0.104)		
Interactions	H1C	Formal credit*Market quality		1.002 (0.003)	1.002 (0.003)			
Interactions	H3	ROSCA-credit*Market quality						0.993 (0.004)
		Constant [fixed effect]	0.187*** (0.044)	0.156*** (0.035)	0.000** (0.000)	0.000*** (0.000)	0.205*** (0.049)	0.188*** (0.045)
		Constant [random effect variance]	0.957** (0.325)	0.711** (0.243)	0.529** (0.182)	0.599** (0.206)	0.984** (0.334)	0.960** (0.326)
		AIC	18611.03	18608.9	18605.75	18602.65	18672.13	18612.34
		BIC	18673.72	18702.93	18707.62	18681.01	18726.99	18690.7
		df	8	12	13	10		10
		Compared with	-	Model 13	Model 14	Model 13		Model 13
		Delta AIC	-	-2.13	-3.15	-8.38		1.31
		Delta BIC	-	29.21	4.69	7.29		16.98
		Delta df	-	4	1	2		2
		LR chi2		10.13*	5.15*	12.38**		2.69

Standard errors in parentheses. Colors highlight groups of hypotheses and associated results. Best model in thick frame.

*** p<0.001, ** p<0.01, * p<0.05

± variable used in robustness assessment

Observations	18,703
Number of groups	18

Table 3. Odds ratios of model estimates using adjusted sample (i.e. without Indian firms)

Odds ratios relevant results per sample			Full sample	Full sample	Resampled	Full sample	Resampled
		VARIABLES	8	11	16	3	19
Controls		Foreign ownership	1.004***	1.004***	1.004***	1.004***	1.004***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
		Managerial experience	1.010***	1.010***	1.009***	1.010***	1.009***
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
		Firm size	1.002**	1.002**	1.002*	1.003***	1.003**
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
		R&D	5.794***	5.793***	5.901***	5.878***	6.057***
			(0.223)	(0.223)	(0.308)	(0.226)	(0.315)
Firm level	H1A	Formal credit use	1.296***	1.297***	1.462***		
			(0.047)	(0.047)	(0.066)		
	H2A	ROSCA-credit use	1.153*	1.151*	1.310**		
			(0.074)	(0.074)	(0.120)		
	H4	Use of both forms of credit				1.574***	1.555***
						(0.154)	(0.168)
Country level		Trust Standardized	0.637*	0.786			
			(0.115)	(0.136)			
	±	Performance orientation Cultural practice		4.403**	6.163***		
				(2.486)	(3.395)		
Interactions	H1C	Formal credit*Market quality	0.995*	0.995*			
			(0.002)	(0.002)			
	H2B	ROSCA-credit*Trust			1.191*		
					(0.104)		
		Constant [fixed effect]	0.167***	0.000**	0.000***	0.205***	0.205***
			(0.034)	(0.000)	(0.000)	(0.046)	(0.049)
		Constant [random effect variance]					

Standard errors in parentheses. Colored hypotheses have support (green), mixed support (orange), or no support (red).

Colors per model indicate support (green) or no support (red) for variable and associated hypothesis

Fields colored red without value, indicate variable was discarded in a previous iteration because of insignifance

*** p<0.001, ** p<0.01, * p<0.05

± Variable used in robustness assessment

Observations full sample (resampled)	25681 (18,703)
Number of groups full sample (resampled)	19 (18)
No significant effects were found for	H1B Model 4 & 14
	H3 Model 9 & 20

Table 4. Odds ratios of relevant results of both full and adjusted sample

4.11. Conclusion results and interpretation

Table 4 summarizes the relevant results, log odds are again displayed in the model overview. Support is found for H1A, H2A and H4, mixed support is found for H2B, while no support is found for H1C, H1B, and H3.[47]

Support

Firms that use formal credit are 1.3-1.5[48] times more likely to innovate than firms that have no formal credit (**H1A**), all else equal. [49] Firms that use ROSCA-credit are 1.15-1.3 times more likely to innovate (**H2A**). Firms that use both forms of credit simultaneously, were 1.6 times more likely to innovate than firms that had none, and also more likely to innovate than firms using only one form (**H4**).

Mixed support

The interaction effect between ROSCA-credit use and trust in people known personally (the proxy for quality of ROSCA-management, **H2B**), was not significant in the full sample, although a significant effect was found in the adjusted sample. In the latter sample, the interaction effect requires a specific interpretation because the main effect of trust was omitted from Model 16. The interaction effect means that if firms use ROSCA-credit, their likelihood of innovativeness has a positive relationship with trust.[50] As trust is standardized, every unit increase equals a standard deviation of the original value. For every unit increase in trust, firms that use ROSCA-credit are 1.2 times more likely to innovate, in addition to the original positive effect of ROSCA-credit use. This means that ROSCA-using firms in Ecuador, the least trusting countries with -2.78 standard deviations from the mean are (1.19^-2.78)=.6 times less likely to be innovative than ROSCA-using firms experiencing the sample average trust. Likewise, ROSCA-using firms in Egypt, the most trusting country, are (1.19*2.4)=1.5 times more likely to be innovative than firms experiencing the sample average trust. Following this statistic, ROSCA-using firms in Egypt are (1.19*5.2)=2.5 times more likely to be innovative than ROSCA-using firms in Ecuador.

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[47] Please refer to par. 2.3 in which the hypotheses are summarized.

[48] These are the minimum and maximum reported values.

[49] This means all other variables are held constantly at 0. For trust and money market quality, which are standardized and mean centered, this translates to average trust/money market quality experienced by a firm).

[50] In other words, the ROSCA*Trust-coefficient differs from 0 only for those firms with a ROSCA-credit, and trust hence has no effect on firms without that credit.

It is noted that although the direct effect of trust on innovation disappeared when the practice of performance orientation was added to the model, the interaction effect remained significant (Model 15 & 16). Furthermore, the odds ratios of performance orientation are high, although so are its standard errors. This shows that the estimated ratios for performance orientation are not reliable – but the overall effect of the variable is significant – presumably caused by the relatively low variance between the countries on this variable. For the purposes of this study however, the most important conclusion regarding performance orientation is that that it negated the direct effect of trust. No further implications of its estimates are hence discussed.

No support

No main effect of money market quality was found (**H1B**), and no interaction effect between money market quality and ROSCA-credit use **(H3)**. **H1C** found no support either, although the full sample – but not the adjusted sample - showed an interaction effect with an unexpected direction. This interaction effect means that if firms use formal credit, their likelihood of innovativeness has a negative relationship with money market quality. As money market quality Is centered, its values can range from -23.35 (money markets with the lowest quality: Ecuador and Thailand) to +26.64 (money market with the highest quality: Colombia). Therefore, in the worst performing money markets, firms are (0.995^-23.35)=1.12 times more likely to innovate than firms with a credit in the sample average money market. In the best performing market, firms are (0.995^26.64)=.88 times less likely to innovate than firms with a credit in the sample average money market. A firm with a credit in Ecuador or Thailand, is (0.995*-50)= 1.28 times more likely to innovate than a firm with a credit in Colombia.[51] To conclude, money market quality negatively moderates the (positive) relationship between formal credit use and innovation.

[51] To facilitate interpretation, random constant effects and other country-level are ignored.

Chapter 5: Discussion

This chapter discusses the results derived in the previous chapter. First, the supported hypotheses 1A, 2A and 4 are examined, which described the main effects of credit use on firm innovation. Secondly, the unsupported H1B – on the effect of money market quality – is scrutinized. Third is H1C, which showed an unexpected interaction between money market quality and formal credit use. Fourth then, is the positive interaction effect between ROSCA-management and ROSCA-credit use (H2B). Last is the unsupported interaction effect between money market quality and ROSCA-credit use.

5.1. The effect of formal credit, ROSCA-credit, and a combination of both (H1A, H2A & H4)

Hypothesis 1A was supported. This confirms research that showed the use of formal credit contributes to better innovative outcomes (Ayyagari et al., 2011; Demirgüç-Kunt & Maksimovic, 1998; Fombang & Adjasi, 2018; Krammer, 2017; Levine et al., 2000). Similarly, hypothesis 2A was supported, as the use of ROSCA-credit aided innovation. This confirms the scarce empirical and conceptual research that indicates ROSCA-credit is a microeconomic solution to the "problem of the indivisible good" (van den Brink & Chavas, 1997, p. 11). Hypothesis 4 was also supported, indicating that firms that use both formal and ROSCA credit are more likely to innovate than firms that use only one or neither forms of credit. The complementarity between formal and informal credit has been noted in research (Banerjee et al., 2017). While this may be due to a tendency for such firms to have accumulated a larger resource base than firms that do not use both forms of credit, this is not necessarily the case.[52] It is argued that firms that have to access both forms of credit – regardless of the total size of the credits – have more leeway to configure and balance the credits in a manner and proportion that best fits their innovative activities. Moreover, it is suggested that firms that have acquired both types of credits, have fulfilled requirements demanded by respectively a formal and an informal context. Such firms are embedded in both environments. Zoogah et al. (2015, p. 9) propose that successfully managing such a "duality of context" is key for firms in Africa; this research empirically confirms their suggestion, and makes clear this duality is also present outside of Africa.

[52] The size of the credits is not measured in this research.

5.2. No effect of money market quality (H1B)

Hypothesis 1B was not supported. More specifically, money market quality did not have an unconditional effect on likelihood to innovate. This finding conflicts with research by Demirgüç-Kunt and Maksimovic (1998), who indeed showed a direct effect: their study found that firms present in a country with better developed financial markets innovated at higher rates. In that research however, large firms quoted on a stock exchange were examined, whereas this research focuses on SMEs in developing markets. It is therefore possible that the direct effect shown by Demirgüç-Kunt and Maksimovic (1998) is not a true direct effect, but rather an effect contingent upon the specific firm characteristics of size and being listed, - i.e. an interaction effect. Perhaps these large and listed firms across developing markets have small within-group variance, as they typically (also) operate in an international context, and therefore experience similar competitive, normative, and mimetic international pressures (DiMaggio & Powell, 1983; O'Connor, Vera-Muñoz, & Chan, 2011). On the other hand, SMEs across developing markets form a group with large within-group variance, as the pressures they experience are typically domestic and nation-specific. Therefore, a homogeneous effect of money market quality on innovation may not exist for SMEs. It is also possible the effect may exist but to a smaller degree – a degree too small to detect in this dataset as the country-level variable of money market quality had only n=19 data points, which is short of the recommended absolute minimum of n=20 (Kreft & de Leeuw, 1998).

This result could also be caused by the variables used in the Global Innovation Index to define the quality of money markets. More specifically, the GII measures applicable collateral and bankruptcy laws - with little attention to their enforceability - and depth of credit information. While these are necessary features to assess the functioning of a money market (Demirgüç-Kunt & Maksimovic, 1998), they are not sufficient. These indicators do not measure whether markets are distorted by, for example, cartel formation, state interference or power imbalances between suppliers and demanders. In this dataset, money market quality and the degree to which access to finance is viewed as an obstacle the individual firms show no correlation (Appendix 11). This reinforces the suggestion that the money market quality measure used, is an incomplete indicator. What is more, the used indicator summarized information on a national level, which may be inadequate. It can be argued that the quality of formal institutions may vary within the regions of a country, especially if the country consists of states with autonomous legislation and enforcement (Barasa et al., 2017; Bruno, Bytchkova, & Estrin, 2013; Del Bo, 2013; Shi, Sun, & Peng, 2012).

5.3. Interaction effect between formal credit use and money market quality contrary to expected (H1C)

Unexpectedly, the interaction effect between formal credit use and money market quality (H1C) was negative. It is emphasized however, that this result was found only in the full sample, and not in the adjusted sample. These estimates are therefore not robust to sample variation, and so possess limited generalizability.

A positive correlation exists between money market quality and the mean use of formal credit per country (Appendix 11). Therefore, as money market quality increases, credits become less unique. A resource-based view (RBV) perspective suggests that the rarity of the financial resource hence decreases: this means the resource offers less competitive advantage. This appears in line with findings by Demirgüç-Kunt and Maksimovic (1998, pp. 2134–2135), who state “that the reported return on capital is lower in countries with active stock markets and well-functioning legal systems. Thus, developed institutions not only permit firms to fund growth externally, but also may indirectly increase dependence on external financing by reducing firms’ profits.”[53]

Differences in credit information depth may also lead to a selection bias (Stiglitz & Weiss, 1981). If a lack of information makes credit worthiness assessments unreliable, banks will err on the safe side and increase credit prices across the board to cover this risk (Listokin & Taibleson, 2010). Better performing firms demonstrate higher return on investment, and will still be able to profitably convert these resources, even though “raising the interest rate decreases the return on projects which succeed” (Stiglitz & Weiss, 1981, p. 393).

[53] From a firm perspective, it is hence beneficial to receive a credit in an environment in which this is more unique. From a nation perspective however, broad access to credit in an inclusive way is preferable and expected to lead to better country-level innovation outcomes (Donges et al., 2019).

Worse performing firms on the other hand, cannot profitably exploit the resources with these inflated prices and will reject a formal credit. The “firms with credit” in this scenario then display a degree of innovativeness that is not only dependent on the credit they have acquired, but moreover upon their intrinsic quality which was the reason they could accept the credit price in the first place. What is more, it is also possible that well-performing firms can command better prices, as they may be more able find ways to reduce the lack of information. For example, well-performing firms are more likely to have engaged in “longstanding relationships with [banks], mitigating the informational asymmetry” (Listokin & Taibleson, 2010, p. 96; Marquis & Raynard, 2015; Tagoe, Nyarko, & Anuwa-Amarh, 2005). In addition, well performing firms are likely to be in possession of more collateral, and are willing to provide this to banks to hedge informational risks (Stiglitz & Weiss, 1981; Tagoe et al., 2005). As well-performing firms do not expect to default on their credit repayments, providing collateral is relatively low-risk. This is different for medium or poorly performing firms, that perceive a higher probability of having their collateral seized.

Consequently, as more (credit) information becomes available, fewer firms will be “credit rationed” (Freel, 2007, p. 23; Stiglitz & Weiss, 1981) and the effect of credit on innovation will decrease, as the medium and poor firms that have now obtained a credit, use that credit less effectively. Banerjee et al. (2017) show something similar: experienced entrepreneurs benefitted more from the availability of credit than did inexperienced entrepreneurs, and this credit availability also persuaded people to start a business even though they lacked the necessary skills to do so effectively.

One other explanation of the significance joins the previously mentioned suggestion that the indicator for money market quality employed is incomplete. Credit institutions can more carefully assess potential borrowers if more credit information is available (i.e. if the variable QUA is higher). Borrowers however, do not necessarily have equally detailed information on their lending counterparts. One-sided detailed credit information may thus exacerbate information asymmetry, especially in the event of distorted competition or poor consumer protection, and make it more likely that credit arrangements are mostly to the advantage of lenders (Khanna & Palepu, 1997). These power imbalances hamper innovation.

5.4. Interaction effect between ROSCA-credit use and ROSCA-management (H2B)

The interaction effect between ROSCA-credit use and ROSCA-management (H2B) - with trust as a proxy - was positive in the adjusted sample and insignificant in the full sample. Like the previous interaction, generalizability is therefore limited and the results should be interpreted with caution. The positive interaction effect confirms that better ROSCA-management is indeed associated with better innovative outcomes, as has been conceptualized by other authors (Henry, 2003; van den Brink & Chavas, 1997). The interaction effect found in the adjusted sample was robust to the insertion of the cultural practice of performance orientation, which did remove the direct effect of trust on innovation. However, this nation-level proxy has some limitations which will be discussed in Chapter 6.

5.5. No interaction effect between money market quality and ROSCA-credit use (H3)

Money market quality showed no interaction with ROSCA-credit use on innovation (H3 not supported). Therefore, no evidence exists to suggest that firms unable to acquire a formal credit, flee to ROSCA-credit use. No significant correlation exists between the country-level percentage of ROSCA-credit use and the degree to which access to finance is viewed as an obstacle (Appendix 11). This suggests the degree of ROSCA-credit use is unaffected by formal money market quality. This finding appears to contradict the framework established by Helmke and Levitsky (2004) which describes complementary, accommodating, substitutive, and competing effects of informal institutions relative to those of formal institutions. However, these authors nuance their own framework in several ways. Firstly, they mainly focus on informal institutions that are created as a response “given the existence of a set of formal rules and rule-making mechanisms” (p. 730). Secondly, they note change for informal institutions that are a “product of culture” tends to be “slow and incremental” (p. 732). As ROSCAs predate formal money markets and are an institution rooted in culture, this may explain why they appear invariant to formal money market quality. Indeed, other authors assert that ROSCAs continue to hold great appeal, even when alternative financial institutions become available (van den Brink & Chavas, 1997; Yawe & Prabhu, 2015).

A second explanation for this insignificant effect is that taking part in a ROSCA may be more deeply culturally rooted in some countries than in others, making the interaction of formal money market quality and the use of credit from ROSCAs variable. In some countries, the impulse needed to persuade SMEs to seek resources on the formal money market may thus be stronger than in others. Panel data analyses per country might be conducted to capture such differences in periods in which the quality of formal money markets varies (Hair et al., 2010).

Chapter 6: Conclusion

Although extant literature establishes that firm innovation in developed markets is driven by (access to) external finance provided by well-performing formal institutions (Levine et al., 2000), it does not detail whether or not these mechanisms hold true in emerging markets and informal contexts (Ayyagari et al., 2011; Fombang & Adjasi, 2018).

To address this gap, the research question to be answered in this study was as follows: *What is the effect of the firm-specific access to external finance on SME firm innovation in developing markets, as moderated by the quality of formal and informal financial institutions?* In this study, a formal and informal way of financing SME-innovation were therefore researched, as well as the interaction with the quality of their respective institution. Firstly, formal credit delivered by a bank, and the associated quality of the money market was assessed. Second to be researched, was informal credit delivered by a Rotating Savings and Credit Association (ROSCA), and the associated quality of ROSCA-management as proxied by trust in people known personally. The results were primarily derived from the World Bank Enterprise Survey (WBES), using multilevel logistic regression, an advanced statistical procedure with several benefits, among others the correct attribution of variables to firm- and country-level.

6.1. Theoretical implications

This research has several academic implications in the contexts of institutional theory, innovation, the resource-based view, and finance in the context of emerging markets.

Contemporary research on formal and informal institutions and innovation commonly suggests that informal institutions can compensate for poor formal institutions (Crost & Kambhampati, 2010; Harriss-White, 2010; Helmke & Levitsky, 2004; Krammer, 2017; Miller et al., 2009; Puffer et al., 2010). This research however, proposes and confirms some more nuanced interactions between formal and informal resources, and their associated institutions. First of all, no evidence was found for a moderating effect of money market quality on ROSCA-credit and innovativeness. This suggests ROSCAs, as culturally-rooted institutions, are relatively invariant to change in formal money market quality, and not solely substitute institutions entrepreneurs turn to out of necessity (Yawe & Prabhu, 2015). This confirms the resilience of socio-cultural institutions to formal change, as some authors have suggested (Helmke & Levitsky, 2004). Secondly, this research revealed that firms that use both formal and informal credit, are more likely to innovate than firms that use one or neither forms of credit. It is suggested that not only the mere possession of the resource (i.e. liquidity) positively influences innovation, but also the fact that such firms have successfully managed to be positively selected in both a formal and informal context, and are, like the respective resources, embedded in their contextual environment. For example, the increased legitimation derived from conforming to this dual institutional environment (Scott, 1995), can be viewed as an additional resource yielding competitive advantage, as it rare, valuable, and hard to imitate (Barney, 2001; Boyd, Bergh, & Ketchen, 2010; Deephouse, 2000). This finding therefore builds on academic work that connects the resource based view to institutional theory (Oliver, 1997; Peng, 2002). Zoogah et al. (2015, p. 9) proposed the conceptual significance of the "duality of context" for African firms, of which this research is therefore an empirical confirmation generalizable to other emerging markets.

Furthermore, this study shows interesting results – their limitations recognized - regarding the effect of formal money market quality on firm innovation, both as a direct effect and in combination with formal credit use. Contrary to research on large and listed firms (Demirgüç-Kunt & Maksimovic, 1998), money market quality did not demonstrate a direct effect in this SME sample. This suggests that even if money market quality increases SMEs do not - or do not in the same way - experience the competitive and mimetic pressures to innovate experiences by large and listed firms. SMEs may form a group that is more heterogeneous than large and listed firms, which are typically (more) internationally orientated. Therefore, connecting this work with cited work, it is proposed the quality of money market does not affect all types of firms equally, and researchers must therefore take care to extrapolate findings on large and listed firms to other firms.

Furthermore, this research unexpectedly demonstrated a negative interaction effect between money market quality and formal credit use. This counters conventional transaction cost economics, which asserts firms will benefit from lower transaction cost in a better market (Listokin & Taibleson, 2010). This benefit however, is apparently canceled out by the decreased rarity of the resource, that according to the resource-based view now delivers less competitive advantage. While academic research commonly concludes that better performing money markets facilitate resource allocation in ways that will lead to more innovation at a country level, this research suggests this is not necessarily beneficial for those individual firms that might actually exploit the possession of a scarcer resource.

Another explanation is that well performing firms in poor money markets can successfully leverage even a credit with increased transaction costs, whereas worse performing firms are unable to do so and will therefore refrain from obtaining one. Also, well performing firms may have engaged in long-term relationships with banks and may be better equipped to provide collateral. These findings therefore point to a selection bias.

Turning to the greater context of financial development literature and the more specific context of ROSCAs, this study has shown that not only is the ROSCA ever-present in contemporary emerging economies, its credit too aids innovative performance. Although the positive economic performance of the ROSCA is well-substantiated conceptually, empirical academic research is scarce (van Rooyen et al., 2012). Addressing this gap, this study therefore provides the first large-scale empirical validation, and in doing so confirms the economic benefits the ROSCA can provide. Indeed, ROSCAs continue to hold great appeal (van den Brink & Chavas, 1997; Yawe & Prabhu, 2015). Also, this research confirms quality of ROSCA-management is beneficial to the added value of ROSCA-credit. This enriches contemporary research on institutions, in which formal institutional quality is often central, and far less attention is paid to the quality of an informal institution (Casson, Della Giusta, & Kambhampati, 2010). Specifically in the context of ROSCA-research and financial development literature, it is important to note that trust in people known personally at a national level, the variable used to proxy ROSCA-quality, is beneficiary to innovative outcomes. This has important practical implications as well, which are discussed next.

6.2. Managerial and societal implications

This research shows that the more trust shown in people known personally (as a measure of ROSCA-quality), the better the innovative outcomes of ROSCA-credits are. It is therefore suggested that if (quasi)-ROSCA schemes are introduced – whether facilitated by NGOs or not - the building of trust among participants and if applicable other stakeholders should be central. This reduces the risk of negative externalities, such as the abuse of dominant positions for economic gain (Mayoux, 2001). It is argued ROSCA-management is both more effective and efficient if governed by mutual trust with proportionate (social) sanctions - rather than mutual suspicion and social ostracism.

For entrepreneurs in emerging markets, this study does not only confirm that financial resources facilitate innovation, but also shows that joining or setting up a ROSCA can be beneficial to innovation, given above-mentioned caveats. Also, this study suggests entrepreneurs with well performing firms may not have to avoid financial markets with financial voids, as they are better equipped to deal with them and, if they successfully do so, obtain a resource that is rarer and hence provides more competitive advantage than if it was obtained in a well-functioning market. This study also suggests that deriving resources from different institutional contexts could prove more beneficial than solely relying on one institutional context. Apart from the extra leeway multiple types of financial resources can provide, successful evaluation by both an informal and formal context could enhance a firm's legitimacy - a rare resource that can amplify firm performance (Scott, 2013).

For policymakers in emerging markets then, this research further uncovers some antecedents of innovation. Unlike large and listed firms that benefit from increased money market quality and associated policies such as trade liberalization (Demirgüç-Kunt & Maksimovic, 1998), this study suggests – its limitations recognized - innovation by SMEs is not directly affected by money market quality. Hence, other policies to encourage their innovativeness should also be considered. For example, governments may even stimulate the diffusion of ROSCAs, to aid economic development. Such an initiative may enable high quality ROSCAs to emerge as competitors to regular banks. This competitive pressure may reduce power imbalances between banks and potential borrowers, as these latter have a "credible threat" to alternatively join a ROSCA. Also, this research suggests informal institution are highly resilient and persisting, even if (better) formal alternatives become available. Policymakers should acknowledge this to manage expectations, especially regarding the pace of institutional change (Helmke & Levitsky, 2004).

6.3. Limitations

Several limitations of this study are now examined, regarding respondent bias, sampling and (associated) statistical implications, and the dependent, independent, and control variables.

Respondent bias

Most variables were self-reported, which is a known source of bias (Field, 2013). Firms may for example overstate their degree of innovativeness, as it could be perceived socially desirable to be innovative. While WBES surveyors take measures to reduce bias, e.g. by cross-examining multiple sources and follow-up questions, this bias can still never be ruled out (World Bank, n.d.-c, 2019b). Also, cultures differ in their manners of response, and may understand concepts differently (Scholderer, Grunert, & Brunsø, 2005). Although the World Bank has carefully translated and piloted their surveys, cultural bias cannot be ruled out either.[54]

Sampling and (associated) statistical limitations

Although the firm-level sample size is large (n=25,681), the country-level sample is small (n=19), and was limited by the availability of measures of trust. It does not meet the absolute minimum of n=20 that is typically recommended in multilevel research (Field, 2013; Kreft & de Leeuw, 1998). What is more, some authors propose a minimum of n=50, especially if interaction effects are to be reliably estimated (Maas & Hox, 2005). Indeed, the robustness of the results regarding interaction effects is deemed a significant limitation of this study. While the significant interaction effects found were robust to same-sample robustness checks, they differed when submitted to adjusted-sample checks, as results appeared to be highly influenced by the large proportion of Indian firms (27.17% of the sample). Also, the p-values found for these interaction effect were approximately p=.04, showing some risk of a Type I error, although they remained within the conventional α=.05 limit.[55]

[54] Methodologists state that, strictly speaking, cross-cultural answers cannot be compared until "measurement equivalence" is established, by executing a multi-group confirmatory factor analysis (MGCFA-SEM) that shows concepts are understood identically across cultures (Lance & Vandenberg, 2002; van Herk, Poortinga, & Verhallen, 2005). This standard however, is rarely met in cross-cultural research.

[55] For the sake of completeness, the p-value for ROSCA-credit also varies up to p=.04, which would be unexpected given the total firm-level sample of n=25,681. However, this is adequately explained by the reduced power as only a small percentage of firms (5.91%) use this credit.

Several software limitations were encountered. First of all, Stata does not fully support multiple imputation in a multilevel logistic regression model, hence only a single imputed database could be used. This was mitigated however, by asserting the robustness of results by repeating analysis on the unimputed database. Furthermore, measures to more carefully assess fit, explained variance, and influential observations were absent.

Dependent variable

This study narrowly operationalized innovation as the introduction of a product new to the firm. Clearly, innovation is a broader concept and more measurements of innovativeness would provide more fine-grained analyses. Ayyagari et al. (2011) for example, distinguished between eight different types of information. Although this dataset offered five measures of innovativeness, analyzing all these separately would have proved too cumbersome, and creating composite measures too would have greatly complicated analyses and interpretation.[56]

Independent variables

The dummies applied for formal and ROSCA-credit too are limited for reasons discussed in Chapter 3, and do not detail the exact source of different financing arrangement. For example, if a firm has a line of credit from a bank abroad, this is not recognized by the survey, which assumes the credit is obtained under national conditions. Furthermore, no distinction was made between "bank types [and] different lending technologies" (Beck, Demirgüç-Kunt, & Pería, 2011, p. 35). Also, financial resources other than these two forms of credit were not assessed. In addition, the country-level variables applied also have limitations. The GII-measure used to define the quality of money market only measures applicable legislation and depth of credit information. These are necessary but not sufficient features to assess the performance of a money market, as market distortion by cartel formation, state interference, and power imbalances, for example, are not assessed (Demirgüç-Kunt & Maksimovic, 1998). Also, possible regional differences in formal money market quality were not taken into account (Barasa et al., 2017). Hence, this variable can be deemed an incomplete and possibly inaccurate indicator, and thus might well be the cause of several insignificant results.

[56] Regular exploratory factor analysis, for example, would not be possible as this requires variables to be metric and continuous, and all measures are binary (Field, 2013).

Furthermore, the use of nation-averaged trust in people known personally as a proxy for firm-level quality of ROSCA-management can be criticized, as this proxy is very distant from the actual ROSCA.[57] What is more, Rauch et al. (2013, pp. 748–749) argue on good grounds that "such designs are oversimplified [and] suffer from ecological fallacy," because country-level variables do not take into account the personal cultural practices and values of individual entrepreneurs, which may be remarkably different from their national average.[58] Such personal cultural information however, was unavailable in this study. Furthermore, the World Values Survey results were gathered from 2004 to 2014 (Inglehart et al., 2014), while the WBES data was gathered in the period ranging from 2010 to 2017 (World Bank, n.d.-c). Cultural values and practices however, are found to be highly stable over the years (Guiso, Sapienza, & Zingales, 2006; Roland, 2004). In sum, as the positive interaction effect between trust and ROSCA-credit use suggests, nation-averaged trust may have been a reliable measure after all.

Control variables

No reliable measure of financial performance (profitability) was available in this study, while it can be expected that this has a big influence on the likelihood of innovation (Ayyagari et al., 2011; Krammer, 2017). Furthermore, Peng (2002) defined market pressure (e.g. intensity of domestic and international competition) and resources and capabilities (e.g. human capital) as important antecedents to innovation: these aspects were not (fully) captured in this research.

6.4. Directions for further research

This research provides several directions for further research. First of all, ROSCAs remain under-researched and could benefit from more empirical validation, both within and beyond the context of microfinance. Secondly, more empirical evidence can be sought for the effect of "duality of context"-management that has been assessed in this research (Zoogah et al.,

[57] Use of World Values Survey (Inglehart et al., 2014) measures of trust appear scarce in research; Krammer (2017) however (successfully) used a measure of societal trust as both an independent variable and within interaction effects.

[58] Within-country cultural variance can also exist because of a high diversity in ethnic groups, of which many African countries are exemplary (Barnard, Cuervo-Cazurra, & Manning, 2017).

2015, p. 9). It is expected that firms that operate successfully in both formal and informal contexts, will show better outcomes than firms that do not.

Thirdly, more research is needed on the link between formal and informal financial resources and innovation by SMEs in emerging markets, especially with regard to those aspects this study did not address. For example, the conditions under which firms will opt for either formal or informal institutions to acquire their resources are unclear: as informal institutions appear to have a "tenacious survival ability" (North, 1990, p. 45) even if formal alternatives arrive, it is expected that not only economic aspects play a role in this selection, but also social-cultural elements. Researching these aspects can help answer the broader question of "how informal institutions influence the nature and quality of more formal institutions, and how the two together are likely to influence the processes of development" (Casson et al., 2010, p. 140). Specific to the subjects of this study, follow-up research could determine under what conditions SMEs prefer formal credit over ROSCAs and vice versa, using for example per-country panel data to gauge variance in national money market quality.[59] Such research could even more carefully distinguish multiple levels in analyses, asserting that concepts such as culture are both measured at the individual and collectively (Rauch et al., 2013).

To conclude, recently, the ROSCA-concept has regained attention as online platforms have taken up the challenge of digitalizing this ancient institution (Sachdev, 2016). As online solutions become increasingly available in emerging markets too, digital ROSCAs could alleviate administrative tasks, reduce fraud, and connect people across communities that wish to set up a ROSCA. Such advances may create fundamentally more opportunities for entrepreneurs to access financial resources, especially in countries where traditional ROSCAs are scarcer, and hence starting a ROSCA is more difficult. However, as physical and social proximity decreases, it will be interesting to see how well ROSCAs – which are ideally built on trust - will fare. These developments open up interesting new avenues for research in the context of institutional voids, financial development, and entrepreneurship; this informal institution that is social, cultural, and economic may well be expanding in the near future.

[59] Another advantage of panel data analysis is the possibility of causal inference, which is not possible in this study (Field, 2013; Nichols, 2007).

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Appendix 1. Variable legend

Dependent variable	**Measurement**	**Description**
h1	Binary	New or improved product or service introduced during last three years
Independent variables		
k8	Binary	Line of credit or loan from a bank
zdummy	Binary	Use of ROSCA-credit
QUA	Continuous	Money market quality (0-100)
C_QUA	Continuous	Money market quality sample mean centered (-68-32)
PER	Continuous	Trust in people known personally (1-4)
STDPER	Continuous	Trust in people known personally standardized (sample range -2.8 to 2.4 standard deviations from the mean)
bothcredit	Binary	Use of both formal and ROSCA-credit
Interaction effects		
zdummyPER	Continuous	zdummy*STDPER (alternatively: zdummy##c.STDPER)
K8QUA	Continuous	k8*C_QUA (alternatively: k8##c.C_QUA)
ZQUA	Continuous	zdummy*C_QUA (alternatively: zdummy##c.C_QUA)
Control variables		
AGE	Continuous	Firm age (years)
size_num	Continuous	Number of employees (FTE)
sector	Categorical	Firm sector
h8	Binary	Firm spent on R&D last fiscal year
b2b	Continuous	Foreign ownership (percent, 0-100)
PERFORMANCE	Continuous	Sales minus labor costs (local currency)
b7	Continuous	Experience in sector of top manager (years)
EXPORT	Continuous	Sales obtained through export (percent of total sales, 0-100)
PPP	Continuous	Gross domestic product based on purchasing power parity, in 2011 USD.
Imputation variables		
b8	Binary	Company possesses internationally recognized certificates
b3	Continuous	Share held by largest owner(s) (percent, 0-100)
b2a	Continuous	Share owned by domestic parties (percent, 0-100)
Variables in robustness checks		
PerformPRAC	Continuous	Cultural practice of performance orientation (1-7)

Appendix 2. Sample characteristics

Tab country

```
. tab country
```

Country	Freq.	Percent	Cum.
Argentina2017	738	2.87	2.87
China2012	1,674	6.52	9.39
Colombia2017	770	3.00	12.39
Ecuador2017	282	1.10	13.49
Egypt2013	2,302	8.96	22.45
Georgia2013	333	1.30	23.75
Hungary2013	261	1.02	24.77
India2014	6,978	27.17	51.94
Indonesia2015	934	3.64	55.57
Kazakhstan2013	526	2.05	57.62
Malaysia2015	686	2.67	60.29
Mexico2010	974	3.79	64.09
Morocco2013	294	1.14	65.23
Nigeria2014	2,487	9.68	74.92
Poland2013	465	1.81	76.73
Russia2012	3,715	14.47	91.19
Thailand2016	724	2.82	94.01
Turkey2013	1,033	4.02	98.03
Zimbabwe2016	505	1.97	100.00
Total	25,681	100.00	

Appendix 3. Quality of money market, ROSCAs (Trust), and GDP

. tabstat QUA PER PPP, statistics(mean sd)

. tabstat QUA PER PPP, by(country) statistics(mean)

```
. tabstat QUA PER PPP, statistics(mean sd)
```

stats	QUA	PER	PPP
mean	68.35273	2.999347	12220.23
sd	15.43287	.2365939	7575.026

country	QUA	PER	PPP
Argentina2017	50	3.06	18585
China2012	62.5	2.92	10384
Colombia2017	95	2.63	13061
Ecuador2017	45	2.34	10461
Egypt2013	56.25	3.57	9823
Georgia2013	93.75	2.93	7881
Hungary2013	68.75	3.12	22582
India2014	81.25	3.06	5074
Indonesia2015	71	3.05	10003
Kazakhstan2013	56.25	3	21986
Malaysia2015	70	2.91	25685
Mexico2010	62.5	2.52	15186
Morocco2013	50	2.96	6791
Nigeria2014	87.5	2.77	5492
Poland2013	93.75	2.96	23218
Russia2012	50	3.01	24310
Thailand2016	45	2.85	15252
Turkey2013	56.25	3.08	20282
Zimbabwe2016	50	2.76	2197
Total	68.35273	2.999347	12220.23

Appendix 4. Sectors

```
. tab sector
```

Cut: Stratification Sector	Freq.	Percent	Cum.
Basic Metals & Metal Products	512	1.99	1.99
Chemicals & Chemical Products	886	3.45	5.44
Chemicals, Plastics & Rubber	208	0.81	6.25
Construction	719	2.80	9.05
Electronics & Communications Equip.	742	2.89	11.94
Fabricated Metal Products	1,101	4.29	16.23
Food	1,914	7.45	23.68
Furniture	584	2.27	25.96
Hotels & Restaurants	736	2.87	28.82
IT & IT Services	406	1.58	30.40
Machinery & Equipment	832	3.24	33.64
Manufacturing	847	3.30	36.94
Motor Vehicles	444	1.73	38.67
Non-Metallic Mineral Products	1,199	4.67	43.34
Other Manufacturing	2,717	10.58	53.92
Other Services	2,568	10.00	63.92
Printing & Publishing	175	0.68	64.60
Retail	2,966	11.55	76.15
Rubber & Plastics Products	1,023	3.98	80.13
Services of Motor Vehicles	547	2.13	82.26
Textiles & Garments	2,019	7.86	90.12
Transport, Storage, & Communications	824	3.21	93.33
Wholesale	1,712	6.67	100.00
Total	25,681	100.00	

Appendix 5. Missing data analysis

. mdesc zdummy k8 h1 b2b b7 size_num EXPORT h8 AGE PERFORMANCE sector

Variable	Missing	Total	Percent Missing
zdummy	1,359	25,681	5.29
k8	650	25,681	2.53
h1	371	25,681	1.44
b2b	295	25,681	1.15
b7	640	25,681	2.49
size_num	183	25,681	0.71
EXPORT	477	25,681	1.86
h8	1,169	25,681	4.55
AGE	471	25,681	1.83
PERFORMANCE	5,346	25,681	20.82
sector	0	25,681	0.00

The total dataset is n=25681. The selected variables show differing degrees of missingness; most variables display around 1-4% of missing values, but financial performance has over 20% missing. 68.63% of all cases are complete, 93.14% of all cases have a maximum of one missing variable. These numbers rise to 84.48% and 96.09% respectively if financial performance is excluded. In the table next to the text, the cell sizes of combinations of the binary variables are examined.

groups h1 zdummy k8 h8, fillin show(f)

h1	zdummy	k8	h8	Freq.
No	No	No	No	10700
No	No	No	Yes	678
No	No	Yes	No	2799
No	No	Yes	Yes	397
No	Yes	No	No	437
No	Yes	No	Yes	49
No	Yes	Yes	No	241
No	Yes	Yes	Yes	47
Yes	No	No	No	3071
Yes	No	No	Yes	1662
Yes	No	Yes	No	1170
Yes	No	Yes	Yes	900
Yes	Yes	No	No	216
Yes	Yes	No	Yes	85
Yes	Yes	Yes	No	137
Yes	Yes	Yes	Yes	113

The combinations of binary variables display no empty cells, and every combination has a frequency of >5 (Field, 2013). However, the categorical sector variable must also be included. Overlapping sectors were collapsed, creating 23 distinct sectors from the original 33 sectors.

```
groups h1 zdummy k8 h8 sector, fillin show(f) saving(Groups.dta)
use groups.dta
tab _freq
```

frequency	Freq.	Percent	Cum.
0	31	8.42	8.42
1	26	7.07	15.49
2	27	7.34	22.83
3	21	5.71	28.53
4	10	2.72	31.25
5	14	3.80	35.05
6	10	2.72	37.77
7	7	1.90	39.67
8	9	2.45	42.12
9	4	1.09	43.21
10	4	1.09	44.29

8.42% of the possible combinations of categorical and binary variables, are not present in the data. In other words, these are empty cells. 26.63% of non-empty group cells, have frequencies of 5 or less. These frequencies are problematic, as logistic regression assumes both the absence of empty cells, and a maximum of 20% of low frequency cells. It is noted that if all selected variables are used, these cell frequencies will worsen further because of the default complete case approach, in which only complete cases are used in analyses.

Appendix 6. Imputation

pwcorr h1 k8 zdummy b2b b7 size_num EXPORT h8 AGE PERFORMANCE b8 b3 b2a

mi set mlong

mi register imputed h8 b8 h1 k8 zdummy b2b b7 size_num EXPORT AGE b3 b2a

mi impute chained (logit, augment) h8 b8 h1 k8 zdummy (truncreg, ll(0) ul(100)) b2b EXPORT size_num b3 b2a (truncreg, ll(0) ul(70)) b7 AGE = i.sector i.CCC, add(1)

	h1	k8	zdummy	b2b	b7	size_num	EXPORT	h8	AGE	PERFOR~E	b8	b3	b2a
h1	1.0000												
k8	0.0986	1.0000											
zdummy	0.0476	0.0878	1.0000										
b2b	0.0317	-0.0063	0.0443	1.0000									
b7	0.0312	0.0875	-0.0369	-0.0088	1.0000								
size_num	0.0781	0.1421	-0.0172	0.0381	0.0495	1.0000							
EXPORT	0.0381	0.0418	0.1488	0.1111	0.0201	0.1092	1.0000						
h8	0.3695	0.1178	0.0346	0.0120	-0.0129	0.1581	0.0753	1.0000					
AGE	0.0412	0.0465	-0.0056	-0.0158	0.4143	0.1070	0.0191	0.0196	1.0000				
PERFORMANCE	-0.0052	0.0106	-0.0038	0.0031	0.0014	0.0191	0.0055	-0.0024	0.0114	1.0000			
b8	0.1155	0.0608	-0.0176	0.0403	0.0078	0.2827	0.1064	0.1992	0.0718	0.0092	1.0000		
b3	-0.0272	-0.1090	0.0230	-0.0317	-0.1670	-0.1598	-0.0418	-0.0577	-0.1218	0.0018	-0.0802	1.0000	
b2a	-0.0389	0.0386	-0.1583	-0.6625	0.0334	-0.0151	-0.1819	0.0039	0.0009	-0.0228	-0.0123	0.0291	1.0000

To aid imputation, variables were selected that have reasonable correlations and hence can predict other variables. Three variables were supplemented that are not selected for model building (International certifications, b8; concentration of ownership, b3; domestic ownership, b2a). It is noted that financial performance displays no correlation with other variables that can be said to be meaningful, as the biggest correlation coefficient is only r=0.0191. Hence, financial performance could not be included in imputation. Sector (i.sector) and country (i.CCC) were specified as complete categorical predictors (i.e. predictors without missing values). The binary variables were specified as such, while the continuous variables were truncated, meaning imputed values cannot be outside acceptable boundaries (e.g. negative percentages and unrealistic firm ages).

Variable	Obs	Mean	Std. Dev.
hl	25,310	.3284077	.4696433
k8	25,031	.2550837	.435917
zdummy	24,322	.0576844	.2331505
b2b	25,386	2.428268	13.61749
b7	25,041	16.10684	10.56808
size_num	25,498	26.22036	22.43708
EXPORT	25,204	6.639898	20.59517
h8	24,512	.1775049	.3821032
AGE	25,210	16.86367	13.09649
PERFORMANCE	20,335	7.17e+09	4.17e+11

Variable	Obs	Mean	Std. Dev.
hl	25,681	.3288813	.4698159
k8	25,681	.2542736	.4354606
zdummy	25,681	.0591098	.2358348
b2b	25,681	2.796711	14.1923
b7	25,681	16.09086	10.55966
size_num	25,681	26.19045	22.42606
EXPORT	25,681	7.344487	21.39578
h8	25,681	.1832094	.3868456
AGE	25,681	16.84399	13.06669
PERFORMANCE	20,335	7.17e+09	4.17e+11

The left table above shows the unimputed variables, while the right table shows the result after imputation. All imputed variables are now complete (n=25681). Also, means and standard deviations have remained comparable. This shows that the imputation conducted has not underestimated variance. All cases are now complete if performance is ignored (n=25681), and 79% is complete if performance is included (n=20335).

frequency	Freq.	Percent	Cum.
0	31	8.42	8.42
1	26	7.07	15.49
2	27	7.34	22.83
3	21	5.71	28.53
4	10	2.72	31.25
5	14	3.80	35.05
6	10	2.72	37.77
7	7	1.90	39.67
8	9	2.45	42.12
9	4	1.09	43.21
10	4	1.09	44.29

frequency	Freq.	Percent	Cum.
0	23	6.25	6.25
1	25	6.79	13.04
2	25	6.79	19.84
3	18	4.89	24.73
4	20	5.43	30.16
5	7	1.90	32.07
6	6	1.63	33.70
7	9	2.45	36.14
8	11	2.99	39.13
9	4	1.09	40.22
10	6	1.63	41.85

The left table shows the cell frequencies shown earlier, while the right table shows the cell frequencies after imputation. Cell size problems have been slightly alleviated, but not solved. The decision was made to impute missing values, partly to alleviate problems with cell frequencies caused by the diversity of the sectors variable. As this objective was not reached, the decision is made to exclude the sector variable from model estimation, to prevent model instability. Furthermore, imputation has caused 79% of all cases to now be complete, rising to 100% if financial performance is excluded.

Appendix 7. Linearity

graph twoway (lowess h1 b2b, yla(, format(%9.2f)) ms(none) title("Foreign ownership (b2b) & New product innovation (h1)") xtitle("Foreign ownership (percents)") ytitle(New product) legend(label(1 "Smoothed (actual slope)") label(2 "Linear (fitted slope)"))) (lfit h1 b2b)

graph twoway (lowess h1 b7, yla(0(0.2)1, format(%9.1f)) ms(none) title("Managerial experience (b7) & New product innovation (h1)") xtitle("Top manager experience (years)") ytitle(New product) legend(label(1 "Smoothed (actual slope)") label(2 "Linear (fitted slope)"))) (lfit h1 b7)

graph twoway (lowess h1 size_num, yla(, format(%9.2f)) ms(none) title("Firm size (size_num) & New product introduction (h1)") xtitle("Firm size (FTE)") ytitle(New product) legend(label(1 "Smoothed (actual slope)") label(2 "Linear (fitted slope)"))) (lfit h1 size_num)

graph twoway (lowess h1 C_QUA, yla(0(0.2)1, format(%9.1f)) ms(none) title("Money market quality (C_QUA) & New product introduction (h1)") xtitle("Money market quality (centered)") ytitle(New product) legend(label(1 "Smoothed (actual slope)") label(2 "Linear (fitted slope)"))) (lfit h1 C_QUA)

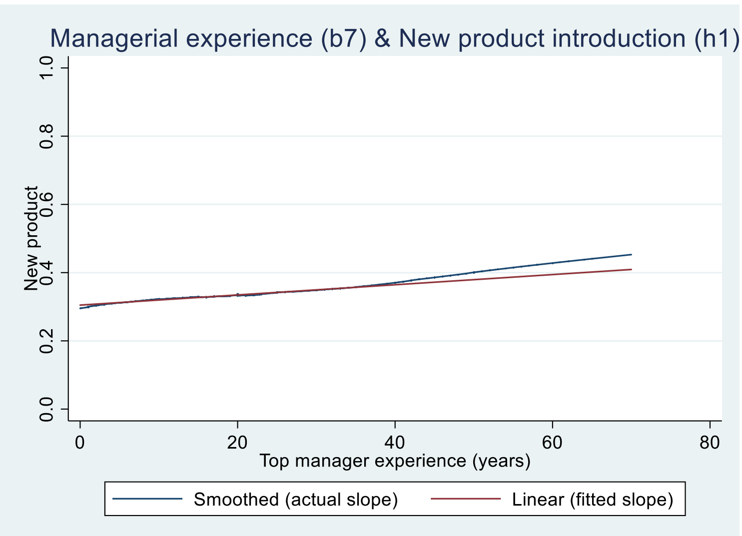
graph twoway (lowess h1 PPP, yla(0(0.2)1, format(%9.1f)) ms(none) title("Gross Domestic Product (PPP) & New product introduction (h1)") xtitle("GDP adjusted for Purchasing Power Paritas ($)") ytitle(New product) legend(label(1 "Smoothed (actual slope)") label(2 "Linear (fitted slope)"))) (lfit h1 PPP)

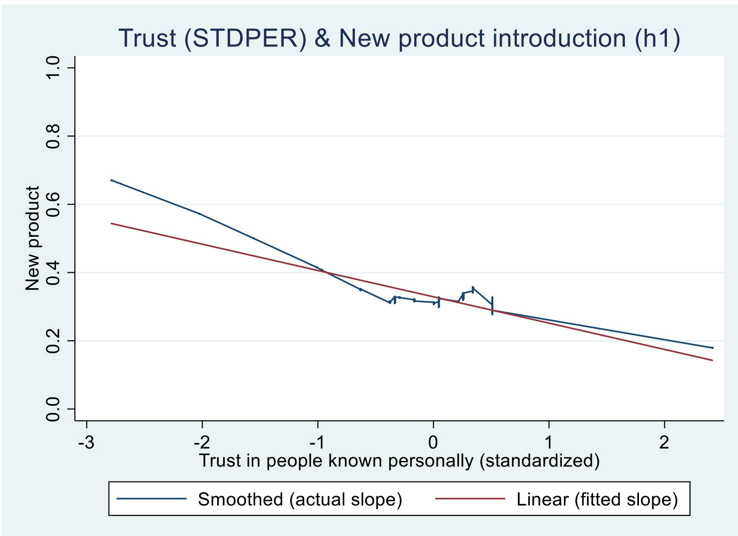
graph twoway (lpoly h1 AGE, yla(0(0.2)1, format(%9.1f)) ms(none) title("Firm age (AGE) & New product introduction (h1)") xtitle("Firm age (years)") ytitle(New product) legend(label(1 "Smoothed (actual slope)") label(2 "Linear (fitted slope)"))) (lfit h1 AGE)

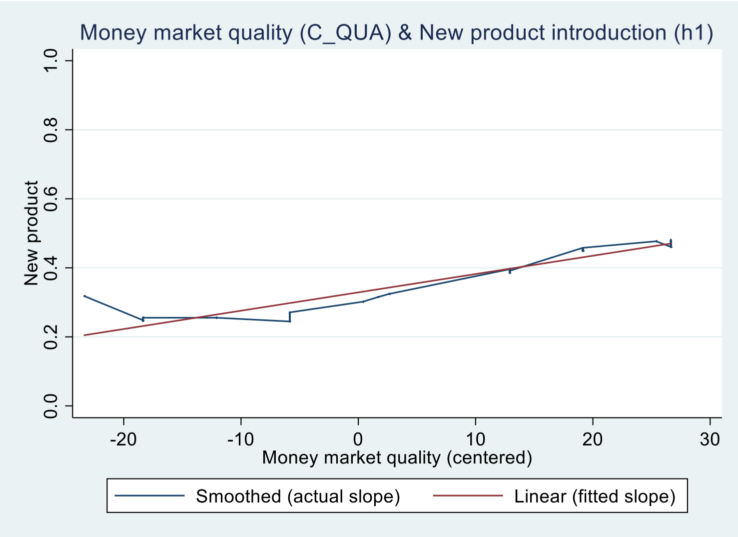
graph twoway (lowess h1 STDPER, yla(0(0.2)1, format(%9.1f)) ms(none) title("Trust (STDPER) & New product introduction (h1)") xtitle("Trust in people known personally (standardized)") ytitle(New product) legend(label(1 "Smoothed (actual slope)") label(2 "Linear (fitted slope)"))) (lfit h1 STDPER)

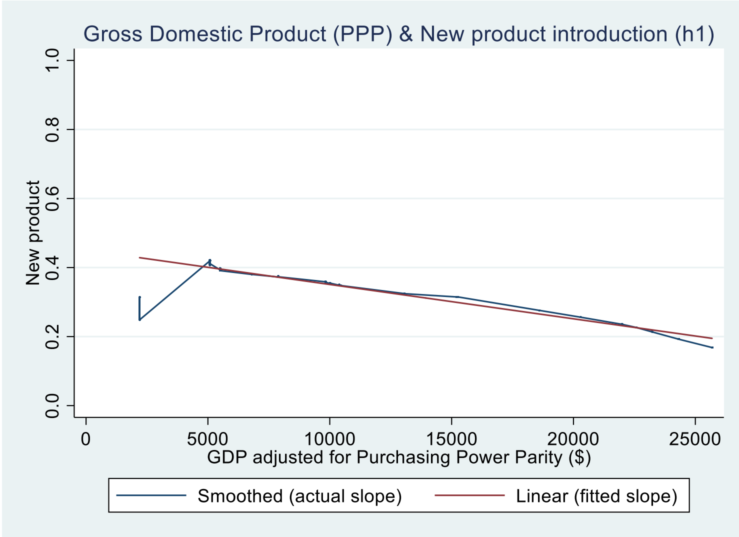
graph twoway (lowess h1 EXPORT, yla(0(0.2)1, format(%9.1f)) ms(none) title("Export (EXPORT) & New product introduction (h1)") xtitle("Export (percentage of sales)") ytitle(New product) legend(label(1 "Smoothed (actual slope)") label(2 "Linear (fitted slope)"))) (lfit h1 EXPORT)

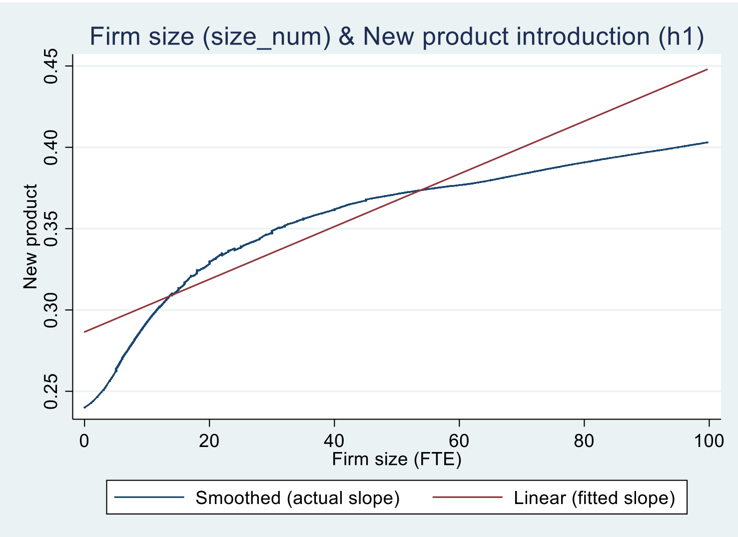
graph twoway (lowess h1 PERFORMANCE, yla(0(0.2)1, format(%9.1f)) ms(none) title("Financial performance (PERFORMANCE) & New product introduction (h1)") xtitle("Financial erformance (LCU)") ytitle(New product) legend(label(1 "Smoothed (actual slope)") label(2 "Linear (fitted slope)"))) (lfit h1 PERFORMANCE)

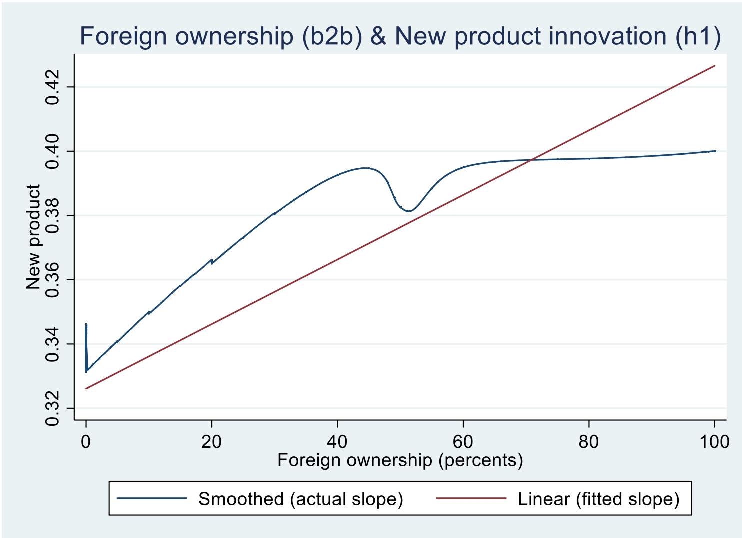


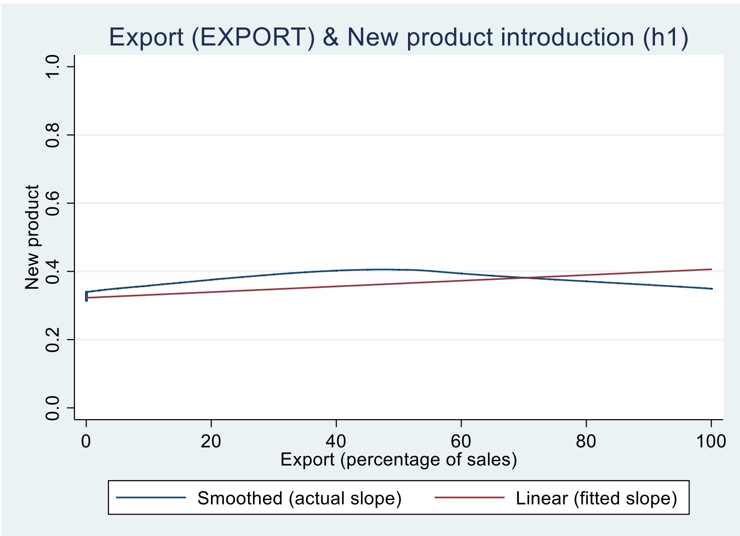


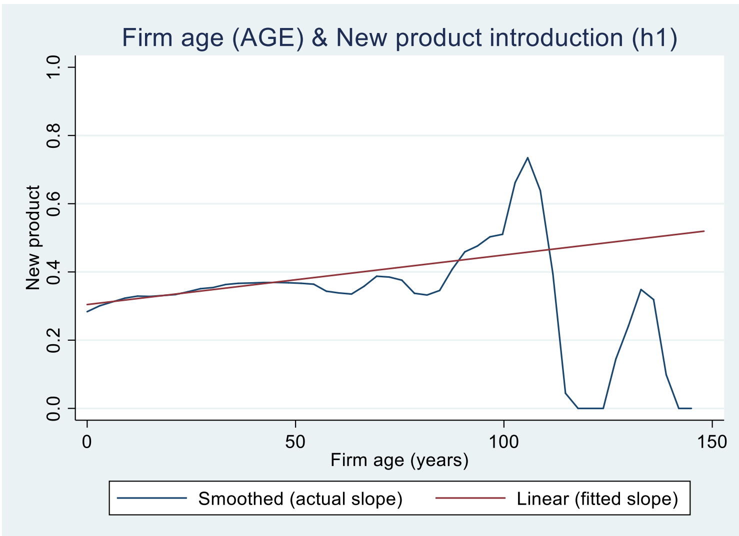

Money market quality (C_QUA) & New product introduction (h1)
New product
Money market quality (centered)
Smoothed (actual slope)
Linear (fitted slope)

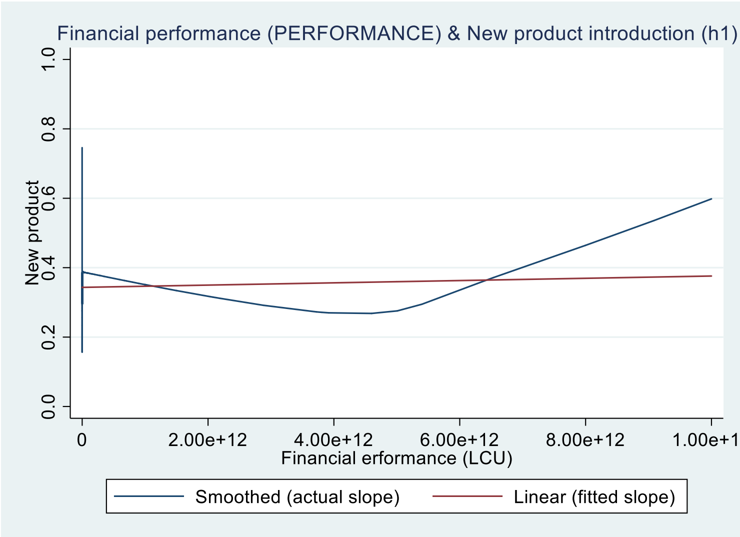

Gross Domestic Product (PPP) & New product introduction (h1)
New product
GDP adjusted for Purchasing Power Parity ($)
Smoothed (actual slope)
Linear (fitted slope)


Firm size (size_num) & New product introduction (h1)
New product
Firm size (FTE)
Smoothed (actual slope)
Linear (fitted slope)


Foreign ownership (b2b) & New product innovation (h1)
New product
Foreign ownership (percents)
Smoothed (actual slope)
Linear (fitted slope)


Export (EXPORT) & New product introduction (h1)
New product
Export (percentage of sales)
Smoothed (actual slope)
Linear (fitted slope)


Firm age (AGE) & New product introduction (h1)
New product
Firm age (years)
Smoothed (actual slope)
Linear (fitted slope)

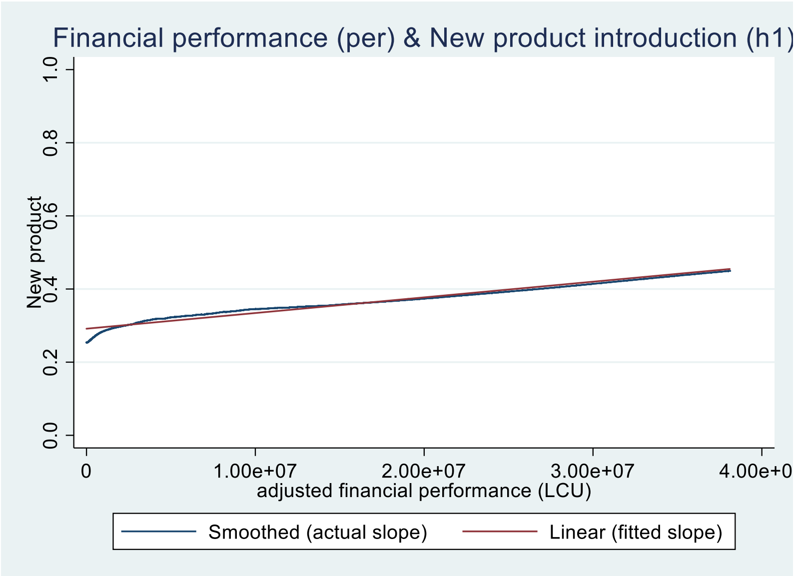


Managerial experience (b7), trust (STDPER), GDP (PPP) and **money market quality (C_QUA)** show a clear linear relationship with new product introduction (h1).[60] Both **firm size (size_num)** and **foreign ownership (b2b)** show a relationship approximately linear; the deviations around the beginning and end of the curves are not unexpected. Transformation for these two variables is hence not considered. **Export (EXPORT)** display a relationship that is approximately linear up to around 60%, after which the relationship decreases. As 96% of the data has an export percentage of 70% or less, the end of the curve is not expected to influence estimation significantly. Hence, the variable is retained. **Firm age (AGE)** too shows a linear relationship up until a certain point, around 75 years. Around 100 years, the actual slope becomes erratic. This is caused by the very small numbers of firms that are older than 75 years (n=42, 0.5%) and 100 years (n=18, 0.1%). Hence, the non-linearity displayed after the age of 100 years is not expected to impact estimations. The variable is retained in an untransformed way.

Financial performance (PERFORMANCE) shows no linear relationship between financial performance, which was defined as sales minus labor costs, and new product introduction. Around 99% of the data reside close to the 0 in this graph, around which no regression slope is interpretable because the data is too compressed. Hence, a new variable is created for values between 0 and 3.81e+07 (i.e. the 75th percentile of PERFORMANCE), to test that segment for linearity.

[60] Remarkably, trust appears to be negatively correlated with new product introduction. This was not hypothesized. If this relationship holds in the full model estimates, it will be interpreted in the Discussion chapter.

graph twoway (lowess h1 per, yla(0(0.2)1, format(%9.1f)) ms(none) title("Financial performance (per) & New product introduction (h1)") xtitle("adjusted financial performance (LCU)") ytitle(New product) legend(label(1 "Smoothed (actual slope)") label(2 "Linear (fitted slope)"))) (lfit h1 per)



This graph shows that a great majority of the financial performance data correlate (approximately)[61] linearly with new product introduction. The (original) PERFORMANCE variable is therefore retained untransformed. This graph also shows however, that the majority of the financial performance correlates only very weakly with new product introduction. Increasing from a financial performance of 0 to 30,000,000 does only raise the probability of innovativeness from 0.3 to 0.4. Concluding, financial performance is expected to be a weak or insignificant control variable based on this data.

[61] This part of the data displays a relationship that also resembles a root function.

Appendix 8. BIC & AIC

	Δ BIC
No support	<2
Positive evidence	2-6
Strong evidence	6-10
Very strong evidence	10>

(Kass & Raftery, 1995, p. 777)

	Δ AIC
No support	<2
Considerable support	4-7
Very strong evidence	10>

(Burnham & Anderson, 2004, p. 271)

Regarding the interpretation of the AIC (and this also applies to the BIC), Burnham and Anderson (2004, pp. 270–271) note the following: “The individual AIC values are not interpretable as they contain arbitrary constants and are much affected by sample size (we have seen AIC values ranging from –600 to 340,000). (...) users often question the importance of a delta = 10 when the two AIC values might be, for example, 280,000 and 280,010. The difference of 10 here might seem trivial. In fact, large AIC values contain large scaling constants, while the delta are free of such constants. Only these differences in AIC are interpretable as to the strength of evidence.”

Appendix 9. Transformation of log odds, probabilities, and odds ratios

Table 3.1 Forward Transformation From Probabilities to Odds to Log Odds

Transformation	Probabilities	Odds	Logit or Log Odds
Forward	p	$\frac{p}{1-p}$	$\ln \frac{p}{1-p}$

Table 3.2 Backward Transformation From Log Odds to Odds to Probabilities

Transformation	Logit or Log Odds	Odds	Probabilities
Backward	$\text{logit}(p)$ or $\ln \frac{p}{1-p}$	Odds = exp(logit)	$p = \frac{\text{odds}}{1+\text{odds}}$

When OR > 1, the odds of success or of having an event for one group are larger than the odds for the other group. For example, OR = 2 indicates the odds of success for one group are two times the odds for the other group.

When OR < 1, the odds in one group are less than the odds in the other group.

For example, OR = 0.5 indicates that the odds for one group are 0.5 times the odds for the other group. In other words, the odds for the second group are two times the odds for the first group. When OR is less than 1, we can take the inverse of it and make it more interpretable.

When OR = 1, the odds for one group are the same as the ones for the other group.

The above-depicted is an excerpt from Xing Liu (2015, pp. 146–147).

Appendix 10. Culture

. pwcorr inno PER DistanceVAL PerformPRAC GenderVAL if pickone==1, sig

	inno	PER	Distan~L	Perfor~C	Gender~L
inno	1.0000				
PER	-0.6021	1.0000			
	0.0064				
DistanceVAL	-0.5002	0.4038	1.0000		
	0.0292	0.0864			
PerformPRAC	0.6563	-0.4593	-0.4192	1.0000	
	0.0023	0.0479	0.0740		
GenderVAL	0.5120	-0.4775	-0.6471	0.3946	1.0000
	0.0250	0.0387	0.0027	0.0945	

. factor PER DistanceVAL PerformPRAC GenderVAL if pickone==1, factor(1)

As this factor analysis is only meant to be indicative, assumptions (e.g. sample size; Field, 2013) are not assessed.

```
(obs=19)

Factor analysis/correlation                        Number of obs    =         19
    Method: principal factors                      Retained factors =          1
    Rotation: (unrotated)                          Number of params =          4
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.80252	1.73215	1.1783	1.1783
Factor2	0.07037	0.19191	0.0460	1.2243
Factor3	-0.12153	0.10010	-0.0794	1.1449
Factor4	-0.22164	.	-0.1449	1.0000

```
    LR test: independent vs. saturated:  chi2(6)  =   19.37 Prob>chi2 = 0.0036

Factor loadings (pattern matrix) and unique variances
```

Variable	Factor1	Uniqueness
PER	0.6173	0.6189
DistanceVAL	0.7240	0.4758
PerformPRAC	-0.5800	0.6636
GenderVAL	-0.7489	0.4391

The output below shows the practice of performance orientation per country, rescaled 1-10 for interpretation. Analyses use the original scale (1-7).

```
. generate PerformPRACC=PerformPRAC*(10/7)

. tabstat PerformPRACC, by(country)

Summary for variables: PerformPRACC
     by categories of: country (Country)
```

country	mean
Argentina2017	9.068571
China2012	8.094286
Colombia2017	9.177142
Ecuador2017	9.025714
Egypt2013	8.422857
Georgia2013	8.125714
Hungary2013	8.514286
India2014	8.641428
Indonesia2015	8.181429
Kazakhstan2013	7.721429
Malaysia2015	8.624286
Mexico2010	8.795714
Morocco2013	8.234285
Nigeria2014	8.95
Poland2013	8.745714
Russia2012	7.907143
Thailand2016	8.205714
Turkey2013	7.7
Zimbabwe2016	9.217143
Total	8.462627

Appendix 11. Correlations

. pwcorr QUA credmean if pickone==1, sig

	QUA	credmean
QUA	1.0000	
credmean	0.1142	1.0000
	0.0000	

. pwcorr QUA obstacle if pickone==1, sig

. pwcorr zdummymean obstacle if pickone==1, sig

	zdummy~n	obstacle
zdummymean	1.0000	
obstacle	0.2231	1.0000
	0.3587	

	QUA	obstacle
QUA	1.0000	
obstacle	-0.0076	1.0000
	0.9754	

Appendix 12. Research integrity form

Research Integrity Form - Master thesis

Name: Sander van Dijk	**Student number:** s4045815
RU e-mail address: Sandervandijk@student.ru.nl	**Master specialisation:** Strategic Management

Thesis title: Formal and informal ways of financing SME innovation in emerging markets
Brief description of the study: In this study, a formal and informal way of financing SME-innovation were researched, as well as the interaction with the quality of their respective institution. Results were primarily derived from the World Bank Enterprise Survey (WBES) using multilevel logistic regression. Firstly, formal credit delivered by a bank was assessed, and the associated quality of the national money market. Second to be examined was informal credit delivered by a Rotating Savings and Credit Association (ROSCA) – a communal fund that periodically distributes a lumpsum of contributions among its members - and the associated quality of ROSCA-management as proxied by national trust in people known personally.

It is my responsibility to follow the university's code of academic integrity and any relevant academic or professional guidelines in the conduct of my study. This includes:

- providing original work or proper use of references;
- providing appropriate information to all involved in my study;
- requesting informed consent from participants;
- transparency in the way data is processed and represented;
- ensuring confidentiality in the storage and use of data;

If there is any significant change in the question, design or conduct over the course of the research, I will complete another Research Integrity Form.

Breaches of the code of conduct with respect to academic integrity (as described / referred to in the thesis handbook) should and will be forwarded to the examination board. Acting contrary to the code of conduct can result in declaring the thesis invalid

Student's Signature: ______________________________ **Date:** 16-06-2019

To be signed by supervisor

I have instructed the student about ethical issues related to their specific study. I hereby declare that I will challenge him / her on ethical aspects through their investigation and to act on any violations that I may encounter.

Supervisor's Signature: ______________________________ **Date:**

Overview log odds models (full sample)

Full sample log odds		VARIABLES	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Controls		Foreign ownership		0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
		Managerial experience		0.010***	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***
				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
		Firm size		0.003***	0.002***	0.003***	0.002***	0.002***	0.002***	0.002**	0.002**	0.002**
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
		R&D		1.778***	1.758***	1.771***	1.758***	1.757***	1.758***	1.757***	1.757***	1.755***
				(0.038)	(0.039)	(0.038)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Firm level	H1A	Formal credit use			0.255***		0.255***	0.254***	0.254***	0.260***	0.260***	0.257***
					(0.036)		(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
	H2A	ROSCA-credit use			0.143*		0.143*	0.142*	0.197**	0.142*	0.142*	0.193**
					(0.064)		(0.064)	(0.064)	(0.076)	(0.064)	(0.064)	(0.070)
	H4	Use of both forms of credit				0.454***						
						(0.098)						
Country level		Trust Standardized						-0.452*	-0.457*	-0.449*	-0.451*	-0.451*
								(0.180)	(0.181)	(0.180)	(0.181)	(0.181)
	H1B	Money market quality Centered					0.004			0.004		
							(0.013)			(0.011)		
Interactions	H2B	ROSCA-credit*Trust							0.106			
									(0.079)			
	H1C	Formal credit*Market quality								-0.005*	-0.005*	-0.004
										(0.002)	(0.002)	(0.002)
	H3	ROSCA-credit*Market quality										-0.007
												(0.004)
		Constant [fixed effect]	-1.012***	-1.568***	-1.639***	-1.583***	-1.629***	-1.786***	-1.788***	-1.777***	-1.790***	-1.791***
			(0.241)	(0.225)	(0.224)	(0.226)	(0.226)	(0.204)	(0.204)	(0.206)	(0.204)	(0.205)
		Constant [random effect variance]	1.095***	0.930**	0.918**	0.937**	0.913**	0.686**	0.690**	0.681**	0.687**	0.693**
			(0.360)	(0.307)	(0.303)	(0.310)	(0.302)	(0.228)	(0.229)	(0.227)	(0.228)	(0.230)
		AIC	29616.76	27107.68	27053.97	27088.50	27055.90	27050.56	27050.81	27050.36	27048.51	27047.52
		BIC	29633.07	27156.61	27119.20	27145.58	27129.28	27123.94	27132.35	27140.05	27130.05	27137.21
		df	2	6	8	7	9	9	10	11	10	11
		Compared with	-	Model 0	Model 1	Model 1	Model 2	Model 2	Model 5	Model 5	Model 5	Model 8
		Delta AIC	-	-2509.08	-53.71	-19.18	1.93	-3.41	0.25	-0.20	-2.05	-0.99
		Delta BIC	-	-2476.46	-37.41	-11.03	10.08	4.74	8.41	16.11	6.11	7.16
		Delta df	-	4	2	1	1	1	1	2	1	1
		LR chi2	-	2517.08***	57.71***	21.18***	0.07	5.42*	1.74	4.20	4.05*	2.99

Standard errors in parentheses. Colors highlight groups of hypotheses and associated results. Best model in thick frame.

*** p<0.001, ** p<0.01, * p<0.05

Observations	25,681
Number of groups	19

Model 0. Null

melogit h1 || country:,

```
Mixed-effects logistic regression               Number of obs     =     25,681
Group variable:         country                 Number of groups  =         19

                                                Obs per group:
                                                              min =        261
                                                              avg =    1,351.6
                                                              max =      6,978

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(0)      =          .
Log likelihood =  -14806.38                     Prob > chi2       =          .
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_cons	-1.011847	.2412443	-4.19	0.000	-1.484677	-.5390167
country var(_cons)	1.094794	.3601799			.5745036	2.086277

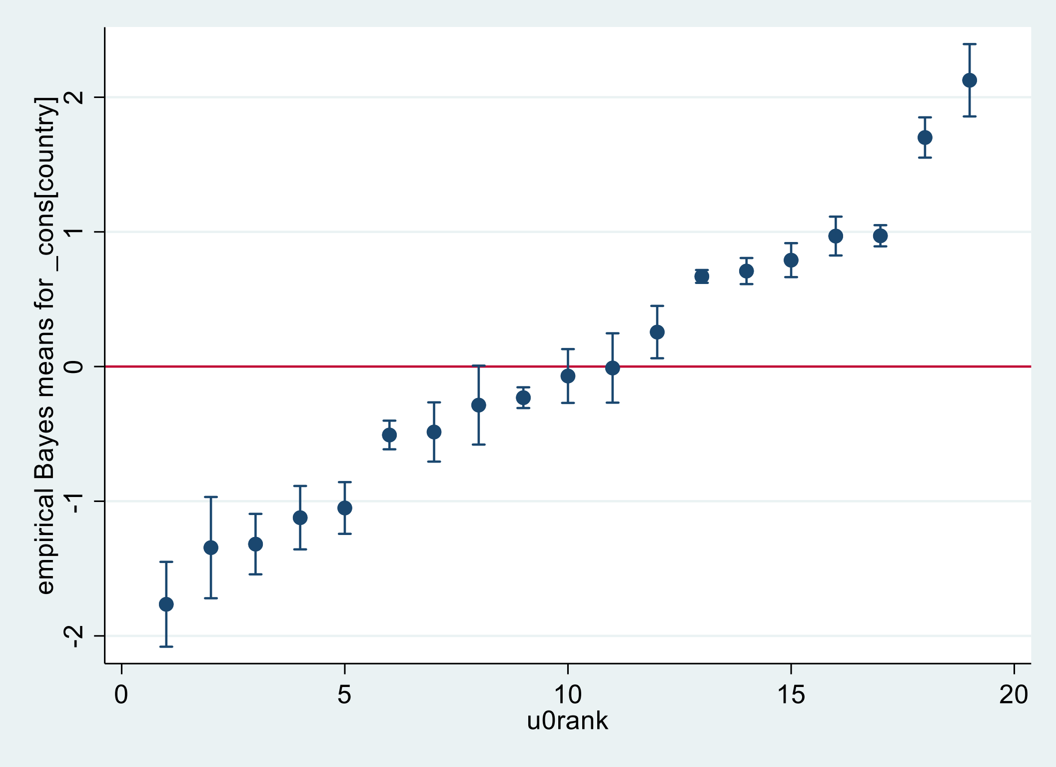
```
LR test vs. logistic model: chibar2(01) = 2919.09     Prob >= chibar2 = 0.0000

.
. fit_meologit_2lev
Fit-measures for the MELOGIT/MEOLOGIT-model:

Intraclass correlation
```

Level	ICC	Std. Err.	[95% Conf.	Interval]
country	.2496872	.0616348	.1486668	.3880619

```
.
. estimates store null

.
. estat ic

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
null	25,681	.	-14806.38	2	29616.76	29633.07

Note: N=Obs used in calculating BIC; see **[R] BIC note**.



empirical Bayes means for _cons[country]
-2
-1
0
1
2
0
5
10
15
20
u0rank

Model 1. Control

```
. correlate b2b b7 size_num EXPORT AGE PERFORMANCE h8
(obs=20,335)
```

	b2b	b7	size_num	EXPORT	AGE	PERFOR~E	h8
b2b	1.0000						
b7	-0.0147	1.0000					
size_num	0.0307	0.0436	1.0000				
EXPORT	0.1163	0.0080	0.1114	1.0000			
AGE	-0.0124	0.4097	0.0954	0.0079	1.0000		
PERFORMANCE	0.0027	0.0014	0.0190	0.0053	0.0116	1.0000	
h8	0.0020	-0.0137	0.1565	0.0710	0.0029	-0.0026	1.0000

```
.
. vif
```

Variable	VIF	1/VIF
AGE	1.21	0.825947
b7	1.20	0.831746
size_num	1.05	0.955763
EXPORT	1.03	0.971796
h8	1.03	0.972048
b2b	1.01	0.985706
PERFORMANCE	1.00	0.999481
Mean VIF	1.08	

The variables managerial experience (b7) and age correlate moderately (r=0.4), R&D (b8), and size are weakly correlated (r=0.15), as well as age and size (r=0.1) and export and foreign ownership (b2b, r=0.12). Performance, as discussed earlier, shows very low covariance. The VIF shows no obvious problem of multicollinearity and remains well below suggested cut-off points of 5-10 (Hair et al., 2010). However, here too performance evidently shows very little correlation with the other variables (VIF=1). As a higher degree of correlation with other control variables would be expected, the univariate effect of performance on innovation is assessed, as well as a log transformation (see next page). Both performance and its log transformation and are highly insignificant and hence dropped as control variables.

melogit h1 PERFORMANCE || country:

```
Iteration 6:   log likelihood = -11883.686
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
PERFORMANCE	2.73e-14	3.79e-14	0.72	0.470	-4.69e-14	1.02e-13
_cons	-1.001077	.2439834	-4.10	0.000	-1.479275	-.5228779
country						
var(_cons)	1.114488	.3676645			.5838049	2.127565

melogit h1 LOGPERFORMANCE || country:

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
LOGPERFORMANCE	.0006687	.3077803	0.00	0.998	-.6025695	.603907
_cons	-1.020334	9.033577	-0.11	0.910	-18.72582	16.68515
country						
var(_cons)	1.113766	.3674318			.5834209	2.126207

A model is now run with foreign ownership, managerial experience, size, exports, age, and R&D as control variables. In the output below, age is highly insignificant and hence dropped as control variable. It is noted that export (p=.103) is also a candidate for deletion in the next iteration. In the next model, export retains its insignificance. Hence, export too is dropped.

. melogit h1 b2b b7 size_num EXPORT AGE h8 || country:, nogroup

```
Mixed-effects logistic regression               Number of obs     =     25,681

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(6)      =    2277.26
Log likelihood = -13546.357                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.0040757	.0010493	3.88	0.000	.0020191	.0061324
b7	.0106247	.0016528	6.43	0.000	.0073852	.0138642
size_num	.0027532	.000692	3.98	0.000	.001397	.0041094
EXPORT	.0012112	.0007422	1.63	0.103	-.0002436	.002666
AGE	-.0007346	.0013004	-0.56	0.572	-.0032833	.0018142
h8	1.773138	.0385505	46.00	0.000	1.69758	1.848695
_cons	-1.567412	.2261711	-6.93	0.000	-2.0107	-1.124125
country						
var(_cons)	.9372939	.3096196			.4905636	1.790838

. melogit h1 b2b b7 size_num EXPORT h8 || country:, nogroup

```
Mixed-effects logistic regression               Number of obs     =     25,681

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(5)      =    2277.15
Log likelihood = -13546.516                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.004082	.0010493	3.89	0.000	.0020254	.0061386
b7	.0102517	.0015152	6.77	0.000	.0072819	.0132214
size_num	.0027169	.000689	3.94	0.000	.0013665	.0040672
EXPORT	.0012111	.0007422	1.63	0.103	-.0002436	.0026658
h8	1.773562	.0385432	46.01	0.000	1.698019	1.849105
_cons	-1.572987	.2258585	-6.96	0.000	-2.015661	-1.130312
country						
var(_cons)	.9364461	.3093467			.4901125	1.789245

melogit h1 b2b b7 size_num h8 || country:, nogroup

```
Mixed-effects logistic regression               Number of obs     =     25,681

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(4)      =    2275.28
Log likelihood = -13547.842                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.0042889	.0010408	4.12	0.000	.0022489	.0063289
b7	.010277	.0015152	6.78	0.000	.0073073	.0132466
size_num	.0028291	.0006854	4.13	0.000	.0014857	.0041726
h8	1.777656	.0384698	46.21	0.000	1.702256	1.853055
_cons	-1.568117	.2251107	-6.97	0.000	-2.009326	-1.126908
country						
var(_cons)	.9302237	.3072996			.4868474	1.777387

```
LR test vs. logistic model: chibar2(01) = 2057.09      Prob >= chibar2 = 0.0000
```

As all level 1 variables are now assessed, the level 2 variable PPP is added. This variable however, is insignificant (p=.207) and hence dropped from the model.

melogit h1 b2b b7 size_num h8 PPP || country:, nogroup

```
Mixed-effects logistic regression               Number of obs     =     25,681

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(5)      =    2276.73
Log likelihood = -13547.079                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.0042826	.0010408	4.11	0.000	.0022428	.0063224
b7	.0102894	.0015151	6.79	0.000	.0073198	.013259
size_num	.0028286	.0006854	4.13	0.000	.0014851	.004172
h8	1.777673	.0384708	46.21	0.000	1.702271	1.853074
PPP	-.0000378	.00003	-1.26	0.207	-.0000965	.0000209
_cons	-1.034729	.4747904	-2.18	0.029	-1.965301	-.1041568
country						
var(_cons)	.8569967	.2836327			.4479859	1.639434

Therefore, the previous model (repeated hereafter) is selected as control model and will be compared to the null model (see main body of text).

quietly melogit h1 b2b b7 size_num h8 || country:, nogroup

estimates store Control

lrtest null Control, stats

```
Likelihood-ratio test                                 LR chi2(4)  =   2517.08
(Assumption: null nested in Control)                  Prob > chi2 =    0.0000

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
null	25,681	.	-14806.38	2	29616.76	29633.07
Control	25,681	.	-13547.84	6	27107.68	27156.61

```
. bfit logit h1 b2b b7 size_num h8 k8 zdummy AGE PERFORMANCE EXPORT
```

bfit logit results sorted by bic

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
_bfit_11	20335	-13079.47	-11619.55	6	23251.1	23298.62
_bfit_18	20335	-13079.47	-11619.23	7	23252.46	23307.9
_bfit_10	20335	-13079.47	-11631.26	5	23272.53	23312.13
_bfit_32	20335	-13079.47	-11617.39	8	23250.78	23314.14
_bfit_25	20335	-13079.47	-11617.78	8	23251.57	23314.93
_bfit_13	20335	-13079.47	-11615.03	9	23248.07	23319.35
_bfit_4	20335	-13079.47	-11635.35	5	23280.69	23320.3
_bfit_17	20335	-13079.47	-11631.06	6	23274.12	23321.64

(best models are listed first; further output omitted, as Stata calculated 200 possible models)

```
Model _bfit_11

Multinomial logistic regression                 Number of obs     =     20,335
                                                LR chi2(5)        =    2919.84
                                                Prob > chi2       =     0.0000
Log likelihood = -11619.552                     Pseudo R2         =     0.1116
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
No	(base outcome)					
Yes						
h8						
Yes	1.917813	.0391238	49.02	0.000	1.841132	1.994495
k8						
Yes	.2660275	.0362229	7.34	0.000	.195032	.337023
1.zdummy	.3227654	.0660875	4.88	0.000	.1932364	.4522945
b2b	.0044954	.0011124	4.04	0.000	.0023151	.0066757
b7	.0086051	.0015263	5.64	0.000	.0056137	.0115966
_cons	-1.316325	.0323347	-40.71	0.000	-1.379699	-1.25295

```
Model _bfit_18

Multinomial logistic regression                 Number of obs     =     20,335
                                                LR chi2(6)        =    2920.48
                                                Prob > chi2       =     0.0000
Log likelihood =  -11619.23                     Pseudo R2         =     0.1116
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
No	(base outcome)					
Yes						
h8						
Yes	1.913222	.0395262	48.40	0.000	1.835752	1.990692
k8						
Yes	.2624696	.0364932	7.19	0.000	.1909443	.3339949
1.zdummy	.3245394	.0661188	4.91	0.000	.1949488	.4541299
b2b	.0044643	.0011131	4.01	0.000	.0022827	.0066459
b7	.0085618	.0015273	5.61	0.000	.0055684	.0115551
size_num	.0005701	.00071	0.80	0.422	-.0008215	.0019617
_cons	-1.329368	.0362088	-36.71	0.000	-1.400336	-1.2584

Model 2. Simple

melogit h1 b2b b7 size_num h8 k8 zdummy || country:, nogroup

estimates store Simple

lrtest Simple Control, stats

```
Mixed-effects logistic regression               Number of obs     =     25,681

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(6)      =    2314.35
Log likelihood = -13518.987                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.0042774	.0010423	4.10	0.000	.0022346	.0063202
b7	.0099579	.0015177	6.56	0.000	.0069834	.0129325
size_num	.0022867	.0006909	3.31	0.001	.0009326	.0036409
h8	1.757576	.0385681	45.57	0.000	1.681984	1.833168
k8	.2549629	.0362795	7.03	0.000	.1838563	.3260695
zdummy	.143161	.0640061	2.24	0.025	.0177114	.2686107
_cons	-1.639215	.2238505	-7.32	0.000	-2.077953	-1.200476
country						
var(_cons)	.9175467	.3032669			.4800535	1.753746

```
Likelihood-ratio test                                 LR chi2(2)  =     57.71
(Assumption: Control nested in Simple)                Prob > chi2 =    0.0000

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
Control	25,681	.	-13547.84	6	27107.68	27156.61
Simple	25,681	.	-13518.99	8	27053.97	27119.2

Model 3. Both credit

melogit h1 b2b b7 size_num h8 bothcredit || country:, nogroup

estimates store Bothcredit

lrtest Bothcredit Simple, stats

```
Mixed-effects logistic regression               Number of obs     =     25,681

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(5)      =    2290.78
Log likelihood = -13537.251                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.0042598	.0010415	4.09	0.000	.0022186	.0063011
b7	.0102767	.0015158	6.78	0.000	.0073058	.0132477
size_num	.0027959	.0006856	4.08	0.000	.0014521	.0041397
h8	1.771161	.0384972	46.01	0.000	1.695708	1.846614
bothcredit	.4537604	.0981236	4.62	0.000	.2614417	.6460791
_cons	-1.582685	.2259629	-7.00	0.000	-2.025565	-1.139806
country						
var(_cons)	.9372512	.3096234			.4905229	1.790823

```
Likelihood-ratio test                                 LR chi2(1)  =      21.18
(Assumption: Control nested in Bothcredit)            Prob > chi2 =     0.0000

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
Control	25,681	.	-13547.84	6	27107.68	27156.61
Bothcredit	25,681	.	-13537.25	7	27088.5	27145.58

Model 4 & 5. Contextual

melogit h1 b2b b7 size_num h8 k8 zdummy C_QUA || country:, nogroup

estimates store Quality

lrtest Simple Quality, stats

Model 4

```
Mixed-effects logistic regression               Number of obs     =     25,681

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(7)      =    2314.43
Log likelihood = -13518.952                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.0042783	.0010423	4.10	0.000	.0022355	.0063212
b7	.0099615	.0015177	6.56	0.000	.0069868	.0129362
size_num	.0022873	.0006909	3.31	0.001	.0009331	.0036415
h8	1.757574	.038568	45.57	0.000	1.681982	1.833166
k8	.2549202	.0362796	7.03	0.000	.1838135	.3260269
zdummy	.1430828	.0640064	2.24	0.025	.0176325	.268533
C_QUA	.0035204	.0131811	0.27	0.789	-.0223141	.0293549
_cons	-1.629187	.2264747	-7.19	0.000	-2.07307	-1.185305
country						
var(_cons)	.9134118	.3022326			.4775495	1.747088

```
Likelihood-ratio test                                 LR chi2(1)  =      0.07
(Assumption: Simple nested in Quality)                Prob > chi2 =    0.7898

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
Simple	25,681	.	-13518.99	8	27053.97	27119.2
Quality	25,681	.	-13518.95	9	27055.9	27129.28

melogit h1 b2b b7 size_num h8 k8 zdummy STDPER || country:, nogroup

estimates store Trust

lrtest Simple Trust, stats

Model 5

```
Mixed-effects logistic regression               Number of obs     =     25,681

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(7)      =    2321.13
Log likelihood = -13516.279                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.0042746	.0010426	4.10	0.000	.0022312	.006318
b7	.0099718	.0015176	6.57	0.000	.0069973	.0129464
size_num	.0022874	.0006909	3.31	0.001	.0009332	.0036415
h8	1.757303	.0385635	45.57	0.000	1.68172	1.832886
k8	.2540905	.0362781	7.00	0.000	.1829867	.3251943
zdummy	.1422822	.0639984	2.22	0.026	.0168477	.2677167
STDPER	-.4518225	.1804937	-2.50	0.012	-.8055838	-.0980613
_cons	-1.786243	.2035642	-8.77	0.000	-2.185221	-1.387264
country						
var(_cons)	.6859465	.2280539			.3575153	1.316091

```
Likelihood-ratio test                                 LR chi2(1)  =      5.42
(Assumption: Simple nested in Trust)                  Prob > chi2 =    0.0199

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
Simple	25,681	.	-13518.99	8	27053.97	27119.2
Trust	25,681	.	-13516.28	9	27050.56	27123.94

Model 6. ROSCA-credit*Trust

melogit h1 b2b b7 size_num h8 k8 zdummy STDPER zdummyPER || country:, or nogroup

estimates store TrustRosca

lrtest TrustRosca Trust, stats

```
Mixed-effects logistic regression               Number of obs     =     25,681

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(8)      =    2322.86
Log likelihood = -13515.407                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.0042827	.0010427	4.11	0.000	.002239	.0063263
b7	.0099895	.0015178	6.58	0.000	.0070146	.0129644
size_num	.0022835	.000691	3.30	0.001	.0009292	.0036378
h8	1.758018	.0385671	45.58	0.000	1.682428	1.833608
k8	.2536978	.0362788	6.99	0.000	.1825926	.3248031
zdummy	.1973404	.0757518	2.61	0.009	.0488697	.3458112
STDPER	-.4568591	.181036	-2.52	0.012	-.8116831	-.1020352
zdummyPER	.1056027	.0793992	1.33	0.184	-.050017	.2612224
_cons	-1.78806	.204119	-8.76	0.000	-2.188125	-1.387994
country						
var(_cons)	.6898106	.2293215			.3595467	1.323441

```
Likelihood-ratio test                                  LR chi2(1)  =      1.74
(Assumption: Trust nested in TrustRosca)               Prob > chi2 =    0.1867

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
Trust	25,681	.	-13516.28	9	27050.56	27123.94
TrustRosca	25,681	.	-13515.41	10	27050.81	27132.35

Model 7. Formal credit*Money market quality

melogit h1 b2b b7 size_num h8 k8 zdummy STDPER C_QUA K8QUA || country:, nogroup

estimates store CredQuaM

lrtest CredQuaM Trust, stats

```
Mixed-effects logistic regression               Number of obs     =     25,681

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(9)      =    2325.92
Log likelihood =  -13514.18                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.0042738	.0010428	4.10	0.000	.0022299	.0063177
b7	.0100469	.0015184	6.62	0.000	.0070708	.013023
size_num	.0022396	.0006913	3.24	0.001	.0008847	.0035945
h8	1.756733	.0385641	45.55	0.000	1.681148	1.832317
k8	.2595505	.0363099	7.15	0.000	.1883844	.3307167
zdummy	.1420164	.063968	2.22	0.026	.0166415	.2673913
STDPER	-.4485826	.1799502	-2.49	0.013	-.8012784	-.0958867
C_QUA	.0044448	.0114486	0.39	0.698	-.017994	.0268836
K8QUA	-.0047569	.0023355	-2.04	0.042	-.0093343	-.0001794
_cons	-1.776881	.2057498	-8.64	0.000	-2.180143	-1.373619
country						
var(_cons)	.6809469	.226653			.3546428	1.307481

```
Likelihood-ratio test                                 LR chi2(2)  =      4.20
(Assumption: Trust nested in CredQuaM)                Prob > chi2 =    0.1226

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
Trust	25,681	.	-13516.28	9	27050.56	27123.94
CredQuaM	25,681	.	-13514.18	11	27050.36	27140.05

Model 8. Formal credit*Money market quality (No main, Final)

melogit h1 b2b b7 size_num h8 k8 zdummy STDPER K8QUA || country:, nogroup

estimates store CredQuaNM

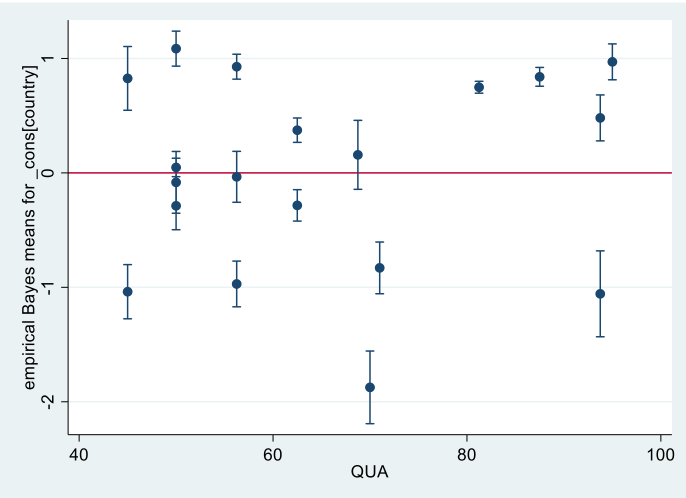
lrtest CredQuaNM Trust, stats

```
Mixed-effects logistic regression               Number of obs     =     25,681

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(8)      =    2325.70
Log likelihood = -13514.255                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.0042722	.0010428	4.10	0.000	.0022283	.0063161
b7	.0100398	.0015183	6.61	0.000	.0070639	.0130156
size_num	.0022394	.0006913	3.24	0.001	.0008845	.0035943
h8	1.756743	.0385642	45.55	0.000	1.681159	1.832328
k8	.2595388	.0363112	7.15	0.000	.1883702	.3307074
zdummy	.1421576	.0639681	2.22	0.026	.0167824	.2675327
STDPER	-.4509699	.1806804	-2.50	0.013	-.8050969	-.0968429
K8QUA	-.0046892	.0023291	-2.01	0.044	-.0092542	-.0001242
_cons	-1.790276	.2037802	-8.79	0.000	-2.189677	-1.390874
country						
var(_cons)	.6873608	.2283797			.3584	1.318261

```
Likelihood-ratio test                                 LR chi2(1)  =      4.05
(Assumption: Trust nested in CredQuaNM)               Prob > chi2 =    0.0442

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
Trust	25,681	.	-13516.28	9	27050.56	27123.94
CredQuaNM	25,681	.	-13514.26	10	27048.51	27130.05



Model 9. ROSCA-credit*Money market quality

melogit h1 b2b b7 size_num h8 k8 zdummy STDPER K8QUA ZQUA || country:, nogroup

estimates store ZQUANM

lrtest CredQuaNM ZQUANM, stats

```
Mixed-effects logistic regression               Number of obs     =     25,681

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(9)      =    2328.34
Log likelihood = -13512.761                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.0043129	.0010429	4.14	0.000	.0022688	.0063569
b7	.0100253	.0015185	6.60	0.000	.0070492	.0130015
size_num	.0022224	.0006914	3.21	0.001	.0008673	.0035775
h8	1.755335	.0385662	45.51	0.000	1.679746	1.830923
k8	.2568354	.0363526	7.07	0.000	.1855857	.3280851
zdummy	.1930397	.069994	2.76	0.006	.0558539	.3302255
STDPER	-.4508256	.1813792	-2.49	0.013	-.8063224	-.0953289
K8QUA	-.0042882	.0023412	-1.83	0.067	-.008877	.0003005
ZQUA	-.0072522	.0041825	-1.73	0.083	-.0154498	.0009454
_cons	-1.791426	.2045463	-8.76	0.000	-2.19233	-1.390523
country						
var(_cons)	.6927578	.230139			.3612487	1.328485

```
Likelihood-ratio test                                 LR chi2(1)  =       2.99
(Assumption: CredQuaNM nested in ZQUANM)              Prob > chi2 =     0.0839

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
CredQuaNM	25,681	.	-13514.26	10	27048.51	27130.05
ZQUANM	25,681	.	-13512.76	11	27047.52	27137.21

Model 10A & 10B. Robustness control & unimputed

Robust Control model (Model 10A)

melogit h1 b2b b7 size_num h8 k8 zdummy STDPER K8QUA i.sector EXPORT AGE || country:, nogroup

estimates store RobustControls

lrtest RobustControls ZQUANM, stats

Mixed-effects logistic regression	Number of obs	=	25,681
Integration method: mvaghermite	Integration pts.	=	7
	Wald chi2(32)	=	2445.67
Log likelihood = -13428.09	Prob > chi2	=	0.0000

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.0041388	.0010521	3.93	0.000	.0020767	.0062008
b7	.0095915	.0016708	5.74	0.000	.0063169	.0128662
size_num	.0017518	.0007128	2.46	0.014	.0003547	.0031489
h8	1.7448	.0389165	44.83	0.000	1.668525	1.821075
k8	.2683968	.0365615	7.34	0.000	.1967376	.340056
zdummy	.1236175	.0647878	1.91	0.056	-.0033643	.2505994
STDPER	-.4478864	.1809251	-2.48	0.013	-.8024931	-.0932796
K8QUA	-.0049315	.0023443	-2.10	0.035	-.0095262	-.0003368
sector						
Chemicals & Chemical Products	.1194433	.1308926	0.91	0.361	-.1371014	.3759881
Chemicals, Plastics & Rubber	.8625186	.191283	4.51	0.000	.4876108	1.237426
Construction	.0354232	.1405445	0.25	0.801	-.2400389	.3108853
Electronics & Communications Equip.	.4313632	.1326726	3.25	0.001	.1713297	.6913967
Fabricated Metal Products	.2471833	.122944	2.01	0.044	.0062175	.488149
Food	.2025788	.1177141	1.72	0.085	-.0281366	.4332942
Furniture	.6611073	.1421909	4.65	0.000	.3824183	.9397963
Hotels & Restaurants	.4698428	.1319633	3.56	0.000	.2111994	.7284862
IT & IT Services	.7039894	.1513956	4.65	0.000	.4072596	1.000719
Machinery & Equipment	.3816263	.1265018	3.02	0.003	.1336873	.6295652
Manufacturing	.7431766	.1417356	5.24	0.000	.4653799	1.020973
Motor Vehicles	.4912998	.1443745	3.40	0.001	.208331	.7742687
Non-Metallic Mineral Products	-.0662505	.1254833	-0.53	0.598	-.3121932	.1796923
Other Manufacturing	.2584156	.1125413	2.30	0.022	.0378387	.4789926
Other Services	.1530952	.1213045	1.26	0.207	-.0846572	.3908477
Printing & Publishing	.2150971	.2027768	1.06	0.289	-.182338	.6125322
Retail	.209222	.1156228	1.81	0.070	-.0173945	.4358385
Rubber & Plastics Products	.1500506	.1255226	1.20	0.232	-.0959692	.3960705
Services of Motor Vehicles	.0744227	.1395635	0.53	0.594	-.1991167	.3479621
Textiles & Garments	.4045015	.1173317	3.45	0.001	.1745357	.6344674
Transport, Storage, & Communications	-.0244307	.1325457	-0.18	0.854	-.2842156	.2353541
Wholesale	.0968661	.1244577	0.78	0.436	-.1470665	.3407987
EXPORT	.0006201	.0007554	0.82	0.412	-.0008605	.0021007
AGE	-.0009025	.0013111	-0.69	0.491	-.0034722	.0016672
_cons	-2.028578	.2304826	-8.80	0.000	-2.480316	-1.576841
country						
var(_cons)	.6886805	.2289077			.3589967	1.321129

Likelihood-ratio test	LR chi2(23)	=	169.34
(Assumption: ZQUANM nested in RobustControls)	Prob > chi2	=	0.0000

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
ZQUANM	25,681	.	-13512.76	11	27047.52	27137.21
RobustCont~s	25,681	.	-13428.09	34	26924.18	27201.4

use SME BEFORE IMPUTATION.dta (Model 10B)

melogit h1 b2b b7 size_num h8 k8 zdummy STDPER K8QUA i.sector EXPORT AGE || country:, nogroup

```
Mixed-effects logistic regression               Number of obs     =     21,695

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(32)     =    2083.21
Log likelihood =  -11192.55                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.0049345	.0012072	4.09	0.000	.0025685	.0073004
b7	.0088896	.0018119	4.91	0.000	.0053383	.012441
size_num	.0025774	.0007863	3.28	0.001	.0010363	.0041185
h8	1.783582	.043414	41.08	0.000	1.698492	1.868672
k8	.2228587	.0399828	5.57	0.000	.1444938	.3012236
zdummy	.1722374	.0721097	2.39	0.017	.030905	.3135699
STDPER	-.4604072	.1859602	-2.48	0.013	-.8248825	-.0959318
K8QUA	-.0050097	.002521	-1.99	0.047	-.0099507	-.0000686
sector						
Chemicals & Chemical Products	-.018649	.1372427	-0.14	0.892	-.2876396	.2503417
Chemicals, Plastics & Rubber	.7305514	.1991665	3.67	0.000	.3401922	1.120911
Construction	-.1530962	.152619	-1.00	0.316	-.4522239	.1460314
Electronics & Communications Equip.	.3751557	.1392428	2.69	0.007	.1022448	.6480665
Fabricated Metal Products	.1657184	.1284656	1.29	0.197	-.0860695	.4175063
Food	.1119893	.1231855	0.91	0.363	-.1294499	.3534284
Furniture	.5962906	.1493022	3.99	0.000	.3036638	.8889175
Hotels & Restaurants	.3609631	.1472946	2.45	0.014	.0722709	.6496553
IT & IT Services	.5048489	.1875233	2.69	0.007	.13731	.8723878
Machinery & Equipment	.319708	.1319977	2.42	0.015	.0609971	.5784188
Manufacturing	.5192871	.1541646	3.37	0.001	.21713	.8214443
Motor Vehicles	.4983168	.1515226	3.29	0.001	.201338	.7952957
Non-Metallic Mineral Products	-.0825554	.1309047	-0.63	0.528	-.339124	.1740131
Other Manufacturing	.1852247	.1173577	1.58	0.114	-.0447921	.4152416
Other Services	.0078932	.1287671	0.06	0.951	-.2444856	.260272
Printing & Publishing	.028089	.2278051	0.12	0.902	-.4184008	.4745787
Retail	-.0157399	.1236783	-0.13	0.899	-.2581449	.2266651
Rubber & Plastics Products	.1490478	.1312348	1.14	0.256	-.1081676	.4062633
Services of Motor Vehicles	-.1333681	.1598163	-0.83	0.404	-.4466022	.1798661
Textiles & Garments	.328826	.1224935	2.68	0.007	.0887432	.5689088
Transport, Storage, & Communications	-.0116279	.1422985	-0.08	0.935	-.2905279	.2672721
Wholesale	-.1287259	.1339938	-0.96	0.337	-.3913489	.1338972
EXPORT	.0015069	.0008681	1.74	0.083	-.0001945	.0032082
AGE	-.0010044	.0014159	-0.71	0.478	-.0037795	.0017708
_cons	-1.922615	.2375618	-8.09	0.000	-2.388228	-1.457003
country						
var(_cons)	.725204	.2412345			.3778447	1.391897

Model 10C. Robustness random slope

melogit h1 b2b b7 size_num h8 k8 STDPER zdummy || country: k8, nogroup

estimates store rk8

estat ic

```
Mixed-effects logistic regression               Number of obs     =     25,681

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(7)      =    2258.62
Log likelihood = -13508.476                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.004326	.0010439	4.14	0.000	.0022801	.0063719
b7	.0101501	.0015209	6.67	0.000	.0071692	.013131
size_num	.0022203	.0006922	3.21	0.001	.0008637	.0035769
h8	1.758469	.0386166	45.54	0.000	1.682782	1.834156
k8	.3801108	.0660248	5.76	0.000	.2507046	.509517
STDPER	-.4548599	.183084	-2.48	0.013	-.813698	-.0960219
zdummy	.1336243	.064242	2.08	0.038	.0077122	.2595363
_cons	-1.837159	.206601	-8.89	0.000	-2.24209	-1.432229
country						
var(k8)	.0328795	.0206081			.0096253	.1123152
var(_cons)	.7025702	.2347889			.3649475	1.352537

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
rk8	25,681	.	-13508.48	10	27036.95	27118.49

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
CredQuaNM	25,681	.	-13514.26	10	27048.51	27130.05

Model 10D. Robustness bootstrapping

. bootstrap, reps(100): melogit h1 b2b b7 size_num h8 k8 zdummy STDPER K8QUA || country:, nogroup

```
. bootstrap, reps(100): melogit h1 b2b b7 size_num h8 k8 zdummy STDPER K8QUA || country:, nogroup
(running melogit on estimation sample)

Bootstrap replications (100)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50
..................................................   100

Mixed-effects logistic regression               Number of obs     =     25,681
                                                Replications      =        100
                                                Wald chi2(8)      =    2873.78
Log likelihood = -13514.255                     Prob > chi2       =     0.0000
```

h1	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
b2b	.0042722	.0010795	3.96	0.000	.0021564	.006388
b7	.0100398	.0013097	7.67	0.000	.0074728	.0126067
size_num	.0022394	.0006242	3.59	0.000	.0010161	.0034627
h8	1.756743	.0392894	44.71	0.000	1.679737	1.833749
k8	.2595388	.0385576	6.73	0.000	.1839672	.3351104
zdummy	.1421576	.0704982	2.02	0.044	.0039836	.2803316
STDPER	-.4509699	.0226197	-19.94	0.000	-.4953036	-.4066362
K8QUA	-.0046892	.0022916	-2.05	0.041	-.0091806	-.0001978
_cons	-1.790276	.0370677	-48.30	0.000	-1.862927	-1.717624
country						
var(_cons)	.6873608	.0421343			.609547	.7751081

. bootstrap, reps(500): melogit h1 b2b b7 size_num h8 k8 zdummy STDPER K8QUA || country:, nogroup

```
(running melogit on estimation sample)

Bootstrap replications (500)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50
..................................................   100
..................................................   150
..................................................   200
..................................................   250
..................................................   300
..................................................   350
..................................................   400
..................................................   450
..................................................   500

Mixed-effects logistic regression               Number of obs     =     25,681
                                                Replications      =        500
                                                Wald chi2(8)      =    2763.78
Log likelihood = -13514.255                     Prob > chi2       =     0.0000
```

h1	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
b2b	.0042722	.0010832	3.94	0.000	.0021492	.0063953
b7	.0100398	.001555	6.46	0.000	.0069921	.0130874
size_num	.0022394	.0007019	3.19	0.001	.0008638	.003615
h8	1.756743	.0383899	45.76	0.000	1.6815	1.831986
k8	.2595388	.0368234	7.05	0.000	.1873663	.3317114
zdummy	.1421576	.0643155	2.21	0.027	.0161016	.2682136
STDPER	-.4509699	.0221923	-20.32	0.000	-.494466	-.4074738
K8QUA	-.0046892	.0023127	-2.03	0.043	-.0092221	-.0001563
_cons	-1.790276	.0451446	-39.66	0.000	-1.878757	-1.701794
country						
var(_cons)	.6873608	.0473936			.6004741	.7868197

. bootstrap, reps(200): melogit h1 b2b b7 size_num h8 k8 zdummy STDPER K8QUA || country:, nogroup

```
. bootstrap, reps(200): melogit h1 b2b b7 size_num h8 k8 zdummy STDPER K8QUA || country:, nogroup
(running melogit on estimation sample)

Bootstrap replications (200)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50
..................................................   100
..................................................   150
..................................................   200

Mixed-effects logistic regression               Number of obs     =     25,681
                                                Replications      =        200
                                                Wald chi2(8)      =    2831.24
Log likelihood = -13514.255                     Prob > chi2       =     0.0000
```

h1	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
b2b	.0042722	.0009899	4.32	0.000	.002332	.0062124
b7	.0100398	.0015167	6.62	0.000	.0070671	.0130124
size_num	.0022394	.0007058	3.17	0.002	.0008561	.0036227
h8	1.756743	.0380464	46.17	0.000	1.682174	1.831313
k8	.2595388	.036268	7.16	0.000	.1884548	.3306228
zdummy	.1421576	.0687546	2.07	0.039	.007401	.2769141
STDPER	-.4509699	.0203662	-22.14	0.000	-.4908869	-.4110529
K8QUA	-.0046892	.0022192	-2.11	0.035	-.0090387	-.0003397
_cons	-1.790276	.0426048	-42.02	0.000	-1.87378	-1.706772
country						
var(_cons)	.6873608	.0469199			.6012858	.7857576

```
. bootstrap, reps(1000): melogit h1 b2b b7 size_num h8 k8 zdummy STDPER K8QUA || country:, nogroup
(running melogit on estimation sample)

Bootstrap replications (1000)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................   900
..................................................   950
..................................................  1000

Mixed-effects logistic regression               Number of obs     =     25,681
                                                Replications      =      1,000
                                                Wald chi2(8)      =    2790.36
Log likelihood = -13514.255                     Prob > chi2       =     0.0000
```

h1	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
b2b	.0042722	.0010433	4.10	0.000	.0022275	.006317
b7	.0100398	.001542	6.51	0.000	.0070175	.013062
size_num	.0022394	.0006778	3.30	0.001	.000911	.0035678
h8	1.756743	.0401956	43.70	0.000	1.677961	1.835525
k8	.2595388	.0382723	6.78	0.000	.1845264	.3345512
zdummy	.1421576	.065164	2.18	0.029	.0144385	.2698766
STDPER	-.4509699	.0212518	-21.22	0.000	-.4926227	-.4093171
K8QUA	-.0046892	.0023667	-1.98	0.048	-.0093279	-.0000505
_cons	-1.790276	.0427767	-41.85	0.000	-1.874116	-1.706435
country						
var(_cons)	.6873608	.0502985			.5955209	.7933641

Model 11. Robustness Culture

melogit h1 b2b b7 size_num h8 k8 zdummy STDPER K8QUA PerformPRAC || country:, nogroup

estimates store Culture

lrtest Culture CredQuaNM, stats

```
Mixed-effects logistic regression               Number of obs     =     25,681

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(9)      =    2335.15
Log likelihood = -13511.326                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.004264	.0010427	4.09	0.000	.0022203	.0063077
b7	.010025	.001518	6.60	0.000	.0070497	.0130003
size_num	.0022454	.0006912	3.25	0.001	.0008905	.0036002
h8	1.75668	.0385605	45.56	0.000	1.681102	1.832257
k8	.2597104	.0363066	7.15	0.000	.1885508	.33087
zdummy	.1407194	.0639538	2.20	0.028	.0153722	.2660666
STDPER	-.2414094	.1735211	-1.39	0.164	-.5815045	.0986857
K8QUA	-.0048141	.0023272	-2.07	0.039	-.0093753	-.0002529
PerformPRAC	1.482355	.5646008	2.63	0.009	.3757581	2.588953
_cons	-10.53198	3.335163	-3.16	0.002	-17.06878	-3.995179
country						
var(_cons)	.4983846	.1677306			.2576878	.9639073

```
LR test vs. logistic model: chibar2(01) = 893.75      Prob >= chibar2 = 0.0000

Likelihood-ratio test                                 LR chi2(1)  =       5.86
(Assumption: CredQuaNM nested in Culture)             Prob > chi2 =     0.0155

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
CredQuaNM	25,681	.	-13514.26	10	27048.51	27130.05
Culture	25,681	.	-13511.33	11	27044.65	27134.34

Model 12. Robustness influence India

quietly melogit h1 b2b b7 size_num h8 i.k8##c.C_QUA i.zdummy##c.STDPER || country:, nogroup

predict anscombe, anscombe

replace anscombe=abs(anscombe)

tabstat anscombe if anscombe>=1.5, by(country) statistics(count)

tabstat anscombe if anscombe>=1.75, by(country) statistics(count)

```
Summary for variables: anscombe
     by categories of: country (Country)
```

country	N
Argentina2017	136
China2012	465
Colombia2017	83
Ecuador2017	65
Egypt2013	353
Georgia2013	27
Hungary2013	46
India2014	2034
Indonesia2015	81
Kazakhstan2013	88
Malaysia2015	39
Mexico2010	282
Morocco2013	54
Nigeria2014	307
Poland2013	146
Russia2012	648
Thailand2016	72
Turkey2013	108
Zimbabwe2016	102
Total	5136

```
Summary for variables: anscombe
     by categories of: country (Country)
```

country	N
Argentina2017	28
China2012	303
Colombia2017	42
Ecuador2017	29
Egypt2013	348
Georgia2013	25
Hungary2013	45
India2014	1242
Indonesia2015	73
Kazakhstan2013	87
Malaysia2015	38
Mexico2010	139
Morocco2013	49
Nigeria2014	88
Poland2013	98
Russia2012	596
Thailand2016	67
Turkey2013	78
Zimbabwe2016	90
Total	3465

Anscombe residuals above 1.5 can be considered highly influential (StataCorp, 2017).

Overview log odds models (resampled)

Resampled log odds		VARIABLES	Model 13	Model 14	Model 15	Model 16	Model 19	Model 20
Controls		Foreign ownership	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
		Managerial experience	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
		Firm size	0.002*	0.002*	0.002*	0.002*	0.003**	0.002*
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
		R&D	1.776***	1.775***	1.775***	1.775***	1.801***	1.775***
			(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
Firm level	H1A	Formal credit use	0.382***	0.392***	0.392***	0.380***		0.378***
			(0.045)	(0.048)	(0.048)	(0.045)		(0.045)
	H2A	ROSCA-credit use	0.152*	0.271**	0.270**	0.270**		0.192*
			(0.071)	(0.092)	(0.092)	(0.092)		(0.075)
	H4	Use of both forms of credit					0.441***	
							(0.108)	
Country level		Trust Standardized		-0.475*	-0.265			
				(0.186)	(0.182)			
	H1B	Money market quality Centered		-0.001	-0.006			0.002
				(0.012)	(0.011)			(0.014)
	±	Performance orientation Cultural practice			1.468*	1.819***		
					(0.601)	(0.551)		
Interactions	H2B	ROSCA-credit*Trust		0.179*	0.178*	0.175*		
				(0.087)	(0.087)	(0.087)		
	H1C	Formal credit*Market quality		0.002	0.002			
				(0.003)	(0.003)			
	H3	ROSCA-credit*Market quality						-0.007
								(0.004)
		Constant [fixed effect]	-1.678***	-1.856***	-10.515**	-12.478***	-1.583***	-1.671***
			(0.236)	(0.221)	(3.550)	(3.277)	(0.239)	(0.242)
		Constant [random effect variance]	0.957**	0.711**	0.529**	0.599**	0.984**	0.960**
			(0.325)	(0.243)	(0.182)	(0.206)	(0.334)	(0.326)
		AIC	18611.03	18608.9	18605.75	18602.65	18672.13	18612.34
		BIC	18673.72	18702.93	18707.62	18681.01	18726.99	18690.7
		df	8	12	13	10		10
		Compared with	-	Model 13	Model 14	Model 13		Model 13
		Delta AIC	-	-2.13	-3.15	-8.38		1.31
		Delta BIC	-	29.21	4.69	7.29		16.98
		Delta df	-	4	1	2		2
		LR chi2		10.13*	5.15*	12.38**		2.69

Standard errors in parentheses. Colors highlight groups of hypotheses and associated results. Best model in thick frame.

*** p<0.001, ** p<0.01, * p<0.05

± variable used in robustness assessment

Observations 18,703

Number of groups 18

Model 13 & 14. Resampled – simple and full

quietly melogit h1 b2b b7 size_num h8 i.k8 i.zdummy if country!="India2014" || country:, nogroup

estimates store NIndiaSimple

melogit h1 b2b b7 size_num h8 i.k8##c.C_QUA i.zdummy##c.STDPER if country!="India2014" || country:, nogroup

estimates store NIndiaFull

lrtest NIndiaSimple NIndiaFull, stats

```
Mixed-effects logistic regression               Number of obs     =     18,703

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(10)     =    1389.04
Log likelihood = -9292.4483                     Prob > chi2       =     0.0000

------------------------------------------------------------------------------
              h1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
             b2b |   .0041537   .0010703     3.88   0.000      .002056    .0062513
              b7 |   .0089553   .0018048     4.96   0.000      .005418    .0124926
        size_num |   .0016935   .0008509     1.99   0.047     .0000257    .0033613
              h8 |   1.774915   .0521677    34.02   0.000     1.672668    1.877162
                 |
              k8 |
             Yes |   .3918534   .0482081     8.13   0.000     .2973672    .4863396
           C_QUA |  -.0010128   .0120378    -0.08   0.933    -.0246065     .022581
                 |
     k8#c.C_QUA |
             Yes |   .0023062   .0028628     0.81   0.420    -.0033048    .0079172
                 |
        1.zdummy |   .2712738   .0917923     2.96   0.003     .0913642    .4511834
          STDPER |  -.4749754   .1857785    -2.56   0.011    -.8390946   -.1108561
                 |
zdummy#c.STDPER |
               1 |   .1786246   .0873612     2.04   0.041     .0073998    .3498495
                 |
           _cons |  -1.856491   .2211217    -8.40   0.000    -2.289882     -1.4231
-----------------+------------------------------------------------------------
country          |
      var(_cons)|    .711117   .2428947                      .3640809    1.388942
------------------------------------------------------------------------------
LR test vs. logistic model: chibar2(01) = 1188.29      Prob >= chibar2 = 0.0000


Likelihood-ratio test                                 LR chi2(4)  =     10.13
(Assumption: NIndiaSimple nested in NIndiaFull)       Prob > chi2 =    0.0383

Akaike's information criterion and Bayesian information criterion

-----------------------------------------------------------------------------
       Model |        Obs  ll(null)  ll(model)      df         AIC        BIC
-------------+---------------------------------------------------------------
NIndiaSimple |     18,703         .  -9297.513       8    18611.03   18673.72
  NIndiaFull |     18,703         .  -9292.448      12     18608.9   18702.93
-----------------------------------------------------------------------------
```

Model 15. Resampled – culture

melogit h1 b2b b7 size_num h8 i.k8##c.C_QUA i.zdummy##c.STDPER PerformPRAC if country!="India2014" || country:, nogroup

estimates store NIndiaCulture

lrtest NIndiaFull NIndiaCulture, stats

```
Mixed-effects logistic regression               Number of obs     =     18,703

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(11)     =    1397.08
Log likelihood = -9289.8748                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.0041428	.0010702	3.87	0.000	.0020453	.0062403
b7	.0089201	.0018044	4.94	0.000	.0053835	.0124567
size_num	.0017021	.0008509	2.00	0.045	.0000345	.0033698
h8	1.774853	.0521606	34.03	0.000	1.67262	1.877086
k8						
Yes	.3917192	.0481974	8.13	0.000	.2972541	.4861843
C_QUA	-.0061199	.0106524	-0.57	0.566	-.0269983	.0147585
k8#c.C_QUA						
Yes	.0022654	.0028626	0.79	0.429	-.0033453	.007876
1.zdummy	.2698446	.091791	2.94	0.003	.0899375	.4497518
STDPER	-.2645705	.1820299	-1.45	0.146	-.6213425	.0922016
zdummy#c.STDPER						
1	.1784747	.0873628	2.04	0.041	.0072467	.3497027
PerformPRAC	1.467769	.6006788	2.44	0.015	.2904602	2.645078
_cons	-10.51451	3.549677	-2.96	0.003	-17.47175	-3.557275
country						
var(_cons)	.5288014	.1824147			.2689448	1.039734

```
Likelihood-ratio test                                 LR chi2(1)  =      5.15
(Assumption: NIndiaFull nested in NIndiaCulture)      Prob > chi2 =    0.0233

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
NIndiaFull	18,703	.	-9292.448	12	18608.9	18702.93
NIndiaCult~e	18,703	.	-9289.875	13	18605.75	18707.62

Model 16. Resampled – Final

melogit h1 b2b b7 size_num h8 i.k8 i.zdummy zdummyPER PerformPRAC if country!="India2014" || country:, nogroup

estimates store NIndiaFinal

lrtest NIndiaFinal NIndiaSimple, stats

```
Mixed-effects logistic regression               Number of obs     =     18,703

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(8)      =    1392.60
Log likelihood = -9291.3241                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.0041333	.0010699	3.86	0.000	.0020364	.0062302
b7	.0089157	.0018041	4.94	0.000	.0053797	.0124516
size_num	.0016967	.0008507	1.99	0.046	.0000294	.003364
h8	1.7752	.0521663	34.03	0.000	1.672956	1.877444
k8						
Yes	.3797909	.0454225	8.36	0.000	.2907645	.4688174
1.zdummy	.2697132	.0918217	2.94	0.003	.0897461	.4496804
zdummyPER	.1750963	.0873681	2.00	0.045	.0038581	.3463346
PerformPRAC	1.818591	.5508574	3.30	0.001	.7389305	2.898252
_cons	-12.47759	3.276914	-3.81	0.000	-18.90022	-6.054957
country						
var(_cons)	.5989094	.2061612			.305038	1.175894

```
LR test vs. logistic model: chibar2(01) = 1005.44     Prob >= chibar2 = 0.0000

Likelihood-ratio test                                 LR chi2(2)  =     12.38
(Assumption: NIndiaSimple nested in NIndiaFinal)      Prob > chi2 =    0.0021

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
NIndiaSimple	18,703	.	-9297.513	8	18611.03	18673.72
NIndiaFinal	18,703	.	-9291.324	10	18602.65	18681.01

Model 17. Resampled – culture & controls

melogit h1 b2b b7 size_num h8 i.k8##c.C_QUA i.zdummy##c.STDPER PerformPRAC i.sector EXPORT PPP AGE EXPORT if country!="India2014" || country:, nogroup

estimates store NIndiaCultureControls

lrtest NIndiaCultureControls NIndiaCulture, stats

```
Mixed-effects logistic regression               Number of obs     =     18,703

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(36)     =    1526.85
Log likelihood = -9200.4866                     Prob > chi2       =     0.0000
```

h1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
b2b	.0039626	.001086	3.65	0.000	.0018342	.0060911
b7	.0076146	.0019705	3.86	0.000	.0037526	.0114766
size_num	.0010341	.0008807	1.17	0.240	-.0006922	.0027603
h8	1.765559	.0528041	33.44	0.000	1.662065	1.869053
k8						
Yes	.4076084	.048523	8.40	0.000	.3125051	.5027117
C_QUA	-.0071624	.0105804	-0.68	0.498	-.0278995	.0135748
k8#c.C_QUA						
Yes	.001989	.0028823	0.69	0.490	-.0036601	.0076382
1.zdummy	.2512682	.0926351	2.71	0.007	.0697066	.4328297
STDPER	-.249997	.1808261	-1.38	0.167	-.6044096	.1044155
zdummy#c.STDPER						
1	.1850337	.08756	2.11	0.035	.0134193	.3566481
PerformPRAC	1.438211	.615327	2.34	0.019	.2321924	2.64423
sector						
Chemicals & Chemical Products	-.6814161	.3418661	-1.99	0.046	-1.351461	-.0113709
Chemicals, Plastics & Rubber	-.1047126	.3587037	-0.29	0.770	-.8077589	.5983338
Construction	-.8174948	.3387002	-2.41	0.016	-1.481335	-.1536546
Electronics & Communications Equip.	-.4226244	.3470755	-1.22	0.223	-1.10288	.257631
Fabricated Metal Products	-.684831	.3334493	-2.05	0.040	-1.33838	-.0312824
Food	-.6832902	.328021	-2.08	0.037	-1.3262	-.040381
Furniture	-.2877545	.3349021	-0.86	0.390	-.9441506	.3686417
Hotels & Restaurants	-.551981	.3365172	-1.64	0.101	-1.211543	.1075805
IT & IT Services	-.0917632	.3432785	-0.27	0.789	-.7645766	.5810502
Machinery & Equipment	-.4563928	.3462884	-1.32	0.188	-1.135106	.2223199
Manufacturing	-.2122258	.3350992	-0.63	0.527	-.8690082	.4445565
Motor Vehicles	-.6239558	.4138008	-1.51	0.132	-1.43499	.187079
Non-Metallic Mineral Products	-.9475471	.3362121	-2.82	0.005	-1.606511	-.2885835
Other Manufacturing	-.6865124	.3265914	-2.10	0.036	-1.32662	-.046405
Other Services	-.7939775	.3269836	-2.43	0.015	-1.434853	-.1531015
Printing & Publishing	-.747416	.365304	-2.05	0.041	-1.463399	-.0314334
Retail	-.7886863	.3253058	-2.42	0.015	-1.426274	-.1510987
Rubber & Plastics Products	-.9129154	.3441137	-2.65	0.008	-1.587366	-.238465
Services of Motor Vehicles	-.8892834	.3450906	-2.58	0.010	-1.565649	-.2129182
Textiles & Garments	-.4416753	.3265395	-1.35	0.176	-1.081681	.1983304
Transport, Storage, & Communications	-1.292901	.3451377	-3.75	0.000	-1.969359	-.6164439
Wholesale	-.9791087	.3286262	-2.98	0.003	-1.623204	-.3350133
EXPORT	.0006739	.0008772	0.77	0.442	-.0010453	.0023931
PPP	-.000013	.0000259	-0.50	0.617	-.0000638	.0000379
AGE	.0001802	.0016235	0.11	0.912	-.0030017	.0033622
_cons	-9.451334	3.764685	-2.51	0.012	-16.82998	-2.072687
country						
var(_cons)	.5188309	.179205			.2636449	1.021015

```
Likelihood-ratio test                                 LR chi2(25) =    178.78
(Assumption: NIndiaCulture nested in NIndiaCultur~s)  Prob > chi2 =    0.0000

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
NIndiaCult~e	18,703	.	-9289.875	13	18605.75	18707.62
NIndiaCult~s	18,703	.	-9200.487	38	18476.97	18774.76

Model 18. Resampled – bootstrapped final

```
. bootstrap, reps(500): melogit h1 b2b b7 size_num h8 i.k8 i.zdummy zdummyPER PerformPRAC if country!="India2014" || country:, n
> ogroup
(running melogit on estimation sample)

Bootstrap replications (500)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50
..................................................   100
..................................................   150
..................................................   200
..................................................   250
..................................................   300
..................................................   350
..................................................   400
..................................................   450
..................................................   500

Mixed-effects logistic regression               Number of obs     =     18,703
                                                Replications      =        500
                                                Wald chi2(8)      =    1997.12
Log likelihood = -9291.3241                     Prob > chi2       =     0.0000

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
          h1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         b2b |   .0041333   .0010724     3.85   0.000     .0020315    .0062351
          b7 |   .0089157   .0018553     4.81   0.000     .0052793    .0125521
    size_num |   .0016967   .0008537     1.99   0.047     .0000236    .0033699
          h8 |     1.7752   .0560582    31.67   0.000     1.665328    1.885072
             |
          k8 |
         Yes |   .3797909   .0428861     8.86   0.000     .2957356    .4638462
    1.zdummy |   .2697132   .0952134     2.83   0.005     .0830985     .456328
   zdummyPER |   .1750963   .0877195     2.00   0.046     .0031693    .3470234
 PerformPRAC |   1.818591    .072955    24.93   0.000     1.675602     1.96158
       _cons |  -12.47759   .4349404   -28.69   0.000    -13.33006   -11.62512
-------------+----------------------------------------------------------------
country      |
   var(_cons)|   .5989094   .0536428                      .5024828    .7138402
------------------------------------------------------------------------------
```

```
. bootstrap, reps(200): melogit h1 b2b b7 size_num h8 i.k8 i.zdummy zdummyPER PerformPRAC if country!="India2014" || country:, n
> ogroup
(running melogit on estimation sample)

Bootstrap replications (200)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50
..................................................   100
..................................................   150
..................................................   200

Mixed-effects logistic regression               Number of obs     =     18,703
                                                Replications      =        200
                                                Wald chi2(8)      =    1882.06
Log likelihood = -9291.3241                     Prob > chi2       =     0.0000

------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
          h1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         b2b |   .0041333   .0010066     4.11   0.000     .0021605    .0061061
          b7 |   .0089157   .0017427     5.12   0.000        .0055    .0123313
    size_num |   .0016967   .0008395     2.02   0.043     .0000514    .0033421
          h8 |     1.7752   .0529432    33.53   0.000     1.671433    1.878966
             |
          k8 |
         Yes |   .3797909   .0476375     7.97   0.000     .2864231    .4731587
    1.zdummy |   .2697132   .0949876     2.84   0.005      .083541    .4558855
   zdummyPER |   .1750963   .0859961     2.04   0.042      .006547    .3436457
 PerformPRAC |   1.818591   .0786253    23.13   0.000     1.664488    1.972694
       _cons |  -12.47759   .4766871   -26.18   0.000    -13.41188    -11.5433
-------------+----------------------------------------------------------------
country      |
   var(_cons)|   .5989094   .0543764                      .5012778    .7155562
------------------------------------------------------------------------------
```

```
. bootstrap, reps(100): melogit h1 b2b b7 size_num h8 i.k8 i.zdummy zdummyPER PerformPRAC if country!="India2014" || country:, n
> ogroup
(running melogit on estimation sample)

Bootstrap replications (100)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50
..................................................   100

Mixed-effects logistic regression               Number of obs     =     18,703
                                                Replications      =        100
                                                Wald chi2(8)      =    2108.20
Log likelihood = -9291.3241                     Prob > chi2       =     0.0000
```

h1	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
b2b	.0041333	.0010048	4.11	0.000	.0021638	.0061027
b7	.0089157	.0019039	4.68	0.000	.0051841	.0126473
size_num	.0016967	.0008355	2.03	0.042	.0000592	.0033343
h8	1.7752	.0515769	34.42	0.000	1.674111	1.876289
k8						
Yes	.3797909	.0526327	7.22	0.000	.2766328	.482949
1.zdummy	.2697132	.1035306	2.61	0.009	.0667969	.4726295
zdummyPER	.1750963	.0871108	2.01	0.044	.0043624	.3458303
PerformPRAC	1.818591	.0795923	22.85	0.000	1.662593	1.974589
_cons	-12.47759	.4690217	-26.60	0.000	-13.39686	-11.55833
country						
var(_cons)	.5989094	.0607935			.4908606	.730742

```
. bootstrap, reps(1000): melogit h1 b2b b7 size_num h8 i.k8 i.zdummy zdummyPER PerformPRAC if country!="India2014" || cou
> ntry:, nogroup
(running melogit on estimation sample)

Bootstrap replications (1000)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50
..................................................   100
..................................................   150
..................................................   200
..................................................   250
..................................................   300
..................................................   350
..................................................   400
..................................................   450
..................................................   500
..................................................   550
..................................................   600
..................................................   650
..................................................   700
..................................................   750
..................................................   800
..................................................   850
..................................................   900
..................................................   950
..................................................  1000

Mixed-effects logistic regression               Number of obs     =     18,703
                                                Replications      =      1,000
                                                Wald chi2(8)      =    1868.64
Log likelihood = -9291.3241                     Prob > chi2       =     0.0000
```

h1	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
b2b	.0041333	.0010454	3.95	0.000	.0020843	.0061823
b7	.0089157	.0017681	5.04	0.000	.0054502	.0123811
size_num	.0016967	.0008361	2.03	0.042	.0000581	.0033354
h8	1.7752	.0555016	31.98	0.000	1.666418	1.883981
k8						
Yes	.3797909	.0441616	8.60	0.000	.2932357	.4663461
1.zdummy	.2697132	.094988	2.84	0.005	.0835402	.4558863
zdummyPER	.1750963	.089036	1.97	0.049	.0005889	.3496037
PerformPRAC	1.818591	.0736745	24.68	0.000	1.674192	1.96299
_cons	-12.47759	.439933	-28.36	0.000	-13.33984	-11.61534
country						
var(_cons)	.5989094	.0535211			.5026829	.7135561

Model 19. Resampled – Both credit

melogit h1 b2b b7 size_num h8 bothcredit if country!="India2014" || country:, nogroup

estimates store NIndiaBoth

estat ic

```
Mixed-effects logistic regression               Number of obs     =     18,703

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(5)      =    1331.35
Log likelihood =  -9329.066                     Prob > chi2       =     0.0000
------------------------------------------------------------------------------
          h1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         b2b |   .0040519    .001068     3.79   0.000     .0019585    .0061452
          b7 |   .0089589   .0017994     4.98   0.000     .0054322    .0124857
    size_num |   .0026428   .0008397     3.15   0.002     .0009969    .0042887
          h8 |   1.801268   .0520165    34.63   0.000     1.699318    1.903219
  bothcredit |    .441303   .1082959     4.07   0.000      .229047    .6535591
       _cons |  -1.582865   .2385206    -6.64   0.000    -2.050357   -1.115374
-------------+----------------------------------------------------------------
country      |
   var(_cons)|   .9835356   .3336539                      .5058586    1.912278
------------------------------------------------------------------------------
LR test vs. logistic model: chibar2(01) = 1972.64     Prob >= chibar2 = 0.0000

-----------------------------------------------------------------------------
       Model |        Obs  ll(null)  ll(model)      df         AIC        BIC
-------------+---------------------------------------------------------------
  NIndiaBoth |     18,703         .  -9329.066       7    18672.13   18726.99
-----------------------------------------------------------------------------
```

Model 20. Resampled - ROSCA-credit*Money market quality

melogit h1 b2b b7 size_num h8 k8 i.zdummy##c.C_QUA if country!="India2014"|| country:, nogroup

estimates store NIndiaH3

lrtest NIndiaH3 NIndiaSimple, stats

```
Mixed-effects logistic regression               Number of obs     =     18,703

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(8)      =    1379.86
Log likelihood =  -9296.168                     Prob > chi2       =     0.0000

------------------------------------------------------------------------------
          h1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         b2b |   .0041902   .0010696     3.92   0.000     .0020937    .0062867
          b7 |   .0088977   .0018044     4.93   0.000     .0053612    .0124343
    size_num |   .0016774   .0008508     1.97   0.049     9.83e-06     .003345
          h8 |   1.774839   .0521774    34.02   0.000     1.672574    1.877105
          k8 |    .378405   .0454686     8.32   0.000     .2892882    .4675218
    1.zdummy |    .191594   .0745062     2.57   0.010     .0455645    .3376236
       C_QUA |   .0021591     .01386     0.16   0.876     -.025006    .0293242
             |
     zdummy#|
     c.C_QUA |
          1  |  -.0069543   .0042426    -1.64   0.101    -.0152696     .001361
             |
       _cons |  -1.670612    .241687    -6.91   0.000     -2.14431   -1.196914
-------------+----------------------------------------------------------------
country      |
   var(_cons)|   .9599883   .3260495                      .4933608    1.867959
------------------------------------------------------------------------------
LR test vs. logistic model: chibar2(01) = 1522.39     Prob >= chibar2 = 0.0000

Likelihood-ratio test                                 LR chi2(2)  =      2.69
(Assumption: NIndiaSimple nested in NIndiaH3)         Prob > chi2 =    0.2606

Akaike's information criterion and Bayesian information criterion

-----------------------------------------------------------------------------
       Model |        Obs  ll(null)  ll(model)      df         AIC        BIC
-------------+---------------------------------------------------------------
NIndiaSimple |     18,703         .  -9297.513       8    18611.03   18673.72
    NIndiaH3 |     18,703         .  -9296.168      10    18612.34    18690.7
-----------------------------------------------------------------------------
```

Overview log odds models (relevant results)

Log odds relevant results per sample			Full sample	Full sample	Resampled	Full sample	Resampled
		VARIABLES	8	11	16	3	19
Controls		Foreign ownership	0.004***	0.004***	0.004***	0.004***	0.004***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
		Managerial experience	0.010***	0.010***	0.009***	0.010***	0.009***
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
		Firm size	0.002**	0.002**	0.002*	0.003***	0.003**
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
		R&D	1.757***	1.757***	1.775***	1.771***	1.801***
			(0.039)	(0.039)	(0.052)	(0.038)	(0.052)
Firm level	H1A	Formal credit use	0.260***	0.260***	0.380***		
			(0.036)	(0.036)	(0.045)		
	H2A	ROSCA-credit use	0.142*	0.141*	0.270**		
			(0.064)	(0.064)	(0.092)		
	H4	Use of both forms of credit				0.454***	0.441***
						(0.098)	(0.108)
Country level		Trust	-0.451*	-0.241			
		Standardized	(0.181)	(0.174)			
	±	Performance orientation		1.482**	1.819***		
		Cultural practice		(0.565)	(0.551)		
Interactions	H1C	Formal credit*Market quality	-0.005*	-0.005*			
			(0.002)	(0.002)			
	H2B	ROSCA-credit*Trust			0.175*		
					(0.087)		
		Constant	-1.790***	-10.532**	-12.478***	-1.583***	-1.583***
		[fixed effect]	(0.204)	(3.335)	(3.277)	(0.226)	(0.239)
		Constant	0.687**	0.498**	0.599**	0.937**	0.984**
		[random effect variance]	(0.228)	(0.168)	(0.206)	(0.310)	(0.334)

Standard errors in parentheses. Colored hypotheses have support (green), mixed support (orange), or no support (red).

Colors per model indicate support (green) or no support (red) for variable and associated hypothesis

Fields colored red without value, indicate variable was discarded in a previous iteration because of insignifance

*** p<0.001, ** p<0.01, * p<0.05

± Variable used in robustness assessment

Observations full sample (resampled)	25681 (18,703)	
Number of groups full sample (resampled)	19 (18)	
No significant effects were found for	H1B	Model 4 & 14
	H3	Model 9 & 20